THE ADJUSTMENT OF LABOR MARKETS TO ROBOTS

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Abstract
We use detailed administrative data to study the adjustment of local labor markets to industrial robots in Germany. Robot exposure, as predicted by a shift-share variable, is associated with displacement effects in manufacturing, but those are fully offset by new jobs in services. The incidence mostly falls on young workers just entering the labor force. Automation is related to more stable employment within firms for incumbents, and this is driven by workers taking over new tasks in their original plants. Several measures indicate that those new jobs are of higher quality than the previous ones. Young workers also adapt their educational choices, and substitute away from vocational training towards colleges and universities. Finally, industrial robots have benefited workers in occupations with complementary tasks, such as managers or technical scientists. (JEL: J24, O33, F16, R11)

1. Introduction

How have new automation technologies, such as industrial robots, transformed the labor market? Theoretical work on this question has identified two main impacts on employment and wages (Acemoglu and Restrepo 2018b, 2019). At first, the adoption of automation technologies causes a displacement effect, as robots take over tasks

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performed by humans. Sooner or later, however, productivity gains lead to new jobs elsewhere in the economy. Careful empirical work is now needed to provide evidence on those two channels. Furthermore, understanding and examining the underlying mechanisms is crucial for a wide range of policy questions currently high on the agenda. Displacements can trigger painful adjustments and large earnings losses (Jacobson, LaLonde, and Sullivan 1993), which might imply a bigger role for policies targeting those hurt by automation technologies. Moreover, incumbent workers might need to be re-trained in order to transition smoothly into new jobs, while young labor market entrants might adapt their educational choices in anticipation of how technologies have affected labor demand. Finally, different labor market institutions might mediate the displacement and productivity effects very differently, thus providing potential lessons how to maximize the positive impacts for society.

In this paper, we examine how firms and individual workers adjust to automation exposure. The labor-replacing technology we focus on are industrial robots, primarily used in the manufacturing sector. Following significant technological 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 5 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 already undergone dramatic changes in the organization of production in the last two decades, and labor markets were deeply affected.

We use Germany as our "laboratory" and make use of local labor market variation as our main source. It is clear that Germany provides an important benchmark case when it comes to the equilibrium effects of how labor markets adjust to the rise of automation technologies. Figure 1 shows the penetration of robots, dividing their stock by the number of workers in different regions of the world between 1994 and 2014. Korea (the world leader) and Germany are technologically much more advanced in robotics than other countries in Europe and the United States.[1] In addition, to get a solid understanding of the adjustment process and to grasp the incidence of automation, one needs high-quality longitudinal data that allow following workers over time across firms, occupations, and sectors. For this purpose, we can leverage the extensive German matched employer–employee data extracted from administrative social security records.

The first part of this paper replicates the strategy by Acemoglu and Restrepo (2019), who have found alarmingly negative impacts on labor demand in the United States. We find no such negative effects of predicted robot exposure on total employment in Germany, but show that this masks the presence of considerable *displacement* and *re-allocation* effects. Within manufacturing, predicted robot exposure leads to fewer

1. Another leading country in robot use is Japan. However, as already pointed out by Graetz and Michaels (2018) and Acemoglu and Restrepo (2019), the data on robots in Japan are difficult to compare to those from other countries, because there was a major re-classification of what kinds of machines are classified as robots.

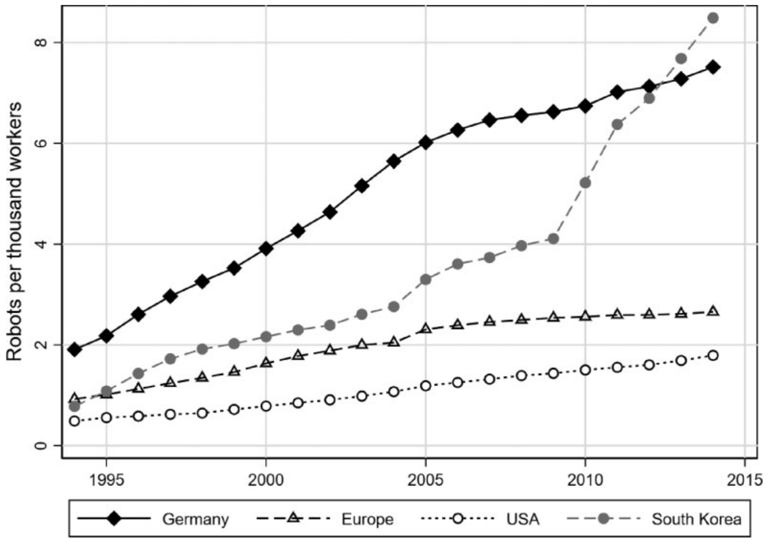


FIGURE 1. Robot penetration, 1994–2014. *Europe* = Germany, France, Italy, Spain, Finland, Sweden, Norway, and the United Kingdom. Robot penetration is the robot stock relative to the dependent employment in full-time equivalents (FTEs). Employment data from the IAB for Germany and from OECD.Stat for the remaining countries. Dependent employment in Korea was imputed from total employment and the ratio of dependent to total employment in the European countries, where data on both dependent and total employment are available. Source: IFR, OECD, BEH V10.01.00, and own calculations.

jobs, but new labor demand in the service sector—in particular local services used by other businesses—leads to an offsetting force. We then extend the literature in three different ways, which we describe now.

The second main contribution of this paper is a complete characterization of the incidence of the displacement and re-allocation effects. The main finding is that the majority falls on young workers just entering the labor force. They face lower labor demand in automating industries and adjust by taking over jobs in the expanding service sector.[2] Incumbent workers, maybe paradoxically at first glance, actually see an *increase* in their plant tenure in response to more automation.

Our third main contribution shows that this latter effect—that is, automation causing more stable employment within firms—is driven by workers taking over new roles within their original plants. Displacement of old tasks, hence, takes place. However, it is swiftly offset by transitions of incumbent workers into new tasks for the same employer. Several measures indicate that those new jobs are of higher quality than the previous ones: The new occupations pay higher wages, are characterized by a larger share of abstract instead of routine tasks, and a higher college share. Young workers

2. Re-allocation for young workers, hence, only happens in a counterfactual sense, as they start their careers in the service sector instead of manufacturing.

in local labor markets with more predicted exposure to automation also adapt their educational choices. They substitute away from vocational training toward colleges and universities. So, although the incidence of displacement out of manufacturing jobs falls mostly on young cohorts, the overall welfare effects of automation on young workers are less clear and might possibly be even positive in the longer term.[3]

In the fourth and final contribution, we shift our focus from local labor market adjustments to individual workers. This complements the previous models, because it allows us to directly study the effects of automation on earnings biographies using a more compelling design. (Comparing wage or earnings growth across local labor markets, in contrast, can lead to biased results because automation changes the composition of employed workers.) At the individual level, we can follow the same workers, who start competing with industrial robots, over time and across all possible margins of adjustments (plants, occupations, sectors). One key result of the analysis is that average earnings are hardly affected by robots. But effects differ strongly across workers with different adjustment patterns: Those who are retained by their plants experience positive earnings effects as they transition into new tasks. Workers who are forced to switch plants, industries, or leave manufacturing see significant earnings losses, however. Finally, we show how industrial robots have benefited workers in occupations with complementary tasks, such as managers or technical scientists, and those in routine-intensive tasks like, for example, machine operators. In contrast, the impact across skill groups, that is, comparing workers with and without tertiary education, is quite homogeneous.

Stated differently, we cannot detect evidence of skill-biased technological change. Automation mostly increases inequality *within* groups of ex-ante similar manufacturing workers. It creates large gaps between those who manage to stay at their original plant (thereby reaping the benefits of automation through longer tenure and higher wages) and those who are forced to leave their original employer, as they typically face an earnings drop and do not easily recover.

The theoretical implications of automation for wages, employment, and productivity have been studied by Acemoglu and Restrepo (2018b, 2019) and Moll, Restrepo, and Rachel (2019).[4] The important empirical paper by Acemoglu and Restrepo (2019) has documented negative effects of robots on wages and employment across US commuting zones, implying strong displacement forces and relatively weak offsetting productivity effects. Replicating this empirical strategy for Germany, we also find significant displacement effects, although around 50% smaller on average. The key difference, however, is that we additionally identify significant and offsetting re-allocation effects. Concerning the displacement effect, we find that it is concentrated

3. Plausibly, as a result of more young workers entering the labor market with a college degree, we also see an increase in jobs held with a higher abstract task share for young cohorts; these jobs are typically higher rewarded.

4. Those papers build on an older literature, which highlights the usefulness of the task framework for explaining a variety of empirical findings concerning the distribution of wages and employment—see Acemoglu and Autor (2011) for an exhaustive survey.

in local labor markets with weaker labor protections (as measured by the strength of unions). This hints at the importance of labor market institutions in explaining how countries adapt differently to new technologies.

The data assembled by the International Federation of Robotics (IFR) was first exploited in the innovative paper by Graetz and Michaels (2018). Consistent with our results, they uncover positive productivity effects and zero effects on total employment, using variation in robot usage across industries in different countries. As our analysis shows, however, this zero overall employment impact can mask substantial displacement and re-allocation effects. We complement Graetz and Michaels (2018) (and also Acemoglu and Restrepo 2019) by providing the first study that leverages administrative labor market data. We can, therefore, investigate the underlying mechanisms in much greater detail; in particular, if workers separate from firms, how the set of tasks carried out by exposed workers evolves in response to automation, and what role the transitions of individual workers across industries and sectors play.[5]

An important part of the adjustment process to automation is the skill-upgrading process, as our evidence shows. Changes in the demand for high-skilled workers also feature prominently in the polarization literature (Autor and Dorn 2013; Goos et al. 2014; Michaels, Natraj, and van Reenen 2014). We document direct and indirect evidence for two margins of human capital adjustments to robots: first, for incumbent workers who are retained but transition into better jobs within their original plants, and, second, for young labor market entrants. The first channel of within-firm upgrading is consistent with the famous plant-level study by Bartel, Ichniowski, and Shaw (2007) on American valve-makers. They chronicle how the adoption of new IT-enhanced capital equipment leads to increases in the skill requirements of machine operators and a transition from routine to abstract/cognitive tasks.[6] Finally, our analysis reveals that the re-allocation effect is driven by increased employment in the business service sector, showing that the spillovers seem to operate locally through firms expanding their demand for complementary tasks. Relatedly, Helm (2019) also finds positive local spillovers of export shocks across German labor markets, consistent with agglomeration economies.

The remainder of this paper is organized as follows. Section 2 describes our empirical approach and the data. Section 3 studies the impact of robots on equilibrium employment, wages, and productivity across local labor markets. Sections 4 and 5 investigate adjustment mechanisms. Section 6 studies the adjustments of individual workers. Section 7 concludes.

5. It is reasonable to assume that displacement and productivity effects are very heterogeneous depending on the type of technology and industry considered. Zator (2019) combines different measures of technological change (software, databases, robots) and argues that technology tends to reduce employment in manufacturing but increases it in finance, IT, and other service industries.

6. Notably, the plants in the study accompanied the transition process with the adoption of new human resource practices to support these skills.

2. Data and Methodology

2.1. Administrative Labor Market Data

Our main source is administrative German labor market data provided by the Institute for Employment Research (IAB) at the German Federal Employment Agency. Specifically, we use data from the Employee History (Beschäftigtenhistorik—BEH, Version 10.01.00). The raw version of the BEH is a spell-dataset of the complete job histories of the universe of private workers from 1978 to 2014, excluding the self-employed and civil servants. Eastern Germany enters the data in 1992. We use a simplified version of this dataset, which contains only one observation for each individual and year, pertaining to the spell of the highest paid job that stretches over June 30 of a given year.[7] The individual-level information contains information on gender, year of birth, educational attainment, a unique plant-id for the current workplace, as well as codes for industrial affiliation, location, and occupations.[8] This allows us to aggregate the dataset to the county level and obtain a precise picture on the size, the industry composition, and the workforce characteristics of local labor markets. Moreover, the worker-level panel structure of the dataset allows us to observe the mobility patterns of individuals as they enter the labor market, move between jobs, firms, industries, and regions, and, finally, when they exit the labor market. We mainly work at the level of local labor markets. Our main outcome is the percentage change in a county's employment. We construct this from the aggregate worker counts on June 30 of the start year 1994 and the end year 2014, where part-time workers are weighted by 0.5 to get a measure for full-time equivalent employment. The information on the industry of the workplace plant allows us to construct this variable separately for the manufacturing and non-manufacturing sectors. The advantage of using percentage changes rather than the log-difference is that this growth rate can be decomposed into the contributions of various groups defined by worker mobility, such as workers who enter the labor market, workers who stay with their original plant, workers who move to a different plant in the same industry, and so forth.

Our second outcome variable is the log change in average wages. To construct this variable, we first impute the individual wages, which are censored at the social security contribution ceiling, using a procedure suggested by Card, Heining, and Kline (2013). We then compute the average daily wage for full-time workers on June 30 of the start and end years for demographic cells defined by gender, three age groups (below 30, 30–44, 45 or more years old), and three education groups (no or unknown degree,

7. In the baseline regressions, we also drop observation on so-called "marginal jobs", since those are only included in the data from 1999 onward. Those jobs are very low-paying (the threshold is around 450 euros per month) in part-time, which get special treatment in the form of heavily reduced social security contributions. We report a robustness check in the Appendix including these jobs. The main results are unaffected.

8. We distinguish between 102 two/three-digit NACE Rev. 2 industries, 402 counties, and 54 occupational fields.

vocational training degree, university degree). A further dependent variable is the total annual wage bill, which is 365 times the individual daily wage, aggregated to the county level. To compare our results to the findings of Acemoglu and Restrepo (2019), we also construct the change in the employment-to-population ratio (*E/POP*) as a further outcome variable. The employment numbers again stem from the aggregate BEH data, while population counts stem from the German Federal Institute for Research on Building, Urban Affairs and Spatial Development (BBSR).[9]

2.2. Robot Usage

We combine our administrative labor market dataset with data on the stock of robots for 25 industries in 50 countries over the period from 1994 to 2014 from the International Federation of Robotics (IFR). This dataset has been used before by Graetz and Michaels (2018) in a cross-country study at the industry level and by Acemoglu and Restrepo (2019) for the United States. 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, no robots in this definition, as they cannot be re-programmed 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.[10] The industry classification of these data conforms to two-digit ISIC Rev. 4 codes, where three-digit information is available for the manufacturing of electronic devices, electrical equipment, and motor vehicles. Since our administrative data have time-consistent NACE Rev. 2 industry codes, which correspond to the ISIC Rev. 4 codes at the two/three-digit level, both datasets can be matched without using any further crosswalk.[11]

The 25 industries consist of 20 manufacturing industries, agriculture, mining, electricity/gas/water supply, construction, and education. Appendix Figure A.1 illustrates the change in the number of robots per 1,000 workers in all 25 industries. We also present the US numbers there to facilitate a comparison. By far the strongest increase can be observed in the different branches of the automobile industry (motor

9. Two final outcome variables come from the German Federal Statistical Office and relate to the productivity of the regional economy. These are the log change in GDP per worker and the percentage point change in total regional GDP.

