Robots and Firm Investment

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Abstract

Automation technologies, and robots in particular, are thought to be massively displacing workers and transforming the future of work. We study firm investment in automation using cross-country data on robotization as well as administrative data from Germany with information on firm-level automation decisions. Our findings suggest that the impact of robots on firms and labor markets has been limited: 1) Investment in robots is small and highly concentrated in a few industries, accounting for less than 0.30% of aggregate expenditures on equipment. 2) Recent increases in robotization do not resemble the explosive growth observed for IT technologies in the past, and are driven mostly by catching-up of developing countries. 3) Robot adoption by firms endogenously responds to labor scarcity, alleviating potential displacement of existing workers. 4) Firms that invest in robots increase employment, while total employment effect in exposed industries and regions is negative, but modest in magnitude. We contrast robots with other digital technologies that are more widespread. Their importance in firms' investment is significantly higher, and their link with labor markets, while sharing some similarities with robots, appears markedly different.

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

Commenting on the disparity between measures of investment in information technology and output productivity, Robert Solow famously quipped at the beginning of the 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 again seems imminent – in what is now called "The Fourth Industrial revolution" a great deal of attention is devoted to automation and industrial robots. Graetz and Michaels (2018) find that robots have brought large productivity increases, comparable with past improvements caused by steam engine and IT, while Acemoglu and Restrepo (2019) 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% in 2014-2019, suggest that robots may significantly transform labor markets and the corporate sector, leading to massive worker displacement and a significant increase in firm's capital intensity.

This paper shows that despite these omnipresent predictions, today it is again hard to see robots not only in the aggregate productivity statistics (Brynjolfsson et al., 2019), but also anywhere else. Using cross-country data on robotization, we show that investment in robots, while somewhat increasing, remains a small share of total investment. Usage of robots is close to zero outside of manufacturing and even within manufacturing robotization is very low for all but few poster-child industries, such as automotive. Crucially, this picture is unlikely to change in the near future. A decade after Solow's observation the economic impact of IT was evident, but the same explosive growth pattern is not visible in robotics. The magnitudes of robot investment are dwarfed by investment in ICT equipment, software and other R&D expenditures in levels, and recent changes do not suggest a reversal. Recent increases in the absolute 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.

All these findings suggest that the predictions of a transformative impact of robots, in particular of large employment losses driven by robotization, may be too pessimistic. Yet, empirically assessing these predictions is challenging because of measurement and identification concerns (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. Using a difference-in-difference framework, we document that robotization significantly reduces employment. Yet, 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 adopting robots was lower, but only by ~0.03% per year. Moreover, we argue that to properly understand the economic consequences of automation, one also needs to 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 their labor scarcity problems. 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. First, we combine cross-country industry-level measure of robotization from the International Federation of Robotics 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 German Employment Agency, which include firm-level measures of automation and detailed employment data. We use these data to study how investment in automation responds to labor market conditions, and how automation affects firms' employment.

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 both 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.

It is of course possible that robots are still in infancy, and 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. Moreover, it remains highly concentrated in selected industries, in particular automotive manufacturing, just as it was 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, in the late 1980s and early 1990s investment in IT was exploding, and by the year 2000 spending on IT equipment alone constituted more than 1.5% of total capital expenditures. The same explosive growth path, however, 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.

The results from our cross-country analysis cast doubt on the notion that industrial robots account for a significant share of capital stock. Yet, the limitations of the data and identification challenges prevent us from using the cross-country setting to credibly study one of the most pressing questions in the automation debate: the relationship between robots and labor markets. To do that, we turn to firm-level data from Germany, and study two questions: 1) how does automation affect employment? and 2) 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 increasing employment, and hence direct displacement effect appears to be limited. It is however possible 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, improving upon the existing literature that relies on industry-level variation. We do find significant 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% decline in employment 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 that is the case, 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 unemployment rate. The results show that firms have higher adoption of automation when they face difficulties in finding suitable workers.[1] 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, or network communications – while less spectacular – can be more important drivers of labor markets. In the last part of

[1] Labor scarcity can be manifested either through 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 being unable 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 interpret the latter as high labor cost as well (e.g. high search cost).

the paper we document that investment in these technologies is much larger and more widespread than investment in robots. At the same time, we demonstrate that their implications are not necessarily the same as those of robots and automation. Employing the methodology analogous to the one used to study the relationships between automation and labor markets, we analyze the extent to which digital technologies substitute and complement labor. While some of these technologies can also substitute workers, just like robots do, their complementarity effect appears to be stronger and dominant in some industries in which digital technologies are commonly adopted.

This paper contributes to the recent literature on automation by taking a firm-centered approach and analyzing patterns of firm investment in robotics, a prominent example of automation technology. Our empirical evidence complements recent theoretical work on automation (Acemoglu and Restrepo, 2018b; Agrawal et al., 2019; Moll et al., 2019), and small but rapidly growing existing empirical literature in this area (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2019; Dauth et al., 2018; Koch et al., 2019; Humlum, 2019). Consistent with some of the existing papers, we find that robots lead to a decline in employment in a difference-in-difference setting that improves the identification of the employment effect. Yet, differently from the existing studies, we demonstrate that the magnitude of that decline is small, consistent with small magnitudes of robot investment that we also document. These findings raise a question about how low adoption can be reconciled with the large impact of robots on aggregate productivity documented in Graetz and Michaels (2018)[2] and suggest that the economic impact of robots is likely smaller than often presented. Instead of focusing on robots, more attention should be devoted to digital technologies that are likely to have larger economic consequences.

The paper also highlights the importance of studying patterns of firms' investment in technology adoption. Using firm-level adoption data, which has been scarce in the existing literature, we show that investment in automation is higher in places with a shortage of labor. Hence, even if robots do lead to lower employment, they do not necessarily lead to a displacement of workers. Instead, they may allow firms to grow even if they have difficulties filling vacant positions. Moreover, even if displacement happens, it is more likely to happen in the areas where jobs are abundant. These findings are important in the context of an aging labor force (Abeliansky and Prettner, 2017; Acemoglu and Restrepo, 2018a) and have implications for designing policy that addresses location or industry specific problems. At the same time, they improve our understanding of the determinants of firm investment and its implications, in particular in new technologies (Bates et al., 2020; Babina et al., 2020), complementing large literature on the role of financial constraints (Fazzari et al., 1988; Han Kim et al., 2019) and demonstrating that firm investment is also shaped by labor constraints (Mao and Wang, 2018; Xu, 2018).

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

The paper is also related to the broader literature on firm innovation and labor (Acharya et al., 2013; Babina and Howell, 2019; Bena et al., 2018) and on new technologies and finance (Chaboud et al., 2014; Buchak et al., 2018; Zhang, 2019; D'Acunto et al., 2019), as well as to a large literature that studies information and communication technologies at the end of the 20th century (Brynjolfsson and Hitt, 2000; Bresnahan et al., 2002; Autor et al., 2003; Autor, 2019). Several other papers analyze older technologies (Doms et al., 1997; Lewis, 2011; Clemens et al., 2018), studying their relationship to workers' skills and the link between technology adoption and immigration.

The rest of the paper is organized as follows. In section 2 we describe the datasets 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.

2 Data and Measures of Technology

This section provides a brief description of the data and documents basic facts about the key variables analyzed in the two empirical settings of the paper.

2.1 Cross-Country Analysis

In the first part of the paper, we combine firm-level financial data from Amadues with measures of robotization by industry, country, and year. The robotics data is novel, and has been first used by Graetz and Michaels (2018). The data comes from International Federation of Robotics (IFR, see IFR (2017)), which collects sales reports from robot manufacturers and covers over 90% of the global robotics market. The manufacturers 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 is available correspond to industries defined on 2-digit level in standard classifications such as NACE, although within some manufacturing industries, e.g., automotive, the classification is finer, while 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 goes back to 1993 for a few European countries and ends in 2016. Over the years, the coverage of different markets significantly improved. Industry-level data for North America is available since 2004. The IFR does not report information of robot prices in the same way as it does for units sold. Nonetheless, they do provide an approximation for average robot price which we use to calculate the value of robots' investment. .

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 which require human operator (e.g. crane) or which have a single purpose and cannot be flexibly reprogrammed (e.g. 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) or Acemoglu and Restrepo (2019).

We supplement IFR data with additional data sources. Among them, 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 1995-2015 period, 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 3), we include 9 developed countries for which all variables were available in both data sources: Austria, Germany, Denmark, Finland, France, Italy, Netherlands, Sweden and United States. Merging IFR and EU KLEMS data requires harmonizing their industry classification, which we do by aggregating selected industries. We therefore analyze 14 2-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; research and development.

We combine IFR and EU KLEMS data with firm-level data from Amadeus and use data for almost 55 thousand "large" or "very large" manufacturing firms from 23 European countries.[3] The data is an unbalanced panel with each firm having at most 10 observations; for most firms, these are the most recent available years which can be merged to robots data, i.e. 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 1000 workers in the whole economy and in several industry groups. Since our sample of industries is skewed towards manufacturing, simple average across industries that are included in the data leads to robotization values that are higher than those of the aggregate economy. While in automotive manufacturing 6.11 new robots per 1000 workers are installed in a typical year, this number is only 0.24 for the whole economy. The implied expenditure of investment in robots per worker is

[3]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 only for a subset of countries.

hence about 11 Euro per year, a very low figure compared to investment in Software & Data (1722 EUR/worker) or ICT equipment (848 EUR/worker).

2.2 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 analysis of German firms studies the impact of labor scarcity on the investment in automation, as well as the impact of robots on employment change in the last 10 years.

The two main administrative data sets used in this paper are IAB Establishment Panel (IAB-EP) and Establishment History Panel (BHP).[4] IAB Establishment Panel is a yearly survey of stratified random sample of German establishments. The version that we analyze spans the 1993-2017 period and covers over 16 thousand establishments from all industries. The IAB Establishment Panel data contain rich information about firms' personnel, investment, business policies, R&D and other areas of firm operations. While some variables are available in every year, others are only present for a subset of years. In particular, the automation and digitization measures used in this paper were included in the 2016 and 2017 waves of the panel. The survey is merged with administrative personnel records, containing information about firms' workforce size and structure.

The Establishment History Panel is a large firm-level data set containing information for a 50% 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.

As we mentioned earlier, firm-level measures of automation come from two waves of IAB-EP and combine subjective measures of intensity of technology adoption with binary indicators of technology usage. In 2016 the Panel contained an extra set of questions asking firms about "Automation and Digitization" technologies. The interviewer specified that these technologies include "autonomous robotics, smart factories, Internet of Things, big data analytics, cloud computing, online platforms, among other technologies". Respondents were asked to assess familiarity, potential and current adoption of the technologies on a scale from 1 to 10 (with an option "Difficult to say"): A) how intensively has the establishment dealt with this topic so far? B) what potential is there for

[4] More precisely, the study uses 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 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. The documentation for the data is contained in Ellguth and Kohaut (2014) and Schmucker et al. (2018).

application of such technologies in the establishment? C) how well is the establishment equipped with these technologies compared to other establishments in the sector?

In 2017, the Panel did not include the same questions but it did add additional 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.

Our main firm-level measure of the technology is the answer to part C of the intensity of automation adoption question. We further interact this measure with usage of robots based on the indicators for 2017 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. Figure A1 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.

