German Robots –

The Impact of Industrial Robots on Workers*

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Abstract

We study the impact of rising robot exposure on the careers of individual manufacturing workers, and the equilibrium impact across industries and local labor markets in Germany. We find no evidence that robots cause total job losses, but they do affect the composition of aggregate employment. Every robot destroys two manufacturing jobs. This accounts for almost 23% of the overall decline of manufacturing employment in Germany over the period 1994–2014, roughly 275,000 jobs. But this loss was fully offset by additional jobs in the service sector. Moreover, robots have not raised the displacement risk for incumbent manufacturing workers. Quite in contrast, more robot exposed workers are even more likely to remain employed in their original workplace, though not necessarily performing the same tasks, and the aggregate manufacturing decline is solely driven by fewer new jobs for young labor market entrants. This enhanced job stability for insiders comes at the cost of lower wages. The negative impact of robots on individual earnings arises mainly for medium-skilled workers in machine-operating occupations, while high-skilled managers gain. In the aggregate, robots raise labor productivity but not wages. Thereby they contribute to the decline of the labor income share.

JEL-Classification: J24, O33, F16, R11

Keywords: Robots, skill-biased technological change, labor market effects, Germany

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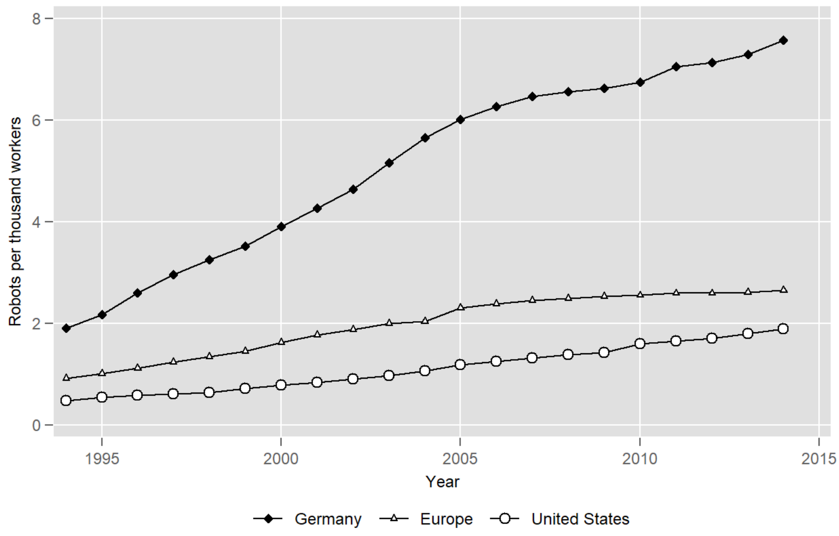
1 Introduction

The fear of an imminent wave of technological unemployment is again one of the dominant economic memes of our time. The popular narrative often goes as follows (see, e.g., Ford 2015; Broy and Precht 2017): As software and artificial intelligence advance, production processes (especially in manufacturing) become increasingly automated. Workers can be replaced by new and smarter machines – *industrial robots*, in particular – which are capable of performing the tasks formerly carried out by humans faster and more efficiently. The robots will therefore make millions of workers redundant, especially those with low and medium qualification, and re-shape society in a fundamental way.

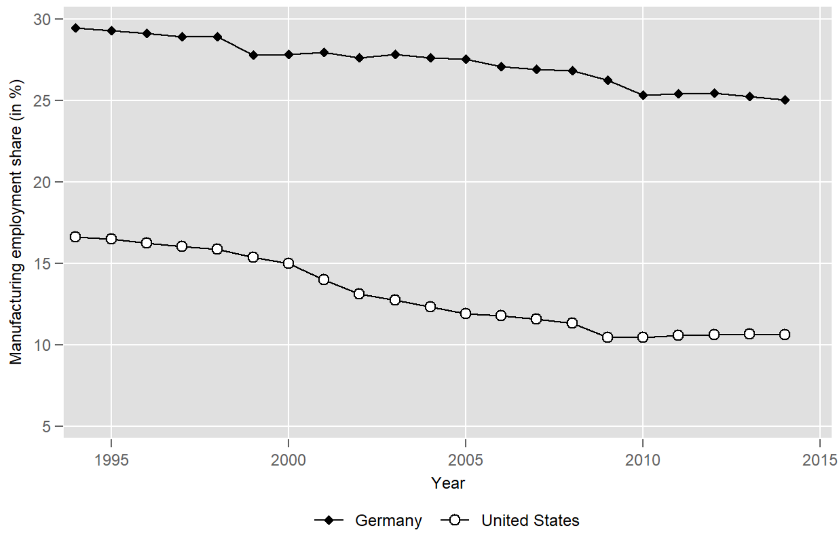
Various estimates have been suggested how many occupations are at risk of being automated given the type of work they usually conduct.[1] But until very recently, there has been surprisingly little work on the *actual* labor market effects of robots and other new technologies. A seminal contribution is the theory by Acemoglu and Restrepo (forthcoming), who show that this equilibrium impact hinges on the trade-off between two forces, dubbed the *displacement* and the *productivity* effect. Robots directly substitute workers when holding output and prices constant, but the resulting cost reductions also increase product and labor demand in the industries where they are installed. Moreover, workers may adapt to the new technology and specialize in complementary tasks. The total effect of robots on jobs is, thus, unclear a priori and ultimately an empirical question.

In this paper we investigate the impact of industrial robots in the German labor market over the period 1994–2014. Using linked employer-employee data, we trace employment biographies and earnings profiles of roughly one million manufacturing workers. This allows us to analyze if robots (and other technology and trade shocks) have causally affected their risk of job displacement and wages. We also study if workers have switched jobs within and across establishments, industries, and occupations in view of the new technology, and how robots have affected young people and returnees from unemployment in their decisions where to (re-)enter the job market. This analysis is, to the best of our knowledge, the first in the literature to address comprehensively how *individual workers* were affected by, and responded to, the rise of the robots. We also consider a complementary local labor market approach as in Acemoglu and Restrepo (2017), in order to quantify the aggregate equilibrium effect of robots on employment and wages.

[1] Frey and Osborne (2017) classify occupations based on their average task profiles and estimate that it would be technologically feasible to replace almost 50 % of all workers in the US by machines. The World Development Report (2016) arrives at a similar conclusion. Arntz et al. (2017) account for task specialization within occupations and put a substantially smaller share of jobs (only 9 %) at risk.



(a) Industrial robots.



(b) Manufacturing employment.

Figure 1: Robot installations and manufacturing employment share, 1994-2014

Notes: *Europe* = Germany, France, Italy, Spain, Finland, Sweden, Norway, UK. Number of employees in full-time equivalents (FTE). Employment data from the Establishment History Panel (BHP) for Germany, and from OECD.Stat (Organisation for Economic Co-Operation and Development) for the remaining European countries and the United States.
Source: International Federation of Robotics (IFR).

Germany is an interesting case to consider when it comes to the equilibrium effects of robots. This is for, at least, three reasons. First, robots are much more prevalent in Germany than in the United States and elsewhere outside Asia. Figure 1a shows that almost two industrial robots were installed per thousand workers in 1994, more than twice as many than in the European average and four times as many than in the US. Usage almost quadrupled over time in Germany, and now stands at 7.6 robots per thousand workers compared to only 2.7 and 1.6, respectively. But despite the fact that there are many more robots around, Germany is still among the world's major manufacturing powerhouses with an exceptionally large employment share. It ranges around 25% in 2014, compared to less than 9% in the US, and has declined less dramatically during the last 25 years (see Figure 1b).[2] Our analysis therefore elicits the causal effect of robots in an environment with many more of them installed in the manufacturing sector, and with many more manufacturing jobs per capita that could potentially be replaced.

Second, Germany is not only a heavy user but also an important engineer of industrial robots. The "robotics world rankings" list eight Japanese firms among the ten largest producers in the world; the remaining two (*Kuka* and *ABB*) have German origin and mostly produce in Germany. Among the twenty largest firms, five are originally German and only one (*Omron*) is from the US. This opens up a new labor market channel, namely direct job and wage gains in the robotic industry from increasing demand for robots, that may potentially be more relevant for Germany than for other countries except Japan.

The third reason to focus on Germany is practical. We merge detailed administrative German labor market data with the same data set on industrial robots that is also used by the two pioneering studies by Graetz and Michaels (2016) and Acemoglu and Restrepo (2017). It comes from the International Federation of Robotics (IFR) and reports the stock of industrial robots installed in different industries and countries over the period 1994-2014. Unlike for the US, that data is available for Germany over the entire observation period, thus allowing for more accurate measurement of robot exposure.

Main findings. Most importantly, we find no evidence that robots have reduced the total number of jobs or average wages in the German economy. The raw correlation between robots and employment or wage growth across local labor markets is even positive. But once local industry structures and demographics are taken into account, we obtain effects very close to zero, both in simple ordinary least square (OLS) regressions and when using robot exposures of other countries as instruments.[3]

Although robots do not affect total employment, they do have strongly negative impacts on *manufacturing* employment in Germany. We calculate that one additional robot

[2]Germany also has more robots per manufacturing worker than the United States (30 versus 18 in the most recent year 2014).

[3]This instrumental variable (IV) strategy follows Autor et al. (2013) and purges potential unobserved Germany-specific shocks that simultaneously affect robot adoption and employment outcomes across industries. See Section 3.3 for a detailed discussion.

leads to two manufacturing jobs less on average. This implies that roughly 275,000 full-time manufacturing jobs were destroyed by robots in the period 1994–2014, which corresponds to roughly 23% of the overall decline in manufacturing employment that is illustrated in Figure 1b above. But those sizable losses were fully offset by job gains outside manufacturing, most importantly in business services. In other words, robots have strongly changed the *composition* but not the aggregate *level* of employment in Germany.

These aggregate empirical findings raise the question how and through which channels robots affect single workers. To shed light on this issue, we turn to our novel approach that analyzes individual work biographies. We find – quite surprisingly – that workers from more robotized industries do *not* face a higher job displacement risk. They are even more likely to remain employed in their original firm. Robots have increased job stability, although some workers change the tasks they perform at the workplace. The negative equilibrium effect of robots on aggregate manufacturing employment, therefore, does not come from exits of incumbent workers. It is instead driven by smaller flows of labor market entrants. Put differently, robots do not destroy existing manufacturing jobs in Germany, but they induce firms to create fewer new jobs for young people. This, in turn, leads to a more rapid aging of workforces in more robotized industries.

For wages and earnings we find considerable heterogeneity at the individual level. Robot exposure causes notable on-the-job earnings gains for high-skilled workers, especially in scientific and management positions. But for low- and especially for medium-skilled manufacturing workers we find clear negative effects, particularly in machine-operating occupations. These empirical patterns are consistent with an insider-outsider view of the German labor market. The workers most vulnerable to the threat of automation (or unions and work councils on their behalf) seem to have accepted lower wages in return for job security. Firms kept those workers, possibly to secure their specific human capital and experience, and repositioned them at the workplace. But there were fewer new jobs for outsiders, as robots have effectively replaced those newcomers.

At the aggregate level we find that robots raise average productivity in the local labor market, but there is no such impulse on average wages or other labor income proxies. Total output net of wage costs increases, i.e., the new technology seems to benefit mostly capital owners and profit claimants, but not labor at large. Robots thus add to the recently documented fall of the labor share (Autor et al. 2017; Kehrig and Vincent 2017).

We conduct a battery of robustness checks and specification tests, including instrumental variable estimation, placebo regressions, sample splits, and so on. We pay special attention to the automobile industry, which is highly spatially concentrated and has by far the most industrial robots. And most importantly, we disentangle other major economic changes that occurred parallel to the rise of robots, namely international trade exposure from China and Eastern Europe,[4] and the adoption of information and communication technologies (ICT) as another form of technological change.

Related literature. Our article contributes to the recent literature on the labor market consequences of automation. In seminal theoretical work, Acemoglu and Restrepo (forthcoming) develop a model summarizing the interplay of two main forces: robots displacing human labor, and augmenting labor productivity. Their model also has implications for wage inequality, which is increasing if robots are closer substitutes to low-skilled workers, while high-skilled workers can adapt better to new and complex tasks.

In their pioneering empirical study on the labor market effects of robots across industries and countries, Graetz and Michaels (2016) find support for the importance of the productivity effect. They do not find evidence for total job displacements, but there is some indication for skill-biased wage effects: robots significantly reduce average wages for low-skilled workers, while the effects on other groups are less clear. Acemoglu and Restrepo (2017) use a regional difference-in-differences framework for local labor markets in the United States. They find that every robot leads to a total employment loss of 3–6 jobs. This evidence is, thus, more in line with displacement effects being the dominant force, as robots seem to reduce labor force participation in the US.

Our paper extends this literature in two different ways. First, we provide detailed evidence for Germany, which is one of the most heavily robotized countries in the world. Second, we complement the aggregate approach with novel evidence at the individual worker-level. This perspective is crucial to fully understand the role of robots in the labor market, because we find negative aggregate effects of robots on manufacturing employment, but no effects on the job stability of individual manufacturing workers.

Our paper is more generally related to the large literature on skill-biased technological change following Katz and Murphy (1992) and surveyed in Acemoglu and Autor (2011). Various studies have argued that technological progress has contributed to rising wage inequality and labor market polarization in advanced countries (e.g., Autor et al. 2003;

[4]In a seminal paper, Autor et al. (2013) find that American commuting zones more strongly exposed to Chinese imports have experienced major job and wage losses. For Germany, Dauth et al. (2014, 2017) argue that import shocks from China and Eastern Europe had only smaller adverse effects, which were more than offset by gains from rising export opportunities.

Autor and Dorn 2013; Goos et al. 2014). A large strand has focused particularly on the labor market effects of information and communication technology (Autor et al. 2003, Michaels et al. 2014, Akerman et al. 2015). We add to this literature by studying the detailed consequences of another particular form of technological change, robots. In line with the first evidence by Graetz and Michaels (2016), our analysis substantiates the observation that robots reduce wages for low- and especially for medium-skilled workers, but lead to notable wage gains for high-skilled workers. Thereby we provide micro-level evidence that robots are a form of *skill-biased technological change*. Our paper identifies those effects from the work biographies of individual workers, and this allows us to also shed light on the important question how workers adjust by moving across industries, occupations, and establishments in response to the new technology.

Our paper is also connected to a group of papers investigating variation in labor demand conditions and skill-bias across local labor markets (Moretti 2011, 2013). Similar as in the paper by Autor et al. (2015), our research design aims to disentangle trade and technology shocks. Relatedly, in a recent paper, Koren and Csillag (2017) show how the import of advanced machinery propagates skill-biased technical change. Finally, we investigate the aggregate impacts on productivity and wages and thereby relate to the recent literature on the fall of the labor share (Autor et al. 2017; Kehrig and Vincent 2017).

The rest of this paper is organized as follows. In Section 2 we introduce our data and give a descriptive overview. Section 3 describes our empirical approaches, and Section 4 studies the impact of robots on equilibrium employment across local labor markets. The impact on individual workers is discussed in Section 5. Section 6 turns to the aggregate impact on productivity and wages, and Section 7 concludes.

2 Data and descriptive overview

2.1 Robot data

Our main data set comes from the International Federation of Robotics (IFR) and reports the stock of robots for 50 countries over the period from 1994 to 2014.[5] A *robot* in this data is defined as an "automatically controlled, re-programmable, and multipurpose machine". As explained in more detail in International Federation of Robotics (2016), this means that robots are "fully autonomous machines that do not need a human operator and that can be programmed to perform several manual tasks such as welding, painting,

[5]This data set has been used before by Graetz and Michaels (2016) in a cross-country study at the industry-level and by Acemoglu and Restrepo (2017) in an analysis about US local labor markets.

assembling, handling materials, or packaging." Single-purpose machines such as elevators or transportation bands are, by contrast, no robots in this definition, as they cannot be reprogrammed to perform other tasks, and/or require a human operator.

The data is based on yearly surveys of robot suppliers, and captures around 90 percent of the world market. The information is broken down at the industry level, but data availability differs across countries.[6] For Germany coverage is comprehensive, and we arrange the IFR data to match the official industrial classification scheme of the German labor market.[7] This allows us to differentiate 53 manufacturing industries for which we observe the number of installed robots over the entire observation period. We also observe robots in 19 non-manufacturing industries from 1998 onwards. Appendix Table A.1 summarizes the information, and Figure 2 illustrates the change in the number of robots per thousand workers separately for the two decades in all 72 industries.

By far the strongest increase can be observed in the different branches of the automobile industry (motor vehicles, auto bodies and parts). Here, 60–100 additional robots are installed per thousand workers in 2014 compared to 1994. This increase took place mostly during the first, but continued during the second decade. Other industries that became vastly more robot-intensive include furniture, domestic appliances, and leather. On the other side of the spectrum we find cases where robot usage has hardly changed, and sometimes (e.g. in the watches and clocks industry) it even decreased over time. In non-manufacturing industries robots are used much less than in manufacturing.

2.2 Labor market data

2.2.1 Individual workers

Our second source are administrative German labor market data provided by the Institute for Employment Research (IAB) at the German Federal Employment Agency. In the individual-level analysis we use the Integrated Employment Biographies (IEB). This is a linked employer-employee spell data set, which allows us to follow single workers within and across establishments and occupations over time.[8]

[6]As Graetz and Michaels (2016), we do not use the IFR industries *all other manufacturing*, *all other non-manufacturing*, and *unspecified*. Those categories cover less than 5% of the total robot stock in Germany.

[7]The IFR data are reported according to ISIC Rev 4, and we adopt an official cross-walk by *Eurostat* to re-classify them to the German WZ 1993 scheme which mostly corresponds to NACE Rev 1. Details about the cross-walk are reported in Appendix A. In Section 4.3.4 we perform robustness checks and rearrange the German data to match the ISIC Rev 4 definition of the original robot data.

[8]We work with a 30% random sample of the IEB V12.00.00 - 2015.09.15., which covers the universe of all workers in Germany except civil servants and the self-employed. A spell is generated by any notification of the employer to the social security insurance, so any employment or earnings information we use has

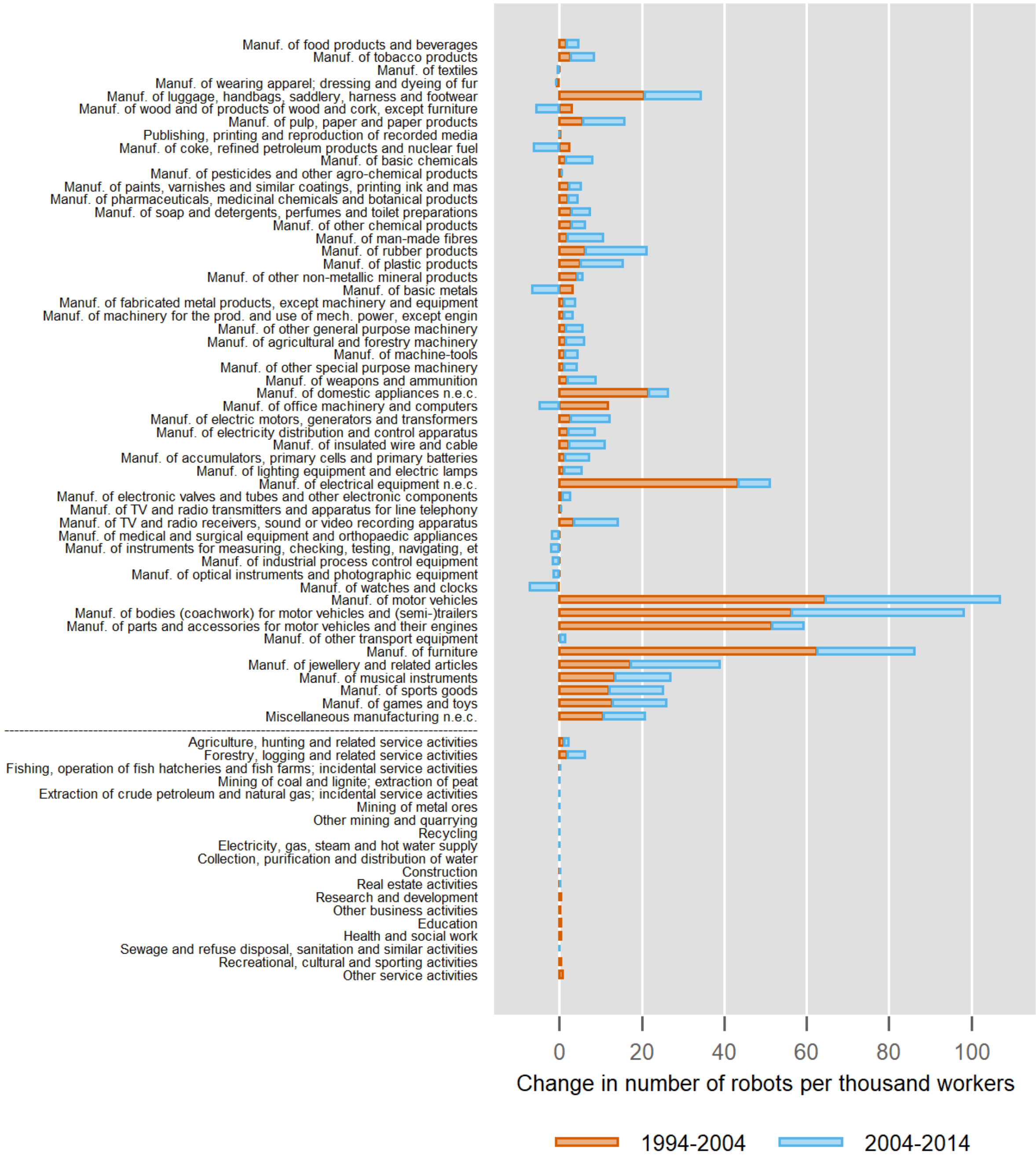


Figure 2: Industry-level distribution of robots

Notes: The figure displays the change in the number of robots per thousand workers by WZ 1993 industries (German Classification of Economic Activities, Edition 1993), for the two subperiods 1994-2004 and 2004-2014. Data for non-manufacturing industries in the first decade are only from 1998-2004. The IFR data are originally reported according to ISIC Rev 4, and we adopt an official cross-walk by *Eurostat* to re-classify them to the German WZ 1993 scheme (see Appendix A for more details).
Source: International Federation of Robotics (IFR).

