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.

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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.

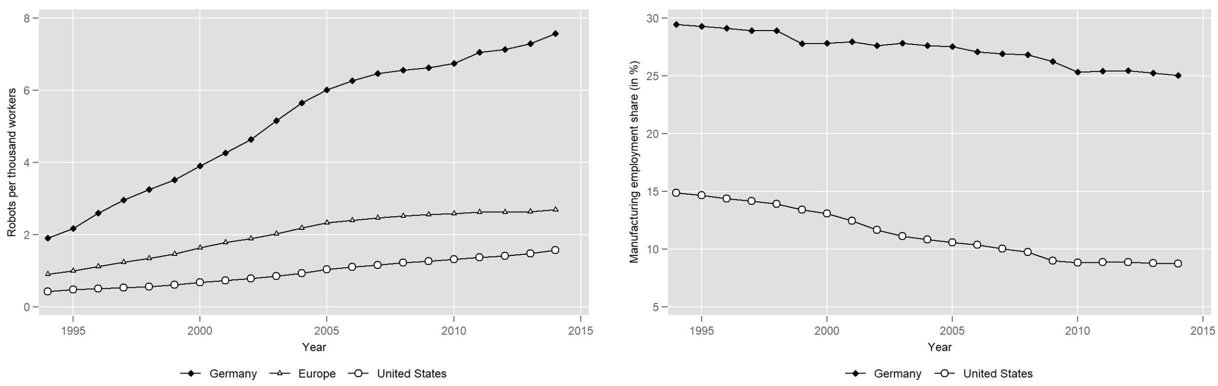
Various studies have indeed argued that technological progress has contributed to rising wage inequality and labor market polarization in advanced countries during the past decades (e.g., Autor et al. 2003; Autor and Dorn 2013; Goos et al. 2014), and estimates have been suggested how many occupations are at risk of being automated given the type of work they usually conduct.[1] Until very recently, however, there has been little systematic analysis about the *general equilibrium* impact of robots and other new technologies, after workers have adjusted to the induced wage and price responses.

Acemoglu and Restrepo (2017a,b, 2016), henceforth labelled AR, 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 can be soaked up by different industries, and specialize in new tasks complementary to robots. The ultimate impact of robots is, therefore, an empirical question which AR address with a local labor market approach for the United States (1993-2014). It turns out that the displacement effect seems to dominate, since AR find pervasive negative responses to robot exposure in the US. Quantitatively, their results imply that one additional robot reduces total employment by around 3–6 jobs. It also reduces average equilibrium wages for almost all groups.

In this paper we focus on Germany. We start with a similar local labor market approach as in AR, and then turn to a more detailed analysis at the individual worker-level. Using linked employer-employee data, we trace employment biographies and earnings profiles of roughly 1 million workers with a varying degree of robot exposure over time.

[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.

This allows us to analyze if robots (and other technology and trade shocks) have causally affected the risk of job displacement and wages for different types of individuals. We also study if workers have switched jobs within and across establishments, industries, and occupations in view of the robots, 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.



(a) Industrial robots.

(b) Manufacturing employment.

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

Notes: Robot data from the International Federation of Robotics (IFR). *Europe* = Germany, France, Italy, Spain, Finland, Sweden, UK. Employment data from the Establishment History Panel (BHP) for Germany, from the Bureau of Labor Statistics (BLS) for the US, and from EUKLEMS for the remaining European countries (for Spain, Italy and UK, employment data is only available from 1995 on. Numbers for 1994 are imputed using average employment growth rates per country from 1995 to 2014).

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). Our analysis will therefore elicit the causal effect of robots in a context with many more manufacturing jobs per capita that could potentially be replaced, but where robot usage itself is already more pervasive and matured.

Second, Germany is not only a heavy user but also an important engineer of industrial robots. The "robotics world rankings" list 8 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 German labor market data with the same data on industrial robots that is also used by AR and in the pioneering study by Graetz and Michaels (2016, 2017) who exploit industry-level variation across countries. 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.[2]

Main findings. Our local labor market analysis reveals substantial differences in how Germany has responded to the rise of the robots. In particular, there is no evidence for negative total employment effects like in the US. The raw correlation between robots and local employment growth is even positive, but this is strongly driven by the automobile industry which is highly spatially concentrated and has by far the most industrial robots (see Section 2). Once local industry structures and demographics are taken into account, we find no effect of robots on total employment, neither in simple ordinary least square (OLS) regressions nor when using robot exposure of other countries as an instrument.[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 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. But those sizable losses are fully offset by job gains outside manufacturing. In other words, robots have strongly changed the *composition* of employment by driving the decline of manufacturing and the rise of service jobs which is illustrated in Figure 1b above. We calculate

[2]The robot data for the US is only broken down at the industry-level from 2004 onwards, so that AR have to construct US robot exposures 1993-2004 based on the distribution of robots across industries as observed in Europe. For Germany, no such imputation is necessary.

[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.

that robots were responsible for almost 23% of this overall decline. But they have *not* destroyed jobs in the aggregate during the observation period, although their impacts have become somewhat more adverse to workers over time.

These aggregate empirical findings raise the question how and through which channels robots have affected single workers. To shed light on this issue, we turn to our novel approach that exploits detailed data for individual work biographies. We find – quite surprisingly – that workers from more robot-exposed industries have indeed a substantially *higher* probability to remain employed. In fact, they are even more likely to keep a job in their original workplace, i.e., robot exposure has increased job stability for them. The negative equilibrium effect of robots on aggregate manufacturing employment is therefore *not* brought about by direct displacements of incumbent manufacturing workers. It is instead driven by smaller flows of labor market entrants into more robot-exposed industries. Put differently, robots do not destroy existing manufacturing jobs in Germany, but they induce manufacturing firms to create fewer new jobs for young people.

What effects do robots have on 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 sizable negative impacts, particularly in machine-operating occupations. As we discuss in more detail below, it seems plausible that those workers (or unions and work councils on their behalf) have accepted, in view of the threat posed by robots, lower wages in return for maintained job security. This hypothesis is consistent with the empirical pattern that robots have negative wage but positive individual employment effects for these groups. At the aggregate level we find that robots enhance average productivity in the local labor market. This is consistent with the view that robots complement humans at the workplace and make them more productive. But there is no such impulse of robots on average wages or other labor income proxies, while total output net of wage costs is positively affected. The new technology therefore seems to benefit mostly the owners of capital and profit claimants, but not labor at large, thus adding 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, dropping of outliers, and so on. Most importantly, we disentangle another major economic shock that has occurred parallel to the robot ascension, namely rising international trade exposure[4], and we also consider the adoption of information and communication technologies (ICT) across industries as another form of technological change.

Related literature. Our article contributes to the new, developing literature on the labor market consequences of automation and robots (Acemoglu and Restrepo 2017a; Graetz and Michaels 2016). Like these papers, we look at the equilibrium impacts at the local and industry level. We extend this literature and present novel evidence by studying the impact on the employment and earnings trajectories of individual workers in the medium- and long-run. It allows us to better quantify the effects across different worker skill groups. This reveals that the impact on high-skilled workers was positive, while robots reduced wages for low- and medium-skilled workers. This is consistent that the increased use of industrial robots represent *skill-biased technological change*. By focusing on the individual worker-level, we also shed light on the important question how workers adjust by moving across industries, occupations, and establishments.

Our paper is more generally related to the large literature on the labor market effects of skill-biased technological change followoing Katz and Murphy (1992) (see the Handbook chapter by Acemoglu and Autor 2011). A large strand of literature has studied the labor market effects of information and communication technology (Autor et al. 2003, Michaels et al. 2014, Akerman et al. 2015). 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). Our findings imply that the increased use of industrial robots contribute to the fall in the labor share.

[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. AR show that different industries are exposed to robots than to Chinese imports, and that both have independently fueled losses in the United States. 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. Our analysis is consistent with their results, i.e., we also find positive effects from net export exposure on employment and wages. The results for robots remain unchanged, however, when taking those trade shocks into account, and we find that robots have more pronounced labor market effects than ICT.

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). It is the same data source as in AR and Graetz and Michaels (2016, 2017), and reports the stock of robots for 50 countries over the period from 1994 to 2014.[5] It 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), which is a large and important sector in the German economy. Here, 60–100 additional robots are installed per thousand workers in 2014 compared to 1994. This dramatic increase took place mostly during the first, but continued in the second decade. Other industries that became vastly more robot-intensive over time include furniture, domestic appliances, and leather. On the other side of the spectrum we find cases where robot usage has hardly changed, and

[5] A *robot* in this data is defined as an "automatically controlled, re-programmable, and multipurpose machine" (International Federation of Robotics, 2016). As explained in more detail by AR, 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, 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.