Our labor scarcity measures come from the IAB Establishment Panel and are defined as binary variables based on the response of firms to questions about whether they are facing "difficulties in finding required workers on the labor market", which is a part of "Staffing Problems" module of the Panel. We confirm that these measures meaningfully represent labor market conditions by checking their correlations with local unemployment rate. Employment change is computed at the area-industry level by aggregating employment records of 50% random sample of all German firms from BHP data set. On average, such 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%, but there is substantial variation in employment changes across industries and local areas.

2.3 Validation of Technology Measures

To cross-validate technology measures, Figure 1 presents the relationship of industry-level measures of robotization and digitization and survey-based measure of familiarity with automation and digitization. While the adoption measure is relative to other firms in the sector, it is highly correlated with familiarity measure (which was 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 relationship with robots is driven by industries within manufacturing. This is simply because almost no robots are being used outside of manufacturing.[5]

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 correlations between overall technology adoption and 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 work force. 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.

3 Robots Investment Around the World

This section analyzes aggregate patterns of investment in robots using robot data from the International Federation of Robotics and firm-level data from Amadeus.

3.1 Magnitudes and Basic Patterns of Robot Investment

Figure 2 shows the evolution of the number of robots sold over time. In recent years, the total number of robots shipped significantly increased, leading to a perception of rapid acceleration in automation. Yet, as demonstrated in Figure 2, that impression might be somewhat misleading from the perspective of European and North American countries. The total number of robots sold have indeed significantly increased, from around 100,000 per year between 2000-2010, to 300,000 in 2016. While robots sales declined during the Global Financial Crisis, sales rebounded between 2011 and 2016. Yet, this growth in robots is predominantly fueled by growth in robot sales outside of Europe and North America. In the Western world, the growth in robot installations was more

[5] Recent survey conducted by World Economic Forum (WEF, 2018) shows that 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 4 out of 6 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, internet of things, machine learning and cloud computing. This primacy of digital technologies highlights the importance of looking at broader of set of technologies rather than focusing on industrial robots.

modest. It has not accelerated in recent years, and merely returned to the its pre-crisis trend after a dip in 2009.

Almost half of the 2006-2016 growth is accounted for by China alone: in 2006 China installed slightly over 5,000 new robots compared to almost 90,000 in 2016. Figure A2 in the Appendix illustrates the evolution of robots shipped to 8 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 has surpassed Japan as the country with the highest number of robot installations by 2013. South Korea has also seen a substantial growth pattern, especially in the last two years. At the same time, the growth in robot shipments was significantly lower in other countries, including the United States, Germany, or Italy.

The number of robots sold is not a sufficient statistic to compare robots and other investment. In 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 EUR 45,000, and use that estimate combined with the number of robots sold to calculate total investment in robotics. According to our estimates, robots constitute 0.2-0.3% of total investment in equipment, and less than 0.1% of total capital formation. Their share in total investment was relatively stable between 1995 and 2005 and has increased by almost 50% between 2005 and 2016. However, as demonstrated in Figure 2, this growth is largely fueled by developing countries.

Figure 4 demonstrates the share of robots in total investment across industries. The first important implication of that graph is driven by what is not shown: we only present the values for a subset of industries. For all remaining industries, the number of robots shipped is zero.[6] Industries presented on the graph include mostly manufacturing. Even among them, there is a clear pattern of concentration. Manufacturing of means of transportation shows the highest share of robots in investment. Other industries with higher-than-average robotization include electrical and metal manufacturing. This distribution is consistent with robots being productive in certain environments, but having limited applicability in other contexts.

High concentration of robots in selected industries is also an important driver behind cross-country differences in robot adoption. The left panel of Figure 5 shows the share of robots in investment in a set of developed countries. Germany and Italy clearly stand out, consistent with those countries having large automotive and heavy manufacturing sector in general. The pattern observed within industries (right panel of Figure 5 demonstrates the share of robots in investments across countries for automotive industry, which adopts the highest number of robots), while also showing some heterogeneity, is different, suggesting that robotization rates vary mostly by

[6]Some robots 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, resulting in IFR not reporting these industries separately.

industry. This creates a challenge for the analysis of the effects of robotization based on country-industry-year data only, since it is difficult to obtain precise estimates after controlling for industry-specific trends. For that reason, Section 4.2 expands on the existing papers based on industry-level variation (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2019) and analyzes employment effects of robotization in a difference in difference specification combining industry- and local area-level variation.

3.2 Correlating Robots with Firm Investment

The analysis in Section 3.1 suggests that investment in robots remains small and highly concentrated. Our calculations, however, are based on the count and average price of robots, and may potentially 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 International Federation of Robotics, the total cost of a robot with peripherals and supplementary investments may be three times as large as the price of the robot. To validate this 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 Amadues. 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% 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 roughly in line with the estimates based on robot prices, although for most manufacturing industries Capex increases less than three times the price of robots. The last column of Table 4 demonstrates that for manufacturing as a whole robots correspond to around 2% of total capital expenditures. Given that manufacturing constitutes around 15% of the economy on average, and that robotization levels are very low in other sectors, this suggests a 0.3% share in total Capex, consistent with our price-based estimates from Section 3.1. These calculations suggest that investments complementary to robots are not the main component of robotics-related expenditure. For some industries, however, including automotive manufacturing, the implied share of robotization in Capex is larger, and roughly consistent with the total amount of robotics-related investment being three times the price of a robot.

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

3.3 The Evolution of Robotization and Past IT Investment

Recent trends in robotization suggest that the share of robots in firm investment is steadily increasing, yet the pace of this increase is relatively stable and modest for developed countries. One can argue, however, that robots are in 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 6. 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 is available), and to 1980 for IT equipment, thus introducing 15-year lag.

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

All these findings suggest that the role of robots in transforming the economy is modest so far, contrasting with some of the views echoed in the literature (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2019). Yet, the evidence presented does not directly speak to the central question of the debate, i.e. 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.

4 Firm Investment in Automation in Germany

In this section, we turn to firm-level data from Germany to enrich our analysis of robotization and investigate the link between investment in robots and labor market conditions and outcomes. We start by presenting several facts that complement the aggregate patterns discussed in Section 3. 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.

4.1 Investment in Automation at the Firm Level – Basic Facts

Figure 7 depicts the variation in the usage of robots and related technologies across industries based on the IAB Establishment Panel firm-level data. Clearly, and similar to the our cross-country analysis, robots are highly concentrated in manufacturing. Since our firm-level measure of automation also captures older technologies, such as CNC machines (see Section 2), the magnitudes are larger than in the IFR data.

The usage of automation technology in Germany varies by geographical area, even after controlling for the industry structure as illustrated by Figure 8. The measure used in the figure is the average of firm assessments of automation adoption relative to other firms in the sector and hence it is not driven by industrial composition, but rather by other factors affecting technology adoption, such as proximity of R&D centers, technological spillovers and labor market conditions.

In addition, technology usage also varies by firm characteristics, see Figure 9. 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 partially explained by the fact that their workforce is more skilled.

Figure 9 illustrates also that high-adopters have been growing faster in the last five years. When we estimate firm-level regressions of employment growth on automation adoption we find a *positive* correlation between employment growth and automation adoption. This relationship is of course subject to endogeneity concerns, and the employment decline may actually be happening in firms that do not adopt robots. Yet, the positive sign of the direct link between robot adoption and employment growth suggests that the relationship between robotization and labor markets is somewhat nuanced.

Figures A4 and A5 in the Appendix document the relationship of technology adoption with wages, innovation, being an exporter and other firm characteristics. High-adopters pay higher wages, are more innovative, are more likely to be exporters and more likely to be a part of multi-establishment group. However, there is no relationship between technology adoption and foreign ownership.

4.2 The Effect of Automation on Employment Growth

We now turn to analyze the effect of automation on employment at the local area-industry level. We regress 10-year changes in total employment on measures of changes in robotization, defined at the industry-area level, controlling for industry and area fixed effects.

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 International Federation of Robotics. 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 (2019). 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 a local area[7] measures of intensity of automation and digitization adoption, computed as the average of firm-level measures from the IAB Establishment Panel.

We use data from the Establishment History Panel (BHP) – an administrative data set with information on 50% of all German establishments – and aggregate up employment information to the industry X area level. The main empirical specification is:

$$\Delta Y_{a,j} = \beta_R \cdot \left(\Delta Robots_j \cdot Adoption_a\right) + X_{ja} + \phi I_j + \xi A_a + \varepsilon_{a,j} \tag{1}$$

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). Subscripts a and j denote area and 2-digit industry, respectively. $\Delta Robots_j$ is the change in number of robots per 1,000 workers used in a given industry, coming from International Federation of Robotics data. $Adoption_a$ 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 Establishment Panel. Since, in their self reporting, firms compare themselves to other firms in the same sector (see Section 2), the measure is not driven by the industrial

[7] 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. While 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.

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 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.

Interpreting the Empirical Specification. There are two ways to interpret the empirical specification. The first one is to consider it to be a difference in differences estimator in which the differences are taken across industries and areas (not across time, as in traditional DiD settings; difference over time is included in the dependent variable, which is the change in employment). The treatment is the change in automation intensity at the industry level and the treated group consists of firms in high-adoption areas, while the control group consists of firms in low-adoption areas. The identifying assumption is that absent the technological change, the difference between the change in outcomes of the treatment and control group would not be systematically different across industries.

The second way to interpret the specification is in terms of the propensity to adopt technology. Two independent forces are pushing for the adoption: large technological change in the industry and being located in a high-adoption area. Looking at firms in industries with large technological change which are located in high-adoption areas and differencing out the effect of industry alone and area alone should therefore allow us to isolate the effect of technology on employment.

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, the other in an area with 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 paper industry – that has a negligible robotization change and therefore "robotization effect" is negligible – allows us to compute the "location effect". Assuming that this effect does not systematically differ across industries, it allows us to back out the "robotization effect" in the car industry.

Endogeneity. Changes in robots density in Germany may be endogenous. For example, when German firms in a given industry face high demand, they may be adopting more robots and at the same time increasing employment – in which case our estimates of the employment effect would be biased upwards. While in our specification the technology coefficient is identified using within-industry variation, which somewhat alleviates this concern, the degree of technological change still influences the estimates (intuitively, the coefficient of technology is a weighted average of differences between high and low adoption areas across industries, with weights equal to intensity of technological change in the industry). To better isolate the exogenous variation in technology, we follow the approach of Autor et al. (2013) and Acemoglu and Restrepo (2019) and use changes in robot density in a group of other European countries.[8] We present both the reduced form estimates with technology abroad as the independent variable and IV estimates in which we use technology abroad as an instrument for domestic technological change.

Differences in adoption across local areas are not random and can be correlated with various other factors affecting employment. We do not assume that high- and low-adoption areas are similar 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.

Assuming that the differences between high- and low-adoption areas are similar across industries, except for the effect of technology, seems more plausible than assuming that all industries are similar, except for the effect of the technology. Nonetheless, the former assumption can still be violated. One such concern is related to agglomeration effects affecting different industries. High-skill industries may be more likely to be located in a few selected business hubs compared to manufacturing firms. The existence of these preferences alone does not pose a problem to our strategy. However, if these preferences are becoming more and more prevalent and if business hubs also have higher levels of technology adoption, we may see that employment in high-skill services (which have low robotization) increases, while employment in manufacturing (in which the share of robotization is higher) decreases in high-adoption areas.

