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Adjusting to Robots: Worker-Level Evidence*

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Abstract

We estimate the effect of industrial robots on employment, wages, and the composition of jobs in German labor markets between 1994 and 2014. We find that the adoption of industrial robots had no effect on total employment in local labor markets specializing in industries with high robot usage. Robot adoption led to job losses in manufacturing that were offset by gains in the business service sector. We analyze the impact on individual workers and find that robot adoption has not increased the risk of displacement for incumbent manufacturing workers. They stay with their original employer, and many workers adjust by switching occupations at their original workplace. The loss of manufacturing jobs is solely driven by fewer new jobs for young labor market entrants. Moreover, we find that, in regions with higher exposure to automation, labor productivity increases while the labor share in total income declines.

JEL-Classification: J24, O33, F16, R11

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1 Introduction

The fear of an imminent wave of technological unemployment is – once more – one of the dominant economic memes of our time. The popular narrative often goes as follows (see, e.g., Ford 2015): 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 tasks, formerly carried out by humans, faster and more efficiently. Robots will therefore make millions of workers redundant, especially those with low and medium qualification. Various estimates have been suggested regarding how many occupations are at risk of being automated given the type of work they usually conduct.[1] This led to very disruptive scenarios which received massive media attention and shaped the popular narrative.

While those studies mainly try to predict the future, the data of the last 25 years show that one wave of automation has yet affected the labor market: following significant technical advances, robotic capabilities have made great strides in limiting the need for human intervention while autonomously operating production processes. According to the International Federation of Robotics (2016), the stock of industrial robots rose by a factor of five between 1993 and 2015 in North America, Europe, and Asia. An estimated 1.5 million industrial robots are currently used. A large number of industries have thus *already* undergone dramatic changes in the organization of production in the last two decades.

In this paper, we examine how this automation affects labor markets and how firms and individual workers adjust to the exposure to industrial robots. Our context is the German labor market over the period 1994–2014. Using linked employer-employee data, we trace out detailed employment biographies and earnings profiles of workers. This allows us to analyze whether robots (and other technology and trade shocks) have causally affected workers' risk of job displacement and their wage profiles. We also study if workers have switched jobs within and across establishments, industries, and occupations in view of the new technology. At the regional level, we measure how the composition of employment adjusts.

In the previous literature, sizable and negative impacts of the rise in robot exposure on employment have been estimated by Acemoglu and Restrepo (2018b) across US commuting zones. In contrast, across countries, no effects on employment have been found by Graetz and Michaels (forthcoming); however, their study does find positive effects on labor productivity. We extend this literature by widening the focus from aggregate equilibrium impacts to mechanisms and adjustment processes at the level of individual workers and firms.

[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 Bank (2016) arrives at a similar conclusion. Arntz, Gregory, and Zierahn (2017) account for task specialization within occupations and put a substantially smaller share of jobs (only 9%) at risk.

Economic theory predicts that labor-saving technologies, such as robots, not only substitute humans in production. There are also indirect effect in general equilibrium. In particular, labor demand should increase in other parts of the economy, which are specialized in tasks and inputs complementary to the production steps carried out by robots. By analyzing adjustment processes in depth, we provide empirical support for this central theoretical proposition. We do find sizable employment reductions in manufacturing industries where industrial robots are installed. But those losses were fully offset by job gains outside manufacturing, most importantly in business services. In other words, robots have strongly changed the composition but not the aggregate level of employment in Germany.

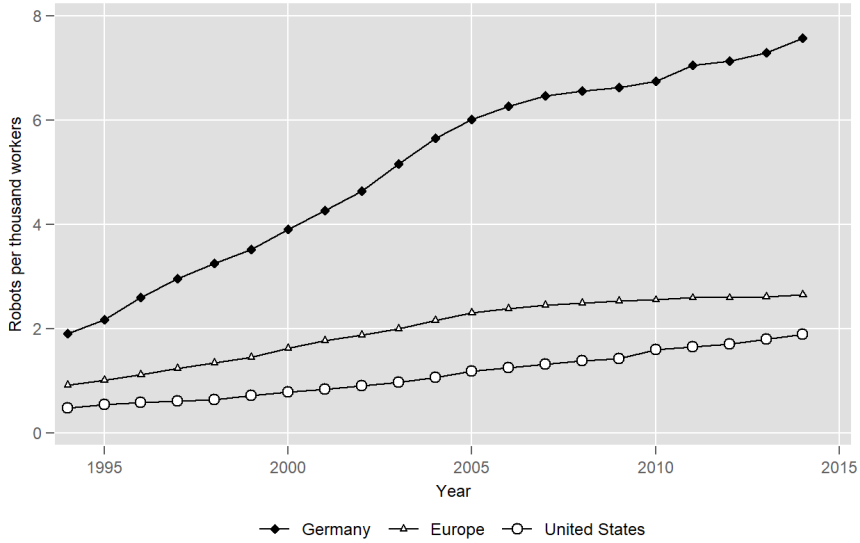
By following exposed workers over time, we are the first to shed light on the individual transitions and adjustments behind those aggregate trends. In a pessimistic view of the labor market, automation is highly disruptive: it may cause layoffs and involuntary job separations. Affected workers may then eventually take up new jobs elsewhere after some initial unemployment phase, but possibly at worse conditions than before.[2]

Our novel evidence suggests, however, that this view may indeed be too pessimistic. Our data allow us to decompose individual employment spells by firms, occupation, and industry, and thus to analyze various adjustment mechanisms. By looking at the occupation margin, we estimate how smoothly workers are able to adapt their tasks and whether those transitions can happen in stable employment relationships inside firms. We find, maybe surprisingly, that a significant part of the adjustment process indeed happens *within* establishments and across occupations. Robot exposure has even increased job stability, but many incumbent workers end up performing different occupations at their workplaces than before. The equilibrium loss of manufacturing jobs is solely driven by fewer new jobs for young labor market entrants.

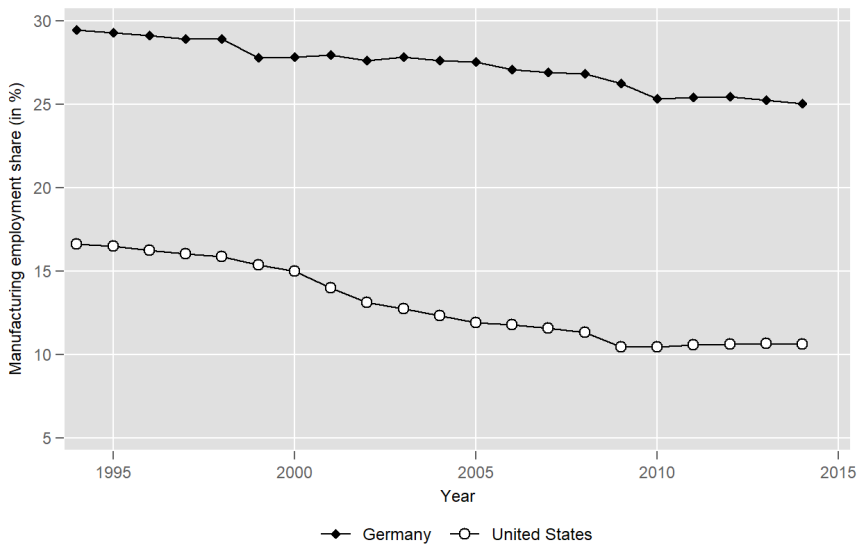
This increased job stability comes at the cost of lower wage growth, however. While automation benefits managers and high-skilled worker engaged in abstract tasks, we do find negative earnings effects for the bulk of medium-skilled and low-skilled workers whose task profiles are easier to substitute by robots. Moreover, using regional variation, we detect that automation imposes losses on labor overall and benefits capital and firm owners, thus reducing the labor income share. These findings suggest that robots have created aggregate rents but also caused notable distributional shifts in the economy.

We believe Germany provides an important benchmark case when it comes to the equilibrium effects of robots and how labor markets adjust to increasing automation. First, robots are much more prevalent in Germany than in the United States and elsewhere outside Asia.

[2]For example, the Insight Report of the World Economic Forum (2018) suggests that without retraining, only 2% of US workers would be able to adjust to an equally well-paid job when displaced by automation, and 16% would not be able to find any adequate work.



(a) Industrial robots.



(b) Manufacturing employment.

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

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

Figure 1a shows that almost two industrial robots were installed per thousand workers in 1994, more than twice as many as 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 even though 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).[3] Our analysis therefore elicits the causal effect of robots in an environment with many more of them installed in the manufacturing sector, and with many more manufacturing jobs per capita that could potentially be replaced.[4] A second reason to focus on Germany is practical. To study the detailed mechanisms how workers adjust to automation technologies, detailed individual-level, longitudinal data are necessary. Leveraging German social security data, we can estimate the impact of robot exposure on cumulative earnings, employment, and movement across sectors, industries, firms, and occupations.

Two previous contributions have studied the labor market effects of industrial robots. Acemoglu and Restrepo (2018b) use a regional difference-in-differences framework for local labor markets in the United States. They find that every robot leads to a total employment loss of three to six jobs. This evidence is, thus, in line with displacement effects being the dominant force, as robots seem to reduce labor force participation in the US. In their empirical study on the labor market effects of robots across industries and countries, Graetz and Michaels (forthcoming) do not find evidence of total job displacements. We extend the literature by shedding light on the adjustment processes of workers and firms in the labor market and how they interact in equilibrium. While we find zero effects of automation on total employment, this finding masks offsetting positive and negative effects in service industries and manufacturing. A central prediction of existing theories of automation (Acemoglu and Restrepo, forthcoming) is that output and labor demand should increase in industries that perform tasks which are complements in the production function relative to tasks performed by robots. We find strong support for these predictions. Second, we expand the literature by following workers after the automation shock and characterize their adjustment responses across different margins.

Our paper is more generally related to the large literature studying how technological change affects wages and employment, as surveyed in Acemoglu and Autor (2011). Various studies have argued that technological progress has contributed to rising wage inequality and labor market polarization in advanced countries (e.g., Autor, Levy, and Murnane 2003; Autor and Dorn 2013; Goos, Manning, and Salomons 2014). Moreover, a recent literature has studied the adjustment of labor markets to trade shocks (Autor, Dorn, and Hanson, 2016).

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

[4]Additionally, 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 10 largest producers in the world; the remaining 2 (*Kuka* and *ABB*) have German origin and mostly produce in Germany. Among the 20 largest firms, 5 are originally German and only 1 (*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, which may potentially be more relevant for Germany than for other countries except Japan.

We pay particular attention to controlling for trade exposure in our analysis. An influential literature – starting with Jacobson, LaLonde, and Sullivan (1993) – studying job displacement of individual workers has found very high costs of job loss and ensuing unemployment for affected workers. Relatedly, recent papers have shown the difficulties of workers in adjusting to industry-level import shocks (see Autor, Dorn, Hanson, and Song 2014), where adjustments are likely hampered by labor market frictions, in contrast to the stringent assumptions made in frictionless models. Findings from those literatures might suggest that we should detect long-lasting negative impacts of automation on affected workers. This is not the case, however. First, our results show that in contrast to popular predictive narratives in the public debate, workers in industries with larger robot exposure see more employment stability over a 20 year period, albeit marginally, which is explained by a higher probability of avoiding separation with the original employer. Second, we find that a large part of this effect is driven by increased occupational mobility within the same firm. Economically, workers and firms react to automation by changing the set of tasks for previously hired employees, thus avoiding layoffs. However, increased employment stability comes at the price of lower wage growth for affected workers who are retained by their original plants.

The rest of this paper is organized as follows. Section 2 describes our empirical approaches. In Section 3, we introduce our data and give a descriptive overview. Section 4 studies the impact of robots on equilibrium employment across local labor markets, and Section 5 dissects the aggregate zero impact. In Section 6, we turn to the effects on productivity and the labor share. Section 7 studies the adjustment process of workers. In Section 8, we analyze worker heterogeneity. Section 9 concludes.

2 Empirical Approach: Overview

In this paper, we are interested in how the labor market and its main actors, firms and workers, adjust to increasing automation possibilities. We work with two different main research designs. First, we use a local labor market approach, exploiting regional differences in the exposure to technological change in the form of industrial robots. Second, we leverage that we can follow workers over time and trace out employment changes and adjustments for differentially affected workers who react to the shock. Both approaches shed light on different adjustment margins of the labor market and are complementary. The first approach encompasses equilibrium adjustments and spillovers from directly affected to indirectly affected industries.[5] The second research design expands the literature by shifting the attention to

[5]Regional difference-in-difference designs have well-known limitations when it comes to gauging absolute or national impacts. The results from various papers show, however, that many equilibrium adjustments take indeed place locally (Moretti, 2011). Prominent local labor market designs have uncovered large discrepancies

adjustments at the worker level. *Ex ante*, it seems plausible that the displacement of labor by robots requires significant and potentially painful adjustment efforts by workers. The evidence on this is so far very limited, however. We asses the empirical importance of different margins of worker adjustments especially the reallocation margin (*switching firms*) and the occupation margin (*switching tasks*).