We focus on incumbent manufacturing workers with strong labor force attachment. In particular, we identify all full-time employees with a recorded main job in a manufacturing industry on June 30 in the base year 1994, who are i) between 22 and 44 years old, ii) earned more than the marginal-job threshold, and iii) had job tenure for at least two years. We then trace the detailed employment biographies of those roughly 1 million workers over the subsequent twenty years.[9] In a complementary short-run approach, we split the observation period and construct analogous work biographies over ten years for all workers (age 22-54) starting out in manufacturing in 1994 or 2004, respectively.

The resulting data sets assign every worker to an establishment at any point in time, and therefore to a 3-digit industry and location where the respective employer is affiliated. We also observe the workers' occupations following the KldB 1988 standard classification. Whenever workers have non-employment spells in their job biographies, this may constitute unemployment, early retirement, or labor market exit, all of which are endogenous labor market outcomes. We treat those spells as periods with zero earnings and employment for the respective worker, and retain the previous establishment affiliation until a new job spell is recorded elsewhere. We also observe the profile of labor income for every worker. As the wage information is truncated at the social security contribution ceiling, we apply the imputation procedure by Card et al. (2013). Moreover, we convert all earnings into constant 2010- € using the consumer price index of the *Bundesbank*.

Appendix Table A.2 reports some descriptive statistics. Panel A shows that the average manufacturing worker was employed on 5,959 out of 7,305 possible days over twenty years, and started off with a daily wage of 120€ . The third line reports cumulative relative to the base year earnings. The average manufacturing worker in our sample has, thus, experienced a real earnings loss, because earnings in the 20-year time window only add up to 19.25 times the base year value. These trends are similar in the two separate 10-year-time windows. Panel B reports some standard individual characteristics of the manufacturing workers in our sample as recorded in the base year. Notice that roughly 9% hold a university-degree (high-skilled), while almost 76% have a completed apprenticeship (medium-skilled), and 15% have no formal qualification (low-skilled).

daily precision. The data is described in detail by Card et al. (2013) and Oberschachtsiek et al. (2009).

[9] The age limit of 44 years is chosen to rule out that workers in the sample reach the regular retirement age (65 years) during the sample period. We also eliminate those who died or moved to a different country.

2.2.2 Local labor markets

For the local labor market analysis we work with the Establishment History Panel (BHP) by the IAB, which covers the universe of all employees in the German labor market subject to social security. [10] We aggregate this data to the local industry level and distinguish 402 local labor markets (*Landkreise and kreisfreie Staedte*), which are roughly comparable to counties in the US. The data encompass both the former West and East Germany. For every district and for every year between 1994 and 2014, we have detailed information about the level and the composition of employment (in full-time equivalents), including the industry structure and the characteristics (age, gender, qualification, etc.) of the local workforces. Some descriptive statistics are reported in Appendix Table A.3.

We merge additional data from the Federal Statistical Office, which breaks down national accounts at this local level. The available information includes population size, total production (GDP), various income and productivity measures, and unemployment rates for every district and year during the observation period.[11]

2.3 Descriptive overview for robot exposure

The average manufacturing worker in our sample has experienced an exposure equal to Δrobots_j = 16.98 (see panel C in Appendix Table A.2). This equals the change in the number of installed robots per thousand workers over the period 1994-2014 in the industry, where the initial job was recorded in the base year. Notice the large variation across individuals. The worker at the $75th$ percentile has seen an increase in exposure that is almost three times larger than for the worker at the $25th$ percentile (9.6 versus 3.4 additional robots per thousand workers), and the comparison of the $90th$ and the $10th$ is even more dramatic (77.1 versus -1,7). This reflects the extremely skewed distribution of robot installation across industries that is illustrated in Figure 2 above.

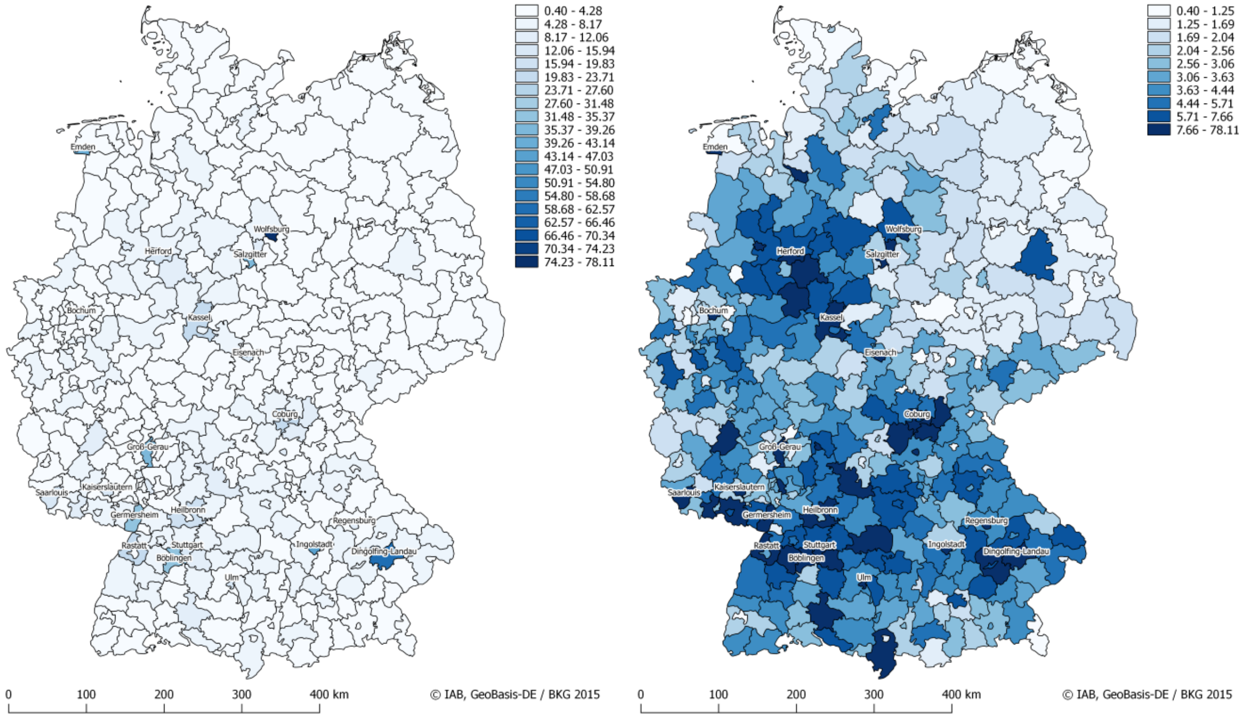
We also construct a measure of local exposure for every region r, namely a weighted average of Δrobots_j, with weights given by the share of employment in industry j in total local employment in the base year:

$$\Delta\text{robots}_r = \sum_{j=1}^{J} \left(\frac{\text{emp}_{jr}}{\text{emp}_r} \times \Delta\text{robots}_j \right) \qquad \text{with} \quad J = 72. \tag{1}$$

[10] A detailed description can be found in Spengler (2008).

[11] In some cases those data are not available for the entire observation period. See Section 6.

Some descriptives are reported in Appendix Table A.3, panel C. On average, local exposure has increased by 4.6 robots per thousand workers, but there is considerable variation across space which reflects the regions' industrial specialization patterns.



(a) Local robot exposure (20 equal intervals) (b) Local robot exposure (10 deciles)

Figure 3: Region-level exposure of robots, trade, and ICT.

Notes: The maps display the regional distribution of the change in the exposure to robots between 1994 and 2014 on the level of 402 German local labor markets. The colors in Panel A represent twenty groups with equal intervals of robot exposure. In Panel B the colors represent ten equally sized decile groups.

The map in panel A of Figure 3 shows that robot exposure has dramatically increased mainly in a few local labor markets. The two most extreme outliers are Wolfsburg and Dingolfing-Landau, which are essentially factory towns for *Volkswagen* and *BMW*, respectively. Exposure has increased by up to 78 robots per thousand workers there. In our empirical analysis we will pay attention to the special role of the automobile industry, and to these regions where automobile production is strongly concentrated. To make the variation better visible, we arrange the data in ten decile bins in panel B. This map indicates that robot exposure in East Germany tends to be lower, which reflects the smaller overall manufacturing share there. Outside the upper decile, we observe notable differences mostly within West Germany. Values range from close to zero in some places in the North up to 7.6 additional robots per thousand workers in other local labor markets.

2.4 Trade and ICT exposure

In our empirical analysis we disentangle robots from two other major economic shocks that affected Germany since the beginning of the 1990s. First, following Autor et al. (2013) and Dauth et al. (2014), we consider rising international trade with China and Eastern Europe. The idea is that some manufacturing branches in Germany saw strongly rising import penetration as China and Eastern Europe developed a comparative advantage after their sudden rises in the world economy, while for other German branches those new markets in "the East" primarily meant new export opportunities. Second, we consider investments in information and communication technologies (ICT) as a distinct form of technological change. Similarly to robots, ICT equipment may also replace some humans, while complementing the productivity of others, thus leading to heterogeneous wage and employment effects for different individuals.

For the measurement of trade exposure we closely follow Dauth et al. (2017), who compute the increase in German net exports vis-a-vis China and 21 Eastern European countries over the period 1994-2014 for every manufacturing industry j using COMTRADE data, normalized by the initial wage bill to account for industry size. For ICT, we exploit information about installed equipment at the industry-level as provided in the EUKLEMS database. It is defined as the change in real gross fixed capital formation volume per worker for computing and communications equipment from 1994-2014.[12]

In Appendix Table A.1 we report the trade and ICT exposures for all industries.[13] The correlation of robot and net export exposure within manufacturing is mildly negative (-0.09). Although the automobile industry stands out as a strongly export-oriented branch with high robot installations, we generally find that import-competing industries tended to install slightly more robots. For robots and ICT the correlation is small (0.04), mostly reflecting the fact that robots are pervasive in manufacturing while ICT investments have been stronger in services. The correlation between ICT and trade exposure is also small (0.05). Finally, we construct regional exposure measures for trade and ICT analogously to (1) and also find low correlations with local robot exposure.[14]

[12]We have also experimented with the alternative measure of ICT capital services provided by EUKLEMS and used in Michaels et al. (2014). We prefer the equipment measure, however, since capital services involve information on rental prices which necessitate assumptions on the rates of return of capital stocks.

[13]Notice that trade exposure is not available for service industries, since the COMTRADE database is confined to manufacturing only. It is possible to construct broader trade exposure measures that encompass services, see Dauth et al. (2016), but we stick to the simpler approach here.

[14]In Appendix Figure A.1 we depict scatter plots of local robot and trade/ICT exposures. At the regional level, the correlations tend to be opposite to what we find at the industry-level. But this is strongly driven by the few automobile regions, which are strongly export- and robot-oriented but have installed little ICT

These low correlations suggests that we capture three types of industry-shocks in our empirical analysis that have been largely orthogonal to each other.

3 Estimation approach

In this section we describe our empirical approaches, discuss identification issues and the instrumental variable strategy, and present results for the first-stage.

3.1 Worker-level analysis

We start with our novel worker-level analysis. For each worker i starting out in a manufacturing industry in 1994, we add up all days in employment and all labor earnings over the subsequent twenty years, irrespective of where they accrued, and divide earnings by the respective base-year value. We then regress this (normalized) cumulated individual labor market outcome Y_{ij} on the increases in the number of installed robots in the worker's *initial* industry j during the respective time period:

$$Y_{ij} = \boldsymbol{\alpha} \cdot \mathbf{x}'_{ij} + \beta_1 \cdot \Delta\text{robots}_j + \phi_{REG(i)} + \phi_{J(j)} + \epsilon_{ij} \tag{2}$$

In the vector $\mathbf{x}'_{ij}$ we include standard worker-level controls, namely dummies for gender, foreign nationality, three skill categories, three tenure categories, two age and six plant size groups. We also include dummies $\phi_{J(j)}$ for four broad manufacturing industry groups, and $\phi_{REG(i)}$ for Federal States. We cluster standard errors by industry $\times$ state.[15]

The main idea behind this approach is that the workers' initial industry affiliations are orthogonal to the subsequent rise in robot exposure. In other words, we assume that workers have not systematically sorted into particular industries prior to the base year in anticipation of the future technology trends. The empirical model (2) then uncovers the long-run impact of this industry shock that persists in the workers' biographies even after they may have adapted by switching to different jobs.[16]

Afterwards we decompose Y_{ij} into several additive parts, and study if rising robot exposure has led to systematic job mobility. More specifically, we start with the industry dimension and analyze if robot exposure causes job switches to other firms within

equipment owing to their low service shares. Those correlations become substantially smaller once we eliminate the regional outliers or condition on the local manufacturing shares.

[15] In the analogous short-run approach we follow workers only for ten years, and stack the two time periods while adding a dummy to differentiate the two decades.

[16] A similar approach has been developed by Autor et al. (2014) to study the worker-level impacts of trade shocks.

the original industry, to a different manufacturing industry, or out of the manufacturing sector altogether. Similarly, we analyze if robot exposure induces workers to switch occupations within or across employers. This approach allows us to analyze if and how individual manufacturing workers have adjusted to the rise of the robots.

Finally, we extend the specification and include the industry-level exposures to net exports (from China and Eastern Europe) and ICT as introduced above,

$$Y_{ij} = \boldsymbol{\alpha} \cdot \mathbf{x}'_{ij} + \beta_1 \cdot \Delta\text{robots}_j + \beta_2 \cdot \Delta\text{trade}_j + \beta_3 \cdot \Delta\text{ICT}_j + \phi_{REG(i)} + \phi_{J(j)} + \epsilon_{ij}, \quad (3)$$

in order to disentangle the rise of the robots from other trade and technology shocks.

3.2 Local labor market approach

The aggregate approach stays as close as possible to Acemoglu and Restrepo (2017), in order to facilitate a comparison of results. Here we regress the change in a local outcome variable (such as total employment, manufacturing employment, the employment-to-population ratio, output per worker, etc.) over the period 1994-2014 on the change in the number of robots per worker, i.e., on Δrobots_r as defined in (1):

$$\Delta Y_r = \boldsymbol{\alpha} \cdot \mathbf{x}'_r + \beta_1 \cdot \Delta\text{robots}_r + \beta_2 \cdot \Delta\text{trade}_r + \beta_3 \cdot \Delta\text{ICT}_r + \phi_{REG(r)} + \epsilon_r \quad (4)$$

In the vector $\mathbf{x}'_r$ we control for standard demographic characteristics of the local workforces (such as age, gender, and qualification), and for the employment shares of nine broadly defined industry groups as reported in Appendix Table A.3. Moreover, we add four broad region dummies to purge the estimates of systematic regional differences, and we add the local exposures to net exports and ICT in some specifications.

3.3 Identification strategy

3.3.1 Fixed effects specification

Some important identification issues arise in both empirical approaches. First, confounding long-run trends could bias our results. In particular, some industries may have been on a declining (or growing) trend well before the 1990s. When robot exposure started to increase, this may not have causally affected workers, but the rising robot installations could be symptoms of the previous industry-specific trajectories. To address this concern, we identify all effects *within* broad industry groups by adding the fixed effects $\phi_{J(j)}$ in our individual-level analysis. Thereby we purge the estimates of differential long-run trends across groups. Similarly, in the aggregate approach we identify the effect of robot exposure conditional on local demographic characteristics and broad industrial structures. Second, to further investigate if unrelated industry trends drive our results, we conduct placebo tests to analyze if past employment growth predict future robot adoptions.

Moreover, one might worry about confounding region-specific trends, since the German reunification and the associated economic changes took place just before the start of our observation period. We therefore identify all effects *within* Federal States, or alternatively add the broad location dummies to capture systematic regional differences.[17]

3.3.2 Instrumental variable estimation

Although these fixed effects already purge certain trends in OLS estimations, there may still be the concern that β_1 only captures a causal effect when there are no parallel unobservable shocks that simultaneously affect robot installations and labor market outcomes.

To address this concern, we adopt an identification strategy similarly as in Autor et al. (2013) and use robot adoptions across industries in other high-income countries as an instrument for German robot exposure. More specifically, we deflate the robot installations across the same set of industries j in each of those k countries with German industry-level employment in j from 1984 to construct k instrumental variables for Δrobots_j. The instruments for local exposure, Δrobots_r, are analogous and also use lagged employment figures from ten years prior to the base period.[18]

The rationale for this strategy is that all countries are exposed to a world-wide technology trend – the rise of the robots – but face potentially different domestic changes, including demographic trends and demand shocks, that may also affect robot installations. When those independent changes are uncorrelated across countries, the instrument purges unobserved Germany-specific shocks and isolates the causal impact of the technological change on labor market outcomes. Moreover, by deflating with lagged employment, we tackle reverse causality issues since those levels are not affected by robots.

For the selection of the "instrument group" we focus on such countries where robot data is available as comprehensively as for Germany. These are Spain, France, Italy, the United Kingdom, Finland, Norway, and Sweden. We do not use Japan, even though robot usage has increased even more heavily there than in Germany, because of major

[17] As a further robustness check we also exclude East Germany entirely and focus only on West German manufacturing workers, but the results turn out to be very similar as in our baseline approach.

[18] In the baseline specification of the two-stage least squares (2SLS) IV approach we use all k instruments and estimate an over-identified model. In a robustness check, we also aggregate the robot exposures of all k countries to build a single instrument in a just identified 2SLS model.

re-classifications in the original IFR data.[19] We also do not use North America (the US and Canada), because the industry breakdown is only available from 2004 onwards.

Finally, when including trade and ICT exposure in the regressions, we also treat them as endogenous variables and construct analogous instruments by using third-country exposures and lagged German employment levels.[20]

3.3.3 First-stage results

Figure A.2 in the Appendix shows our first-stage results. Panels (a) and (b) pertain to the individual-level analysis and plot the actual change in robot installations across industries against predicted changes from the fitted values of our first-stage regression. As can be seen, the instrument is very powerful as the industry-level pattern of robot usage in other countries is a strong predictor for the pattern observed in Germany. This is true in a basic specification of the first-stage regression where we only add demographic controls, but also when we include the full set of controls as described in Appendix Table A.2.

Panels (c) and (d) analogously show the first-stage results for local robot exposure. Both in a simple specification with broad location dummies only, and in the full specification with all controls, we find that the pattern of robot installations in the instrument countries is a strong predictor for robot exposure across German regions.

