Digitization and Automation:  
Firm Investment and Labor Outcomes  

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Abstract  
AI, automation and other digital technologies are thought to be transforming the economy, but the empirical evidence on their diffusion and impact is scarce. This paper uses new firm-level administrative data from Germany to analyze causes and consequences of firms’ investment in the new technology - digitization and automation. Main results characterize relationship of technology and labor: (1) investment in technology is typically increased by labor scarcity; (2) new technologies typically reduce employment. Both results hide important heterogeneity across industries: aggregate substitution patterns are driven e.g. by manufacturing or trade, but complementarity dominates e.g. in IT or finance. For identification, in (1) I use variation in labor scarcity driven by population aging, and in (2) differences-in-differences across high- and low-adoption areas and industries. Additional results demonstrate that financial constraints impede technology adoption and that technology increases skill level of the workforce and labor productivity. Overall, the effects of new technologies significantly vary across industries, firms and types of workers, highlighting the importance of considering a broad set of technologies and studying patterns of their adoption by firms.  

Keywords: technological change, adoption, labor scarcity, corporate investment  
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1 Introduction

Recent advances in artificial intelligence, robotics and other digital technologies suggest that global economy is facing another important technological change (Brynjolfsson and McAfee, 2014; Schwab, 2017). In the past, steam engine, electricity and computers vastly improved productivity and standards of living, but at the same time caused widespread reorganization of economic activity. Today, new technologies again raise hopes and fears, demonstrating impressive capabilities and attracting broad business and public interest. How will these technologies affect the economy and how will their adoption and impact vary across industries, areas and types of workers?

Answering these questions empirically is difficult. Recent technological progress is very broad and includes advances in many distinct technology classes such as data processing, robotics, 3D printing and networks. To have an economic impact, all these technologies must first be adopted by firms, which does not happen at random. Therefore, to fully understand the effects of technological change we need to consider a broad set of technologies and study patterns of their adoption. Existing empirical literature, however, focuses on robotics, relies on industry-level data and abstracts from the endogeneity of technology adoption. (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2018c)

This paper studies the adoption and impact of the last wave of digitization and automation technologies. I use firm-level administrative data from Germany which cover wide range of industries and contain measures of a broad set of new technologies. The main part of the paper studies relationship between technology and labor and contains two results. First, exogenous increase in labor scarcity faced by the firm increases investment in the technology. Second, technology leads to lower employment. Both results reveal that new technology typically substitutes for workers but the average effects hide significant heterogeneity. Aggregate substitution pattern is driven by industries such as manufacturing or trade, but in industries such as finance or IT the complementarity effect dominates, creating the opposite patterns of adoption and employment changes. Remaining parts of the paper contain additional results which reveal significant heterogeneity by worker’s skill and occupation, demonstrate that firm’s financial constraints impede technology adoption and show how technology affects productivity, number and size of firms.

The setting of the analysis is Germany - a large country at the frontier of modern technology. The data contains establishment-level measures of digitization and automation coming

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1 In 2015 ImageNet Competition, algorithms accuracy in image recognition exceeded the typical levels recorded for humans. Numerous companies have made large investment in digital technologies (e.g. in 2018 Samsung announced $22 bln investment in AI and 5G). Many countries, including Canada, China, or Germany, have created their national strategies for AI.

2 For example, robot density in German manufacturing is now 32.2 robots per 1000 workers, with world
from IAB Establishment Panel - a survey conducted yearly by German Employment Agency and merged with social security records. The measures reflect adoption of a wide set of new technologies, including automation (e.g. industrial robots) and modern digital technologies related to communication (e.g. Internet of Things) and data processing (e.g. cloud computing). I combine these measures with a rich set of variables related to firm personnel, investment, finances and output in 1993-2017, as well as with additional industry-level measures of technology - count of robots and capital stock of software and databases.