2.1 Local Labor Markets

At the local labor market level, our main variable of interest is the following measure:

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

This expression defines the change in robot exposure in a region r. The term Δrobots_j is the change in robot adoption per worker – with the number of workers fixed at the starting level in 1994 – in industry j:

$$\Delta\text{robots}_j = \frac{\Delta Robots_j}{emp1994_j}. \tag{2}$$

In this expression, $Robots_j$ is national industry robot adoption, where we observe robot counts at the industry level j. We allocate $\Delta Robots_j$ according to regional shares of national industry employment by multiplying Δrobots_j with emp_{jr} which is initial employment in industry-region cell jr. For each local labor market r, we sum the exposures of all local industries and scale it by the region's total employment emp_r, also measured in the base year 1994, to proportion appropriately for labor market size.[6] This part of the paper closely follows the important contribution by Acemoglu and Restrepo (2018b), who also provide a theoretical micro foundation for the robot exposure measure. Our findings for the local labor market analysis are still of independent and general interest, however, because the German economy exhibits a much stronger industrial robot exposure than the United States. Understanding first the regional equilibrium impacts of robots in Germany is also crucial to interpret the results for the worker-level adjustments in the second part of the paper.

We also adopt their instrumental variable strategy to address endogeneity concerns. In this approach, we employ robot adoptions across industries in other high-income countries as an instrument for German robot exposure.[7] More specifically, we deflate the robot installations

between regions caused by trade (Autor, Dorn, and Hanson, 2013), TFP shocks (Hornbeck and Moretti, 2018), or the Great Recession (Yagan, forthcoming).

[6]Broadly speaking, measuring exposure in this way bears resemblance to a Bartik (1991) style approach. Whereas the original contribution interacts local industry shares and national industry growth rates, national industry robot usage growth rates are employed here. Similarly, Autor, Dorn, and Hanson (2013) have used growth rates in Chinese import concentration and apportioned them according to initial industry shares.

[7]See Autor, Dorn, and Hanson (2013) and Bloom, Draca, and van Reenen (2016) for similar approaches to study the effects of Chinese import competition.

across the same set of industries j in each of those k countries with German industry-level employment in j from 1984 to construct k instrumental variables for Δrobots_j. The instruments for local exposure, Δrobots_r, are analogous and also use lagged employment figures from ten years prior to the base period.[8]

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

Finally, as is the case in many local labor market research designs, mobility responses by workers would imply that we are unlikely to detect a significant effect of automation on local labor market outcomes because there would be a diffusion of the initial "robot shock". As we show in Section 6, however, we find no evidence that the population distribution was systematically altered by the strong increase in industrial robot adoption.

2.2 Worker Level Analysis

Our approach to studying adjustments to task automation at the worker level is related to the international trade and labor literature (for example Autor, Dorn, Hanson, and Song 2014). There are two main similarities. First, we exploit industry variation and, second, we study adjustments in a setting where the source of the shock (i.e., robot automation) is known. This is different from the large literature following Jacobson, LaLonde, and Sullivan (1993), which studies worker layoffs and by definition focuses on outcomes conditional on job loss. As it turns out, the results for the automation shock are quite distinct from the typical effects found for negative labor demand shocks such as import competition.

Empirically, we capture changes in robot exposure for workers, who at the start of the investigation period work in industry j by our measure Δrobots_j, characterized in equation (2). Note that each worker gets assigned only the change in exposure at her original industry

[8] In the baseline specification of the two-stage least squares (2SLS) IV approach we use all k instruments and estimate an over-identified model. In a robustness check, we also aggregate the robot exposures of all k countries to build a single instrument in a just identified 2SLS model. Notice that it is not possible to use time lags for East German regions; here we are confined to use 1994 in the deflator.

of employment; intuitively, this avoids contamination of the treatment variable by endogenous moves across industries, which are – plausibly – related to automation.

A natural concern with the measure of robot exposure from equation (2) is that it may partly reflect domestic shocks to German industries. In line with our discussion from the previous section, we instrument using non-German high-income countries and their cross-industry patterns of robot adoption. As described above, we deflate the increase in the industry-level robot installations over the 20 year period by the industry size in 1984, rather than 1994, to resolve the issue that the industry size may have already been affected by previous robot installations.

When robot exposure started to increase, this may not have causally affected workers, but the rising robot installations could be symptoms of the previous industry-specific trajectories. To address this concern, we identify all effects within broad industry groups by adding fixed effects for broad manufacturing industry groups (food, consumer, industrial, and capital goods). In this way we purge the estimates of differential long-run trends across industry groups. Moreover, one might worry about confounding region-specific trends, since the German reunification and the associated economic changes took place just before the start of our observation period. We therefore identify all effects *within* federal states, or alternatively add the broad location dummies to capture systematic regional differences.[9] Finally, we consider placebo regressions and test if previous employment trends predict future robot installations.

3 Data and Descriptives

3.1 Labor market data

3.1.1 Workers

Our main source is administrative German labor market data provided by the Institute for Employment Research (IAB) at the German Federal Employment Agency. In the individual-level analysis, we use the Integrated Employment Biographies (IEB). This is a linked employer-employee spell data set, which allows us to follow single workers within and across establishments and occupations over time.[10] We focus on incumbent manufacturing workers with strong labor force attachment. In particular, we identify all full-time employees with a recorded

[9] 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.

[10] We work with a 30% random sample of the IEB V12.00.00 - 2015.09.15, which covers the universe of all workers in Germany except civil servants and the self-employed. A spell is generated by any notification of the employer to the social security insurance, so any employment or earnings information we use has daily precision. The data is described in detail by Card, Heining, and Kline (2013) and Oberschachtsiek, Scioch, Seysen, and Heining (2009).

main job in a manufacturing industry on June 30 in the base year 1994, who are i) between 22 and 44 years old, ii) earned more than the marginal-job threshold, and iii) had job tenure for at least two years. We then trace the detailed employment biographies of those roughly 1 million workers over the subsequent 20 years.[11] In a complementary short-run approach, we split the observation period and construct analogous work biographies over 10 years for all workers (age 22-54) starting out in manufacturing in 1994 or 2004, respectively. The resulting data sets assign every worker to an establishment at any point in time, and therefore to a 3-digit industry and location where the respective employer is affiliated. We also observe the workers' occupations following the KldB 1988 standard classification. Whenever workers have non-employment spells in their job biographies, this may constitute unemployment, early retirement, or labor market exit, all of which are endogenous labor market outcomes. We treat those spells as periods with zero earnings and employment for the respective worker and retain the previous establishment affiliation until a new job spell is recorded elsewhere. We also observe the profile of labor income for every worker. As the wage information is truncated at the social security contribution ceiling, we apply the imputation procedure by Card, Heining, and Kline (2013). Moreover, we convert all earnings into constant 2010 euros using the consumer price index of the *Bundesbank*.

Appendix Table A.1 reports some descriptive statistics. Panel A shows that the average manufacturing worker was employed on 5,959 out of 7,305 possible days over 20 years, and started off with a daily wage of 120€. The third line reports cumulative relative to the base year earnings. The average manufacturing worker in our sample has thus experienced a real loss because earnings in the 20-year time window only add up to 19.25 times the base year value. These trends are similar in the two separate 10-year-time windows. Panel B reports some standard individual characteristics of the manufacturing workers in our sample as recorded in the base year. Notice that roughly 9% hold a university degree (high skilled), while almost 76% have a completed apprenticeship (medium skilled), and 15% have no formal qualification (low skilled).

3.1.2 Local Labor Markets

For the local labor market analysis, we work with the Establishment History Panel (BHP) by the IAB, which covers the universe of all employees in the German labor market subject to social security.[12] We aggregate these data to the local industry level and distinguish 402 local labor markets (*Landkreise and kreisfreie Staedte*), which are roughly comparable to counties in the US. The data encompass both the former West and East Germany. For every county

[11] 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.

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

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.2.

3.2 Robot Usage

Our data set comes from the International Federation of Robotics (IFR) and reports the stock of robots for 50 countries over the period from 1994 to 2014. This data set has been used before by Graetz and Michaels (forthcoming) in a cross-country study at the industry level and by Acemoglu and Restrepo (2018b) for the US. A *robot* in these data is defined as an "automatically controlled, re-programmable, and multipurpose machine". As explained in more detail in International Federation of Robotics (2016), this means that robots are "fully autonomous machines that do not need a human operator and that can be programmed to perform several manual tasks such as welding, painting, assembling, handling materials, or packaging." Single-purpose machines such as elevators or transportation bands are, by contrast, not robots in this definition, as they cannot be reprogrammed to perform other tasks, require a human operator, or both. These data are based on yearly surveys of robot suppliers and capture around 90 % of the world market. The information is broken down at the industry level, but data availability differs across countries.[13] For Germany coverage is comprehensive, and we arrange the IFR data to match the official industrial classification scheme of the German labor market.[14] 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 onward. Appendix Table A.3 summarizes the information, and Figure A.2 illustrates the change in the number of robots per thousand workers separately for the two decades in all 72 industries. By far, the strongest increase can be observed in the different branches of the automobile industry (motor vehicles, auto bodies and parts). Here, 60–100 additional robots were installed per thousand workers in 2014 compared to 1994. This increase took place mostly during the first decade but continued during the second decade. Other industries that became vastly more robot-intensive include furniture, domestic appliances, and leather. On the other side of the spectrum we find cases where robot usage has hardly changed, and sometimes (e.g., in the watches and clocks industry) it

[13] As Graetz and Michaels (forthcoming), 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.

[14] The IFR data are reported according to ISIC Rev. 4, and we adopt an official cross-walk by *Eurostat* to reclassify them to the German WZ 1993 scheme which corresponds mostly to NACE Rev 1. Details about the cross-walk are reported in Appendix A. In Section 5.2 we perform robustness checks and rearrange the German data to match the ISIC Rev. 4 definition of the original robot data.

even decreased over time. In non-manufacturing industries, robots are used much less than in manufacturing.

3.3 Descriptive Overview

The average manufacturing worker in our sample has experienced an exposure equal to $\Delta\text{robots}_j = 16.98$ (see panel C in Appendix Table A.1). This equals the change in the number of installed robots per thousand workers over the period 1994-2014 in the industry, where the initial job was recorded in the base year. Notice the large variation across individuals. The worker at the 75th percentile has seen an increase in exposure that is almost three times larger than for the worker at the 25th percentile (9.6 versus 3.4 additional robots per thousand workers), and the comparison between the 90th and the 10th percentiles 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 A.2.

Next we turn to variation in the local exposure. The map in panel A of Figure A.1 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 two large German carmakers. Exposure has increased by up to 78 robots per thousand workers there. In our empirical analysis we will pay attention to the special role of the automobile industry and to these regions where automobile production is strongly concentrated. To make the variation more visible, we arrange the data in 10 decile bins in panel B. This map indicates that robot exposure in East Germany tends to be lower, which reflects the smaller overall manufacturing share there. Outside the upper decile, we observe notable differences mostly within West Germany. Values range from close to zero in some places in the North up to 7.6 additional robots per thousand workers in other local labor markets.

3.4 Trade and ICT Exposure

In our empirical analysis, we disentangle robots from two other major economic shocks that have affected Germany since the beginning of the 1990s. First, following Autor, Dorn, and Hanson (2013) and Dauth, Findeisen, and Suedekum (2014), we consider rising international trade with China and Eastern Europe. The idea is that some manufacturing branches in Germany saw strongly rising import penetration as China and Eastern Europe developed a comparative advantage after their sudden rises in the world economy, while for other German branches those new markets in "the East" primarily meant new export opportunities. Second, we consider investments in ICT as a distinct form of technological change. Similarly to robots,

ICT equipment may also replace some humans while complementing the productivity of others, thus leading to heterogeneous wage and employment effects for different individuals.

For the measurement of trade exposure, we closely follow Dauth, Findeisen, and Suedekum (2017) and Dauth, Findeisen, and Suedekum (2018), who compute the increase in German net exports vis-à-vis China and 21 Eastern European countries over the period 1994-2014 for every manufacturing industry j using UN Comtrade data, normalized by the initial wage bill to account for industry size. For ICT, we exploit information about installed equipment at the industry level as provided in the EU KLEMS database. It is defined as the change in real gross fixed capital formation volume per worker for computing and communications equipment from 1994 to 2014. In Appendix Table A.3, we report the trade and ICT exposures for all industries. The correlation of robot and net export exposure within manufacturing is mildly negative (-0.09). Although the automobile industry stands out as a strongly export-oriented branch with high robot installations, we generally find that import-competing industries tend to install slightly more robots. For robots and ICT, the correlation is small (0.04), mostly reflecting the fact that robots are pervasive in manufacturing while ICT investments have been stronger in services. The correlation between ICT and trade exposure is also small (0.05). Finally, we construct regional exposure measures for trade and ICT analogously to equation (1) and also find low correlations with local robot exposure.[15] These low correlations suggest that we capture three types of industry shocks in our empirical analysis that have been largely orthogonal to each other.

4 The Impact on Total Employment

In the first part of the paper, we estimate models of the following form at the local labor market level:

$$\Delta Y_r = \boldsymbol{\alpha} \cdot \mathbf{x}_r' + \beta_1 \cdot \Delta\text{robots}_r + \beta_2 \cdot \Delta\text{trade}_r + \beta_3 \cdot \Delta\text{ICT}_r + \phi_{REG(r)} + \epsilon_r. \tag{3}$$

Here we regress the change in a local outcome variable (such as total employment, manufacturing employment, the employment-to-population ratio, and the labor share) over the period 1994-2014 on the change in the number of robots per worker (i.e., on Δrobots_r as defined in (1). In the vector $\mathbf{x}_r'$ we control for detailed demographic characteristics of the local workforce (such as age, gender, and qualification) in levels, aggregated up from the universe of individual

[15] In Appendix Figure A.3, we depict scatter plots of local robot and trade/ICT exposures. At the regional level, the correlations tend to be opposite to what we find at the industry level. But this is strongly driven by the few automobile regions, which are strongly export and robot oriented but have installed little ICT 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.

