Robots and Firm Investment

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Abstract

Using cross-country and German administrative data on robotization, we show that the impact of robots on firms has been limited. First, investment in robots is small and highly concentrated in a few industries, representing less than 0.30% of aggregate expenditures on equipment. Second, robotization does not grow as rapidly as IT did in the past, and current growth is driven by catching-up of developing countries. Third, firms invest in robots when they face difficulties in finding workers and subsequently increase employment after the investment. The total employment effect in exposed industries and regions is negative, but modest in magnitude.

Keywords: automation, robots, technology adoption, labor scarcity, corporate investment
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I Introduction

Commenting on the disparity between measures of investment in information technology and output productivity, Robert Solow famously quipped at the beginning of the information technology (IT) driven technological revolution that "you can see the computer age everywhere but in the productivity statistics" (Solow, 1987). More than 30 years later, another technological revolution seems imminent. In what is called "the fourth industrial revolution," attention is devoted to automation and industrial robots, which according to prominent studies have already had a significant impact on the economy. Graetz and Michaels (2018) find that robots have brought productivity increases comparable with past improvements caused by the steam engine and IT, while Acemoglu and Restrepo (2020) and Acemoglu (2021) argue that robots are a key driver of worker displacement in recent decades. These effects, combined with robots' compounded annual growth rate of 11 percent in 2014-19, suggest that robots may significantly transform labor markets and the corporate sector, leading to massive worker displacement and a significant increase in firms' capital intensity.

This paper shows that despite these omnipresent predictions, this time it is hard to find robots not only in aggregate productivity statistics (Brynjolfsson et al., 2019) but also anywhere else. Using cross-country data on robotization, we show that investment in robots, though increasing, remains a small share of total investment. Use of robots is almost zero outside of manufacturing, and even within manufacturing, robotization is very low for all but a few poster-child industries, such as automotive. Crucially, there is no evidence that this is picture is likely to change in the near future. A decade after Solow's observation, IT investment exploded and the economic impact of IT was evident, but the same explosive growth pattern is not visible in robotics. Investment in information and communication technoloy (ICT) equipment, software, and other R&D expenditures dwarf investment in robotics and current trends do not suggest a reversal. Recent increases in numbers of robots sold are driven mostly by catching-up of manufacturing in China and other developing nations rather than by increasing robotization in developed countries.

These findings suggest that predictions of a transformative impact of robots, in particular of large employment losses driven by robotization, may be unwarranted. Yet measurement and identification concerns make it difficult to empirically assess these predictions (Raj and Seamans, 2019). To address these challenges, we combine industry-level measures of robotization with firm-level measures of automation adoption to study the link between labor markets and automation in Germany. We first show that firms adopting robots are increasing employment, which signals that the direct displacement effect is limited. Even so, the displacement may be indirect, occuring among non adopters in the same industry. We shed light on this effect using a difference-in-difference framework, comparing high- and low-adopting industries and local areas. We find some evidence that robotization reduces employment, but, consistent with previous findings about the limited prevalence of robots, the magnitude of the employment effect is modest. Back-of-envelope calculations suggest that in Germany employment growth in regions and industries with high adoption of robots is lower, but only by ~0.03 percent per year. Moreover, we argue that to understand the economic consequences of automation, one must also study how labor market conditions affect firms' decisions to invest in automation technologies. Using various approaches, we demonstrate that German firms invest in automation largely to alleviate labor scarcity. Hence, even the small observed reduction of employment may have little to do with actual worker displacement and is more likely to happen in well-functioning labor markets.

Our analysis is based on two data sets and empirical settings, which allows us to overcome measurement challenges that are common in this area of research. First, we combine a cross-country industry-level measure of robotization from the International Federation of Robotics (IFR) with firm-level financial data from Amadeus. We use these data sets to estimate the prevalence of robotics across industries and countries and its importance in firms' capital expenditures. Second, we use administrative data from the institute for Employment Research (IAB) of the German Employment Agency, which include firm-level measures of automation and detailed employment data. We use these data to study how automation affects firms' employment and how investment in automation responds to labor market conditions.

We start by evaluating the impact of robotization on firms' capital expenditures using cross-country data. The magnitude of robot-related investment is small both in absolute terms, and in comparison to other similar types of investment. We rely on the reports of the numbers of robots installed combined with estimates of average price of robots, as well as on a regression-based approach that attempts to estimate the share of robots in firms' capital investment. Both approaches lead to estimates that are of the same order of magnitude and suggest that even after additional supplementary investment is included, robots do not account for a significant share of firm-level investment. In manufacturing, its share in capital expenditure is almost 2 percent, while in the whole economy it is close to 0.3 percent. Annual robotics-related expenditures amount to roughly $40/worker.

It is of course possible that robots are still in their infancy and that their dynamic growth will soon make them much more prevalent. The data, however, offers limited support for this hypothesis. Studying the evolution of the number of robots around the world, we show that recent increases in robotization are driven not by accelerating automation in developed countries, but rather by catching-up of developing nations. In the West, robotization grows at a stable and moderate pace.[1] Moreover, robots remain highly concentrated in selected industries, especially automotive

[1] Naturally, robots in developing countries are no less important than those in developed countries. However, the distinction is crucial because it suggests that recent acceleration in robotization is not a shift in technology frontier

manufacturing, just as they were a couple of decades ago. Using historical data on investment in IT equipment, we contrast recent developments in robotics with the evolution of IT investment in the past. Robots in 1995 accounted for a larger share of firm investment than IT equipment in 1980. Yet investment in IT was exploding in the late 1980s and early 1990s , and by the year 2000 it constituted more than 1.5 percent of total capital expenditures with continued dynamic growth. This explosive growth is not visible for robotics. In 2015, 20 years after the base year, investment in robotics remains an order of magnitude lower than IT investment in 2000. In addition, whereas investment in IT equipment generated sizable spending on software and databases, the importance of a similar complementary investment seems smaller for robots.

The results from our cross-country analysis show that industrial robots do not account for a significant share of capital stock. Yet data limitations and identification challenges prevent us from using the cross-country setting to credibly examine one of the most pressing questions in the automation debate: the relation between robots and labor markets. To do that, we turn to firm-level data from Germany and study two questions: How does automation affect employment, and how does labor scarcity affect firms' investment in automation?

We study the evolution of employment in firms directly adopting robots and in industries and areas most exposed to automation. Our analysis shows that firms adopting robots are also significantly increasing employment, and hence any direct displacement effect appears to be limited. It is possible, however, that the negative employment effects documented in the existing literature are driven by employment declines in other firms. To test that, we employ difference-in-difference specification across industries and local areas. We exploit industry-level variation in robotization intensity and area-level variation in the level of technology adoption, complementing the existing literature that relies only on the industry-level variation. We do find some evidence for negative employment effects of robotization. Yet the magnitudes of these effects are modest. Back-of-envelope calculations suggest that over the 10-year period between 2005 and 2015, robotization contributed to a ~0.3 percent slower employment growth in industries and regions with higher exposure. This estimate is obtained based on a difference-in-difference framework and hence may reflect the growth of non-adopting industries.

The modest employment decline caused by robotization would be even less concerning if it did not involve worker displacement, but rather allowed firms to grow even if they could not find employees. To analyze whether this is so, we study the impact of labor scarcity on automation adoption. We regress firm-level measures of investment in automation from the IAB survey of German establishments on several measures of difficulties in finding workers. These measures combine firms' survey responses with actual hiring decisions and are strongly correlated with local

that leads to using robots in new industries and settings that were not automated before. Instead, it is an expansion of robots into new countries, but within the same activities that they performed earlier.

unemployment rates. The results show that firms have a higher adoption of automation when they face difficulties in finding suitable workers.[2] This association is robust to using local labor scarcity and limiting the analysis to exporters in attempt to alleviate some of the endogeneity concerns about local demand. The results suggest that robotization may help firms alleviate labor scarcity problems rather than lead to a displacement of existing workers.

Overall, our results suggest that the impact of robots on firm balance sheets and on labor markets is likely to be limited. They do not imply, however, that technological change as a whole is not significantly affecting the economy. Instead, we argue that other modern technologies that are more widespread than robots will have more important economic consequences. In particular, digital technologies such as advances in data processing, cloud computing, and network communication – while less spectacular – can be more important drivers of labor market changes. In the last part of the paper we document that investment in these technologies is much larger and more widespread than investment in robots, even in automotive manufacturing. At the same time, we demonstrate that the implications of this investment are not necessarily the same as those of robots and automation. Employing the methodology analogous to the one used to study the relation between automation and labor markets, we analyze the extent to which digital technologies substitute and complement labor. Although some of these technologies substitute workers, just as robots do, their complementarity effect appears to be stronger and dominant in industries in which digital technologies are commonly adopted.

Several recent papers higlight the sizable impact of robots on rising aggregate productivity (Graetz and Michaels, 2018) and displacing workers (Acemoglu and Restrepo, 2020). Other studies argue that the link between automation and employment is more nuanced: robots can cause large displacement of production workers but employment may grow in other occupations (Dauth et al., 2021; Humlum, 2019); and while employment effects of robots and other narrowly defined automation technologies may be negative, more broadly defined technology has had positive impact on employment in the recent past (Aghion et al., 2022; Hirvonen et al., 2021). All these findings are consistent with a general theoretical framework, in which technology can have both *displacement* and *productivity* effects, and the magnitudes of these effects vary by the type of worker (Acemoglu and Restrepo, 2018; Agrawal et al., 2019). Nonetheless, one of the key concerns in the debate about technological change is that the *displacement effect* has became much stronger in the recent years, as showcased by robotization, and that its importance continues to

[2] Labor scarcity can be manifested either through a higher price of labor or through difficulties in finding suitable workers. In a perfectly competitive labor market, the price of labor should adjust. However, because of many labor market rigidities (e.g., industry-wide and firm-wide wage agreements), the German labor market is not perfectly competitive, and labor scarcity is often manifested by firms' inability to find suitable workers. Nevertheless, the economic intuition remains the same regardless of whether scarcity affects prices or the ability to find workers, since we can also interpret the latter as high labor cost (e.g., high search cost).

grow rapidly.[3] Our findings speak to that concern in two ways. Our first contribution is quantifying the importance of robots in firms' investment and contrasting it with other technologies. We show that current magnitude of robot investment is small both in absolute terms and in comparison to other digital technologies, and that recent trends in developed countries do not suggest that robotization is rapidly accelerating. These findings suggest that the economic impact of robots is likely smaller than often presented.[4] Second, using data from Germany, which offers a good setting to measure and identify employment effects of robots in a novel way, we show that employment effects of robots are negative but small, consistent with their low prevalence.[5] Robots are, therefore, a good laboratory for studying the effects of labor-displacing technology, but their empirical revalence for the economy as a whole is limited.

Our paper also highlights the importance of studying patterns of firms' investment in technology adoption. We find that robot adopters are generally more productive and increase employment following the adoption (consistent with Koch et al. (2021)), and that investment in automation is higher in places with a shortage of labor. Hence, robots may allow firms to grow even if they have difficulties filling vacant positions and may not necessarily lead to a displacement of existing workers.[6]. At the same time, our results improve our understanding of the determinants of firm investment and its implications, in particular in new technologies (Babina et al., 2022), complementing the large literature on the role of financial constraints (Fazzari et al., 1988) and demonstrating that firm investment is also shaped by labor constraints.

The rest of the paper is organized as follows. In section 2 we describe the data sets used in the analysis. Section 3 analyzes the magnitudes and patterns in robots investment using cross-country data. In section 4, we turn to analyzing the interaction of robots and labor markets using data from Germany. In section 5, we contrast robots with other digital technologies. Section 6 concludes.

[3]The extent to which that concern is valid also influences the current applicability of findings from a large literature on information and communication technologies at the end of the twentieth century (Brynjolfsson and Hitt, 2000; Bresnahan et al., 2002; Autor et al., 2003; Autor, 2019) and various older technologies (Doms et al., 1997; Lewis, 2011). On the other hand, historical instances of technologies that had a clear displacement effects may be useful laboratories for learning about potential consequences of labor-displacing technology today (Clemens et al., 2018; Feigenbaum and Gross, 2020).

[4]The skepticism about the large potential productivity increases coming from robotics, among other technologies, is also voiced by Gordon (2017).

[5]Even though they are identified in a different way (based on both regional and industry-level variation, as opposed to industry-level only), our estimates in per-robot terms are of similar order of magnitude as those in some existing studies, e.g. Acemoglu and Restrepo (2020). However, we highlight that the aggregate impact of robots on the whole economy is small.

[6]Moreover, even if the displacement happens, it is more likely to occur in areas where jobs are abundant. These findings are particularly important in the context of an aging labor force (Abeliansky and Prettner, 2023; Acemoglu and Restrepo, 2022a).

II Data and Measures of Technology

We provide a brief description of the data and document basic facts about the key variables analyzed in the two empirical settings of the paper.

A Cross-Country Analysis

In the first part of the paper, we combine firm-level financial data from Amadeus with measures of robotization by industry, country, and year. The robotics data are novel, and are introduced to economic literature by Graetz and Michaels (2018). The data comes from the International Federation of Robotics (IFR, see IFR (2017)), which collects sales reports from robot manufacturers and covers over 90 percent of the global robotics market. The manufacturers, which are located mostly in Japan, Switzerland, or Germany, report the number of robots sold at the country-industry-year level, and the flow in each year is then used to calculate the stock of robots in operation. Most of the 26 industries for which the data are available correspond to industries defined on a two digit level in standard classifications such as NACE, although within some manufacturing industries, such as automotive, the classification is finer, whereas outside of manufacturing it is much coarser. Some robots in the reports cannot be assigned to a specific industry. We allocate unclassified robots to industries based on the empirical distribution of classified robots.

The data begin in 1993 for a few European countries and end in 2016. Over the years, the coverage of different markets has significantly improved. Industry-level data for North America are available since 2004. The IFR does not report information of robot prices in the same way as it does for units sold. Nonetheless, it does provide an approximation for average robot price, which we use to calculate the value of investment in robots.

In the data, a robot is defined as "an automatically controlled, reprogrammable, and multipurpose (machine)," which means that it is fully autonomous and can perform several tasks. According to this definition, a typical robot is a machine used in car manufacturing, capable of painting, assembling, or labeling different parts. This definition excludes several technological inventions that require a human operator (e.g., a crane) or that have a single purpose and cannot be flexibly reprogrammed (e.g., an elevator). Further discussion of the IFR data is provided in the recent papers in the automation literature which also used the data, such as Graetz and Michaels (2018) and Acemoglu and Restrepo (2020).

We supplement the IFR data with additional data sources. Among them, the EU KLEMS database (Jäger, 2016) contains information on employment and total capital formation, as well as several investment categories, by country-industry-year. It covers European Union countries and the United States, and its data coverage is best for the period 1995-2015, although some variables go as far back as 1970s. We use employment hours to calculate per-full-time-equivalent-worker measures of robotization.

For most figures, we merge IFR and EU KLEMS data to meaningfully compute robot density. For country-specific results in the aggregate analysis of robotization (Section III), we include nine developed countries for which all variables are available in both data sources: Austria, Germany, Denmark, Finland, France, Italy, Netherlands, Sweden, and the United States. Merging IFR and EU KLEMS data requires harmonizing their industry classification, which we do by aggregating selected industries. We therefore analyze 14 two digit industries: agriculture; mining; several manufacturing groups: food, beverage, tobacco; textiles and leather; wood and paper; chemicals; metal; electrical and electronic; machinery; automotive; and other manufacturing; construction; utilities; and research and development.