While this is a possible concern, 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 (Fig. 8) reveals that many areas with high adoption (e.g. northeastern Bavaria or 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.

Results. Table 5 presents the results from estimating the effects of technology adoption on employment growth. We estimate Eq. 1 with the dependent variable being the percentage change in employment between 2005 and 2015. The results for the main specification, presented in column 3, show that robotization has a negative and significant effect on employment. One additional robot per 1000 workers reduces employment in high adoption areas by 0.36% in the 10-year period, compared to firms in the same industry in low adoption areas. On average, between 2005-2015

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

the German economy increased robotization density by 0.84. We do not know how the increase in areas with above-median intensity of automation compared 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 less than 0.3% during that decade, corresponding to a 0.03% per year (the effect of compounding is small). Interestingly, a simpler approach of regressing employment change on area- or industry-level measures of technological change (columns 1) shows much smaller and insignificant results, highlighting the importance of properly accounting for other industry-level changes.

To alleviate endogeneity concerns, we estimate an alternative specification that, instead of using domestic change in technology, uses change in the technology abroad (column 3) or instrument domestic changes with the changes abroad (column 4). Both results confirm the negative and significant effect of automation. Our estimates suggests that endogeneity concerns can indeed, to some extent, bias the coefficients upwards. They do, however, remain in the same order of magnitude.

Columns 5-8 analyze alternative periods. The signs of the coefficients remain unchanged, although the negative effect of robotization is more evident in the more recent period. While this suggests that the effect of robotization might be larger in the later periods, this interpretation should be treated with caution. In particular, the 2010-2015 period is the time in which the German economy recovered from the Global Financial Crisis, and hence may reflect heterogeneous rebound of employment across industries.

Table A3 presents the results of robustness tests of the main findings. The main result 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. In addition, the table presents the first stage of the IV regression as well as the results of analogous regression for wages. Automation does not have significant effects on wages, but this result should be interpreted with caution given the widespread central bargaining and wage rigidity in Germany.

4.3 Automation Adoption and Labor Scarcity

While automation can potentially affect employment – technological adoption can also be affected by existing labor market conditions. We next analyze how the availability of labor influences firm's investment in automation. We use firm-level data from the IAB Establishment Panel and estimate following basic OLS specification:

$$Technology_i = \beta \cdot Labor\,Scarcity_i + \gamma \cdot I_j + \phi \cdot Z_i + e_i \tag{2}$$

The dependent variable is a measure of automation and digitization that comes from the IAB Establishment Panel. 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 a binary indicator of adoption being above the median and an interaction of this indicator with a dummy variables that takes the value of one if the ratio of investment to sales is above median. I_j denotes a set of industry fixed effects that correspond to 2-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 which 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 or being a public firm are included in the robustness checks. Due to limited data availability, including additional controls significantly reduces sample size. 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. Another potentially important control variable is the area fixed effect, since part of the variation in labor scarcity is common for all firms in the area. We present the results both with and without area fixed effects. Standard errors in the main specification are clustered at the industry level.

The main independent variable, $LaborScarcity_i$, is a binary indicator based on the firm's assessment that they have difficulties finding workers. It is defined based on answers to the 2014 survey that predates the technology-adoption measure by 2 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 Table A5). We also present results with three other measures of labor scarcity.[9]

Table 6 presents the results. Columns 1-7 report the results with the adoption measure being a continuous assessment of adoption from the survey; columns 8-9 present the results using an interaction between above-median adoption assessment and above-median capital expenditures as the dependent variable. Each measure points to a clear positive relationship 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 increases technology adoption by 10-15% of a standard deviation. Inclusion of area fixed effects, in columns 4 and 9, slightly decreases the magnitude of the effect,

[9]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. firm's declaration that they are unable to increase the production without hiring new staff. The fourth measure, only available for a subset of firms, is a binary indicator that equals one of the firms reports abandoning a project because of personnel shortage. All firms are asked whether they had an innovative project that they planned to carry out but did not. If the answer is positive, firms are asked about different possible reasons for abandoning the project, including personnel shortage.

consistent with the notion that some of the variation in labor scarcity is driven by area-level characteristics. However, even when those characteristics are purged off, significant variation across firms remains and is positively related to technology adoption.

Table A4 in the Appendix shows that the estimate remains similar after including additional controls. Our baseline labor scarcity measures are defined based on data from 2014, but Table A5 shows the results for measures from different periods. Overall, the relationship seems to be somewhat persistent, but it is no longer significant if the measures are constructed based on years earlier than 2010. Table A6 presents the results for other staffing problem variables, which may be thought of as placebo checks. There is no relationship between technology adoption and firms declarations about problems with worker motivation or with having too many employees. Interestingly, there is also no relationship with an indicator that takes the value of one if a firm reports high labor costs as one of their staffing problems. This might be because of labor market institutions in Germany that lead to wage rigidity. There exists a positive relationship between adoption and the demand for further training. While there are several ways of interpreting this relationship, 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 1-9 of Table 6 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 less difficulties recruiting, OLS coefficient may be downward biased. But those firms may also have higher demand for their products, which can be accommodate 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 their 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.[10] The analysis is performed with ca. 400 districts, but it is robust to using ca. 100 larger areas (Raumordnungsregionen) instead.

However, 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

[10] We employ 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

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 a significant share 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.

Columns 10-11 of Table 6 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% of its standard deviation. The effect is even stronger if we limit our sample to firms that export at least 20% of their production, suggesting that the demand channel is unlikely to explain our findings.

Heterogeneity of Labor Scarcity Effect. Figure 10 shows the effects labor scarcity on the adoption of automation and digitization defined jointly (the main measure), and for robotization alone (using the measures from 2017 IAB-EP interacted with adoption intensity from 2016) by industry. The Figure illustrate the heterogeneity of the effect by industry and technology class. Overall, labor scarcity is associated with higher levels of automation and digitization adoption in most industries, but selected industries demonstrate the opposite pattern. Robots drive the 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 3, the magnitudes of robot investment is limited. Figure 10 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 relationship with labor market conditions. These patterns illustrate the importance of analyzing other technologies, which we discuss further in Section 5.

5 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.

5.1 Prevalence of Robots and Other Technologies

Figure 11 displays the evolution of expenditures on robots, Information and Communication Technology equipment, and software and databases between 1995 and 2015. The data is based on the aggregate variables from IFR and EU KLEMS data. We present the data graphically for the manufacturing sector because that the share of robots would be too small to be legible on the graph for the whole economy. Yet, even within manufacturing, the expenditures on robots are dwarfed by the two other categories. There does not seem to be a reversal of this trend. While the relative growth rate of software and databases expenditures 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 Figure 12. There is no indicator of robots becoming significantly more important recently, and robot investment remained flat in the last decade, suggesting that when robotization reaches relatively high level, the growth is likely to be lower. In contrast, we observe a stable growth of the expenditures on software and data, even though this category is much larger to begin with.

5.2 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, 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 creates a new task of data entry. More importantly, it may significantly increase the productivity of bookkeepers, allowing them to perform more tasks at the same amount of time. That is, the aggregate effect of algorithms on the future of work may be very different from the impact of robots.

Figure 13 demonstrates this point. Using methods analogous to those previously employed to study automation (see Figure 10), 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 Establishment Panel). The results reveal a heterogeneous effect across different industries. This contrasts with the clear positive association between labor scarcity and adoption for robotics in mining and manufacturing, documented in Figure 10. While 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, Professional Services, Education and Health) we observe opposite patterns, suggesting that different features of technologies in these industries dominate over potential similarities to robots.

Heterogeneous patterns of the link between labor scarcity and technology adoption suggest that the employment effects of different technologies may also differ from the employment effects of robots. Table 7 analyzes this question directly and reports digitization coefficients analogous to robotization effects shown in Table 5. Controlling for robotization, digitization seems to have a positive effect on employment. The main effects are insignificant, although large in magnitude, consistent with significant heterogeneity of the labor-technology relationships across industries documented in Figure 13. The effect appears significant between 2005 and 2010, yet we again interpret it with caution because of potentially heterogeneous impact of the Global Financial Crisis on the evolution of employment in different industries.

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.

6 Conclusion

The main contribution of this paper is to critically examine the importance of automation – in particular industrial robots – in aggregate and firm investment, as well as for labor markets. While we do confirm that firms invest in robotization and that they have the potential to reduce employment, their share in total investment is very small, and their employment effect is mitigated by endogenous adoption patterns. Industrial robots are spectacular technology, but their applications remain limited. While in recent years their importance have been steadily growing, this growth has been relatively stable and the pattern does not resemble the explosive growth observed e.g. for IT technologies in previous decades.

It does not appear, therefore, that we should expect a “robocalypse” in the foreseeable future. Instead, however, we will be facing steady growth in other technologies, which are much more prevalent than robots today, and recent trends do not appear to shrink that difference. Digital technologies related to data processing and analysis and network communications are likely to have much bigger economic implications, and their economic 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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Figures and Tables

Figure 1: Cross-Validation of Firm-Level and Industry-Level Measures of Technology

The left panel presents the relationship between robot density at the industry level and the intensity of dealings with automation and digitization based on firm-level data. Each dot represents one of 2-digit industries. Robot density is defined as the standardized logarithm of the count of robots per 1000 workers from IFR data. Robots are concentrated in manufacturing and only 14 industries have separately reported positive number of robots. For remaining industries robot density is calculated using "Other" category and is close to zero. Automation and digitization is the average of firms' responses to part A of the automation and digitization question from the IAB Establishment Panel (how intensively have you dealt with it so far, scale 1-10). The right panel presents the relationship between software & databases capital stock at the industry level and the intensity of dealings with automation and digitization based on firm-level data. Software and databases capital stock is the standardized natural logarithm of per-worker software & database capital stock from EU KLEMS.

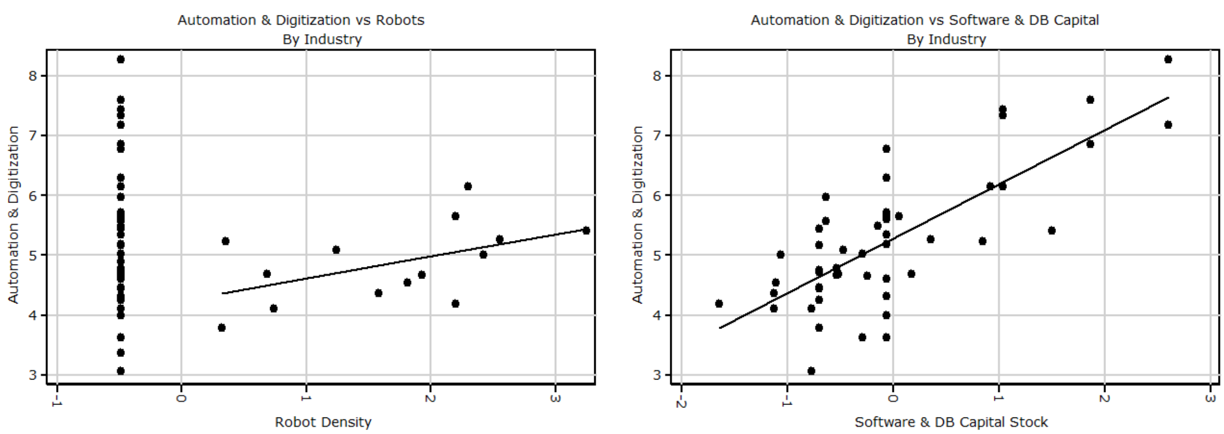


Figure 2: Total Sales of Robots around the World and in Western Countries

The Figure presents the evolution of robots sales between 1993-2016. The values come from International Federation of Robotics 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, as reported by IFR.