10. Data availability differs across countries, but coverage is comprehensive for Germany. As Graetz and Michaels (2018), 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.

11. Data used for a previous version of this paper (Dauth et al. 2017b) only had time-consistent NACE Rev. 1 codes. This required us to construct a crosswalk from the IFR classification to the classification of the labor market data, where we apportioned ambiguous cases according to employment shares. The results were qualitatively very similar.

vehicles, auto bodies and parts). Here, more than 100 additional robots were installed per 1,000 workers in 2014 compared to 1994. Other industries that became vastly more robot-intensive include rubber and plastic products, electronic components, and domestic appliances. On the other side of the spectrum, we find cases where robot usage has hardly changed, and sometimes (e.g. in manufacturing of instruments for measuring) it even decreased over time. In non-manufacturing industries, robots are used much less than in manufacturing.

2.3. Local Labor Market Approach

Our research design, which is motivated by the important paper from Acemoglu and Restrepo (2019), is based on the fact that local labor markets differ markedly in their industry compositions. Those differences create varying predicted exposure to technological change, such as rising availability of industrial robots.[12] The regional perspective allows us to observe equilibrium adjustments and spillovers from directly affected to indirectly affected industries.[13]

Ideally, we would observe the actual number of robots in each region. However, the comprehensive IFR data on robot use are available only at the country-by-industry level. We therefore follow Acemoglu and Restrepo (2019) and use a shift-share design to apportion each industry's robot adoptions across regions according to their shares of the industry's total employment. This approach is common practice in studies where an industry-level shock has differential effects on regions due to differences in local industry structures, for example, in the case of import competition (Autor, Dorn, and Hanson 2013). Concretely, as our main variable of interest throughout the regional analysis, we refer to the change in *predicted* robot exposure in region R, which is constructed as follows:

$$\widehat{\Delta\text{robots}}_r = \sum_{j=1}^{J} \left(\frac{\text{emp}_{jr}}{\text{emp}_r} \times \frac{\Delta\text{robots}_j}{\text{emp}_j} \right) \qquad \text{with} \quad J = 25. \tag{1}$$

The term $\frac{\Delta\text{robots}_j}{\text{emp}_j}$ measures the national industry robot adoption as the increase in the robot count in industry j relative to its workforce size in the base year 1994. We allocate this industry-level exposure to regions according to their shares of national industry employment by multiplying Δrobots_j with emp_{jr}, which is the initial employment in industry-region cell jR. For each local labor market R, we sum the predicted exposures of all local industries and scale it by the region's total employment emp_R, also measured

12. Faber (2020) extends this approach and regresses employment changes in Mexican labor markets on an adjusted measure of exposure to robots adopted in other countries, US robots in their particular study.

13. As is widely discussed in the literature, regional difference-in-differences designs have well-known limitations when it comes to gauging absolute or national impacts. But, relative to other structural approaches, the design offers more transparent and clearer identification. The results from various strands of literature show that many equilibrium adjustments indeed take place at the local labor market level (Moretti 2011).

in the base year 1994. $\widehat{\Delta\text{robots}_r}$, therefore, does not measure the actual increase in the number of robots in region R but rather the predicted increase, assuming that robot adoption per worker in each industry was uniform across regions.

In a recent paper, Adão, Kolesár, and Morales (2019) point out that such a shift-share explanatory variable can cause problems with statistical inference: Regions with similar industry structures are likely to have correlated error terms, which means that conventional standard errors may be underestimated. Adão, Kolesár, and Morales (2019) propose to account for this by calculating standard errors in a cluster-robust fashion, where the correlation structure of the error terms is represented by a matrix of regional industry shares rather than by discrete clusters. We adopt their construction of robust standard errors and also apply their adjustment for small industry numbers by imposing the null hypothesis of the true coefficient being zero.[14]

The identification of the effects of robots on the labor market builds on the assumption that differences in predicted robot exposure across industries are generated because robots have become better usable in some industries than in others. However, the pattern of predicted robot exposure in Germany may be the result of domestic industry-specific demand shocks. To address this endogeneity concern, we also apply the instrumental variable (IV) strategy proposed by Acemoglu and Restrepo (2019). In this approach, we employ robot adoptions across industries in other high-income countries as an instrument for German-predicted robot exposure.[15] More specifically, we construct the IVs analogously to equation (1) but use the increases in the robot count in the same set of industries in each other country, and lagged employment counts from 1984 for normalization and apportioning across regions.[16]

Figure 2 summarizes our empirical approach. The horizontal axis shows the variation of the predicted regional robot exposure, conditional on regional employment shares in nine broad industry groups and federal state dummies. The most robotized regions are Wolfsburg, Dingolfing-Landau, and Ingolstadt, which are heavily concentrated in the automotive industry (Volkswagen, Audi, and BMW are produced there, respectively). In our empirical analysis, we will pay attention to the special role of the automobile industry in robustness checks. But also aside from those extremes, the variation across regions is substantial. There is no positive relation with employment growth. In our empirical analysis in Section 3, we discuss this result in more detail.

14. The exact procedure is laid out in Remarks 5 and 6 in Adão, Kolesár, and Morales (2019). We thank Michal Kolesár for very valuable advice on how to adapt their standard error adjustment for the overidentified IV case.

15. See Autor, Dorn, and Hanson (2013) and Bloom, Draca, and van Reenen (2016) for similar approaches to study the effects of Chinese import competition. The validity of this approach hinges on the assumption that the industry pattern of robot adoption is an exogenous shock, while the allocation of industries across regions may be endogenous (see Borusyak, Hull, and Jaravel 2018, for technical details).

16. We construct one instrument for each country k = (Spain, Finland, France, Italy, Norway, Sweden, and the United Kingdom) and estimate an over-identified model. In a further robustness check, we also aggregate the robot exposures of all k countries to build a single instrument in a just identified two-stage least-squares (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.

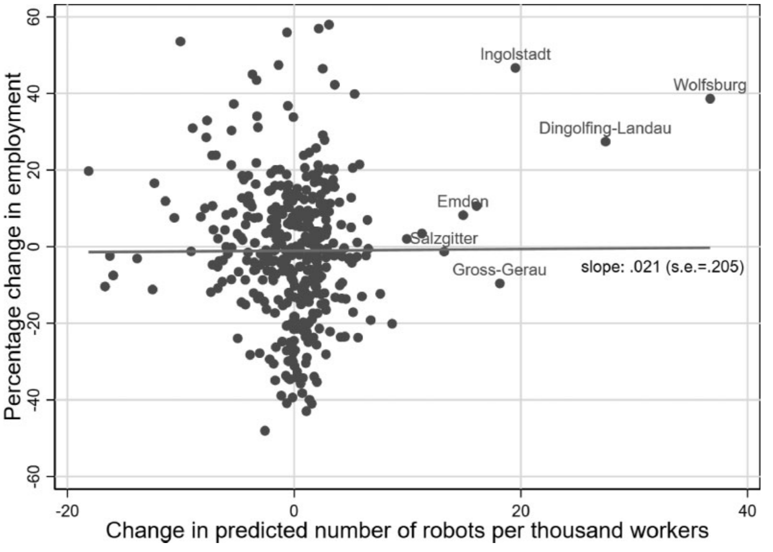


FIGURE 2. Region-level predicted exposure to robots and employment growth. The figure displays the correlation of the predicted increase in exposure to robots (conditional on regional employment shares in nine broad industry groups and federal state dummies) and the growth rate of full-time equivalent jobs between 1994 and 2014 at the level of 402 German local labor markets. Sources: IFR and BEH V10.01.00, own calculations.

2.4. Descriptive Overview

Table 1 provides a descriptive overview of the data for the local labor market analysis. The average region saw a slight decline in employment. When weighting by the number of full-time equivalent jobs in 1994, this decline becomes sharper, which demonstrates that larger regions declined more strongly.[17] The overall decline stems mostly from the declining manufacturing sector, which has not been compensated by growth of non-manufacturing industries. Wages (deflated to 2,010 euros) have increased on average, but more strongly in the manufacturing sector than in other sectors. These insights are also reflected in the changes of the total wage bill (the product of employment and wage) and the *E/POP*.

Panel B of this table presents averages and standard deviations of control variables. We control for the shares of women, foreigners, workers older than 50, and workers with a college degree, as well as the employment shares of nine broad industry categories. In our empirical analysis, we also disentangle robots from two other major economic shocks that have affected Germany since the beginning of the 1990s: the increasing international trade with China and Eastern Europe and increasing investments in information and communications technology (ICT). Both may have

17. Note that this picture changes when part-time jobs are not weighted down. In this case, the growth rate of the total number of jobs is positive.

TABLE 1. Summary statistics, region level, 1994–2014.

	Unweighted 402		Weighted 23,884,076	
Observations	Mean	(SD)	Mean	(SD)
[A] Outcomes				
% change in total employment	– 1.048	(17.944)	– 2.923	(15.854)
% change in manufacturing employment	– 9.716	(25.432)	– 16.859	(23.710)
% change in non-manufuring employment	4.736	(22.406)	3.737	(20.723)
100 × ln-change in average wage	32.640	(10.022)	32.751	(9.468)
100 × ln-change in average wage, manufacturing	40.033	(15.692)	40.479	(14.178)
100 × ln-change in average wage, non-manufacturing	28.922	(11.731)	29.536	(11.143)
100 × ln-change in total wage bill	37.076	(18.774)	36.236	(16.832)
100 × ln-change in total wage bill, manufuring	33.004	(32.597)	26.152	(31.625)
100 × ln-change in total wage bill, non-manufacturing	38.184	(20.795)	39.073	(19.610)
Percentage point change in *E/POP*	– 0.369	(3.643)	– 1.131	(3.549)
Percentage point change in *E/POP*, manufacturing	– 0.851	(2.328)	– 1.417	(2.285)
Percentage point change in *E/POP*, non-manufacturing	0.482	(3.281)	0.286	(3.294)
100 × ln-change in GDP per worker	46.529	(21.149)	43.455	(19.419)
[B] Control variables				
% female	34.715	(4.674)	35.155	(4.706)
% foreign	6.981	(4.782)	8.071	(5.147)
% age ≥ 50 years	20.101	(2.366)	21.192	(2.450)
% unskilled	11.063	(4.435)	10.794	(4.218)
% vocational training	80.296	(4.117)	78.220	(4.851)
% university degree	7.956	(3.965)	10.154	(4.592)
% manufacturing	30.473	(12.559)	27.773	(12.880)
% food products	3.443	(2.076)	2.814	(1.752)
% consumer goods	4.609	(4.012)	3.876	(3.494)
% industrial goods	11.846	(7.516)	10.491	(7.725)
% capital goods	11.048	(8.733)	11.069	(8.315)
% construction	13.562	(4.717)	12.514	(4.773)
% maintenance: hotel and catering	19.231	(4.469)	19.594	(4.193)
% services	14.186	(5.271)	17.908	(7.864)
% public sector	19.913	(6.397)	19.963	(6.312)
dummy, 1 = north	0.159	(0.366)	0.149	(0.357)
dummy, 1 = south	0.348	(0.477)	0.282	(0.451)
dummy, 1 = east	0.192	(0.394)	0.230	(0.421)
Δ net exports in 1,000 euros per worker	0.956	(3.146)	1.002	(2.758)
Δ ICT equipment in euros per worker	661.942	(157.081)	733.603	(185.298)
[C] Predicted exposure to robots				
Δ predicted robot exposure	4.617	(8.028)	4.642	(7.808)
p10–p90 interval	[0.982; 8.527]		[0.982; 8.527]	
p25–p75 interval	[1.438; 4.540]		[1.394; 5.108]	

Notes: Summary statistics of region-level variables. In columns 3 and 4, the data are weighted by full-time-equivalent number of jobs in 1994. The variable of interest is the change in predicted robot exposure per 1,000 workers between 1994 and 2014.

Sources: IFR, COMTRADE, EU KLEMS, BEH V10.01.00, and BHP 7514 v1, own calculations.

contributed (positively or negatively) to the probability of displacement for workers, thus leading to heterogeneous wage and employment effects for different individuals. We therefore use data from the UN Comtrade database and EU KLEMS on industry-level net exports and ICT investment, respectively, to construct two further shift-share variables, which both have positive averages.[18]

Finally, we report the means and deciles of the measure of predicted robot exposure in panel C. In the average region, the predicted number of robots has increased by around 4.6 robots per 1,000 workers. However, as shown in Figure 2, the distribution is skewed to the right, with a handful of very large values.

2.5. Regressions Models

In Sections 3–5, we estimate the following model at the local labor market level:

$$\Delta Y_r = \boldsymbol{\alpha} \cdot \mathbf{x}_r' + \beta_1 \cdot \widehat{\Delta \text{robots}_r} + \beta_2 \cdot \widehat{\Delta \text{trade}_r} + \beta_3 \cdot \widehat{\Delta \text{ICT}_r} + \varphi_{REG(r)} + \varepsilon_r. \quad (2)$$

We regress a change—sometimes a percentage change—of an outcome variable, such as total employment, manufacturing employment, or *E/POP*, over the period 1994–2014, on the change in the predicted number of robots per worker (i.e. on Δrobots_r as defined in equation (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 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 rather than changes. We also include the employment shares of nine broadly defined industry groups, four broad region dummies, and the predicted local exposures to net exports and ICT usage.

As discussed in Section 2.3, for inference, we apply the method proposed by Adão, Kolesár, and Morales (2019). In the tables, we label them shift-share standard errors. We additionally present conventional standard errors, using 50 clusters that represent a higher geographical aggregation of local labor markets.[19] On average, the shift-share standard errors tend to be larger, thus making inference more conservative.