We combine IFR and EU KLEMS data with firm-level data from Amadeus and use data for almost 55,000 "large" or "very large" manufacturing firms from 23 European countries.[7] The data comprise an unbalanced panel with each firm having at most 10 observations; for most firms, these are the most recent available years that can be merged to robots' data, that is 2008-2016.

Table 1 presents summary statistics of the main variables from IFR, EU KLEMS, and Amadeus data sets. We show the number of total robots shipped as well as the number of robots per 1,000 workers in the whole economy and in several industry groups. Since our sample of industries is skewed toward manufacturing, a simple average across industries that are included in the data leads to robotization values that are higher than those of the aggregate economy. Although 6.11 new robots per 1,000 workers are installed in a typical year in automotive manufacturing, this number is only 0.24 for the whole economy. The implied expenditure of investment in robots per worker is hence about €11 per year, a very low figure compared to investment in software and data (€1,722/worker) or ICT equipment (€848/worker).

B Firm-Level Analysis within Germany

In the second part of the paper, we rely on data from the Institute for Employment Research (IAB) of the German Employment Agency, which administers several data sets based on social security records and other complementary data collection efforts.

The two main administrative data sets we use are the IAB Establishment Panel (IAB-EP) and the Establishment History Panel (BHP).[8] IAB-EP is a yearly survey of stratified random sample of

[7] We include more countries than in the aggregate analysis, because firm-level regressions do not use measures of other types of investment, such as investment in IT equipment, that we analyze at the country level and that are available in EU KLEMS for only a subset of countries.

[8] More precisely, the study uses the following data sets: weakly anonymous Establishment History Panel, 1975-2016, DOI: 10.5164/IAB.BHP7516.de.en.v1; IAB Establishment Panel (years 1993-2017), DOI: 10.5164/IAB.IABBP9317.de.en.v1; and Sample of Integrated Labor Market Biographies (years 1975-2014). Data

German establishments. The data cover over 16,000 establishments from all industries and span the years 1993-2019. The IAB-EP data contain rich information about firms' personnel, investment, business policies, research and development, and other areas of firm operations. Although some variables are available in every year, others are present for only a subset of years. In particular, our main automation and digitization measures are included in the 2016 and 2017 waves of the panel, while the count of industrial robots is included only in 2019. The survey is merged with administrative personnel records, which contain information about firms' workforce size and structure.

The BHP is a large, firm-level data set containing information for a 50 percent random sample of all German establishments. It covers over 2 million establishments during the years 1976-2016 and contains yearly snapshots of firms' personnel structure and wage information, based on Social Security records. The data include establishment location and industry classification.

Our measures of automation come from three questions included in three waves of the IAB-EP: 2016, 2017, and 2019. In 2016, the data contained an extra set of questions asking firms about "Automation and Digitization" technologies that were defined as "autonomous robotics, smart factories, Internet of Things, big data analytics, cloud computing, online platforms, among other technologies." Respondents were asked to assess familiarity with and the potential and current adoption of the technologies on a scale from 1 to 10 (with an option of "Difficult to say"): (A) how intensively has the establishment dealt with this topic so far? (B) what potential is there for application of such technologies in the establishment? and (C) how well is the establishment equipped with these technologies compared to other establishments in the sector?

In 2017, the IAB-EP did not include the same questions, but it added other measures of automation and digitization. In particular, firms were asked whether they use different classes of technology. These technologies included "program controlled means of production requiring indirect handling by humans (industrial robots, CNC machines)," as well as other digital technologies, including data processing and network technologies. It is worth noting that the binary measure directly captures the usage of robots but at the same time reflects the adoption of older, not necessarily autonomous technologies with similar purpose as robotics, such as CNC machines.

In 2019, the survey asked firms about the number of robots they currently use, and have used in each of the past five years. The robot was specified as "any automated machine with multiple axis or directions of movement, programmed to perform specific tasks (partially) without human intervention," and it was explicitly noted that tools such as CNC machines should not be counted. As a result, a much smaller number of firms reported usage of robots: whereas in 2017, ~ 15

access was provided via on-site use at the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB) and remote data access. Documentation for the data are contained in Ellguth and Kohaut (2014) and Schmucker et al. (2018).

percent reported using a robot, in 2019 the 95th percentile of number of robots used was zero, and the 99th percentile was 4. At the same time, the mean was above 1, due to the very high number of robots used in a small number of establishments.

Our main measure of the technology is the answer to part C of the intensity of automation adoption question, which – importantly for our employment effects analysis – is likely the best way to capture spatial factors affecting the adoption of technology. In the firm-level analysis, we further interact this measure with usage of robots based on the indicators for 2017, and we use 2019 measures of the number of robots per worker to demonstrate that the overall patterns we observe for more broadly defined automation are the same as the patterns estimated for robots only.

We perform an initial analysis of the quality of firm-level measures. For the 2016 adoption intensity measure, asking for relative assessment makes it easier for respondents to give a meaningful answer by providing some reference point. Panel A of table 2 demonstrates that firms do not overshoot their assessment of adoption: the median response is 6, and the average response is 5.7. Appendix figure A.4 shows that this remains true across most sectors and in particular for manufacturing, which is the major adopter of robotization. Summary statistics of all measures are presented in table 2.

Employment change at the area-industry level is computed by aggregating employment records of 50 percent random sample of all German firms from the BHP data set. On average, each industry-area cell has over 3,000 workers. The size of the German workforce increased between 2005 and 2015, with median area-industry cell increasing employment by 14 percent, but there is substantial variation in employment changes across industries and local areas.

The part of our analysis that studies how labor market conditions affect technology adoption uses labor scarcity measure based on firms' response to the question of if they are facing "difficulties in finding required workers on the labor market." The measures are correlated with local unemployment rate but at the same time provide a unique firm-level source of variation in the degree of being affected by labor market tightness.

C Validation of Technology Measures

To cross-validate technology measures, figure 1 presents the relation of industry-level measures of robotization and digitization and survey-based measure of familiarity with automation and digiti-

[9] A survey conducted by the World Economic Forum (WEF, 2018) shows that a relatively small share of technology-adopting firms expect to be using robots. Among 19 technology classes included in the survey, different types of robots occupy four out of six bottom spots when technologies are ranked according to the probability of adoption in near future. The list is led by big data analytics, followed by app- and web-enabled markets, the internet of things, machine learning, and cloud computing. Similar findings are also obtained in a larger and more systematic attempt of measuring technology by US Census, which is described in Zolas et al. (2021) – robots are adopted by 1.4-1.9% of US firms only, and other modern technologies are much more popular.

zation. Although the adoption measure is relative to other firms in the sector, it is highly correlated with familiarity measure (which is part of the same survey module), which is absolute and hence can be validated with industry-level data. There is a positive and significant correlation between survey responses and industry-level measures of technology, which confirms that the survey does capture information about technology in a meaningful way. The relation with robots is driven by industries within manufacturing. This is simply because almost no robots are being used outside of manufacturing.[9]

Panel B of table 2 presents the relationship of the survey-based measure of automation and digitization adoption with other firm-level variables, including binary indicators of technology usage from 2017. There is a strong and positive correlation between overall technology adoption and the probability of using each particular technology. Moreover, firms reporting higher adoption have higher investment (normalized by sales). Firms with higher adoption of automation and digitization have newer equipment and a higher share of R&D workers in their workforce. The fact that self-reported measures of adoption are strongly correlated with hard information on investment and personnel composition again suggests that the adoption measure captures differences in technology adoption across firms.

III Robots Investment around the World

We next analyze aggregate patterns of investment in robots using robot data from the IFR and firm-level data from Amadeus.

A Magnitudes and Basic Patterns of Robot Investment

Figure 2 shows the evolution of the number of robots sold over time. The total number of robots shipped increased significantly from around 100,000 per year between 2000 and 2010, to 300,000 in 2016, leading to the perception of a rapid acceleration in automation. Although robots sales declined during the Global Financial Crisis, sales rebounded between 2011 and 2016, and the positive trend became stronger. Yet, as demonstrated in the figure, the perception of rapidly accelerating automation may be misleading from the perspective of European and North American countries. The growth in robot sales is fueled predominantly by growth in other parts of the globe. In the West, the growth in robot installations is more modest: it has not accelerated in recent years but merely returned to the its pre-crisis trend after a dip in 2009.

China accounts for almost half of the 2006-16 growth: in 2006 China installed slightly over 5,000 new robots compared to almost 90,000 in 2016. Appendix figure A.1 in the Appendix illustrates the evolution of robots shipped to eight countries with the highest number of robots in use in 2016. China has seen the most dramatic increase in the number of robots shipped and by 2013 has surpassed Japan as the country with the highest number of robot installations. South Korea, with its vibrant automotive sector, has also seen a substantial growth pattern, especially in the last two years. At the same time, the growth in robot shipments is significantly lower in other countries, including the United States, Germany, and Italy.

The number of robots sold is not a sufficient statistic to compare robots and other investment. In panel A of figure 3 we attempt to measure the value – rather than the number – of robots. The figure demonstrates the evolution of the value of robot shipments compared to total capital formation and investment in equipment. Guided by IFR estimates, we assume that the average price of a robot is €45,000, and use that estimate combined with the number of robots sold to calculate total investment in robotics. We use a single fixed price of a robot because there are no good data on robot prices. Data for earlier periods analyzed by Graetz and Michaels (2018) suggests that robots prices were actually declining, despite the economy-wide inflation. We take a conservative approach and assume that the price remains constant. This approach is certainly crude, and we will return to the measurement question later on. Given the basic measure, however, our estimates suggest that robots constitute 0.2-0.3 percent of total investment in equipment, and less than 0.1 percent of total capital formation. Their share in total investment is relatively stable between 1995 and 2005 and increases by almost 50 percent between 2005 and 2016. However, as demonstrated in figure 2, this growth is largely fueled by developing countries.

Panel B of figure 3 demonstrates the share of robots in total investment across industry groups in the years 1995-97 and 2013-15. Robots are very strongly concentrated in manufacturing and the bar for non-manufacturing is too small to be legible. A small number of robots can be found in agriculture, mining, and the R&D sectors, but the vast majority of the economy does not use robots at all.[10] Yet even within manufacturing, robots are concentrated in selected industries, mainly automotive. Robotization levels are much lower in other manufacturing industries, especially those representing light manufacturing (food, wood and paper, and textiles). Appendix figure A.2 presents a more fine-grained comparison of robotization levels singling out every industry for which data on robots and investment are available. High skewness of the distribution of robots across the economy is consistent with robots being productive in certain environments, but having limited applicability in other contexts. Importantly, a comparison of the average share of investment in robots in 1995-97 to more recent data from 2013-15 does not suggest that the skewness is significantly reduced, even though the levels of robotization more than double. Just as in two decades earlier, robots in the 2010s are highly concentrated in automotive manufacturing, quite

[10] Some robots in the IFR data are classified as shipped to "Other" industries, and hence in reality other industries may also see some robot installations. Yet, the volume is very low, which is why the IFR does not report these industries separately.

rare in light manufacturing, and almost nonexistent elsewhere.

The high concentration of robots in selected industries is an important driver behind cross-country differences in robot adoption. Appendix figure A.3 shows the share of robots in investment in a set of developed countries. Overall, Germany and Italy clearly stand out, consistent with the large automotive and heavy manufacturing sectors in these countries. The pattern observed within the automotive industry (which is the most influential, but not atypical in comparison to other industries) looks markedly different, however. This difference suggests that robotization rates vary mostly by industry and that country-level totals are strongly influenced by industry structure. In such an environment, an analysis of the effects of robotization based on country-industry-year data only is challenging, since it is difficult to obtain precise estimates after controlling for industry-specific trends. For that reason, Section B expands on the literature based on industry-level variation (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020) and analyzes employment effects of robotization in a difference-in-differences specification combining industry- and local area-level variation.

B Correlating Robots with Firm Investment

The analysis in Section A suggests that investment in robots remains small and highly concentrated. Our calculations, however, are based on the count and average price of robots, which perhaps may underestimate the impact of robotics. When a firm is buying a robot, it is also likely to make other, complementary investments that are not reflected in the price of a robot. Hence, the actual expenditure on robotics-related investments may be significantly larger than those implied by the costs of robots.

According to the IFR, the total cost of a robot with peripherals and supplementary investments may be three times as large as the price of the robot itself. To validate this crude estimate, and to provide an alternative measure of the share of robots in total investment, we link data on robots' usage to firm-level financial data from Amadeus. We then use regression analysis to estimate the correlation between firm-level investment and robots.

Table 3 reports the results from regressions of firms' capital expenditures on the level of robot shipments in a given country-industry-year. Our results suggest that one additional robot per worker is associated with an increase of 0.04-0.1 percent in CapEx/Asset ratio. Interestingly, columns 4 and 5 demonstrate that this effect is driven predominantly by large firms.

In table 4 we compare the regression-implied estimates of robot investment with the value of shipments from the IFR. On average, our estimates suggest that the impact on firm's CapEx is in between the estimates implied by robot prices alone, and those that triple robot prices to include peripherials. For the automotive industry, regression-based estimates in the last column of table 4 suggest that robot-related expenditures represent 15.3 percent of total Capex, which is in line with the 16.7 percent figure implied by assuming that peripherials triple the cost of a robot purchase. However, for manufacturing as a whole, robots correspond to around 2.1 percent of total CapEx, which is similar to the ~2.4 percent (7.1/3 percent) estimated share of robots in investment based on robot price only. Given that manufacturing constitutes around 15 percent of the economy on average, and that robotization levels are very low in other sectors, this suggests a 0.3 percent share in total investment in equipment, again consistent with our price-based estimates for the whole economy (Section A). These calculations suggest that investments complementary to robots may be substantial in some industries, but in total are unlikely to significantly increase robotics-related expenditure.

Overall, our analysis suggests that the share of robot-related investment in total investment is low. And although in selected industries, especially automotive manufacturing, robots and their peripherials may constitute up to 15 percent of total expenditures on equipment, overall this share is much lower and close to 0.3 percent on average.[11]

C The Evolution of Robotization and Past IT Investment

Low levels of robotization cast doubt on the transformative role of robots in the economy. One can argue, however, that robots are in their infancy, and the current levels of adoption are not informative about their future impact, and that even some of the most influential technologies did not appear as such at the beginning. It may be therefore appropriate to contrast robots today with digital technologies several years ago to assess whether investment in robotics resembles the historical patterns of investment in IT technologies, which significantly transformed the economy in recent decades. This approach is taken in figure 4. We contrast the evolution of robots with the early years of IT equipment. That is, we normalize the event time so that year zero corresponds to 1995 for robots (this is the first year in which robot data are available for us) and to 1980 for IT equipment, thus introducing a 15-year lag.

The approach reveals that the total spending on robotics in 1995, including peripherals and supplementary investment, is significantly higher than spending on IT equipment in 1980. Yet, whereas spending on IT equipment accelerates sharply 10 years later and reaches much higher levels at the end of the second decade, the same is not true for robots. The robotics series, while

[11] These estimates are also in line with the crude approximations based on summary statistics from table 1. Summary statistics suggest that in the whole economy the investment in robots is €11/worker per year, investment in various kinds of machines is about €5,000, while total capital formation is about €23,000. With peripherials tripling the price of robots, we recover the share of robots in spending on equipment and in total investment as 0.66 percent and 0.15 percent. It has to be noted that these figures also represent nonfirm investment, including investment in structures, and that spending on equipment does not cover all capital expenditures, which explains why the 0.3 percent estimate is in between the bounds derived from table 1.

growing, remains relatively close to its initial level. Investment in robotics, therefore, does not display such an explosive pattern of growth as IT investment did in the past.