The figure already suggests that weak instrument bias is unlikely to be a major concern. This is corroborated by the large F-Statistics for joint significance of the robot exposure in other countries in the first-stage, which are well beyond the critical values of 10 suggested by Stock et al. (2002). The Kleibergen-Paap rk LM statistics for weak identification of the robot exposure also remain above their critical values, even in the specifications with multiple endogenous variables.

4 The impact of robots on local labor markets

This section summarizes our empirical findings. We start with the local labor market approach, because we can directly compare our results for Germany with previous results for the United States. Afterwards we turn to our novel individual-level analysis, which provides detailed evidence how single workers have responded to the rise of the robots.

[19] Until 2000, Japan reported data on both multipurpose industrial robots and dedicated industrial robots. After 2000, Japan's data only covered multipurpose industrial robots, as it was already the case for the other countries in the entire observation period (International Federation of Robotics, 2016).

[20] The rationale for the instrument for trade exposure follows the seminal approach by Autor et al. (2013) and our specification closely follows Dauth et al. (2017). The instrument for ICT exposure is constructed analogously to robot exposure, but Norway is not in the instrument group because of missing data.

4.1 Total local employment and average wages

Table 1 reports how robot exposure has affected total local employment growth, which we measure by the change in log total employment in region r between 1994 and 2014.[21] The upper panel shows OLS results, and the lower panel the analogous IV estimations.

Column 1 starts with a simple specification where we only include robots and the broad location dummies in the regression. We find a positive coefficient for robot exposure both in the OLS and in the IV estimation, i.e., regions with more robot installations tended to have higher total employment growth. The effect becomes even stronger when we condition on the local manufacturing employment shares as in column 2.[22] But once we include standard demographic characteristics of the local workforces in the regressions, see column 3, we find that the coefficient for robot exposure shrinks by a factor of ten, almost down to zero, and turns insignificant. This finding reflects that robot installations covary with other characteristics that are positively associated with local employment growth. More specifically, the detailed results in Appendix Tables A.4 and A.5 show that growth tends to be higher in regions with a larger share of highly educated, young and foreign workers, all of which are also positively correlated with robot exposure. Once we control for those omitted factors, we no longer find any significant impact of robots on employment growth, neither in OLS nor in IV estimations.

In column 4 we investigate direct labor market effects of robotic production. As argued in the introduction, Germany is not only a heavy user but also an important engineer of industrial robots. In Appendix Table A.6 we report the 20 largest robot producers according to the IFR "robotics world rankings". Eight of those firms are based, or run major facilities in Germany. We have contacted those firms and received consistent information about the location of headquarters for the five German firms, and respectively, about the location of production within Germany for the three remaining firms whose headquarters are registered in Switzerland or Austria. Detailed information about the number of employees in those plants is unfortunately not available, but as a proxy we construct a dummy variable for those local labor markets which host a major robotic production facility.[23] The results in column 4 of Table 1 do not show stronger growth in those locations; if anything, the effect is even negative. This finding may simply be driven by the

[21] The complete results for all control variables are shown in Appendix Tables A.4 and A.5.

[22] The explanation is simple. Recall that robots are mainly installed in manufacturing industries (see Figure 2), so that local robot exposure correlates with the local manufacturing share. Yet, the latter is negatively correlated with the outcome variable as job growth tends to be stronger in services.

[23] These are the districts of Augsburg, Mannheim, Nuremberg, Bayreuth, Chemnitz, Ludwigsburg, Fulda, Maerkischer Kreis, and Lahn-Dill-Kreis. See Appendix Table A.6.

Table 1: Robot exposure and employment.

	Dependent variable: 100 x Log-△ in total employment between 1994 and 2014							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: OLS							
△ robots per 1000 workers	0.2324**	0.3637***	0.0416	0.0332	0.0328	0.0243	-0.0005	-0.1025
	(0.095)	(0.106)	(0.126)	(0.125)	(0.126)	(0.123)	(0.132)	(0.172)
dummy, 1=robot producer				-4.8877	-4.2592	-4.2083	-3.9931	-4.1504
				(4.350)	(4.519)	(4.562)	(4.652)	(4.626)
△ net exports in 1000 € per worker						0.1956	0.2375	0.2161
						(0.242)	(0.242)	(0.249)
△ ICT equipment in € per worker							-0.0163	-0.0166
							(0.017)	(0.017)
R^2	0.432	0.439	0.541	0.543	0.623	0.623	0.625	0.623
	Panel B: 2SLS							
△ robots per 1000 workers	0.2410**	0.3845***	0.0399	0.0344	0.0139	-0.0227	-0.0058	-0.0848
	(0.095)	(0.105)	(0.124)	(0.124)	(0.128)	(0.121)	(0.120)	(0.150)
dummy, 1=robot producer				-4.8847	-4.3063	-4.1351	-4.2004	-4.2992
				(4.250)	(4.365)	(4.533)	(4.467)	(4.464)
△ net exports in 1000 € per worker						0.7123**	0.6232*	0.5975
						(0.359)	(0.370)	(0.376)
△ ICT equipment in € per worker							0.0046	0.0027
							(0.015)	(0.014)
Broad region dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Manufacturing share	No	Yes	Yes	Yes	No	No	No	No
Demographics	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Broad industry shares	No	No	No	No	Yes	Yes	Yes	Yes
Exclude top auto regions	No	No	No	No	No	No	No	Yes

Notes: $N = 402$ local labor market regions (*Landkreise und kreisfreie Staedte*). We are interested in the impact of the change in robot exposure between 1994 and 2014 on the log-difference in total employment. All regressions include a constant. The specification in column (1) only includes broad region dummies indicating if the region is located in the north, west, south, or east of Germany. Columns (2) and (3) successively add regional control variables that are measured in the base year (i.e. 1994) and are constructed as the number of workers in a particular group relative to total employment. Column (2) adds the manufacturing share (i.e. manufacture of food products, consumer goods, industrial goods, and capital goods), and column (3) adds demographic controls. Demographic controls contain % female, % foreign, % age $\geq$ 50, % medium skilled (percentage of workers with completed apprenticeship), and % high skilled (percentage of workers with a university-degree). Column (4) additionally includes a dummy variable indicating if a robot producer is located in the respective region (see Table A.6 for an overview). In column (5), instead of the manufacturing share, broad industry shares are included to control better for regional industry patterns. 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) in the base year 1994. Column (6) includes the change in German net exports vis-a-vis China and 21 Eastern European countries (in 1000 € per worker), and column (7) adds the change in ICT equipment (in € per worker), both between 1994 and 2014. Column (8) drops the German regions with the highest automobile shares (Wolfsburg and Dingolfing-Landau). Panel A reports results of ordinary least squares (OLS) regressions. Panel B reports results of a two-stage least squares (2SLS) IV approach. German robot exposure is instrumented with robot installations across industries in other high-income countries. Similarly, in columns (6)-(8), the changes in net exports vis-a-vis China and Eastern Europe and ICT equipment are instrumented with the analogous trade-flows and industry-level investments in ICT of other high-income countries, respectively. Standard errors clustered at the level of 50 aggregate labor market regions in parentheses. Levels of significance: *** 1 %, ** 5 %, * 10 %.
Sources: IFR, COMTRADE, EUKLEMS, and IEB V12.00.00 - 2015.09.15, own calculations.

rough measurement of robotic production, or by the small overall size of the robotic industry. But we tentatively conclude that direct employment gains from the concentration of robotic production seem to be absent, possibly reflecting the fact that robot production is itself not very labor-intensive.

Next, in column 6 we add local net export exposure with China and Eastern Europe to the list of controls. This is important, because Germany is a strongly export-oriented economy. Foreign demand for German manufacturing goods vastly increased during the observation period. If export intensive industries also rely more heavily on robots, this might actually alleviate possible job losses from technological change. Conversely, robots might have lowered production costs and thus spurred demand for German products. In either case, by conditioning on local trade exposure, one might thus expect that the effect of robots on jobs could become more negative. However, we find no evidence that this is actually the case. First, as in Dauth et al. (2014, 2017), we find a positive impact of net export exposure on local employment growth, especially in the IV estimation where third-country trade flows are used as instruments. We thus corroborate their finding that local labor markets with a more export-oriented industry structure exhibited stronger subsequent growth. The coefficient for robot exposure decreases slightly in the lower panel, but it remains close to zero and statistically insignificant. In other words, the technology shock from robots and the trade shock from the rise of China and Eastern Europe seem to have affected German local labor markets in a fairly orthogonal manner.[24]

Adding local ICT exposure, as in column 7, we find that stronger local investments in ICT do not seem to have notable employment effects per se, since the respective coefficients are small and insignificant in both panels. Moreover, the central coefficients for robot exposure are also unaffected, reflecting the small correlation between robots and ICT across industries and local labor markets that we have documented above.

Our estimations have so far controlled for the overall local manufacturing shares in the base year. But there may be more fine-grained industry trends within the manufacturing sector, which are correlated with employment outcomes and robot installations. To address this issue, we now use the initial employment shares of nine industry groups instead of the overall manufacturing share. Thereby we condition our estimates on more detailed local employment compositions, which in turn purges the coefficients from possibly confounding industry trends. The results in column 8 remain very similar, however,

[24]This conclusion is also corroborated by the small correlation shown in Appendix Figure A.1 that is solely driven by the few regions with strong concentration of the automobile industry.

especially in the IV approach. Finally, we drop the two major outliers (Wolfsburg and Dingolfing-Landau) where vastly more robots are installed than in any other German region, because of their strong focus on automobile production (see Figure 3). Column 8 shows that our key results are not driven by those outliers. In particular, the coefficient for robot exposure hardly changes and remains insignificant.[25]

Table 2: Robot exposure and average wages.

	Dependent variable: 100 x Log-△ in average wages between 1994 and 2014							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: OLS							
△ robots per 1000 workers	0.1684***	0.1164***	0.0485	0.0460	-0.0136	-0.0178	-0.0262	-0.0181
	(0.032)	(0.037)	(0.042)	(0.043)	(0.050)	(0.050)	(0.051)	(0.071)
dummy, 1=robot producer				-1.4864*	-1.4220*	-1.3931*	-1.3182	-1.3116
				(0.842)	(0.774)	(0.808)	(0.829)	(0.836)
△ net exports in 1000 € per worker						0.0960	0.1100*	0.1137*
						(0.065)	(0.064)	(0.066)
△ ICT equipment in € per worker							-0.0056	-0.0056
							(0.004)	(0.004)
R^2	0.583	0.584	0.587	0.587	0.589	0.589	0.589	0.589
	Panel B: 2SLS							
△ robots per 1000 workers	0.1677***	0.1122***	0.0413	0.0399	-0.0100	-0.0185	-0.0360	-0.0238
	(0.036)	(0.043)	(0.048)	(0.048)	(0.054)	(0.053)	(0.057)	(0.083)
dummy, 1=robot producer				-1.5009*	-1.4132*	-1.3606	-1.2458	-1.2376
				(0.839)	(0.769)	(0.843)	(0.882)	(0.891)
△ net exports in 1000 € per worker						0.1799**	0.2144***	0.2206***
						(0.087)	(0.082)	(0.086)
△ ICT equipment in € per worker							-0.0090	-0.0086
							(0.006)	(0.006)
Broad region dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Manufacturing share	No	Yes	Yes	Yes	No	No	No	No
Demographics	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Broad industry shares	No	No	No	No	Yes	Yes	Yes	Yes
Exclude top auto regions	No	No	No	No	No	No	No	Yes

Notes: $N = 7149$. We are interested in the impact of the change in robot exposure between 1994 and 2014 on the log-difference in average wages. Average wages are computed within local labor market region x demographic cells, while the latter are defined by gender, three age groups, and three education groups. We only include cells containing at least 10 observations, and perform the regressions at the region x demographic cell level including fixed effects for gender, age groups and education groups. See Table 1 for a description of control variables. Panel A reports results of ordinary least squares (OLS) regressions. Panel B reports results of a two-stage least squares (2SLS) IV approach. German robot exposure is instrumented with robot installations across industries in other high-income countries. Similarly, in columns (6)-(8), the changes in net exports vis-a-vis China and Eastern Europe and ICT equipment are instrumented with the analogous trade-flows and industry-level investments in ICT of other high-income countries, respectively. Standard errors clustered at the level of local labor markets in parentheses. Levels of significance: *** 1 %, ** 5 %, * 10 %. Sources: IFR, COMTRADE, EUKLEMS, and IEB V12.00.00 - 2015.09.15, own calculations.

In Table 2 we repeat the analysis using the change in local average wages as the outcome variable. The results by and large mirror the employment effects from Table 1. That is, we find a positive effect of robots on average wages in simple regressions, but this stems from an omitted variable bias. The effect disappears once we condition on the characteristics of the local workforces. Higher net export exposure raises local wages,

[25]Below we consider further robustness checks to shed light on the special role of the automobile sector.

while there are no wage effects from ICT. Again we find that those shocks are orthogonal to robot exposure, because our central coefficient hardly changes when including the additional controls. Finally, our key finding that local robot exposure has no effect on average wages stays intact when conditioning the estimates on more fine-grained local industry structures and when dropping outlier regions.

Summing up, there is no evidence that rising robot exposure causes negative aggregate employment or wage effects in Germany, quite in contrast to previous findings for US local labor markets. In other words, our evidence does not support the claim that robots have been major job or wage killers, at least not during the period 1994-2014.

4.2 Manufacturing versus non-manufacturing employment and wages

In Table 3 we investigate the impact of robots on local employment and wage growth inside and outside manufacturing, respectively. For brevity, we only present results for the full IV specification (column 7 in panel B of Tables 1 and 2) from now on, and focus on the central coefficient for robot exposure.[26]

In panel A of Table 3 we first repeat the coefficient for the overall impact that we have seen before, and columns 2 and 3 show how this zero effect comes about. We find a strongly significant and negative effect of robots on manufacturing, but a positive effect on non-manufacturing employment growth. In other words, robots seem to have no effect on the overall *level*, but on the sectoral *composition* of employment because job losses in manufacturing are fully offset by additional jobs outside manufacturing.

The pattern for average wages is similar. Column 4 reminds us that robots have no impact on average regional wages, but they do affect sectoral wage growth as shown in columns 5 and 6. In particular, robots seem to decrease average manufacturing wages but they increase non-manufacturing wages. We postpone the detailed discussion of those wage patterns to Section 6, where we relate them to our findings how individual-level wages and earnings are affected by robots.

4.2.1 Quantitative benchmarking and comparison to the United States

In panel B we consider the change in the employment-to-population ratio in region r. This specification of the outcome variable in column 1 follows Acemoglu and Restrepo (2017) and allows us to directly compare results. Moreover, in columns 2 and 3 we analogously compute the change in the ratio of local sectoral employment over population.

[26]The detailed results for the other control variables are available upon request from the authors.

Table 3: Manufacturing versus non-manufacturing industries.

	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			
[C] Placebo check: 100 x Log-△ in employment (average wages) between 1984 and 1994						
△ 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: In all regressions, 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. Demographic cells are defined by gender, three age groups, and three education groups. We only include cells containing at least 10 observations, and perform the regressions at the region x demographic cell level including fixed effects for gender, age groups, and education groups. Columns (1) to (6) display estimates for total employment, employment in manufacturing, employment in non-manufacturing, total average wages, average wages in manufacturing, and average wages in non-manufacturing, respectively. 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 full set of control variables as in column (7) of Table 1 respectively Table 2. 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 %.

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

For the United States, Acemoglu and Restrepo (2017) estimate that one more robot per thousand workers reduces the employment-to-population ratio by 0.37 percentage points (see their Table 5, panel B, column 4). Considering that the average employment-to-population ratio is 0.6 in the US, this implies that one robot reduces the total number of jobs by 6.2 $(= 0.37/100 \times 1000/0.6)$. Our analogous specification in column 1 of panel B in Table 3 shows that the marginal effect of robot exposure on the total employment-to-population (-0.0190) is much weaker in Germany, in fact, it is statistically indistinguishable from zero. Hence, we find no evidence that robots cause overall job losses.

Column 2 in panel B confirms that robots cause significant employment losses in *manufacturing*, and we can use this estimate for an analogous quantitative benchmarking. In particular, one more robot per thousand workers reduces the manufacturing employment-to-population ratio by 0.0595 percentage points. Taking into account that the average ratio at the beginning of our observation period is 0.2812, this means that one more robot causes a loss of 2.12 $(= 0.0595/100 \times 1000/0.2812)$ manufacturing jobs.

To put this number into perspective, consider that a total stock of 130,428 robots has been installed in Germany over the period 1994–2014. A quick back-of-the-envelope calculation therefore implies a loss of 276,507 manufacturing jobs. Bearing in mind that manufacturing employment in Germany has declined by 1.2 million (from roughly 7 million full-time equivalent jobs in 1994 to 5.8 million in 2014), see Figure 1b above, this means that robots have been responsible for around 23% of this overall decline.[27] This is quite a sizable impact, given that robots are just one dimension of technological change.[28]

But recall that robots have not reduced the *total* number of jobs in the German economy, i.e., the loss in manufacturing is fully offset by job gains elsewhere.[29] What types of non-manufacturing jobs grow in more robot-exposed local labor markets? In Appendix Table A.9 we decompose non-manufacturing employment growth into different branches, and find that the overall impact is mostly driven by business services while for other types of jobs, including the public sector, we find no clear patterns.

Acemoglu and Restrepo (2017) also find that robots had more adverse effects within US manufacturing, see their Figure 10, but employment and wage losses arose even in other industries. In Germany, we find no such negative spillovers, but offsetting positive effects in non-manufacturing. Our worker-level analysis will offer insights why this different equilibrium response may have occurred. We discuss this in Section 7.

4.2.2 Placebo test

In panel C of Table 3 we conduct a placebo test to investigate if pre-trends could bias our results. In particular, some manufacturing industries may have been on an downward trajectory already prior to the base period. If those industries installed more robots in order to save labor costs, we would expect to see a negative effect of robots on manufacturing employment even in absence of a causal effect. The coefficients for robots on manufacturing employment could then be biased downwards.

Our instrumental variable approach should already mitigate this concern, at least to the extent that the instrument countries do not face the same trend. But to further address this issue, we now regress lagged employment growth (1984-1994) on robot exposure 1994-2014, to check if past trends predict future robot installations. The results in panel C

[27] We will provide a quantitative benchmarking of wage effects in our individual-level analysis below.

[28] The rise of international trade exposure with China and Eastern Europe, by contrast, has contributed nothing to this decline; if anything, the impact of net export exposure on the manufacturing employment share is even positive. See Dauth et al. (2017) for a detailed analysis. In the US, on the other hand, both robots and Chinese imports seem to have fulled the manufacturing decline.

[29] In panel F we find a large and positive coefficient in column 5, like in panel A, but the standard errors in this specification are somewhat too large to achieve statistical significance at conventional levels.

suggest that they do not, neither for employment nor for wages. All coefficients are small and insignificant, thus suggesting that our main findings are not driven by pre-trends.

4.3 Robustness checks

We have conducted a battery of robustness checks. In this section we briefly discuss the main insights, but relegate the detailed results to the Appendix.

4.3.1 The automobile industry

The automobile industry is a large and important sector in the German economy, and has by far the most robots. To shed light on the special role of cars, we differentiate the local employment and wage effects of robots separately for the different branches of the automobile industry (motor vehicles, car bodies, and car parts) and for all other manufacturing industries in Appendix Table A.10. For employment we find strongly negative effects in both cases. The impact of robots on wages is even more pervasive in the other manufacturing branches. From this exercise we conclude that our main results are not solely driven by cars, but that robots affect the manufacturing sector more broadly.[30]

4.3.2 The changing impact of robots over time

In Appendix Table A.11 we address timing issues. Instead of computing local employment and wage growth rates over twenty years as in the baseline, we now split the observation period into two separate time windows (1994-2004 and 2004-2014). We then repeat the baseline specifications with all instrumental variables adjusted accordingly. In panel A we stack the two decades, and panels B and C show the two periods separately.

We find no effects of robots on overall employment or wage growth in the stacked model in panel A. Most interestingly, Panels B and C suggest that the negative employment and wage effects in the manufacturing sector have become more adverse over time. In the first period (see panel B) we find no notable employment and smaller wage effects. In the second period, however, negative effects dominate the picture. There is even evidence for some overall job losses during the period 2004-2014. Notice that this pattern is not driven by more robot installations in the more recent years. If anything, we can infer from Figure 2 that robot exposure increased by more during the first decade. But the economic impacts of robots have apparently become stronger over time.