After describing the data and presenting several facts about technology usage, I introduce a theoretical framework which guides the analysis and illustrates the interplay of the three elements of firm’s production function - technology, labor and capital. The firm considers the adoption of a new technology in partial equilibrium model with a task-based production function (Acemoglu and Autor, 2011). The technology can be characterized by the extent to which it substitutes or complements labor. The model shows that if the substitution effect dominates, technology reduces employment and at the same time the adoption is higher for firms facing high labor cost (or, more generally, high labor scarcity). Conversely, if complementarity effect dominates, technology increases employment and labor cost decreases the adoption.

Motivated by the model, I analyze both how labor scarcity affects technology adoption and how technology affects employment. These two approaches can be viewed as two alternative strategies for identification of the unknown technology characteristics. Both paint similar picture of substitution and complementarity patterns across industries. At the same time, both bring a unique perspective, shedding light not only on the characteristics of the technology but also on the determinants of corporate investment.

The first empirical part of the paper studies how labor scarcity affects firms’ investment in the new technology. Firms have higher level of digitization and automation adoption when they have difficulties in finding suitable workers.\(^3\) This association is robust to various controls, specifications and variables definitions. Difficulties in finding workers are measured in 4 different ways, combining firms’ survey declarations with their actual hiring decisions. Technology adoption measure is based on firms’ responses to questions about intensity of average being 8.5 and the comparable figure for US or France being 20 and 13.7, respectively (based on International Federation of Robotics data).

\(^3\)Labor scarcity can be manifested either through higher price of labor or through difficulties in finding suitable workers. While in perfectly competitive labor market we expect price of labor to adjust, in reality this need not be the case. Because of many labor market rigidities (e.g. industry-wide and firm-wide wage agreements), German labor market is not perfectly competitive and labor scarcity is often manifested by firms being unable to find suitable workers. Economic intuition remains the same independently on whether scarcity affects prices or ability to find workers, since the latter could be interpreted as high labor cost as well (e.g. high search cost).
digitization and automation, combined with firms’ investment expenditures. I alleviate endogeneity concerns using couple of approaches. I show that technology adoption is accelerated by labor scarcity measured on the local area level, and hence not directly related to firm characteristics. I then demonstrate that this relationship holds also for exporters, thus easing concerns that local labor scarcity proxies for local product market demand. Finally, I use plausibly exogenous variation in local area labor scarcity driven by aging patterns. Share of older workers in the local labor market - which is driven mostly by fertility decisions made many years ago - is positively related to firms’ difficulties in finding workers. 2SLS regression with the 10-year change in the share of older workers as an instrument confirms the positive and significant impact of labor scarcity on technology adoption. Additional tests use predicted aging and analyze the effect on exporters to alleviate remaining concerns related to migration and changes in product markets.

The aggregate positive effect of labor scarcity hides significant heterogeneity across industries. Substitution - defined as positive relationship between labor scarcity and technology adoption - is observed not only in manufacturing (where robots are ubiquitous) but also in retail and wholesale trade and in hospitality industry, among others. At the same time, industries such as finance or health and education are characterized by complementarity - defined as negative relationship between labor scarcity and technology adoption - or no clear relationship. This suggests that while the substitution effect typically dominates, in some industries the positive productivity effect is large enough to produce employment growth.\(^4\) The effects are heterogeneous because different industries adopt different technologies and because they employ different types of workers who perform different tasks. Further heterogeneity analyses show that the substitution effect is especially pronounced for firms which employ many low skilled workers and for those with higher share of non-administrative workers. This last effect is in contrast to IT in the early 2000s, for which I also perform similar analysis and find that it mostly affected office workers.

The second empirical part of the paper studies employment effects of new technologies. It employs another data set, with employment records for over 2 mln establishments, and uses other measures of technology which combine industry-level measures of digitization and automation with an area-level measure of intensity of technology adoption. Unlike other existing papers which rely only on industry-level variation in technology, I study the effects of robots and digitization using within-industry variation. I analyze 10-year changes in

\(^4\)An example of such phenomenon is the introduction of ATM in the US which did not lead to the decrease of bank clerks employment (even though ATMs clearly substituted for some workers) because banks reacted to increased productivity by opening more branches (Bessen, 2016). Other technological advances in banking, such as improvement in communication technologies, could have also contributed to the increase in productivity and employment.
employment in a difference in differences framework: industry-level change in technology is a treatment (with an intensity continuously varying across industries); treatment group are firms in high-adoption areas and control group are firms in low-adoption areas. The identifying assumption is that absent technological change, the difference in employment change between high- and low-adoption areas would be the same across industries.