[6] As Graetz and Michaels (2016, 2017), 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. More details about the industry cross-walk are reported in Appendix A. Also see Section 4.4.4. for robustness checks.

sometimes (e.g. in the watches and clocks industry) it even decreased over time. Robot usage across non-manufacturing industries is shown in the bottom of the figure. It is substantially lower than in manufacturing.

2.2 Labor market data

Our second source are administrative German labor market data provided by the Institute for Employment Research (IAB) at the German Federal Employment Agency.

2.2.1 Individual workers

In the individual-level analysis we use the Integrated Employment Biographies (IEB). This is a longitudinal linked employer-employee data set, which is allows to follow single workers within and across establishments and occupations over time.[8]

We focus on incumbent manufacturing workers with strong labor force attachment. In particular, we identify all individuals age 22 to 44 in the base year 1994, who are employed full-time in a manufacturing industry, earned more than the marginal-job threshold and had a job tenure for at least two years. For those roughly 1 million workers we then build a balanced annual panel which captures their work biographies over the subsequent twenty years.[9] In a complementary short-run approach, we split the observation period into two time windows, 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 annual panel data sets assign every worker to an establishment, and therefore to a 3-digit industry and location where the respective employer is affiliated, pertaining to the main job held on June 30 in the base year. We also observe the workers' occupations, following the standard classification of occupations in its version of 1988 (KldB 1988). Whenever workers have non-employment spells in their job biographies, this may constitute long-term unemployment, early retirement, or labor market exit, all of which are endogenous labor market outcomes. When we construct our dependent variables, we treat those spells as periods with zero earnings and employment, and assign the respective worker to the last recorded employer, occupation, industry and location until he or she takes up a new job elsewhere.

[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 the German labor market except for civil servants and the self-employed. It is described in detail in the papers 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.

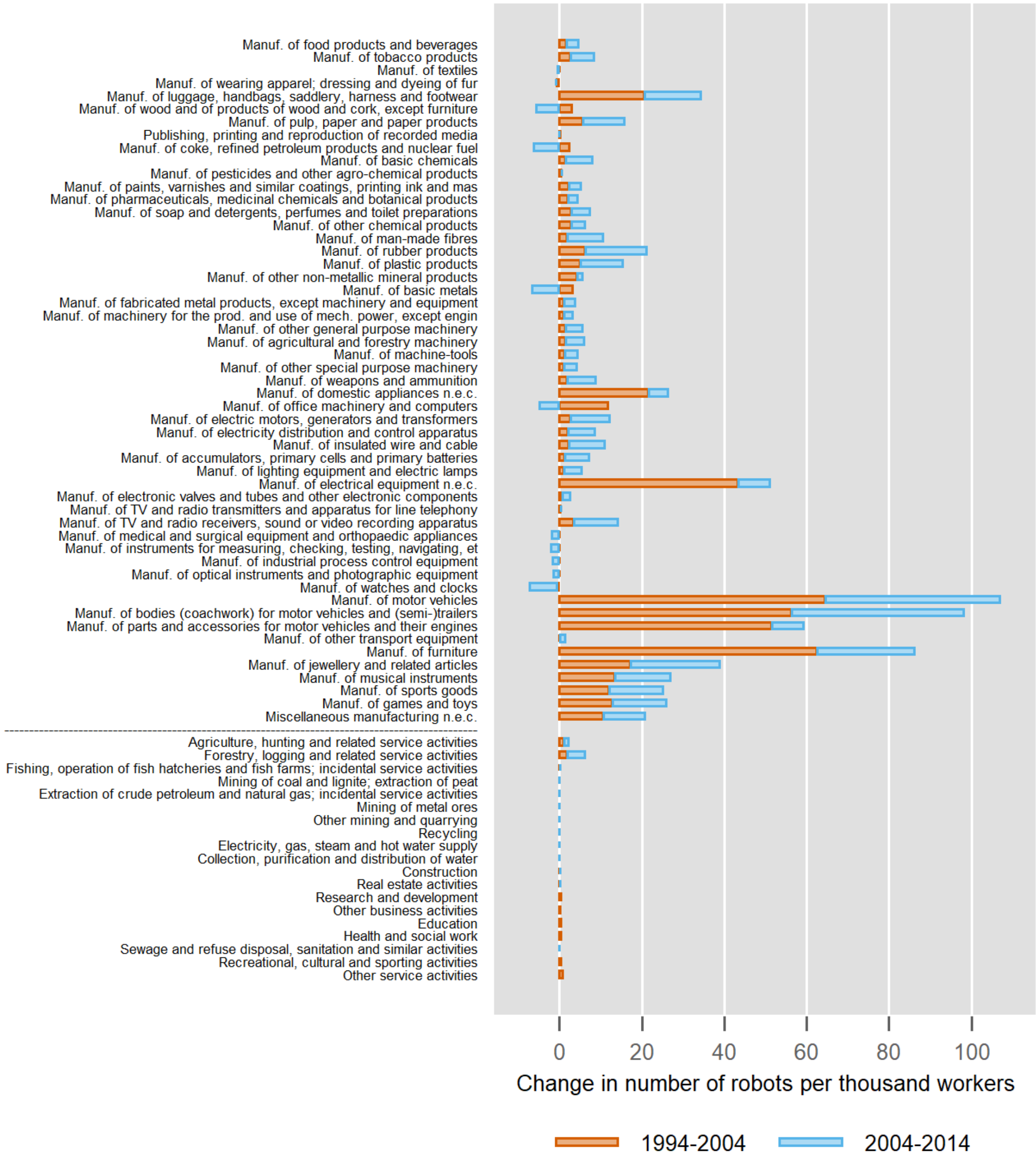


Figure 2: Industry-level distribution of robots

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.

We also observe the detailed profile of labor income for every worker in the sample. As the wage information is subject to right-censoring 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€. He or she has experienced a real earnings loss, because cumulated earnings over the subsequent 20-year time window only add up to 19.25 times the base year value on average. 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. Notice that roughly 9% hold a university-degree (high-skilled), while more than 75% have a completed apprenticeship (medium-skilled), and 15% have no formal qualification (low-skilled).

2.2.2 Local labor markets

For the local labor market analysis we work with the Establishment History Panel (BHP) by the IAB. It is an annual panel of the aggregated registry data of all employees of all German establishments with at least one employee, pertaining to 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 kreisefreie Staedte*), which correspond to the European NUTS3-level and are 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 the local level. This includes population size, total production (GDP), various income and productivity measures, unemployment rates, and so on, for every district and every year during the observation period.[11]

[10]Civil servants and the self-employed are exempted from the social security system, and are therefore the only groups not covered by this data. 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.

2.3 Descriptive overview for robot exposure

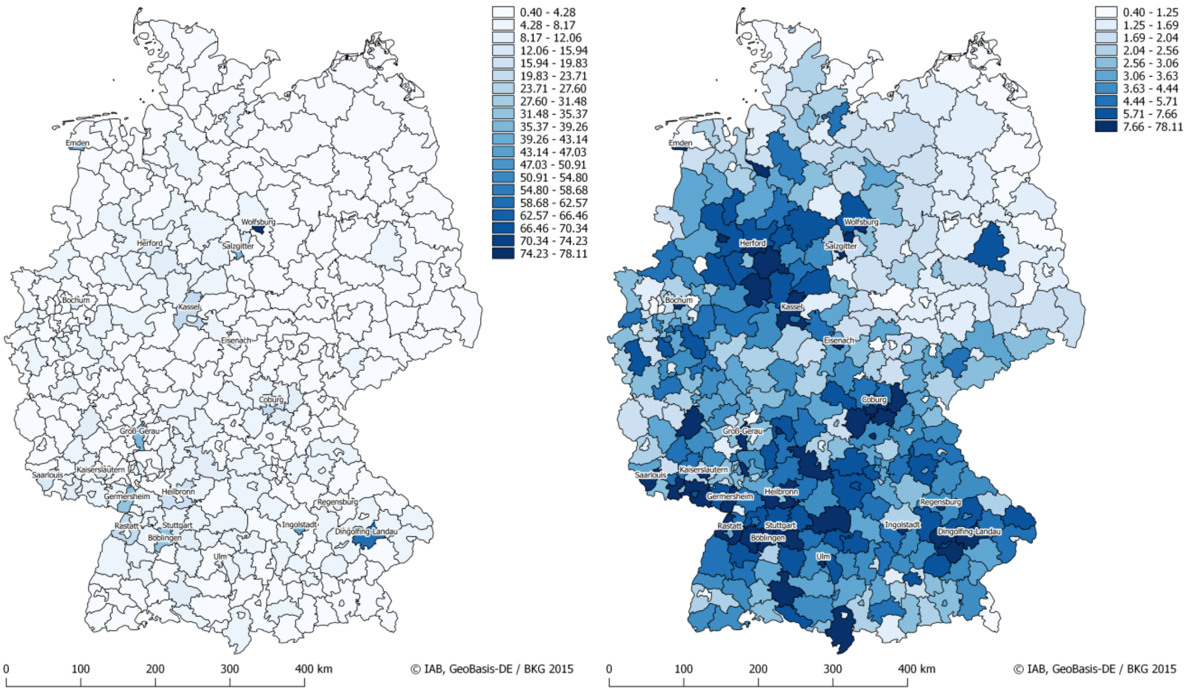
The average manufacturing worker in our sample has experienced a robot exposure equal to Δrobots_j = 16.98 (see panel C in Appendix Table A.2). This exposure equals the change in the number of installed robots per thousand workers over the period 1994-2014 in the initial industry, where we record his or her job 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 robot exposure for every region r, namely a weighted average of Δrobots_j, with weights given by local over national employment in industry j in the base year, and normalized by total local employment:

$$\Delta\text{robots}_r = \sum_{j=1}^{J} \left(\frac{emp_{jr}}{emp_j} \cdot \frac{\Delta\text{robots}_j}{emp_r} \right) \qquad \text{with} \quad J = 72. \tag{1}$$

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 again considerable variation which reflects the regions' industrial specialization patterns.

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, where exposure has increased by up to 78 robots per thousand workers. In our empirical analysis below 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 of local exposure, 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, a variation that is considerably stronger than in the US.



(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 displays the regional distribution of the change in the exposure of robots between 1994 and 2014 on the level of 402 German local labor markets. The colors in Panel A represent twenty equally sized percentile groups of robot exposure. In Panel B the colors represent ten equally sized decile groups.

2.4 Trade and ICT exposure

In our empirical analysis we disentangle robot exposure from two other major economic shocks that occurred since the beginning of the 1990s in Germany. First, we consider rising international trade with China and Eastern Europe. The idea is that some manufacturing branches 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 branches those new markets in "the East" primarily meant new opportunities to export. Second, we consider investments in information and communication technologies (ICT) as another distinct form of technological change. Similarly to robots, ICT equipment may also replace the tasks formerly carried out by 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 1993-2014 for every manufacturing industry j using COMTRADE data, normalized by the initial wage bill to account for industry size. To measure

(a) Robots versus trade.

(b) Robots versus ICT.

Figure 4: 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. Robot data from the International Federation of Robotics (IFR). Trade data from the United Nations Commodity Trade Statistics Database (COMTRADE). Data on ICT equipment from EUKLEMS. Region-level exposure is calculated from the available (national) industry-level exposure and the region's initial distribution of employment across industries as well as its share in national industry employment.

ICT exposure, we rely on information about installed equipment at the industry-level as provided by EUKLEMS. 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 across industries 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 the more communication-intensive services. The correlation between ICT and trade exposure is also small (0.05). More generally, this suggests that we capture three types of industry-shocks in our empirical analysis that have been largely orthogonal. In other words, we find that different industries have been affected by robots, trade and ICT, respectively, so that workers also perceived differential individual exposures to those shocks given their initial industry affiliations.

Finally, for trade and ICT we can also construct regional exposure measures analogous to (1). In Figure 4 we depict scatter plots of local robot and trade/ICT exposures. At the

[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 stock.

[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.

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 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.

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 them 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* 3-digit 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.[14]

The main idea behind this approach is that the workers' initial industry affiliations are orthogonal to the subsequent rising 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 technology shock in the initial industry that persists in the workers' biographies even after they may have adapted by switching to different jobs.[15]

Afterwards we decompose Y_{ij} into several additive parts, and study if rising robot

[14]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.

[15]A similar approach has been developed by Autor et al. (2014) and is also used in Dauth et al. (2016) to study the worker-level impacts of trade shocks.

exposure has led to systematic job mobility. More specifically, we start with the industry dimension and ask if robot exposure causes job switches to other firms within 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 AR, 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 contemporaneous local robot exposure, Δrobots_r , as defined above 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 also be symptoms of the previous industry-specific trajectories. To address this concern, we identify all effects in our individual-level analysis *within* broad industry groups by adding the fixed effects $\phi_{J(j)}$. Thereby we purge the estimates of long-run differences across groups. Similarly, in the aggregate approach we identify the effect of robot exposure conditional on local demographic characteristics and the regions' broad industrial structures. We also conduct placebo tests to analyze if past employment trends predict future robot adoptions, and do not find such a correlation.

Second, 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, in order to filter out systematic regional differences.[16]

3.3.2 Instrumental variable estimation

Although these fixed effects purge certain trends already in OLS estimations, there may still be the concern that the main coefficient β_1 only captures the causal effect of robots when there are no parallel unobservable shocks that simultaneously affect robot installations and labor market outcomes. To address this concern, we adopt an instrumental variable approach similar as in AR, where robot installations across industries in other high-income countries are used as an instrument for German robot exposure.

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 re-classifications in the original IFR data.[17] We also do not use North America (the US and Canada), because the industry breakdown is only available from 2004 onwards.

We deflate the robot installations across industries j in each of those $k = 7$ 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.

The rationale for this instrument is that all countries were exposed to a similar worldwide technology trend – the rise of the robots – but face potentially different domestic (demand or supply) shocks, which do not directly affect robot installations or labor

[16] 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.

[17] 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).

market outcomes in Germany. The instrument therefore purges unobserved Germany-specific shocks and identifies the causal impact of robots on German labor market outcomes. Moreover, by deflating with lagged employment, we avoid issues of reverse causality, since those levels cannot be themselves affected by robots.

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 which case the 2SLS model is just identified. 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.[18]

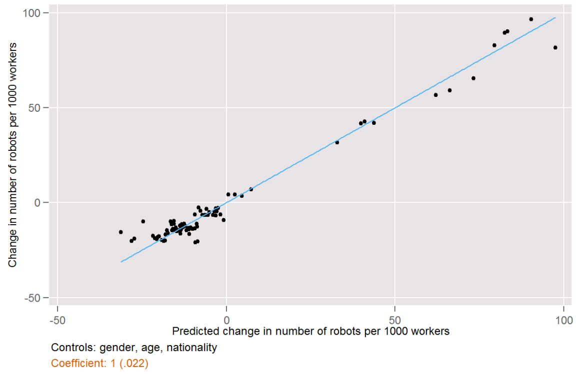
3.3.3 First-stage results

Figure 5 summarizes 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 the predicted change from the fitted values of our first-stage regression. As can be seen, the instrument seems to be quite 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.

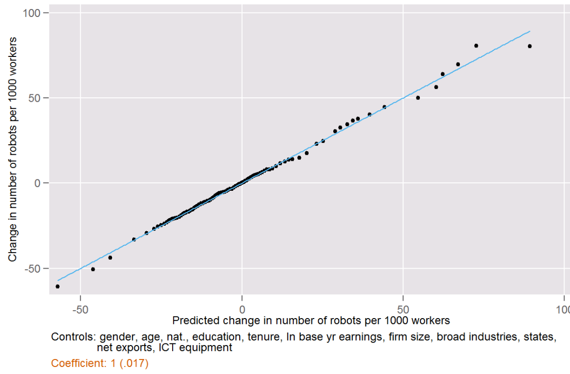
Panels (c) and (d) analogously show the first-stage results for local robot exposure. Both in a simple specification with broad location dummies only, and in the full specification with all controls, we find that the pattern of robot installations in the instrument countries is a strong predictor for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

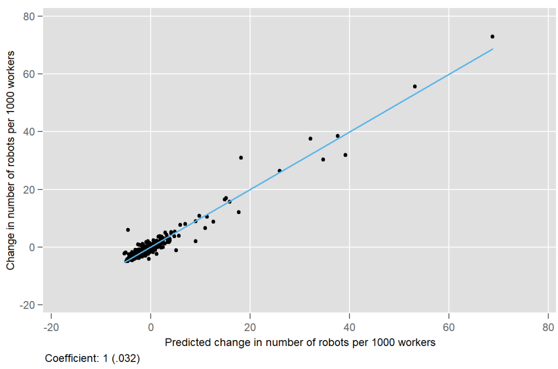
[18] The rationale for the instrument for trade exposure follows the seminal approach by Autor et al. (2013) and our specification closely follows Dauth et al. (2017). The instrument for ICT exposure is constructed analogously to robot exposure, but Norway is not in the instrument group because of missing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



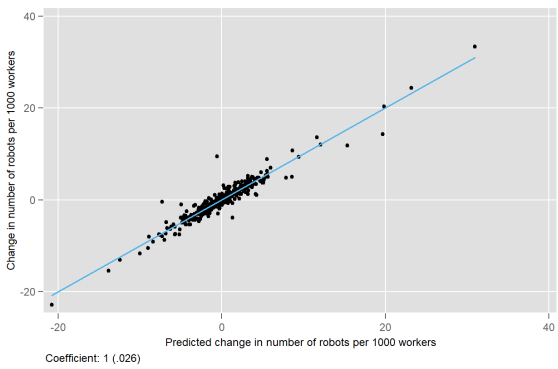
(a) Industry-level: only demographics



(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	175.401	20.593
F-Statistic	360.1	574.0	199.602	1541.098

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 3 (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).