Table 1: Robot Exposure and Employment.

[A] 2SLS	Dependent variable: 100 x Log-△ in total employment between 1994 and 2014				
	(1)	(2)	(3)	(4)	(5)
△ robots per 1000 workers	-0.0072	-0.0918	-0.0270	-0.0019	0.0023
	(0.111)	(0.108)	(0.118)	(0.112)	(0.119)
	(0.462)	(0.497)	(0.496)	(0.519)	(0.493)
△ net exports in 1000 € per worker		0.8954**	0.7297**	0.7449**	0.6322*
		(0.366)	(0.330)	(0.313)	(0.375)
△ ICT equipment in € per worker			0.0178	0.0139	0.0045
			(0.012)	(0.014)	(0.014)
% manufacturing				-0.0680	
				(0.204)	
% food products					2.3543***
					(0.393)
% consumer goods					0.5768*
					(0.311)
% industrial goods					0.6021**
					(0.238)
% capital goods					0.9498***
					(0.251)
% construction					1.5534***
					(0.319)
% maintenance					1.6306***
					(0.370)
% services					0.5126*
					(0.264)
% education					0.9458***
					(0.266)
[B] OLS					
△ robots per 1000 workers	-0.0036	-0.0305	-0.0423	0.0139	0.0098
	(0.110)	(0.106)	(0.112)	(0.116)	(0.131)

Notes: $N = 402$ local labor market regions (*Landkreise und kreisfreie Staedte*). We are interested in the impact of the change in robot exposure between 1994 and 2014 on the log-difference in total employment. The table reports results of a two-stage least squares (2SLS) IV approach where German robot exposure is instrumented with robot installations across industries in other high-income countries. All regressions include a constant. The specification in column (1) includes broad region dummies indicating if the region is located in the north, west, south, or east of Germany, and demographics. Demographic control variables are measured in the base year 1994 and are constructed as the number of workers in a particular group relative to total employment. They contain % female, % foreign, % age ≥ 50, % medium skilled (percentage of workers with completed apprenticeship), and % high skilled (percentage of workers with a university-degree). Columns (2) and (3) successively take into account the change in German net exports vis-à-vis China and 21 Eastern European countries (in 1000 € per worker), and the change in ICT equipment (in € per worker), both between 1994 and 2014. Column (4) adds the baseline manufacturing share (i.e. manufacture of food products, consumer goods, industrial goods, and capital goods). In column (5), instead of the manufacturing share, broad industry shares are included to control better for regional industry patterns. Industry shares cover the percentage of workers in nine broad industry groups (agriculture; food products; consumer goods; industrial goods; capital goods; construction; maintenance, hotels and restaurants; education, social work, other organizations) in the base year 1994. In columns (2)-(5), similar to the IV for German robot exposure, the changes in net exports vis-a-vis China and Eastern Europe and ICT equipment are instrumented with the analogous trade-flows and industry-level investments in ICT of other high-income countries, respectively. Standard errors clustered at the level of 50 aggregate labor market regions in parentheses. Levels of significance: *** 1 %, ** 5 %, * 10 %.

Sources: IFR, Comtrade, EU KLEMS, and BHP 7514 v1, own calculations.

social security records. To avoid contamination by the endogenous adjustment of the local labor force after the shock, we use levels before the start of the periods and not changes. We also include controls for the employment shares of nine broadly defined industry groups as reported in Appendix Table A.4 in one model. 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 specifications. Standard errors are clustered at a higher level of local market aggregation to account for spatial correlation, and we allow for 50 clusters.

The first and main dependent variable is the change in log employment. Table 1 presents the estimates. Panel A shows the 2SLS coefficients and panel B the corresponding OLS estimates, and for brevity, the OLS panel only contains the main effect of robot exposure but the other included control variables are the same as in the 2SLS models. All of the five models contain the start-of-period labor force and demographic composition controls and regional fixed effects (comparable to US census division dummies).

The 2SLS coefficient of -0.0072 is statistically insignificant at conventional levels. In Panel B, one sees that the OLS estimate is slightly larger (less negative) and also lacks statistical significance. This is consistent with an upward bias of OLS, such that regions on a more favorable labor market trend tend to be more exposed to increased robot usage.

Next, in column 2 we add local net export exposure with China and Eastern Europe to the list of controls. This is important because Germany is a strongly export-oriented economy and automation cannot be analyzed in a vacuum without accounting for increasing international trade.[16] The coefficient for robot exposure decreases, but it remains close to zero and is statistically insignificant. Consistent with Dauth, Findeisen, and Suedekum (2014), we find a positive impact of net export exposure on local employment growth. Adding local ICT exposure, as in column 3 we find that stronger local investments in ICT do not seem to have notable employment effects per se, since the respective coefficients are small and insignificant in both panels. Moreover, the central coefficients for robot exposure are also unaffected, reflecting the small correlation between robots and ICT across industries and local labor markets that we have documented above.

Column 4 augments the regression by controlling for the initial manufacturing employment share. Since robots are almost exclusively used in the manufacturing sector, the exposure variable could in part pick up a general trend decline in manufacturing and not only variation across different manufacturing industries. Controlling for the initial manufacturing share decreases the size of the robot coefficient and does not alter the conclusions. There may be more fine-grained industry trends within the manufacturing sector, which are correlated with

[16] If export intensive industries also rely more heavily on robots, this might alleviate possible job losses from technological change. Conversely, robots might have lowered production costs and thus spurred demand for German products.

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. In this way 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 5 remain very similar, however, and the point estimate turns marginally positive but statistically indistinguishable from zero.

Finally, notice the coefficient for trade exposure remains positive throughout and that the OLS estimates also tend to be small, albeit a bit larger than the 2SLS estimates, suggesting a moderate upward bias of OLS (i.e. robot-adopting regions performing better in terms of employment for reasons other than their robot exposure). The results in columns 1 to 5 establish a stable picture: one cannot detect a significant association between robot exposure and employment across labor markets. The remainder of the empirical analysis builds on the most demanding model in column 5, which we prefer on the grounds that it conditions on industry shares, regional dummies, and the detailed local labor force composition.

5 Spillovers: How Employment Adjusts

5.1 Main Results

The results so far strongly suggest no effects of robot exposure on total employment. This finding could mask important compositional effects, however. Indeed, models of automation (Acemoglu and Restrepo, 2018b) predict that output should expand in local industries with higher robot adaption. At the same time, the demand for labor in all other local industries increases when industries are gross complements in the production of a final consumption good. Spillovers may also be interpreted as stemming from changes in local demand for output produced in non-tradable industries.[17] The direction of these spillovers is therefore an empirical question. Increased productivity of adopting firms will lead to higher local demand for non-tradable output. Negative effects may arise if a decline in employment and wages in affected industries triggers a reduction in expenditures by workers, which outweighs the first positive expenditure effect from businesses.

How Employment Adjusts. We now explore the relevance of composition effects. The coefficients in Table 2 come from 2SLS regressions analogous to our earlier models (with the full set of control variables in column 5 of Table 1). The dependent variable is now the change in log employment in manufacturing in the first model and in non-manufacturing in the second

[17] Mian and Sufi (2014) have prominently argued that these local spillovers are important in understanding the US employment drop during the Great Recession.

Table 2: Composition Effects

	Employment			Average Wages		
	(1) Total	(2) Manuf.	(3) Non-manuf.	(4) Total	(5) Manuf.	(6) Non-manuf.
[A] Baseline: 100 x Log-△ in employment (average wages) between 1994 and 2014						
△ robots per 1000 workers	0.0023	-0.3832**	0.4257**	-0.0336	-0.1373*	0.0852*
	(0.119)	(0.149)	(0.205)	(0.056)	(0.073)	(0.050)
[B] Alternative employment measure: 100 x △ in employment/population between 1994 and 2014						
△ robots per 1000 workers	-0.0177	-0.0594**	0.0417			
	(0.065)	(0.027)	(0.050)			
N	402	402	402	7149	6038	7095

Notes: In all regressions, the variable of interest is the change in robot exposure between 1994 and 2014. The employment estimates in columns (1) to (3) are based on one observation per region, while the unit of observation in the wage estimates in columns (4) to (6) are region x demographic cells. Demographic cells are defined by gender, three age groups, and three education groups. We only include cells containing at least 10 observations, and perform the regressions at the region x demographic cell level including fixed effects for gender, age groups, and education groups. Columns (1) to (6) display estimates for total employment, employment in manufacturing, employment in non-manufacturing, total average wages, average wages in manufacturing, and average wages in non-manufacturing, respectively. The regressions are estimated by applying the 2SLS IV approach where German robot exposure is instrumented with robot installations in other high-income countries. Net exports to China and Eastern Europe and ICT are instrumented with their respective counterparts in other high-income countries. The regressions include the full set of control variables as in column (5) of Table 1. Standard errors clustered at the level of 50 aggregate labor market regions (employment regressions) or local labor markets (wage regressions) in parentheses. Levels of significance: *** 1 %, ** 5 %, * 10 %.

Sources: IFR, Comtrade, EU KLEMS, and BHP 7514 v1, own calculations.

model. As we have seen in Section 3, robot adoption is almost exclusively happening in the manufacturing sector, which is why we first cut the data in this simple way. This simple sample split also captures very well the distinction between the tradable and non-tradable sectors.

The model estimates in column 2 of Table 2 show a negative effect on manufacturing employment with a statistically significant coefficient of -0.38, in contrast to the null found for total employment (which we repeat in column 1). The estimate in column 3, in contrast, shows a positive significant effect on service employment with a coefficient of 0.41. These estimates imply that the null effect on total employment is indeed the result of offsetting job growth and job decline in manufacturing versus services.

The results represent strong evidence that the adoption of robots has led to *positive employment spillovers* on other local industries. Our data allow us to further look at this channel. Table 3 presents estimates when we split up the service sector into several subsectors. We differentiate business services, consumer services, construction, and public government services. The first category includes employment in establishments that render their services to other businesses on a contract or fee basis.[18] This includes services related to information and com-

[18]See appendix Table A.4 for the detailed categorization.

munication technology, cleaning, or security. The second category, consumer services, contains employment in hotel and restaurant services, as well as beauty services such as haircutting.

By far, the largest employment effect is on business services with a coefficient of 0.76, followed by 0.21 for consumer services. The consumer service coefficient lacks statistical significance at conventional levels. The coefficients on construction employment and public sector employment are close to zero. Positive employment spillovers are hence driven by spending from local firms on local services. This result is consistent with the model by Acemoglu and Restrepo (2018b) where increased robot adoption raises demand for complementarity inputs by producers.[19]

Wages. In columns 4-6 of Table 2, we repeat the analysis using the change in local average log wages as the outcome variable.[20] We note that the wage estimates must be interpreted with some caution. Robot exposure displaces workers at least in the manufacturing sector, which creates selection since wage outcomes are only available for employed workers. We circumvent these issues when we look at labor earnings directly for individual workers in the second main part of the paper.

Still reassuringly, the results by and large mirror the employment effects. Column 4 shows a small and insignificant impact of robot exposure on wage growth. Consistent with the employment results, however, we see negative effects within manufacturing in column 5 and positive effects in the service sector in column 6. The results strongly suppport the hypothesis of decreased manufacturing labor demand in regions with high robot exposure and an offsetting increase in labor demand for local services.

Placebo. A concern for our analysis is that some manufacturing industries may have already been on a downward trajectory 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 the absence of a causal effect. The coefficients for robots on manufacturing employment could then be biased downward. By the same token, employment in service industries may have been trending upward in regions specialized in declining but robot-adopting industries.

To address this issue, we regress lagged employment growth (1984-1994) on future robot exposure (1994-2014), to check if past trends can predict future robot installations. Table 4 contains the estimates and columns 1 to 3 show the employment results. For manufacturing,

[19]Relatedly, Goldschmidt and Schmieder (2017) show that task outsourcing (within the same country) has increased in Germany. It is conceivable that increased automation may be related to changing boundaries of the firm, as it may accelerate these processes. We leave a further empirical investigation of this issue for further research.

[20]We conduct our analysis at the demographic group-region cell level, as in Acemoglu and Restrepo (2018b).

Table 3: Type of Spillovers

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

Notes: $N = 402$. Column (1) displays estimates for the whole non-manufacturing sector. Columns (2) to (5) split the non-manufacturing sector into several subsectors, namely construction, consumer services, business services, and the public sector, respectively. The regressions are estimated by applying the 2SLS IV approach where German robot exposure is instrumented with robot installations in other high-income countries. Net exports to China and Eastern Europe and ICT are instrumented with their respective counterparts in other high-income countries. The regressions include the full set of control variables as in column (5) of Table 1. Standard errors clustered at the level of 50 aggregate labor market regions in parentheses. Levels of significance: *** 1 %, ** 5 %, * 10 %.

Sources: IFR, COMTRADE, EUKLEMS, and BHP 7514 v1, own calculations.

Table 4: Pre-Trends.

	Employment			**Average Wages**		
	(1) Total	(2) Manuf.	(3) Non-manuf.	(4) Total	(5) Manuf.	(6) Non-manuf.
100 x Log-△ in employment (average wages) between 1984 and 1994						
△ robots per 1000 workers	-0.0916	0.0151	-0.0565	0.0282	0.0519	0.0306
	(0.106)	(0.152)	(0.098)	(0.030)	(0.033)	(0.033)
N	326	326	326	5640	4836	5555

Notes: In order to verify if pre-trends drive the results in Table 2, the change in employment (average wages) between 1984 and 1994 is regressed on the robot exposure between 1994 and 2014. The specifications are the same as in Table 2. Standard errors clustered at the level of 50 aggregate labor market regions (employment regressions) or local labor markets (wage regressions) in parentheses. Levels of significance: *** 1 %, ** 5 %, * 10 %.