I find negative employment effects of automation and insignificant positive effects of digitization on average. Comparing employment change in high- and low-adoption areas reveals that technology reduces employment in industries such as manufacturing or trade, but increases it in finance, IT or education and health. This pattern mimics the heterogeneous effect of labor scarcity on adoption, consistent with the prediction of my theoretical model.

After studying the relationship between technology and labor, I analyze another determinant of technology adoption: financial constraints. I show that firms which report difficulties in obtaining credit are less likely to adopt digitization and automation. These results, which hold also outside of manufacturing, confirm the importance of access to finance even though many new technologies are explicitly designed to limit capital investment (e.g. cloud computing). To ease endogeneity concerns, I use local variation in firms’ exposure to Commerzbank, which significantly cut its lending after the financial crisis (Huber, 2018), as an instrument for financial constraints.

The remaining part of the paper analyzes the effect of technology on skill structure of the workforce, number of firms, firm size and labor productivity. Both digitization and automation lead to compositional shift towards workers with higher skill level, although the pattern for digitization is not always significant. Digitization increases number of establishments and reduces average size of the establishment, but automation appears to have the opposite effects. The impact of new technologies on labor productivity is positive and it is driven mostly by robotization.

Overall, my results show that while the last wave of new technologies typically substitutes for workers, this average effect hides significant heterogeneity across industries, worker types and technology classes. Substitution effect dominates in manufacturing, retail or hospitality, but technology mostly complements workers in IT, finance or education and health. This empirical evidence complements recent theoretical work on digitization and automation (Acemoglu and Restrepo, 2018b; Agrawal et al., 2019), improving upon small empirical literature in this area (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2018c; Dauth et al., 2018) in several ways: I analyze broader set of technologies and full set of industries, study determinants of technology adoption, use firm-level data, study most recent time period.

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5Recently, some contemporaneous papers also analyze firm-level data (Cheng et al., 2019; Koch et al., 2019; Bessen et al., 2019) but their focus is on automation and industrial robots. I analyze broader set
and improve identification in the employment effects analysis. My results suggest that while the overall decline in number of available jobs may be a concern, facilitation of workers’ reallocation between industries is likely to be a more pressing challenge associated with the current technological change.

The paper also highlights the importance of studying patterns of firms’ investment in technology adoption. Adoption is higher in places where labor is scarce, which means that while in many industries technology is indeed associated with lower employment, it does not necessarily lead to a displacement of workers. Instead, it may allow firms to fill vacancies which they have troubles filling with labor. Moreover, even if the displacement happens, it is more likely to happen in the areas where jobs are abundant. These findings are important in the context of society aging (Abeliansky and Prettner, 2017; Acemoglu and Restrepo, 2018a) and have implications for designing place-based and industry-based policies.

Documented patterns of technology adoption improve also our understanding of the determinants of firm investment. While the negative effect of financial constraints is well known (Fazzari et al., 1988; Han Kim et al., 2019), my findings highlight the important role of labor scarcity in driving firm’s investment decisions. Contrary to financial constraints, labor scarcity does not necessarily decrease the investment: depending on the characteristic of particular investment project, it may both encourage it or impede it (Xu, 2018). The paper also demonstrates how the analysis of corporate investment can be used to infer the effects of technological change and is related to broader literature on firm innovation and labor (Acharya et al., 2013; Babina and Howell, 2018; Bena et al., 2018) and on new technologies and finance (Chaboud et al., 2014; Buchak et al., 2018; Zhang, 2019).

The paper is also related to the older literature on the effects of technological change on firms and workers. Large literature studies ICT technology at the end of 20th century (Brynjolfsson and Hitt, 2000; Bresnahan et al., 2002; Autor et al., 2003; Autor, 2019), documenting that it leads to job and wage polarization and influences firm organization and productivity. 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.