2.6. Balancing Tests

We conduct several balancing tests on how important regional economic indicators in the base year are correlated with predicted robot exposure between 1994 and 2014. Although our model specification should filter out long-run level differences between

18. For the measurement of predicted trade exposure, we closely follow Dauth, Findeisen, and Suedekum (2017a, 2021), 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 communication equipment from 1994 to 2014.

19. These 50 clusters are highly aggregated labor market regions defined for use in German regional policy. Most economic interactions should be confined to those areas.

TABLE 2. Balancing tests for regional characteristics in 1994.

	Dependent variable:				
	ln(GDP capita)	% unemployment rate	% high skilled	% un-skilled	% manufacturing employment
	(1)	(2)	(3)	(4)	(5)
[A] Unconditional					
Δ predicted robot exposure	0.0099	− 0.0153	− 0.0335	0.0685	0.6580
	(0.002)	(0.035)	(0.022)	(0.039)	(0.076)
	[0.010]	[0.040]	[0.039]	[0.042]	[0.464]
R^2	0.067	0.002	0.005	0.017	0.204
[B] Conditional on full controls					
Δ predicted robot exposure	− 0.0018	0.0119			
	(0.003)	(0.023)			
	[0.002]	[0.033]			
R^2	0.779	0.682			

Notes: $N = 402$ local labor market regions (*Landkreise und kreisfreie Staedte*, GDP data not available for the two East German regions Eisenach and Wartburgkreis). 2SLS IV regressions, where German-predicted robot exposure is instrumented with robot installations across industries in other high-income countries. Each entry represents the coefficient of a regression of the respective variable on the change in predicted robot exposure per 1,000 workers between 1994 and 2014. All specifications include a constant. In panel B, we control for broad region dummies [west (reference), north, south, or east], employment shares of female, foreign, age ≥50, medium-skilled (with completed apprenticeship), and high-skilled (with a university degree) workers relative to total employment (reference category: unskilled workers and with unknown education), broad industry shares [agriculture (reference), food products, consumer goods, industrial goods, capital goods, construction, consumer-related services, business-related services, public sector], and the change in German net exports vis-à-vis China and 21 Eastern European countries (in 1,000 euros per worker) and the change in ICT equipment (in euros per worker), both between 1994 and 2014. Standard errors clustered at the level of 50 aggregate labor market regions in parentheses. Shift-share standard errors in brackets.

Sources: IFR, Comtrade, EU KLEMS, BEH V10.01.00, and BHP 7514 v1, own calculations.

regions, it is informative to gauge if other regional characteristics might be confounded with predicted automation.

Panel A of Table 2 shows the coefficients when five different baseline variables from 1994 are regressed on predicted robot exposure and a constant. Robot-exposed labor markets tend to have a slightly higher income (GDP) per capita. (However, the standard error is relatively large when using the inference suggested by Adão, Kolesár, and Morales (2019).) The unemployment rate and skill shares are not associated with future predicted robot exposure. The last column shows a strong association with the relative size of the manufacturing sector, but this should not be surprising: Almost all automation analyzed in this paper happens in the manufacturing sector, as discussed in Section 2.2. Nonetheless, it becomes clear why controlling for sectoral employment shares in local labor markets is important.[20] In further robustness checks,

20. We use employment shares for nine industry groups, which also controls for secular trends within manufacturing categories. The groups are agriculture, food products, consumer goods, industrial goods, capital goods, construction, consumer-related services, business-related services, and public sector.

we additionally control for pre-trends in manufacturing sector growth and not only for the initial levels.

In panel B, we present the coefficients on future predicted robot exposure when including our set of control variables in the regressions. The skill shares and sectoral employment shares are among our set of controls, which is why these variables drop out. The coefficient in column (1) is now very close to zero in the log income regression, and the coefficient in the unemployment regression stays small in magnitude. In Appendix Table A.1, we additionally go further back in time and present the conditional correlation of similar regional indicators in 1978 and 1984 with future predicted robot exposure. The results are unaffected and only the relative size of the manufacturing sector is associated with future predicted exposure to automation, once control variables are taken into account.[21]

3. Baseline Effects

In this section, we present our baseline results for the impact of robots on employment, wages, wage bills, and *E/POP*s, and we conduct a number of robustness checks.

3.1. Employment Effects

In Table 3, we first look at employment changes in percentage terms, using ordinary least-squares (OLS) regressions in panel A.[22] We include a separate row for the shift-share standard errors using the method proposed by Adão, Kolesár, and Morales (2019) while reporting the conventional standard errors (allowing for 50 regional clusters) in parentheses below the estimates.

Column (1) presents a parsimonious specification with the initial manufacturing and regional dummies as the only additional control variables. The estimated effect is positive, but very small and statistically insignificant. Quantitatively, comparing a local labor market at the 75th percentile of predicted robot exposure to a local labor market at the 25th percentile, the magnitudes imply that the highly exposed market experiences 0.155% point ($[4.540 - 1.438] \times 0.05 = 0.155$) higher employment growth, which translates into roughly 100 additional (full-time equivalent) jobs for an average region.

The estimates remain small and statistically insignificant as we enrich the specifications. First, we include the initial employment shares of nine broad industry groups instead of the overall manufacturing share, as there may be more fine-grained

21. We can naturally only use Western German regions here. Because total income (GDP) is not available for those years, we use average residualized log wages instead. Here, gender and age effects are controlled in worker-level regressions in a first step, and, in a second step, residualized log wages are averaged at the local labor market level.

22. Using changes in log employment yields very similar results. We prefer the percentage changes, since they allow for a clean additive decomposition into various channels. This will be the focus of Section 4.

TABLE 3. Robot exposure and employment.

	Dependent variable: % change in total employment between 1994 and 2014			
	(1)	(2)	(3)	(4)
[A] OLS				
Δ predicted robot exposure	0.0541	−0.0357	−0.0635	0.0866
	(0.107)	(0.126)	(0.122)	(0.122)
	[0.088]	[0.119]	[0.121]	[0.163]
R^2	0.503	0.567	0.571	0.583
[B] 2SLS				
Δ predicted robot exposure	0.0675	−0.0519	−0.0780	0.0686
	(0.106)	(0.133)	(0.129)	(0.137)
	[0.084]	[0.136]	[0.136]	[0.177]
% manufacturing	−0.0992			
	(0.166)			
% food products		2.4866	2.4577	2.3962
		(0.460)	(0.459)	(0.438)
% consumer goods		0.4806	0.5593	0.5320
		(0.314)	(0.319)	(0.305)
% industrial goods		0.5793	0.5487	0.5418
		(0.278)	(0.285)	(0.267)
% capital goods		0.9418	0.9051	0.9130
		(0.273)	(0.284)	(0.264)
% construction		1.0271	1.0108	1.0287
		(0.295)	(0.298)	(0.279)
% consumer services		1.4895	1.4837	1.6150
		(0.354)	(0.359)	(0.347)
% business services		0.4554	0.4495	0.8158
		(0.294)	(0.295)	(0.269)
% public sector		0.9016	0.8935	1.0742
		(0.271)	(0.273)	(0.260)
Δ net exports in 1,000 euros per worker			0.3879	0.3743
			(0.218)	(0.216)
Δ ICT equipment in 1,000 euros per worker				−0.0245
				(0.007)
Kleibergen–Paap weak ID test	562.668	391.407	383.098	378.041
Hansen J P-value	0.426	0.235	0.227	0.210

Notes: $N = 402$ local labor market regions (*Landkreise und kreisfreie Staedte*). Regressions of total employment growth (in %) on the change in predicted robot exposure per 1,000 workers between 1994 and 2014. All specifications include a constant and broad region dummies indicating if the region is located in the north, west, south, or east of Germany and demographic control variables, measured in the base year 1994. The demographic control variables are the employment shares of female, foreign, age ≥50, medium-skilled (with completed apprenticeship), and high-skilled (with a university degree) workers relative to total employment (reference category: unskilled workers and with unknown education). In column (1), we control for the manufacturing share in total employment. In columns (2)–(4), we instead include broad industry shares to control better for regional industry patterns. Industry shares cover the percentage of workers in nine broad industry groups [agriculture (reference), food products, consumer goods, industrial goods, capital goods, construction, consumer-related services, business-related services, and public sector) in the base year 1994. Columns (3) and (4) successively take into account the change in German net exports vis-à-vis China and 21 Eastern European countries (in 1,000 euros per worker) and the change in ICT equipment (in euros per worker), both between 1994 and 2014. Panel B reports results of a 2SLS IV approach where German-predicted robot exposure is instrumented with robot installations across industries in other high-income countries. Standard errors clustered at the level of 50 aggregate labor market regions in parentheses. Shift-share standard errors in brackets.

Sources: IFR, Comtrade, EU KLEMS, BEH V10.01.00, and BHP 7514 v1, own calculations.

industry trends (correlated with employment outcomes and robot installations) within the manufacturing sector. Yet, the coefficient in column (2) stays close to zero.

Column (3) adds the predicted trade exposure of local labor markets, using exports and imports with Eastern Europe and China, as described in Section 2.4.[23] Column (4) additionally includes predicted exposure to ICT investments. The inclusion of both variables clearly has a visible effect on the main coefficient, moving its magnitude by around 0.03 and 0.15 points. However, the main results remain unaffected, and the coefficient estimates imply only small employment effects of automation.

Panel B shows the results when the regressions are estimated with 2SLS. First, across the different specifications, the 2SLS estimates are close to their OLS counterparts. The Kleibergen and Paap (2006) statistic indicates there is no problem of weak instruments, and the Hansen test values imply no rejection of the null hypothesis of valid instruments. For the remainder of this paper, we will focus on the IV estimates; the corresponding OLS estimates are shown in the Online Appendix.

3.2. Displacement versus Re-allocation

3.2.1. Manufacturing and Services. We next study the displacement and re-allocation/productivity effects of automation separately. To analyze decomposition effects, we opt for (arguably) the most transparent cut of the data. In particular, the displacement of workers should occur within the robot-adopting manufacturing sector. 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. A plausible hypothesis is thus that service industries should see an increase in labor demand.

Panel A in Table 4 presents the results for employment changes. Column (1) repeats the main estimate from column (4) in Table 3, which was the fully specified model with the most control variables. The models in columns (2)–(4) use the (percentage) change in manufacturing employment as the outcome variable. Column (2) has the same control variables as column (2) of Table 4, namely broad industry employment shares and regional dummies. The next columns add predicted trade and ICT exposure, respectively. The estimates in all three columns show a negative coefficient, and, importantly, the effect size is around one order of magnitude larger than the effects on total employment. Columns (5)–(7) investigate the impact on employment in the service sector. The positive coefficients reveal the presence of substantial re-allocation forces, offsetting the adverse impact of the displacement effects. Approximately, displacement and re-allocation effects tend to be of similar magnitudes, which explains the robust finding of a zero total employment effect.

23. As is well known, Germany is a very export-oriented economy. 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.

TABLE 4. Composition effects.

	Total	Manufacturing			Non-manufacturing		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
[A] Employment: % change in total employment between 1994 and 2014							
Δ predicted robot exposure	0.0686	−0.5938	−0.6212	−0.4663	0.5847	0.5638	0.7243
	(0.137)	(0.166)	(0.158)	(0.160)	(0.325)	(0.321)	(0.327)
	[0.177]	[0.314]	[0.311]	[0.293]	[0.394]	[0.401]	[0.458]
[B] ***E/POP***: 100 × Δ in employment/population between 1994 and 2014							
Δ predicted robot exposure	0.0084	−0.0512	−0.0557	−0.0479	0.0457	0.0445	0.0563
	(0.062)	(0.025)	(0.025)	(0.027)	(0.046)	(0.046)	(0.046)
	[0.031]	[0.034]	[0.033]	[0.030]	[0.037]	[0.038]	[0.044]
Effect of one robot	0.3	−1.8	−2.0	−1.7	1.6	1.6	2.0
[C] Wages: 100 × log-Δ in average wage between 1994 and 2014)							
Δ predicted robot exposure	−0.0402	−0.1459	−0.1540	−0.1116	0.0912	0.0834	0.0929
	(0.045)	(0.051)	(0.052)	(0.066)	(0.042)	(0.042)	(0.042)
	[0.031]	[0.082]	[0.083]	[0.079]	[0.062]	[0.061]	[0.064]
[D] Wage bill: 100 × log-Δ in total wage bill on June 30							
Δ predicted robot exposure	0.0568	−0.6980	−0.7414	−0.5245	0.4428	0.4176	0.5742
	(0.153)	(0.173)	(0.164)	(0.201)	(0.251)	(0.248)	(0.254)
	[0.207]	[0.366]	[0.363]	[0.356]	[0.316]	[0.322]	[0.384]
Δ net exports in 1,000 euros per worker	Yes	No	Yes	Yes	No	Yes	Yes
Δ ICT equipment in euros per worker	Yes	No	No	Yes	No	No	Yes

Notes: 2SLS IV regressions, where German-predicted robot exposure is instrumented with robot installations across industries in other high-income countries. In all regressions, the variable of interest is the change in predicted robot exposure per 1,000 workers between 1994 and 2014. The estimates in panels A, B, and D are based on $N = 402$ local labor market regions (*Landkreise und kreisfreie Staedte*), while the unit of observation in the wage estimates in panel C is $N = 7{,}235$ regions × demographic cells. Demographic cells are defined by gender, three age groups, and three education groups. We only include cells containing at least ten observations, and perform the regressions at the region × demographic cell level including fixed effects for demographic cells. The dependent variable in panel D is the log-difference total amount of gross salaries paid to employees subject to social security on June 30 in 1994 and 2014. All specifications include a constant, broad region dummies, demographic control variables, and employment shares of nine aggregate industry groups, measured in the base year 1994. Standard errors clustered at the level of 50 aggregate labor market regions in parentheses. Shift-share standard errors in brackets.

Sources: IFR, Comtrade, EU KLEMS, BEH V10.01.00, and BHP 7514 v1, own calculations.

We re-estimate the models in panel B with the change in *E/POP* as the dependent variable.[24] Column (1) shows an effect close to zero, but again this hides significant displacements in columns (2)–(4) and strong re-allocation effects in columns (5)–(7).

24. We measure employment by all jobs in Germany subject to social security. This yields small *E/POP*s 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 (6) of Appendix Table A.4, which shows no effect of robots on public employment.