D Can Robots Be Impactful Even if They Are Rare?

Is small number of robots indicative of their limited impact? Perhaps a single robot can be very productive, and thus even a small number of robots can displace large amount of workers and significantly transform the economy. To better understand that possibility it is useful to consider the way in which robotization is often modelled in economic theory. In a simple task-based model of production, commonly used in the context of automation (Acemoglu and Restrepo, 2018, 2020), firm's output is created by a combination of a continuum of tasks in the unit interval [0,1]:

$$Y = A \cdot exp\left[\int_0^1 a \cdot lny(i)di\right], \tag{1}$$

where each task can be produced either by robots or by labor:

$$y(i) = \alpha_R(i)r(i) + \alpha_L(i)l(i) \tag{2}$$

Vector $\alpha(i) = [\alpha_R(i), \alpha_L(i)]$ determines the productivity of robots and labor at task i. Terms $r(i)$ and $l(i)$ represent the amounts of robots and labor assigned to the production of task i. In such a model, robots are used for each task for which $\frac{\alpha_L}{w} < \frac{\alpha_R}{r}$, i.e., the productivity of labor adjusted by wage w is lower than productivity of robots adjusted by cost of robots r. Without loss of generality we can reorder the tasks so that all tasks performed by robots belong to interval [0,R], and all tasks performed by humans belong to interval [R,1], with R being the automation threshold – a marginal task for which cost-adjusted productivity of robots and workers is the same. In such a setting, a profit-maximizing firm that takes prices as given has the following total labor demand:

$$L = (1-R)\left(\frac{Aa\theta^a}{w}\right)^{\frac{1}{1-a}} \tag{3}$$

where $\theta = exp(\int_0^R ln[\alpha_R(i)\frac{w}{r}]di + \int_R^1 ln[\alpha_L(i)]di)$ captures overall productivity. Thus, robotization affects the firm and its labor demand in two ways. First, advances in robotization that make robots more widespread (increases in R) reduce labor demand. Second, improvements in robots productivity (increases in α_R) increase overall productivity and increase labor demand.

Two implications follow from this basic model. First, if robots are to displace large amount of workers, they need to be widespread, i.e., perform a large number of tasks. Second, if robots are very productive, they will actually increase labor demand through the complementarity effect – because robots are very effective at performing tasks [0,R], the marginal benefit of performing tasks [R,1] that are still done by labor is higher, and thus labor demand is higher. Both implications suggest that it is unlikely that a small number of robots can lead to a substantial worker displacement.

Naturally, the model that we present, even though it is in line with the way in which automation has been modelled in the literature, may be missing some features of reality. In particular, the Cobb-Douglas form of task aggregation assumes complementarity between tasks, and it is possible that in reality such complementarity is limited. If that were the case, increased robot productivity would not increase labor demand but would simply lead to an increase in the number of tasks that are automated. Even so, a small number of robots can lead to large worker displacement only if a single robot is versatile and highly productive, i.e., can efficiently perform many tasks. High concentration of robots in a specific sets of industries, which we document, suggests that the range of tasks that robots can performed is limited. In addition, existing literature casts doubt on the importance of robot-driven increases in productivity. For example, Acemoglu and Restrepo (2022b) argue that the productivity gains from automations are modest, and the overarching concern is that robots may be an example of "so-so automation", i.e., a technology that is only slightly more productive than workers, which is enough to displace some labor but not enough to significantly increase overall productivity.

Overall, a small number of robots can have transformative impact only if robots are very productive across a wide range of tasks and the complementarity between different tasks in the production process is limited. Existing evidence in the literature, together with our findings about industry concentration of robots, provides little evidence that this is the case.

IV Firm Investment in Automation in Germany

The findings presented so far suggest that the role of robots in transforming the economy has been modest, contrasting some views in the literature (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020). Yet, this evidence does not address the central question of the debate, that is, the impact of robots on the recent past and future of work. Examining the link between robotization and employment is difficult because of measurement and identification challenges. To explore it in a more appropriate setting, we turn to an analysis that is based on firm-level data from Germany, in which we can more credibly explore the link between firm-level investment in automation and labor market outcomes.

We start by presenting several facts that complement the aggregate patterns discussed in Section III. We then turn to the analysis of the two directions of the link between robotization and labor markets: the impact of robotization on employment, and the impact of labor market conditions on firm's adoption decisions.

A Investment in Automation at the Firm Level: Basic Facts

Figure 5 depicts the variation in the usage of robots across industries based on the IAB-EP firm-level data. As in the cross-country analysis, robots are highly concentrated in manufacturing: on average, manufacturing firms report 24 robots per 1,000 workers. Even though there are some differences in how employment is measured and how manufacturing industry is minimal, that estimate approaches the ~30 robots per 1,000 workers in manufacturing implied by the IFR data. Values for other industries confirm that robotization outside manufacturing is very small: while one might be concerned that the lack of robots reported by the IFR simply reflects the lack of data collection efforts for other industries, the firm-level data confirm that beyond manufacturing, agriculture and mining, and the IT industry, robotization is negligible. Both the IFR data and the 2019 measure from the IAB-EP employ a rather restrictive definition of a robot. When we employ a less restrictive measure based on our 2017 usage-of-robots question, we still find that robots are highly concentrated in manufacturing: 50 percent manufacturing use robotlike machines; that share is ~15 percent in agriculture and mining and below 10 percent in other industries.

The usage of automation technology in Germany varies by geographical area, even after controlling for the industry structure, as illustrated by figure 6. The measure used in the figure is the average of firm assessments of automation adoption relative to other firms in the sector. Compared to a raw robot usage, which varies mostly by industry (see Section III), this measure is driven not by industrial composition but rather by other factors affecting technology adoption, such as proximity of R&D centers, technological spillovers, and labor market conditions. The existence of variation is important for our analysis of the employment effects later on.

In addition, technology usage also varies by firm characteristics (appendix figure A.5). Large firms are more likely to report using robots and digital technologies, consistent with our results from table 3. Firms with high levels of adoption are also more productive, which can be explained in part by a more skilled workforce. High adopters also pay higher wages, are more innovative, are more likely to be exporters, are more likely to be a part of multi-establishment group, and have been growing faster in the last five years – a relation we explore in more details in the next section. However, there is no relation between technology adoption and foreign ownership.

B The Effect of Automation on Employment Growth

We now turn to analyze the effect of automation on employment. We present evidence on the employment changes in automation-adopting firms. We then move to local area-by-industry level and regress ten- or five-year changes in total employment on industry-area level measures of robotization, controlling for industry and area fixed effects.

B.1 Employment in Firms Adopting Automation

Table 5 presents the relation between measures of automation adoption and employment changes. The four measures of automation that we use vary in specificity: the broadest is the adoption of automation and digitization that firms report in the survey. The advantage of this measure is its intensive margin character and inclusion of various technology classes. The latter, however, may also be a downside. To focus on a narrower definition of automation, we interact the adoption intensity measure with the 2017 indicator for using robots, use the indicator itself, or use the five-year change in robot density based on 2019 measures of the number of robots used. The downside of the last measure is that it is highly skewed and only positive for a small number of establishments, including very few establishments outside of manufacturing. To minimize the impact of outliers, we winsorize the change in robot density at 1 and 99 percentiles, and only include manufacturing firms in the sample used in column 6.

Across all measures, we find a positive and statistically significant association between the adoption of automation and firm-level employment growth. A one standard deviation increase in the intensity of automation is associated with 5 percentage points higher employment growth in the last five years (column 3), while robot users grow 10 percentage points faster compared to non-users (column 5). Each additional robot per 1,000 workers installed in the last 5 years is associated with a 5-year employment growth being higher by 0.15 percentage point (column 6). Naturally, these specifications do not estimate the causal impact of technology on employment growth, because adoption of automation is endogenous and correlated with several firm qualities, including innovativeness and higher productivity (see figure A.5). Yet the positive association between automation and employment growth suggests that the direct substitution effect of automation is limited and does not dominate over other determinants of firms' employment growth. Similar evidence was also obtained by Domini et al. (2021) who demonstrate that following a "spike" in automation, employment growth in the automating firm is higher. Combined with low levels of robotization throughout the economy, this low likelihood of strong substitution effects casts doubt on whether robotization has an important impact on the labor markets as a whole.

B.2 Employment Effects by Local Area and Industry

Patterns documented in table 5 suggest that the direct negative employment effects in firms that automate are limited. Yet, it is possible that automation causes employment losses in other firms, which downsize in response to their competitors becoming more efficient through automation. Indeed, such a possibility would be consistent with the results obtained for French firms in Acemoglu et al. (2020). To shed light on this question in our context, we perform the analysis on the industry-area level, exploiting industry-level variation in the levels of robotization and local area-level variation in the intensity of automation adoption (figure 6).

Methodology. To estimate the impact of robotization on employment, we combine industry-level measures of robotization with firm-level administrative data from Germany. We use the number of robots per 1,000 workers, based on robot shipments data from the IFR. The variation in this measure across industries can be used to analyze the employment effects of technology, as demonstrated by Graetz and Michaels (2018) and Acemoglu and Restrepo (2020). However, if all the identifying variation is at the industry level, it is difficult to disentangle the effects of technology from other industry-level changes that might be correlated with technology adoption. To address this concern, we combine the variation in the intensity of robotization across industries with variation in technology adoption levels across local areas. Doing this allows us to use within industry variation and identify the effect of technology by comparing firms in high-adoption areas to those in low-adoption areas. The geographic variation in adoption is captured by local area[12] measures of intensity of automation and digitization adoption, computed as the average of firm-level measures from the IAB-EP.

We use data from the BHP – an administrative data set with information on 50 percent of all German establishments – and aggregate up employment information to the industry-area level. The main empirical specification is:

$$\Delta Y_{a,j} = \beta_R \cdot \left(\Delta Robots_j \cdot Adoption_a\right) + X_{ja} + \phi I_j + \xi A_a + \varepsilon_{a,j}. \quad (4)$$

This is a long differences specification with all changes in the above equation, denoted by Δ, corresponding to 10-year change between 2005 and 2015 (in the main model; other periods are considered in alternative specifications). To increase precision, we measure employment in year t as the average of employment levels in the $[t-1, t+1]$ window. Subscripts a and j denote area and two-digit industry, respectively. $\Delta Robots_j$ is the change in number of robots per 1,000 workers used in a given industry, coming from IFR data (appendix figure A.6 shows values for that variable by industry). $Adoption_a$ is a measure of automation and digitization adoption in area a. In the basic specification, this is an indicator of the intensity of adoption being above median. The intensity of adoption is the average of firms' self-reported adoption from the IAB-EP. Since, in their self-reporting, firms compare themselves to other firms in the same sector (see Section II), the measure is not driven by the industrial composition of the area. The independent variables include vectors of industry fixed effects, I_j, and area fixed effects, A_a. In addition, X_{ja} includes a control for area-industry measure of digitization, defined similarly to the measure of the robotization x adoption

[12] Area in this section is defined using spatial planning regions (ROR, Raumordnungsregionen), constructed by the German Federal Authority of Construction and Regional Planning (BBR) taking into account the commuting patterns of workers. Germany is divided into 96 ROR regions. Although RORs are good proxies for local labor markets, a possible alternative definition would use districts, which are smaller. However, for data confidentiality reasons, performing the analysis on the level of districts is not possible.

interaction, but instead based on software and databases investment per worker from EU KLEMS. In the basic specification, we weight all observations by the level of employment in 2005.

To intuitively understand the specification, consider an example of two industries – car manufacturing and paper manufacturing – with two firms in both of them. Let us assume that there is a large increase in robotization in car manufacturing, but negligible change in paper manufacturing. In each industry, one firm is located in a high-adoption area and the other in an area with a low adoption level. We are interested in estimating the effect of technology on employment. To calculate this effect we need to compare the change in employment between high- and low-adoption-area firms in car manufacturing. The observed difference is a combination of the "robotization effect" and of the "location effect." Comparing high- and low-adoption-area firms within the paper industry – which has a negligible robotization change and therefore the "robotization effect" is negligible – allows us to compute the "location effect." Assuming that this effect does not systematically differ across industries – which is our identifying assumption – allows us to back out the "robotization effect" in the car industry.

Changes in robot density in Germany may be endogenous. For example, when German firms in a given industry face high demand, they may adopt more robots and increase employment – in which case our estimates of the employment effect would be biased upward. To better isolate the exogenous variation in technology, we follow the approach of Autor et al. (2013) and Acemoglu and Restrepo (2020) and supplement specifications using the number of robots in Germany with those using changes in robot density in a group of other European countries.[13]

Results. Table 6 presents the results from estimating the effects of technology adoption on employment growth. We estimate equation 4 with the dependent variable being the percentage change in employment between 2005 and 2015 (columns 1 and 2), and between 2005-2010 (columns 3 and 4), as well as 2010 and 2015 (columns 5 and 6). We find no statistically significant effect of robots on employment in the period 2005-15, although the estimate is negative and suggests that firms in high-adoption areas are growing 0.2 percent slower with every additional robot per 1,000 workers.[14] The negative employment effect is close to 0.4 percent and marginally significant (at 15 percent level) when we use robotization abroad. The employment effect is significant and larger in magnitude in the first half of the analyzed period, suggesting that firms in high-adopting areas were growing 0.3-0.6 percent more slowly with every additional robot per 1,000 workers. The lower estimates is again obtained when using robots installed in Germany, while the larger estimate

[13]France, Italy, Denmark, Netherlands, Sweden, and the United Kingdom.

[14]In the previous version of the paper, we reported a slightly larger estimate of the negative employment effects, which were also marginally statistically significant (~ -0.3, significant at the 10 percent level). These results were obtained with an older version of the BHP data. Our data were subsequently updated to the newest available version. With the new data, which include some updates and corrections, we obtain estimates that are slightly smaller in magnitude.

is based on robotization abroad, consistent with the fact that domestic adoption may endogenously respond to growth opportunities. Between 2010 and 2015, the estimated employment effects are close to zero.

On average, between 2005 and 2015 the German economy increased robotization density by 0.84. We do not know how the increase in areas with above-median intensity of automation compares to that in areas with below-median automation. Under an extreme assumption that all robots were installed in above-median areas, back-of-envelope calculations suggest that robots reduced employment by 0.02-0.06 percent per year, with 0.03 percent per year being the average effect from columns 1 and 2. These magnitudes are modest when compared to overall volatility of employment in Germany: 0.3 percent change in employment growth per decade accounts for only 6.4 percent of the difference in 2005-15 employment growth betweeen high- and low-adopting areas, and for 3.7 percent of the area-level standard deviation in employment growth in the same period.

Appendix table A.2 presents the results of robustness tests of the main findings. Our main conclusion is robust to alternative measures of adoption, excluding the automotive industry, assigning equal weights to each observation (as opposed to weighting by employment in 2005) or adding controls for past employment changes.

Comparison with Other Studies. Our estimates are based on a novel strategy that combines industry-level measures of automation with local area intensity of adoption. Given our findings that robotization varies mostly by industry and is nonnegligible only for a small number of manufacturing industries, any identification strategy that relies on industry-level data only may face significant challenges. In particular, one can be worried that what is believed to be the effect of automation (e.g., in Graetz and Michaels (2018); Acemoglu and Restrepo (2020); Dauth et al. (2021)) is rather a reflection of general decline in manufacturing, which is likely to have other reasons as well. In light of this concern, our ability to augment industry-level data with local area variation seems valuable.