2 Data and Measures of Technology

The main data used in this paper comes from German Employment Agency and is a combination of administrative personnel records and establishment survey conducted by the
Agency every year. The establishment data contains firm-level measures of digitization and automation adoption. The data is supplemented with industry-level measures of digitization and automation coming from independent sources. This section provides a brief description of the data and a descriptive analysis of the technology measures. Additional details about the data sources are presented in the Online Appendix.

2.1 Data Sources

I use the data from the Institute for Employment Research (IAB) of German Employment Agency which administers several data sets based on social security records and other complementary data collection efforts. The main two administrative data sets used in this paper are IAB Establishment Panel (IAB-EP) and Establishment History Panel (BHP). The documentation for the data is contained in Ellguth and Kohaut (2014) and Schmucker et al. (2018).

IAB Establishment Panel is a yearly survey of stratified random sample of German establishments. It covers years 1993-2017 and, as of now, over 16 thousand establishments from all industries. It contains 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 digitization and automation measures used in this paper were included in 2016 and 2017 waves of the panel. The survey is merged with administrative personnel records, containing information about firms’ workforce size and structure.

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 over the years 1976-2016. It contains yearly snapshots of firms’ personnel structure and wage information, based on Social Security records. The data contains establishment location and industry code, but no firm-level data on technology adoption nor output.

I supplement the IAB data with two independent country-industry-year data sources. The first is robot data from International Federation of Robotics, available for 1993-2016. The second is EU KLEMS database which contains information on employment and the stock of various types of capital, including that related to digital technologies: software & databases and ICT equipment for 1995-2015.

2.2 Measures of Digitization and Automation

I measure digitization and automation using several firm-level and industry-level measures. Various ways of measuring technology usage have advantages and disadvantages (see McEl-
heran (2018) for a related discussion). The benefits of those based on hard information, such as stock of robots, include the objective nature, natural quantitative interpretation and comparability across time and space. The drawbacks are focus on single technology class (i.e., in the robots example, inability to capture related automation technologies which do not meet the definition of robot) and quality and availability of measures.\(^6\) The alternative method is based on surveys - an approach which is dominant in the existing literature on the adoption and impact of technology (Doms et al., 1997; Bresnahan et al., 2002; Lewis, 2011; Bloom et al., 2016). Surveys allow to overcome data availability issues and provide a measurement of technologies for which constructing an objective measure of usage would be hard (e.g. big data analytics), or which are hard to define and can take different form in different firms (e.g. Internet of Things). Main drawbacks are related to concerns about informativeness of the survey and limited ability to perform international and intertemporal comparisons.

In this paper I combine various measures of technology, trying to balance their strengths and weaknesses and provide more convincing and comprehensive results. In section 4 I analyze firm-level responses based on the survey data. In section 5 I use industry-level data. I apply these two types of measures in two very different specifications, showing that both paint a similar picture of the technology and thus improving the credibility of the analysis.

Firm-Level Measures. Firm-level measures come from 2 waves of IAB-EP and combine subjective measures of intensity 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 application of such technologies in the establishment? C) how well is the establishment equipped with these technologies compared to other establishments in the sector? My main measure of technology is the answer to part C of the question, which measures the adoption. Importantly, adoption measure is relative to other firms in the sector and hence should not capture differences in technologies across industries. Asking for relative assessment also

\(^6\)Counting robots is not an ideal way to aggregate robots of different types and sizes. Data is also not widely available: Raj and Seamans (2019) discuss the lack of firm-level data on the usage of automation and AI. Recently, however, there are attempts to use existing customs data to measure robot usage. Fort et al. (2018) and ongoing project of Kwon and Zator (2019) use firm-level customs data on direct imports of robots, which have several advantages but also many limitations.
makes it easier for respondent to give a meaningful answer by providing some reference point. Upper panel of Table 1 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 of the industries. The median response is 6 in 8 out of 10 broad industry groups. In ICT and Finance the median is higher (which can be partially explained by IT firms identifying themselves with other sectors, e.g. IT firm providing solutions to car manufacturers can compare themselves to other automotive firms) and hence in my analysis I appropriately take into account industry fixed effects. To compare survey responses to industry-level technology measures I use answer to part A of the question, which is highly correlated with adoption but includes industry-wide differences in technology.