Figure 5: First stage.

4 The impact of robots on local labor markets

We now discuss our empirical findings. In this section, we start with the aggregate local labor market approach, because we can directly compare our results for Germany with those by AR for the United States. Afterwards we turn to our individual-level analysis, which provides detailed evidence how single workers have responded to robot exposure.

4.1 Baseline results for total employment

Table 1 summarizes our key findings 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.[19] The upper panel reports the OLS results, and the lower panel refers to the analogous IV estimations.

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	0.0091	0.0065	-0.0005	-0.1025
	(0.095)	(0.106)	(0.126)	(0.125)	(0.117)	(0.116)	(0.132)	(0.172)
dummy, 1=robot producer				-4.8877	-4.7980	-4.5733	-3.9931	-4.1504
				(4.350)	(4.369)	(4.418)	(4.652)	(4.626)
△ net exports in 1000 € per worker					0.3374	0.3479	0.2375	0.2161
					(0.220)	(0.220)	(0.242)	(0.249)
△ ICT equipment in € per worker						-0.0110	-0.0163	-0.0166
						(0.016)	(0.017)	(0.017)
R^2	0.432	0.439	0.541	0.543	0.545	0.546	0.625	0.623
	Panel B: 2SLS							
△ robots per 1000 workers	0.2410**	0.3845***	0.0399	0.0344	-0.0398	-0.0054	-0.0058	-0.0848
	(0.095)	(0.105)	(0.124)	(0.124)	(0.109)	(0.112)	(0.120)	(0.150)
dummy, 1=robot producer				-4.8847	-4.7046	-4.9525	-4.2004	-4.2992
				(4.250)	(4.332)	(4.212)	(4.467)	(4.464)
△ net exports in 1000 € per worker					0.8197***	0.7319**	0.6232*	0.5975
					(0.293)	(0.304)	(0.370)	(0.376)
△ ICT equipment in € per worker						0.0142	0.0046	0.0027
						(0.014)	(0.015)	(0.014)
R^2	0.432	0.439	0.541	0.543	0.540	0.537	0.618	0.617
Broad region dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Manufacturing share	No	Yes	Yes	Yes	Yes	Yes	No	No
Demographics	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Broad industry shares	No	No	No	No	No	No	Yes	Yes
Exclude top auto regions	No	No	No	No	No	No	No	Yes

Notes: $N = 402$. All regressions include a constant. The control variables are measured in the base year and are constructed as the number of workers in a particular group relative to total employment. Demographic controls contain % female, % foreign, % age ≥ 50, % medium skilled (percentage of workers with completed apprenticeship), and % high skilled (percentage of workers with a university-degree). 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). Manufacturing includes the manufacture of food products, consumer goods, industrial goods, and capital goods. Broad region dummies indicate if the region is located in the north, west, south, or east of Germany. Column (8) drops the german regions with the highest automobile shares (Wolfsburg and Dingolfing-Landau). Standard errors clustered at the level of 50 aggregate labour market regions in parentheses. Levels of significance: *** 1 %, ** 5 %, * 10 %.

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

Column 1 starts with a simple specification where the only additional controls are the broad location dummies, which mainly filter out systematic differences between East and West Germany. 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 positive effect becomes even stronger when we condition on the local manufacturing employment shares as in column 2. This reflects that robots are mainly installed in manufacturing industries (see Figure 2), so that local robot exposure correlates with the local manufacturing share, but the latter is negatively correlated with the outcome variable as job growth tends to be stronger in services. Once we include standard demographic characteristics of the local workforces in the regressions, however, we find that the coefficient for robot exposure shrinks by a factor of ten, almost down to zero, and turns insignificant (see column 3). 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 total local employment growth, neither in the OLS, nor in the IV estimation.

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 to inquire about their activities, 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.[20] 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 rough measurement of robotic production, or by the small overall size of the robotic industry. But we tentatively conclude that direct employment

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

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 5 we add local net export exposure with China and Eastern Europe to the list of controls. As in Dauth et al. (2014, 2017) we find a positive impact on local employment, which is highly significant in the IV approach where third-country trade flows are now used as additional instruments. In other words, we corroborate their finding that local labor markets with a more export-oriented industry structure exhibited stronger subsequent growth. The coefficient for robot exposure decreases and even turns negative in the lower panel. This reflects the positive correlation of local robot and trade exposures, which is shown above in Figure 4. The coefficient for robots remains statistically indistinguishable from zero, however. Adding local ICT exposure, as in column 6, does also not affect our main results. Moreover, 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.

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 7 remain very similar, however, 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 becomes stronger negative, but it remains insignificant.[21]

Summing up, our baseline results do not provide evidence for negative total employment effects of rising robot exposure like in the US.[22] Once local workforce characteristics and unobserved industry trends are taken into account, as in our benchmark specification in column 7, we find a causal effect of robots on employment growth equal to zero. We cannot decisively rule out that robots have an impact, as the standard errors for the respective coefficient tend to be quite large. Still, our evidence does not support the claim

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

[22] A detailed quantitative comparison of our results with those by AR is relegated to section 4.3. below.

that robots have been major job killers in the German labor market, at least not during the period 1994-2014. Moreover, we find that rising ICT exposure, which is another dimension of technological change, also does not have notable employment effects, while rising export exposure indeed causes job gains across German local labor markets.

4.2 Manufacturing and non-manufacturing employment

In Table 2 we now distinguish the impact of robots on sectoral employment growth. More specifically, while the outcome variable in column 1 is still total employment, we consider manufacturing and non-manufacturing separately in columns 2 and 5, and in columns 3 and 4 we further differentiate the former into automobile and all other manufacturing branches. For brevity, we only present results for the full IV specification (column 7 in panel B of Table 1) from now on, and focus on the central coefficient for robot exposure.[23]

Panel A reports the results for overall local robot exposure. The coefficient in column 1 is the same as in Table 1 above, and the other columns show how this zero effect comes about. Namely, we find a negative impact of robots on manufacturing employment growth, mainly but not only in the automobile sector, but a significantly positive effect on non-manufacturing. Put differently, robots reduce the number of manufacturing jobs in the local labor market, in the car industry and beyond, but this loss is fully offset by additional jobs in the service or public sector (in non-manufacturing). Hence, there is no effect of robots on the overall *level* of local employment, but on its *composition*.

In panel B we shed light on the special role of the car industry in a different way. We differentiate robots installed in the automobile branch (motor vehicles, car bodies, and car parts) from robots installed in all other industries, and calculate two corresponding local exposure measures. The results for automobile robots turn out to be very similar to the overall pattern from panel A. The robots in other industries also have no total employment effects (see column 1), but their impact on employment compositions is somewhat less clear. We even find some slightly positive effects on own-industry employment, but only at borderline significance levels. Overall, panel B suggests that the automobile robots, which form the majority among all robots, are very important for the understanding of the overall impact of this technology. But their counterparts in other industries do not seem to have systematically different employment effects.

In panels C–E we differentiate the impact of robots on local employment of three different skill groups. The general pattern appears to be quite similar for all groups. That

[23]The detailed results are available upon request from the authors.

Table 2: Manufacturing versus non-manufacturing employment.