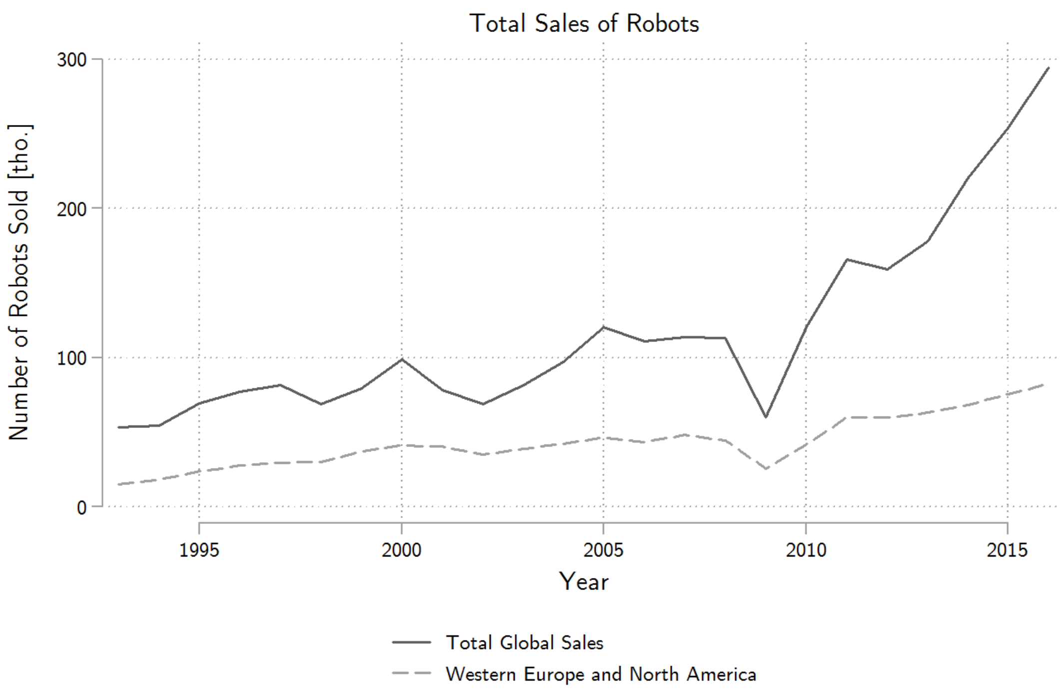


Figure 3: Share of Robots in Investment over Time

The Figure presents the evolution of share of robot expenditures in investment between 1995-2015. The value for robot sales comes from International Federation of Robotics data; the price of a robot is assumed to be 45 tho. Euro on average. The solid black line shows the ratio of robot sales value to total capital formation; the dashed line shows the ratio of robot sales value to the value of investment in equipment, defined as IT and communication equipment and other machinery. All investment series come from EU KLEMS data and are real values expressed in 2010 prices. The values were converted from national currencies to Euro. 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.

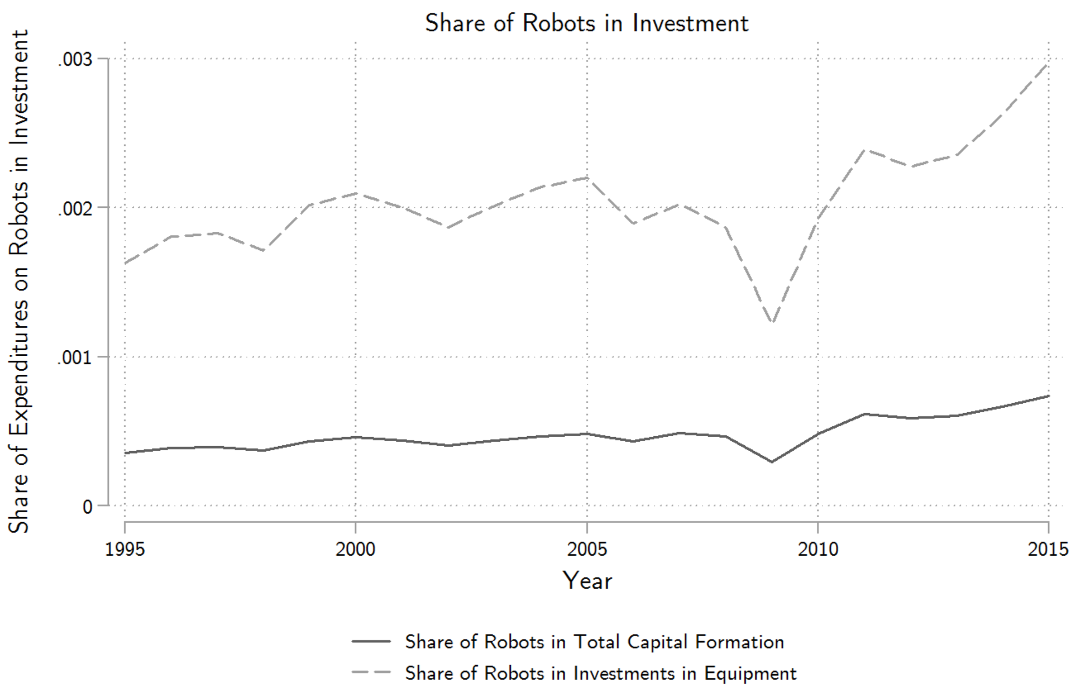


Figure 4: Share of Robots in Investment by Industry

The Figure presents the share of robot expenditures in investment across industries. The shares are computed by adding sales and investment values over all industries, countries and 3 years: 2013-2015; hence, they reflect the relative size of industries and countries in the sample. The value for robot sales comes from International Federation of Robotics data; the price of a robot is assumed to be 45 tho. Euro 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 IT and communication equipment and other machinery. All investment series come from EU KLEMS data and are real values expressed in 2010 prices.

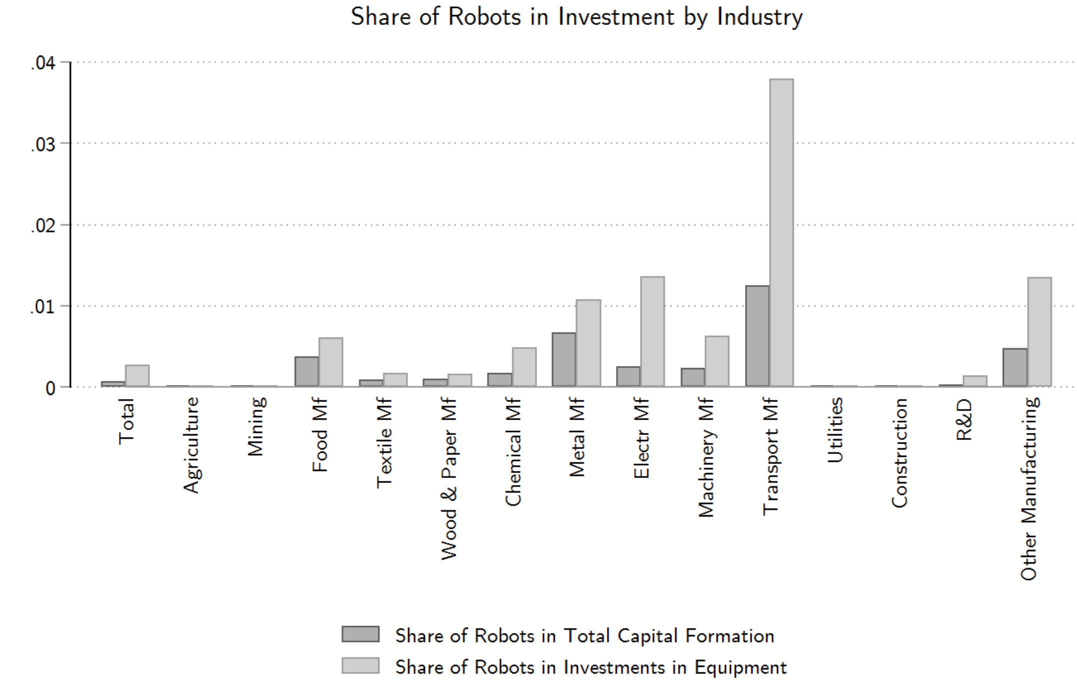


Figure 5: Share of Robots in Investment by Country

The Figure presents the share of robot expenditures in investment across countries for the whole economy. The left panel presents values for the whole economy, and hence it is largely driven by industry composition. The right panel shows the distribution within a single industry - manufacturing of the means of transportation. The shares are computed by adding sales and investment values over all industries and 3 years: 2013-2015; hence, they reflect the relative size of industry in each country. The value for robot sales comes from International Federation of Robotics data; the price of a robot is assumed to be 45 tho. Euro 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 IT and communication equipment and other machinery. All investment series come from EU KLEMS data and are real values expressed in 2010 prices.

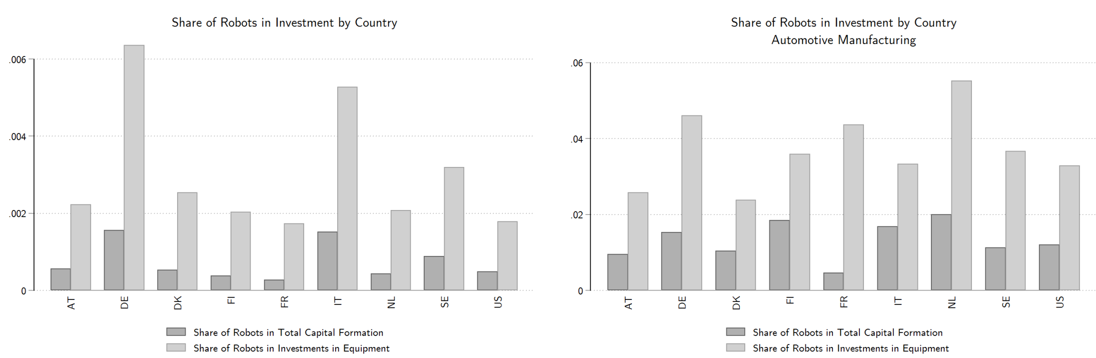


Figure 6: Share of Robots+Peripherals and IT Equipment in Total Investment Relative to Base Year

The 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 investment. Both series were 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 9 countries in our sample. Due to data limitations, share of IT expenditures is based on data from United States only. The value for robot sales comes from International Federation of Robotics data; the price of a robot+peripherals is assumed to be 135 tho. Euro on average. IT investment values come from EU KLEMS data and are real values expressed in 2010 prices. The denominator is total capital formation.