Sources: IFR, COMTRADE, EUKLEMS, and BHP 7514 v1, own calculations.

we see a very small positive and insignificant coefficient. For non-manufacturing, the estimate is negative and insignificant. This finding indicates the absence of significant pre-trends. The results for wages are contained in columns 4 to 6, and confirm the interpretation of the employment results, as one cannot detect significant trends in regions correlated with future robot exposure.

The Job Multiplier of Robots. In the public debate, there is a lot of speculation about how many jobs in head counts have been destroyed or are expected to be lost because of increased robot adoption. We follow Acemoglu and Restrepo (2018b) and conduct an exercise gauging the total job effect of robots. To put the analysis on equal footing, we reestimate the model in panel B of Table 2 with the change in the employment-to-population ratio as

the dependent variable.[21] We estimate that one more robot per thousand workers reduces the manufacturing employment-to-population ratio by 0.059 percentage points with an offsetting effect on service jobs of 0.042 percentage points for a total small negative effect of 0.018 percentage points.

We can translate these numbers into head counts, which imply that one installed industrial robot per 1,000 workers replaced 2.11 manufacturing jobs in Germany.[22] This has been offset by job growth of almost two jobs per industrial robot in the service sector.[23]

5.2 Robustness

In this section, we discuss several important robustness checks and how they affect the results. We consider the estimates for employment and wage effects on the aggregate and separated by manufacturing and non-manufacturing.

East Germany. 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. To address this concern, we drop East Germany in panel A of Table A.5 in the Appendix. In panel B, we change the specification of $\phi_{REG(r)}$ and include federal state fixed effects instead of the four broad location dummies. Our main results also remain unchanged in those robustness checks.

[21] We measure employment by all jobs in Germany subject to social security. This yields smaller *E/POP* ratios between 0.25 and 0.5 in our sample since we have excluded civil servants and self-employed workers. Including civil servants and self-employed workers in the *E/POP* with data from the German Federal Statistical Office does not affect our results. See also column 5 of Table 3, which showed no effect of robots on public employment.

[22] If we have two time periods, E_t is job head counts in t, R installed robots, and Pop population, then:

$$\frac{E_2}{Pop_2} - \frac{E_1}{Pop_1} = \beta \left(\frac{R_2 - R_1}{E_1} \right) \times 1000.$$

If we assume a constant population, we get:

$$E_2 - E_1 = \beta \left(\frac{R_2 - R_1}{E_1 / Pop_1} \right).$$

Finally, normalizing to one additional robot per 1,000 workers, and using a ratio of the number of jobs covered by social security relative to the population of 0.28, which is the average value across regions in 1994, we get 2.11.

[23] To put this number into perspective, consider that a total stock of 130,428 robots have been installed in Germany over the period 1994–2014. A quick back-of-the-envelope calculation therefore implies a loss of 276,507 manufacturing jobs. Bearing in mind that manufacturing employment in Germany has declined by 1.2 million (from roughly 7 million full-time equivalent jobs in 1994 to 5.8 million in 2014; see Figure 1b), this means that robots have been responsible for around 23% of this overall decline. Such an exercise supposes that increased exposure to robots influences the absolute level of employment nationwide. Using the model from Acemoglu and Restrepo (2018b) , one can calibrate the impact assuming dampening general equilibrium effects to arrive at numbers which are around 10-15% smaller.

Different Local Labor Market Aggregation. A very important robustness check is to consider a broader definition of local labor markets. In panel C of Table A.5 in the Appendix, we use an aggregation up to 258 local labor markets, based on commuter flows.[24] Reassuringly, the main conclusions are unaffected.

Cars. The automobile industry is a large and important sector in the German economy and has by far the most robots. To shed light on the special role of cars, we differentiate the local employment and wage effects of robots separately for the different branches of the automobile industry (motor vehicles, car bodies, and car parts) and for all other manufacturing industries in Appendix Table A.6. For employment, we find strongly negative effects in both cases. The impact of robots on wages is even more pervasive in the other manufacturing branches. From this exercise we conclude that our main results are not solely driven by cars, but that robots affect the manufacturing sector more broadly.[25]

Industry Cross-walk. 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. We 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.5 as in our baseline.

Instruments. 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 their comprehensive data availability. The exclusion restriction requires that robot installations, and the associated labor market effects in the instrument countries, shall not have direct impacts on the German labor market. One may worry that this requirement could not be met for important and large instrument countries with strong economic ties to Germany. In panel E we drop all countries from the Eurozone (i.e., France, Italy, Spain, and Finland) since shocks may be correlated within the monetary union. The results are very similar to our baseline findings, however.

[24] The aggregation of counties to 258 local labor markets is provided by the German Federal Institute for Research on Building, Urban Affairs and Spatial Development, `https://www.bbsr.bund.de/BBSR/DE/Raumbeobachtung/Raumabgrenzungen/AMR/amr_node.html`

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

6 Productivity, the Labor Share, and Population

So far, we have studied the effects of industrial robot adoption on employment and wage growth. Additional data also permit us to investigate the effects on labor productivity, the distribution of income between capital and labor, and population at the local labor market level.[26]

The models we estimate in Table 5 follow the same specification as in column 5 of Table 1. In column 1 of Table 5, the dependent variable is the change in labor productivity measured by the change in log output per worker between 2004 and 2014 (we focus on the second decade (2004-2014) in this analysis, because most data from this source are not available for earlier years). The effect of robot exposure on labor productivity is sizable and statistically significant. It implies that a local labor market with robot exposure at the 75th percentile saw 1.75% higher growth compared to a labor market at the 25th percentile.

Higher labor productivity from automation, however, *did not* lead to an increase in the labor share. In contrast, we find in column 2 a negative coefficient of -0.438.[27] The dependent variable is the first difference in the labor share from 2004 to 2014. The coefficient, hence, implies that a labor market at the 75th percentile of the exposure distribution experienced a 1.32 percentage points decline in the labor share relative to the labor market at the 25th percentile. This is a substantial effect, and to the best of our knowledge, we are the first study to provide evidence on the effects of increased automation on the decline in the labor share.

Finally, column 3 shows that robots also have no effects on population growth. Hence, they do not seem to induce notable migration responses, such as moves away from more robot exposed regions. This finding is reassuring because it suggests that our local labor market approach seems to be adequate for studying the labor market effects of robots. Our regions may be considered as small subeconomies of Germany across which migratory responses to aggregate shocks appear to be weak.

7 Individual Workers

Our estimates of the effects of automation, identified from variation across local labor markets, implies economically meaningful labor displacement effects concentrated in manufacturing industries, but no effect on total employment as the composition of jobs changed. Do our estimates imply that affected workers could quickly and smoothly adjust, for example, by transitioning across firms, sectors, tasks and occupations? Several findings in the literature

[26] With the exception of the population variable (which is provided by the BHP, see Section 3.1.2), the measures in this section come from the German Federal Statistical Office, which break down national accounts at the regional level, see Appendix B for a detailed description how the data can be obtained.

[27] Notice that, unfortunately, data is missing for 30 regions in column 2.

Table 5: Other Important Outcomes

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

Notes: Local labor market regions N. The dependent variable in column (1) is the log change in output per worker x 100, in column (2) the percentage point change in gross pay per employee over output per worker x 100, and in column (3) the log change in population x 100. The regressions are estimated by applying the 2SLS IV approach where German robot exposure is instrumented with robot installations in other high-income countries. Net exports to China and Eastern Europe and ICT are instrumented with their respective counterparts in other high-income countries. The full set of control variables as in column (5) of Table 1 is included. Standard errors clustered at the level of 50 aggregate labor market regions in parentheses. Levels of significance: *** 1 %, ** 5 %, * 10 %.

Sources: IFR, COMTRADE, EUKLEMS, German Federal Statistical Office, and BHP 7514 v1, own calculations.

suggest that one should be skeptical that this is happening. An influential literature – starting with Jacobson, LaLonde, and Sullivan (1993) – studying the job displacement of individual workers has found very high costs of job loss and ensuing unemployment for affected workers.[28] Relatedly, recent papers have shown the difficulties of workers in adjusting to industry-level import shocks (see Autor, Dorn, Hanson, and Song 2014), where adjustments are likely hampered by labor market frictions, in contrast to the stringent assumptions made in frictionless models.[29]

We now show that in the case of automation, the picture is more pronounced and multifaceted. First, we detect that, maybe surprisingly and in contrast to popular predictive narratives in the public debate, workers in industries with larger robot exposure, see more employment stability over the 20 year period. Second, we find that a large part of this effect is driven by increased *occupational mobility within the same firm*, which suggests that workers and firms react to automation by changing the set of tasks for their incumbent employees.

7.1 Mobility Across Occupations and Industries

Our sample in this section includes all workers which were employed in a manufacturing industry in 1994, as outlined in Section 3, who are i) between 22 and 44 years old, ii) earned more than the marginal-job threshold, and iii) had job tenure for at least two years.[30] We work with the following specification:

[28] See also Schmieder, Wachter, and Heining (2018), who show that the costs of layoff are also very high in Germany.

[29] See also Dauth, Findeisen, and Suedekum (2018), who study adjustments and reallocations to export shocks.

[30] We follow the standard practice in the literature and focus on workers with high labor force attachment. Results are very similar, however, when including also worker with lower attachment.

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

In this section, Y_{ij} are the cumulated number of days spent in employment – irrespective if employed in a manufacturing or a different sector – over the 1994-2014 period. In the vector $\mathbf{x}'_{ij}$ we include standard worker-level controls: dummies for gender, foreign nationality, three skill categories, and three tenure categories. In addition we include a full set of age dummies and dummies for six plant size groups. We also include dummies $\phi_{J(j)}$ for four broad manufacturing industry groups and $\phi_{REG(i)}$ for federal states. The plant size, industry, and region variables refer to the worker's employer in 1994. We also control for the log of yearly earnings of a worker in the base year.

In this analysis, we hence compare workers with similar observable demographic characteristics. In addition, we compare workers with similar firm characteristics (i.e. type of manufacturing industry and plant size). Importantly, we also conduct the analysis within region (16 federal states). Within these cells, some workers were employed in industries subject to strong automation while others were not, which is the source of our variation and captured by Δrobots_j, defined above in equation (2).

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

$$Y_{ij} = \boldsymbol{\alpha} \cdot \mathbf{x}'_{ij} + \beta_1 \cdot \Delta\text{robots}_j + \beta_2 \cdot \Delta\text{trade}_j + \beta_3 \cdot \Delta\text{ICT}_j + \phi_{REG(i)} + \phi_{J(j)} + \epsilon_{ij}, \qquad (4)$$

in order to disentangle the rise of the robots from other trade and technology shocks. All standard errors are clustered by industry.

The advantage of this empirical model, where the left-hand side is given by a cumulative variable in levels, is that employment and earnings over the 20 year period can be cleanly decomposed into its various sources.[31] In this section, we start with employment and exploit that we measure employment with *daily frequency* in our data. Afterwards we decompose Y_{ij} into several additive parts and study whether rising robot exposure has led to systematic job mobility. More specifically, we start with the industry dimension and analyze if robot exposure causes job switches to other firms within the original industry, to a different manufacturing industry, or out of the manufacturing sector altogether. Similarly, we analyze whether 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.

[31] This approach has also been used by Autor, Dorn, Hanson, and Song (2014) to study the worker-level impacts of trade shocks.

Table 6: Individual Adjustment to Robot Exposure (Employment)

[A] Industry mobility	(1)	(2)	(3)	(4)	(5)
	all employers		same sector		Service Sector
Same industry		yes	yes	no	no
Same employer		yes	no	no	no
Δ robots per 1000 workers	0.7397*	11.4254***	-4.6569**	-2.0471	-3.9816***
	(0.446)	(2.716)	(2.287)	(2.875)	(1.387)

[B] Occupational mobility	(1)	(2)	(3)	(4)	(5)
	all jobs	same employer		other employer	
Same occupational field		yes	no	yes	no
Δ robots per 1000 workers	0.7397*	6.3814***	5.0440***	-7.6399***	-3.0457***
	(0.446)	(1.557)	(1.385)	(2.193)	(0.641)

Notes: Based on 993,187 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 20 years following the base year. Panel A: For column (2) employment days are cumulated only when they occurred at the original workplace. For the other columns, employment days are cumulated only when they occurred at a different plant in the same industry (3), at a plant in a different manufacturing industry (4), and outside the manufacturing sector (5), respectively. Panel B: Employment days are cumulated only when they occurred in the original occupation and workplace column (2), in a different occupation but at the original workplace column (3), in the original occupation but at a different workplace column (4), and in a different occupation and workplace, respectively. The regressions are estimated by applying the 2SLS IV approach where German robot exposure, net exports to China and Eastern Europe, and ICT are instrumented with their respective counterparts in other high-income countries and the industry's share of routine tasks in production. Control variables are log base year earnings and indicator variables for gender, foreign nationality, birth year, educational degree (3 categories), tenure (3 categories), plant size (6 categories), broad manufacturing industry groups (4 categories), and 16 federal states. Standard errors clustered by industry in parentheses. Levels of significance: *** 1 %, ** 5 %, * 10 %.

Sources: IFR, Comtrade, EU KLEMS, and IEB V12.00.00 - 2015.09.15, own calculations.