	Dependent variable: 100 x Log-△ in employment between 1994 and 2014				
	(1) Total	(2) Manuf.	(3) Manuf. auto	(4) Manuf. other	(5) Non-manuf.
	Panel A: All robots				
△ robots	-0.0058	-0.3837**	-3.4084***	-0.6525***	0.4177**
	(0.120)	(0.152)	(1.142)	(0.210)	(0.206)
	Panel B: Robots in automotive and other sectors separately				
△ robots in automotive	-0.0187	-0.4139***	-3.5042***	-0.6862***	0.4123*
	(0.130)	(0.143)	(1.127)	(0.201)	(0.219)
△ robots in other sectors	0.8651	1.5587*	-4.3114	1.3251*	0.8907
	(0.635)	(0.856)	(5.765)	(0.799)	(0.610)
	Estimates by skill group				
	Panel C: Low skilled				
△ robots	-0.0907	-0.7549**	-1.3138	-0.3725	0.0658
	(0.178)	(0.315)	(1.002)	(0.265)	(0.219)
	Panel D: Medium skilled				
△ robots	-0.1528	-0.3346**	-3.2693***	-0.3676*	0.1647
	(0.115)	(0.151)	(1.197)	(0.205)	(0.158)
	Panel E: High skilled				
△ robots	0.3284	-0.1559	-1.5995	-0.0840	0.6287**
	(0.248)	(0.333)	(0.976)	(0.459)	(0.245)
	Panel F: Dependent variable 100 x △ in employment/population between 1994 and 2014				
△ robots	-0.0190	-0.0595**	0.0144	-0.0739***	0.0405
	(0.065)	(0.027)	(0.023)	(0.027)	(0.050)

Notes: $N = 402$ resp. $N = 368$ in column 3. The outcome variables are log-differences in employment between 1994 and 2014. Columns (1) to (7) display estimates for total employment, employment in manufacturing, employment in manufacturing of motor vehicles, employment in manufacturing except motor vehicles, employment in non-manufacturing, respectively. Panels C-E: Log-differences in employment are separately analyzed for low, medium, and high skilled individuals. In panel F the outcome variables are constructed as the change in the employment to population ratio rather than the log-change in employment. All regressions include the full set of control variables as in column (7) of Table 1, Panel B (2SLS). Standard errors clustered at the level of 50 aggregate labour market regions. Levels of significance: *** 1 %, ** 5 %, * 10 %.

is, we find negative effects on manufacturing and positive effects on non-manufacturing in all panels, but the magnitude and statistical significance of the estimators differ somewhat. The loss of manufacturing jobs is most visible for low- and medium-skilled workers, while the job gains in non-manufacturing are clearest for high-skilled workers. The combined total employment effects in column 1 are all insignificant, however. In other words, we find no clear evidence that robots have destroyed jobs, not even for workers without university education who may be most vulnerable to the threats of automation by this technology. Still, the results in panels C–E already hint at distributional effects of robots that we analyze in further detail below.

4.3 Quantitative benchmarking and comparison to the United States

Finally, in panel F of Table 2 we specify the outcome variable differently and consider the change in the ratio of total employment-to-population in region r. This specification in column 1 follows AR, which allows us to directly compare the results. Moreover, in columns 2-5 we analogously compute the change in the ratio of local sectoral employment over population size in the local labor market over time.

For the United States, AR estimate that one more robot per thousand workers reduces the employment-to-population ratio by 0.37 percentage points (see their Table 4, 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 F in Table 2 reveals 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, as argued before, we find no evidence that robots cause overall job losses.

Yet, column 2 in panel F confirms that robots cause significant employment losses in *manufacturing*, and we can use this point estimate for an analogous quantitative benchmarking. In particular, we find that 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.[24] But this loss is fully offset by job gains outside of manufacturing.[25]

[24]Note that AR also find that robots have more adverse employment effects on manufacturing employment, see their Figure 10. Our estimate for the loss of manufacturing jobs (2.1 jobs per one robot) is therefore substantially smaller than the comparable number in the United States, which ranges well above 6.2.

[25]In panel F we find a large and positive coefficient in column 5, like in panel A, but the standard errors

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 thus suggests 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. This is quite a sizable impact, given that robots are just one dimension of technological change that has affected the manufacturing sector.[26] But it is worth emphasizing again that robots do not seem to have destroyed the *total* number of jobs but rather changed the composition of employment in the German economy.

4.4 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.

4.4.1 The changing impact of robots over time

First, in Appendix Table A.7 we address timing issues. Instead of computing local employment 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 analogously compute robot exposure and the change in log employment separately for the two decades, and repeat the baseline specifications with all instrumental variables adjusted accordingly. In panel A we stack the two decades while adding region x time interaction terms, and panels B and C show results for the two periods separately. The first line in each panel reports the overall employment effects, and the next lines consider the effect on the three skill groups.

Most importantly, we find no effects of robots on overall employment growth in the stacked model in panel A. The compositional effects are also similar, though somewhat smaller, than in the baseline specification. For example, the negative impact of robots on manufacturing jobs seems to be most strongly confined to the automobile industry in this specification. Across skill groups there continue to be no job losses caused by robots for low- and medium-skilled workers, and for high-skilled workers we now even find a

in this specification are somewhat too large to achieve statistical significance at conventional levels.

[26]The rise of international trade exposure with China and Eastern Eurpe, 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, see AR and Autor et al. (2014).

positive overall effect solely driven by the non-manufacturing sector. By and large, we conclude that the stacked short-run model in panel A of Appendix Table A.7 yields a similar overall picture as the long-run model reported in Table 2.

Interestingly, Panels B and C suggest that there have been some changes in the impact of robots on local employment over time, and in particular, that they have become less friendly. In the first period (see panel B) we find no notable adverse employment effects, and if anything, only a positive impact of robots on non-manufacturing employment for high-skilled workers. In the second period, however, negative effects dominate the picture. As shown in the first line of panel C, there is even evidence for significant overall job losses caused by robots during the period 2004-2014. Notice that this pattern is not driven by the fact that more robots have been installed 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 employment effects of those robots have apparently become worse, especially for low- and medium-skilled workers.

4.4.2 Placebo test

In panel D of Appendix Table A.7 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 across industries. The results in panel D suggest that they do not. All coefficients are small and insignificant, thus suggesting that our main findings are not driven by pre-trends.

4.4.3 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.8 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, ought not have direct impacts on the German labor market. Otherwise the instrument is not valid. One may worry that this requirement could not be met for important and large instrument countries, with which Germany is closely interconnected through various channels. 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.

4.4.4 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.8 as in our baseline.

Finally, we conduct robustness checks with respect to the regional dimension in our data. We drop East Germany in panel E and focus only on the variation in robot exposure and employment growth across West German local labor markets. And in panel F we change the specification of $\phi_{REG(r)}$ and now include Federal State fixed effects instead of the four broad location dummies. Our main results remain robust to those changes.

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 more light on the detailed channels behind the equilibrium outcomes identified so far.

5.1 Individual employment outcomes

Table 3 reports our main results for the worker-level estimation (2). To recap, we regress cumulated days in employment for the incumbent manufacturing worker i over the period 1994-2014 on the contemporaneous robot exposure of industry j where worker i was initially employed in the base year. Starting from a simple regression in column 1, we successively add further control variables until we reach a comprehensive specification in column 5, which takes into account various observable individual characteristics, his or her 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 6 we drop all workers from the automobile industry, the key outlier when it comes to robot exposure. Panels A and B show the results for the OLS and IV estimation approach, respectively, with third-country robot installations at the industry level as instruments.[27]

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, but it always remains significant in the IV model. Moreover, in Appendix Table A.11 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 mainly driven by the first decade.

Investigating those patterns further, we now separate *where* the additional employment time caused by robots occurs. Table 4 decomposes the cumulative days in employment into different additive parts.[28] 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 3 and the coefficients in columns 2–5 add up, by construction, to this

[27] In the main text we focus again on the central coefficients only, while relegating the detailed results to Appendix Tables A.9 and A.10.

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

Table 3: 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 (Panels A and B), 1,431,576 (Panel C), 1,246,414 (Panel D), and 2,677,990 workers (Panel E). The outcome variable is the number of days employed, cumulated over the twenty years following the base year. In panel E, 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 %.

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 jobs from the point of view of individual manufacturing workers in Germany.

Table 4: 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 1,017,988 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. All regressions include the same control variables as in column (5) of table 3. Standard errors, clustered by industry x federal state in parentheses. Levels of significance: *** 1 %, ** 5 %, * 10 %.

Panel B gives a more nuanced result. We find that robot exposure raises the probability to remain in the same occupation (column 2), and also to switch to a different occupation at the same workplace (column 3). Actual employer switches become consistently less likely for more robot exposed workers, however, which is in line with the results in panel A. Put differently, robots seem to stabilize existing manufacturing jobs. But some workers end up conducting different tasks than before, yet still in the same establishment.

Interestingly, Tables 3 and 4 show that ICT exposure seems to have no effect on individual employment, while net export exposure also has a stabilizing effect on jobs both at the industry and the occupational dimension. This result is noteworthy, because export opportunities may be thought of as a positive shock on industry-level labor demand, while robots supposedly represent a shock in the opposite direction. Moreover, the previous section has shown that net exports have positive equilibrium employment effects, while robots have led to fewer manufacturing jobs across local labor markets. The next subsection offers a possible reconciliation of those results.