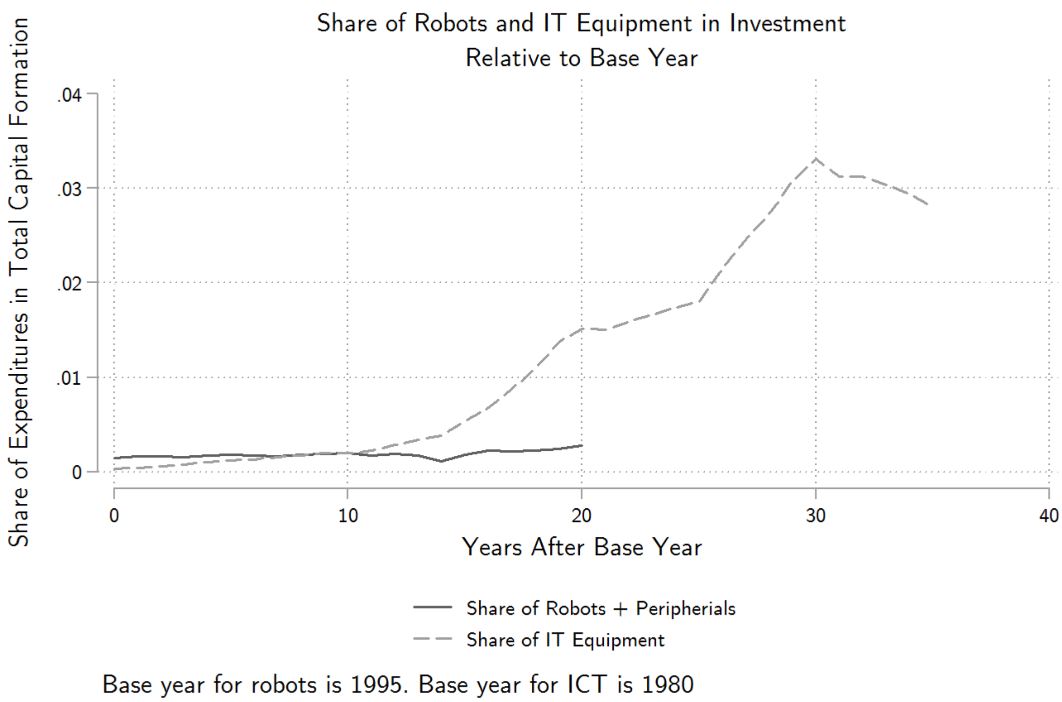


Figure 7: Robots in IAB Establishment Panel

The graph shows the share of firms declaring use of "means of production requiring indirect human intervention (robots, CNC machines)", based on firm-level responses from 2017 IAB Establishment Panel.

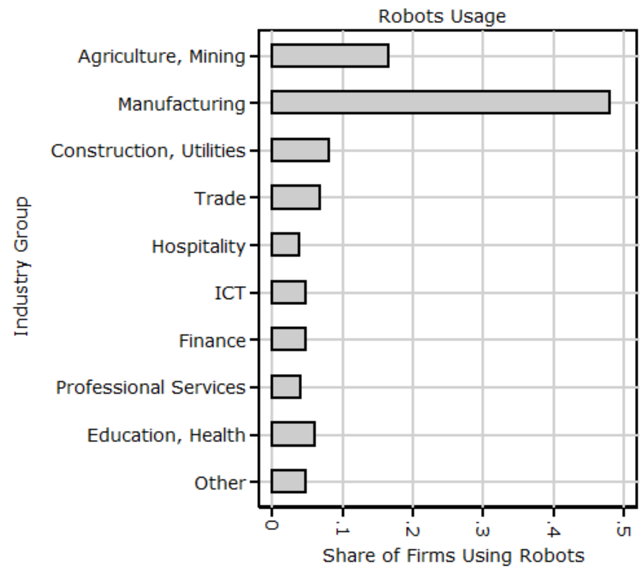


Figure 8: Geographic Distribution of Automation and Digitization Adoption

The map presents values of automation and digitization adoption index from 2016 IAB Establishment Panel. The original index is computed at the district level but for data confidentiality reasons presented values were computed on the spatial planning regions (RORs) level – each ROR contains ca. 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 2016 wave of IAB Establishment Panel, but industry-level averages are subtracted and economy-wide average is added (so that the local index does not depend on industry composition). The response are on scale (1,10) and ROR-level averages vary between 3.41 and 7.04.

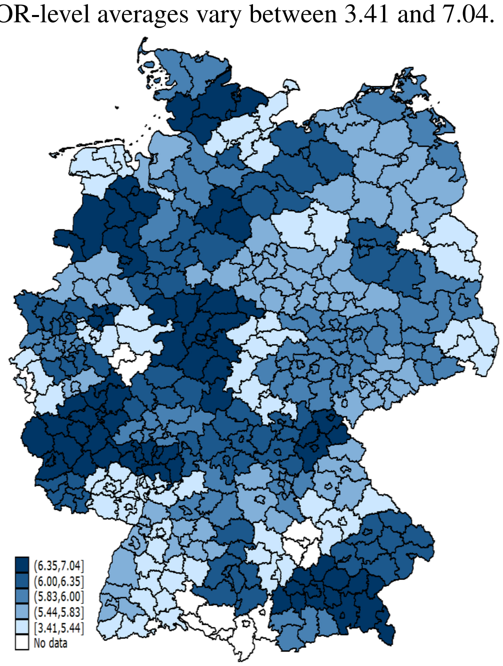


Figure 9: Automation and Digitization Usage and Firm Characteristics

The left panel shows how firm size (measured by count of employees) and firm growth (measured by 5-year relative change in number of employees) varies with different levels of automation and digitization adoption. High-adopting firms are larger and typically have been growing faster. Right panel shows how labor productivity (measured by sales per worker) and skill level of the workforce (measured by share of skilled workers, defined based on skilled/unskilled assignment of 12 occupational groups) varies with adoption intensity. High-adoption firms are more productive and have higher share of skilled workers.

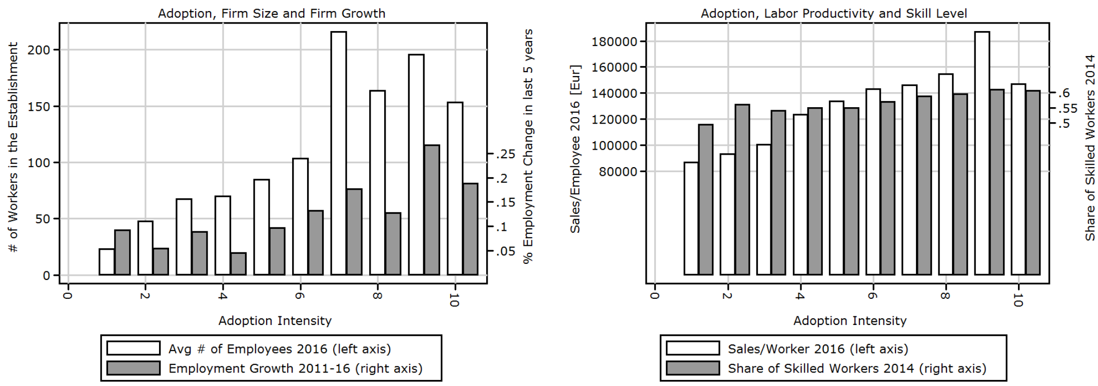


Figure 10: Labor Scarcity Effect by Industry and Technology

The Figure presents coefficients from regression of two technology measures – automation and digitization, and automation defined separately – on labor scarcity interacted with indicators for 10 industry groups, controlling for industry fixed effects and firm size. Automation and digitization is the main measure of the intensity of adoption (from IAB-EP 2016); automation alone is an interaction of that measure with an indicator for using robots (from IAB-EP 2017) and considering them at least somewhat important (>=3 on 1-5 scale).

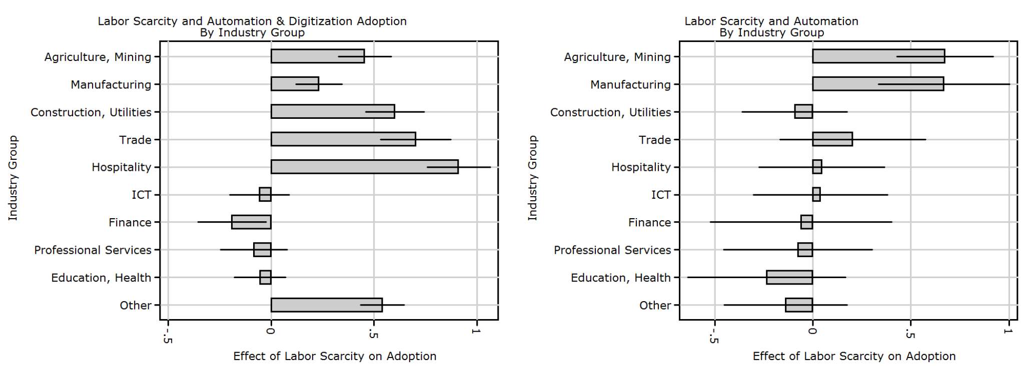


Figure 11: Share of Selected Investment Categories in Total Investment: Manufacturing

The 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 all countries and industries within manufacturing. The value for robot sales comes from International Federation of Robotics data; the price of a robot is assumed to be 45 tho. Euro 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.

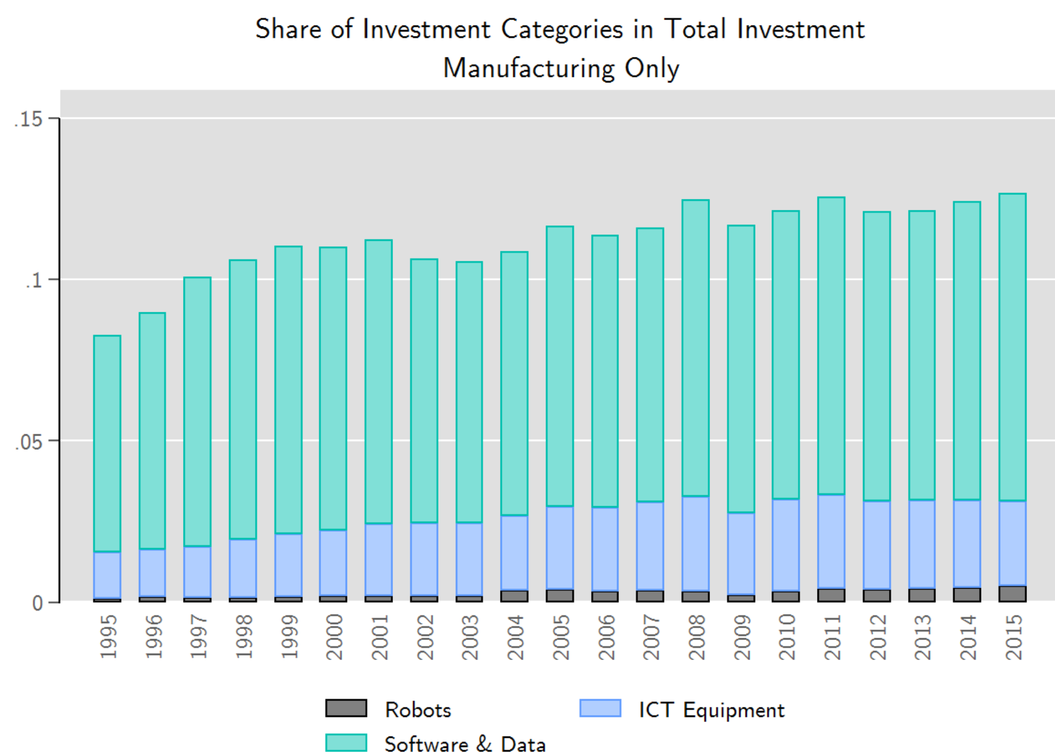


Figure 12: Share of Selected Investment Categories in Total Investment: Automotive Manufacturing

The 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 all countries for automotive manufacturing industry. The value for robot sales comes from International Federation of Robotics data; the price of a robot is assumed to be 45 tho. Euro 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.