Table 6 presents the 2SLS baseline estimates of equation (4). In column 1 of panel A, the dependent variable is the total number of days of employment over the 20 year period. Greater exposure to robots is associated with higher employment. The magnitude of the effect can be interpreted by comparing a worker at the 75th percentile of the robot exposure distribution to an otherwise equal worker at the 25th percentile. Quantitatively, the difference is 4.6 days of employment, a small impact. Since the distribution is highly skewed, impact increases to 58 days when comparing a 90th percentile to a 10th percentile worker.

In columns 2 to 5, employment is disaggregated into mutually exclusive (and exhaustive) channels. As a result, the estimates from those models sum up to the first one on total employment shown in column 1. Strikingly, in column 2 the coefficient is more than an order of magnitude larger. Employment at the original plant increases by robot exposure. The economic impact of this effect is large and around 15 times larger than for the total employment effect. Quantitatively, it translates into an increase of around 900 days of employment for a 90th percentile relative to a 10th percentile manufacturing worker. This increase is counteracted by reduced employment across other firms from the same industry, different industries, and the service sector, as can be seen in columns 3 to 5.

In panel B, we analyze mobility across occupations. Column 1 repeats the baseline estimate on total employment for completeness. Columns 2 and 3 are based on models, where the dependent variable is employment at a worker's original firm, split into a part working in one's initial occupation at the start of the period versus any other occupation. By construction, the estimates sum up to column 2 from panel A, since it is an additive decomposition (6.3814 + 5.0440=11.4254). Approximately half of the employment effect at the original plant effect is driven by employment in a different occupation.

To get a total occupational mobility effect across all firms, we can add columns 2 and 4 to obtain the effect of robot exposure on time spent in one's original occupation and compare it to the sum of column 3 and 5, which encompasses time spent in a different occupation. This gives $6.3814 - 7.6399 = -1.2585$ versus $5.0440 - 3.0457 = 1.9983$: automation has hence significantly increased occupational mobility.

A popular narrative in the public debate is that affected workers will have to be flexible and mobile across tasks and occupations to be "one step ahead" of labor displacing technologies. Our sets of results imply that workers in Germany already responded by switching to the rise of industrial robots and – surprisingly – the reassignment of workers to new tasks tends to happen frequently within a worker's original firm. This mechanism is in turn consistent with firm-specific human capital, and also firing costs which may make firms reluctant to separate from incumbent workers.[32]

7.2 Individual Earnings and Wages

We now analyze earnings and wage responses. In Table 7, we replace the dependent variable with a) cumulative earnings and b) average log wages over the 20-year period. Column 1 presents the estimates on earnings with all control variables except for trade and ICT exposure. In sharp contrast to the employment effects, one obtains a negative effect from robot exposure with an insignificant point estimate of -0.6794. This result remains robust and even becomes somewhat stronger when adding net export and ICT exposure. The point estimate is now also statistically significant. To interpret the coefficient estimates, we again compare a worker at the 90th percentile of the robot exposure distribution to an otherwise equal worker at the 10th percentile. The coefficient in column 3 indicates that over the 20-year period, the cumulative earnings of those two workers differ by 88 % of their initial earnings. This means that if both earned the average earnings in 1994, their cumulative

[32]Some of these firing costs may be institutional. Employees are protected from layoffs in Germany, for example, if the employer is not actively downsizing its workforce. While one would expect in general that automation leads to downsizing so that the protection is not binding, plausibly there might also be plants who are expanding their workforce even during automation episodes by increasing hiring in other departments which are not directly involved in physical production.

Table 7: Individual earnings and average wages

Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	100 x cumulative earnings all employers			100 x log average wages all employers			original firm
Δ robots per 1000 workers	-0.6794	-0.8241**	-1.1165	-0.0327**	-0.0369**	-0.0602*	-0.0114
	(0.420)	(0.389)	(0.967)	(0.016)	(0.016)	(0.032)	(0.014)
Δ net exports / wagebill in %		0.4043*	0.3851*		0.0108	0.0088	0.0123**
		(0.207)	(0.203)		(0.008)	(0.007)	(0.006)
Δ ICT equipment in € per worker		0.0163	0.0166		0.0009	0.0009	0.0010
		(0.044)	(0.044)		(0.002)	(0.002)	(0.001)
Observations	993,187	993,187	890,556	986,349	986,349	884,079	924,299

Notes: 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 (Columns 1-3) and 100 x log average wages over the twenty years following the base year (Columns 4-7). German robot exposure is instrumented with robot installations across industries in other high-income countries. Similarly, in columns 5 and 6, the changes in net exports vis-a-vis China and Eastern Europe and ICT equipment are instrumented with the analogous trade-flows and industry-level investments in ICT of other high-income countries, respectively. Standard errors clustered by industry in parentheses. Levels of significance: *** 1 %, ** 5 %, * 10 %.
Sources: IFR, Comtrade, EU KLEMS, and IEB V12.00.00 - 2015.09.15, own calculations.

earnings would differ by around 34,245 euros. We conduct a robustness check with respect to the automotive industries and drop them from the specification in column 3. The main conclusions are unaffected and support that robot exposure has lowered earnings growth for affected workers, despite a somewhat imprecise estimate.

If robot exposure has increased employment but decreased earnings, it follows that earned wages must have been negatively affected. In columns 4 to 6 we confirm this mechanism by estimating a set of models where the outcome is average log wages over the 20-year period for every worker. The results imply that a unit increase in robot exposure has decreased wages by respectively 0.032, 0.036, and 0.058 percent, using the formula $(\exp(\hat{\beta}_1/100)-1)\times 100$. All estimates are significant at the conventional 5% level. When comparing two manufacturing workers at the 10th and the 90th percentile, we find that automation decreases wages by 4.86 %. This can be scaled relative to the growth rate of average wages in German manufacturing over the whole two decades of 20.5 %.

To sum up, our results suggests that employment stability in a worker's original job increases but total earnings decrease in response to automation. This could be the result of a renewed bargaining situation between affected workers and firms. Automation may reshuffle more bargaining power to employers. In situations where it is still efficient to keep a worker-firm match alive, for example, because of acquired firm-specific human capital of the worker or firing costs, wages on the job should decrease. We explore this hypothesis by focusing on wages on the original job only. Column 7 shows a negative impact, consistent with this mechanism, and the effect implies a 0.011 % wage decline for each unit increase of robot exposure, but also lacks statistical significance at standard levels.

Unions and Wage Bargaining Protocols. Table A.7 in the Appendix explores separate effects depending on the influence of unions and the wage bargaining protocol. We use industry-level variation in the share of workers who are covered by a collective bargaining agreement for wages either at the firm or industry level. Collective agreements at the firm level allow firms to adjust wages much more flexibly compared to agreements at the industry level. We interact these shares with the increase in robot exposure, and columns 1 and 2 display the results for employment. Column 1 shows that the interaction with the industry share is strongly negative, while the interaction with the firm share is estimated around 0. Automation tends to reduce employment the most when firms are not able to adjust wages but are bound to industry-wide agreements. Column 2 confirms this when we look at employment with the original firm, where only the industry coverage interaction is negative, although the estimates are not statistically significant. We find the same patterns for earnings in columns 3 and 4. These findings support the interpretation that firms share the rents created by automation in the form of employment stability, but only if wages can be flexibly adjusted simultaneously.

7.3 Entrants

How can robots lead to fewer manufacturing jobs in equilibrium but stabilize existing individual employment relationships, as we have seen in Section 7.1? One explanation is that manufacturing firms do not displace incumbent workers when installing robots, but create fewer new jobs.

In Table 8 we investigate this hypothesis. Here we return to our local labor market approach, and now consider patterns of (re-)entry of young workers and returnees from unemployment as the outcome variable.[33] More specifically, we compute the entry share into manufacturing in region r in 1994, that is, the average probability that a young worker who takes up his or her first job ever does so in manufacturing in region r. For returnees who have been unemployed for at least one year prior to the base period, we proceed analogously. Next, we compute the same variables for the year 2014, and then the change in those regional (re-)entry probabilities into manufacturing over time. Finally, we regress those changes on local robot exposure, following the same baseline specification as in column 5 of Table 1.

Column 1 shows that the entry probability into manufacturing for young workers has indeed significantly decreased in more robot-exposed regions. The negative impact of robots on

[33] This setup follows Dauth, Findeisen, and Suedekum (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 8: Robot Exposure and Entry Into Manufacturing Employment.

	△ manuf. (re-)entry		△ avg. age	
	(1) Entry	(2) Re-entry	(3) Manuf.	(4) Non-manuf.
△ robots per 1000 workers	-0.1320**	0.0308	0.0251***	-0.0291***
	(0.067)	(0.079)	(0.008)	(0.010)

Notes: $N = 402$ local labor market regions. The dependent variables in columns (1) and (2) measure the change in the share of manufacturing entrants respectively returnees in all entries (in %-points) between 1994 and 2014. In columns (3) and (4), the dependent variables are the change in the average age in manufacturing and non-manufacturing between 1994 and 2014. The regressions are estimated by applying the 2SLS IV approach where German robot exposure is instrumented with robot installations in other high-income countries. Net exports to China and Eastern Europe and ICT are instrumented with their respective counterparts in other high-income countries. The full set of control variables as in column (5) of Table 1 is included. Standard errors clustered at the level of 50 aggregate labor market regions in parentheses. Levels of significance: *** 1 %, ** 5 %, * 10 %.

Sources: IFR, Comtrade, EU KLEMS, and IEB V12.00.00 - 2015.09.15, own calculations.

equilibrium employment growth in manufacturing, which we have found in Section 4, therefore seems to come from lower rates of entry into new manufacturing jobs, but not from a direct destruction of existing jobs. Stated differently, robots seem to "foreclose" entry into manufacturing for young people, for example, through omitted replacements when a vacancy arises from natural turnover. For returnees from non-employment, we find no such effect in column 2.

A direct implication of this finding is that the manufacturing workforces in more robot-exposed regions should then age more rapidly because there is a smaller inflow of young people, while the opposite should happen in non-manufacturing where entrants go instead. In columns 3 and 4 we investigate this hypothesis. We compute, for every region r, the change in the average employee age within manufacturing and non-manufacturing, respectively, and regress these age changes on local robot exposure. Our findings indeed confirm this aging hypothesis for more robotized manufacturing sectors.[34]

8 Effects Across Occupations and Skill Groups

In the last step of our analysis we explore heterogeneous impacts across occupations and skill groups. A very influential literature has investigated the *skill bias* of technological change (Katz and Murphy (1992) is the seminal reference). A newer literature has instead emphasized the *task bias* of technological developments.[35] Up to now, the evidence how automation

[34]Our results are consistent with a two-way interaction between automation and ageing. Acemoglu and Restrepo (2018a) investigate the effect of an older population on more automation. We find that more automation causes an increase in the average age of the working population in regions more affected by automation. These effects could reinforce each other.

[35]See Acemoglu and Autor (2011) for a survey and Autor and Dorn (2013) for a prominent application across US labor markets and Goos, Manning, and Salomons (2014) across countries.

and robots have affected earnings trends between these groups – either formal education or occupations – has been very scarce, however.

The results are contained in Figure 2, where we show the point estimates and 95% confidence intervals for different groups of workers. The specifications follow Section 7 exactly – so we include controls for skill categories, tenure categories age, plant size groups, initial industry and region – and the dependent variable is cumulated labor earnings.[36] Panel a differentiates six broad occupational categories that can be found among the individual manufacturing workers in our sample, and Panel b distinguishes three skill categories.

In Panel a, one can identify two occupation groups for which the estimated impact is economically meaningful and positive. These are managers and legal specialists as well as technical and natural science occupations. Only the point estimate for the latter group is statistically significant at the conventional 5% level. Our results indicate that automation has benefited these groups by complementing their set of tasks. We find significant earnings losses mainly for machine operators. Industrial robots – by definition – do not require a human operator anymore but have the potential of conducting many production steps autonomously. Robots therefore directly substitute the task sets of those occupations.

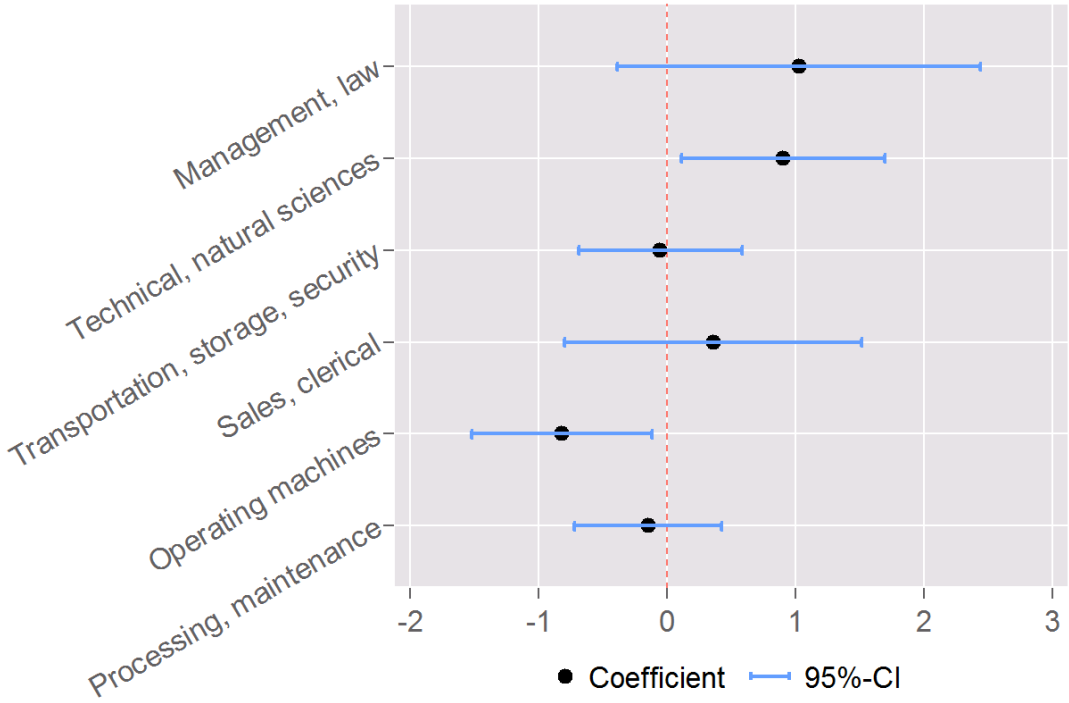
A second natural way to cut the data is to consider impacts across education groups, following an enormous literature investigating how technological change affects relative skill demand. In the German context, because of the prevalence of the apprenticeship system, it makes sense to split the population not just into two but three skill groups. In panel b, high skilled is defined as having a degree from a university or college, and medium skilled is defined as having a vocational training degree. All other educational levels are subsumed as low skilled (i.e., high school graduates and high school dropouts).