5.2 Entry and re-entry into manufacturing

How can robots lead to fewer manufacturing jobs in equilibrium but stabilize existing employment relationship in manufacturing firms? One explanation is that robots mainly induce firms to create fewer *new* jobs, but not to directly displace incumbent workers.

In Table 5 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.[29] 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 the local technology and trade exposures, following the same baseline specification as in column 7 of Table 1 above (using the IV model).

The results show that the probability that young workers enter into manufacturing has indeed become significantly smaller in more robot exposed regions. The negative impact of robots on equilibrium employment growth in manufacturing, which we have found in Section 4, may therefore result from lower rates of new entry (for returnees we find no such effect) but not from a direct destruction of existing jobs. Stated differently, if robots are a negative shock to industry-level labor demand, it materializes mainly by fewer new vacancies that are created, or by omitted replacements when a vacancy arises from natural turnover. Robots "foreclose" entry into manufacturing for young people.

[29]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.

Table 5: Robot exposure and entry into manufacturing employment.

	Dependent variable: △ manuf. entrants (returnees) in all entries between 1994 and 2014 (in %-pts)	
	(1) Entry	(2) Re-entry
△ robots per 1000 workers	-0.1335**	0.0297
	(0.068)	(0.079)
△ net exports in 1000 € per worker	0.0797	0.3840***
	(0.106)	(0.100)
△ ICT equipment in € per worker	-0.0185***	-0.0143*
	(0.007)	(0.009)
R^2	0.480	0.417

Notes: $N = 402$. The dependent variables measure the change in the share of manufacturing entrants (column 1) respectively returnees (column 2) in all entries (in %) between 1994 and 2014. The regressions include the full set of control variables as in column (7) of Table 1, Panel B (2SLS). Standard errors clustered at the level of 50 aggregate labour market regions in parentheses. Levels of significance: *** 1 %, ** 5 %, * 10 %.

Notice that local net export exposure has positive effects on (re-)entry probabilities into manufacturing, here mainly driven by the returnees. The positive overall effect on equilibrium employment growth, therefore, seems to come from a combination of more new jobs and more stable existing jobs in more export-oriented regions. Finally, recall that ICT exposure neither has an impact on individual job stability (see Tables 3 and 4), nor on equilibrium growth of (manufacturing) jobs. Still, we find some slightly negative effects on (re-)entry probabilities, i.e., ICT technology also seems to substitute new jobs.

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 and thereby to lower employment growth there, why do incumbent manufacturing workers not also face an increased risk of job displacement?

Table 6 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 over 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 3 and successively add further controls.

Table 6: 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). Standard errors, clustered by industry x federal state in parentheses. Levels of significance: *** 1 %, ** 5 %, * 10 %.

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 when adding net export and ICT exposure in column 5, which have positive and no effects respectively, and when dropping automobile workers in column 6.

In Appendix Table A.12 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.

To benchmark the wage effects quantitatively, we can 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 6B implies that the more robot exposed worker receives a loss of 0.31 € per day.[30] Since the average worker is employed on 5,959 days over twenty years, the total loss is thus 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 3B we calculate that this is equivalent to $0.8003 \times (9.6 - 3.7) = 5$ additional days in employment for the more strongly robot 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. 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 quantitative 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 = 15,930 € over twenty years, or almost 800 € per year, which is no longer a negligible number.

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.

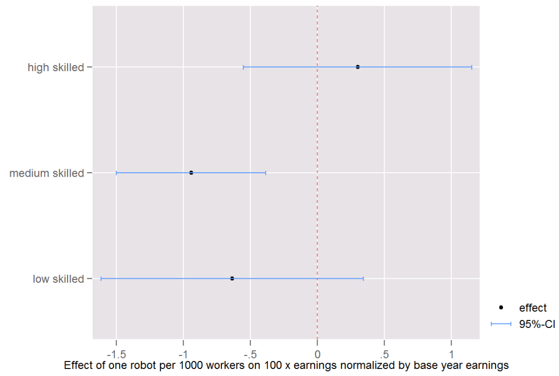
5.4 Heterogeneous effects for different workers

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 more 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.[31] The results are illustrated in Figure 6.

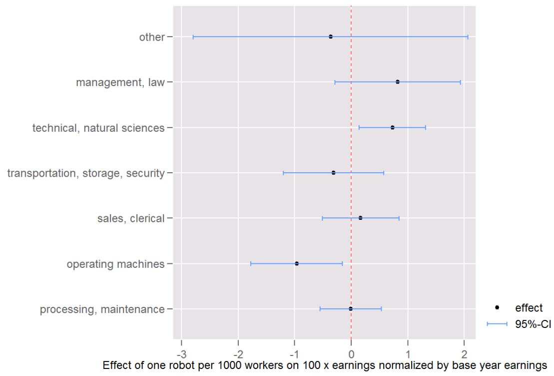
Here, panels (a) and (b) refer to the long-run model over twenty years, while panels (c) and (d) refer to the stacked short-run model. For every labor market group we report the point estimate for the impact of robot exposure on cumulated earnings, and the respective confidence interval. The left two panels (a) and (c) distinguish three skill cat-

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

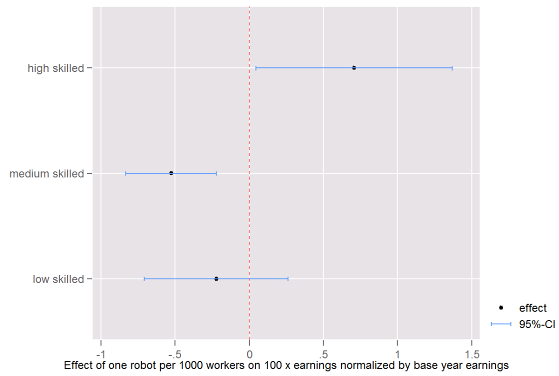
[31]We have also experimented with sample splits and obtained very similar results.



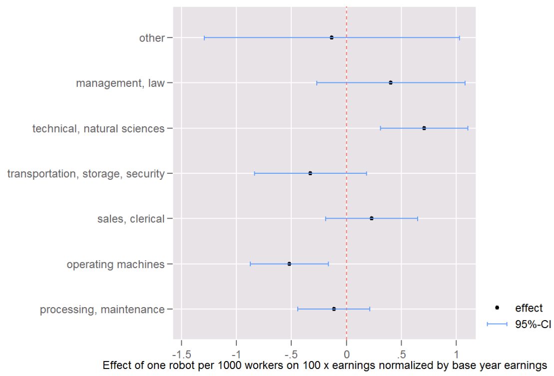
(a) by education, long period



(b) by occupation, long period



(c) by education, stacked short periods



(d) 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 3. The confidence intervals are constructed from standard errors clustered by industry x federal state.

Figure 6: Heterogeneous earnings effects

egories, while panels (b) and (d) differentiate 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, and those losses drive the average effects in Table 6 because completed apprenticeship is the typical profile for manufacturing workers in Germany and this group accounts for almost 75% 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, especially in in panel (c). 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. This hypothesis is supported by the analysis at the occupational dimension in panels (b) and (d). 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 3 and 6 for the average impact of robots on worker-level employment, wages and earnings). 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, 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, as they benefit some workers considerably more than others. In this final section of the paper we study the effects of robots on productivity and distribution from a more aggregate perspective, by moving back to the local labor market approach and exploiting additional data from the German Federal Statistical Office which breaks 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 7.

As can be seen in column 1, we find notable and significant effects of robots on average labor productivity. More specifically, every additional robot per thousand workers in the local labor market raises the growth rate of GDP per person employed by 0.5365 per cent. Columns 2 and 3 consider wage data from two different sources, namely the IAB and the Federal Statistical Office, respectively, where the latter reports average gross pay per employee at the local level.[32] In both cases we find no effect of robots on average wage growth; if anything, the impact even tends to be negative (but is imprecisely estimated), which is broadly in line with or results for individual-level wages in Section 5.

Table 7: Robots and other regional outcomes.

	Dependent variable: Change between 2004 and 2014						
	(1) Labor prod.	(2) Average wage	(3) Gross pay per empl.	(4) Labor prod. - Gross pay per empl.	(5) Total emp./ pop.	(6) Pop.	(7) Unempl. rate
△ robots per 1000 workers	0.5365**	-0.0766	-0.3109	2.0757**	-0.1026	0.0173	-0.0693*
	(0.268)	(0.129)	(0.249)	(0.945)	(0.158)	(0.190)	(0.038)
N	402	402	372	372	395	395	402

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

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 4 in Table 7. 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.,

[32]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.

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 7 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 6, which suggests that *some* workers with high individual human capital still benefited from robots, despite the falling aggregate labor share.