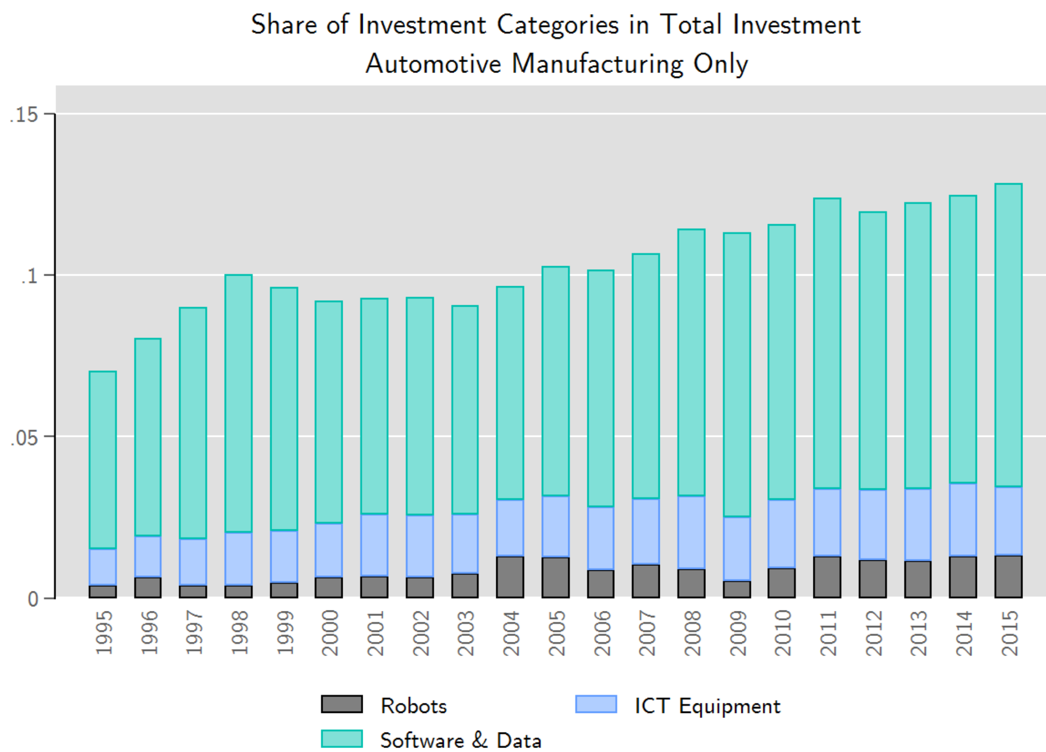
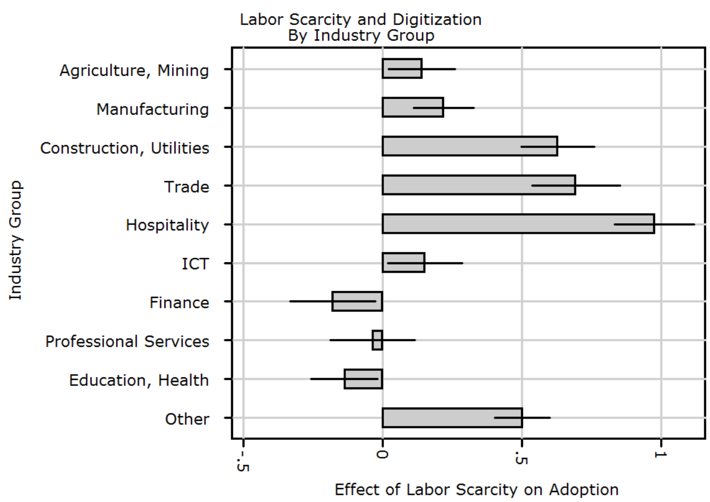


Figure 13: Labor Scarcity Effect of Digitization

The 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.



Data Source	Variable	Sector	Mean	Median	Std Dev	P25	P75	Min	Max	N
IFR	Robot Shipments [units]	All	314	16	1218	0	122	0	17361	2534
		Food, Textiles, Wood	100	20	213	4	69	0	1244	543
		Chemical, Metal	526	182	679	80	683	0	2965	362
		Electr., Machinery	290	52	778	10	182	0	6786	362
		Automotive	2280	486	3723	86	2149	0	17361	181
		Non-Manufacturing	9	0	35	0	5	0	581	905
		Whole Economy	4278.6	1001	6230.3	377	5335.5	35	31404	216
	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 [est. value, € mln]	Whole Economy	193	45	280	17	240	1.6	1413	216
	Robot Shipments [est. value, € tho/worker]		0.011	0.009	0.007	0.006	0.014	0.001	0.038	194
	Robot Stock [units]		38514	8915	55112	3899	56572	568	250479	216
	Robot Stock [units/1000 workers]		2.223	1.907	1.502	1.133	2.723	0.364	7.538	194
EU KLEMS	Total Investment [€ tho/worker]	Whole Economy	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]		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

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

The Table present summary statistics for key variables from IFR and EU KLEMS data for our sample. The sample contains data for 9 countries: Austria, Germany, Denmark, Finland, France, Italy, Netherlands, Sweden, United States and covers years 1993-2016. In the rows for "Whole Economy", we report statistics based on country-year observations. In 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 & 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 tho. Euro, consistent with IFR information. Monetary value 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)	4.89	3.02	2	5	8	14036
and Automation	C (adoption)	5.72	2.68	4	6	8	10255
2017 Robots		0.154	0.361	0	0	0	11577
2017 Digitization	(Data)	0.525	0.499	0	1	1	11577
2017 Digitization	(Networks)	0.127	0.332	0	0	0	11577

Panel B: Relation to Other Variables

	Y = ADOPTION OF AUTOMATION AND DIGITIZATION					
	(1)	(2)	(3)	(4)	(5)	(6)
Robots (2017)	0.86***					
	(0.089)					
Digitization: Data (2017)		1.16***				
		(0.057)				
Digitization: Networks (2017)			1.15***			
			(0.084)			
Investment (% sales)				2.39***		
				(0.383)		
Age of Equipment					-1.08***	
					(0.032)	
Share of R&D Workers						1.28***
						(0.419)
N	8407	8407	8407	10255	10255	10255
Industry FE	✓	✓	✓	✓	✓	✓

Top panel shows summary statistics for the firm-level measures of technology. Summary statistics for other variables are presented in Table A1. In the bottom panel regressions, the dependent variable is adoption of automation and digitization from the IAB Establishment Panel (wave 2016, part C). Independent variables are binary indicators of usage of different technology classes coming from 2017 wave of the IAB-EP; 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		
Robot Shipments	0.000373*	0.00105***	0.00106***	-0.000142	0.000416
	(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	Y			Y	
Country X Ind FE		Y			
Industry FE	Y			Y	
Year FE		Y	Y		Y
Firm FE			Y		Y

Standard errors in parentheses

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

The dependent variable in each column is firm-level ratio of capital expenditures to 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%

The Table shows the value of robot-related expenditures in investment based on combining IFR & 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 tho. Eur, 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 column 2 and 3 in Table 3

Table 5: Employment Effects of Technology

	Y=%ΔEmployment							
		(2005-2015)			(2005-2010)		(2010-2015)	
	Naive Approach	Basic Specification	Technology Abroad		Basic Specification		Basic Specification	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Robots	-0.022							
	(0.328)							
Robots X Adoption>P(50)		-0.357*		-0.544*	-0.185		-0.768**	
		(0.194)		(0.298)	(0.157)		(0.379)	
Robots Abroad X Adoption>P(50)			-0.635**			-0.325		-0.970***
			(0.308)			(0.285)		(0.324)
N	5275	5275	5275	5275	5202	5202	5202	5202
Area FE	✓	✓	✓	✓	✓	✓	✓	✓
Industry FE		✓	✓	✓	✓	✓	✓	✓
IV				✓				
Cragg-Donald F-Stat				30.26				

The Dependent variable in all columns is the relative change in employment between 2005 and 2015 for a given industry-area cell expressed in percentage points. Independent variables are robotization – measured as the 2005-2015 change in number of robots per 1000 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 (2-digit industry; RORs/commuting zones). The local indicator for adoption is is defined based on area-level average of responses to automation and digitization adoption question from IAB Establishment Panel (measured in 2016). High adoption area (Adoption>P(50)) is defined as having the adoption indicator above median. Robots abroad are defined analogously to German measures, except they are averages for several other European countries. Column 3 presents their reduced form relationship to employment change, while column 4 presents Instrumental Variable regression in which robots abroad interacted with adoption, serve as instruments. The first stage of the IV specification is presented in the Appendix. All regressions, except column 1, include industry and area fixed effects and are weighted using employment levels from 2005. Standard errors, reported in parentheses, are two-way clustered by area and industry. (*) denotes significance at 10% level, (**) at 5% level and (***) at 1% level.

Table 6: Automation and Digitization Adoption and Labor Scarcity

	Basic Specification				Alternative Measures of Labor Scarcity			Alternative Measure of Technology		Labor Scarcity in local area	
	Y = Automation and Digitization Adoption							*Y = High Adoption X High Investment*		*Y = Automation and Digitization Adoption*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Hard to Find Workers	0.307***	0.285***	0.372***	0.260***				0.066***	0.065***		
	(0.072)	(0.076)	(0.105)	(0.070)				(0.011)	(0.013)		
Demand for Hiring > Hired					0.180**						
					(0.083)						
Can't Increase Sales without New Staff						0.361***					
						(0.083)					
Investment Prevented By Lack of Personnel							0.381**				
							(0.159)				
Hard to Find Workers (Local Index)										0.078*	0.170**
										(0.047)	(0.081)
N	7469	5855	3479	7469	7449	6260	1431	5781	5781	10250	1006
Industry FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Size	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Profits & Growth		✓	✓								
Firm Type			✓								
Area FE				✓					✓		

The dependent variable in columns 1-7 is the automation and digitization adoption measure from IAB Establishment Panel. Dependent variable in columns 8-12 is the binary indicator for the adoption measure being above median and the investment to sales ratio (average from 2011-2016) being above industry-wide median. Independent variables are various measures of labor scarcity from IAB Establishment Panel: "Hard to Find Workers" is a binary variable that takes value 1 when establishment confirmed that they face this staffing problem; "Demand for Hiring > Hired" is the dummy variable taking value 1 if establishment declared that they would like to hire more workers than they did hire; "Can't Increase Sales Without New Staff" takes value 1 when establishment declares that they are capacity constrained and would have to hire new staff to increase production; "Investment Prevented by Lack of Personnel" is defined only for a subset of firms that declare that they have abandoned an investment in product or process innovation (and thus smaller sample size). It takes value 1 if the establishment declares "lack of qualified personnel" as a reason for abandoning the project. Control variables include 5 binary variables for different size quintiles (by employment) and industry fixed effects (2-digit). Additional controls under "Profits & Growth" include categorical measure of firm's profitability, employment growth in the last 3 years and establishment age. Further controls under "Firm type" include 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 significance at 5% level and (***) at 1% level.