[30]In further unreported robustness checks we have also differentiated robots installed in the automobile branches from robots installed elsewhere. We consistently find that both measures of local robot exposure negatively affect local manufacturing employment.

4.3.3 Countries in the instrument group

Our baseline specification uses an instrument group consisting of seven countries (Spain, France, Italy, the United Kingdom, Finland, Norway, and Sweden) which have been chosen for the reason of comprehensive data availability. Panels A-C in Appendix Table A.12 show robustness checks regarding this instrumental variable specification.

First, while we use robot installations in all seven countries as separate instruments in an over-identified IV model (see Section 3.3), we now aggregate them to a single instrument for robot exposure in Germany and repeat the estimation in a just-identified model. The results are reported in panel A, and turn out to be similar to our baseline findings.

The exclusion restriction requires that robot installations, and the associated labor market effects in the instrument countries, shall not have direct impacts on the German labor market. One may worry that this requirement could not be met for important and large instrument countries with strong economic ties to Germany. France is the most obvious candidate, and also the only country in the instrument group sharing a common border with Germany. In panel B, we return to our previous over-identified IV model, but drop France from the instrument group. In panel C we even go one step further, and drop all countries from the Eurozone (i.e., France, Italy, Spain, and Finland) since shocks may be more strongly correlated within the monetary union. The results in panels B and C are very similar to our baseline findings, however.

4.3.4 Industries and regional specifications

Next we conduct a robustness check on the industry cross-walk that we needed to take in order to merge the robotic data from the IFR with the official industrial classification system in the German data. In our approach, described in Appendix A, we allocated the original 25 ISIC Rev. 4 industries from the IFR to 72 German NACE Rev.1 industries. One may argue that we have, thereby, artificially inflated the number of observations for our empirical analysis. We therefore consider an alternative approach here, also explained in greater detail in Appendix A, where we aggregate the German data up to the ISIC level. We then repeat our estimations for this alternative classification system with fewer industries, but find roughly similar (though somewhat less precisely estimated) effects in panel D of Appendix Table A.12 as in our baseline.

Finally, we drop East Germany in panel E, and in panel F we change the specification of $\phi_{REG(r)}$ and include Federal State fixed effects instead of the four broad location dummies. Our main results also remain unchanged in those robustness checks.

5 Worker-level evidence

The analysis has so far investigated the equilibrium impact of robots in local labor markets. In this section, we shift our focus to the work biographies and earnings profiles of individual manufacturing workers. This allows us to shed light on the underlying channels of the equilibrium outcomes identified so far.

5.1 Individual employment outcomes

Table 4 reports our main results for the worker-level estimation (2). We regress cumulated days in employment for incumbent manufacturing worker i over the period 1994-2014 on the contemporaneous robot exposure of the initial industry j.

Table 4: Robot exposure and individual employment outcomes

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)
Δ net exports / wagebill in %					0.8422***	0.8541***
					(0.125)	(0.133)
Δ ICT equipment in € per worker					0.0323	0.0330
					(0.029)	(0.029)
R^2	0.056	0.078	0.089	0.095	0.096	0.089
[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. The outcome variable is the number of days employed, cumulated over the twenty years following the base year. Panel A reports results of ordinary least squares (OLS) regressions. Panel B reports results of a two-stage least squares (2SLS) IV approach. German robot exposure is instrumented with robot installations across industries in other high-income countries. Similarly, in columns 5 and 6, the changes in net exports vis-a-vis China and Eastern Europe and ICT equipment are instrumented with the analogous trade-flows and industry-level investments in ICT of other high-income countries, respectively. Standard errors clustered by industry x federal state in parentheses. Levels of significance: *** 1 %, ** 5 %, * 10 %.

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

Starting from a simple regression in column 1, we successively add further control variables until we reach a comprehensive specification in column 4, which takes into account various observable individual characteristics, base year earnings as a proxy for unobservable ability, as well as controls pertaining to the initial establishment, industry, and region of employment. In column 5 we add the industry-level trade and ICT exposures, and in column 6 we drop all workers from the automobile industry as an important robustness check. Panels A and B show the results for the OLS and IV estimation approach, respectively, with third-country variables at the industry-level as instruments.[31]

There is a consistent picture across all specifications, namely a positive effect of robots on worker-level employment. In other words, more robot-exposed workers are employed on more days during the subsequent twenty years than comparable colleagues from less exposed manufacturing industries. The effect becomes smaller when we control for initial plant size or broad industry groups, in order to purge possibly confounding trends. The effects also become smaller when including the other industry-level shocks. But the central finding, that higher robot exposure raises worker-level employment, always remains significant. Moreover, in Appendix Table A.15 we show that similar results emerge in the short-run approach where single workers are followed only for ten years, and it seems to be stronger during the first decade.

Investigating those patterns further, we now separate *where* the additional employment time occurs. Table 5 decomposes the cumulative days in employment into different additive parts.[32] Panel A refers to the industry, and panel B to the occupational dimension. Column 1 in both panels repeats the previous baseline specification from Table 4 and the coefficients in columns 2–5 add up, by construction, to this overall cumulative effect. Starting with the industry dimension in panel A, we find that the positive total effect is solely driven by a substantially higher probability for worker i to remain employed in his or her original establishment (see column 2), while it becomes less likely that workers switch to other firms in the same industry (column 3), in different manufacturing industries (column 4) or outside of manufacturing (column 5).

In other words, robot exposure increases the stability of existing employment relationships from the point of view of individual manufacturing workers in Germany. Robots do *not* increase individual displacement risks, but they make existing jobs more secure.

[31] In the main text we focus again on the central coefficients only, while relegating the detailed results to Appendix Tables A.13 and A.14.

[32] For brevity we only show the IV results from now on.

Table 5: Individual adjustment to robot exposure (employment)

[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)
Δ net exports / wagebill in %	0.5644***	1.7617***	-0.3971	0.6215	-1.4217***
	(0.168)	(0.635)	(0.432)	(0.453)	(0.363)
Δ ICT equipment in € per worker	0.0279	0.0556	-0.0963	0.1202	-0.0515
	(0.031)	(0.086)	(0.126)	(0.106)	(0.047)

[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)
Δ net exports / wagebill in %	0.5644***	1.4603***	0.3014**	-0.2700	-0.9272***
	(0.168)	(0.513)	(0.147)	(0.381)	(0.204)
Δ ICT equipment in € per worker	0.0279	0.0048	0.0508*	-0.0574	0.0298
	(0.031)	(0.069)	(0.027)	(0.075)	(0.029)

Notes: Based on 993,184 workers. 2SLS results for period 1994-2014. The outcome variables are cumulated days of employment. For column (1), employment days are cumulated over all employment spells in the twenty years following the base year. Panel A: For column (2) employment days are cumulated only when they occurred at the original workplace. For the other columns, employment days are cumulated only when they occurred at a different plant in the same industry (3), at a plant in a different manufacturing industry (4), and outside the manufacturing sector (5), respectively. Panel B: Employment days are cumulated only when they occurred in the original occupation and workplace column (2), in a different occupation but at the original workplace column (3), in the original occupation but at a different workplace column (4), and in a different occupation and workplace, respectively. 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 4. Standard errors clustered by industry x federal state in parentheses. Levels of significance: *** 1 %, ** 5 %, * 10 %.

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

Panel B turns to the occupational dimension. We find that robots raise the probability to remain in the same occupation (column 2), and also to switch to a different occupation at the same establishment (column 3). Actual employer switches become less likely, however, which is in line with the results in panel A. Put differently, although robots stabilize existing manufacturing jobs, some workers end up performing different tasks at their workplace than before. This pattern is consistent with skill upgrading, e.g. through re-training, or with a repositioning of workers to different professions inside the firm.

5.2 Entry and re-entry into manufacturing

How can robots lead to fewer manufacturing jobs in equilibrium but stabilize existing individual employment relationships? One explanation is that manufacturing firms do not displace incumbent workers when installing robots, but create fewer *new* jobs.

In Table 6 we investigate this hypothesis. Here we step back to our local labor market approach, and now consider patterns of (re-)entry of young workers and returnees from unemployment as the outcome variable.[33] More specifically, we compute the entry share into manufacturing in region r in 1994, i.e., the average probability that a young worker who takes up his or her first job ever does so in manufacturing in region r. For returnees who have been unemployed for at least one year prior to the base period we proceed analogously. Next, we compute the same variables for the year 2014, and then the change in those regional (re-)entry probabilities into manufacturing over time. Finally, we regress those changes on local robot exposure, following the same baseline specification as in column 7 of Table 1 above (using the IV model).

Table 6: Robot exposure and entry into manufacturing employment.

	△ 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 market regions. The dependent variables in columns (1) and (2) measure the change in the share of manufacturing entrants respectively returnees in all entries (in %-points) between 1994 and 2014. In columns (3) and (4), the dependent variables are the change in the average age in manufacturing and non-manufacturing between 1994 and 2014. The regressions are estimated by applying the 2SLS IV approach where German robot exposure is instrumented with robot installations across industries in other high-income countries. Similarly, the changes in net exports and ICT equipment are instrumented with third-country flows of other high-income countries vis-a-vis China and Eastern Europe, and industry-level investments in ICT in other high-income countries, respectively. The full set of control variables as in column (7) of Table 1 is included. Standard errors clustered at the level of 50 aggregate labor market regions in parentheses. Levels of significance: *** 1 %, ** 5 %, * 10 %.
Sources: IFR, COMTRADE, EUKLEMS, and IEB V12.00.00 - 2015.09.15, own calculations.

Column 1 shows that the entry probability into manufacturing for young workers has indeed significantly decreased in more robot-exposed regions. The negative impact of robots on equilibrium employment growth in manufacturing, which we have found in Section 4, therefore seems to come from lower rates of entry into new manufacturing jobs, but not from a direct destruction of existing jobs. Stated differently, robots seem to "foreclose" entry into manufacturing for young people, for example through omitted

[33]This setup follows Dauth et al. (2017) who show that changing industry compositions of employment in Germany are driven only to a lesser extent by workers who smoothly change jobs across industries. Most of the observed changes are driven by young workers who enter the labor market for the first time, and by formerly unemployed workers who return into a job. In particular, they have a much lower probability of (re-)entry into manufacturing than previous generations, thus fueling the aggregate decline of that sector.

replacements when a vacancy arises from natural turnover. For returnees from non-employment we find no such effect in column 2.[34]

A direct implication of this finding is that the manufacturing workforces in more robot-exposed regions should then age more rapidly, because there is a smaller inflow of young people, while the opposite should happen in non-manufacturing where entrants go instead. In columns 3 and 4 we investigate this hypothesis. We compute, for every region r, the change in the average employee age within manufacturing and non-manufacturing, respectively, and regress these age changes on local robot exposure. Our findings indeed confirm this aging hypothesis for more robotized manufacturing sectors.

5.3 Individual earnings and wages

The question remains *why* robots stabilize existing manufacturing jobs. If robots can replace human tasks in manufacturing, which apparently happens since robots lead to fewer new jobs, why do incumbent workers not face an increased job displacement risk?

Table 7 gives a possible explanation. We move back to the worker-level analysis of equation (2) and now explore individual earnings profiles. More specifically, in panel A we use the cumulated individual earnings (normalized by base year earnings) over twenty years as the outcome variable Y_{ij}. In panel B we use (non-normalized) cumulated earnings divided by days employed to construct a measure of the average daily wage that worker i has earned during the subsequent two decades. The single columns follow the same structure as in Table 4 and successively add further controls.

At first there are positive coefficients, but once we control for broad industry and regional trends by adding the dummies $\phi_{J(j)}$ and $\phi_{REG(i)}$ in column 4, we find significantly *negative* effects of robot exposure on individual earnings and wages. This result remains robust and even becomes somewhat stronger when adding net export and ICT exposure in column 5, and when dropping automobile workers in column 6.[35]

To benchmark the wage effects quantitatively, we compare a worker at the 75th and the 25th percentile of individual robot exposure facing Δrobots_j equal to 9.60 and 3.37, respectively. If both earn the average daily wage of 120.70€ , then column 5 of Table 7B im-

[34]Notice that net export exposure has positive effects on (re-)entry probabilities into manufacturing, which is mainly driven by the returnees. The positive overall effect on equilibrium employment, therefore, seems to come from a combination of more job creation and more stable existing jobs in more export-oriented regions. For ICT we also find that entry is slightly diverted from more exposed industries.

[35]In Appendix Table A.16 we report the results for the shorter time intervals, both stacked and separately. They confirm the negative wage and earnings effects caused by robots, and furthermore show that the adverse effects have become more severe over time. This can be seen by comparing the coefficient in column 5 of Panels B and C, which has more than doubled from the first to the second decade.

plies that the more robot exposed worker receives a loss of 0.31 € per day.[36] Since the average worker is employed on 5,959 days over twenty years, the total loss is 1,867€ relative to the equivalent worker with low exposure. Yet, there is also a positive causal effect of robots on individual employment. From column 5 of Table 4B we calculate that this is equivalent to $0.8003 \times (9.6 - 3.7) = 5$ additional days in employment for the more strongly exposed worker. He or she, thus, makes up for $5 \times (120.70 - 0.31) = 600.91$ €. Hence, in the overall comparison, we conclude that the worker at the 75th percentile experiences a cumulative earnings loss of 1,266 € over twenty years, slightly more than 63 € per year, compared to the less robot exposed colleague.

Table 7: Individual earnings and average wages

[A] Earnings	(1)	(2)	(3)	(4)	(5)	(6)
Δ robots per 1000 workers	1.3583*	1.7025**	-0.2585	-0.6550**	-0.7989***	-1.0822***
	(0.761)	(0.736)	(0.523)	(0.292)	(0.286)	(0.388)
Δ net exports / wagebill in %					0.4025***	0.3828***
					(0.106)	(0.103)
Δ ICT equipment in € per worker					0.0159	0.0162
					(0.020)	(0.019)
R^2	0.056	0.093	0.126	0.140	0.141	0.134
[B] Average Wages	(1)	(2)	(3)	(4)	(5)	
Δ robots per 1000 workers	0.1361**	0.0523*	-0.0222	-0.0374***	-0.0417***	-0.0649***
	(0.062)	(0.027)	(0.018)	(0.012)	(0.011)	(0.015)
Δ net exports / wagebill in %					0.0117***	0.0095**
					(0.004)	(0.004)
Δ ICT equipment in € per worker					0.0007	0.0006
					(0.001)	(0.001)
R^2	0.176	0.677	0.690	0.696	0.696	0.691
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 (Panel A) and 986,353 workers (Panel B). 2SLS results for period 1994-2014. The outcome variables are 100 x earnings normalized by earnings in the base year and cumulated over the twenty years following the base year (Panel A) and 100 x log average wages over the twenty years following the base year (Panel B). German robot exposure is instrumented with robot installations across industries in other high-income countries. Similarly, in columns 5 and 6, the changes in net exports vis-a-vis China and Eastern Europe and ICT equipment are instrumented with the analogous trade-flows and industry-level investments in ICT of other high-income countries, respectively. Standard errors clustered by industry x federal state in parentheses. Levels of significance: *** 1 %, ** 5 %, * 10 %.

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

This is still a moderate number. However, bear in mind how skewed robot installations are at the industry-level (see Figure 2). Therefore we obtain much larger quantita-

[36]The calculation is $[exp\,(-0.0417/100 \times (9.60 - 1)) - exp\,(-0.0417/100 \times (3.37 - 1))] \times 120.70$ = -0.31.

tive magnitudes in more extreme comparisons. For example, an analogous computation for average workers at the 90th and the 10th percentile of exposure yields an overall earnings loss caused by robots of (23,303 - 7,373)/20 = 796.5 € per year.

Summing up, robots have stabilized the careers of manufacturing workers in Germany in the sense that they increased the probability of keeping a job at the original establishment (though not necessarily performing the same tasks). But this stability apparently came at a cost, namely significantly lower wages and earnings for the same job.[37]

5.4 Heterogeneous effects for different workers

There is wide heterogeneity across different types of individuals both with respect to the qualification level, and to the tasks (the occupation) that the workers perform. Robots may directly substitute some of those, and thereby replace certain professions, while they are complementary to other skills and tasks. The new technology is thus likely to affect single workers very differently. We investigate this effect heterogeneity by interacting robot exposure with the various dummies for skill and occupational categories.[38]

The results are illustrated in Figure 4 which refers to the long-run model over twenty years.[39] For every labor market group we report the point estimate for the impact of robot exposure on cumulated earnings, and the respective confidence interval. Panels (a) distinguishes three skill categories, and panel (b) differentiates seven broad occupational categories that can be found among the individual manufacturing workers in our sample.

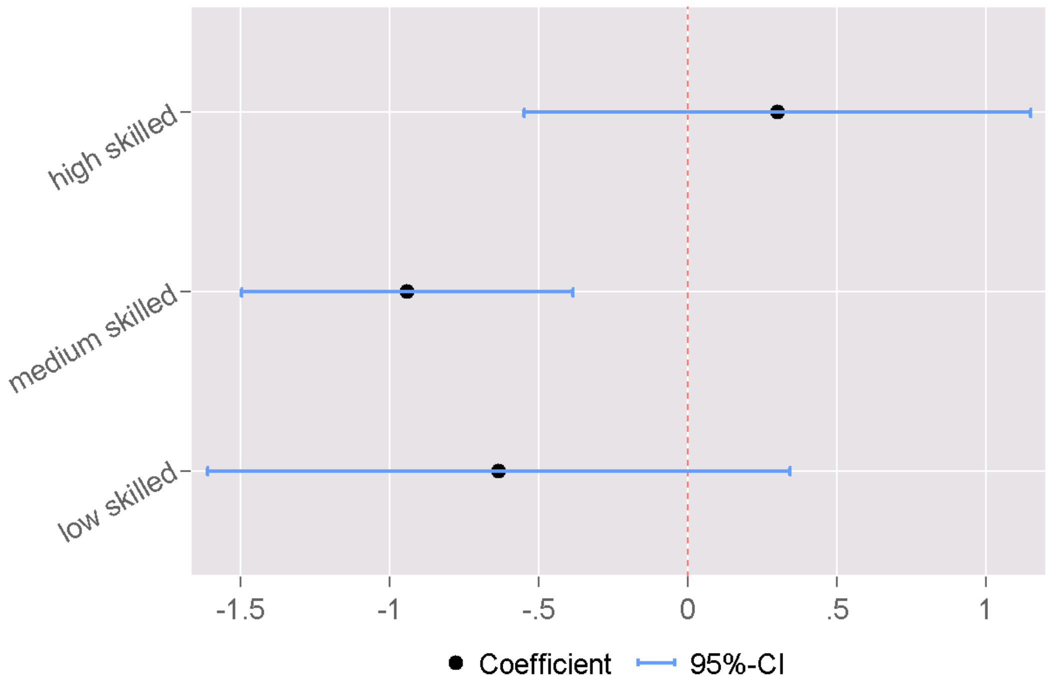
The picture that emerges is clear-cut. Robot exposure decreases earnings especially for medium-skilled workers with completed apprenticeship. For this group we find strongly negative and significant effects both in the long- and in the short-run model. Those losses drive the average effects in Table 7, because completed apprenticeship is the typical profile for manufacturing workers in Germany accounting for almost 76% of all individuals in our sample. Robots also tend to reduce the earnings of low-skilled workers without formal education, but the effects are less precisely estimated.

By contrast, we find significant earnings gains for the roughly 9% of high-skilled workers with completed university education. Those workers may gain from robots, because they possess human capital that is complementary to this technology, and they perform tasks that are not as easily replaceable by robots.