Since the sum of the *E/POP*s in the two sectors equals the total *E/POP* in a region, the coefficients of the fully specified models in columns (4) and (7) sum up to 1. We can translate these numbers into head counts.[25] This makes the estimates directly comparable to Acemoglu and Restrepo (2019) for the United States, since our *E/POP* is calculated differently here (see footnote 24). The numbers are shown in the second to last row of panel B. The preferred estimate from column (4) implies a displacement effect of −1.7 workers per newly installed robot.

In panel C, we repeat the analysis using the change in local average daily log wages as the outcome variable. We note that the wage estimates must be interpreted with some caution. Predicted robot exposure displaces workers at least in the manufacturing sector, which creates selection since wage outcomes are only available for employed workers.[26] We circumvent those selection issues in Section 6, when we look at labor earnings directly for exposed individual workers. The results, by and large, mirror the employment effects. Column (1) shows a small, negative, and insignificant impact of predicted robot exposure on wage growth. Consistent with the employment results, however, we see negative effects within manufacturing in columns (2)–(4), and positive effects in the service sector in columns (5)–(7). The results strongly support the hypothesis of decreased manufacturing labor demand in regions with higher predicted robot exposure, and an offsetting increase in labor demand for local services.

Panel D combines the wage and employment information by calculating sectoral total wage bills (based on the universe of social security records). The results in columns (1)–(7) strongly support the interpretation of reduced manufacturing labor demand in regions strongly exposed to automation, but increasing labor demand in local service industries.

The results represent evidence that the adoption of robots has led to *positive employment spillovers* on other local industries in non-manufacturing.[27] Our data allow us to further look at this channel. Appendix Table A.4 presents estimates when

25. 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 the numbers from Table 4.

26. We conduct our analysis at the demographic group-region cell level, as in Acemoglu and Restrepo (2019), to deal with the changing observables of employed workers. Using residualized wages from Mincer regressions gives us very similar effects.

27. Any negative spillover effects from the displacement forces of automation, hence, appear to be dominated by new labor demand, at least for service industries. Gathmann, Helm, and Schönberg (2019) consider the regional effects of mass layoffs and detect significant negative spillovers. While the displacement effects we document are economically significant, industrial robots did not trigger mass layoff episodes in Germany, which limits the scope for negative spillovers.

we split up the non-manufacturing sector into several subsectors. We differentiate business services, consumer services, construction, and the public sector. The first category includes employment in establishments that render their services to other businesses on a contractual basis. This includes ICT, cleaning, or security. The second category, consumer services, contains hotels and restaurants, as well as beauty services such as haircutting.

By far the largest employment effect is on business services with a coefficient of 0.638. The consumer service coefficient, in contrast, is only estimated to have a value of 0.051. The other 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 (2019), where increased robot adoption raises demand for complementarity inputs by producers. Relatedly, Goldschmidt and Schmieder (2017) show that task outsourcing has increased within Germany. It is conceivable that increased automation may be related to changing boundaries of the firm, and may accelerate these processes. This would be consistent with a positive effect of automation on business service employment.

The Appendix contains important robustness checks to our findings (Appendix Table A.2). After repeating our baseline results, we first check for the presence of pre-trends by regressing lagged outcome variables on future exposure.[28] Second, we restrict the time window for the analysis to stop before the global great recession in 2007. Third, we include “marginal workers”. Those very low-paying part-time jobs are only covered in the social security data starting in 1999. In this robustness check, we include this group in the worker counts at the end of our observation period, and count them as zero in the beginning of the period. It turns out that our main results are not affected. Next, we conduct various checks concerning the regional dimensions. Leaving out East Germany does not change the results. They also remain very similar when we include time trends at the level of 16 federal states. Another robustness check is to use different regional aggregations to define local labor markets. We change the boundaries, making labor markets broader (reducing the number of units from 402 to 258 labor market areas used for the “joint task of the federal government and the states for the improvement of regional economic structures” (GRW) or to 141 commuting zones delineated by Kosfeld and Werner 2012). We observe the same pattern of displacement and re-allocation, although imprecision increases when the sample size decreases.

Finally, we pay special attention to the car industry, which plays a dominant role in the German economy and is highly robotized. We split up the treatment variable into predicted exposure to robots in automobile production and to robots in other industries. The displacement effect is relatively homogeneous across sectors. Re-allocation is driven by the predicted exposure to robots in automobile production, in contrast.

28. The results here imply that labor demand in manufacturing and services was trending in the opposite direction, so that higher future predicted robot exposure was correlated with higher manufacturing employment growth.

This suggests that the productivity effects were particularly large in this sector.[29] An alternative way to look at the automotive sector is to distinguish between automotive and other manufacturing when constructing the outcome variables, as we show in panel H. While the effect of robots on other manufacturing industries is quantitatively similar to the overall effect, we find an exorbitant but also very imprecisely estimated negative coefficient for car manufacturing. We conclude that our main results are not exclusively driven by this sector, but are rather representative for manufacturing as a whole.

3.2.2. Effects within Manufacturing and Task Shares. So far, we have looked at displacement and re-allocation at the sectoral level. An additional way to split the data is to separate employment effects within manufacturing. In particular, predicted robot exposure will plausibly have different effects on routine versus non-routine jobs even within the sector. Table 5 shows the results for such a sample split within manufacturing, using employment growth as a dependent variable. Comparing columns (1) and (4) from panel A, one can see how the displacement effect is more pronounced for routine jobs (coefficients −0.466 and −0.660), as expected. The point estimate for non-routine jobs from column (7) is much smaller but also negative (−0.266) and statistically insignificant. As before, panel B shows the results using *E/POP*s as a dependent variable. The coefficients in columns (4) and (7) add to the total effect in column (1). In contrast to panel A, the point estimate from column (7) on non-routine jobs is positive in this specification, but also statistically insignificant.[30] These results are not totally conclusive on the strength of re-allocation within the sector.

We obtain clearer results, however, when estimating a version of the empirical model, which uses changes in the task utilization within manufacturing directly. In Table 6, the dependent variable is the percentage point change in the share of routine/abstract/manual tasks relative to all tasks in manufacturing in a local labor market. Columns (1) and (2) document the shift in the task composition of manufacturing sector jobs associated with automation. The estimates imply almost an exact offset for the routine and abstract task shares. Later in Section 5, we build on those results, and show that predicted robot exposure is also strongly associated with occupational transitions of routine job workers into occupations with a higher abstract task share, for those workers who are retained by their original employers.

29. It also points to an interaction of automation with trade, since Germany is a large exporter of cars, and one would expect that productivity effects are increasing in market size.

30. The coefficients in columns (4)–(7) flip signs from panel A to B, since panel A is estimated in growth rates and panel B in changes in the absolute number of jobs, normalized by population. More non-routine jobs were added in those regions that had a higher than average share of non-routine jobs within manufacturing to begin with. So one obtains a negative effect of predicted robot exposure on growth rates but a positive one on the absolute number of non-routine jobs within manufacturing.

TABLE 5. Composition effects: routine versus non-routine intensive manufacturing.

	Total	Routine			Non-Routine		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
[A] Employment: % change in total employment between 1994 and 2014							
Δ predicted robot exposure	−0.4663	−0.7920	−0.7785	−0.6601	−0.3773	−0.4531	−0.2656
	(0.160)	(0.218)	(0.205)	(0.223)	(0.240)	(0.233)	(0.236)
	[0.293]	[0.447]	[0.447]	[0.423]	[0.312]	[0.278]	[0.283]
[B] ***E/POP***: 100 × Δ in employment/population between 1994 and 2014							
Δ predicted robot exposure	−0.0479	−0.0692	−0.0683	−0.0662	0.0180	0.0126	0.0183
	(0.027)	(0.024)	(0.024)	(0.026)	(0.037)	(0.037)	(0.039)
	[0.030]	[0.043]	[0.043]	[0.041]	[0.022]	[0.020]	[0.021]
Effect of one robot	−1.7	−2.4	−2.4	−2.3	0.6	0.4	0.6
Δ net exports in 1,000 euros per worker	Yes	No	Yes	Yes	No	Yes	Yes
Δ ICT equipment in euros per worker	Yes	No	No	Yes	No	No	Yes

Notes: 2SLS IV regressions, where German-predicted robot exposure is instrumented with robot installations across industries in other high-income countries. In all regressions, the variable of interest is the change in predicted robot exposure per 1,000 workers between 1994 and 2014. The estimates in panels A and B are based on $N = 402$ local labor market regions (*Landkreise und kreisfreie Staedte*), while the unit of observation in the wage estimates in panel C is $N = 7{,}217$ regions × demographic cells. Demographic cells are defined by gender, three age groups, and three education groups. We only include cells containing at least ten observations, and perform the regressions at the region × demographic cell level including fixed effects for demographic cells. All specifications include a constant, broad region dummies, demographic control variables, and employment shares of nine aggregate industry groups, measured in the base year 1994. Routine intensive is defined as being employed in an occupation that ranks above the 66th percentile of the share of routine tasks relative to all tasks (see Spitz-Oener 2006; Autor and Dorn 2013). Standard errors clustered at the level of 50 aggregate labor market regions in parentheses. Shift-share standard errors in brackets.

Sources: IFR, Comtrade, EU KLEMS, BEH V10.01.00, and BHP 7514 v1, own calculations.

TABLE 6. Composition effects: change in task intensity.

	(1) Routine	(2) Abstract	(3) Manual
Manufacturing			
Δ predicted robot exposure	−0.0939	0.0815	0.0109
	(0.024)	(0.039)	(0.031)
	[0.064]	[0.061]	[0.019]

Notes: 2SLS IV regressions, where German-predicted robot exposure is instrumented with robot installations across industries in other high-income countries. In all regressions, the variable of interest is the change in predicted robot exposure per 1,000 workers between 1994 and 2014. The dependent variable is the percentage point change in the share of routine/abstract/manual tasks relative to all tasks. Task intensity is measured at the level of occupations according to the BIBB/BAuA Survey in 1991. The estimates are based $N = 402$ local labor market regions (*Landkreise und kreisfreie Staedte*). The regressions include the full set of control variables as in column (4) of Table 3. Standard errors clustered at the level of 50 aggregate labor market regions in parentheses. Shift-share standard errors in brackets.

Sources: IFR, Comtrade, EU KLEMS, BEH V10.01.00, and BHP 7514 v1, own calculations.

4. Adjust Mechanism I: Reduced Creation of New Jobs for Young Workers

We have documented the presence of substantial displacement and re-allocation effects of automation by using a local labor market approach. In this section, we leverage the availability of detailed administrative panel data to understand better which kinds of workers are actually displaced and reallocated in response to automation. One of the main results will highlight that a large portion of the incidence of displacement and re-allocation is borne by young workers, who face reduced (increased) job creation in the manufacturing (service) sector. However, as an important qualifier, this does not imply that young workers only bear the costs of labor market adjustments and are left behind by automation. In Section 5, we will show that as a response to predicted robot exposure, labor market entrants also are more likely to attend college and hold jobs that are more abstract and less routine intensive. This suggests that net-welfare effect for young entrants could plausibly also be positive. In addition, it should be clarified that re-allocation for young workers only happens in a counterfactual sense, as they start their careers in the service sector instead of manufacturing.

We analyze the adjustment process by decomposing the employment variables from Section 3 into mutually exclusive channels. The decomposition is additive and, hence, easy to interpret. We start by characterizing the displacement effect. Conceptually, we distinguish between workers who were working in the exposed manufacturing sector at the start of the observation period in 1994 and non-incumbents who were not working in manufacturing.

The set of different channels for the displacement effect are listed in the seven columns of panel A of Table 7. Columns (1) and (2) summarize the outcomes for incumbent manufacturing workers. They include employment at the same plant[31] and employment at other plants within the manufacturing sector.[32] Columns (4)–(6) encompass all margins related to workers not in the manufacturing sector at the start of the period in 1994. They comprise workers who had not entered the labor market yet in 1994, workers who were already in the same local labor market but not in the manufacturing sector, workers who were employed in a different region, and temporarily non-employed workers in 1994. The coefficients from columns (1)–(6) add up to the coefficient from column (7), which is the full effect on manufacturing employment from column (4) of Table 4 and re-stated here to facilitate the interpretation.

Column (1) in panel A starts with a—perhaps—surprising finding. Predicted exposure to automation increases employment at one's original employer. The effect is sizable and around a third of the total displacement effect from column (7). We will devote parts of the next section to explain the mechanisms, and document how workers relocate within firms across tasks and occupations. While incumbent workers

31. In our data, we only observe plants but not firms. On a few occasions in this paper, we use these terms interchangeably.

32. In an older version of this paper, we also presented results for employment in different plants within the original industry. The results are omitted here for brevity.

TABLE 7. Adjustment.

	Dependent variable: 100 × number of workers in 2014/total employment in 1994						
	Incumbent workers		Entrants				Total
Same plant as in 1994 Same sector as in 1994	Yes Yes	No Yes	Entered labor market after 1994	Same region, different sector in 1994	In different region in 1994	Not employed in 1994	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
[A] Manufacturing							
Δ predicted robot exposure	0.1723	−0.2503	−0.2473	−0.0493	−0.0040	−0.0877	−0.4663
	(0.051)	(0.051)	(0.089)	(0.027)	(0.040)	(0.025)	(0.160)
	[0.080]	[0.123]	[0.141]	[0.044]	[0.063]	[0.041]	[0.293]
[B] Non-Manufacturing							
Δ predicted robot exposure	−0.0504	−0.0376	0.5676	−0.0153	0.2101	0.0499	0.7243
	(0.014)	(0.027)	(0.230)	(0.013)	(0.059)	(0.046)	(0.327)
	[0.030]	[0.027]	[0.348]	[0.006]	[0.113]	[0.039]	[0.458]

Notes: N = 402.2SLS IV regressions, where German-predicted robot exposure is instrumented with robot installations across industries in other high-income countries. In this table, the employment growth rate is additively split up into the contributions of different groups of incumbent workers or workers that enter the region's manufacturing (panel A) or non-manufacturing sector (panel B) between 1994 and 2014. The coefficients of columns (1)–(6) sum up to the coefficient in column 7. In all regressions, the variable of interest is the change in predicted robot exposure per 1,000 workers between 1994 and 2014. The regressions include the full set of control variables as in column (4) of Table 3. Standard errors clustered at the level of 50 aggregate labor market regions in parentheses. Shift-share standard errors in brackets.