At the same time, because our analysis relies on comparison of different local areas, some other endogeneity concerns may arise. It is important to clarify that we do not need to assume that high- and low-adoption areas are the same except for the levels of technology adoption. Instead, we include area fixed effects with the goal of capturing all time-invariant area-specific factors other than technology. The key identifying assumption is that the effects of these factors do not systematically vary across industries in a way that is correlated with robotization. Our strategy is similar to the strategy used on country-industry level by Rajan and Zingales (1998). One concern about the strategy is related to agglomeration effects affecting different industries in different ways. Over time, high-skill industries may have become more likely to be located in a few selected business hubs compared to manufacturing firms, which could bias our estimates. Our employment effects also hold when controlling for past employment changes and hence are unlikely to be driven by differential employment trends across industry-area pairs. In addition, the analysis of adoption patterns across Germany (figure 6) reveals that many areas with high adoption (e.g., northeastern Bavaria and western Lower Saxony) are not the typical business centers. Finally, the differential importance of agglomeration effects can be to a large extent driven by technology, and hence it may be viewed as a mechanism through which technology affects employment, rather than as an alternative explanation.

Yet, at the end of the day, the novel strategy that we propose has both advantages and disadvantages, and it is unclear how it compares to an alternative strategy that relies on industry-level variation only. Importantly, however, our broad conclusions do not rely on using the particular strategy that we introduce, and can also be obtained when employing methods used by other papers. In particular, Acemoglu and Restrepo (2020) for United States, and Dauth et al. (2021) for Germany have used a strategy that calculates local labor market exposure to robotics based on its industry composition. The change in that measure over time can then be related to changes in employment to recover estimates of the employment effects of robots.

The exact comparison of the employment effects based on our estimates to those obtained in the two other studies may be problematic, because our and their strategies lie on a different spectrum between partial and general equilibrium analysis. However, back-of-envelope calculations suggest that per-robot impact on employment estimated in all studies is similar. Acemoglu and Restrepo (2020) report that one extra robot per 1,000 workers reduces the employment-to-population ratio by 0.2 percentage points. Using the same approach, Dauth et al. (2021) report the displacement effect to be around 50 percent smaller in Germany. While these authors do not highlight the small magnitudes of these effects, they are similar to the ones reported in table 6. In fact, the similarity is quite striking given several differences in measurement, empirical specification, and largely (though not completely) different underlying variation. We view the similarity of estimates as an indicator that our main conclusion is robust: both our estimates, and those obtained by other studies, suggest that aggregate employment effects of automation have been small. This is mostly because automation itself has been limited and confined to a subset of manufacturing industries.

C Automation Adoption and Labor Scarcity

Discussion about automation typically highlights concerns about the displacement of existing workers, which may be particularly problematic for older workers who may have difficulties in adjusting to new conditions. In light of these concerns, it is important to understand whether the moderate negative employment effect of automation represents actual displacement of existing workers or whether automation is a way of enabling firm growth with lower hiring intensity. Even though both scenarios may result in similar estimates of the employment effect, their societal implications may by significantly different.

To shed light on this question, we study the effect that labor market conditions have on automation adoption. We use firm-level data from the IAB-EP and estimate following specification:

$$Technology_i = \beta \cdot Labor\,Scarcity_i + \gamma \cdot I_j + \phi \cdot Z_i + e_i. \tag{5}$$

The dependent variable is a measure of automation and digitization that comes from the IAB-EP. The main measure is the firm assessment of intensity of adoption: a continuous variable varying from 1 to 10. We also employ alternative measures, such as an interaction of above-median adoption with above-median capital expenditures, or change in the number of robots used between 2014 and 2018. I_j denotes a set of industry fixed effects that correspond to the two-digit classification based on NACE Rev. 2. Z_i contains a set of firm-level controls. In the main specification we control for firm size (measured as total employment, but robust to using total sales). Several additional controls that do not substantially influence the main coefficients of interest, such as profitability, establishment age, past employment growth, type of management, international ownership, being part of a group, and being a public firm, are included in the robustness checks. Due to limited data availability, including additional controls significantly reduces sample size (compare columns 1 and 2 of table 7). We choose the main specification to be parsimonious but also present results that demonstrate that including additional controls does not meaningfully change the magnitudes of the coefficients. Standard errors in the main specification are clustered at the industry level.

The main independent variable, $Labor\,Scarcity_i$, is a binary indicator based on the firm's assessment that it has difficulty finding workers. It is defined based on answers to the 2014 survey that predates the technology-adoption measure by two years. Lagging the independent variable is the first attempt to circumvent the reverse causality problem, but the results remain similar if we use measures from 2016 instead (see appendix table A.3). We also present results with two other measures of labor scarcity.[15]

Table 7 presents the results. Columns 1-4 and 8-9 report the results with the adoption measure being a continuous assessment of adoption from the survey; column 5 uses an indicator for above-median adoption interacted with an indicator for an above-median ratio of investment to sales; column 6 uses interaction of adoption and an indicator of using robots (from 2017 IAB-EP); and column 7 uses the change in the number of robots installed in the firm between 2014 and 2018. Each measure points to a clear positive relation between technology adoption and labor scarcity: the harder it is to find workers, the higher is the level of technology adoption. The magnitudes suggested by the different measures are similar: changing labor constraints measure from 0 to 1

[15]The second measure is a binary indicator that the firm would like to recruit additional staff, on top of the staff they actually recruited, and is based on the "Recruitment" module. The third measure captures labor-driven capacity constraints, i.e., the firm's declaration that it is unable to increase the production without hiring new staff.

increases technology adoption by 10-15 percent of a standard deviation.

Our baseline labor scarcity measures are defined based on data from 2014, but appendix table A.3 shows the results for measures from different periods. Overall, the relation seems to be somewhat persistent, but it is no longer significant if the measures are constructed based on years earlier than 2010. Appendix table A.4 presents the results for other staffing problem variables, which may be thought of as placebo checks. There is no relation between technology adoption and firms' declarations about problems of worker motivation or of having too many employees. Interestingly, there is also no relation with an indicator that takes the value of one if a firm reports high labor costs as a staffing problem. This might be because of labor market institutions in Germany that lead to wage rigidity. There exists a positive relation between adoption and the demand for further training. Although there are several ways to interpret this relation, one possibility is that firms that have difficulties finding suitable workers are also forced to hire employees that require intensive training.

Endogeneity Concerns. The results presented in columns 1-7 of table 7 are subject to endogeneity concerns. First, there is a concern about reverse causality: a firm that adopted new, sophisticated technology may have troubles finding workers because skills required to operate the technology are scarce. Second, there is a concern about omitted variables: firms that adopt new technology more intensely may be different in a way that is unobserved. Typically we would expect such firms to be more productive and successful than other firms. If such firms are more attractive to workers and hence have fewer difficulties recruiting, OLS coefficient may be downward biased. But those firms may also have higher demand for their products, which can be accommodated both by hiring more workers (and thus having more problems finding them) and technology adoption, introducing upward bias to OLS coefficients.

To alleviate these concerns, we use a labor scarcity measure that is not specific to the firm but captures labor market conditions in the firm's local area. Because each firm is small compared to its local labor market, firm-specific factors do not influence local labor scarcity. Labor scarcity in the local area is the share of firms in the area that report difficulties in finding workers.[16] The analysis is performed with about 400 districts, but it is robust to using about 100 larger areas (Raumordnungsregionen) instead. Local productivity shocks may affect both the labor market and the output market: when the local economy is booming, the demand for goods sold locally is high and it is hard to find workers, because unemployment is low. High demand, in turn, may lead to higher technology adoption. To deal with this possibility, we limit the sample to those firms that export at least 20% of their production, and hence are unlikely to be sensitive to the local economic conditions in their district differently than to conditions in the rest of Germany.

[16] We employ the leave-one-out procedure: for each firm in the sample we exclude its own declaration when calculating local averages. Therefore, denoting the variable with subscript a slightly abuses the notation.

Columns 8 and 9 of table 7 present the results. Being located in an area where many other firms declare that they have troubles finding workers is associated with higher levels of automation and digitization adoption. Moving the local labor constraints index from the 10th percentile to the 90th percentile increases adoption by around 10 percent of its standard deviation. The effect is even stronger if we limit our sample to firms that export at least 20 percent of their production, suggesting that the demand channel is unlikely to explain our findings.

Heterogeneity of Labor Scarcity Effect. Figure 7 shows the effects of labor scarcity on the adoption of automation (using the measures from 2017 IAB-EP interacted with adoption intensity from 2016) by industry. Robots display a substitution pattern in manufacturing and mining but play no significant role in other industries, consistent with their low prevalence in other sectors.

Overall, the results of this section illustrate a significant impact of labor market conditions on investment in automation. In places where labor is scarcer and harder to find, firms are more likely to invest in automation technologies. This finding, besides improving our understanding of firm investment patterns, has important implications for the impact of robotization on labor market. Robots may in fact alleviate labor scarcity problems, and hence the extent to which they displace existing workers is limited. In addition, even if they displace some workers, they are most likely to do so in places where labor supply is limited.

At the same time, as demonstrated by Section III, the magnitude of robot investment is limited. Figure 7 shows that the effects of robots are confined to manufacturing and mining, but other technologies are present in a broader set of industries and their adoption displays a heterogeneous relation with labor market conditions. These patterns illustrate the importance of analyzing other technologies, which we discuss further in Section V.

V Automation and Other Technologies

Our results suggest that the impact of robotics does not appear to be the central driver of economic change in recent years, suggesting that more attention should be devoted to other technologies. In this section, we contrast the prevalence and impact of robots with those of other digital technologies.

A Prevalence of Robots and Other Technologies

Figure 8 displays the evolution of expenditures on robots, ICT equipment, and software and databases between 1995 and 2015. The data are based on the aggregate variables from IFR and EU KLEMS data. We present the data graphically for the manufacturing sector because the share of robots would be too small to be legible on the graph for the whole economy. Yet even within manufacturing, expenditures on robots are dwarfed by the other two categories. There does not seem to be a reversal of this trend. Although the relative growth rate of software and databases expenditure is lower than that for robotics, the former have much higher base, and hence the difference between the two types of capital is widening.

Furthermore, even the difference in the relative growth rates may disappear when robotization levels increase. This is consistent with the evidence from the automotive industry – which has much higher rates of robotization than any other industry – presented in appendix figure A.8. Robot investment remained flat in the last decade, suggesting that when robotization reaches a relatively high level, the growth is likely to be lower. In contrast, we observe a stable growth of the expenditures on software and databases, even though this category is much larger to begin with.

B Comparison of the Effects of Robots and Other Technologies

Our analysis shows that robots accounted for a small share of total investment and have had a limited impact on employment growth in Germany. However, other types of technology may have much larger effect on the economy and on the future of work. We argue that instead of focusing on robots and narrowly defined forms of automation we should evaluate the effects of other technologies that are likely to have more important economic consequences.

Is it just a labeling issue? Perhaps even if industrial robots do not account for a significant share of total investment, their impact may be similar to the impact of other technologies that are more widespread. Therefore, studying robots may provide important insights that are more broadly applicable and can potentially have a significant effect on aggregate economic outcomes.

Certainly, robots do share some similarities with other technologies. At the very core, automation means that a task previously done by humans is performed by machines, whether that machine is an industrial robot or a computer algorithm. However, there are important differences between these technologies. With a fluid definition of a task, a large group of technologies can be described as automation. For example, an Excel spreadsheet may automate the task of manually adding numbers, yet at the same time it creates a new task of data entry. More importantly, it may significantly increase the productivity of bookkeepers, allowing them to perform more tasks in the same amount of time. Thus, even if they share some similarities, the aggregate effect of algorithms may be very different from the impact of robots.

Figure 9 demonstrates this point. Using methods analogous to those previously employed to study automation (see figure 7), we analyze the impact of labor scarcity on the adoption of digitization – defined as high adoption of data- and network-related technologies (based on measures from 2016 and 2017 measures of IAB-EP). A positive association between labor scarcity and investment in technology suggests that the technology mostly substitutes for labor, while the negative relation suggests that the complementarity effect dominates.

The results reveal a heterogeneous effect of digital technologies across different industries. This contrasts with the clear positive association between labor scarcity and adoption for robotics in mining and manufacturing, documented in figure 7. The patterns observed in some industries (retail, hospitality) are similar to those observed for robots, even though technologies in these industries are not directly related to robotics. Yet, in other industries (finance, education and health, professional services) we observe the opposite patterns, suggesting that complementarity effects of technology in these industries dominate over robot-resembling substitution effects.

Heterogeneous patterns of the relationship between labor scarcity and technology adoption suggest that the employment effects of different technologies may also differ from the employment effects of robots. Table 8 analyzes this question directly and reports digitization coefficients analogous to robotization effects shown in table 6. Controlling for robotization, we find no evidence of the negative employment effects of digital technologies. In fact, we find some suggestive evidence for positive employment effects: all coefficients are positive, although only some of them are precisely estimated.

Overall, the evidence suggest that other technologies are more prevalent than robotics, and can have different economic implications. These findings suggest that we should exert caution when analyzing the impact of robotics and extrapolating their measured impact to other technologies.

VI Conclusion

This paper critically examines the importance of automation – in particular, industrial robots – in aggregate and for firm investment as well as for labor markets. We confirm that firms are steadily increasing their investment in robotization and that robots have the potential to reduce employment, yet their share in total investment is very small, and their employment effects are small and mitigated by endogenous adoption patterns. Industrial robots are spectacular technology, but their applications remain limited. Although their importance has been growing in recent years, this growth has been relatively stable, and the pattern does not resemble the explosive growth observed fo example for IT technologies in previous decades.

Instead, other digital technologies are much more prevalent than robots today, and recent trends do not appear to shrink that difference. Due to their higher prevalence, digital technologies related to data processing and analysis and network communications are likely to have much bigger economic implications, and their impact is likely significantly different from the impact of robots. We certainly can learn something about them by studying robots, yet it is important not to extrapolate too far, given their potentially different characteristics.

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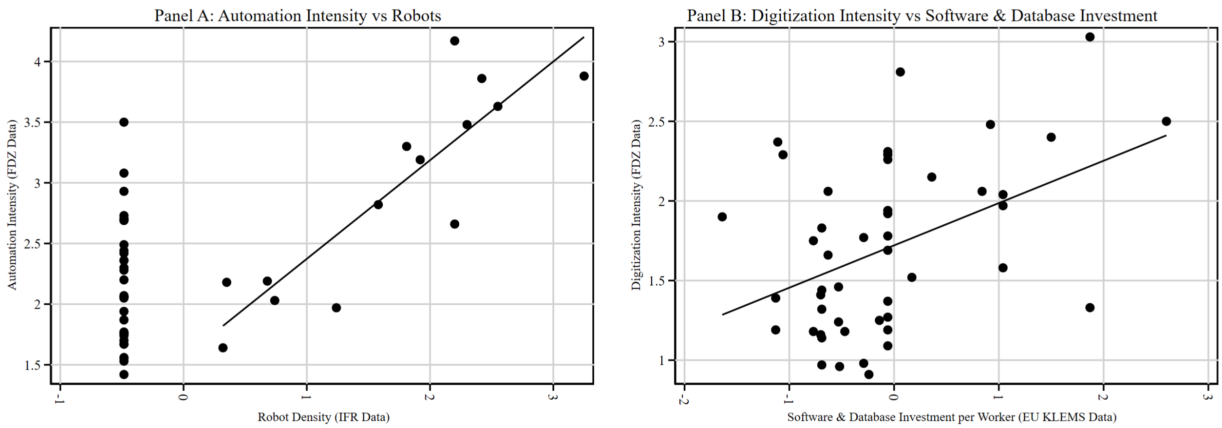


Figure 1: Cross-Validation of Firm-Level and Industry-Level Measures of Technology
Panel A presents the two-digit industry-level relation between robot density based on theIFR data and the intensity of automation based on firm-level IAB data. Each dot represents one of two-digit industries. Robot density is defined as the standardized logarithm of the count of robots per 1,000 workers from IFR data. Robots are concentrated in manufacturing, and only 14 industries have separately reported a positive number of robots. For the remaining industries robot density is calculated using the “Other” category andapproaches zero. Automation intensity is the industry-level average of firms’ intensity of dealing with automation and digitization technologies (part A of the automation and digitization question from 2016 IAB-EP, scale 1-10) multiplied by a binary indicator of using robots and considering them somewhat important (based on the 2017 IAB-EP). Panel B presents the relations between the standardized natural logarithm of per-worker software and databases capital stock from EU KLEMS and the firms’ intensity of dealings with automation and digitization technologies multiplied by a binary indicator of using digital technologies (data or network technologies, based on the 2017 IAB-EP) based on firm-level data.