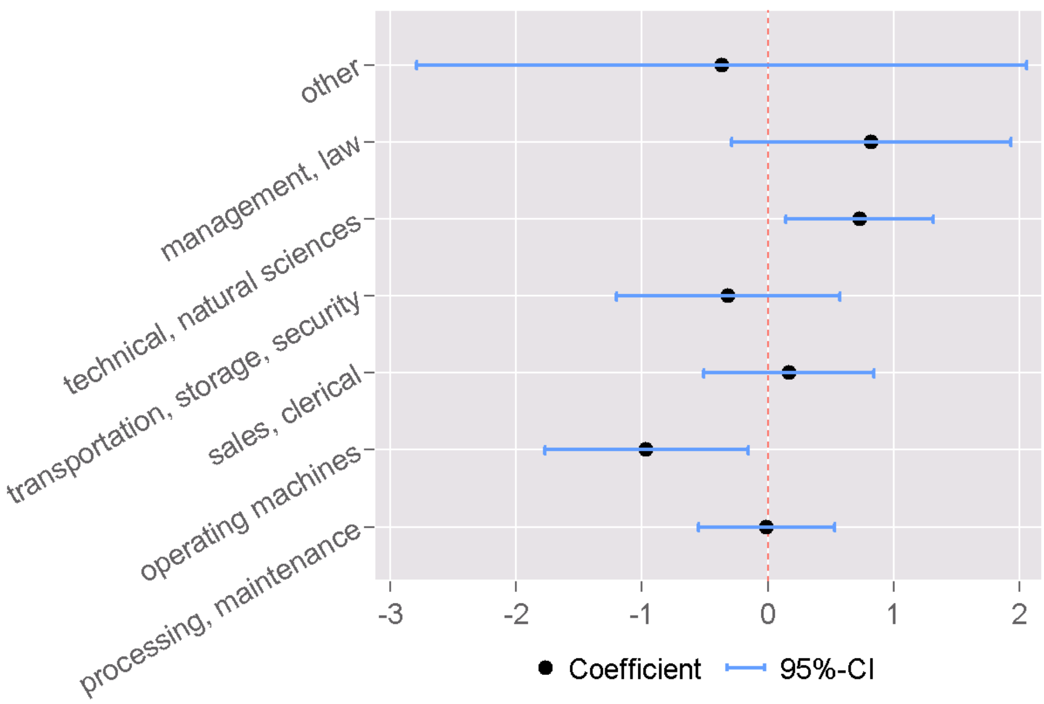
[37]It can be shown that wage reductions arise indeed at the same workplace, and do not reflect possible compositional changes. This is done by repeating the analysis from Table 5 for wages and earnings. This estimation yields consistently negative effects of robot exposure in all specifications.

[38]We have also experimented with sample splits and obtained very similar results.

[39]In Appendix Figure A.3 show the respective results for the stacked short-run model.



(a) by education, long period



(b) by occupation, long period

Notes: The figures report the coefficients of interaction terms of Δ robots per 1000 workers and dummies indicating the respective worker group. The outcome variables are 100 x earnings (normalized by earnings in the base year) cumulated over the twenty years following the base year. All regressions include the same control variables as in column (5) of Table 4. The confidence intervals are constructed from standard errors clustered by industry x federal state.

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

Figure 4: Heterogeneous earnings effects

This hypothesis is supported by the analysis at the occupational dimension. We find significant earnings losses mainly for machine operators, who mostly tend to be medium-skilled workers. Their previous tasks may become somewhat obsolete, because robots – by definition – do not require a human operator anymore but have the potential of conducting many production steps autonomously. Earnings gains, however, are realized in occupations such as management and law, as well as technical and natural sciences, where university-trained workers are strongly over-represented.

Recall that robots cause, on average, more stable jobs but lower wages for individual manufacturing workers in Germany (see Tables 4 and 7). The positive effect on cumulated days in employment do not differ strongly across different groups, but the wage and earnings effects do. High-skilled workers in non-routine occupations tend to benefit both in terms of job stability and wages. Medium-skilled workers who mainly perform routine and manual tasks, however, face significant earnings losses from increasing robot exposure. Those losses do not come from displacements or interruptions in work biographies, however, but they mainly arise on existing jobs through lower wages.

6 The aggregate impact of robots

The analysis in Section 5 suggests that robots have notable distributional effects at the individual level. In this final section of the paper we study the effects of robots on productivity and the income distribution from a more aggregate perspective. We move back to the local labor market approach, and exploit additional data from the German Federal Statistical Office, which break down national accounts at the regional level.

We focus on the second decade (2004-2014) in this analysis, because most data from this source are not available for earlier years. We follow the previous local labor market approach (2) and use the IV specification from column 7 of Table 1, panel B. The main results for various outcome variables ΔY_r are summarized in Table 8.

In column 1 we find notable effects of robots on average labor productivity. Every additional robot per thousand workers in the local labor market raises the growth rate of GDP per worker by 0.5365 per cent. Column 2 considers wage data from the Federal Statistical Office, namely average gross pay per employee at the local level.[40] Consistent with the previously used IAB data, we find no effect of robots on average wages; if anything, the impact even tends to be negative but is imprecisely estimated.

[40]Notice that, unfortunately, data is missing for 30 regions in column 3. The average wage data in column 2 is from the IAB data source described above in Section 2.

Table 8: Robots and other regional outcomes.

	Dependent variable: Change between 2004 and 2014					
	(1) Labor prod.	(2) Gross pay per empl.	(3) Output per empl. - gross pay per empl.	(4) Total emp./ pop.	(5) Pop.	(6) Unempl. rate
△ robots per 1000 workers	0.5365**	-0.3109	2.0757**	-0.1026	0.0173	-0.0693*
	(0.268)	(0.249)	(0.945)	(0.158)	(0.190)	(0.038)
N	402	372	372	395	395	402

Notes: Local labor market regions N. The dependent variable in column (1) is the log change in GDP per person employed x 100, in column (2) the log change in gross pay per employee x 100, in column (3) the log change of the difference between GDP per person employed and gross pay per employee x 100, and in column (5) the log change in population x 100. The dependent variables in columns (4) and (6) are, respectively, the percentage point change in the number of all workers/unemployed persons in the local population x 100. 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 full set of control variables as in column (7) of Table 1. Standard errors clustered at the level of 50 aggregate labor market regions in parentheses. Levels of significance: *** 1 %, ** 5 %, * 10 %.

Sources: IFR, COMTRADE, EUKLEMS, German Federal Statistical Office, and IEB V12.00.00 - 2015.09.15, own calculations.

In other words, we find that the increase in labor productivity caused by robots is *not* reflected in higher average wages. This suggests that the rents created by this technology are not captured by labor at large, but mostly by the owners of other factors, such as capital, or by residual profit claimants. This hypothesis is supported by column 3 in Table 8. Here we compute the change in GDP per person employed and the wage bill per employee in region r between 2004 and 2014, and use the difference as a proxy for growth in aggregate non-labor income. We find strongly positive effects of robots, i.e., they drive output and income growth that is not accruing to labor.

The data do not allow us to distinguish this non-labor income further into factor remunerations and profit components, but Table 8 suggests that robots have contributed to the fall of the aggregate labor income share. This decline has been noted in various high-income countries over the last decades (Autor et al. 2017; Kehrig and Vincent 2017), including in Germany. Notice that this aggregate distributive impact, i.e., the reallocation of income shares away from labor and towards other factors, is still compatible with the pattern shown above in Figure 4, which suggests that *some* workers with high individual human capital still benefited from robots, despite the falling aggregate labor share.

In columns 4-6 in Table 8 we exploit employment and population data from the Federal Statistical Office to check the consistency of some of our previous results. In particular, in column 4 we re-compute the change in the employment-to-population ratio from this data set and, as in panel B of Table 3, find no effect of robots. Similarly, column 5 shows that robots also have no effects on population growth alone. Hence, they do not seem to induce notable migration responses, such as moves away from more robot exposed regions. This is reassuring, because it suggests that our local labor market approach seems to be adequate to study the labor market effects of robots. The single 402 regions may be considered as small sub-economies of Germany across which migratory responses to aggregate shocks appear to be weak. Finally, in column 6 we consider the change in local unemployment rates and find that robots even tend to reduce unemployment slightly, although the effect is barely significant.[41] This is consistent with our previous result that robots have not led to fewer jobs in total.

7 Conclusion

In this paper we have studied the impact of rising robot exposure on the careers of individual manufacturing workers, and the equilibrium impact across industries and local labor markets in Germany. Unlike in the United States, we find no evidence that robots have been major job killers so far. They do not cause overall job losses, but they do affect the composition of aggregate employment in Germany. We estimate that every robot destroys roughly two manufacturing jobs. This implies a total loss of 275,000 manufacturing jobs in the period 1994-2014, which accounts for roughly 23% of the overall decline during those two decades. But this loss was fully offset by additional jobs outside the manufacturing sector, especially in business services.

We then investigate the detailed channels behind those aggregate effects in a worker-level analysis. Most importantly, we find that robots have not raised the displacement risk for incumbent manufacturing workers. Quite in contrast, more robot exposed workers are even more likely to remain employed in their original workplace, though not necessarily performing the same tasks as before. The aggregate decline in manufacturing employment is therefore not caused by destruction of existing jobs, but it is solely driven by fewer new manufacturing jobs for young labor market entrants.

The enhanced job stability for insiders comes at a cost, namely lower wages. Those impacts differ strongly across individuals. High-skilled workers in managerial and scientific occupations tend to benefit both in terms of job stability and wages. Medium-skilled workers who mainly conduct routine and manual tasks, however, face wage and earnings losses on the job. The magnitude is still moderate so far, but there is some evidence that those wage effects became more pronounced over time.

[41] Here we again make use of the IAB data because of missing values in the unemployment data from the Federal Statistical Office. The change in the local unemployment rate is calculated based on average monthly values on unemployed persons in 2004 and 2014, respectively.

The empirical patters that we find in the data reflect, in our view, some key features of industrial relations in the German labor market: the manufacturing sector is still highly unionized, and especially blue-collar wages are typically determined collectively with strong involvement of work councils. It has been frequently argued that German unions have a strong preference for maintaining high employment levels, and are willing to accept flexible wage setting arrangements, such as opening clauses, in the presence of negative shocks in order to keep jobs.[42] This flexibility of unions, and the resulting wage restraints, are actually one of the leading hypotheses for the strong overall performance of the German labor market since the mid-2000s (see, e.g., Dustmann et al. 2014).

Our analysis suggests that the rise of the robots may have triggered a similar response, namely wage cuts to stabilize jobs for incumbent insiders. This channel is most relevant for medium-skilled workers, who appear to be most vulnerable to the threat of automation. Our analysis shows that they were often repositioned, and switched to different occupations inside the firm. This repositioning probably followed some initial retraining. But even if that involved also skill upgrading for the individual workers, we observe that they are still left with lower wages in their new jobs thanks to the robots.

By keeping their original workers, firms have supposedly retained firm-specific human capital and work experience. But this enhanced job stability for insiders, in turn, led to reduced entry of new workers that would otherwise have started their careers in manufacturing. These "potential jobs" for newcomers were effectively replaced by robots. The workforces of more robotized industries aged more rapidly as a consequence.

Instead of entering in manufacturing, more newcomers started their careers in the service sector. Wages there have even increased in response to robots, possibly because of rising demand from the manufacturing sector for specialized business consulting and other types of business services. In the aggregate, we have therefore not seen any negative effects of robots on average wages, despite the negative wage effects for many incumbents in manufacturing. Vice versa, we also find no aggregate wage increases from robots despite notably positive impacts on labor productivity. Most rents of this new technology, therefore, seem to be captured by profit claimants and factors other than labor. Robots thus seem to have contributed to the declining labor income share.

Comparing the impact of robots in the German and American labor markets, we find some notable differences to the aggregate results by Acemoglu and Restrepo (2017). They

[42]This point has been made, for example, in the context of offshoring after the fall of the iron curtain, where many firms threatened to move production to Eastern Europe.

argue that labor force participation was reduced and every robot destroyed between 3–6 jobs in the US. Moreover, while effects in manufacturing are stronger also in their case, there are even job and wage losses through robots in other sectors.

Why could this be different in Germany? The differences across countries are unlikely to be driven by a general boom in Germany, or by strong export growth in particular. In the first decade of our observation period there was no general boom, but rather an overall stagnation in Germany. Moreover, we have shown at various points that the labor market effects of robots seem to be orthogonal to the effects of rising export exposure to emerging markets in China and Eastern Europe.

A more promising explanation is that the particular mix of labor market institutions and industrial relations could be behind the relatively more friendly response of the German labor market. Our analysis suggests that direct job displacements of incumbent manufacturing workers were largely prevented.[43] This may have led to smaller negative demand spillovers into the local service sector, such as reduced spending on restaurants or hairdressers, and the associated local multiplier effects on non-manufacturing wages and jobs. Quite in contrast, we even obtain evidence for positive demand spillovers into more advanced service branches. Robots increase output, productivity, and non-labor income, and this seems to create additional demand for specialized local business services.[44] The latter effects seem to be relatively stronger in Germany than in the US. This could, in turn, explain the positive overall impact of robots on the average wage in the service sector, paid to the young entrants who no longer start in manufacturing.

More generally, we believe that our results show that the same technology shock – the rise of the robots – can have very different overall effects in different countries, given their particular institutional arrangements. We have taken a first step in this paper and provided detailed evidence for Germany. More work is needed in the future to show how institutions affect the way labor markets respond to automation, digitalization, and the rise of new technologies, and which policies are most appropriate to respond to the resulting challenges for workers.

[43] The micro-level evidence for the United States is still missing, but supposedly there was more direct firing of workers due to lower unionization rates, more business-friendly labor laws, and so forth.

[44] These positive demand spillovers could be less localized in the United States.

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Appendix

A ISIC-NACE cross-walk

A technical challenge prior to our empirical analysis is to link the data on robots from the IFR with German labor market data. This requires to harmonize two different but related industrial classifications. The IFR uses an industry classification that is based on the International Standard Industrial Classification of All Economic Activities (ISIC) Rev. 4. In essence, the IFR classification coincides with the 2-digit aggregation of ISIC with some industries being further aggregated (e.g. 13-15: textiles, leather, wearing apparel) and some available at the 3-digit level (the 3-digit branches within 26-27: electrical, electronics and the 3-digit branches within 29: automotive). Industries outside of manufacturing are aggregate to very broad groups. In total, this classification distinguishes between 25 industries.

Our labor market data are classified by various revisions of the German equivalent to the statistical classification of economic activities in the European Community (NACE). In an attempt to provide a consistent long time series, IAB data contain NACE Rev. 1 codes that have been extrapolated before/after the period of 1999-2003 when this revision was originally used (Eberle et al., 2011).

To harmonize the two classifications, we start with raw correspondence tables (both 2-digit and 3-digit level) between ISIC Rev. 3 and NACE Rev. 1 (cross-walk A), ISIC Rev. 3.1 and ISIC Rev. 3 (cross-walk B), and ISIC Rev. 4 and ISIC Rev. 3.1 (cross-walk C), all provided by EUROSTAT. [45] In a first step, cross-walk C is merged to cross-walk B, and the result is in turn merged to cross-walk A. We then keep all ISIC Rev. 4 industries with available IFR data and aggregate the codes according to the IFR classification. This produces ambiguous cases: the 25 IFR industries codes now relate to 73 NACE Rev. 1 codes. In total, there are 128 relations (cross-walk D). We use employment data from Germany in 1978 to gauge the size of each NACE industry and produce weights for those ambiguous cases.

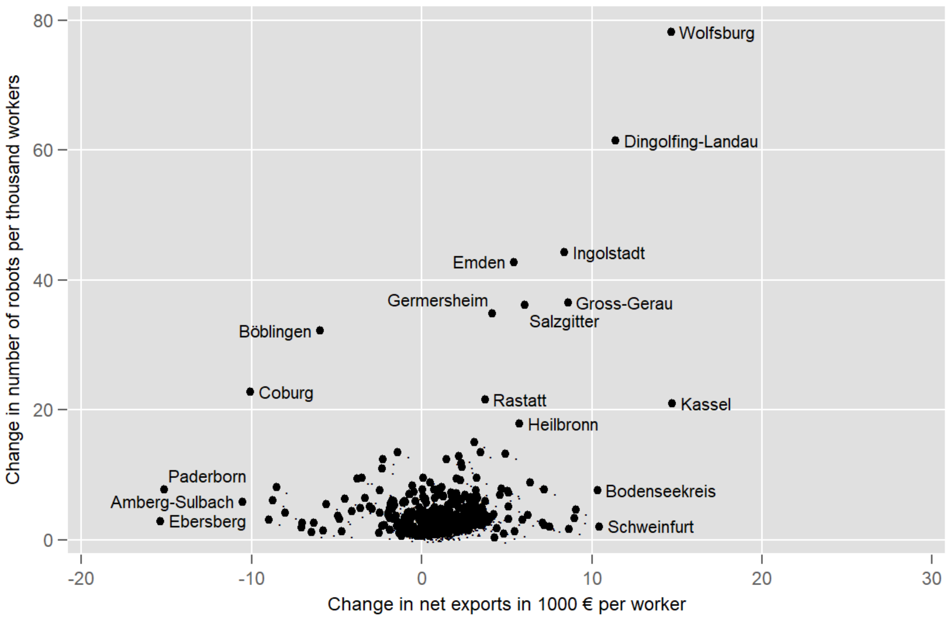
Cross-walk D now contains relations between 3-digit industries and relations between 2-digit industries. In some cases, these overlap. For example, ISIC code 10 relates to NACE codes 1, 2, 15, 16, and 24. At the same time, ISIC code 261 relates to NACE codes 242, 243, 244, 245, 246, 252, 300, 311, 312, 313, 321, 323. This means that cross-walk D contains NACE code 24 both at the 2 and 3-digit levels. We hence expand this cross-walk so that ISIC code 10 relates to NACE codes 1, 2, 15, 16, and all 3-digit industries within 24 and proceed analogously with all similar cases. This does not increase the number of industries but increases the number of relations from 128 to 243 (Cross-walk E).

Finally, we aggregate the full sample of all employment notifications on June 30 1978 to 2/3-digit NACE codes and merge this to cross-walk E (at this point, we lose the NACE industry 12 "Mining of uranium and thorium ores" as there were no employees in 1978). Our final cross-walk now entails 241 relations of 25 ISIC to 72 NACE codes. For the ambiguous cases, where one ISIC relates to several NACE codes, we construct the employment share of each NACE code in all assigned codes as weights. For example, ISIC code 24 relates to NACE codes 23 (41,499 employees in 1978) and 27 (509,031 employees). 23 thus gets a weight of 0.075 and 27 a weight of 0.925.

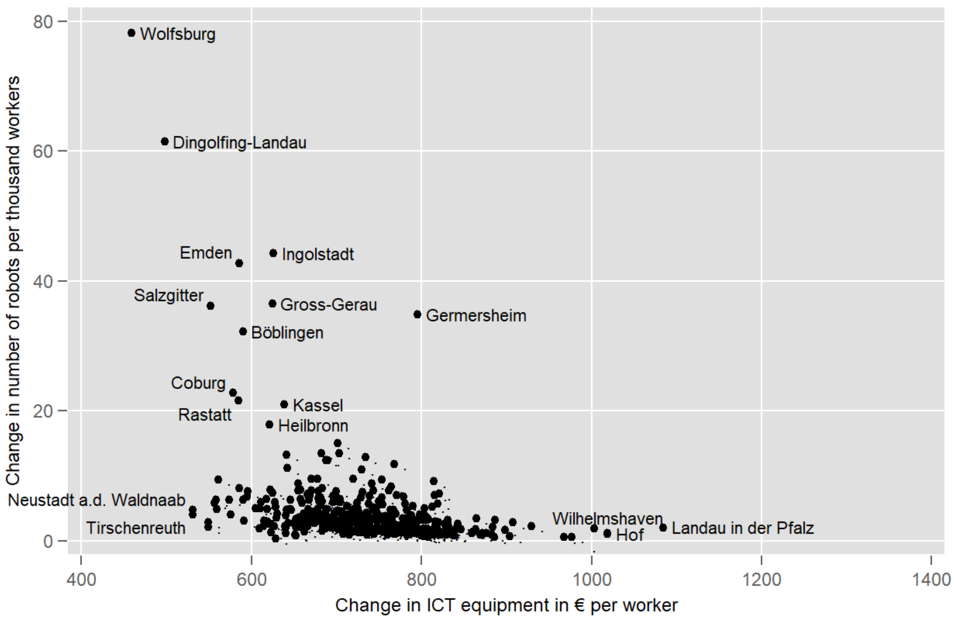
[45] `http://ec.europa.eu/eurostat/ramon/relations/index.cfm?TargetUrl=LST_REL&StrLanguageCode=EN&IntCurrentPage=8`

In Section 4.3, we check whether the increase in the number of industries drives our results. We do this by constructing a reverse cross-walk assigning one of the 25 ISIC codes to each of the 73 NACE codes. Departing from cross-walk E, we now need a measure for the relative size of each ISIC code. Unfortunately, German employment data classified by ISIC codes is not available, so we need to content ourselves with robot data from 2004 (the very first year when all industry codes are filled) to construct weights for all ambiguous cases. This reverse cross-walk then allows us to aggregate our local industry level employment data to the level of ISIC x county cells.