Table 7: Employment Effects of Digitization

	Y=%ΔEmployment							
	(2005-2015)				(2005-2010)		(2010-2015)	
	Naive Approach	Basic Specification	Technology Abroad		Basic Specification		Basic Specification	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Digitization	-1.674							
	(1.204)							
Digitization X		0.756		0.700	0.746**		1.054	
Adoption>P(50)		(0.464)		(0.542)	(0.380)		(0.882)	
Digitization Abroad X			0.179			0.271**		0.053
Adoption>P(50)			(0.174)			(0.113)		(0.231)
N	5275	5275	5275	5275	5202	5202	5202	5202
Area FE	✓	✓	✓	✓	✓	✓	✓	✓
Industry FE		✓	✓	✓	✓	✓	✓	✓
IV				✓				
Cragg-Donald F-Stat				163.6				

This table presents coefficients analogous to those presented in Table, but for digitization instead of robotization. Dependent variable in all columns is the relative change in employment between 2005 and 2015 for a given industry-area cell expressed in percentage points. Independent variables are digitization – measured as the 2004-2014 change in the stock of Software & Databases capital per worker 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 (2-digit industry; RORs/commuting zones). The local indicator for adoption is is defined based on area-level average of responses to automation and digitization adoption question from IAB Establishment Panel (measured in 2016). High adoption area (Adoption>P(50)) is defined as having the adoption indicator above median. Digitization abroad are defined analogously to German measures, except they are averages for several other European countries. Column 3 presents their reduced form relationship to employment change, while column 4 presents Instrumental Variable regression in which digitization abroad interacted with adoption, serve as instruments. All regressions, except column 1, include industry and area fixed effects and are weighted using employment levels from 2005. Standard errors, reported in parentheses, are two-way clustered by area and industry. (*) denotes significance at 10% level, (**) at 5% level and (***) at 1% level.

Appendix Figures and Tables

Figure A1: Automation and Digitization Adoption: Summary Statistics by Industry Group

The Figure presents summary statistics for the intensity of automation and digitization adoption from the IAB Establishment Panel (part C - intensity of adoption on the scale from 1 to 10) by industry group. Bold line inside the box represents the median of firms declarations. 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 10th and 90th percentile of the declarations. Minimum and maximum for each group, not depicted, equals 1 and 10 respectively. 10 broad industry groups are defined based on grouping consecutive 2-digit NACE Rev. 2 codes – the details are reported in the Online Appendix.

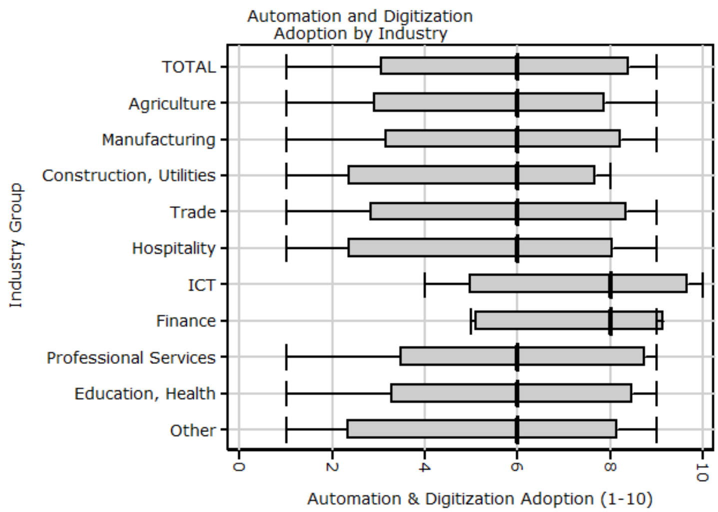


Figure A2: Total Sales of Robots in Top 8 User Countries

The Figure presents the evolution of robots sales between 1993-2016 for 8 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 was subject to reclassification, as learned from International Federation of Robotics, and hence should be interpreted with caution. Data for China is available since 1999.

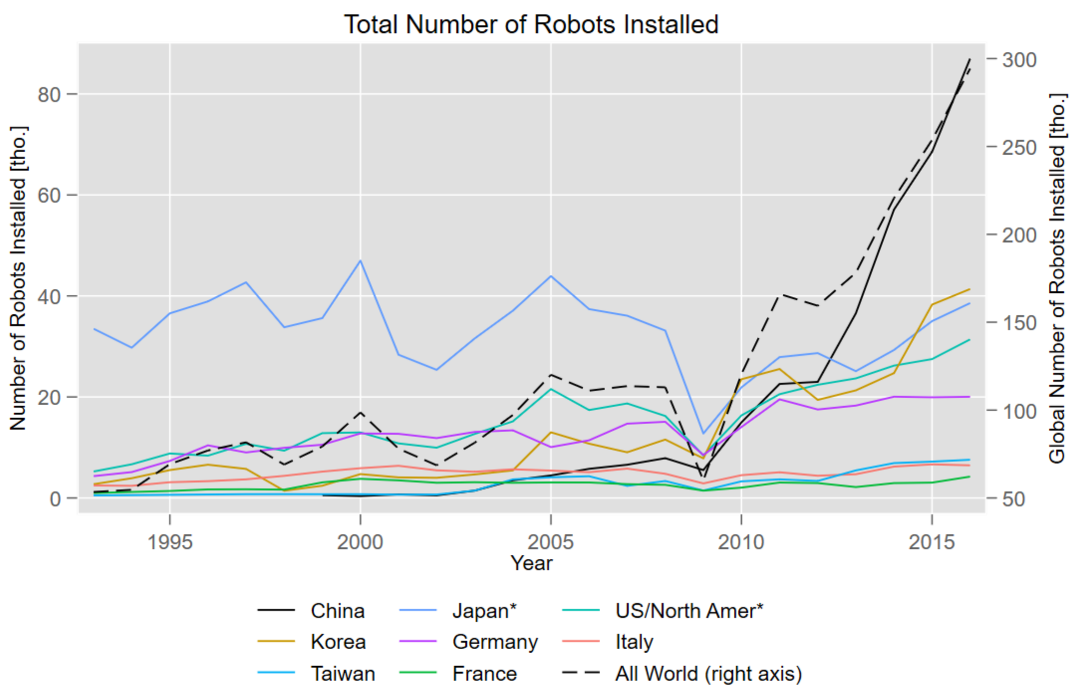


Figure A3: Changes in Robotization and Digitization in 2005-2014/15

The Figure shows the 2005-2015 change of robot density (number of robots per 1000 workers, based on IFR data) and 2004-2014 change of digitization (stock of software and databases capital per worker, in tho. Euro, based on EU KLEMS data) in Germany and other European countries. Both for robots and digitization we use 6 other countries but the group is different because of data availability. For robots, it includes France, Italy, Denmark, Netherlands, Sweden and United Kingdom. For software and databases capital, the group includes France, Italy, Belgium, Netherlands, Finland and Austria.

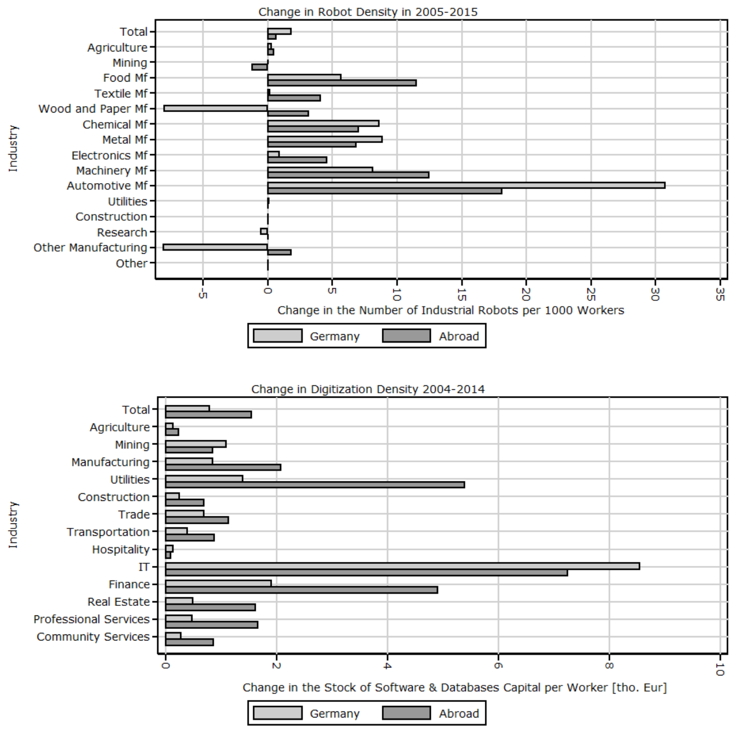


Figure A4: Automation and Digitization Usage and Other Firm Characteristics

The Figure shows the relationship between Automation and Digitization adoption and various firm characteristics: introducing product innovation in the last year, establishment being part of a multi-establishment firm, establishment having foreign owner, and being part of public firm. All variables come from the most recent wave of the IAB Establishment Panel in which a variable is available.

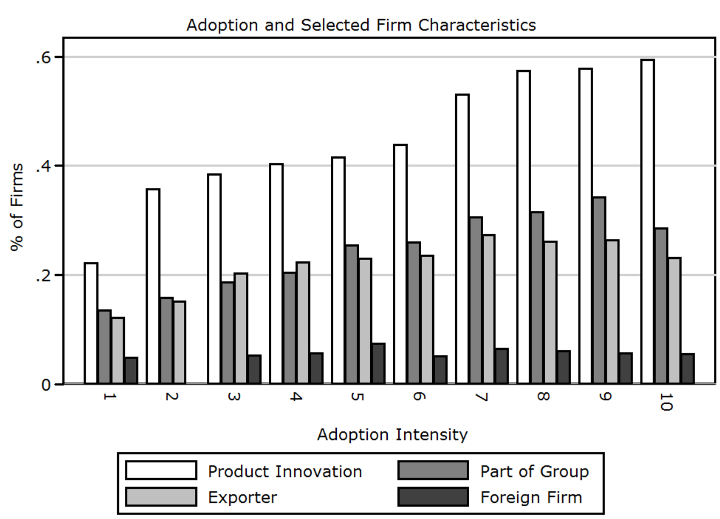


Figure A5: Automation and Digitization Usage and Wages

The graph shows the relationship between Automation and Digitization adoption and average wage in the establishment. Both adoption and wages data come from IAB Establishment Panel.