The most negative impact is found for medium-skilled workers. Those losses drive the average effects in Table 7 because completed apprenticeship is the typical profile for manufacturing workers in Germany accounting for almost 76% of all individuals in our sample. Robots also tend to reduce the earnings of low-skilled workers without formal education, but the effects are less precisely estimated.

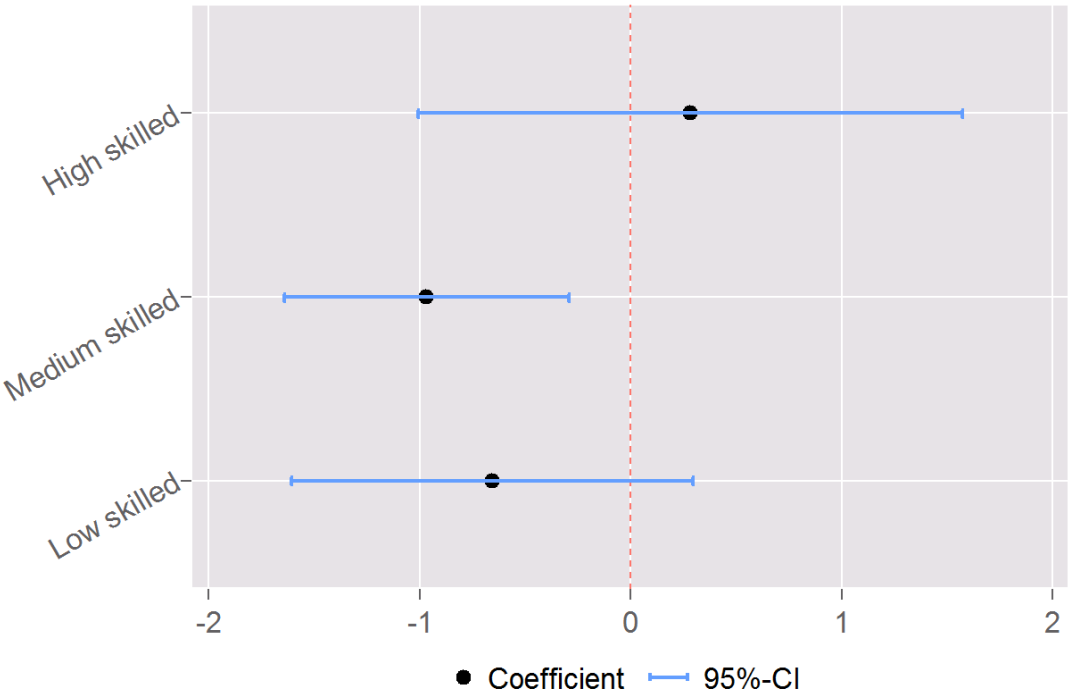
9 Conclusion

The industrial robot density in Germany is one of the highest in the world: around three times higher than the average across the US and other developed countries. If anywhere, the impact of robots on the labor market should be felt in Germany. We leverage this strong robot

[36] We obtain similar effects for wages but prefer the earnings models since they avoid the classical selection problem that wage are not observed for non-employed people.



(a) Occupation: Heterogenous Impacts



(b) Education: Heterogenous Impacts

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 20 years following the base year. All regressions include the same full set of control variables as described in Section 7. The confidence intervals are constructed from standard errors clustered by industry. In panel a, occupations base on the definition of occupational fields by the German Federal Institute for Vocational Education and Training (BIBB) with the following modifications: Sales and clerical occupations are combined and agriculture, mining, and construction (that would have a point estimate of zero with a huge standard error) are omitted. In panel b, high skilled is defined as having a degree from a university or university of applied sciences, and medium skilled is defined as having a vocational training degree. All other educational levels are subsumed as low skilled.

Figure 2: Heterogeneous earnings effects

penetration of the German labor market to study how the labor market adjusts to this recent wave of automation. A small number of previous papers has studied the impact of robots on productivity and employment. We extend this research beyond aggregate equilibrium outcomes and towards understanding of the mechanisms in workers' and firms' responses to automation.

Our analysis finds no evidence that robots have been job killers. But they have affected the composition of aggregate employment. First, we find that industrial robots displaced labor in the German manufacturing sector. Economic theory suggests, however, that labor demand for other tasks or in other industries should increase. The magnitude determining the total effect on employment is an empirical question. Our paper is the first to show that the complementarity and expansion of economic activity in other industries is an important adjustment mechanism. Our second finding is that we find an almost exactly offsetting employment effect in industries which complement tasks carried out by robots. These local sectoral adjustments happen relatively quickly, such that the overall impact on employment is zero.

Our analysis finds that the impact of automation on incumbent workers is more complex than a simple displacement story would suggest. Workers, maybe surprisingly, do not face long-lasting adverse employment consequences (Jacobson, LaLonde, and Sullivan, 1993). Existing firm and worker matches, in contrast, adjust by switching the set of tasks a worker performs. Increased job stability comes at the price of lower future wage growth, suggesting that rents from automation are shared via more stable employment instead of higher wages. Wage rigidity in the form of collective bargaining agreements at the industry level is associated with a more negative impact on employment.

While robots have not depressed total employment, three of our findings highlight the distributional consequences of automation. First, exposed workers in existing matches seem to trade off job stability for lower wage growth. As a consequence, the total effect of robot exposure on labor earnings for exposed workers is negative. Second, automation causes labor shares in regions with larger exposure to decline. Third, automation widens the earnings gap between managerial and skilled technical occupations and routine-intensive ones.

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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 that we 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, Jacobebbinghaus, Ludsteck, and Witter, 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. [37] 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

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

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.

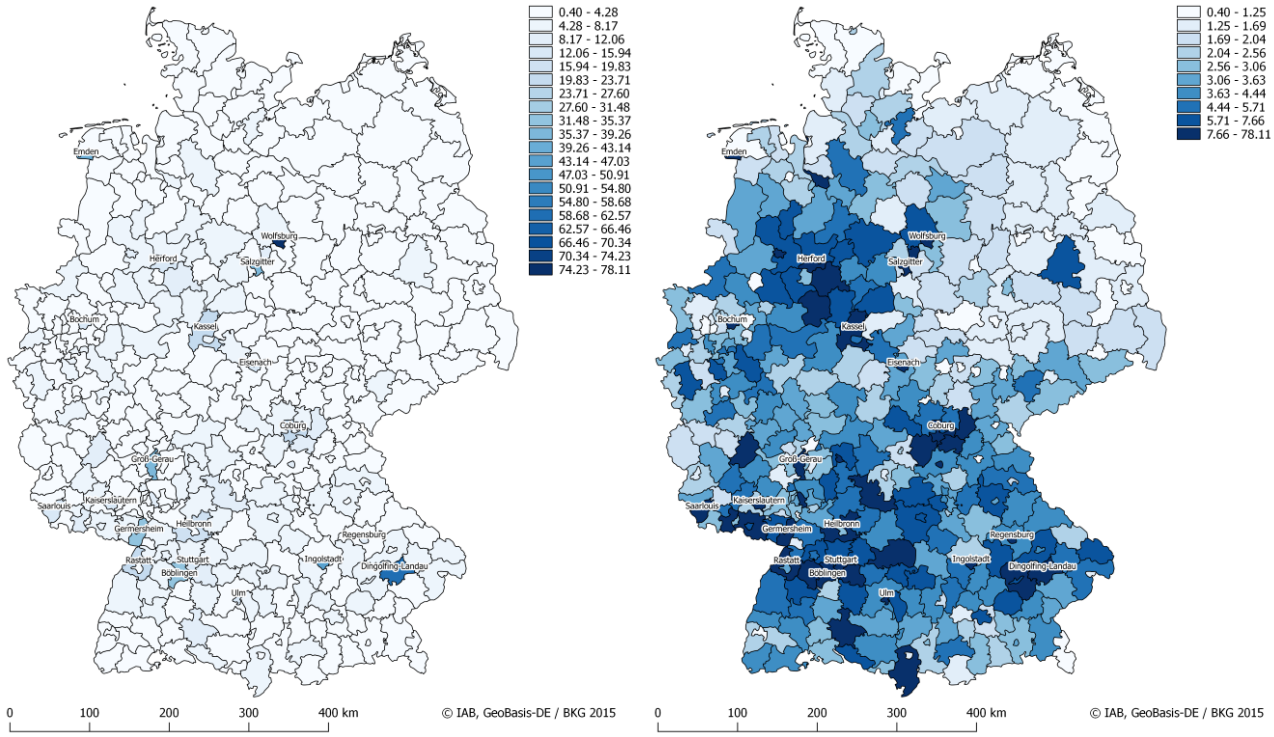
In Section 5.2, we check whether the increase in the number of industries drives our results. We do this by constructing a reverse cross-walk assigning one of the 25 ISIC codes to each of the 73 NACE codes. Departing from cross-walk E, we now need a measure for the relative size of each ISIC code. Unfortunately, German employment data classified by ISIC codes are 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 Data from German Federal Statistical Office

To analyze the effects of robots on labor productivity and the labor share, we exploit data from the German Federal Statistical Office, which break down national accounts at the regional level (*Regionaldatenbank Deutschland*). The data are freely available and can be downloaded online at `https://www.regionalstatistik.de/genesis/online/` (tab *Themes*).

For our purpose we always use the regional breakdown by *Kreise und kreisfreie Städte*. Labor productivity is calculated as output per worker. The variable is obtained from the production account of the regional economic accounts of the Laender (code 82111, *Bruttoinlandsprodukt je Erwerbstätigen*). To get a measure for the labor share, we divide the gross pay per employee by output per worker. The gross pay per employee is sourced from the *regional atlas* exploiting the indicators of the subject area *industry* (code 99910, *Bruttoentgelte je Beschäftigten*).

Appendix Figures



(a) Local robot exposure (20 equal intervals)

(b) Local robot exposure (10 deciles)