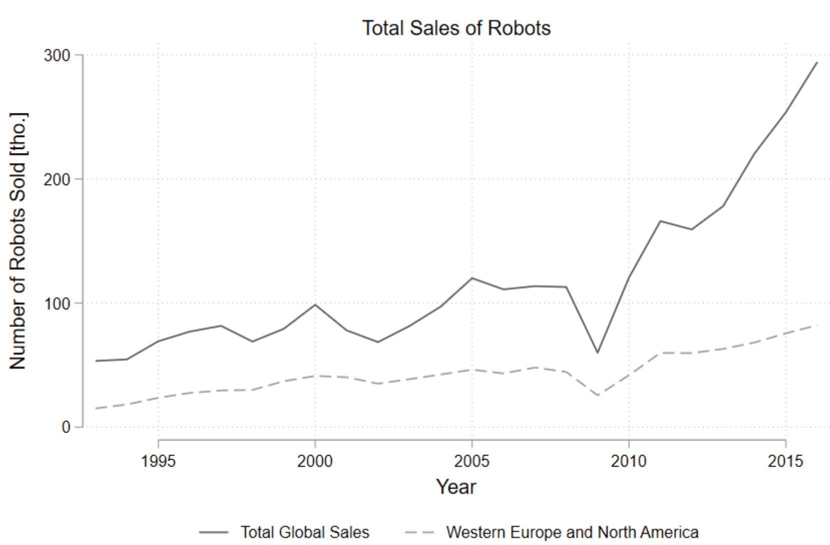
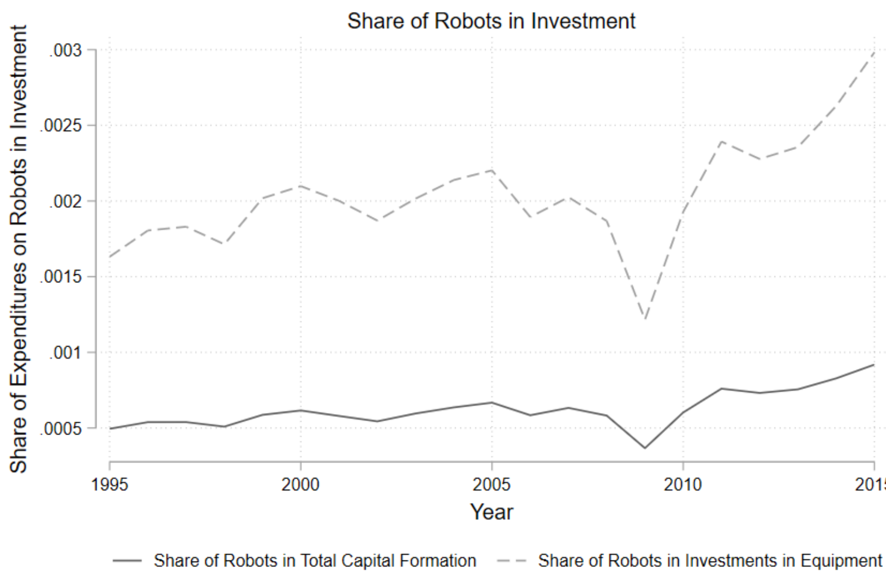


Figure 2: Total Sales of Robots around the World and in Western Countries
This figure presents the evolution of the number of robots sold between 1993 and 2016, based on IFR data. The solid black line shows the aggregate number of robots sold around the world, in thousands of units. The dashed line shows the aggregate number of robots sold to Western Europe and North America.

Panel A. Robot Investment Over Time



Panel B. Robot Investment by Industry

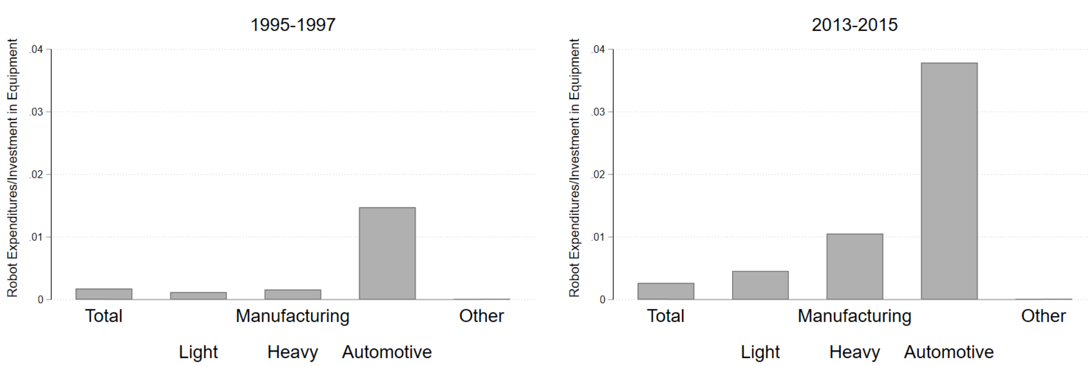


Figure 3: Share of Robots in Total Investment

Panel A presents the evolution of share of robot expenditures in investment between 1995 and 2015. The shares are computed by adding sales and investment values over all industries and countries, and hence reflect the relative size of industries and countries in the sample. Panel B presents the share of robot expenditures in investment across industry groups. The shares are computed by adding sales and investment values over all countries and three years: 2013-2015; hence, they reflect the relative size of countries in the sample. The value for robot sales comes from the IFR data; the price of a robot is assumed to be €45,000 on average. The solid black line (dark bars) shows the ratio of robot sales value to total capital formation; the dashed line (light bars) shows the ratio of robot sales value to the value of investment in equipment, defined as ICT equipment and other machinery. All investment series come from EU KLEMS data and are real values expressed in 2010 prices. The values are converted from national currencies to Euro. Light manufacturing represents manufacturing of food and beverages, textiles, wood and paper, and chemicals. Heavy manufacturing represents production of metal, electrical, and machinery products.

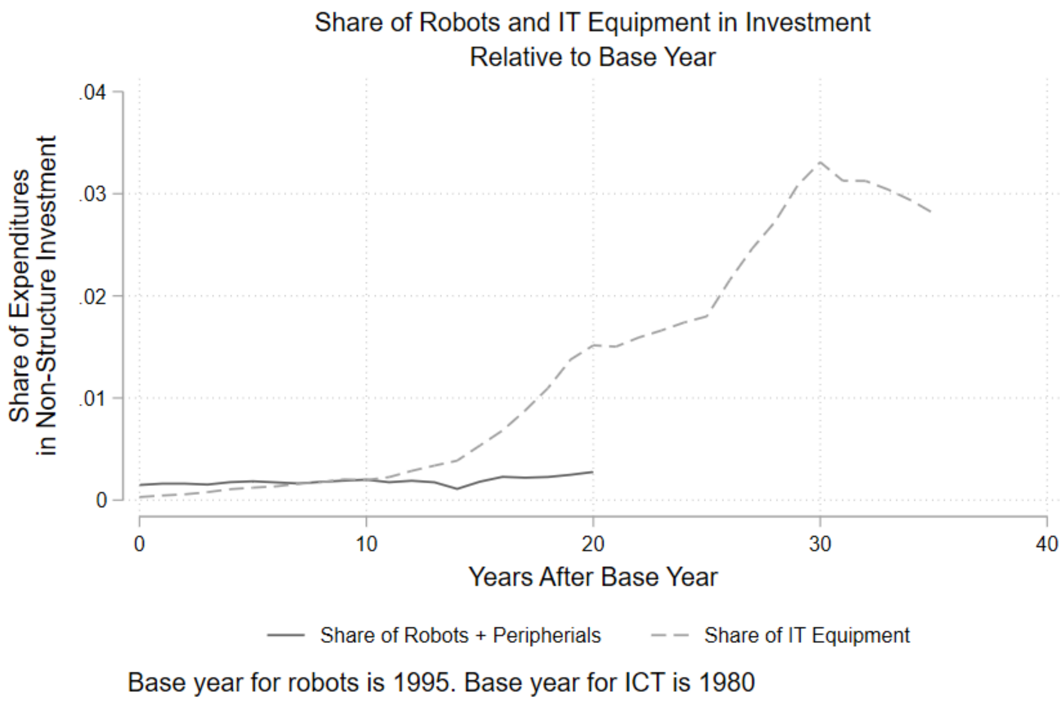


Figure 4: Share of Robots+Peripherals and IT Equipment in Total Investment Relative to Base Year

This figure presents the evolution of the share of expenditures on robots and peripherals (defined as total price of robots x 3) and on Information Technology (IT) equipment in total non-structure investment. Both series are shifted in time, so that year zero corresponds to 1995 for robots and to 1980 for IT equipment. Share for robots is computed based on values for nine countries in the sample. Due to data limitations, share of IT expenditures is based on data from United States only. The value for robot sales comes from the IFR data; the price of a robot+peripherals is assumed to be €135,000 on average. IT investment values come from EU KLEMS data and are real values expressed in 2010 prices. The denominator is total capital formation minus investment in structures.

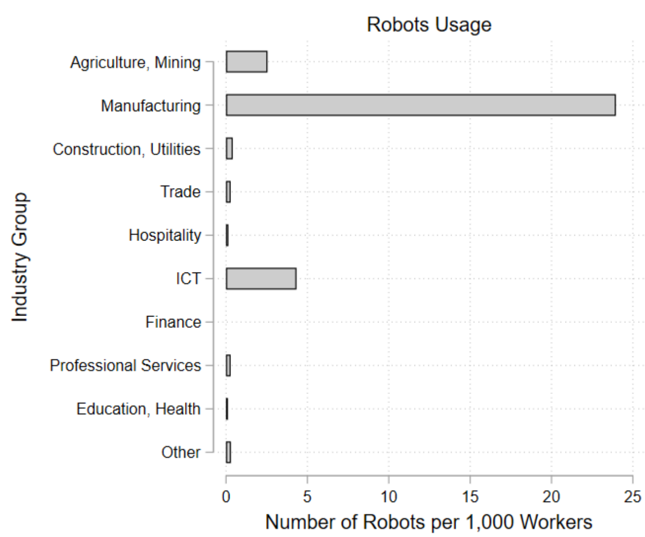


Figure 5: Robots in the IAB Establishment Panel

The graph shows the average number of robots per 1,000 workers in 2018, based on firm-level data from the IAB-EP.

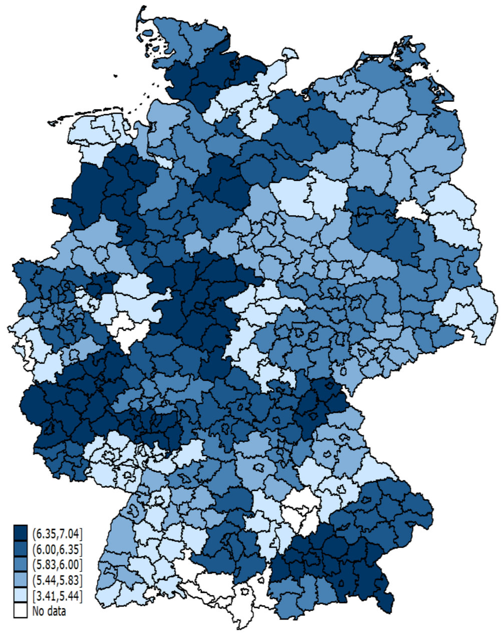


Figure 6: Geographic Distribution of Automation and Digitization Adoption
This map presents values of the automation and digitization adoption index from the 2016 IAB-EP. The original index is computed at the district level, but for data confidentiality reasons the presented values are computed on the spatial planning regions (RORs) level – each ROR contains about 4 districts. Moreover, some values cannot be shown due to data provider restrictions. The index is the average of firms' responses to a question about the intensity of automation and digitization adoption from the 2016 wave of IAB-EP, but industry-level averages are subtracted and the economy-wide average is added. The response are on scale (1,10), and ROR-level averages vary between 3.41 and 7.04.

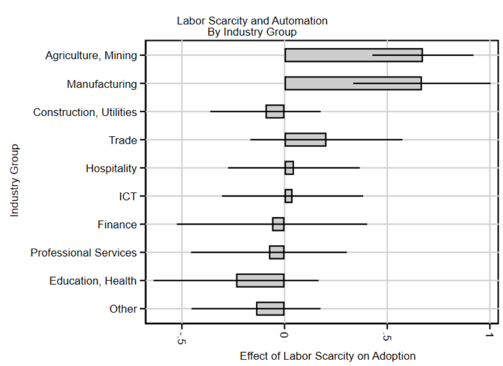


Figure 7: Labor Scarcity Effect by Industry and Technology
This figure presents coefficients from the regression of automation on labor scarcity interacted with indicators for 10 industry groups, controlling for industry fixed effects and firm size. The automation measure is an interaction of the intensity of automation and digitization adoption measure (from IAB-EP 2016) with an indicator for using robots (from IAB-EP 2017) and considering them at least somewhat important (>=3 on 1-5 scale).