Sources: IFR, COMTRADE, EU KLEMS, BEH V10.01.00, and BHP 7514 v1, own calculations.

face a lower layoff risk, this is offset by decreased employment in other firms in manufacturing, as evidenced by the estimate in column (2).[33]

These two findings are consistent with the following interpretation(s). Labor market institutions in the form of firing costs make it costly to lay off workers even though the tasks previously performed by those workers are now carried out by industrial robots. At the same time, productivity effects are plausibly occurring mostly within the same firms adopting robots, which allows the re-shuffling of workers from automated tasks to other tasks, since the new demand for non-automated tasks arises in those firms. These two forces explain why robot adoption actually increases employment within the original plant. In Section 5, we document how automation is related to the re-shuffling of workers across tasks within plants. In addition, below, we present (indirect) evidence on how variation in labor market institutions influences the retainment effect from column (1). However, the estimate in column (2) shows that—conditional on a separation—workers have a harder time regaining employment in similar industries,

33. These results are in line with Koch, Manuylov, and Smolka (2019), who find that Spanish firms create jobs after investing in robots. By contrast, Bessen et al. (2019) find that in particular older workers are more likely to leave firms that invested in automation technologies in a broader sense.

consistent with the general reduced labor demand in robot-adopting industries. This leads to reduced employment in the manufacturing sector for incumbent workers.

The main part of the displacement incidence falls on non-incumbent workers, however. The negative coefficient in column (3) reveals that the largest burden falls on young workers, who had not entered the labor market in 1994 (and subsequently entered in some year between 1995 and 2014). Automation also reduces flows from the service into the manufacturing sector and lowers entry from unemployment, as evidenced by columns (4) and (6). The effect sizes, however, are much smaller compared to the entrant margin. Reduced netmigration, as measured by column (5), plays no role in explaining the displacement force.

Panel B provides the same decomposition for the non-manufacturing sector to study the re-allocation effect. By construction, the sum of columns (1)–(6) equals the estimate from column (7) (and column (7) from Table 4). We expect zero or only very small impacts for non-manufacturing incumbent workers, since their task set is not exposed to automation. This is confirmed in columns (1) and (2). An important open question is if the manufacturing displacement experienced by entering labor market cohorts leads to offsetting gains for young workers in services. The estimate in column (3) provides the answer and implies gains for young workers. The larger coefficient in panel B combined with the larger denominator of the outcome implies that those gains overcompensate the adverse impacts from displacement. If productivity effects also spill over into the service sector—something that should be expected, given that tasks in this sector are complements to automated tasks—predicted robot exposure should presumably also increase labor demand in services at other margins. There is indeed a positive effect—shown in column (5) of panel B—on pulling in workers into an expanding service sector from other regions.

Given that the incidence of the re-allocation effect falls primarily on young workers, one should expect that the age structure in the manufacturing sector evolves differently from that in the service sector. In Appendix Table A.5, we find that automation reduces the average age of workers in the service sector and increases the average age of manufacturing workers (although the latter effect is small and imprecisely estimated). Our results are consistent with a two-way interaction between automation and aging. Acemoglu and Restrepo (2018a) investigate the effect of an older population on more automation. We find that more automation leads to an increase in the average age of the working population in more affected regions. These effects could reinforce each other.

4.1. Heterogeneity by Unionization Rates

In this subsection, we present additional results for the displacement and re-allocation effects, splitting labor markets into the relative strengths of trade unions.[34] We are not explicit about specific mechanisms how regional union strength affects outcomes

34. In an older version of this paper (Dauth et al. 2019), we used the vote share of the Social Democratic Party (SPD) in the 1980s as a proxy for the strength of labor market institutions favoring workers. SPD vote shares in the 1980s and net union density rates in 1993 are highly but not perfectly correlated with a

directly. Rather, we interpret it as a proxy for different labor market institutions strengthening incumbent workers' rights. Examples include higher wage bargaining power, more powerful work councils, which are deeply involved in organizational decisions at the firm level and can negotiate deviations from collective bargaining arrangements in order to prevent mass layoffs, and so forth. Net trade union density rates, measured as the fraction of workers who are union members, at the regional level are calculated using the German Social Economic Panel (GSOEP) in the year 1993.[35] To illustrate heterogeneous impacts, we split local labor markets into either a high or low worker protection group.[36] The results do not necessarily reflect the causal effect of union density, since we cannot rule out that those groups also differ in other dimensions, such as local preferences. However, we gain confidence since controlling for federal-state fixed effects does not change the results qualitatively.

Above in this section, we presented a worker retention result: Workers in more exposed local labor markets are more likely to stay with their original plant. Are firms retaining their workers voluntarily at higher rates in the wake of automation, because they value their firm-specific human capital? Or does this finding capture high firing costs? We try to examine this in Table 8. Comparing the coefficients in column (1) from panels A and B reveals that the retention effect is twice as large in areas with higher worker protection. At least part of the retention, therefore, seems to reflect institutional constraints on firms to adjust to technological change. In contrast, conditional on leaving the original plant, workers are not protected by these institutions any more. Consistent with this, column (2) shows that the effects of robots on mobility to other plants within the manufacturing sector do not differ between regions with higher and lower job protection. In columns (3)–(6), we again report the effects on entrants into the local manufacturing sector. Aside from the lower retention of incumbent workers, the manufacturing sector in low job protection regions also attracts fewer young entrants, formerly unemployed, and workers changing between sectors. In total, column (7) shows that the displacement effect measured by manufacturing employment was much stronger in environments with low worker protection.

5. Adjust Mechanism II: Skill Upgrading

In this section, we turn our attention to different mechanisms of adjustment: the re-assignment of workers to new tasks and the upgrading of skills. The analysis will

coefficient slightly above 0.50. However, qualitatively, the main findings of this subsection are similar for both measures.

35. The GSOEP is a yearly panel survey of individuals, similar to the US PSID. We calculate union shares in the GSOEP at the administrative regional classification of so-called Raumordnungsregionen (ROR), of which there are 96 in the year 1993. Calculating region shares at the county level is, unfortunately, not possible since some cells are too sparsely filled. The mapping from counties to ROR is unique so we can assign counties to either being high or low in unionization rates without further assumptions.

36. The split of the 402 counties/local labor markets is not exactly even in Table 8, because, as explained above, we measure unionization at a higher level of aggregation, namely ROR. We split the sample along the median of the ROR distribution.

TABLE 8. Manufacturing adjustment—by shares of union members (SOEP).

	Dependent variable: 100 × number of workers in 2014/total employment in 1994						
	Incumbent workers		Entrants				Total
Same plant as in 1994	Yes	No	Entered	Same region,	In different	Not	
Same sector as in 1994	Yes	Yes	labor market after 1994	different sector in 1994	region in 1994	employed in 1994	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
[A] Above median share of union members							
Δ predicted robot exposure	0.2567	−0.2596	−0.1322	−0.0570	0.0183	−0.0823	−0.2561
	(0.069)	(0.050)	(0.130)	(0.050)	(0.047)	(0.043)	(0.248)
	[0.121]	[0.130]	[0.138]	[0.060]	[0.074]	[0.042]	[0.280]
[B] Below median share of union members							
Δ predicted robot exposure	0.1281	−0.2908	−0.4217	−0.0557	−0.0111	−0.1028	−0.7540
	(0.084)	(0.109)	(0.179)	(0.026)	(0.098)	(0.062)	(0.371)
	[0.077]	[0.120]	[0.262]	[0.063]	[0.132]	[0.094]	[0.543]

Notes: $N = 199$ (panel A) and 203 (panel B). 2SLS IV regressions, where German-predicted robot exposure is instrumented with robot installations across industries in other high-income countries. In this table, the employment growth rate is additively split up into the contributions of different groups of incumbent workers or workers that enter the region's manufacturing sector between 1994 and 2014. The coefficients of columns (1)–(6) sum up to the coefficient in column (7). In all regressions, the variable of interest is the change in predicted robot exposure per 1,000 workers between 1994 and 2014. The regressions include the full set of control variables as in column (4) of Table 3. Standard errors clustered at the level of 50 aggregate labor market regions in parentheses. Shift-share standard errors in brackets.

Sources: IFR, COMTRADE, EU KLEMS, BEH V10.01.00, and BHP 7514 v1, and SOEP, own calculations.

establish four new results. First, a majority of workers who are retained by their firms in the wake of automation are re-assigned to new occupations. Second, their new occupations feature more abstract and less routine intensive task contents. Third, they are higher up in the wage ladder, and are characterized by a higher college share. Finally, the skill (college) share among labor market entrants increases significantly, the apprentice share goes down, and the jobs held by labor market entrants become more abstract and less routine intensive.

Table 9 presents the results from models that analyze the adjustment process for incumbent manufacturing workers. They all follow the specification with the most comprehensive set of control variables, as in Sections 3 and 4. Our linked employer–employee data allow us to observe the workplace of every worker at all points in time. We also observe three-digit occupation codes, which we aggregate to 54 economically more meaningful occupational fields according to the German Federal Institute for Vocational Education and Training (Tiemann et al. 2008). We measure the quality of occupations according to four dimensions: the median wage of all full-time employees, the share of workers with a college degree, and the intensity in abstract and routine tasks. For the latter two, we follow Spitz-Oener (2006) and construct task intensities as the average shares of abstract or routine tasks in all tasks

TABLE 9. Occupational upgrading within and across firms.

	(1)	(2)	(3)	(4)
[A] Occupational adjustment				
	Dependent variable: 100 × number of workers in 2014/ total employment in 1994			
Same plant as in 1994	Yes	Yes	Yes	
Same occupation as in 1994	Yes	No	(total)	
Δ predicted robot exposure	0.0437	0.1287	0.1723	
	(0.027)	(0.030)	(0.051)	
	[0.025]	[0.062]	[0.080]	
[B] Occupational upgrading: wages and skills				
	Dependent variables:			
	Δ log median wage in euros		100 × Δ college share	
Same plant as in 1994	Yes	No	Yes	No
Δ predicted robot exposure	0.0633	0.0258	0.0583	0.0146
	(0.024)	(0.032)	(0.024)	(0.022)
	[0.046]	[0.035]	[0.039]	[0.016]
[C] Occupational upgrading: tasks				
	Dependent variables:			
	100 × Δ abstract task intensity		100 × Δ routine task intensity	
Same plant as in 1994	Yes	No	Yes	No
Δ predicted robot exposure	0.0719	– 0.0227	– 0.1229	– 0.0470
	(0.025)	(0.023)	(0.028)	(0.026)
	[0.045]	[0.019]	[0.077]	[0.031]

Notes: $N = 402$. 2SLS IV regressions, where German-predicted robot exposure is instrumented with robot installations across industries in other high-income countries. In this table, we analyze the effect of robots on the occupation dimension of exposed workers. In panel A, the dependent variables are 100 × the number of workers who stay in the manufacturing sector of their original region but show different kinds of job mobility, relative to total employment in 1994. The coefficients of panel A, columns (1) and (2), add up to the coefficient in column (1) of panel A, Table 7 [also reported in column (3)]. In panels B and C, we focus on the occupational quality of workers who stay in the manufacturing sector of their original region but possibly switch into a different occupation. The dependent variable in columns (1) and (2) of panel B is the average difference of the median wage, measured in 1994, of the occupation of workers staying in the same plant in 2014 versus the occupation in 1994. The dependent variable in columns (3) and (4) of Panel B is the average difference of the percentage of people with a college degree (measured in 1994) of the occupation of workers staying in the same plant in 2014 versus the same percentage of those workers' occupation in 1994. The dependent variable in panel C is the average difference of the abstract (columns (1) and (2)) and routine (columns (3) and (4)) task intensities, measured in 1994, and of the occupation of workers staying in the same plant in 2014 versus the occupation in 1994. In all regressions, the variable of interest is the change in predicted robot exposure per 1,000 workers between 1994 and 2014. The regressions include the full set of control variables as in column (4) of Table 3. Standard errors clustered at the level of 50 aggregate labor market regions in parentheses. Shift-share standard errors in brackets.

Sources: IFR, COMTRADE, EU KLEMS, BEH V10.01.00, and BHP 7514 v1, own calculations.

performed by around 20,000 workers surveyed in the 1991 BIBB/IAB Employment Survey.[37]

Panel A starts with a decomposition of the retainment effect, shedding light on the question how plants keep workers around in the wake of automation. Column (3) repeats this retainment effect from column (1) of Table 7. In columns (1) and (2), the coefficient is additively decomposed into the contribution of days employed *in the same plant* in a worker's original occupation in 1994 and of days employed in other occupations by defining the dependent variables in this way. The magnitudes imply that 75% (0.1287/0.1723) of the total effect stems from days worked in a different occupation.

It is not clear yet to what extent workers profit from those occupational transitions. To address this, the next set of models in panels B and C investigates several dimensions of the occupational quality of jobs. All dependent variables in these two panels are constructed as follows: First, we measure the quality of each occupation in terms of either wage, education, or task intensity. Second, for each worker who stays in the manufacturing sector of her or his original region, we calculate the difference in occupational quality between 1994 and 2014. Third, we average those individual-level differences over all workers in each region.

The first measure is the change in median occupational wages. Concretely, we measure the quality of an occupation at any point in time as the median wage of all workers in this occupation in 1994.[38] The outcome variable is the average log-difference of the median wage of the occupation a worker held in 2014 versus the median wage of the occupation the same worker held in 1994. In column (1) of panel B, this variable is constructed only from workers who stayed in their initial plant, while in column (2) the outcome is analogously defined for workers who switched between plants. Positive coefficients would indicate that predicted robot exposure leads to occupational upgrading. Column (1) displays a positive coefficient, around twice the size of the coefficient in column (2). So, on average, higher predicted robot exposure is associated with occupational mobility up the wage ladder, and the effect is much stronger within plants, that is, for workers who were retained by their original employer.

In column (3) of panel B, we measure the quality of an occupation at any point in time as the percentage of workers with a college degree in 1994. The dependent variable is average of the difference in the college share of the occupation a worker held in 2014 versus the college percentage of the same worker's occupation in 1994.[39] The results

37. A third task category is manual tasks, which we omit here as it is mostly relevant for individual-related services.

38. Using median wages from earlier years as measure leaves the results unaffected.

39. Again, using lagged college shares produces almost the same results, since skill shares remained fairly stable during this time period.

TABLE 10. Robots and skill share of people younger than 30.