In columns 5-6 in Table 7 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 5 we re-compute the change in the employment-to-population ratio from this data set and, as in panel F of Table 2, find no effect of robots. Similarly, column 6 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 7 we consider the change in local unemployment rates and find that robots even tend to reduce unemployment slightly, although the effect is barely significant.[33] 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 no 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

[33] 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.

decline during those two decades. But this loss was fully offset (or even slightly overcompensated) by additional jobs in the service sector.

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 robot ascension. 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 for individual workers, namely lower wages due to rising robot exposure. Those impacts differ strongly across individuals. High-skilled workers in managerial and science occupations tend to benefit both in terms of job stability and wages. Medium-skilled workers who mainly conduct routine and manual tasks, however, face significant earnings losses from increasing robot exposure. Those loses do not come from displacements or interruptions in work biographies, but mainly arise on existing jobs through lower wages.

We believe that this finding reflects a key feature 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.[34] 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 (the "employment miracle") 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, and in turn led to reduced entry of new workers into the robot exposed manufacturing industries.

In the aggregate we find that robots raise labor productivity, but not wages. Most rents of this new technology, therefore, seem to be captured by profit claimants and factors other than labor. We thus conclude that robots seem to have contributed to the declin-

[34]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.

ing labor income share, which has been noted in many countries and which is perhaps among the most important economic challenges for the future.

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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. [35] 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.

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

In section 4.4, 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 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.

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						
100 x earnings / base year earnings	1925	(1001)	940	(449)	950	(353)
days employed	5959	(2014)	3015	(1001)	3261	(802)
average daily wage	120.7	(71.6)	121.7	(74.4)	126.8	(73.9)
[B] control variables, measured in base year						
base year earnings	38880	(20775)	40273	(22441)	44862	(28322)
dummy, 1=female	0.239	(0.426)	0.237	(0.425)	0.215	(0.411)
dummy, 1=foreign	0.100	(0.301)	0.110	(0.312)	0.086	(0.280)
dummy, 1=age $\leq$34 yrs	0.554	(0.497)	0.388	(0.487)	0.251	(0.434)
dummy, 1=age 35-44 yrs	0.446	(0.497)	0.316	(0.465)	0.411	(0.492)
dummy, 1=age $\geq$45 yrs	-	(-)	0.281	(0.449)	0.319	(0.466)
dummy, 1=low skilled	0.153	(0.360)	0.170	(0.375)	0.118	(0.323)
dummy, 1=medium skilled	0.756	(0.430)	0.740	(0.438)	0.757	(0.429)
dummy, 1=high skilled	0.091	(0.288)	0.090	(0.286)	0.125	(0.331)
dummy, 1=tenure 2-4 yrs	0.405	(0.491)	0.357	(0.479)	0.285	(0.451)
dummy, 1=tenure 5-9 yrs	0.315	(0.464)	0.270	(0.444)	0.287	(0.452)
dummy, 1=tenure $\geq$10 yrs	0.243	(0.429)	0.338	(0.473)	0.387	(0.487)
dummy, 1=plant size $\leq$9	0.059	(0.236)	0.056	(0.230)	0.045	(0.207)
dummy, 1=plant size 10-99	0.232	(0.422)	0.230	(0.421)	0.251	(0.434)
dummy, 1=plant size 100-499	0.287	(0.453)	0.288	(0.453)	0.320	(0.466)
dummy, 1=plant size 500-999	0.121	(0.326)	0.122	(0.328)	0.118	(0.322)
dummy, 1=plant size 1000-9999	0.219	(0.414)	0.222	(0.415)	0.189	(0.392)
dummy, 1=plant size $\geq$10000	0.079	(0.269)	0.080	(0.271)	0.075	(0.263)
dummy, 1=food products	0.084	(0.277)	0.083	(0.276)	0.085	(0.279)
dummy, 1=consumer goods	0.123	(0.328)	0.124	(0.330)	0.099	(0.299)
dummy, 1=industrial goods	0.362	(0.480)	0.362	(0.481)	0.363	(0.481)
dummy, 1=capital goods	0.432	(0.495)	0.430	(0.495)	0.453	(0.498)
[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)

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 ($\triangle$ 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]	
Δ robots per 1000 workers in automotive	2.026	(6.851)	1.322	(4.165)	0.710	(2.595)
Δ robots per 1000 workers in other sectors	2.618	(1.970)	1.722	(1.471)	1.013	(0.690)
[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)

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

	Dependent variable: 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	0.0091	0.0065	-0.0005	-0.1025
	(0.095)	(0.106)	(0.126)	(0.125)	(0.117)	(0.116)	(0.132)	(0.172)
dummy, 1=north	2.8598	1.6878	8.8323***	8.7607***	8.6703***	8.4877***	3.0493	2.9438
	(2.986)	(3.047)	(3.040)	(3.089)	(3.069)	(3.123)	(2.597)	(2.614)
dummy, 1=south	9.4435**	10.1838***	9.2276***	9.3125***	9.5010***	9.2831***	7.3637**	7.5935**
	(3.588)	(3.414)	(3.443)	(3.425)	(3.445)	(3.463)	(2.923)	(2.950)
dummy, 1=east	-23.9257***	-26.8097***	-19.9017***	-19.7888***	-20.0067***	-21.1800***	-14.2909***	-13.0432**
	(3.287)	(3.472)	(5.501)	(5.564)	(5.584)	(5.391)	(5.124)	(5.000)
% manufacturing		-0.1875**	-0.0979	-0.0922	-0.0990	-0.1370		
		(0.088)	(0.189)	(0.189)	(0.191)	(0.213)		
% female			-0.6439	-0.6607	-0.5853	-0.5130	-1.1367***	-1.2205***
			(0.451)	(0.461)	(0.467)	(0.452)	(0.356)	(0.352)
% foreign			1.0258***	1.0261***	0.9936***	0.9654***	0.5996*	0.6149*
			(0.262)	(0.261)	(0.254)	(0.260)	(0.323)	(0.314)
% age ≥50 yrs			-2.9117***	-2.8899***	-2.9123***	-2.8297***	-2.1610***	-2.1998***
			(0.495)	(0.501)	(0.514)	(0.501)	(0.489)	(0.493)
% medium skilled			0.6455	0.6443	0.6117	0.6423	-0.1045	-0.1514
			(0.535)	(0.534)	(0.534)	(0.536)	(0.475)	(0.479)
% high skilled			1.3220**	1.3331**	1.2776**	1.2665**	1.1835***	1.1082***
			(0.526)	(0.521)	(0.529)	(0.541)	(0.416)	(0.412)
dummy, 1=robot producer				-4.8877	-4.7980	-4.5733	-3.9931	-4.1504
				(4.350)	(4.369)	(4.418)	(4.652)	(4.626)
△ net exports in 1000 € per worker					0.3374	0.3479	0.2375	0.2161
					(0.220)	(0.220)	(0.242)	(0.249)
△ ICT equip. in € per worker						-0.0110	-0.0163	-0.0166
						(0.016)	(0.017)	(0.017)
% food products							2.4246***	2.4400***
							(0.402)	(0.403)
% consumer goods							0.5921**	0.6396**
							(0.293)	(0.307)
% industrial goods							0.6622***	0.6846***
							(0.244)	(0.252)
% capital goods							1.0118***	1.0371***
							(0.260)	(0.271)
% construction							1.5571***	1.5597***
							(0.338)	(0.342)
% maintenance							1.7592***	1.7993***
							(0.369)	(0.370)
% services							0.6603***	0.7095***
							(0.241)	(0.247)
% education							1.1429***	1.1966***
R^2	0.432	0.439	0.541	0.543	0.545	0.546	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. Column (8) drops the german regions with the highest automobile shares (Wolfsburg and Dingolfing-Landau). See Table 1 for a description of control variables. Standard errors clustered at the level of 50 aggregate labour market regions in parentheses. Levels of significance: *** 1 %, ** 5 %, * 10 %.