B Appendix Figures



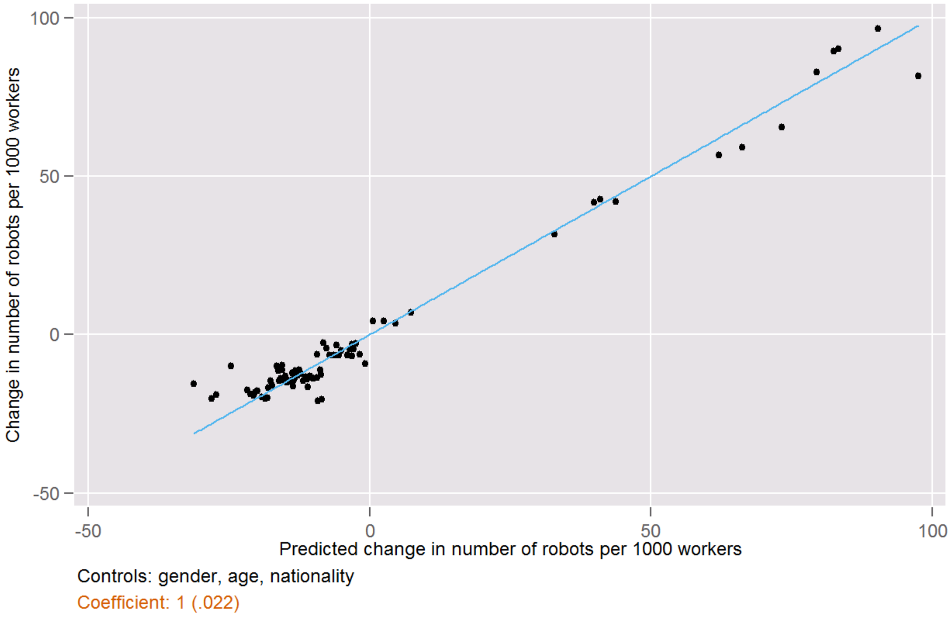
(a) Robots versus trade.



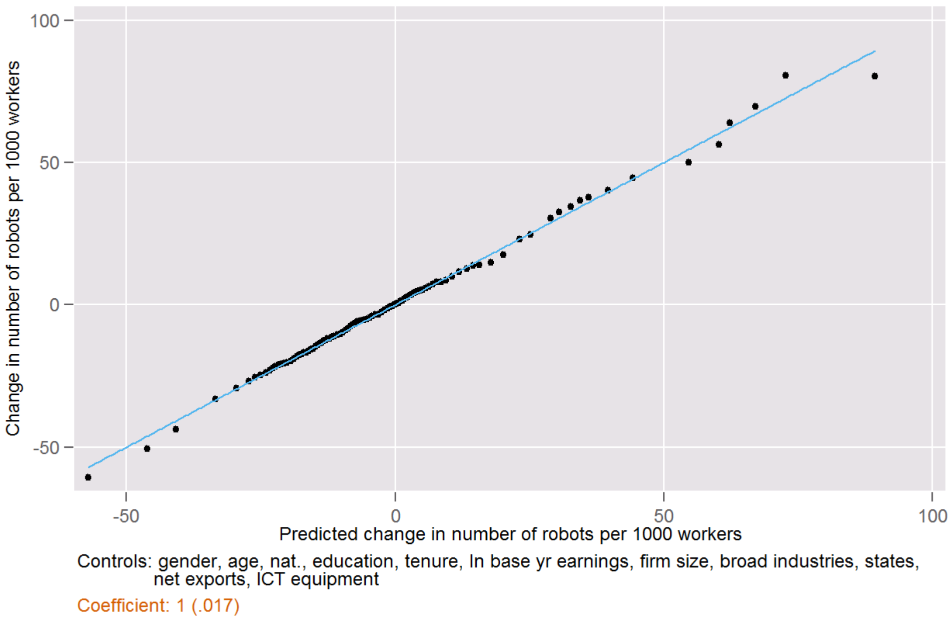
(b) Robots versus ICT.

Figure A.1: Region-level exposure of robots, trade, and ICT.

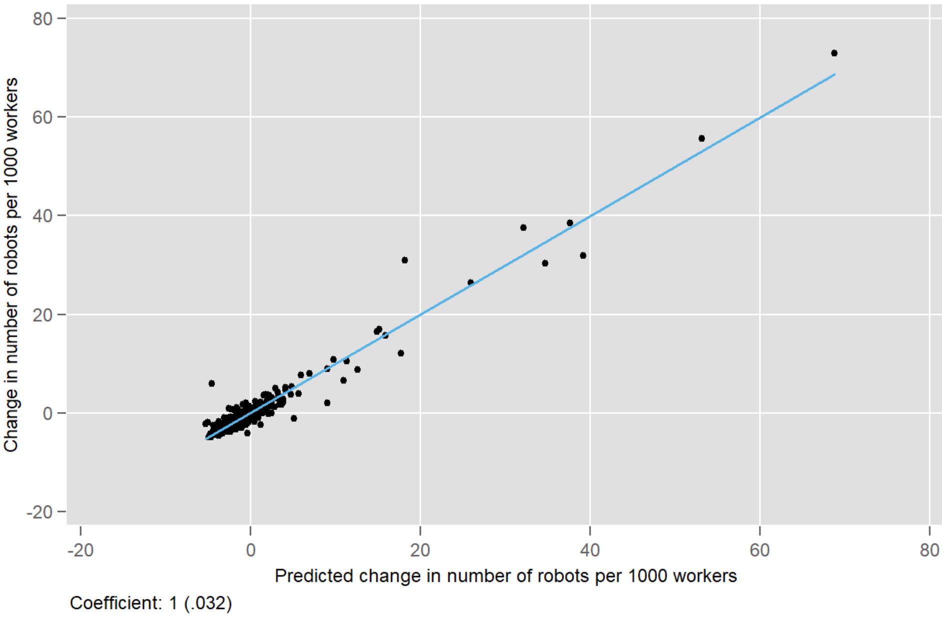
Notes: The figures contrast the change in the exposure of robots and trade (Panel A), and that of robots and ICT (Panel B) between 1994 and 2014 on the level of 402 German local labor markets.
Sources: IFR, COMTRADE, EUKLEMS, and IEB V12.00.00 - 2015.09.15, own calculations.



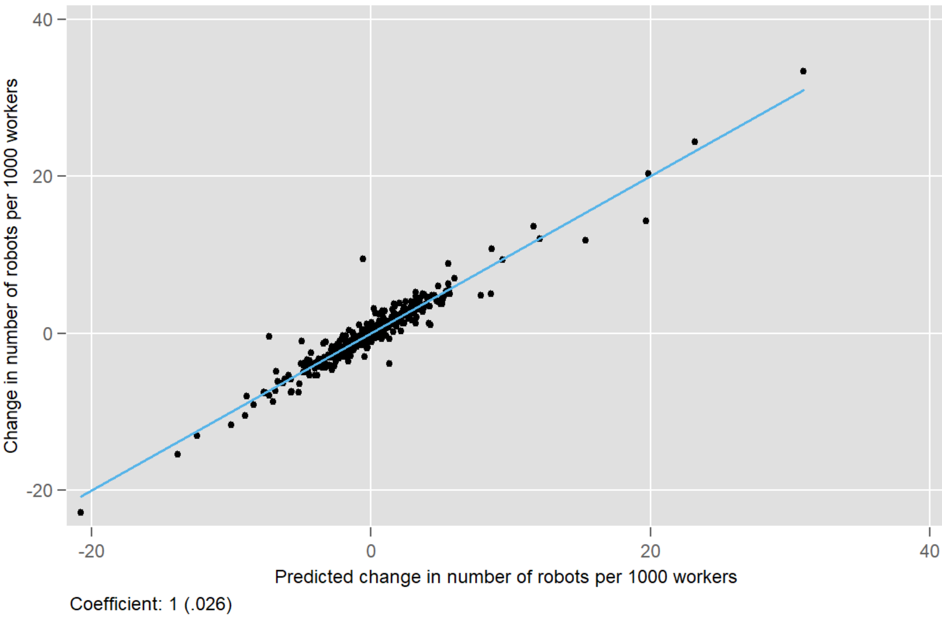
(a) Industry-level: only demographics



(b) Industry-level: Full controls



(c) Region-level: Broad region dummies

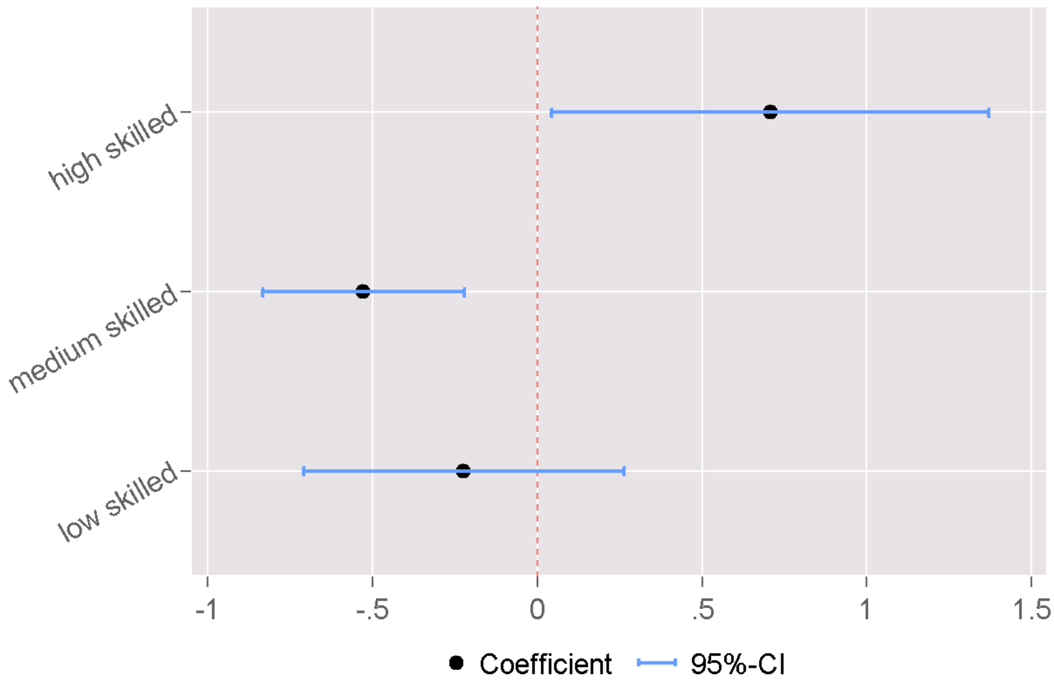


(d) Region-level: Full controls

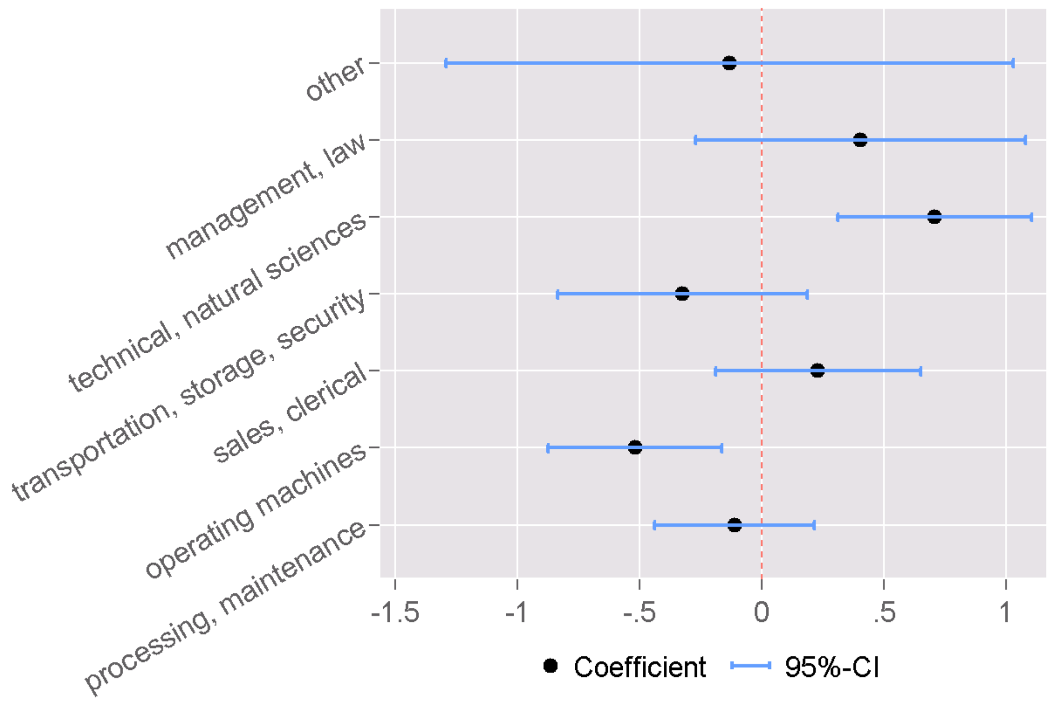
	(a)	(b)	(c)	(d)
Kleibergen-Paap weak ID test	393.1	71.8	175.4	20.6
F-Statistic	393.1	669.3	199.6	1541.1

Notes: The figures visualize the correlations of our robot exposure measures and their fitted values from the first stage. Panels (a) and (b) pertain to the individual-level approach and are based on 993,184 workers. First, both variables are residualized from demographics (Panel a), and from the instruments relating to the exposure to trade and ICT and all control variables from Table 4 (Panel b). Then the residuals of the predicted robot exposure are classified into 100 percentiles. The dots represent the average values of both residualized variables for each of the 100 bins. Panels (c) and (d) pertain to the local labor market approach and show the actual value of the local robot exposure measure and its fitted value from the first stage for all 402 regions. Both variables are residualized from broad region dummies (Panel c), and from the instruments relating to the exposure to trade and ICT and all control variables from Table 1 (Panel d).
Sources: IFR, COMTRADE, EUKLEMS, and IEB V12.00.00 - 2015.09.15, own calculations.

Figure A.2: First stage.



(a) by education, stacked short periods



(b) by occupation, stacked short periods

Notes: The figures report the coefficients of interaction terms of Δ robots per 1000 workers and dummies indicating the respective worker group. The outcome variables are 100 x earnings (normalized by earnings in the base year) cumulated over the twenty years following the base year. All regressions include the same control variables as in column (5) of Table 4. The confidence intervals are constructed from standard errors clustered by industry x federal state.

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

Figure A.3: Heterogeneous earnings effects

C Appendix Tables

Table A.1: Industry-level exposure of robots, trade, and ICT equipment.

		Robot exposure			Trade Exposure			ICT exposure		
WZ 1993	Code	1994-2014	1994-2004	2004-2014	1994-2014	1994-2004	2004-2014	1994-2014	1994-2004	2004-2014
Panel A: Manufacturing industries.										
Manuf. of food products and beverages	15	4.148	1.674	2.992	9.939	-2.981	15.002	417.099	100.005	383.472
Manuf. of tobacco products	16	6.685	2.723	5.684	-40.010	-0.978	-47.363	75.212	21.123	77.580
Manuf. of textiles	17	-0.222	-0.006	-0.408	-53.258	-2.424	-89.195	1863.364	749.411	2104.040
Manuf. of wearing apparel; dressing and dyeing of fur	18	-0.732	-0.603	-0.332	-38.809	-25.523	-27.344	31.144	1.949	74.918
Manuf. of luggage, handbags, saddlery, harness and footwear	19	28.702	20.637	13.833	-147.567	-37.310	-156.492	249.264	57.899	328.212
Manuf. of wood and of products of wood and cork, except furniture	20	-1.308	3.111	-5.640	-10.650	0.600	-14.435	51.583	26.422	32.108
Manuf. of pulp, paper and paper products	21	14.364	5.710	10.088	32.136	23.305	9.051	93.946	24.049	81.475
Publishing, printing and reproduction of recorded media	22	0.167	0.223	-0.071	-3.149	0.623	-4.327	196.418	64.002	168.014
Manuf. of coke, refined petroleum products and nuclear fuel	23	-1.748	2.557	-6.322	-	-	-	492.140	101.726	573.331
Manuf. of basic chemicals	24.1	5.633	1.582	6.491	26.191	17.736	11.614	530.681	131.903	512.647
Manuf. of pesticides and other agro-chemical products	24.2	0.932	0.443	0.323	461.856	33.540	213.066	530.681	131.903	512.647
Manuf. of paints, varnishes and similar coatings, printing ink and mas	24.3	5.031	2.389	2.845	70.051	45.330	21.707	530.681	131.903	512.647
Manuf. of pharmaceuticals, medicinal chemicals and botanical products	24.4	4.607	2.187	2.308	85.224	22.179	47.254	530.681	131.903	512.647
Manuf. of soap and detergents, perfumes and toilet preparations	24.5	6.282	2.982	4.461	47.294	25.394	26.776	530.681	131.903	512.647
Manuf. of other chemical products	24.6	6.115	2.903	3.380	93.632	27.333	56.757	530.681	131.903	512.647
Manuf. of man-made fibres	24.7	6.682	1.877	8.733	-5.481	4.646	-15.076	530.681	131.903	512.647
Manuf. of rubber products	25.1	18.198	6.248	15.065	-44.554	-3.331	-46.225	121.353	30.151	94.366
Manuf. of plastic products	25.2	15.640	5.151	10.334	24.048	19.234	4.337	121.353	30.151	94.366
Manuf. of other non-metallic mineral products	26	5.212	4.337	1.301	6.037	10.767	-6.657	57.076	-6.072	93.791
Manuf. of basic metals	27	-2.371	3.370	-6.751	23.038	12.855	10.415	65.376	16.497	57.478
Manuf. of fabricated metal products, except machinery and equipment	28	3.628	1.079	2.852	6.018	3.260	2.867	1066.639	414.038	730.020
Manuf. of machinery for the prod. and use of mech. power, except engin	29.1	3.512	1.008	2.337	52.066	31.115	16.078	366.091	176.183	216.453
Manuf. of other general purpose machinery	29.2	4.956	1.423	4.366	32.714	13.163	20.516	366.091	176.183	216.453
Manuf. of agricultural and forestry machinery	29.3	5.459	1.567	4.467	83.563	30.978	51.014	366.091	176.183	216.453
Manuf. of machine-tools	29.4	4.210	1.209	3.263	47.274	21.610	24.237	366.091	176.183	216.453
Manuf. of other special purpose machinery	29.5	3.831	1.100	3.273	32.424	28.507	4.037	366.091	176.183	216.453
Manuf. of weapons and ammunition	29.6	6.416	1.842	7.041	-5.401	-0.761	-6.029	366.091	176.183	216.453
Manuf. of domestic appliances n.e.c.	29.7	25.102	21.556	4.906	-54.742	-10.745	-46.255	366.091	176.183	216.453
Manuf. of office machinery and computers	30	8.072	11.894	-4.823	-348.906	-182.425	-170.700	84.856	35.313	62.516
Manuf. of electric motors, generators and transformers	31.1	9.606	2.736	9.580	1.795	-3.266	5.166	336.507	161.945	210.479
Manuf. of electricity distribution and control apparatus	31.2	7.489	2.133	6.646	103.082	64.955	37.039	336.507	161.945	210.479
Manuf. of insulated wire and cable	31.3	8.146	2.320	8.847	-49.500	-20.221	-37.690	336.507	161.945	210.479
Manuf. of accumulators, primary cells and primary batteries	31.4	5.090	1.248	6.038	-6.313	-4.670	-2.198	336.507	161.945	210.479
Manuf. of lighting equipment and electric lamps	31.5	4.848	1.189	4.399	-57.858	-23.004	-33.335	336.507	161.945	210.479
Manuf. of electrical equipment n.e.c.	31.6	52.379	43.460	7.813	-67.591	-35.521	-20.449	336.507	161.945	210.479
Manuf. of electronic valves and tubes and other electronic components	32.1	3.369	0.721	1.926	0.261	29.663	-15.934	164.603	71.454	94.248
Manuf. of TV and radio transmitters and apparatus for line telephony	32.2	0.514	0.231	0.297	-139.537	-89.689	-42.219	164.603	71.454	94.248
Manuf. of TV and radio receivers, sound or video recording apparatus	32.3	9.514	3.410	10.891	-208.090	-143.159	-94.557	164.603	71.454	94.248
Manuf. of medical and surgical equipment and orthopaedic appliances	33.1	-1.751	-0.161	-1.748	23.636	6.837	18.351	96.770	40.271	63.291
Manuf. of instruments for measuring, checking, testing, navigating, et	33.2	-1.895	-0.174	-1.886	34.934	9.847	22.062	96.770	40.271	63.291
Manuf. of industrial process control equipment	33.3	-1.822	-0.167	-1.522	2.479	1.281	0.937	96.770	40.271	63.291
Manuf. of optical instruments and photographic equipment	33.4	-1.058	-0.093	-1.336	-3.253	-9.455	6.746	96.770	40.271	63.291
Manuf. of watches and clocks	33.5	-4.429	-0.406	-6.934	-115.926	-33.579	-125.342	96.770	40.271	63.291
Manuf. of motor vehicles	34.1	108.253	64.582	42.559	40.112	-14.272	39.861	267.386	136.375	123.225
Manuf. of bodies (coachwork) for motor vehicles and (semi-)trailers	34.2	94.652	56.468	41.838	-46.946	-40.924	-6.059	267.386	136.375	123.225
Manuf. of parts and accessories for motor vehicles and their engines	34.3	60.821	51.499	7.829	103.837	47.843	38.426	267.386	136.375	123.225
Manuf. of other transport equipment	35	1.349	0.020	1.502	31.363	8.559	19.739	236.177	123.126	127.749
Manuf. of furniture	36.1	77.141	62.579	23.650	-62.781	-29.408	-53.258	595.077	247.894	534.009
Manuf. of jewellery and related articles	36.2	30.668	17.170	21.789	-1.657	-3.333	2.434	595.077	247.894	534.009
Manuf. of musical instruments	36.3	24.194	13.545	13.573	-14.745	-8.987	-7.317	595.077	247.894	534.009
Manuf. of sports goods	36.4	21.597	12.091	13.117	-291.911	-181.992	-138.225	595.077	247.894	534.009
Manuf. of games and toys	36.5	22.911	12.827	13.308	-287.249	-196.974	-102.437	595.077	247.894	534.009
Miscellaneous manufacturing n.e.c.	36.6	19.082	10.683	10.253	-63.526	-25.778	-40.811	595.077	247.894	534.009

Table A.1: Industry-level exposure of robots, trade, and ICT equipment (continued).