	Dependent variable:			
	100 × Δ Share of workers with:		Task intensity	
	University degree (1)	Apprenticeship degree (2)	Abstract (3)	Routine (4)
Δ predicted robot exposure	0.1091	– 0.0876	0.0835	– 0.0606
	(0.048)	(0.038)	(0.036)	(0.023)
	[0.051]	[0.043]	[0.042]	[0.039]

Notes: 2SLS IV regressions, where German-predicted robot exposure is instrumented with robot installations across industries in other high-income countries. In this table, we analyze the effect of robots on occupational quality of younger workers. The estimates are based on $N = 402$ local labor market regions (*Landkreise und kreisfreie Staedte*). The dependent variable is the change in various measures for occupation quality of workers 30 years old or less between 1994 and 2014: share of workers with a university degree (column (1)), share of workers with an apprenticeship degree (column (2)), average abstract task intensity (column (3)), and average routine task intensity (column (4)). In all regressions, the variable of interest is the change in predicted robot exposure per 1,000 workers between 1994 and 2014. The regressions include the full set of control variables as in column (4) of Table 3. Standard errors clustered at the level of 50 aggregate labor market regions in parentheses. Shift-share standard errors in brackets.

Sources: IFR, COMTRADE, EU KLEMS, BEH V10.01.00, and BHP 7514 v1, own calculations.

imply a positive effect of automation on occupational quality,[40] and the comparison with column (4) shows that the effect is again much larger for firm stayers.[41]

Finally, panel C studies the re-assignment of tasks for exposed workers. The dependent variable in panel C is the average difference of the abstract (columns (1) and (2)) and routine (columns (3) and (4)) task intensities, measured in 1994, of the occupation of workers in 2014 versus their occupation in 1994. Columns (1) and (3) present evidence that automation seems to cause a shift in the careers of workers away from routine and toward abstract tasks within plants. The coefficients in columns (2) and (4) show much smaller effects across plants.

We next turn to human capital adjustments of young cohorts. The first dependent variable of Table 10 is the change in the share of college-educated workers aged 30 or lower. To be included, workers need to hold a degree that requires at least three years of tertiary education. The positive coefficient indicates that young people adjust to local automation by increasing their level of education. Column (2) shows that is counteracted by a significant reduction in the apprenticeship share. Importantly, the table also shows that the adjustment efforts of young workers extend beyond

40. To be clear: This is driven by incumbent workers moving across occupations; there is no evidence of incumbent workers engaging in further formal training at universities.

41. Comparing plant stayers and switchers may be difficult if automation changes the composition of workers who stay/leave their original firm. We found no significant differences in the difference between stayers and leavers in highly exposed versus weakly exposed regions in terms of observables.

educational and into occupational choices. In columns (3) and (4), we measure the effect of robots on changes in the task contents of jobs held by people below age 30. In more robot exposed regions, we observe a stronger re-allocation from routine toward abstract tasks. These results are robust to using different age cutoffs from 30; in Appendix Table A.3, we present the results with an age cutoff of 40 as an example.

6. Individual Workers

We now shift the focus from local labor market adjustments to individual workers. This complements the previous models, because it allows to directly study the effects of automation on earnings and wages using a more compelling design. Comparing wage or earnings growth across local labor markets, in contrast, can lead to biased results because automation changes the composition of employed workers. By following the same workers, we can circumvent such selection issues.

6.1. Earnings and Employment

6.1.1. Design and Data. We use an exposure to automation design that compares the outcomes of workers who were employed in a manufacturing industry in 1994.[42] We follow the standard practice in the literature and focus on workers with sufficiently high labor force attachment. This means that we restrict the sample to workers who were (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 in the base year 1994.[43] Finally, we keep only workers in manufacturing industries that can be matched to the IFR data. The specification is

$$Y_{ij} = \boldsymbol{\alpha} \cdot \mathbf{x}'_{ij} + \beta \cdot \Delta\text{robots}_j + \boldsymbol{\gamma} \cdot \mathbf{z}'_j + \varepsilon_{ij}.$$

Y_{ij} represents the cumulated number of days spent in employment—irrespective of whether employed in a manufacturing or a different sector—over the 1995–2014 period in the first set of regressions. In the vector $\mathbf{x}'_{ij}$, we include worker-level controls, measured in the base year 1994: dummies for gender, foreign nationality, three skill categories, and three tenure categories. In addition, we include a full set of age dummies, federal state dummies, and dummies for six plant size groups. We also control for the log of yearly earnings of a worker at the start of the period in 1994.

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. As described in Section 2, the IFR classification allows us to distinguish 20 manufacturing industries. To account for this, we cluster standard errors at the levels of the IFR classification with 20 clusters.

42. This approach has also been used by Autor et al. (2014) to study the worker-level impacts of trade shocks. We follow their method here.

43. Results are very similar, however, when including also workers with lower attachment.

$\mathbf{z}'_j$ is a vector of industry controls with dummies for broad industry groups.[44] It also contains changes in trade exposure at the three-digit level and ICT exposure at the two-digit level.[45]

As for the data in this section, we use a 30% random sample of the Integrated Labor Market Biographies (IEB V12.00.00) of the Institute for Employment Research. These data are similar to those introduced in Section 2.1 but cover the complete employment biographies with daily precision and not only the main observation on June 30.[46] Since East Germany saw a very strong wage growth up until 1995, related to other factors besides automation, we drop workers who were employed there in 1994 in a robustness check. Our results are unaffected, consistent with the analogous robustness checks at the regional level.

Table 11 reports descriptive statistics of the variables used in the worker-level analysis. The average manufacturing worker in our sample has experienced an exposure equal to $\Delta\text{robots}_j = 24.4$ (see panel C). Notice the large variation across individuals. The worker at the 75th percentile has seen an increase in robot exposure that is almost five times larger than for the worker at the 25th percentile (26.1 versus 5.5 additional robots per 1,000 workers), and the comparison between the 90th and the 10th percentiles is even more dramatic (104.3 versus −2.7). This reflects the extremely skewed distribution of robot installation across industries, which is illustrated in Appendix Figure A.1. The average worker in our sample is employed for 5,980 days during the 20 years after 1994, which amounts to 82% of the duration of this period (7,305 days). We measure the cumulative earnings over the 20-year period in multiples of the worker's earnings in the base year. If, after adjusting for inflation, a worker earned exactly the base year's earnings in each year of the period, the outcome would be $1 \times 20 \times 100 = 2{,}000$. In fact, workers have on average almost exactly retained their base year earnings.

In Table 12, we present a balancing analysis similar to the one at the regional level, where we regress individual worker characteristics at the start of the period (in 1994) on future robot exposure. The first column, labeled unconditional, shows the coefficient when the listed variables at the start of the period are regressed on predicted robot exposure and a constant. Workers with higher earnings and wages seem to be more exposed, although the coefficients are not statistically significant at the 5% level. Demographic characteristics are not strongly associated with robot exposure. In contrast, firm size and job tenure are. In the second column, we include our control variables into the regressions. Naturally, when a variable is the left-hand

44. The categories are, as in Section 3, food products, consumer products, capital goods, and industrial goods.

45. See the data part in Section 2 for a description. See Dauth, Findeisen, and Suedekum (2021) for details on the trade variables.

46. Due to its size and design, these data perfectly capture the aggregate data on wages and employment in Germany. However, the restriction to prime age manufacturing workers with high labor force attachment in the base year implies that wages are higher and employment careers are more stable compared to the average German worker.

TABLE 11. Summary statistics, worker level.

Observations	720,562	
	Mean	(SD)
[A] Outcomes, cumulated over years following base year		
Days employed	5,980	(1,986)
Average daily wage	121.3	(71.2)
100 × earnings/base year earnings	1,949.8	(1,000.3)
[B] Control variables, measured in base year		
Base year earnings	38,683	(20,599)
Base year average wage	106.55	(55.14)
Dummy, 1 = female	0.211	(0.408)
Dummy, 1 = foreign	0.110	(0.313)
Birth year	1960	(6)
Dummy, 1 = low skilled	0.160	(0.366)
Dummy, 1 = medium skilled	0.751	(0.432)
Dummy, 1 = high skilled	0.089	(0.285)
Dummy, 1 = tenure 2–4 years	0.397	(0.489)
Dummy, 1 = tenure 5–9 years	0.317	(0.465)
Dummy, 1 = tenure ≥10 years	0.247	(0.431)
Dummy, 1 = plant size ≤ 9	0.054	(0.225)
Dummy, 1 = plant size 10–99	0.224	(0.417)
Dummy, 1 = plant size 100–499	0.289	(0.453)
Dummy, 1 = plant size 500–999	0.122	(0.328)
Dummy, 1 = plant size 1000–9999	0.225	(0.418)
Dummy, 1 = plant size ≥10000	0.084	(0.277)
Dummy, 1 = food products	0.095	(0.293)
Dummy, 1 = textiles	0.028	(0.164)
Dummy, 1 = wood, paper products	0.057	(0.232)
Dummy, 1 = chemicals, plastic products	0.143	(0.350)
Dummy, 1 = metal products	0.201	(0.401)
Dummy, 1 = electronics	0.081	(0.272)
Dummy, 1 = machines, appliances	0.223	(0.417)
Dummy, 1 = vehicles	0.172	(0.377)
Δ net exports/wage bill in %	14.413	(57.996)
Δ ICT equipment in euros per worker	254.9	(271.7)
[C] Exposure to robots		
Δ robots per 1,000 workers	24.400	(40.119)
p10–p90 interval	[−2.721; 104.258]	
p25–p75 interval	[5.547; 26.052]	

Notes: Summary statistics of worker-level variables.
Sources: IFR, COMTRADE, EU KLEMS, and IEB V12.00.00, own calculations.

side variable, all controls that are constructed from that variable are left out in the respective specification.[47] This column shows that foreign and low-skilled workers

47. Earnings are not included in the regression on wages and vice versa. In the regressions for skill levels, none of the skill-level variables appear on the right-hand side.

TABLE 12. Balancing checks, worker level.

	Unconditional		Conditional	
	Coefficient	(SE)	Coefficient	(SE)
Manufacturing workers in 1994 (720,562 observations)				
100 × ln (base year earnings)	0.130	(0.076)	– 0.050	(0.047)
100 × ln (base year average wage)	12.085	(7.415)	– 6.145	(4.673)
100 × dummy, 1 = female	– 0.067	(0.042)	0.056	(0.041)
100 × dummy, 1 = foreign	0.027	(0.021)	0.040	(0.015)
Birth year	0.001	(0.001)	0.000	(0.001)
100 × dummy, 1 = low skilled	0.002	(0.034)	0.049	(0.024)
100 × dummy, 1 = medium skilled	0.023	(0.027)	– 0.017	(0.033)
100 × dummy, 1 = high skilled	– 0.025	(0.024)	– 0.032	(0.019)
Tenure (in years)	0.016	(0.004)	– 0.004	(0.001)
100 × ln (plant size)	2.614	(0.710)	1.684	(0.801)

Notes: Coefficients from 2SLS regressions of the respective individual characteristics on Δ robots per 1,000 workers (instrumented with robot installations across industries in other high-income countries). Control variables are log base year earnings and indicator variables for gender, foreign nationality, birth year, educational degree (three categories), tenure (three categories), plant size (six categories), manufacturing industry groups (eight categories), and 16 federal states, excluding the respective dependent variable. Earnings are not included in the regression on wages and vice versa. In the regressions for skills levels, none of the skill-level variables appear on the right-hand side. Standard errors clustered by 20 ISIC Rev. 4 industries in parentheses.

Sources: IFR, COMTRADE, EU KLEMS, and IEB V12.00.00, own calculations.

faced a slightly higher risk of automation, conditional on all other control variables. Plant size again is positively associated with automation exposure.

6.1.2. Results. Table 13 shows how workers have adjusted in response to the rise of industrial robots. In both panels, the coefficients listed in columns (2)–(5) sum up to the total effect in 1. Column (1) shows a small, positive impact on employment. From column (2) of panel A, it becomes clear that this positive effect is driven by increased employment at one's original plant, echoing the local labor market results from Table 7. The economic magnitude of this effect is large and around eleven times the size of the total employment effect. Quantitatively, it translates into an increase of 171 ($= 8.3594 \times [26.052 - 5.547]$) days of employment (over 20 years) in one's original plant for a worker starting out in the manufacturing industry at the 75th percentile of robot exposure relative to a worker from the 25th percentile. This number grows to 894 days when comparing the 90th and 10th percentiles.

Column (3) shows reduced transitions into other firms within the same industry.[48] This is consistent with our interpretation that workers are institutionally protected from displacement at one's own firm, but have a hard time finding other gainful employment within the same industry in the face of automation. Movements to other industries are reduced, as shown by columns (4) and (5).

48. Industry mobility is classified according to the 20 IFR industries, so at the level of robot adoption variation.

TABLE 13. Individual adjustment to robot exposure (employment).

[A] Industry mobility	(1) All employers	(2) Manufacturing	(3)	(4) Service sector	
Same employer		Yes	No	No	
Δ robots per 1,000 workers	1.4732	8.3594	− 4.4239	− 2.4623	
	(1.393)	(1.843)	(2.446)	(1.442)	
[B] Occupational mobility	(1) All jobs	(2) Same employer	(3)	(4) Other employer	(5)
Same occupational field		Yes	No	Yes	No
Δ robots per 1,000 workers	1.4732	3.4427	4.9168	− 6.0282	− 0.8580
	(1.393)	(1.590)	(1.360)	(1.619)	(0.738)

Notes: Based on 720,562 workers. 2SLS IV regressions, where German robot exposure is instrumented with robot installations across industries in other high-income countries. The outcome variable is 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 manufacturing sector (column (3)) or outside the manufacturing sector (column (4)), 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 (column (5)), respectively. Control variables are log base year earnings and indicator variables for gender, foreign nationality, birth year, educational degree (three categories), tenure (three categories), plant size (six categories), manufacturing industry groups (eight categories), and 16 federal states. Standard errors are clustered by 20 ISIC Rev. 4 industries in parentheses.

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

Panel B extends the analysis to individual adjustments across occupations, using the same classification of 54 occupational fields as in Section 5. Again, of high interest here is how adjustments within firms take place, given displacement by robots. Columns (2) and (3) examine this by splitting employment within spells at the original plant into time worked in the base year occupation and other occupations—consequently, the two estimates sum up to the coefficient in column (2) of panel A. Approximately two-thirds of the employment at the original plant effects are driven by employment in a different occupation. Both coefficients are statistically and economically significant. The decomposition can also be used 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 columns (3) and (5), which encompasses time spent in a different occupation. This gives $3.4427 - 6.0282 = -2.5855$ versus $4.9168 - 0.8580 = 4.0588$: In sum, automation has increased occupational mobility.