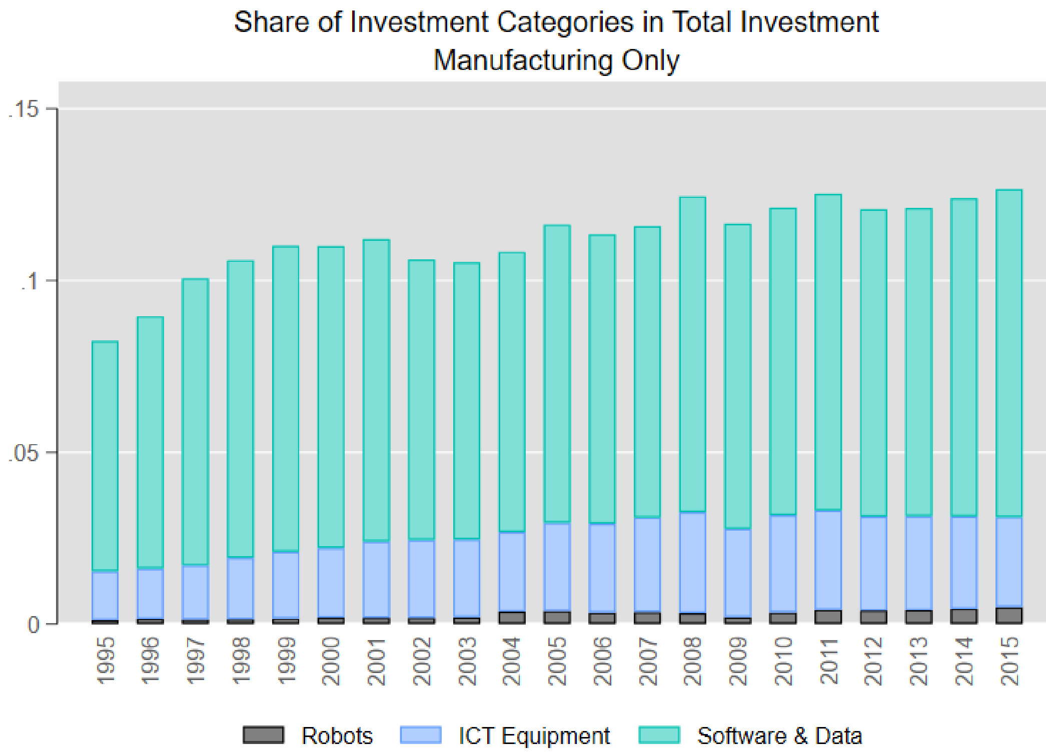


Figure 8: Share of Selected Investment Categories in Total Investment: Manufacturing
This figure presents the evolution of the share of various investment categories in total non-residential investment. The shares are computed by adding sales and investment values overall for all countries and industries within manufacturing. The value for robot sales comes from the IFR data; the price of a robot is assumed to be €45,000 on average. Remaining values of investment flows come from EU KLEMS data and are real values expressed in 2010 prices. ICT equipment includes information technology equipment and communication technology equipment. The denominator is the difference between total capital formation and investment in residential buildings.

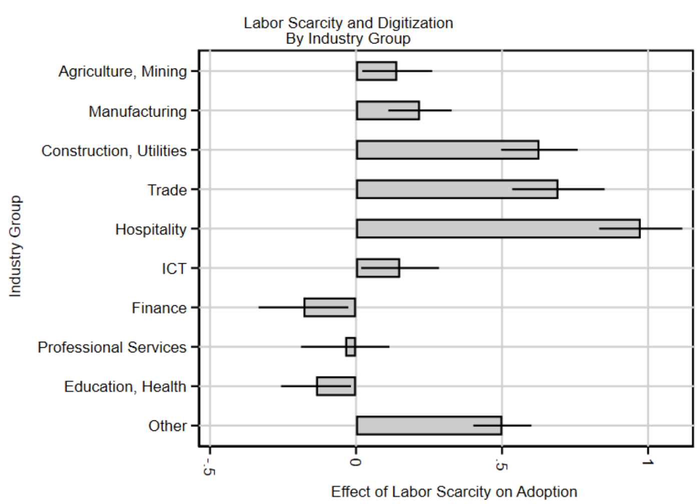


Figure 9: Labor Scarcity Effect of Digitization
This figure presents coefficients from regression of digitization – defined as the interaction of the main measure of the intensity of adoption (from IAB-EP 2016) with an indicator for using data- or network-related technologies (from IAB-EP 2017) – on labor scarcity interacted with indicators for 10 industry groups, controlling for industry fixed effects and firm size.

Table 1: Summary Statistics: Robot Sales from IFR data, Investment from EU KLEMS and Firm-Level data from Amadeus

Data Source	Variable	Sector	Mean	Median	Std Dev	P25	P75	Min	Max	N
IFR	Robot Shipments [units/1000 workers]	All	0.967	0.151	2.080	0	0.997	0	20.356	2352
		Food, Textiles, Wood	0.568	0.227	1.035	0.051	0.663	0	12.939	504
		Chemical, Metal	1.576	1.352	1.007	0.825	2.136	0	5.521	336
		Electr., Machinery	0.914	0.650	1.074	0.166	1.238	0	7.512	336
		Automotive	6.108	5.328	4.436	2.723	9.153	0	20.356	168
		Non-Manufacturing	0.049	0	0.258	0	0.019	0	5.118	840
		Whole Economy	0.242	0.200	0.158	0.141	0.310	0.022	0.838	194
	Robot Shipments [units]		4278.6	1001	6230.3	377	5335.5	35	31404	216
	Robot Shipments [est. value, € mln]		193	45	280	17	240	1.6	1413	216
	Robot Shipments [est. value, € tho/worker]	Whole Economy	0.011	0.009	0.007	0.006	0.014	0.001	0.038	194
	Robot Stock [units]		38513	8915	55112	3899	56572	568	250479	216
	Robot Stock [units/1000 workers]		2.229	1.907	1.502	1.133	2.723	0.364	7.538	194
EU KLEMS	Total Investment [€ tho/worker]		23.7	23.9	3.08	21.2	25.8	16.0	30.4	192
	ICT Equipment [€ tho/worker]		0.848	0.782	0.416	0.534	1.160	0.074	1.866	192
	Software & Data [€ tho/worker]	Whole Economy	1.722	1.616	0.741	1.270	2.191	0.357	3.844	192
	R&D and Other IP [€ tho/worker]		2.937	2.698	1.037	2.343	3.526	1.056	5.455	192
	Other Equipment [€ tho/worker]		4.323	4.334	0.731	3.753	4.810	2.815	6.171	192
Amadeus	Capex/Lag(Total Assets)	All	0.0588	0.0589	0.077	0.014	0.072	-0.071	0.624	372207
	Employment		362	105	4463	51	218	0	601384	332193

This table presents summary statistics for key variables from IFR and EU KLEMS data for our sample. The sample contains data for nine countries: Austria, Germany, Denmark, Finland, France, Italy, Netherlands, Sweden, and the United States, and covers the years 1993-2016. In the rows for "Whole Economy," we report statistics based on country-year observations. In the remaining rows, we report statistics based on country-industry-year observations. Our data set, constructed by merging IFR and EU KLEMS data, contains contains observations for 14 industries and for the whole economy (notice that the 14 industries do not represent the whole economy since IFR reports industry-level data for a subset of industries only). We group them as follows: "Food, Textiles and Wood" refers to food manufacturing, textiles manufacturing, and wood and paper manufacturing; "Chemical, Metal" refers to chemical manufacturing and metal products manufacturing; "Electr., Machinery" refers to electrical and electronic products manufacturing and other machinery manufacturing; "Automotive" refers to means of transportaiton manufacturing. "Non-Manufacturing" includes agriculture, mining, construction, utilities, and research and development. The remaining industry is Other manufacturing. Values per worker are calculated using count of hours worked from EU KLEMS divided by 2080 (to get full-time equivalent figures). Monetary values of robot shipments are calculated by assuming that an average robot costs €45,000, consistent with IFR information. Investment is based on EU KLEMS figures reported in national currencies in 2010 prices. Monetary values from EU KLEMS are converted to EUR from national currencies using following exchange rates: 1.339 for USD, 7.45 for DKK, 8.96 for SEK. Amadeus sample was obtained through WRDS and includes all "large" or "very large" companies. Capex is defined as the difference between current year and last year total fixed assets plus depreciation.

Table 2: Automation and Digitization Measures in IAB Panel: Summary Statistics and Relation to Other Variables

Panel A: Summary Statistics

VARIABLE		MEAN	STD DEV	P25	MEDIAN	P75	NUM OBS
2016 Digitization	A (familiarity)	4.83	3.02	2	5	8	14445
and Automation	C (adoption)	5.72	2.68	4	6	8	10255
2017 Robots		0.153	0.360	0	0	0	11837
2017 Digitization	(Data)	0.522	0.500	0	1	1	11837
2017 Digitization	(Networks)	0.126	0.332	0	0	0	11837
2018 Robots Used		1.38	70.1	0	0	0	8518

Panel B: Relation to Other Variables

	Y = ADOPTION OF AUTOMATION AND DIGITIZATION					
	(1)	(2)	(3)	(4)	(5)	(6)
Robots (2017)	0.87***					
	(0.09)					
Digitization: Data (2017)		1.13***				
		(0.03)				
Digitization: Networks (2017)			1.13***			
			(0.08)			
Investment (% sales)				2.39***		
				(0.38)		
Age of Equipment					-1.08***	
					(0.03)	
Share of R&D Workers						1.27***
						(0.42)
N	8407	8407	8407	10255	10255	10255
Industry FE	✓	✓	✓	✓	✓	✓

Panel A shows summary statistics for the firm-level measures of technology. Summary statistics for other variables from IAB data are presented in appendix table A.1. In panel B regressions, the dependent variable is adoption of automation and digitization from the 2016 IAB-EP Establishment Panel (wave 2016, part C). Independent variables are binary indicators of usage of different technology classes coming from the IAB-EP 2017; share of gross investment in sales; firm assessment of their equipment age; and share of R&D workers in total employment. Industry fixed effects are included as a control variable. (*) denotes significance at 10% level, (**) at 5% level, and (***) at 1% level.

Table 3: Regressing Capital Expenditures on Robot Shipments

	(1)	(2)	(3)	(4)	(5)
	Capex/Assets(t-1)				
Robot Shipments	0.000373*	0.00105***	0.00106***	-0.000142	0.000416
/Worker	(0.000169)	(0.000250)	(0.000245)	(0.000294)	(0.000427)
Robots X Q2 Size				0.000467	0.000441
				(0.000315)	(0.000400)
Robots X Q3 Size				0.000624*	0.000759
				(0.000312)	(0.000487)
Robots X Q4 Size				0.000985***	0.000907*
				(0.000284)	(0.000496)
Observations	372207	372207	372207	332193	332193
R^2	0.050	0.045	0.022	0.054	0.026
Country X Year FE	✓			✓	
Country X Ind FE		✓			
Industry FE	✓			✓	
Year FE		✓	✓		✓
Firm FE			✓		✓

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$,*** $p < 0.001$

The dependent variable in each column is the firm-level ratio of capital expenditures to lagged assets. The ratio is trimmed at 1% and 99%. The main independent variable is the value of robot shipments in a given country-industry-year. Rows in the bottom of the table show which fixed effects are included. Standard errors are clustered on country-industry-year level.

Table 4: Comparing Magnitudes of Robot Investment Based on Aggregate and Firm-Level Data

	IFR & EU KLEMS Data					IFR & Amadeus Data		
	Tot Invst [mln EUR]	Investment in Machinery [mln EUR]	Num Robots Shipped	%Robots +Periph.in Tot. Invst.	%Robots +Periph. in Mach. Invst.	Av. Capex /L.Assets	Robots Shipped /1000 Workers	Implied %Robots in Capex
Total			19945					
Total Manufacturing	117559.00	46070.99	19703	2.8%	7.1%	6.4%	1.31	2.1%
Automotive	39481.36	11681.05	11790	4.9%	16.7%	7.4%	11.36	15.3%
Chemical	17729.16	6536.67	2396	2.2%	6.1%	6.4%	2.22	3.5%
Food Manuf	6813.64	4668.84	557	1.4%	2.0%	9.3%	0.56	0.6%
Textiles	916.00	459.00	27	0.5%	1.0%	5.5%	0.15	0.3%
Wood and Paper	3609.00	2186.00	188	0.9%	1.4%	6.4%	0.42	0.7%
Glass, Mineral	6412.00	3892.00	228	0.6%	1.0%	6.9%	0.8	1.2%
Metal	9343.00	5985.00	2678	4.7%	7.4%	6.8%	1.14	1.7%
Industrial Machinery	13050.00	4901.00	1318	1.7%	4.5%	4.7%	0.97	2.1%
Electrical/electronics	15864.00	3939.00	1058	1.1%	4.4%	5.6%	0.48	0.9%

This table shows the value of robot-related expenditures in investment based on combining IFR and EU KLEMS data as well as based on a combination of IFR and Amadeus data and coefficients from regressing Capex on the shipments of robots. The analysis is conducted using 2015 values for Germany. Value of robots in IFR+KLEMS data is calculated by multiplying the number of robots shipped by €156,000, which is based on the IFR-estimated price of robots and peripherals. Implied share of Capex in robots is calculated using 0.001 as the sensitivity of Capex/Assets to robots' flows, consistent with columns 2 and 3 in table 3.

Table 5: Employment Changes for Firms Adopting Automation

	(1)	(2)	(3)	(4)	(5)	(6)
	5-Year %ΔNumber of Workers					
Automation & Digitization	0.0165***	0.0110**	0.0183***			
Adoption	(0.0043)	(0.0046)	(0.0071)			
Automation Adoption				0.0184***		
				(0.0075)		
Usage of Robots					0.1067**	
					(0.0450)	
$\Delta 5Y$-Robots/Worker						1.495**
						(0.716)
Observations	4961	4961	2894	2894	3576	129
R^2	0.003	0.020	0.023	0.022	0.025	0.133
Industry FE		✓	✓	✓	✓	✓
Firm Size FE		✓	✓	✓	✓	✓
Firm Controls			✓	✓	✓	✓

The dependent variable in each column is relative change in the number of employees for a given firm (2011-16 for columns 1-5, 2014-18 for column 6) . The independent variables are: (1) intensity of automation and digitization adoption (2016 IAB-EP, scale 1-10); (2) intensity of automation, defined as intensity of automation and digitization adoption interacted with binary indicator for using robots and considering them important; (3) binary indicator for usage of industrial robots; (4) 2014-18 change in the number of robots used per worker. In columns 3-6 firm-level controls include sales per employee, average salary, exporter status, having introduced a new product in the last year, being a foreign firm, being part of group, and public firm indicator (all as of 2016). Standard errors are shown in parentheses. * $p < 0.1$, ** $p < 0.05$,*** $p < 0.01$.

Table 6: Employment Effects of Robotization at Industry-Area Level

	Y=%ΔEmployment					
	(2005-2015)		(2005-2010)		(2010-2015)	
	(1)	(2)	(3)	(4)	(5)	(6)
Robots X	-0.211		-0.277*		-0.022	
Adoption>P(50)	(0.175)		(0.147)		(0.093)	
Robots Abroad X		-0.396+		-0.600**		-0.049
Adoption>P(50)		(0.269)		(0.246)		(0.156)
N	5278	5278	5278	5278	5205	5205
Area FE	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓

The dependent variable in all columns is the relative change in employment for a given industry-area cell expressed in percentage points. Columns 1 and 2 present the results for 2005-15, while columns 3-6 present the results for subperiods 2005-10 and 2010-15. The employment in a given year is measured as the average value in (t-1,t+1) window, to increase precision. For example, employment change between 2005 and 2015 is the %-change in average employment between 2004 and 2006 and average employment between 2014 and 2016. Independent variables are robotization – measured as the 2005-2015 (in column 2; 2005-10 in columns 3-4, and 2010-15 in columns 5-6) change in number of robots per 1,000 workers on industry level in Germany, and its interaction with indicators of a firm being located in high-technology-adoption area. The analysis is conducted on the industry-area level (two-digit industry; RORs/commuting zones). The local indicator for adoption is is defined based on area-level average of responses to the automation and digitization adoption question from the 2016 IAB-EP. High-adoption area (Adoption>P(50)) is defined as having the adoption indicator above median. Robots abroad are defined analogously to German measures, except that they are averages for several other European countries. All regressions include industry and area fixed effects and are weighted using employment levels from 2005 (or 2010 for columns 5 and 6). Standard errors, reported in parentheses, are two-way clustered by area and industry. (+) denotes significance at 15% level, (*) at 10% level, (**) at 5% level, and (***) at 1% level.