WZ 1993	Code	Robot exposure 1994-2014	Robot exposure 1994-2004	Robot exposure 2004-2014	Trade Exposure 1994-2014	Trade Exposure 1994-2004	Trade Exposure 2004-2014	ICT exposure 1994-2014	ICT exposure 1994-2004	ICT exposure 2004-2014
Panel B: Non-manufacturing industries.										
Agriculture, hunting and related service activities	1	1.996	1.010	1.196	-	-	-	506.394	188.780	385.256
Forestry, logging and related service activities	2	4.517	1.806	4.537	-	-	-	1123.621	428.525	1163.305
Fishing, operation of fish hatcheries and fish farms; incidental service activities	5	0.155	0.012	0.234	-	-	-	128.810	32.449	157.542
Mining of coal and lignite; extraction of peat	10	0.038	-	0.106	-	-	-	15.244	-21.198	101.098
Extraction of crude petroleum and natural gas; incidental service activities	11	0.002	-	0.003	-	-	-	11.476	-3.472	22.396
Mining of uranium and thorium ores	12	-	-	-	-	-	-	0	0	0
Mining of metal ores	13	0.003	-	0.007	-	-	-	19.392	-5.867	54.739
Other mining and quarrying	14	0.001	-	0.002	-	-	-	7.557	-2.287	13.796
Recycling	37	0.002	0.000	0.001	-	-	-	36.174	7.884	14.707
Electricity, gas, steam and hot water supply	40	0.013	0.001	0.017	-	-	-	227.076	49.493	263.788
Collection, purification and distribution of water	41	0.009	0.001	0.009	-	-	-	159.640	34.795	142.208
Construction	45	0.072	0.024	0.083	-	-	-	298.836	32.532	461.060
Sale, maintenance and repair of motor vehicles and motorcycles; retail sale of automotive fuel	50	-	-	-	-	-	-	3601.081	579.306	2693.265
Wholesale trade and commission trade, except of motor vehicles and motorcycles	51	-	-	-	-	-	-	0	0	0
Retail trade, except of motor vehicles and motorcycles; repair of personal and household goods	52	-	-	-	-	-	-	1400.247	474.589	1089.509
Hotels and restaurants	55	-	-	-	-	-	-	72.203	-2.770	75.644
Land transport; transport via pipelines	60	-	-	-	-	-	-	367.350	143.793	263.211
Water transport	61	-	-	-	-	-	-	898.571	351.732	848.759
Air transport	62	-	-	-	-	-	-	332.322	130.082	240.667
Supporting and auxiliary transport activities; activities of travel agencies	63	-	-	-	-	-	-	928.091	363.520	489.391
Post and telecommunications	64	-	-	-	-	-	-	1864.932	1255.343	723.388
Financial intermediation, except insurance and pension funding	65	-	-	-	-	-	-	1207.089	410.532	912.702
Insurance and pension funding, except compulsory social security	66	-	-	-	-	-	-	464.192	116.613	351.531
Activities auxiliary to financial intermediation	67	-	-	-	-	-	-	503.480	126.483	369.598
Real estate activities	70	0.046	0.018	0.029	-	-	-	675.711	213.981	475.999
Renting of machinery and equipment without operator and of personal and household goods	71	-	-	-	-	-	-	440.854	173.797	237.339
Computer and related activities	72	-	-	-	-	-	-	493.254	183.905	113.052
Research and development	73	0.462	0.557	-	-	-	-	644.454	254.062	321.221
Other business activities	74	0.316	0.380	-	-	-	-	1125.425	431.826	493.481
Public administration and defence; compulsory social security	75	-	-	-	-	-	-	1535.462	724.570	1136.930
Education	80	0.343	0.414	-	-	-	-	98.453	31.869	64.696
Health and social work	85	0.364	0.439	-	-	-	-	886.714	356.368	469.116
Sewage and refuse disposal, sanitation and similar activities	90	0.006	0.001	0.007	-	-	-	438.961	153.362	331.201
Activities of membership organizations n.e.c.	91	-	-	-	-	-	-	18.025	8.811	9.412
Recreational, cultural and sporting activities	92	0.360	0.434	-	-	-	-	1867.687	741.049	999.727
Other service activities	93	0.691	0.833	-	-	-	-	3591.214	2341.837	1295.600
Private households with employed persons	95	-	-	-	-	-	-	0	0	0
Extra-territorial organizations and bodies	99	-	-	-	-	-	-	0	0	0

Notes: The table displays the changes in robot exposure (Δ robots per 1000 workers), trade exposure (Δ net exports / wagebill in %), and ICT exposure (Δ ICT equipment in 1000 € per worker) by WZ 1993 industries (German Classification of Economic Activities, Edition 1993), each separately for the whole observation period (1994-2014), and the two subperiods (1994-2004 and 2004-2014). The numbers are presented at the level of the robot industry aggregation (mix of 2-digit and 3-digit level, see column 2). Trade exposure (3-digit level throughout) is summed up over 3-digit industries if the robot exposure is only available at the 2-digit level. For the ICT exposure (2-digit level throughout), the 2-digit industry level exposure is assigned to the subjacent 3-digit industries.
Sources: IFR, COMTRADE, EUKLEMS, and IEB V12.00.00 - 2015.09.15, own calculations.

Table A.2: Summary statistics, worker level.

	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)
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)
[C] Exposure to robots						
Δ robots per 1000 workers	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]	
[D] Exposure to trade and ICT						
Δ net exports / wagebill in %	7.803	(65.234)	2.537	(32.433)	4.542	(45.275)
Δ ICT equipment in € per worker	391.5	(354.1)	150.5	(143.0)	288.7	(307.9)

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

Table A.3: Summary statistics, region level.

	1994-2014		1994-2004		2004-2014	
observations	402		402		402	
	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)
[C] Exposure to robots						
Δ robots per 1000 workers	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]	
[D] Robot production						
dummy, 1=robot producer	0.022	(0.148)	0.022	(0.148)	0.022	(0.148)
[E] Exposure to trade and ICT						
Δ net exports in 1000 € per worker	0.956	(3.146)	0.373	(1.663)	0.609	(2.259)
Δ ICT equipment in € per worker	728.371	(82.917)	267.754	(36.184)	523.693	(57.602)

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

Table A.4: Robot exposure and employment, detailed version (OLS).

	Dependent variable: 100 x Log-△ in total employment between 1994 and 2014							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
△ robots per 1000 workers	0.2324**	0.3637***	0.0416	0.0332	0.0328	0.0243	-0.0005	-0.1025
	(0.095)	(0.106)	(0.126)	(0.125)	(0.126)	(0.123)	(0.132)	(0.172)
dummy, 1=north	2.8598	1.6878	8.8323***	8.7607***	2.9096	2.9669	3.0493	2.9438
	(2.986)	(3.047)	(3.040)	(3.089)	(2.595)	(2.581)	(2.597)	(2.614)
dummy, 1=south	9.4435**	10.1838***	9.2276***	9.3125***	7.3774**	7.4606**	7.3637**	7.5935**
	(3.588)	(3.414)	(3.443)	(3.425)	(2.863)	(2.901)	(2.923)	(2.950)
dummy, 1=east	-23.9257***	-26.8097***	-19.9017***	-19.7888***	-15.2028***	-15.1443***	-14.2909***	-13.0432**
	(3.287)	(3.472)	(5.501)	(5.564)	(4.946)	(4.937)	(5.124)	(5.000)
% manufacturing		-0.1875**	-0.0979	-0.0922				
		(0.088)	(0.189)	(0.189)				
% high skilled			1.3220**	1.3331**	1.2854***	1.2762***	1.1835***	1.1082***
			(0.526)	(0.521)	(0.392)	(0.393)	(0.416)	(0.412)
% medium skilled			0.6455	0.6443	-0.1102	-0.1266	-0.1045	-0.1514
			(0.535)	(0.534)	(0.467)	(0.468)	(0.475)	(0.479)
% female			-0.6439	-0.6607	-1.1373***	-1.1154***	-1.1367***	-1.2205***
			(0.451)	(0.461)	(0.346)	(0.351)	(0.356)	(0.352)
% age $\geq$50 yrs			-2.9117***	-2.8899***	-2.1699***	-2.2021***	-2.1610***	-2.1998***
			(0.495)	(0.501)	(0.482)	(0.496)	(0.489)	(0.493)
% foreign			1.0258***	1.0261***	0.5890*	0.5854*	0.5996*	0.6149*
			(0.262)	(0.261)	(0.315)	(0.317)	(0.323)	(0.314)
dummy, 1=robot producer				-4.8877	-4.2592	-4.2083	-3.9931	-4.1504
				(4.350)	(4.519)	(4.562)	(4.652)	(4.626)
% food products					2.4018***	2.3893***	2.4246***	2.4400***
					(0.407)	(0.406)	(0.402)	(0.403)
% consumer goods					0.4398	0.4920	0.5921**	0.6396**
					(0.292)	(0.300)	(0.293)	(0.307)
% industrial goods					0.6554***	0.6439**	0.6622***	0.6846***
					(0.239)	(0.242)	(0.244)	(0.252)
% capital goods					1.0181***	0.9991***	1.0118***	1.0371***
					(0.246)	(0.255)	(0.260)	(0.271)
% construction					1.5623***	1.5616***	1.5571***	1.5597***
					(0.332)	(0.332)	(0.338)	(0.342)
% maintenance					1.6670***	1.6665***	1.7592***	1.7993***
					(0.375)	(0.375)	(0.369)	(0.370)
% services					0.5555**	0.5548**	0.6603***	0.7095***
					(0.255)	(0.255)	(0.241)	(0.247)
% education					0.9915***	0.9915***	1.1429***	1.1966***
					(0.238)	(0.239)	(0.271)	(0.270)
△ net exports in 1000 €per worker						0.1956	0.2375	0.2161
						(0.242)	(0.242)	(0.249)
△ ICT equipment in €per worker							-0.0163	-0.0166
							(0.017)	(0.017)
R^2	0.432	0.439	0.541	0.543	0.623	0.623	0.625	0.623
Exclude top auto regions	No	No	No	No	No	No	No	Yes

Notes: $N = 402$. Detailed version of Table 1, Panel A. Standard errors clustered at the level of 50 aggregate labor market regions in parentheses. Levels of significance: *** 1 %, ** 5 %, * 10 %.
Sources: IFR, COMTRADE, EUKLEMS, and IEB V12.00.00 - 2015.09.15, own calculations.

Table A.5: Robot exposure and employment, detailed version (2SLS).

	Dependent variable: 100 x Log-△ in total employment between 1994 and 2014							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
△ robots per 1000 workers	0.2410**	0.3845***	0.0399	0.0344	0.0139	-0.0227	-0.0058	-0.0848
	(0.095)	(0.105)	(0.124)	(0.124)	(0.128)	(0.121)	(0.120)	(0.150)
dummy, 1=north	2.8530	1.6300	8.8386***	8.7563***	2.9547	3.1767	3.1153	2.9901
	(2.944)	(3.008)	(2.972)	(3.017)	(2.523)	(2.504)	(2.508)	(2.515)
dummy, 1=south	9.4321***	10.1916***	9.2274***	9.3126***	7.3483***	7.6424***	7.6471***	7.8588***
	(3.538)	(3.347)	(3.367)	(3.343)	(2.778)	(2.869)	(2.844)	(2.889)
dummy, 1=east	-23.9046***	-26.8825***	-19.8971***	-19.7922***	-15.0626***	-14.8076***	-15.1214***	-13.9563***
	(3.232)	(3.424)	(5.386)	(5.436)	(4.737)	(4.789)	(4.809)	(4.678)
% manufacturing		-0.1947**	-0.0973	-0.0927				
		(0.087)	(0.184)	(0.184)				
% high skilled			1.3234***	1.3321***	1.2834***	1.2496***	1.2802***	1.2008***
			(0.511)	(0.507)	(0.378)	(0.381)	(0.395)	(0.394)
% medium skilled			0.6465	0.6436	-0.1050	-0.1630	-0.1646	-0.2088
			(0.520)	(0.519)	(0.450)	(0.452)	(0.451)	(0.456)
% female			-0.6444	-0.6603	-1.1438***	-1.0661***	-1.0664***	-1.1411***
			(0.441)	(0.449)	(0.330)	(0.354)	(0.353)	(0.347)
% age $\geq$50 yrs			-2.9126***	-2.8892***	-2.1807***	-2.3013***	-2.2967***	-2.3267***
			(0.484)	(0.489)	(0.471)	(0.496)	(0.495)	(0.498)
% foreign			1.0263***	1.0257***	0.5940*	0.5826*	0.5783*	0.5872**
			(0.257)	(0.256)	(0.304)	(0.314)	(0.311)	(0.299)
dummy, 1=robot producer				-4.8847	-4.3063	-4.1351	-4.2004	-4.2992
				(4.250)	(4.365)	(4.533)	(4.467)	(4.464)
% food products					2.4014***	2.3558***	2.3508***	2.3708***
					(0.393)	(0.391)	(0.394)	(0.394)
% consumer goods					0.4476	0.6400**	0.5882*	0.6329**
					(0.280)	(0.307)	(0.305)	(0.317)
% industrial goods					0.6576***	0.6164***	0.6149***	0.6363***
					(0.231)	(0.237)	(0.237)	(0.246)
% capital goods					1.0300***	0.9645***	0.9643***	0.9856***
					(0.239)	(0.251)	(0.248)	(0.260)
% construction					1.5589***	1.5551***	1.5578***	1.5604***
					(0.319)	(0.318)	(0.317)	(0.321)
% maintenance					1.6671***	1.6654***	1.6392***	1.6862***
					(0.362)	(0.362)	(0.367)	(0.370)
% services					0.5595**	0.5584**	0.5272**	0.5819**
					(0.246)	(0.249)	(0.261)	(0.267)
% education					0.9949***	0.9961***	0.9518***	1.0136***
					(0.229)	(0.234)	(0.267)	(0.266)
△ net exports in 1000 €per worker						0.7123**	0.6232*	0.5975
						(0.359)	(0.370)	(0.376)
△ ICT equipment in €per worker							0.0046	0.0027
							(0.015)	(0.014)
R^2	0.432	0.439	0.541	0.543	0.623	0.618	0.618	0.617
Exclude top auto regions	No	No	No	No	No	No	No	Yes

Notes: $N = 402$. Detailed version of Table 1, Panel B. 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. Standard errors clustered at the level of 50 aggregate labor market regions in parentheses. Levels of significance: *** 1 %, ** 5 %, * 10 %.
Sources: IFR, COMTRADE, EUKLEMS, and IEB V12.00.00 - 2015.09.15, own calculations.

Table A.6: Robot producers.

Name	Headquarter	Production facility in Germany
	Headquarter in Germany	
ABB	**Mannheim** (ABB Germany) Baden (CH, ABB International)	Mannheim, Friedberg (Wetteraukreis), Hamburg
Kuka	**Augsburg**	Augsburg, Wolfsburg, Siegen, Braunschweig Hude-Wuesting (Kreis Oldenburg)
Cloos	Haigar (**Lahn-Dill Kreis**)	Haigar (Lahn-Dill Kreis), Berlin
Duerr	Bietigheim-Bissingen (Kreis **Ludwigsburg**)	Bietigheim-Bissingen (Kreis Ludwigsburg)
b+m	Eiterfeld (Kreis **Fulda**)	Eiterfeld (Kreis Fulda)
	Headquarter outside Germany	
Wittmann	Wien (AT)	**Nuremberg**, Meinerzhagen (**Maerkischer Kreis**)
Staeubli	Pfaeffikon SZ (CH)	**Bayreuth**, **Chemnitz**
igm	Wiener Neudorf (AT)	Kornwestheim (Kreis **Ludwigsburg**)

Table A.7: Robot exposure and average wages, detailed version (OLS).

	Dependent variable: 100 x Log-△ in average wages between 1994 and 2014							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
△ robots per 1000 workers	0.1684***	0.1164***	0.0485	0.0460	-0.0136	-0.0178	-0.0262	-0.0181
	(0.032)	(0.037)	(0.042)	(0.043)	(0.050)	(0.050)	(0.051)	(0.071)
dummy, 1=north	-2.0007***	-1.5381***	-0.3590	-0.3809	-1.4080**	-1.3789**	-1.3483**	-1.3805**
	(0.421)	(0.492)	(0.583)	(0.583)	(0.656)	(0.656)	(0.652)	(0.653)
dummy, 1=south	3.1077***	2.8153***	3.0566***	3.0825***	2.3227***	2.3618***	2.3290***	2.3549***
	(0.525)	(0.497)	(0.563)	(0.563)	(0.596)	(0.600)	(0.604)	(0.609)
dummy, 1=east	11.9557***	13.0959***	13.3830***	13.4180***	10.1149***	10.1432***	10.4378***	10.4759***
	(0.577)	(0.729)	(1.193)	(1.196)	(1.665)	(1.666)	(1.674)	(1.683)
% manufacturing		0.0742***	0.1007***	0.1024***				
		(0.025)	(0.034)	(0.034)				
% high skilled			0.4376***	0.4409***	0.3964***	0.3923***	0.3596***	0.3530***
			(0.113)	(0.113)	(0.120)	(0.119)	(0.123)	(0.123)
% medium skilled			0.1374	0.1369	0.1343	0.1266	0.1334	0.1263
			(0.104)	(0.105)	(0.102)	(0.102)	(0.102)	(0.102)
% female			-0.1660**	-0.1711**	0.0332	0.0440	0.0365	0.0369
			(0.080)	(0.080)	(0.090)	(0.090)	(0.091)	(0.092)
% age ≥50 yrs			-0.3593***	-0.3526***	-0.2041*	-0.2205*	-0.2057*	-0.2135*
			(0.107)	(0.106)	(0.118)	(0.119)	(0.120)	(0.120)
% foreign			0.1213	0.1214	0.0136	0.0121	0.0168	0.0106
			(0.084)	(0.084)	(0.090)	(0.089)	(0.089)	(0.088)
dummy, 1=robot producer				-1.4864*	-1.4220*	-1.3931*	-1.3182	-1.3116
				(0.842)	(0.774)	(0.808)	(0.829)	(0.836)
% food products					0.0434	0.0375	0.0497	0.0518
					(0.145)	(0.144)	(0.143)	(0.143)
% consumer goods					-0.1884	-0.1628	-0.1285	-0.1301
					(0.117)	(0.119)	(0.120)	(0.122)
% industrial goods					-0.0359	-0.0415	-0.0352	-0.0354
					(0.104)	(0.104)	(0.104)	(0.104)
% capital goods					0.1171	0.1079	0.1121	0.1119
					(0.108)	(0.108)	(0.108)	(0.109)
% construction					-0.0063	-0.0069	-0.0080	-0.0083
					(0.132)	(0.132)	(0.132)	(0.132)
% maintenance					-0.1338	-0.1341	-0.1025	-0.0998
					(0.123)	(0.123)	(0.124)	(0.124)
% services					-0.1230	-0.1233	-0.0869	-0.0849
					(0.114)	(0.114)	(0.116)	(0.116)
% education					-0.1910	-0.1911	-0.1387	-0.1389
					(0.124)	(0.124)	(0.129)	(0.130)
△ net exports in 1000 €per worker						0.0960	0.1100*	0.1137*
						(0.065)	(0.064)	(0.066)
△ ICT equipment in €per worker							-0.0056	-0.0056
							(0.004)	(0.004)
R^2	0.583	0.584	0.587	0.587	0.589	0.589	0.589	0.589
Exclude top auto regions	No	No	No	No	No	No	No	Yes

Notes: $N = 7149$. Detailed version of Table 2, Panel A. Standard errors clustered at the level of local labor markets in parentheses.
Levels of significance: *** 1 %, ** 5 %, * 10 %.
Sources: IFR, COMTRADE, EUKLEMS, and IEB V12.00.00 - 2015.09.15, own calculations.