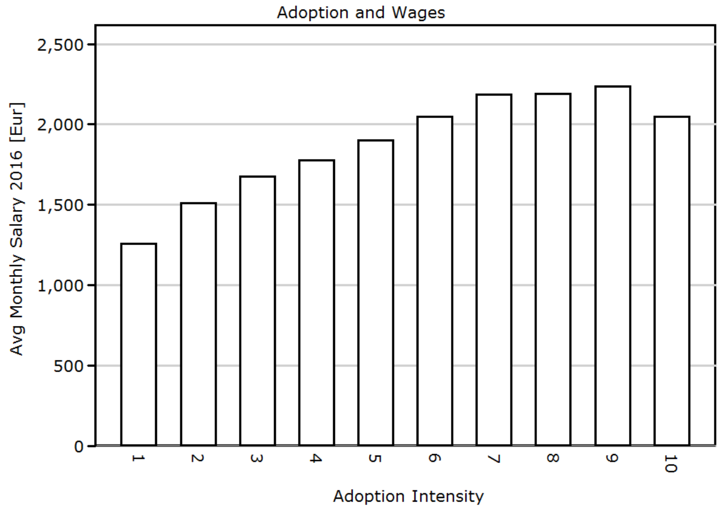


Figure A6: Changes in Employment by Industry in 2005-2015 for Germany and Other Countries

Based on EU KLEMS data. Foreign countries include Austria, Belgium, France, Finland, Italy and Netherlands.

Table A1: Summary Statistics of Selected Variables
Labor Scarcity and Employment Measures

Variable	Mean	Std Dev	P25	Median	P75	Num Obs
Labor Scarcity Measures						
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
Project Abandoned – Can't Find Workers	0.21	0.39	0	0	0	1812
Hard to Find Workers - Agricul., Manufacturing	0.46	0.50	0	0	1	2619
Hard to Find Workers - Construction, Trade	0.37	0.48	0	0	1	3461
Hard to Find Workers - Prof. Services	0.41	0.49	0	0	1	3776
Hard to Find Workers (Area Index)	0.40	0.11	0.35	0.39	0.47	14202
Employment Measures						
Employment	3154	5615	283	1276	3503	5703
Δ%Employment (2005-2015)	33.7	189.8	-6.2	14.2	43.4	5592

Top panel shows summary statistics for the firm-level measures of labor scarcity and area-industry-level measures of employment changes. Labor scarcity measures come from 2014 wave of the IAB-EP, except for the last measure – Project Abandoned Because of Lack of Suitable Personnel – which is an average from waves 2009, 2011, 2013 and 2015. "Agricul., Manufacturing" refers to all industries in agriculture, mining and manufacturing, i.e. 1-31 industry codes. "Construction, Trade" refers to industry codes 35-57, which includes construction, utilities, trade, hospitality, transport. "Prof. Services" refers to industries with codes (58-90), which includes IT, finance, professional services, health, and education. Employment and its percentage change is computed for industry-area cells based on the Establishment History Panel data. In the bottom panel regressions, the dependent variable is firm-level measure of difficulties in finding workers. Local unemployment rate comes from German Statistical Office and varies by district. Industry index is an average of labor scarcity declarations of all firms in the same industry, excluding firm's own declaration. Labor productivity is sales per worker in 2015 measured in EUR/worker.

Table A2: Summary Statistics of Selected Variables (Continued)

		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
Unemployment Rate	(Area)	7.56	3.00	5.2	7.3	9.8	13109
Share of Workers >55	(Area)	0.25	0.03	0.23	0.25	0.27	12761
Financial Constraints		0.04	0.18	0	0	0	3010
Debt/Other Sources		0.47	1.68	0	0	0	2894
Number of Employees		106.8	853.3	4	14	59	14202
Share Unskilled		0.36	0.35	0.03	0.25	0.67	12141
Share Admin		0.29	0.33	0.02	0.14	0.47	12141
Share Workers Trained		0.31	0.29	0.06	0.24	0.50	12160
Sales	(mln Euro)	25.7	640	0.25	1.03	5.4	7874
Sales per Employee	(tho Eur)	131	230	42	75	140	7874
Δ%Sales Per Employee	(2005-15)	28.9	97.4	-11.2	13.0	44.6	2223
Robots (Ind)	(2015)	4.1	18.7	0	0	0	5511
Digitization (Ind)	(2015)	4.2	7.6	1.0	1.5	2.2	5640
ΔRobots (Ind)	(2005-15)	0.84	4.79	0	0	0	5402
ΔDigitization (Ind)	(2005-15)	1.56	3.41	0.17	0.45	0.50	5535
Adoption (Area)	2016	5.78	0.65	5.48	5.88	6.25	5642
% Low Skill	(2015)	11.9	8.5	6.7	10.5	15.2	5655
% Medium Skill	(2015)	72.8	13.9	66.7	75.8	81.8	5655
Δ% Low Skill	(2005-15)	-3.3	7.6	-5.6	-2.9	-0.6	5557
Δ% Medium Skill	(2005-15)	-1.1	9.7	-4.5	-0.6	0.3	5557

Summary statistics for technology measures are presented in Table 2, while summary statistics for labor scarcity and employment measure in the first panel of this table. Investment is the average value of investment in 2011-2016, expressed as the share of firm's sales. Variable is missing if a firm has not reported any positive investment in that period. High adoption is a binary measure that combines survey declaration about automation and digitization adoption (part C) with information about firm investment: it equals 1 if both adoption and investment are above industry-wide median. District-level unemployment rate and share of workers above 55 are from 2014. Share of unskilled and administrative workers comes from BHP extension to IAB-EP and represents 2014 value for the share of workers performing unskilled and administrative tasks, based on 12-group Blossfeld Occupational Classification used in Social Security records. Share of workers trained is based on average of firms' declarations in in 2005-2015 waves of IAB Establishment Panel. Financial constraints is firms' declaration that they had troubles getting credit (from 2008). Leverage is the ratio of debt to other sources (equity and subsidies) of investment financing in 2008. Sales are in thousands of Euro and are from 2015. Change in sales per worker is in relative terms and only available for a subset of firms for whom both 2005 and 2015 IAB Establishment Panel responses are observed. Robots and their change are expressed as number of robots per 1000 workers and come from International Federation of Robotics data (employment comes from 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 2016 IAB Establishment Panel. Shares of low- and medium- workers are based on workers' three educational groups reported in the BHP data. High-skill workers are the remaining group, omitted for brevity.

Table A3: Robustness Checks of Employment Changes Regression and Additional Results

	Y=%ΔEmployment (2005-2015)										Y=ΔAverage Wage		Y=ΔRobotization X High Adoption
	Basic Specification		Quartiles Dummies		Not Weighted By Employment		Control for Past Empl. Changes		Exclude Automotive				First Stage Regression
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Robots X Adoption>P(50)	-0.357*				-1.470***		-0.352*		-0.616		0.031		
	(0.194)				(0.440)		(0.195)		(0.390)		(0.090)		
Robots Abroad X Adoption>P(50)		-0.635**				-2.446***		-0.630**		-0.801**		0.012	1.155***
		(0.308)				(0.662)		(0.309)		(0.392)		(0.109)	(0.271)
Robots X Adoption>P(75)			-0.635***										
			(0.134)										
Robots Abroad X Adoption>P(75)				-0.816**									
				(0.324)									
N	5275	5275	5275	5275	5275	5275	5275	5275	5275	5275	5275	5275	5275
Area FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
F-Stat													30.26

The Table present robustness checks for the main specification presented in column 3 of Table 5. Columns 1 and 2 present the basic specification from Table 5. Columns 3 and 4 use quartiles of adoption instead of above-median indicator (all quartile dummies are included, but only 4th quartile is presented, the value is relative to the first quartile). Columns 5 and 6 present basic specification with equal weights for every industry-area cell (as opposed to weighting by initial employment). Columns 7 and 8 include change in employment between 1995 and 2000 as a control. Columns 9 and 10 exclude automotive industry, which has the highest robot density. In columns 11 and 12, the dependent variable is the change in average daily wage (in Euro) between 2005 and 2015 for a given industry-area cell. Columns 13 and 14 present first stage regressions for 2SLS specification (second stage is presented in column 6 of Table 5). All regressions are weighted using employment levels from 2005 (except for columns 7 and 8). Standard errors, reported in parentheses, are two-way clustered by area and industry. (*) denotes significance at 10% level, (**) at 5% level and (***) at 1% level.

Table A4: OLS Regression of Automation and Digitization Adoption on Labor Scarcity with Additional Control Variables

	Y = Automation and Digitization Adoption (2016)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Hard to Find Workers	0.294***	0.301***	0.308***	0.299***	0.312***	0.347***	0.334***	0.396***	0.372***
	(0.067)	(0.068)	(0.064)	(0.068)	(0.066)	(0.070)	(0.073)	(0.094)	(0.105)
N	7469	7346	7401	7469	7434	6590	6232	4419	3479
Industry FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Size	✓	✓	✓	✓	✓	✓	✓	✓	✓
Profitability	✓								✓
Part of Group		✓							✓
Establishment Age			✓						✓
Employment Growth				✓					✓
Public Firm					✓				✓
Foreign Owner						✓			✓
Professional Management							✓		✓
Startup (not Spin-out)								✓	✓

All columns present specification analogous to column 1 from Table 6, but with additional controls. The controls include dummies for profitability assessment, being part of multi-establishment group; dummies for establishment age, the speed of employment growth in last 3 years, being a public firm, having a foreign owner, being managed by a professional manager and being a startup (i.e. the establishment was started as startup, as opposed to being spun off from other existing establishment). Because of missing values in additional control variables the sample size varies between columns.

Table A5: Persistence of the Labor Scarcity Effect

	Y = Automation and Digitization Adoption (2016)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Hard to Find Workers (2016)	0.272***						
	(0.057)						
Hard to Find Workers (2014)		0.308***					
		(0.068)					
Hard to Find Workers (2012)			0.286***				
			(0.087)				
Hard to Find Workers (2010)				0.225***			
				(0.076)			
Hard to Find Workers (2008)					0.142		
					(0.087)		
Hard to Find Workers (2006)						0.089	
						(0.116)	
Hard to Find Workers (2004)							0.132
							(0.128)
N	10196	7469	5666	4498	3604	2832	2262
Industry FE	✓	✓	✓	✓	✓	✓	✓
Size	✓	✓	✓	✓	✓	✓	✓

All columns present specification analogous to column 1 from Table 6, but with labor scarcity measures coming from different waves of the IAB Establishment Panel.

Table A6: Other Staffing Problems

	Y = AUTOMATION AND DIGITIZATION ADOPTION (2016)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Too Many Employees	-0.017							
	(0.136)							
High Labor Costs		-0.043						
		(0.068)						
Aging Population			-0.114					
			(0.066)					
High Labor Turnover				0.164				
				(0.111)				
Demand For					0.343***			
Further Training					(0.127)			
Lacking Motivation						0.018		
						(0.120)		
Many Absences							-0.093	
							(0.010)	
Staff Shortage								0.125
								(0.078)
N	7469	7469	7469	7469	7469	7469	7469	7469
Industry FE	✓	✓	✓	✓	✓	✓	✓	✓
Size	✓	✓	✓	✓	✓	✓	✓	✓

All columns present specification analogous to column 1 from Table 6, 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 Establishment Panel. Standard errors are clustered on the industry level. (*) denotes significance at 10% level, (**) at 5% level and (***) at 1% level.