Table 7: Automation Adoption and Labor Scarcity

	Basic Specification		Alternative Measures of Labor Scarcity		Alternative Measure of Technology			Labor Scarcity in local area	
	Automation and Digitization Adoption				*Adoption X High Invst*	*Adoption X Robots*	*ΔRobots (2014-18)*	*Automation and Digitization Adoption*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Hard to Find Workers	0.307***	0.380***			0.066***	0.093+	0.0017**		
	(0.072)	(0.111)			(0.011)	(0.060)	(0.0008)		
Demand for Hiring > Hired			0.180**						
			(0.083)						
Can't Increase Sales without New Staff				0.361***					
				(0.083)					
Hard to Find Workers (Local Index)								0.078*	0.175**
								(0.047)	(0.086)
N	7469	3441	7449	6260	5781	9584	1462	10250	1006
Industry FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Size	✓	✓	✓	✓	✓	✓	✓	✓	✓
Add. Controls		✓							

The dependent variable in columns 1-4 and 8-9 is the automation and digitization adoption measure from the IAB-EP. The dependent variable in column 5 is the adoption interacted with an indicator of capital expenditures to sales ratio (average for 2011-16) being above the industry-wide median; in column 6 the interaction with an indicator of using robots (based on 2017 IAB-EP), while in column 7 the relative change in the number of robots used by the firm over 2014-18 (based on the 2019 IAB-EP). Independent variables are various measures of labor scarcity from IAB-EP: "Hard to Find Workers" is a binary variable that takes a value of 1 when the establishment confirms that it faces this staffing problem; "Demand for Hiring > Hired" is the dummy variable that takes a value of 1 if the establishment declares that it would like to hire more workers than it did hire; "Can't Increase Sales Without New Staff" takes a value of 1 when the establishment declares that it is capacity constrained and would have to hire new staff to increase production. In columns 8-9 the independent variable is a measure of local labor scarcity, computed as the average of "Hard to Find Workers" declarations among all firms in the same district, excluding given firm (leave-one-out method). Sample in column 8 includes all firms, while column 9 only includes firms that export at least 20% of their production. Control variables include five binary variables for different size quintiles (by employment) and industry fixed effects (two-digit). Additional controls include categorical measure of firm's profitability, employment growth in the last three years, establishment age, categorical measures of type of management, being part of a group, establishment age, public ownership, foreign ownership, and being a startup. Standard errors are clustered on the industry level. (+) denotes the significance at 15% level, (*) at 10% level, (**) at 5% level, and (***) at 1% level.

Table 8: Employment Effects of Digitization

	Y=%ΔEmployment					
	(2005-2015)		(2005-2010)		(2010-2015)	
	(1)	(2)	(3)	(4)	(5)	(6)
Digitization X	0.513		0.325		0.520**	
Adoption>P(50)	(0.593)		(0.727)		(0.240)	
Digitization Abroad X		0.113		0.349+		0.091
Adoption>P(50)		(0.172)		(0.213)		(0.094)
N	5278	5278	5278	5278	5278	5278
Area FE	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓

This table presents coefficients analogous to those presented in table 6, but for digitization instead of robotization. The dependent variable in all columns is the relative change in employment for a given industry-area cell expressed in percentage points. Columns 1 and 2 present the results for the baseline period 2005-15, while columns 3-6 show results for subperiods 2005-10 and 2010-15. The employment in a given year is measured as average value in (t-1,t+1) window, to increase precision. That is, employment change between 2005 and 2015 is the %-change in average employment between 2004 and 2006 and average employment between 2014 and 2016. Independent variables are digitization – measured as the 2004-14 change in the stock of software and databases capital per worker in Germany, and its interaction with indicators of a firm being located in high-technology-adoption area. Digitization abroad are defined analogously to German measures, except they are averages for several other European countries. The analysis is conducted on the industry-area level (two-digit industry; RORs/commuting zones). The local indicator for adoption is is defined based on area-level average of responses to the automation and digitization adoption question from the 2016 IAB-EP. High-adoption area (Adoption>P(50)) is defined as having the adoption indicator above median. Standard errors, reported in parentheses, are two-way clustered by area and industry. (+) denotes significance at 15% level, (*) at 10% level, (**) at 5% level, and (***) at 1% level.

Appendix Figures and Tables

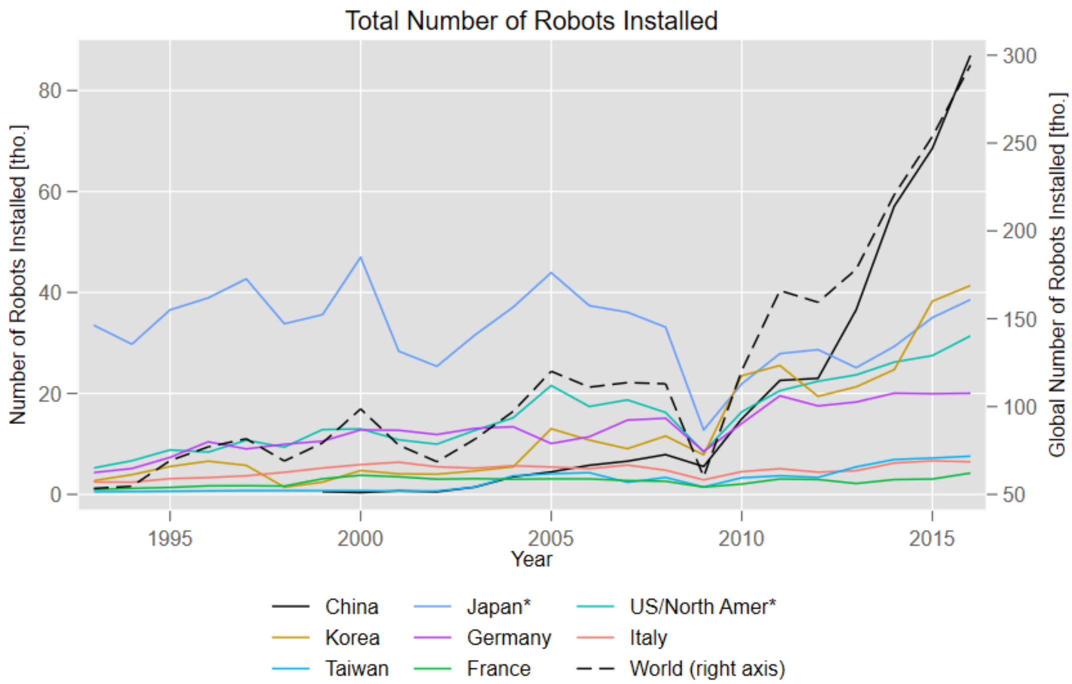


Figure A.1: Total Sales of Robots in Top 8 User Countries

This figure presents the evolution of robots sales between 1993 and 2016 for eight countries with the highest number of robots in use in 2016, based on IFR data. United States includes other North American countries until 2010. Japan data were subject to reclassification, as learned from the IFR, and hence should be interpreted with caution. Data for China are available since 1999.

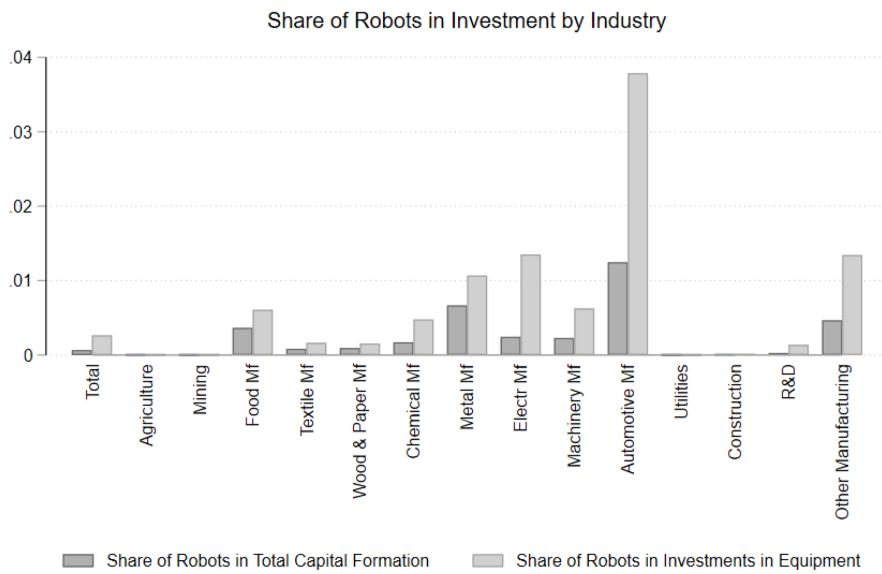


Figure A.2: Share of Robots in Investment by Industry

This figure presents the share of robot expenditures in investment across industries. The shares are computed by adding sales and investment values over all countries and three years: 2013-2015; hence, they reflect the relative size of countries in the sample. The value for robot sales comes from the IFR data; the price of a robot is assumed to be €45,000 on average. Dark bars show the ratio of robot sales value to total capital formation; light bars show the ratio of robot sales value to the value of investment in equipment, defined asICT equipment and other machinery. All investment series come from EU KLEMS data and are real values expressed in 2010 prices. The values are converted from national currencies to Euro.

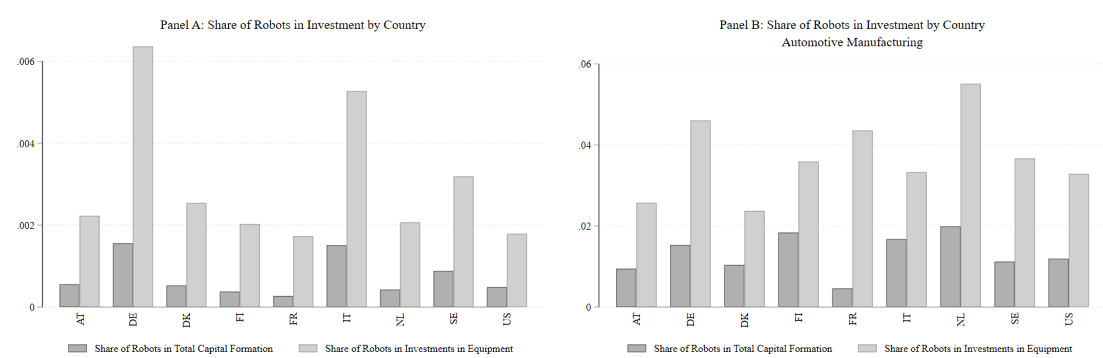


Figure A.3: Share of Robots in Investment by Country

This figure presents the share of robot expenditures in investment across countries. Panel A presents values for the whole economy, and hence it is largely driven by industry composition. Panel B shows the distribution within a single industry - manufacturing of the means of transportation. In the left panel, the shares are computed by adding sales and investment values over all industries and three years: 2013-2015; hence, they reflect the relative size of industry in each country. The value for robot sales comes from the IFR data; the price of a robot is assumed to be €45,000 on average. Dark bars show the ratio of robot sales value to total capital formation; light bars show the ratio of robot sales value to the value of investment in equipment, defined as ICT equipment and other machinery. All investment series come from EU KLEMS data and are real values expressed in 2010 prices.

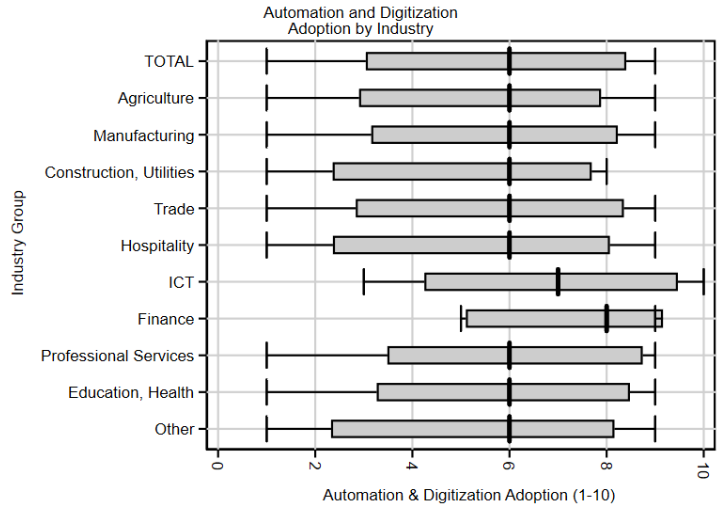


Figure A.4: Automation and Digitization Adoption: Summary Statistics by Industry Group
This figure presents summary statistics for the intensity of automation and digitization adoption from the IAB-EP (part C - intensity of adoption on the scale from 1 to 10) by industry group. The bold line inside the box represents the median of firms declarations. The box limits represent one standard deviation below and above the mean declaration (and hence the center of the box represents the mean). The whiskers represent the 10th and 90th percentile of the declarations. Minimum and maximum for each group, not depicted, equals 1 and 10, respectively.

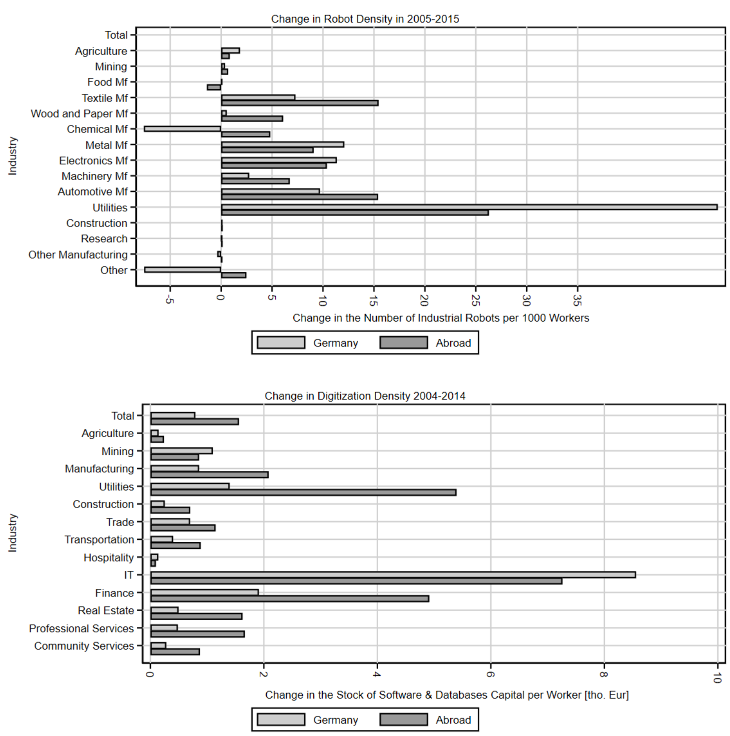


Figure A.6: Changes in Robotization and Digitization in 2005-2014/15
This figure shows the 2005-15 change of robot density (number of robots per 1,000 workers, based on IFR data) and 2004-2014 change of digitization (stock of software and databases capital per worker, in thousands of Euro, based on EU KLEMS data) in Germany and other European countries. For both robots and digitization we use six other countries, but the group differs because of data availability. For robots, it consists of France, Italy, Denmark, Netherlands, Sweden, and the United Kingdom. For software and databases capital, the group consists of France, Italy, Belgium, Netherlands, Finland, and Austria.