Table A.8: Robot exposure and average wages, detailed version (2SLS).

	Dependent variable: 100 x Log-△ in average wages between 1994 and 2014							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
△ robots per 1000 workers	0.1677***	0.1122***	0.0413	0.0399	-0.0100	-0.0185	-0.0360	-0.0238
	(0.036)	(0.043)	(0.048)	(0.048)	(0.054)	(0.053)	(0.057)	(0.083)
dummy, 1=north	-2.0001***	-1.5267***	-0.3325	-0.3590	-1.4167**	-1.3605**	-1.2994**	-1.3345**
	(0.422)	(0.499)	(0.589)	(0.588)	(0.658)	(0.662)	(0.662)	(0.663)
dummy, 1=south	3.1086***	2.8137***	3.0559***	3.0821***	2.3282***	2.4005***	2.3475***	2.3738***
	(0.526)	(0.495)	(0.561)	(0.561)	(0.591)	(0.598)	(0.606)	(0.610)
dummy, 1=east	11.9540***	13.1104***	13.4027***	13.4347***	10.0881***	10.1459***	10.6468***	10.6436***
	(0.575)	(0.733)	(1.187)	(1.190)	(1.651)	(1.661)	(1.727)	(1.744)
% manufacturing		0.0756***	0.1033***	0.1046***				
		(0.025)	(0.035)	(0.035)				
% high skilled			0.4436***	0.4459***	0.3967***	0.3889***	0.3359***	0.3319***
			(0.113)	(0.113)	(0.119)	(0.119)	(0.122)	(0.123)
% medium skilled			0.1416	0.1404	0.1332	0.1191	0.1300	0.1226
			(0.105)	(0.105)	(0.102)	(0.102)	(0.104)	(0.103)
% female			-0.1680**	-0.1728**	0.0344	0.0546	0.0427	0.0459
			(0.080)	(0.080)	(0.089)	(0.091)	(0.093)	(0.095)
% age ≥50 yrs			-0.3633***	-0.3559***	-0.2021*	-0.2331*	-0.2135*	-0.2226*
			(0.107)	(0.106)	(0.117)	(0.120)	(0.119)	(0.120)
% foreign			0.1235	0.1232	0.0126	0.0100	0.0184	0.0106
			(0.083)	(0.083)	(0.089)	(0.088)	(0.088)	(0.087)
dummy, 1=robot producer				-1.5009*	-1.4132*	-1.3606	-1.2458	-1.2376
				(0.839)	(0.769)	(0.843)	(0.882)	(0.891)
% food products					0.0435	0.0323	0.0510	0.0523
					(0.144)	(0.143)	(0.145)	(0.145)
% consumer goods					-0.1898	-0.1417	-0.0821	-0.0864
					(0.116)	(0.119)	(0.128)	(0.130)
% industrial goods					-0.0363	-0.0467	-0.0369	-0.0383
					(0.103)	(0.104)	(0.104)	(0.105)
% capital goods					0.1149	0.0979	0.1057	0.1044
					(0.107)	(0.108)	(0.109)	(0.110)
% construction					-0.0057	-0.0068	-0.0093	-0.0097
					(0.132)	(0.131)	(0.131)	(0.131)
% maintenance					-0.1338	-0.1343	-0.0838	-0.0835
					(0.123)	(0.123)	(0.130)	(0.130)
% services					-0.1238	-0.1242	-0.0653	-0.0662
					(0.113)	(0.114)	(0.122)	(0.123)
% education					-0.1917	-0.1917	-0.1073	-0.1117
					(0.124)	(0.124)	(0.137)	(0.138)
△ net exports in 1000 €per worker						0.1799**	0.2144***	0.2206***
						(0.087)	(0.082)	(0.086)
△ ICT equipment in €per worker							-0.0090	-0.0086
							(0.006)	(0.006)
R^2	0.583	0.584	0.587	0.587	0.589	0.589	0.589	0.589
Exclude top auto regions	No	No	No	No	No	No	No	Yes

Notes: $N = 7149$. Detailed version of Table 2, Panel B. 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. Standard errors clustered at the level of local labor markets in parentheses. Levels of significance: *** 1 %, ** 5 %, * 10 %.
Sources: IFR, COMTRADE, EUKLEMS, and IEB V12.00.00 - 2015.09.15, own calculations.

Table A.9: The effect of robots on non-manufacturing employment.

	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: $N = 402$. 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. 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 full set of control variables as in column (7) of Table 1. Standard errors clustered at the level of 50 aggregate labor market regions in parentheses. Levels of significance: *** 1 %, ** 5 %, * 10 %.

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

Table A.10: The effect of robots in the automotive sector.

	(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: The employment estimates in Panel A are based on one observation per region, while the wage estimates in Panel B exploit region x demographic cells. Columns (1) to (3) display estimates for the whole manufacturing sector, manufacturing of motor vehicles, and manufacturing except motor vehicles, respectively. 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 full set of control variables as in column (7) of Table 1 respectively Table 2. 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 %.

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

Table A.11: Employment and average wage effects in different time periods.

	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: 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 outcome variables are log-differences in employment and average wages: Total employment (1), employment in manufacturing (2), employment in non-manufacturing (3), total average wages (4), average wages in manufacturing (5), and average wages in non-manufacturing (6). Panels B and C: 10-year changes for 1994-2004 (first period) and 2004-2014 (second period), respectively. Panel A: Stacked differences (first and second period). 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 full set of control variables as in column (7) of Table 1 respectively Table 2. 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 %.

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

Table A.12: Robustness checks. Region-level.

	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

Notes: This table presents robustness checks for the baseline specifications for employment and average wages as of Table 3, Panel A. The dependent variables are log-differences in employment respectively average wages between 1994 and 2014. Panels A-C present variants of the IV estimation: a just-identified rather than an overidentified IV, an overidentified IV but excluding direct neighbors from the instrument group (i.e. France), and excluding members of the European Monetary Union (i.e. France, Spain, Italy, Finland). In Panel D, the robustness of the results with regard to the cross-walk between ISIC Rev. 4 and NACE Rev. 1 industries - which was necessary to link the data on robots with German labor market data - is checked. We construct a reverse cross-walk assigning one of the 25 ISIC codes to each of the 73 NACE codes (for more details see Appendix A), and recalculate the local robot exposure. Panels E und F perform the regressions for West Germany only and include federal state dummies instead of broad regional dummies, respectively. 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 full set of control variables as in column (7) of Table 1 respectively Table 2. Standard errors clustered at the level of 50 aggregate labor market regions (employment regressions) or at the level of local labor markets (wage regressions) in parentheses. Levels of significance: *** 1 %, ** 5 %, * 10 %.

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

Table A.13: Robot exposure and individual employment outcomes, detailed version.

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)
Δ net exports / wagebill in %					0.8422***	0.8541***
					(0.125)	(0.133)
Δ ICT equipment in € per worker					0.0323	0.0330
					(0.029)	(0.029)
dummy, 1=female	-917.7947***	-648.8021***	-671.4804***	-628.9431***	-624.7951***	-612.5067***
	(23.071)	(22.496)	(21.081)	(19.595)	(19.552)	(20.296)
dummy, 1=foreign	-736.1391***	-626.2524***	-655.2834***	-637.9227***	-636.5159***	-659.8171***
	(24.746)	(21.813)	(22.444)	(20.167)	(20.358)	(20.149)
dummy, 1=age 35-44 yrs	-161.1827***	-265.7044***	-251.3286***	-277.1321***	-276.6233***	-267.9716***
	(14.237)	(14.974)	(13.569)	(13.655)	(13.651)	(14.680)
dummy, 1=low skilled		-144.0824***	-187.8435***	-154.1180***	-149.6269***	-149.7873***
		(14.118)	(12.944)	(10.737)	(10.471)	(11.206)
dummy, 1=high skilled		-282.5842***	-285.7575***	-340.4808***	-333.1758***	-339.1940***
		(20.082)	(17.736)	(16.001)	(15.696)	(16.912)
dummy, 1=tenure 5-9 yrs		93.4181***	60.6774***	103.6687***	101.4863***	104.6909***
		(12.772)	(11.246)	(8.061)	(7.985)	(8.512)
dummy, 1=tenure ≥10 yrs		218.9896***	167.2056***	213.6360***	210.4657***	236.0762***
		(17.031)	(15.236)	(13.607)	(13.443)	(11.194)
log base year earnings		715.5460***	538.2000***	616.6627***	613.8873***	605.0080***
		(24.029)	(22.293)	(20.471)	(20.120)	(20.664)
dummy, 1=plant size 10-99			443.8309***	425.5094***	424.0372***	425.1091***
			(23.350)	(21.989)	(21.627)	(21.529)
dummy, 1=plant size 100-499			657.3304***	628.5894***	627.1175***	626.2540***
			(26.112)	(23.980)	(23.545)	(23.429)
dummy, 1=plant size 500-999			759.6757***	708.0179***	708.9422***	711.1334***
			(29.240)	(27.516)	(27.090)	(27.119)
dummy, 1=plant size 1,000-9,999			889.5952***	813.9533***	814.3005***	813.7919***
			(33.569)	(30.796)	(29.862)	(30.277)
dummy, 1=plant size ≥10,000			863.5093***	771.4514***	754.3875***	792.8549***
			(55.860)	(50.933)	(50.387)	(72.047)
dummy, 1=consumer goods				-221.3766***	-181.8988***	-188.2315***
				(30.985)	(33.304)	(36.371)
dummy, 1=industrial goods				53.5966**	47.8951*	48.4795*
				(25.080)	(25.337)	(26.126)
dummy, 1=capital goods				120.0419***	124.9539***	128.5595***
				(22.648)	(21.858)	(23.082)
constant	6267.0989***	-1266.3391***	-1.4563	-842.3314***	-831.6840***	-765.9009***
	(28.385)	(251.717)	(229.138)	(209.701)	(205.595)	(212.003)
federal state dummies	No	No	No	Yes	Yes	Yes
drop automotive industries	No	No	No	No	No	Yes
R^2	0.056	0.078	0.089	0.095	0.096	0.089

Notes: Based on 993,184 workers. The outcome variable is the number of days employed, cumulated over the twenty years following the base year. Standard errors clustered by industry x federal state in parentheses. Levels of significance: *** 1 %, ** 5 %, * 10 %.
Sources: IFR, COMTRADE, EUKLEMS, and IEB V12.00.00 - 2015.09.15, own calculations.

Table A.14: Robot exposure and individual employment outcomes, detailed version.

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)
dummy, 1=female	-916.3624***	-647.6965***	-670.1007***	-627.0416***	-624.8930***	-612.3579***
	(22.888)	(22.394)	(21.051)	(19.530)	(19.590)	(20.305)
dummy, 1=foreign	-736.4797***	-626.8389***	-655.7479***	-638.5468***	-637.3995***	-660.5146***
	(24.689)	(21.746)	(22.393)	(20.076)	(20.273)	(20.114)
dummy, 1=age 35-44 yrs	-161.0488***	-265.0483***	-251.1314***	-276.9416***	-276.6659***	-267.9559***
	(14.207)	(14.914)	(13.564)	(13.643)	(13.657)	(14.685)
dummy, 1=low skilled		-144.0167***	-187.7218***	-154.4592***	-151.2735***	-150.8625***
		(14.121)	(12.961)	(10.734)	(10.547)	(11.252)
dummy, 1=high skilled		-280.7540***	-283.5540***	-338.0439***	-334.2656***	-340.0433***
		(19.939)	(17.678)	(15.849)	(15.657)	(16.912)
dummy, 1=tenure 5-9 yrs		92.8145***	60.6728***	103.7963***	102.2399***	104.9934***
		(12.778)	(11.248)	(8.027)	(7.997)	(8.527)
dummy, 1=tenure $\geq$10 yrs		217.5659***	167.1306***	213.7207***	211.5353***	236.7164***
		(17.117)	(15.230)	(13.580)	(13.497)	(11.232)
log base year earnings		713.1527***	538.3001***	616.9674***	615.2080***	606.0764***
		(24.026)	(22.196)	(20.387)	(20.148)	(20.671)
dummy, 1=plant size 10-99			444.0151***	425.8716***	424.6279***	425.3802***
			(23.382)	(21.977)	(21.721)	(21.560)
dummy, 1=plant size 100-499			657.0994***	628.6551***	627.6092***	626.3821***
			(26.144)	(23.953)	(23.685)	(23.503)
dummy, 1=plant size 500-999			758.8889***	707.6903***	708.6290***	710.8671***
			(29.360)	(27.495)	(27.208)	(27.202)
dummy, 1=plant size 1,000-9,999			885.5871***	810.8296***	812.5834***	812.7519***
			(34.190)	(30.742)	(30.106)	(30.380)
dummy, 1=plant size $\geq$10,000			843.6919***	753.6554***	750.1966***	794.0963***
			(58.190)	(49.725)	(50.370)	(72.617)
dummy, 1=consumer goods				-227.3537***	-199.3871***	-199.5957***
				(31.077)	(32.933)	(36.132)
dummy, 1=industrial goods				54.4785**	49.9778*	49.1561*
				(25.172)	(25.584)	(26.256)
dummy, 1=capital goods				115.4287***	121.5162***	127.5449***
				(22.936)	(22.436)	(23.273)
constant	6263.3545***	-1246.1240***	-6.3783	-847.1495***	-842.8232***	-778.2982***
	(27.614)	(251.852)	(228.247)	(209.247)	(206.162)	(212.061)
federal state dummies	No	No	No	Yes	Yes	Yes
drop automotive industries	No	No	No	No	No	Yes
R^2	0.056	0.078	0.089	0.095	0.096	0.089

Notes: Based on 993,184 workers. The outcome variable is the number of days employed, cumulated over the twenty years following the base year. 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. Standard errors clustered by industry x federal state in parentheses. Levels of significance: *** 1 %, ** 5 %, * 10 %.
Sources: IFR, COMTRADE, EUKLEMS, and IEB V12.00.00 - 2015.09.15, own calculations.

Table A.15: Robot exposure and individual employment outcomes – changes over time.

Dependent variable: Number of days employed, cumulated over full observation period following the base year						
[A] 2SLS, Stacked periods	(1)	(2)	(3)	(4)	(5)	(6)
Δ robots per 1000 workers	1.7140***	0.7109	0.7912*	0.7828**	0.7142**	0.4611
	(0.545)	(0.476)	(0.454)	(0.311)	(0.309)	(0.325)
Δ net exports / wagebill in %					0.2255*	0.3148***
					(0.119)	(0.114)
Δ ICT equipment in € per worker					0.0009	0.0156
					(0.018)	(0.016)
[B] 2SLS, period 1994-2004	(1)	(2)	(3)	(4)	(5)	(6)
Δ robots per 1000 workers	1.1738*	0.4840	0.4258	0.4471	0.6048**	0.2679
	(0.689)	(0.537)	(0.472)	(0.315)	(0.307)	(0.360)
Δ net exports / wagebill in %					0.5780***	0.6146***
					(0.161)	(0.161)
Δ ICT equipment in € per worker					0.0372	0.0376
					(0.025)	(0.025)
[C] 2SLS, period 2004-2014	(1)	(2)	(3)	(4)	(5)	(6)
Δ robots per 1000 workers	1.6159***	-0.1806	0.0570	-0.0387	-0.4638	1.5189
	(0.523)	(0.462)	(0.636)	(0.644)	(0.652)	(0.983)
Δ net exports / wagebill in %					0.0772	0.1192
					(0.082)	(0.084)
Δ ICT equipment in € per worker					0.0080	0.0081
					(0.011)	(0.011)
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 2,677,990 (Panel A), 1,431,576 (Panel B), and 1,246,414 workers (Panel C). The outcome variable is the number of days employed, cumulated over the twenty years following the base year. 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. In panel A, federal state dummies are interacted with a time dummy. Standard errors clustered by industry x federal state in parentheses. Levels of significance: *** 1 %, ** 5 %, * 10 %.

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

Table A.16: Individual earnings and average wages – changes over time.

[A] 2SLS, Stacked periods	(1)	(2)	(3)	(4)	(5)	(6)
		Earnings			Average Wages	
Δ robots per 1000 workers	-0.2737	-0.3735**	-0.4452**	-0.0430***	-0.0508***	-0.0502***
	(0.179)	(0.181)	(0.220)	(0.012)	(0.012)	(0.014)
Δ net exports / wagebill in %		0.1668***	0.1994***		0.0114***	0.0133***
		(0.054)	(0.052)		(0.004)	(0.004)
Δ ICT equipment in € per worker		0.0274**	0.0311***		0.0023***	0.0023***
		(0.011)	(0.010)		(0.001)	(0.001)
[B] 2SLS, period 1994-2004	(1)	(2)	(3)	(4)	(5)	(6)
		Earnings			Average Wages	
Δ robots per 1000 workers	-0.4420**	-0.3922**	-0.6908***	-0.0516***	-0.0500***	-0.0724***
	(0.173)	(0.170)	(0.231)	(0.012)	(0.012)	(0.015)
Δ net exports / wagebill in %		0.1387**	0.1271*		0.0015	0.0001
		(0.070)	(0.074)		(0.005)	(0.005)
Δ ICT equipment in € per worker		-0.0026	-0.0024		-0.0012	-0.0012
		(0.019)	(0.018)		(0.001)	(0.001)
[C] 2SLS, period 2004-2014	(1)	(2)	(3)	(4)	(5)	(6)
		Earnings			Average Wages	
Δ robots per 1000 workers	-1.1664***	-1.2008***	-0.5072	-0.1089***	-0.1043***	-0.0750***
	(0.313)	(0.307)	(0.398)	(0.026)	(0.024)	(0.026)
Δ net exports / wagebill in %		0.1324***	0.1685***		0.0109***	0.0138***
		(0.044)	(0.047)		(0.003)	(0.004)
Δ ICT equipment in € per worker		0.0330***	0.0319***		0.0030***	0.0029***
		(0.009)	(0.008)		(0.001)	(0.001)
age, gender, nationality dummies	Yes	Yes	Yes	Yes	Yes	Yes
education and tenure dummies	Yes	Yes	Yes	Yes	Yes	Yes
ln base yr earnings	Yes	Yes	Yes	Yes	Yes	Yes
plant size dummies	Yes	Yes	Yes	Yes	Yes	Yes
broad industry dummies	Yes	Yes	Yes	Yes	Yes	Yes
federal state dummies	Yes	Yes	Yes	Yes	Yes	Yes
drop automotive industries	No	No	Yes	No	No	Yes

Notes: Based on 2,677,990 (Panel A), 1,431,576 (Panel B), and 1,246,414 workers (Panel C). The outcome variables are 100 x earnings normalized by earnings in the base year and cumulated over the twenty years following the base year (columns 1-3) and 100 x log average wages over the twenty years following the base year (columns 4-6). 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. In panel A, federal state dummies are interacted with a time dummy. Standard errors clustered by industry x federal state in parentheses. Levels of significance: *** 1 %, ** 5 %, * 10 %.

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