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

	Dependent variable: 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	-0.0398	-0.0054	-0.0058	-0.0848
	(0.095)	(0.105)	(0.124)	(0.124)	(0.109)	(0.112)	(0.120)	(0.150)
dummy, 1=north	2.8530	1.6300	8.8386***	8.7563***	8.5930***	8.7560***	3.1153	2.9901
	(2.944)	(3.008)	(2.972)	(3.017)	(2.967)	(2.947)	(2.508)	(2.515)
dummy, 1=south	9.4321***	10.1916***	9.2274***	9.3126***	9.7696***	10.0112***	7.6471***	7.8588***
	(3.538)	(3.347)	(3.367)	(3.343)	(3.412)	(3.387)	(2.844)	(2.889)
dummy, 1=east	-23.9046***	-26.8825***	-19.8971***	-19.7922***	-20.2784***	-18.7843***	-15.1214***	-13.9563***
	(3.232)	(3.424)	(5.386)	(5.436)	(5.487)	(5.305)	(4.809)	(4.678)
% manufacturing		-0.1947**	-0.0973	-0.0927	-0.1035	-0.0624		
		(0.087)	(0.184)	(0.184)	(0.189)	(0.205)		
% female			-0.6444	-0.6603	-0.4818	-0.5845	-1.0664***	-1.1411***
			(0.441)	(0.449)	(0.464)	(0.424)	(0.353)	(0.347)
% foreign			1.0263***	1.0257***	0.9514***	0.9872***	0.5783*	0.5872**
			(0.257)	(0.256)	(0.242)	(0.249)	(0.311)	(0.299)
% age $\geq$50 yrs			-2.9126***	-2.8892***	-2.9523***	-3.0401***	-2.2967***	-2.3267***
			(0.484)	(0.489)	(0.517)	(0.524)	(0.495)	(0.498)
% medium skilled			0.6465	0.6436	0.5734	0.5264	-0.1646	-0.2088
			(0.520)	(0.519)	(0.519)	(0.498)	(0.451)	(0.456)
% high skilled			1.3234***	1.3321***	1.2101**	1.2153**	1.2802***	1.2008***
			(0.511)	(0.507)	(0.516)	(0.513)	(0.395)	(0.394)
dummy, 1=robot producer				-4.8847	-4.7046	-4.9525	-4.2004	-4.2992
				(4.250)	(4.332)	(4.212)	(4.467)	(4.464)
△ net exports in 1000 €per worker					0.8197***	0.7319**	0.6232*	0.5975
					(0.293)	(0.304)	(0.370)	(0.376)
△ ICT equipment in €per worker						0.0142	0.0046	0.0027
						(0.014)	(0.015)	(0.014)
% food products							2.3508***	2.3708***
							(0.394)	(0.394)
% consumer goods							0.5882*	0.6329**
							(0.305)	(0.317)
% industrial goods							0.6149***	0.6363***
							(0.237)	(0.246)
% capital goods							0.9643***	0.9856***
							(0.248)	(0.260)
% construction							1.5578***	1.5604***
							(0.317)	(0.321)
% maintenance							1.6392***	1.6862***
							(0.367)	(0.370)
% services							0.5272**	0.5819**
							(0.261)	(0.267)
% education							0.9518***	1.0136***
							(0.267)	(0.266)
R^2	0.432	0.439	0.541	0.543	0.540	0.537	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. Column (8) drops the german regions with the highest automobile shares (Wolfsburg and Dingolfing-Landau). See Table 1 for a description of control variables. Standard errors clustered at the level of 50 aggregate labour market regions in parentheses. Levels of significance: *** 1 %, ** 5 %, * 10 %.

Table A.6: Robot producers.

Name	Headquarter	Production facility in Germany
	Headquarter in Germany	
ABB	**Mannheim** (ABB Germany)	Mannheim, Friedberg (Wetteraukreis), Hamburg
	Baden (CH, ABB International)	
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: Employment effects in different time periods.

	(1) Total	(2) Manuf.	(3) Manuf. auto	(4) Manuf. other	(5) Non-manuf.
[A] Stacked periods: 100 x Log-△ in employment (1994-2004 and 2004-2014)					
△ robots	0.0324	-0.1028	-2.8671**	-0.2607	0.3033
	(0.100)	(0.155)	(1.282)	(0.213)	(0.199)
Low skilled					
△ robots	-0.1894	-0.4508	-1.9740**	0.1858	0.0097
	(0.196)	(0.291)	(0.914)	(0.272)	(0.210)
Medium skilled					
△ robots	-0.1356	-0.1124	-3.1614***	-0.0263	0.1547
	(0.107)	(0.163)	(1.197)	(0.219)	(0.142)
High skilled					
△ robots	0.5463**	0.3754	-0.6375	0.6251	0.6281**
	(0.226)	(0.270)	(0.976)	(0.397)	(0.262)
[B] First period: 100 x Log-△ in employment between 1994 and 2004					
△ robots	0.1302	-0.0415	-2.5407	-0.2244	0.3121
	(0.145)	(0.318)	(1.656)	(0.349)	(0.301)
Low skilled					
△ robots	0.1680	0.6036	-3.9314**	1.4587***	-0.1465
	(0.328)	(0.545)	(1.592)	(0.477)	(0.295)
Medium skilled					
△ robots	-0.0056	-0.0042	-2.1087	0.0797	0.1569
	(0.159)	(0.299)	(1.544)	(0.335)	(0.203)
High skilled					
△ robots	0.7783***	0.5171	-2.2122	1.0506**	0.8370**
	(0.292)	(0.360)	(1.577)	(0.481)	(0.410)
[C] Second period: 100 x Log-△ in employment between 2004 and 2014					
△ robots	-0.8339***	-2.0943***	-2.5792	-2.6022***	0.1170
	(0.230)	(0.371)	(2.407)	(0.272)	(0.321)
Low skilled					
△ robots	-0.8917*	-3.0223***	-1.3650	-2.9979***	-0.1475
	(0.539)	(0.963)	(2.328)	(0.516)	(0.628)
Medium skilled					
△ robots	-0.6041***	-1.6044***	-2.8900	-1.8487***	0.0693
	(0.176)	(0.360)	(2.236)	(0.295)	(0.218)
High skilled					
△ robots	-0.6320	-2.4863***	-5.0034	-3.0943***	0.2747
	(0.410)	(0.741)	(3.577)	(0.671)	(0.436)
[D] Placebo check: 100 x Log-△ in employment between 1984 and 1994					
△ robots	-0.0366	-0.0346	0.4649	0.0703	0.0669
	(0.095)	(0.130)	(0.987)	(0.165)	(0.123)

Notes: The outcome variables are log-differences in employment: Total employment (1), employment in manufacturing (2), employment in manufacturing of motor vehicles (3), employment in manufacturing except motor vehicles (4), and employment in non-manufacturing (5). Panels B and C: 10-year changes in employment for 1994-2004 (first period) and 2004-2014 (second period), respectively. Panel A: Stacked differences (first and second period). Panel D: Log-differences in employment between 1984 and 1994 are regressed on the change in robot exposure between 1994 and 2014. All regressions include the full set of control variables as in column (7) of Table 1, Panel B (2SLS). The regressions in Panel A additionally include region x time interaction terms. Standard errors clustered at the level of 50 aggregate labour market regions in parentheses. Levels of significance: *** 1 %, ** 5 %, * 10 %.

Table A.8: Robustness checks. Region-level.

	Dependent variable: 100 x Log-△ in employment between 1994 and 2014				
	(1) Total	(2) Manuf.	(3) Manuf. auto	(4) Manuf. other	(5) Non-manuf.
	Panel A: Just-identified IV				
△ robots	0.0867	-0.1752	-2.8090**	-0.4526*	0.4655**
	(0.139)	(0.192)	(1.189)	(0.247)	(0.220)
	Panel B: IV without direct neighbors				
△ robots	-0.0189	-0.3999***	-3.1361***	-0.6731***	0.4088*
	(0.122)	(0.148)	(1.144)	(0.205)	(0.209)
	Panel C: IV without members of the European Monetary Union				
△ robots	-0.0025	-0.3423**	-3.1806**	-0.5887***	0.4051*
	(0.117)	(0.157)	(1.250)	(0.217)	(0.210)
	Panel D: Cross-walk				
△ robots	0.0043	-0.1601	-1.4099*	-0.3886***	0.2252
	(0.093)	(0.101)	(0.722)	(0.131)	(0.147)
	Panel E: West Germany				
△ robots	-0.0223	-0.4147**	-3.7743***	-0.6879***	0.4178**
	(0.123)	(0.164)	(1.188)	(0.230)	(0.199)
	Panel F: Federal state dummies				
△ robots	-0.0528	-0.4166***	-3.2837***	-0.6831***	0.3625*
	(0.138)	(0.153)	(1.243)	(0.206)	(0.218)

Notes: This table presents robustness checks for the baseline specification as of Panel A in Table 2. 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. Standard errors clustered at the level of 50 aggregate labour market regions in parentheses. Levels of significance: *** 1 %, ** 5 %, * 10 %.

Table A.9: 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 %.

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

Table A.11: 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)
dummy, 1=base year 2004	247.7496***	223.5501***	224.7857***			
	(10.235)	(8.581)	(8.119)			
[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. 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 %.

Table A.12: 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)
		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). 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 %.