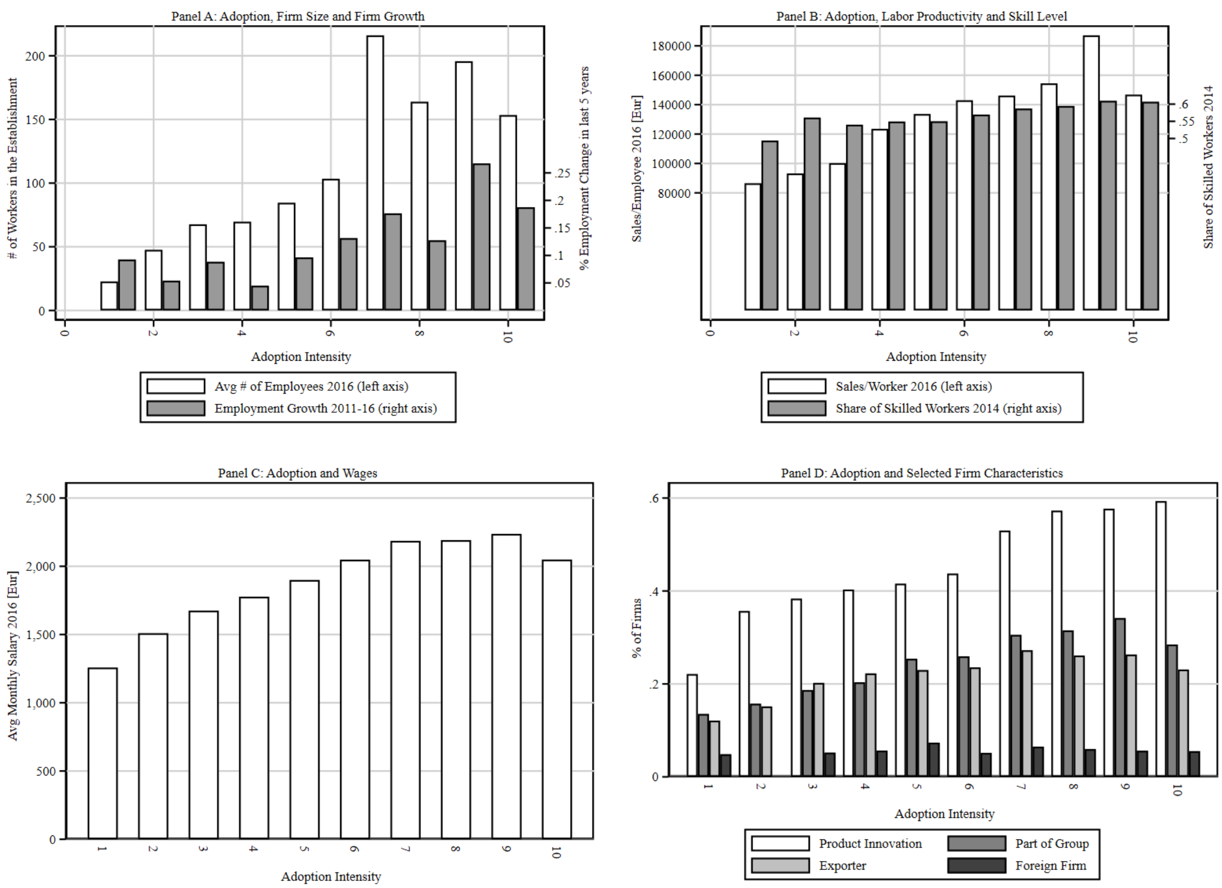


Figure A.5: Automation and Digitization Usage and Firm Characteristics

The graphs show the relation between levels of automation and digitization adoption and various firm characteristics: number of employees, five-year relative change in number of employees (panel A), sales per worker, share of skilled workers (panel B), average monthly wage (panel C) introducing product innovation in the last year, establishment being part of a multi-establishment firm, establishment having foreign owner, and being part of a public firm (panel D). All variables come from the most recent wave of the IAB-EP in which a variable is available.

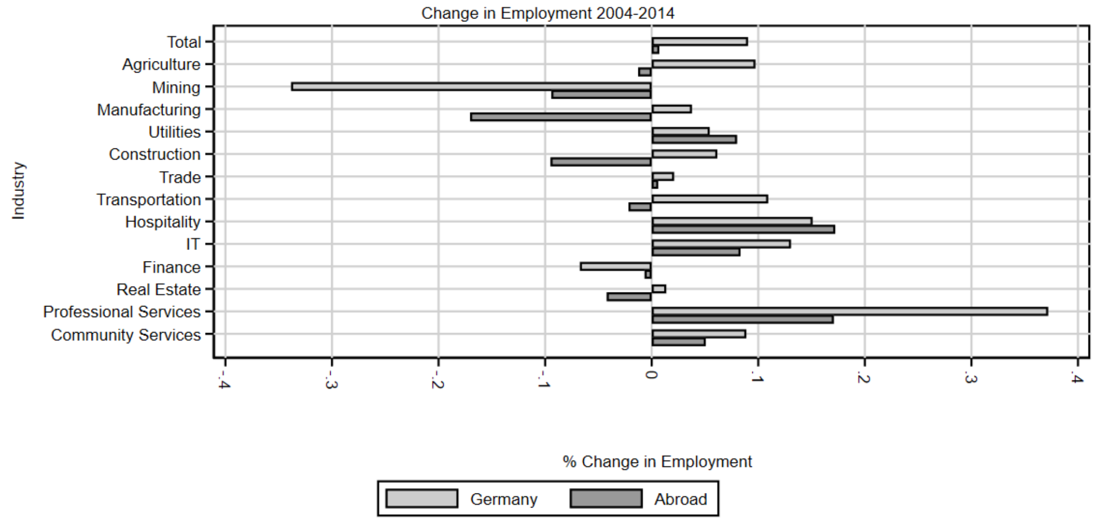


Figure A.7: Changes in Employment by Industry for 2005-2015 in Germany and Other Countries
Based on EU KLEMS data. Foreign countries consist of Austria, Belgium, France, Finland, Italy, and Netherlands.

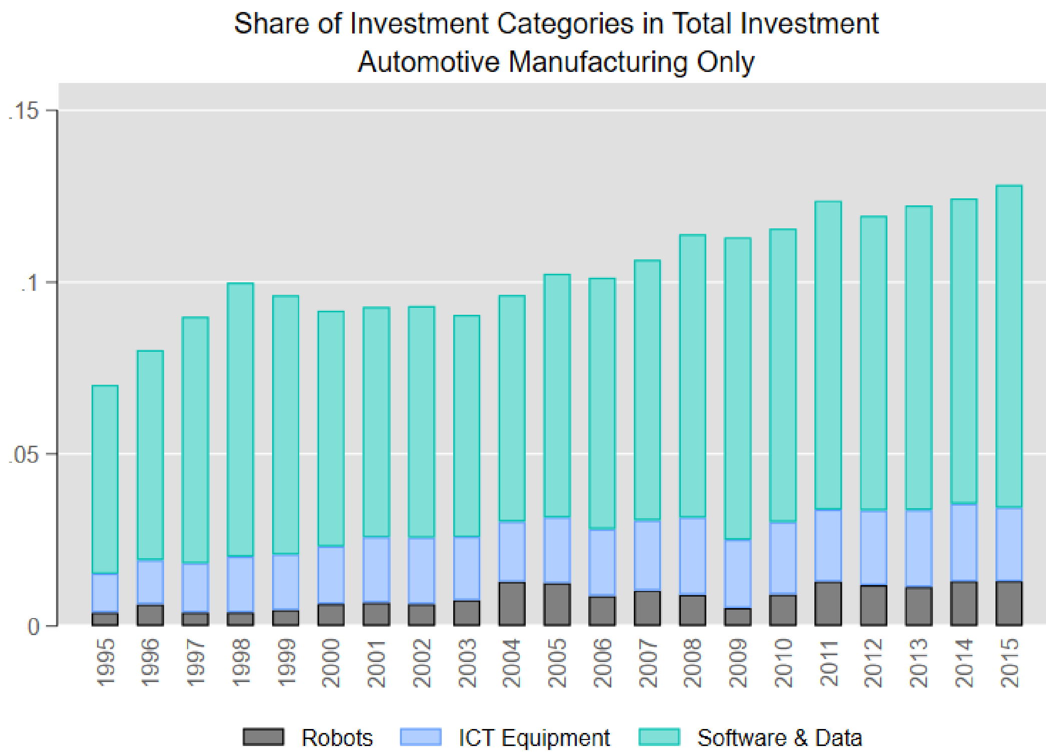


Figure A.8: Share of Selected Investment Categories in Total Investment: Automotive Manufacturing

This figure presents the evolution of the share of various investment categories in total non-residential investment. The shares are computed by adding sales and investment values overall for all countries for the automotive manufacturing industry. The value for robot sales comes from the IFR data; the price of a robot is assumed to be €45,000 on average. Remaining values of investment flows come from EU KLEMS data and are real values expressed in 2010 prices. ICT equipment includes information technology equipment and communication technology equipment. The denominator is the difference between total capital formation and investment in residential buildings.

Table A.1: Summary Statistics of Additional Variables

		Mean	Std Dev	P25	Median	P75	Num Obs
Investment	(% sales)	6.81	24.80	0.5	2.37	6.55	10302
High Adoption		0.33	0.47	0	0	1	7512
Hard to Find Workers		0.40	0.49	0	0	1	10391
Would Like to Hire More Workers		0.19	0.39	0	0	0	10365
Can't Produce More w/o Hiring Extra Labor		0.41	0.49	0	0	1	8777
Hard to Find Workers (Area Index)		0.40	0.11	0.35	0.39	0.47	14202
Number of Employees		106.8	853.3	4	14	59	14202
Share Low-Skilled		0.16	0.24	0	0.02	0.25	14101
Share High-Skilled		0.62	0.29	0.49	0.69	0.86	13239
Share Admin		0.29	0.33	0.02	0.15	0.47	12444
Sales	(mln Euro)	23.5	450	0.24	1.0	5.2	9155
Sales per Employee	(tho Eur)	132	243	43	75	140	9155
Robots (Ind)	(2015)	4.1	18.7	0	0	0	5525
Digitization (Ind)	(2014)	4.2	7.6	1.0	1.5	2.2	5643
ΔRobots (Ind)	(2005-15)	0.84	4.79	0	0	0	5424
ΔDigitization (Ind)	(2004-14)	1.56	3.41	0.17	0.45	0.50	5539
Adoption (Area)	2016	5.78	0.65	5.48	5.88	6.25	5642
Employment	(2015)	3156	5603	273	1268	3498	5717

All rows, except the six bottom ones, are based on IAB-EP data. Robots and Digitization are based on IFR and EU KLEMS data merged to the BHP establishment-level data set, while employment in the last row is the area-industry level measure from the BHP. Investment is the average value of investment in 2011-16, expressed as the share of firm's sales. The variable is missing if a firm has not reported any positive investment in that period. High adoption is a binary measure that combines the survey declaration about automation and digitization adoption (part C) with information about firm investment: it equals 1 if both adoption and investment are above the industry-wide median. Robots and their change are expressed as number of robots per 1,000 workers and come from the IFR data (employment comes from the EU KLEMS database). Digitization is the stock of software and databases capital in thousands of Euro per worker, coming from EU KLEMS database. Adoption is the Raumordnungsregion (ROR/commuting zone) average of firm declarations about intensity of automation and digitization adoption from the 2016 IAB-EP.

Table A.2: Robustness Checks of Employment Changes Regression

	4th Quartile of Adoption		Not Weighted by Employment		Control for Past Empl. Changes		Exclude Automotive	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Baseline Period (2005-2015)								
Robots X	-0.029		0.009		-0.209		-0.346	
High Adoption	(0.076)		(0.191)		(0.175)		(0.385)	
Robots Abroad X		-0.054		-0.586*		-0.394+		-0.510
High Adoption		(0.115)		(0.347)		(0.268)		(0.396)
N	5278	5278	5278	5278	5234	5234	5183	5183
Panel B: 2005-2010								
Robots X	-0.120*		-0.487***		-0.270+		-0.663***	
High Adoption	(0.066)		(0.120)		(0.162)		(0.193)	
Robots Abroad X		-0.237**		1.088***		-0.595**		-0.832***
High Adoption		(0.098)		(0.286)		(0.246)		(0.294)
N	5278	5278	5278	5278	5234	5234	5183	5183
Panel C: 2010-2015								
Robots X	0.296		0.535		0.228		0.346	
High Adoption	(0.245)		(0.451)		(0.478)		(0.722)	
Robots Abroad X		0.298		-0.102		0.183		0.179
High Adoption		(0.223)		(0.327)		(0.398)		(0.153)
N	5276	5276	5276	5276	5232	5232	5181	5181

This table present robustness checks for the main specification presented in table 6. The three panels show results for the baseline period (2005-15) as well as two sub-periods. The employment in a given year is measured as average value in (t-1,t+1) window, to increase precision. For example, employment change between 2005 and 2015 is the %-change in average employment between 2004 and 2006 and average employment between 2014 and 2016. Columns 1 and 2 use quartiles of adoption instead of an above-median indicator. Columns 3 and 4 present basic specification with equal weights for every industry-area cell (as opposed to weighting by initial employment). Columns 5 and 6 include past change in employment between 1995 and 2005 as a control. Columns 7 and 8 exclude the automotive industry, which has the highest robot density. Except columns 3 and 4, all regressions are weighted using employment levels from 2005 (panels A and B) or 2010 (panel C). Standard errors, reported in parentheses, are two-way clustered by area and industry. (+) denotes significance at 15% level, (*) at 10% level, (**) at 5% level, and (***) at 1% level.

Table A.3: Persistence of the Labor Scarcity Effect

	Y = AUTOMATION AND DIGITIZATION ADOPTION (2016)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Hard to Find Workers (2016)	0.268***						
	(0.060)						
Hard to Find Workers (2014)		0.307***					
		(0.072)					
Hard to Find Workers (2012)			0.277***				
			(0.080)				
Hard to Find Workers (2010)				0.209***			
				(0.076)			
Hard to Find Workers (2008)					0.137+		
					(0.086)		
Hard to Find Workers (2006)						0.086	
						(0.114)	
Hard to Find Workers (2004)							0.132
							(0.127)
N	10226	7469	5666	4498	3604	2832	2262
Industry FE	✓	✓	✓	✓	✓	✓	✓
Size	✓	✓	✓	✓	✓	✓	✓

All columns present specifications analogous to column 1 from table 7, but with labor scarcity measures coming from different waves of the IAB-EP. Standard errors are clustered at the industry level. (+) denotes significance at 15% level, (*) at 10% level, (**) at 5% level, and (***) at 1% level.

Table A.4: Other Staffing Problems

	Y = Automation and Digitization Adoption (2016)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Too Many Employees	-0.024							
	(0.138)							
High Labor Costs		-0.038						
		(0.066)						
Aging Population			-0.125*					
			(0.069)					
High Labor Turnover				0.145				
				(0.112)				
Demand for					0.347***			
Further Training					(0.124)			
Lacking Motivation						0.004		
						(0.125)		
Many Absences							-0.100	
							(0.100)	
Staff Shortage								0.125+
								(0.080)
N	7469	7469	7469	7469	7469	7469	7469	7469
Industry FE	✓	✓	✓	✓	✓	✓	✓	✓
Size	✓	✓	✓	✓	✓	✓	✓	✓

All columns present specifications analogous to column 1 from Table 7, but with the main independent variable being an indicator for different types of labor problems. All indicators are defined based on firm response to the same module ("Staffing problems") of the 2014 IAB-EP. Standard errors are clustered at the industry level. (+) denotes significance at 15% level, (*) at 10% level, (**) at 5% level, and (***) at 1% level.