A popular narrative is that affected workers will have to be flexible and mobile across tasks and occupations to be "one step ahead" of labor-displacing technologies. Those sets of results first imply that workers in Germany already responded by

TABLE 14. Individual adjustment to robot exposure (earnings).

[A] Industry mobility	(1) All employers	(2) Manufacturing	(3)	(4) Service sector	
Same employer		Yes	No		
Δ robots per 1,000 workers	−0.4233	2.1093	−1.7920	−0.7406	
	(1.113)	(0.722)	(0.988)	(0.493)	
[B] Occupational mobility	(1) All jobs	(2) Same employer	(3)	(4) Other employer	(5)
Same occupational field		yes	no	yes	no
Δ robots per 1,000 workers	−0.4233	0.6128	1.4965	−2.1939	−0.3388
	(1.113)	(0.608)	(0.481)	(0.695)	(0.342)

Notes: Based on 720,562 workers. 2SLS IV regressions, where German robot exposure is instrumented with robot installations across industries in other high-income countries. The outcome variables are 100 × earnings (normalized by earnings in the base year) cumulated over the 20 years following the base year. For column (1), earnings are cumulated over all employment spells in the 20 years following the base year. Panel A: For column (2), earnings 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 manufacturing sector (column (3)) or outside the manufacturing sector (column (4)). 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 (4), and in a different occupation and workplace (column (5)). Control variables are log base year earnings and indicator variables for gender, foreign nationality, birth year, educational degree (three categories), tenure (three categories), plant size (six categories), manufacturing industry groups (eight categories), and 16 federal states. Standard errors clustered by 20 ISIC Rev. 4 industries in parentheses.

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

switching tasks to the rise of industrial robots. Second, the reassignment of workers to new tasks happens frequently within a worker's original firm.

Table 14 extends the analysis to earnings. These models are an important complement, since they paint a more complete picture about workers' labor market performance than looking at employment outcomes alone. Following Autor et al. (2014), to create the outcome variable, we accumulate all earnings over the whole period and divide them by average earnings in 1994. The regressions can hence be interpreted as difference-in-differences designs.

We begin in panel A by studying the effect on earnings from all sources. In contrast to the employment effects, one obtains a negative albeit very small and insignificant point estimate of −0.42. To interpret the coefficient, we calculate the quartile spread again, comparing an industry at the 75th percentile of robot exposure to an industry at the 25th percentile. The implied reduction in earnings (over the whole 20 year period and *not* per year) would be 8.7% of annual initial earnings, equivalent to around 3,357 euros in absolute terms for the average worker.

The coefficient vastly increases to 2.11, and turns highly statistically significant, for earnings at the original plant. This is offset, approximately equally across the different channels, by reduced earnings in other plants, industries, and the service sector, however.

To measure the role of occupational adjustments, panel B examines the effects of earnings across occupations. Did occupational switching help workers to respond to automation? Of particular interest are the coefficients in columns (2) and (3), which decompose the original plant earnings effect into impacts for the starting versus other occupations. The split is very close to 75%. Occupational (and presumably task) transitions within firms, hence, play a large role for the labor earnings impacts of automation. Columns (4) and (5) complete this picture. While earnings at other firms decrease in all occupations, the decrease is much more pronounced for a worker's original occupation.

In Appendix Table A.6, we also replicate our main results using lagged outcome variables, showing how individual employment and earnings outcomes from the pre-period 1978-1994 correlated with future robot exposure. Naturally, they are for the most part different workers from those used in the main analysis (i.e. those being in manufacturing in 1978). Total employment is positively correlated with future robot exposure already in the pre-period with a coefficient of similar magnitude. But, importantly, future robots do not correlate with increased employment at one's original employer. There are also no effects of future robot exposure on transitions within or out of manufacturing. Next, one can see that occupational transitions within the original employment spell are increased in the main analysis, but there is only weak evidence for this in the placebo. Finally, there is no evidence of a pre-trend in employment in the same occupation at a different firm, but a strong reduction in the main specification.[49]

6.2. Skill or Task Bias?

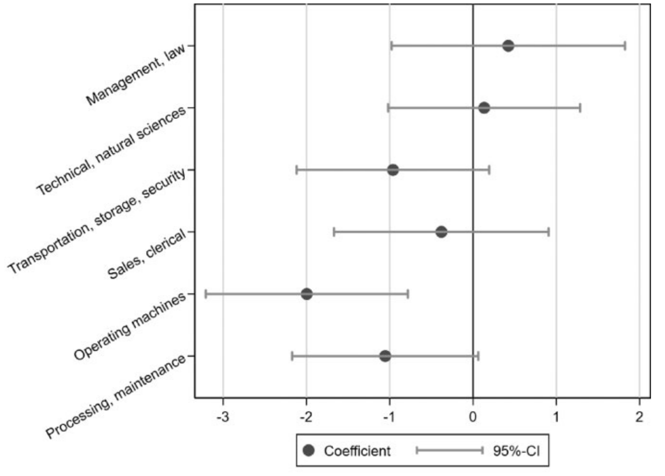
In the final step of our analysis, we explore heterogeneous impacts across occupations and skill groups. A very influential literature has investigated the *skill bias* of technological change (Katz and Murphy 1992). A newer literature has instead emphasized the *task bias* of technological developments.[50] This section presents new evidence on how the advancements of industrial robot technology have affected different occupation and task groups.

The results are contained in Figure 3, where we show the point estimates of interaction terms of the increase in robot exposure and 95% confidence intervals, based on clustered standard errors across the 20 IFR manufacturing industries, for different groups of workers. The regression models for earnings are the same as in the last section. So we include controls for skill categories, tenure categories, age, plant size categories, initial industry, and region—and the dependent variable is cumulative labor earnings.[51] Panel A differentiates six broad occupational categories that can be found

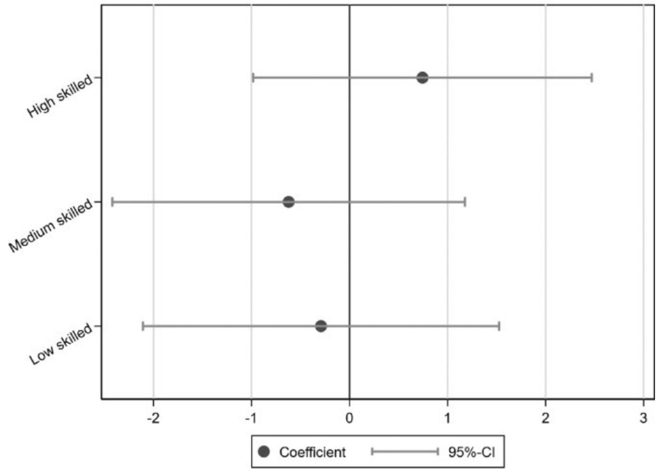
49. The Appendix table also contains the lagged outcome variable checks for earnings as the dependent variable.

50. See Acemoglu and Autor (2011) for a survey of both literatures and Autor and Dorn (2013) or Goos et al. (2014) for prominent empirical applications.

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



(a) Occupation: Heterogenous Impacts



(b) Education: Heterogenous Impacts

FIGURE 3. Heterogeneous earnings effects by occupation and education. The figures report the coefficients of interaction terms of Δ predicted robot exposure per 1,000 workers and dummies indicating the respective worker group. 2SLS IV regressions, where German robot exposure is instrumented with robot installations across industries in other high-income countries. The outcome variables are 100 × earnings (normalized by earnings in the base year) cumulated over the 20 years following the base year. In panel (a), occupations base on the definition of aggregate 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 (which 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. All regressions include the same full set of control variables as in Table 14. The confidence intervals are constructed from standard errors clustered by 20 ISIC Rev. 4 industries.

among the individual manufacturing workers in our sample. Panel B distinguishes three skill categories.

In panel A, for two occupation groups, the estimated impact is positive but small and not statistically significant at the conventional 5% level. These are managers and legal specialists, as well as occupations in the fields of technical science and natural science. This group encompasses, for example, all kinds of engineers as well as chemists. Automation through robots has arguably benefited these occupations, which are very highly skilled and heavily rely on cognitive-intensive tasks.

In the middle of the spectrum, with small and negative coefficients, one finds the point estimates for clerical/sales workers and a bundle of occupations, encompassing, for example, security and transportation workers. The common theme here is that the task set of those occupations is mostly non-routine and, hence, at least during the period we study, technically harder to automate. Interestingly, the rents from robots are seemingly passed on at higher rates to the set of skilled, technical occupations discussed in the preceding paragraph.

The next lines present the results for a set of occupations, which are suspected to be strongly exposed to replacement. Indeed, 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 this group. The point estimate here implies that a manufacturing worker at the third quartile of exposure sees an earnings reduction of around 41% of initial annual earnings, relative to a worker at the first quartile of exposure. A qualitatively similar finding is obtained for workers in processing and maintenance, but the effect size here is only a half of the effect for machine operators.

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 into 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 completed a vocational training degree. All other educational levels are subsumed as low skilled (i.e. high school graduates and high school dropouts). Completed apprenticeship is the typical profile for manufacturing workers in Germany, accounting for almost 75% of all individuals in the sample. A total of 16% are low skilled and 9% high skilled according to the classification.

The general takeaway here is that occupations represent a much more powerful cut of the data. Although for each of the three skill groups sample sizes are much larger than for the occupation split, confidence bands are much wider. The figure shows approximately equal negative point estimates for low- and medium-skilled workers. In contrast, college-educated workers see earnings increases.[52]

52. We also show results by initial earnings tercile in Appendix Figure A.2. In line with the skill results, automation impacts seem to be homogeneous.

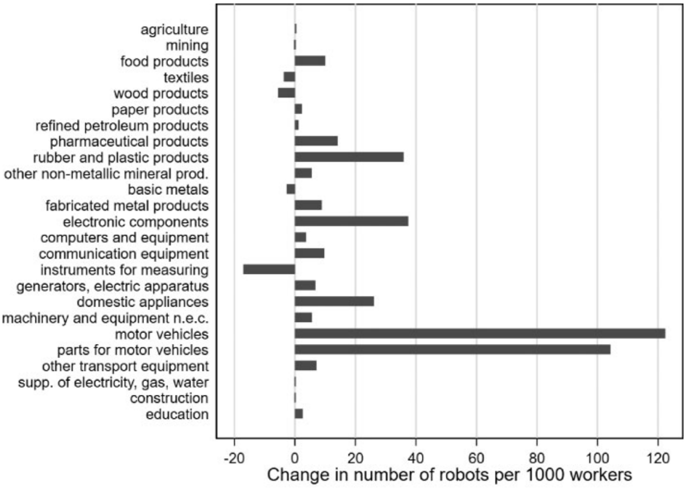
7. Conclusion

Many people foresee a further rise of robots, artificial intelligence, and other automation technologies, which can potentially disrupt labor markets. The small but growing empirical literature on this topic, most importantly Acemoglu and Restrepo (2019) and Graetz and Michaels (2018), has documented the (negative) effects of industrial robots on employment and wages and (positive) impacts on productivity. Nevertheless, there has been little work on studying the adjustment processes of labor markets and its main actors (workers and firms) in response to new automation technologies. This paper has focused on Germany, whose manufacturing sector is among the most robotized ones in the world. Administrative labor market data provide us with a rare longitudinal perspective on how workers and firms have responded to the increase in automation that happened between 1994 and 2014.

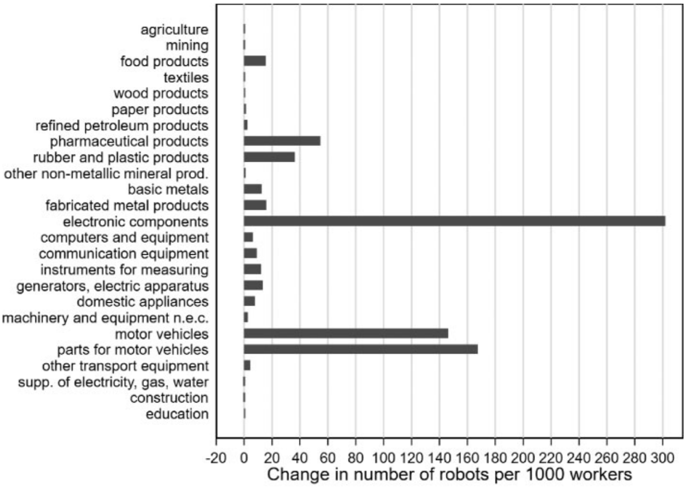
The results paint a nuanced picture. They also point to a strong interaction with labor market institutions. Relatively strong protections for incumbent workers shift the incidence of job displacement on young workers and labor market entrants. In order to retain workers, whose task sets were automated, we observe a notable transition into new occupations and tasks at the same workplace. We find several pieces of evidence that these transitions contribute significantly to soften the blow of automation. Encouragingly, the data suggest that skill upgrading goes hand-in-hand with those transitions. Such skill upgrading is also observed for young workers and labor market entrants.

Labor market institutions are an important mediator of the effects of technological advances. How the next generation of advances in artificial intelligence, machine learning, and new manufacturing technologies will impact workers will also depend on the future design of these institutions. We believe these questions should be investigated with more empirical evidence on the interaction, but also theoretical work incorporating institutional aspects and the frictions inherent in labor markets.

Appendix



(a) German robots.



(b) US robots.

FIGURE A.1. Industry-level distribution of increase in the number of robots. The figure displays the change in the number of robots per thousand workers by ISIC Rev. 4 industries (German Classification of Economic Activities, Edition 2008), for the period 1994–2014. Increase in the number of US robots in panel (b) is also normalized by German industry-level employment. Sources: International Federation of Robotics (IFR) and BHP 7514 v1, own calculations.

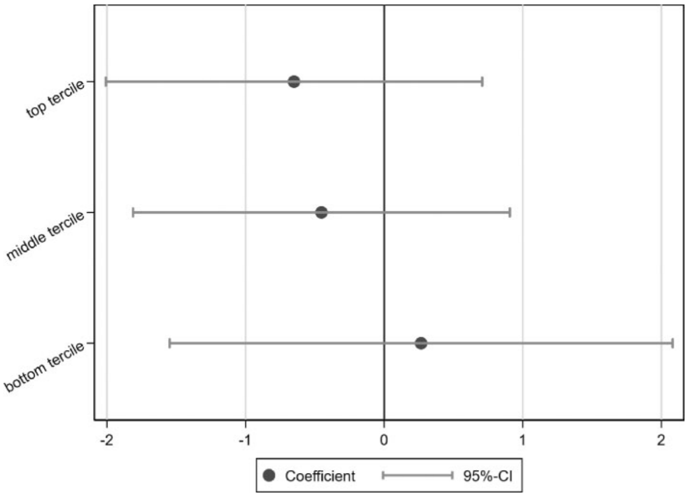


FIGURE A.2. Heterogeneous earnings effects by earnings tercile. The figures report the coefficients of interaction terms of Δ predicted robot exposure per 1,000 workers and dummies indicating the respective worker group. 2SLS IV regressions, where German robot exposure is instrumented with robot installations across industries in other high-income countries. The outcome variables are 100 × 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 in Table 14. The confidence intervals are constructed from standard errors clustered by 20 ISIC Rev. 4 industries.