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

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

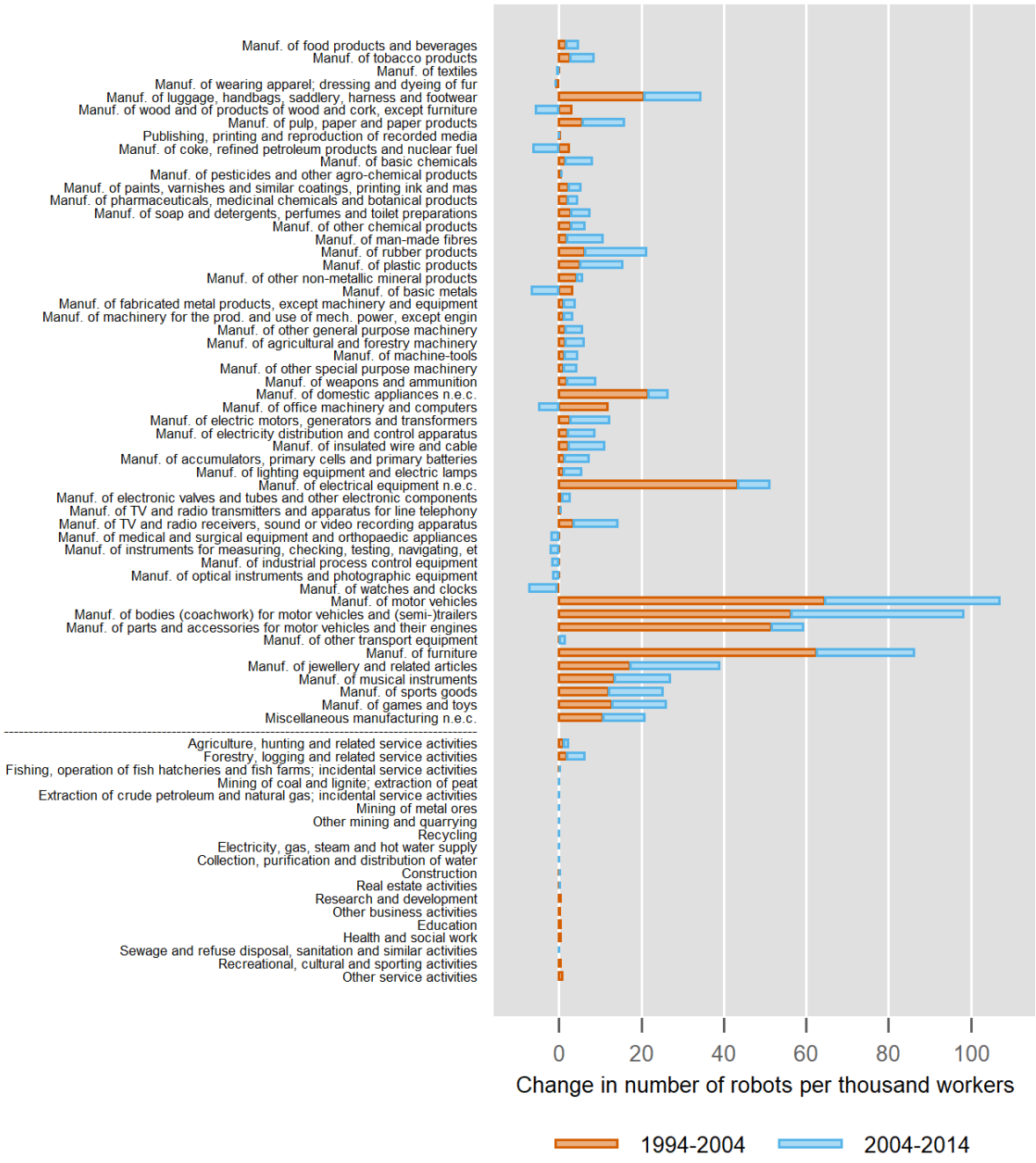
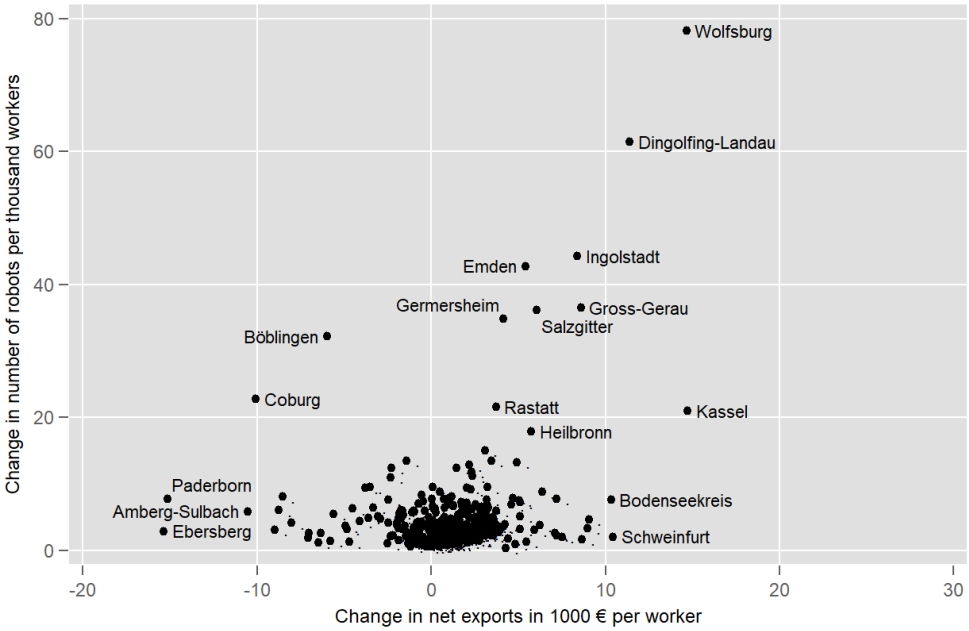
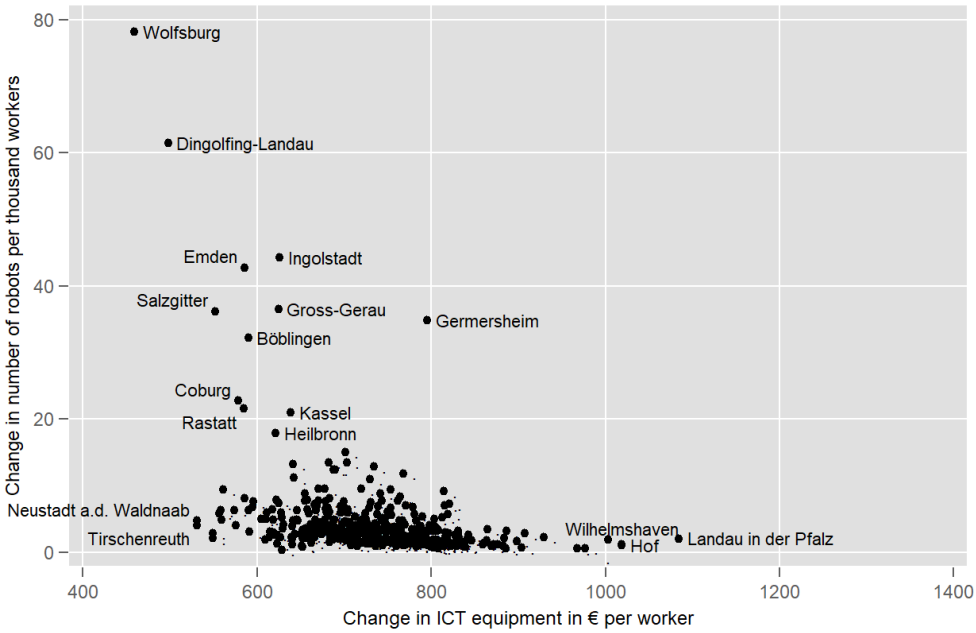


Figure A.2: Industry-level distribution of robots

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



(a) Robots versus trade.



(b) Robots versus ICT.

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

Notes: The figures contrast the change in the exposure of robots and trade (Panel A), and that of robots and ICT (Panel B) between 1994 and 2014 on the level of 402 German local labor markets.
Sources: IFR, COMTRADE, EUKLEMS, and BHP 7514 v1, own calculations.

Appendix Tables

Table A.1: Summary statistics, worker level.

	1994-2014		1994-2004		2004-2014	
Observations	993,187		1,431,579		1,246,414	
	mean	(sd)	mean	(sd)	mean	(sd)
[A] Outcomes, cumulated over years following base year						
Days employed	5,959	(2,014)	3,015	(1,001)	3,261	(802)
Average daily wage	120.7	(71.6)	121.7	(74.4)	126.8	(73.9)
100 x earnings / base year earnings	1,924.6	(1,001.1)	0,940.3	(0,449.4)	0,949.5	(0,352.5)
[B] Control variables, measured in base year						
Base year earnings	38,880	(20,775)	40,273	(22,441)	44,862	(28,322)
Dummy, 1=female	0.239	(0.426)	0.237	(0.425)	0.215	(0.411)
Dummy, 1=foreign	0.100	(0.301)	0.110	(0.312)	0.086	(0.280)
Birth year	1960	(6)	1955	(9)	1963	(8)
Dummy, 1=low skilled	0.153	(0.360)	0.170	(0.375)	0.118	(0.323)
Dummy, 1=medium skilled	0.756	(0.430)	0.740	(0.438)	0.757	(0.429)
Dummy, 1=high skilled	0.091	(0.288)	0.090	(0.286)	0.125	(0.331)
Dummy, 1=tenure 2-4 yrs	0.405	(0.491)	0.357	(0.479)	0.285	(0.451)
Dummy, 1=tenure 5-9 yrs	0.315	(0.464)	0.270	(0.444)	0.287	(0.452)
Dummy, 1=tenure $\geq$10 yrs	0.243	(0.429)	0.338	(0.473)	0.387	(0.487)
Dummy, 1=plant size $\leq$9	0.059	(0.236)	0.056	(0.230)	0.045	(0.207)
Dummy, 1=plant size 10-99	0.232	(0.422)	0.230	(0.421)	0.251	(0.434)
Dummy, 1=plant size 100-499	0.287	(0.453)	0.288	(0.453)	0.320	(0.466)
Dummy, 1=plant size 500-999	0.121	(0.326)	0.122	(0.328)	0.118	(0.322)
Dummy, 1=plant size 1000-9999	0.219	(0.414)	0.222	(0.415)	0.189	(0.392)
Dummy, 1=plant size $\geq$10000	0.079	(0.269)	0.080	(0.271)	0.075	(0.263)
Dummy, 1=food products	0.084	(0.277)	0.083	(0.276)	0.085	(0.279)
Dummy, 1=consumer goods	0.123	(0.328)	0.124	(0.330)	0.099	(0.299)
Dummy, 1=industrial goods	0.362	(0.480)	0.362	(0.481)	0.363	(0.481)
Dummy, 1=capital goods	0.432	(0.495)	0.430	(0.495)	0.453	(0.498)
[C] Exposure to robots						
Δ robots per 1000 workers	16.976	(30.942)	10.620	(20.373)	6.915	(12.158)
p10-p90 interval	[-1.748 ; 77.141]		[0.020 ; 56.468]		[-1.886 ; 23.650]	
p25-p75 interval	[3.369 ; 9.606]		[1.079 ; 4.337]		[1.502 ; 7.829]	
[D] Exposure to trade and ICT						
Δ net exports / wagebill in %	7.803	(65.234)	2.537	(32.433)	4.542	(45.275)
Δ ICT equipment in € per worker	391.5	(354.1)	150.5	(143.0)	288.7	(307.9)

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

Table A.2: Summary statistics, region level.

	1994-2014		1994-2004		2004-2014	
observations	402		402		402	
	mean	(sd)	mean	(sd)	mean	(sd)
[A] Outcomes (△ in logs)						
employment	-0.020	(0.187)	-0.099	(0.131)	0.078	(0.076)
manufacturing employment	-0.161	(0.280)	-0.158	(0.189)	-0.003	(0.142)
manufacturing employment in automotive	0.238	(1.312)	0.109	(0.831)	0.127	(1.077)
manufacturing employment in other sectors	-0.180	(0.279)	-0.172	(0.189)	-0.008	(0.143)
non-manufacturing employment	0.043	(0.229)	-0.069	(0.158)	0.112	(0.092)
[B] Control variables, shares in base year (in %)						
female	34.716	(4.674)	34.716	(4.674)	34.454	(5.071)
foreign	6.981	(4.781)	6.981	(4.781)	5.565	(3.842)
age $\geq$ 50 yrs	20.101	(2.366)	20.101	(2.366)	20.903	(2.347)
low skilled	11.063	(4.435)	11.063	(4.435)	8.020	(3.342)
medium skilled	80.296	(4.117)	80.296	(4.117)	80.308	(5.205)
high skilled	7.956	(3.965)	7.956	(3.965)	11.009	(4.899)
manufacturing	31.830	(12.496)	31.830	(12.496)	29.969	(11.768)
food products	3.490	(2.078)	3.490	(2.078)	3.279	(2.158)
consumer goods	4.513	(3.866)	4.513	(3.866)	3.151	(2.670)
industrial goods	12.176	(7.710)	12.176	(7.710)	11.651	(6.933)
capital goods	11.651	(9.005)	11.651	(9.005)	11.888	(8.969)
construction	11.607	(4.527)	11.607	(4.527)	7.843	(3.072)
maintenance; hotels and restaurants	18.642	(4.303)	18.642	(4.303)	19.369	(4.157)
services	13.452	(5.159)	13.452	(5.159)	17.572	(6.485)
education; social work; other organizations	19.934	(6.391)	19.934	(6.391)	21.273	(6.041)
dummy, 1=north	0.159	(0.366)	0.159	(0.366)	0.159	(0.366)
dummy, 1=south	0.348	(0.477)	0.348	(0.477)	0.348	(0.477)
dummy, 1=east	0.192	(0.394)	0.192	(0.394)	0.192	(0.394)
[C] Exposure to robots						
Δ robots per 1000 workers	4.644	(6.921)	3.044	(4.297)	1.723	(2.585)
p10-p90 interval	[1.249 ; 7.659]		[0.796 ; 5.543]		[0.440 ; 2.602]	
p25-p75 interval	[1.871 ; 4.898]		[1.187 ; 3.374]		[0.741 ; 1.832]	
[D] Robot production						
dummy, 1=robot producer	0.022	(0.148)	0.022	(0.148)	0.022	(0.148)
[E] Exposure to trade and ICT						
Δ net exports in 1000 € per worker	0.956	(3.146)	0.373	(1.663)	0.609	(2.259)
Δ ICT equipment in € per worker	728.371	(82.917)	267.754	(36.184)	523.693	(57.602)

Sources: IFR, COMTRADE, EUKLEMS, and BHP 7514 v1, own calculations.

Table A.3: 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

Table A.3: Industry-level exposure of robots, trade, and ICT equipment (continued).

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

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

Notes: The table displays the changes in robot exposure (Δ robots per 1000 workers), trade exposure (Δ net exports / wagebill in %), and ICT exposure (Δ ICT equipment in 1000 € per worker) by WZ 1993 industries (German Classification of Economic Activities, Edition 1993), each separately for the whole observation period (1994-2014), and the two subperiods (1994-2004 and 2004-2014). The numbers are presented at the level of the robot industry aggregation (mix of 2-digit and 3-digit level, see column 2). Trade exposure (3-digit level throughout) is summed up over 3-digit industries if the robot exposure is only available at the 2-digit level. For the ICT exposure (2-digit level throughout), the 2-digit industry level exposure is assigned to the subjacent 3-digit industries.
Sources: IFR, COMTRADE, EUKLEMS, and BHP 7514 v1, own calculations.