TABLE A.1. Balancing tests for regional characteristics in 1978 and 1984.

	Dependent variable:				
	ln(residualized wage)	% unemployment rate	% high skilled	% unskilled	% manufacturing employment
	(1)	(2)	(3)	(4)	(5)
[A1] Unconditional, 1978					
Δ predicted robot exposure	0.2522	−0.0953	0.3009	0.0038	0.5793
	(0.040)	(0.069)	(0.057)	(0.011)	(0.071)
	[0.238]	[0.106]	[0.299]	[0.012]	[0.436]
R^2	0.078	0.014	0.080	−0.000	0.157
[A2] Conditional on full controls, 1978					
Δ predicted robot exposure	−0.0124	0.0047			
	(0.036)	(0.012)			
	[0.042]	[0.008]			
R^2	0.856	0.984			
[B1] Unconditional, 1984					
Δ predicted robot exposure	0.2545	0.2941	0.0029	−0.0317	0.6070
	(0.029)	(0.071)	(0.012)	(0.045)	(0.060)
	[0.246]	[0.286]	[0.018]	[0.049]	[0.451]
R^2	0.103	0.084	0.000	0.001	0.193
[B2] Conditional on full controls, 1984					
Δ predicted robot exposure	0.0445	−0.0252			
	(0.042)	(0.100)			
	[0.050]	[0.055]			
R^2	0.855	0.706			

Notes: $N = 325$ West German local labor market regions (*Landkreise und kreisfreie Staedte*, data for East Germany not available before 1990). 2SLS IV regressions, where German-predicted robot exposure is instrumented with robot installations across industries in other high-income countries. Each entry represents the coefficient of a regression of the respective variable on the change in predicted robot exposure per 1,000 workers between 1994 and 2014. The dependent variable in column (1) is the regional average residual of a worker-level regression of log wage on dummies for gender, education, and a squared polynomial of age. All specifications include a constant. In panel B, we control for broad region dummies [west (reference), north, south, or east], employment shares of female, foreign, age ≥50, medium skilled (with completed apprenticeship), and high skilled (with a university degree) workers relative to total employment (reference category: unskilled workers and with unknown education), broad industry shares [agriculture (reference), food products, consumer goods, industrial goods, capital goods, construction, consumer-related services, business-related services, and public sector), and the change in German net exports vis-à-vis China and 21 Eastern European countries (in 1,000 euros per worker), and the change in ICT equipment (in euros per worker), both between 1994 and 2014. Standard errors clustered at the level of 50 aggregate labor market regions in parentheses. Shift-share standard errors in brackets.

Sources: IFR, Comtrade, EU KLEMS, BEH V10.01.00, and BHP 7514 v1, own calculations.

TABLE A.2. Robustness checks.

	Employment			Average wages		
	(1) Total	(2) Manufacturing	(3) Non-manufacturing	(4) Total	(5) Manufacturing	(6) Non-manufacturing
Baseline results, 1994–2014						
Δ predicted robot exposure	0.0686	−0.4663	0.7243	−0.0402	−0.1116	0.0929
	(0.137)	(0.160)	(0.327)	(0.045)	(0.066)	(0.042)
	[0.177]	[0.293]	[0.458]	[0.031]	[0.079]	[0.064]
N	402	402	402	7,235	6,896	7,231
[A1] Pre-trends, 1984–1994						
Δ predicted robot exposure	0.2334	0.3532	0.2135	0.0179	−0.0273	0.0540
	(0.185)	(0.223)	(0.158)	(0.028)	(0.031)	(0.034)
	[0.133]	[0.229]	[0.116]	[0.025]	[0.022]	[0.045]
N	325	325	325	5,828	5,224	5,810
[A2] Include lagged dependent outcome (to check for mean reversion), 1984–1994						
Δ predicted robot exposure	−0.0600	−0.4550	0.5409	−0.0397	−0.1787	0.1237
	(0.179)	(0.171)	(0.354)	(0.043)	(0.062)	(0.036)
	[0.136]	[0.247]	[0.403]	[0.029]	[0.074]	[0.077]
Outcome in 1984–1994	0.3778	0.2945	0.3632	−0.2133	−0.1741	−0.2347
	(0.108)	(0.090)	(0.118)	(0.032)	(0.040)	(0.024)
N	325	325	325	5,828	5,224	5,810
[B] 1994–2007						
Δ predicted robot exposure	0.2004	−0.1328	0.3985	0.0176	−0.0175	0.0822
	(0.118)	(0.223)	(0.266)	(0.043)	(0.087)	(0.055)
	[0.143]	[0.270]	[0.202]	[0.040]	[0.109]	[0.057]
N	402	402	402	7,235	6,897	7,231

TABLE A.2. (Continued)

	Employment			Average wages		
	(1) Total	(2) Manufacturing	(3) Non-manufacturing	(4) Total	(5) Manufacturing	(6) Non-manufacturing
[C] Include “marginal” workers						
Δ predicted robot exposure	0.0347	−0.4736	0.6934	−0.0402	−0.1116	0.0929
	(0.144)	(0.162)	(0.336)	(0.045)	(0.066)	(0.042)
	[0.176]	[0.297]	[0.449]	[0.031]	[0.079]	[0.064]
N	402	402	402	7,235	6,896	7,231
[D] West Germany						
Δ predicted robot exposure	0.0044	−0.4619	0.6849	−0.0466	−0.1618	0.1078
	(0.154)	(0.170)	(0.330)	(0.044)	(0.064)	(0.041)
	[0.138]	[0.258]	[0.416]	[0.031]	[0.077]	[0.069]
N	325	325	325	5,849	5,545	5,845
[E] Federal state dummies						
Δ predicted robot exposure	0.0593	−0.4472	0.7155	−0.0481	−0.1480	0.0987
	(0.147)	(0.165)	(0.331)	(0.046)	(0.067)	(0.042)
	[0.174]	[0.282]	[0.427]	[0.032]	[0.085]	[0.062]
N	402	402	402	7,235	6,896	7,231
[F1] 258 local labor markets						
Δ predicted robot exposure	−0.1074	−0.6404	0.5218	−0.0431	−0.0940	0.1026
	(0.153)	(0.293)	(0.214)	(0.064)	(0.071)	(0.054)
	[0.168]	[0.441]	[0.291]	[0.036]	[0.093]	[0.070]
N	258	258	258	4,643	4,489	4,643

TABLE A.2. (Continued)

	Employment			Average wages		
	(1) Total	(2) Manufacturing	(3) Non-manufacturing	(4) Total	(5) Manufacturing	(6) Non-manufacturing
[F2] 141 local labor markets						
Δ predicted robot exposure	0.0668	−0.4073	0.4271	−0.0259	0.0164	0.1210
	(0.301)	(0.409)	(0.340)	(0.064)	(0.108)	(0.066)
	[0.308]	[0.439]	[0.408]	[0.054]	[0.130]	[0.083]
N	141	141	141	2,538	2,489	2,538
[G] Split automotive and other manufacturing in treatment variables						
Δ predicted robot exposure	0.0828	−0.4372	0.7148	−0.0414	−0.1152	0.0997
automobile industry	(0.130)	(0.152)	(0.308)	(0.045)	(0.067)	(0.041)
	[0.232]	[0.332]	[0.452]	[0.031]	[0.078]	[0.049]
Δ predicted robot exposure	−0.0940	−0.4729	0.0736	−0.0738	−0.1083	−0.0584
other industries	(0.275)	(0.366)	(0.358)	(0.066)	(0.115)	(0.055)
	[0.215]	[0.535]	[0.295]	[0.071]	[0.123]	[0.071]
N	402	402	402	7,235	6,896	7,231
[H] Split automotive and other manufacturing in outcome variables						
	Total manufacturing	Car manufacturing	Other manufacturing	Total manufacturing	Car manufacturing	Other manufacturing
Δ predicted robot exposure	−0.4663	−5.4236	−0.5796	−0.1122	−0.2943	−0.1461
	(0.160)	(21.910)	(0.188)	(0.067)	(0.139)	(0.087)
	[0.293]	[20.667]	[0.343]	[0.078]	[0.139]	[0.084]
N	402	382	402	6,896	2,830	6,866

Notes: This table presents modifications of the baseline specifications for employment and average wages as of columns (1), (4), and (7) of Table 4. The dependent variables are employment growth rates (columns (1)–(3)) and log-differences in average wages (columns (4)–(6)). Standard errors clustered at the level of 50 aggregate labor market regions in parentheses. Shift-share standard errors in brackets.

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

TABLE A.3. Robots and skill share of people younger than 40.

	Dependent variable:			
	100 × Δ Share of workers with		Task intensity	
	university degree	apprenticeship degree	Abstract	Routine
	(1)	(2)	(3)	(4)
Δ predicted robot exposure	0.1111	− 0.1106	0.0809	− 0.0601
	(0.055)	(0.040)	(0.035)	(0.019)
	[0.055]	[0.062]	[0.042]	[0.039]

Notes: In this table, we analyze the effect of robots on the occupational quality of younger workers. The estimates are based on $N = 402$ local labor market regions (*Landkreise und kreisfreie Staedte*). The dependent variable is the change in various measures for occupation quality of workers 40 years old or less between 1994 and 2014: share of workers with a university degree (column (1)), share of workers with an apprenticeship degree (column (2)), average abstract task intensity (column (3)), and average routine task intensity (column (4)). In all regressions, the variable of interest is the change in robot predicted exposure per 1,000 workers between 1994 and 2014. The regressions include the full set of control variables as in column (4) of Table 3. Standard errors clustered at the level of 50 aggregate labor market regions in parentheses. Shift-share standard errors in brackets.

Sources: IFR, COMTRADE, EU KLEMS, BEH V10.01.00, and BHP 7514 v1, own calculations.

TABLE A.4. Disaggregating the service sector.

	Dependent variable: 100 × 2014 employment in industry/total non-manufacturing employment in 1994					
	(1)	(2)	(3)	(4)	(5)	(6)
[A] Broad industry groups						
	Non-manufacturing	Aggregate/ mining	Construction	Consumer service	Business service	Public sector
Δ predicted robot exposure	0.7243	0.0196	− 0.0218	0.0510	0.6378	0.0309
	(0.327)	(0.020)	(0.027)	(0.062)	(0.270)	(0.039)
	[0.458]	[0.027]	[0.033]	[0.053]	[0.366]	[0.055]

Notes: $N = 402$. In this table, the employment growth rate in the non-manufacturing sector is the contributions of different industries. The dependent variables are constructed as 100 × the number of employees in 2014 in each industry relative to total non-manufacturing employment in 1994. Consequently, the coefficients in each panel sum up to the coefficient in column 7 of panel A, Table 4. In all regressions, the variable of interest is the change in predicted robot exposure per 1,000 workers between 1994 and 2014. The regressions include the full set of control variables as in column (4) of Table 3. Standard errors clustered at the level of 50 aggregate labor market regions in parentheses. Shift-share standard errors in brackets.

Sources: IFR, COMTRADE, EU KLEMS, BEH V10.01.00, and BHP 7514 v1, own calculations.

TABLE A.5. Change in average age.

	Dependent variable: Change in average age between 1994 and 2014	
	Manufacturing (1)	Non-manufacturing (2)
Δ predicted robot exposure	0.1096	−2.4257
	(0.810)	(1.225)
	[1.012]	[1.721]

Notes: $N = 402$. The dependent variable is the change in the average age of workers in 1994 versus 2014. In all regressions, the variable of interest is the change in predicted robot exposure per 1,000 workers between 1994 and 2014. The regressions include the full set of control variables as in column (4) of Table 3. Standard errors clustered at the level of 50 aggregate labor market regions in parentheses. Shift-share standard errors in brackets.

Sources: IFR, COMTRADE, EU KLEMS, BEH V10.01.00, and BHP 7514 v1, own calculations.

TABLE A.6. Pre-trends for individual adjustment to robot exposure.

[A] Industry mobility	(1) All employers	(2) Manufacturing	(3)	(4) Service sector	
Same employer		Yes	No	No	
[A1] Employment					
Δ robots per 1,000 workers	1.9012	0.5052	2.0827	– 0.6867	
	(0.553)	(2.108)	(1.603)	(1.000)	
[A2] Earnings					
Δ robots per 1,000 workers	0.5034	0.0173	0.6785	– 0.1923	
	(0.417)	(0.810)	(0.533)	(0.302)	
[B] Occupational mobility	(1) All jobs	(2) Same employer	(3)	(4) Other employer	(5)
Same occupational field		Yes	No	Yes	No
[B1] Employment					
Δ robots per 1,000 workers	1.9012	– 0.8999	1.4051	0.1293	1.2668
	(0.553)	(2.064)	(0.779)	(1.284)	(0.669)
[B2] Earnings					
Δ robots per 1,000 workers	0.5034	– 0.5178	0.5351	0.0210	0.4651
	(0.417)	(0.741)	(0.301)	(0.391)	(0.221)

Notes: Based on 770,360 workers. 2SLS IV regressions, where German robot exposure is instrumented with robot installations across industries in other high-income countries. The outcome variables are days of employment (panels A1 and B1) and 100 × earnings (normalized by earnings in the base year, panels A2 and B2), each cumulated over the 16 years following the base year 1978 and scaled to conform to a 20-year period. For column (1), employment days are cumulated over all employment spells in the 20 years following the base year. Panel A: For column (2), the outcomes 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 manufacturing sector (column (3)) or outside the manufacturing sector (column (4)). 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 (column (5)). Control variables are log base year earnings and indicator variables for gender, foreign nationality, birth year, educational degree (three categories), tenure (three categories), plant size (six categories), manufacturing industry groups (eight categories), and 16 federal states. Standard errors are clustered by 20 ISIC Rev. 4 industries in parentheses.

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

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Supplementary Data

Supplementary data are available at *JEEA* online.