Table A.4: Categorization of industries into broader groups

Code	Industry
Primary sector, comunity supply	
11	growing of crops; market gardening; horticulture
12	farming of animals
13	growing of crops combined with farming of animals (mixed farming)
14	agricultural and animal husbandry service activities, ex. veterinary act.
15	hunting, trapping and game propagation, incl. related service act.
20	forestry, logging and related service activities
50	fishing, operation of fish hatcheries and farms; incidental service act.
101	mining and agglomeration of hard coal
102	mining and agglomeration of lignite
103	extraction and agglomeration of peat
111	extraction of crude petroleum and natural gas
112	service activities incidental to oil and gas extraction, excluding surveying
120	mining of uranium and thorium ores
131	mining of iron ores
132	mining of non-ferrous metal ores, except uranium and thorium ores
141	quarrying of stone
142	quarrying of sand and clay
143	mining of chemical and fertilizer minerals
144	production of salt
145	other mining and quarrying n.e.c.
371	recycling of metal waste and scrap
372	recycling of non-metal waste and scrap
401	production and distribution of electricity
402	gas; distribution of gaseous fuels through mains
403	steam and hot water supply
410	collection, purification and distribution of water
900	sewage and refuse disposal, sanitation and similar activities
Food products	
151	production, processing and preserving of meat and meat products
152	processing and preserving of fish and fish products
153	processing and preserving of fruit and vegetables
154	vegetable and animal oils and fats
155	dairy products
156	grain mill products, starches and starch products
157	prepared animal feeds
158	other food products
159	beverages
160	tobacco products
Consumer goods	
171	preparation and spinning of textile fibres
172	textile weaving
173	finishing of textiles
174	made-up textile articles, except apparel
175	other textiles
176	knitted and crocheted fabrics
177	knitted and crocheted articles
181	leather clothes
182	wearing apparel
183	dressing and dyeing of fur; articles of fur
191	tanning and dressing of leather
192	luggage, handbags and the like, saddlery and harness
193	footwear
221	publishing
222	printing and service activities related to printing
223	reproduction of recorded media
361	furniture
362	jewellery and related articles
363	musical instruments
364	sports goods
365	games and toys
366	miscellaneous manufacturing n.e.c.
Industrial goods	
201	sawmilling and planing of wood; impregnation of wood
202	veneer sheets, plywood, laminboard and other panels and boards
203	builders' carpentry and joinery
204	wooden containers
205	other products of wood, cork, straw and plaiting materials
211	pulp, paper and paperboard
212	articles of paper and paperboard
231	coke oven products
232	refined petroleum products
233	processing of nuclear fuel
241	basic chemicals
242	pesticides and other agro-chemical products
243	paints, varnishes and similar coatings, printing ink and mastics
244	pharmaceuticals, medicinal chemicals and botanical products
245	soap and detergents, perfumes and toilet preparations
Industrial goods (continued)	
246	other chemical products
247	man-made fibres
251	rubber products
252	plastic products
261	glass and glass products
262	ceramic goods other than for construction purposes
263	ceramic tiles and flags
264	bricks, tiles and construction products, in baked clay
265	cement, lime and plaster
266	articles of concrete, plaster and cement
267	cutting, shaping and finishing of stone
268	other non-metallic mineral products
271	basic iron and steel and of ferro-alloys (ecsc1)
272	tubes
273	other first processing of iron and steel
274	basic precious and non-ferrous metals
275	casting of metals
281	structural metal products
282	tanks, reservoirs and containers of metal
283	steam generators, except central heating hot water boilers
284	forging, pressing, stamping, roll forming of metal; powder metallurgy
285	general mechanical engineering
286	cutlery, tools and general hardware
287	other fabricated metal products
Capital goods	
291	pumps, valves, bearings, etc.
292	other general purpose machinery
293	agricultural and forestry machinery
294	machine-tools
295	other special purpose machinery
296	weapons and ammunition
297	domestic appliances
300	office machinery and computers
311	electric motors, generators and transformers
312	electricity distribution apparatus
313	insulated wire and cable
314	accumulators, primary cells and primary batteries
315	lighting equipment
316	electrical equipment n.e.c.
321	electronic valves and tubes and other electronic components
322	tv and radio transmitters
323	tv and radio receivers
331	medical and surgical equipment and orthopaedic appliances
332	measuring instruments
333	industrial process control equipment
334	optical instruments and photographic equipment
335	watches and clocks
341	motor vehicles
342	bodies (coachwork) for motor vehicles and (semi-)trailers
343	auto parts and accessories
351	building and repairing of ships and boats
352	railway and tramway locomotives and rolling stock
353	aircraft and spacecraft
354	motorcycles and bicycles
355	other transport equipment n.e.c.
Construction	
451	site preparation
452	building of complete constructions or parts thereof; civil engineering
453	building installation
454	building completion
455	renting of construction or demolition equipment with operator
Personal services	
501	sale of motor vehicles
502	maintenance and repair of motor vehicles
503	sale of motor vehicle parts and accessories
504	sale, maintenance and repair of motorcycles and parts and accessories
505	retail sale of automotive fuel
511	wholesale on a fee or contract basis
512	wholesale of agricultural raw materials and live animals
513	wholesale of food, beverages and tobacco
514	wholesale of household goods
515	wholesale of non-agricultural intermediate products, waste and scrap
516	wholesale of machinery, equipment and supplies
517	other wholesale
521	retail sale in non-specialized stores
522	retail sale of food, beverages and tobacco in specialized stores
523	retail sale of pharmaceutical and medical goods, cosmetic, toilet articles
Personal services (continued)	
524	other retail sale of new goods in specialized stores
525	retail sale of second-hand goods in stores
526	retail sale not in stores
527	repair of personal and household goods
551	hotels
552	camping sites and other provision of short-stay accommodation
553	restaurants
554	bars
555	canteens and catering
921	motion picture and video activities
922	radio and television activities
923	other entertainment activities
924	news agency activities
925	library, archives, museums and other cultural activities
926	sporting activities
927	other recreational activities
930	other service activities
950	private households with employed persons
Business services	
601	transport via railways
602	other land transport
603	transport via pipelines
611	sea and coastal water transport
612	inland water transport
621	scheduled air transport
622	non-scheduled air transport
623	space transport
631	cargo handling and storage
632	other supporting transport activities
633	activities of travel agencies and tour operators
634	activities of other transport agencies
641	post and courier activities
642	telecommunications
651	monetary intermediation
652	other financial intermediation
660	insurance and pension funding, except compulsory social security
671	act. aux. to financial intermediation, ex. insurance and pension funding
672	activities auxiliary to insurance and pension funding
701	real estate activities with own property
702	letting of own property
703	real estate activities on a fee or contract basis
711	renting of automobiles
712	renting of other transport equipment
713	renting of other machinery and equipment
714	renting of personal and household goods n.e.c.
721	hardware consultancy
722	software consultancy and supply
723	data processing
724	database activities
725	maintenance and repair of office, accounting and computing machinery
726	other computer related activities
731	r&d on natural sciences and engineering
732	r&d on social sciences and humanities
741	accounting; market research; tax, management consultancy; holdings
742	architectural and engineering activities and related technical consultancy
743	technical testing and analysis
744	advertising
745	labour recruitment and provision of personnel
746	investigation and security activities
747	industrial cleaning
748	miscellaneous business activities n.e.c.
Public sector	
751	administration of the state and community policy
752	provision of services to the community as a whole
753	compulsory social security activities
801	primary education
802	secondary education
803	higher education
804	adult and other education
851	human health activities
852	veterinary activities
853	social work activities
911	activities of business, employers' and professional organizations
912	activities of trade unions
913	activities of other membership organizations
990	extra-territorial organizations and bodies

Sources: Own calculations.

Table A.5: Robustness checks. Region-level.

	Employment			Average Wages		
	(1)	(2)	(3)	(4)	(5)	(6)
	Total	Manuf.	Non-Manuf.	Total	Manuf.	Non-Manuf.
	[A] West Germany					
△ robots	-0.0176	-0.4156**	0.4227**	-0.0532	-0.1844***	0.0795
	(0.122)	(0.162)	(0.198)	(0.058)	(0.071)	(0.051)
N	325	325	325	5766	5019	5717
	[B] Federal state dummies					
△ robots	-0.0443	-0.4145***	0.3702*	-0.0521	-0.1702**	0.0747
	(0.137)	(0.153)	(0.216)	(0.055)	(0.071)	(0.049)
N	402	402	402	7149	6038	7095
	[C] 258 Local labor markets					
△ robots	-0.1019	-0.6382**	0.3644*	0.0152	-0.0951	0.1802***
	(0.197)	(0.321)	(0.210)	(0.056)	(0.082)	(0.046)
N	258	258	258	4606	3965	4579
	[D] Cross-walk					
△ robots	0.0105	-0.1600	0.2316	-0.0058	-0.0348	0.0555
	(0.093)	(0.100)	(0.147)	(0.040)	(0.054)	(0.038)
N	402	402	402	7149	6038	7095
	[E] IV without members of the European Monetary Union					
△ robots	0.0046	-0.3424**	0.4124**	-0.0524	-0.1494*	0.0676
	(0.116)	(0.153)	(0.208)	(0.060)	(0.079)	(0.051)
N	402	402	402	7149	6038	7095

Notes: This table presents robustness checks for the baseline specifications for employment and average wages as of Table 2, Panel A. The dependent variables are log-differences in employment respectively average wages between 1994 and 2014. Panels A and B perform the regressions for West Germany only and include federal state dummies instead of broad regional dummies, respectively. Panel C uses a model of 258 instead of 402 local labor markets. 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. Panel E presents a variant of the IV specification where members of the European Monetary Union (i.e. France, Spain, Italy, Finland) are excluded from the instrument group, i.e. German robot exposure is instrumented with robot installations in Norway, Sweden and the United Kingdom. Standard errors clustered at the level of 50 aggregate labor market regions (employment regressions) or at the level of local labor markets (wage regressions) in parentheses. The only exception are the employment regressions in Panel C where only (heteroskedastic-consistent) robust standard errors are used. Levels of significance: *** 1 %, ** 5 %, * 10 %.

Sources: IFR, COMTRADE, EUKLEMS, and BHP 7514 v1, own calculations.

Table A.6: The effect of robots in the automotive sector.

	(1) Manuf.	(2) Manuf. auto	(3) Manuf. other
[A] Employment: 100 x Log-△ in employment between 1994 and 2014			
△ robots	-0.3832**	-3.4203***	-0.6539***
	(0.149)	(1.119)	(0.206)
N	402	368	402
[B] Average Wages: 100 x Log-△ in average wages between 1994 and 2014			
△ robots	-0.1373*	-0.1497	-0.3558***
	(0.073)	(0.165)	(0.064)
N	6038	1137	5990

Notes: The employment estimates in Panel A are based on one observation per region, while the wage estimates in Panel B exploit region x demographic cells. Columns (1) to (3) display estimates for the whole manufacturing sector, manufacturing of motor vehicles, and manufacturing except motor vehicles, respectively. The regressions are estimated by applying the 2SLS IV approach where German robot exposure is instrumented with robot installations in other high-income countries. Net exports to China and Eastern Europe and ICT are instrumented with their respective counterparts in other high-income countries. The regressions include the full set of control variables as in column (5) of Table 1. Standard errors clustered at the level of 50 aggregate labor market regions (employment regressions) or local labor markets (wage regressions) in parentheses. Levels of significance: *** 1 %, ** 5 %, * 10 %.

Sources: IFR, COMTRADE, EUKLEMS, and BHP 7514 v1, own calculations.

Table A.7: Individual outcomes and union influence

	Employment		Earnings	
	All employers	Original firm	All employers	Original firm
2SLS results	(1)	(2)	(3)	(4)
Δ robots per 1000 workers	0.6621	11.9657***	-0.7601	3.5350***
	(0.517)	(2.629)	(0.482)	(1.010)
× % firm agreements	0.2243	3.0820	0.3021	0.8250
	(1.266)	(5.091)	(0.998)	(1.953)
× % industry agreements	-4.3358***	-3.9292	-2.2167*	-1.9411
	(1.614)	(4.314)	(1.213)	(1.641)
Δ net exports / wagebill in %	0.5194	2.2753*	0.1946	0.8481**
	(0.369)	(1.175)	(0.236)	(0.411)
Δ ICT equipment in € per worker	0.0614	0.0834	0.0317	0.0451
	(0.045)	(0.123)	(0.042)	(0.049)
% firm agreements (standardized)	-20.2974	-17.7491	-16.8619	-6.6122
	(24.824)	(74.071)	(24.188)	(27.577)
% industry agreements (standardized)	63.5841***	91.2120	33.4625*	43.6598*
	(21.876)	(70.285)	(18.090)	(24.608)
Birth year, gender, nationality dummies	Yes	Yes	Yes	Yes
Education and tenure dummies	Yes	Yes	Yes	Yes
Ln base yr outcome	Yes	Yes	Yes	Yes
Plant size dummies	Yes	Yes	Yes	Yes
Broad industry dummies	Yes	Yes	Yes	Yes
Federal state dummies	Yes	Yes	Yes	Yes

Notes: Based on 989,913 observations from industries that are covered in the IAB establishment panel. Union influence is measured as percentage of workers covered by a collective agreement (Standardized to have a standard deviation of 1). The outcome variables are the number of days employed, cumulated over the twenty years following the base year (columns 1-2), 100 x earnings normalized by earnings in the base year and cumulated over the twenty years following the base year (columns 3-4). The regressions are estimated by applying the 2SLS IV approach where German robot exposure, net exports to China and Eastern Europe, and ICT are instrumented with their respective counterparts in other high-income countries. Standard errors clustered by industry parentheses. Levels of significance: *** 1 %, ** 5 %, * 10 %.
Sources: IFR, COMTRADE, EUKLEMS, and IEB V12.00.00 - 2015.09.15, own calculations.