In 2017 the Panel did not contain the same questions but it did contain additional measures of digitization and automation. In particular, firms were asked whether they use different classes of technology. These technologies included 1) program controlled means of production requiring indirect handling by humans (e.g. industrial robots, CNC machines); 2) Software, algorithms and web interfaces for IT-based optimization of business processes (e.g. big data analytics, cloud computing); 3) networking and data exchange between facilities, processes or products (e.g. Smart Factory, drones, Internet of Things). Firms were also asked about how important each technology class is for them. I use 3 binary indicators of usage and technology being important (i.e. I define the measure as 1 if firm uses the technology and reports its importance to be at least 3 on a scale from 1 to 5) - robotics, data and networks - to measure the three respective technology classes. I will use these measures to analyze heterogeneous effect of different technologies.

Summary statistics of all measures are presented in Table A1. The exact wording of the questions is presented in the Online Appendix. Notice that in the survey firms were also asked about usage of other technologies, which will not be the focus of this paper (e.g. usage of computers or mobile phones, which is positive for almost all firms). The limitation of the data is that it is only available for a cross-section of firms, instead of being observed over time. These measures are used as the dependent variable in section 4 and are used to construct local adoption intensity which is one of the independent variables in section 5.

Industry-Level Measures. Industry-level measures are stock of robots and stock of software and databases capital. They are available in the time-series and are used to construct technology measures which are independent variables in section 5. Robot density, i.e. number of robots per 1000 employees, is calculated by combining the count of robots from International Federation of Robotics with employment data from EU KLEMS. For Germany, robot density is available since 1993, the longest period among all countries. The Federation
computes the robot count based on the information from robot suppliers which are responsible for over 90% of world industrial robot production. Robots are highly concentrated in manufacturing, although small count of robots is also reported for mining, construction and some other industries.

Stock of software and databases capital comes from EU KLEMS database. I combine the capital stock with employment levels, also from EU KLEMS, and calculate stock of software and databases capital per worker, expressed in thousands of Euros. I use the real value expressed in 2010 prices. Because data collection and publication practice changed for Germany in 2014, the capital series experiences an unexpected shift. To deal with this problem I use changes of capital stock between 2004 and 2014, instead of changes between 2005 and 2015 in section 5.

Validation of Measures. To cross-validate technology measures, Figure 1 presents the relationship of industry-level measures and survey-based measure of familiarity with automation and digitization (Online Appendix confirms these results in a tabular form). There is a positive and significant correlation between survey responses and industry-level measures of technology, which confirms that the survey does capture the information about technology in a meaningful way. Interestingly, while the correlation of survey measures with digitization is visible across all industries, the relationship with robots is driven only by industries within manufacturing. This is simply because almost no robots are being used outside of manufacturing.7

Bottom panel of Table 1 presents correlation 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 (share in sales). They also report lower age of their equipment and the share of R&D workers in their personnel records is higher. The fact that self-reported measure of adoption is strongly correlated with hard information on investment and personnel structure again suggests that the adoption measure captures the real differences in technology across firms, as opposed to incorrect perceptions.

7Recent 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 opened 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 than just industrial robots.
2.3 Descriptive Analysis of Digitization and Automation

In this section I present several facts about digitization and automation adoption, based both on firm-level and industry-level measures. Figure 2 shows how usage of various technologies varies across industries, based both on IAB Establishment Panel firm-level measure and on industry-level measures from International Federation of Robotics and EU KLEMS. Clearly, robots are highly concentrated in manufacturing. The strict and narrow definition of a robot used in IFR data implies that there is almost no robots in other sectors. The looser definition used in IAB-EP causes firms in other sectors to report some usage of robots\textsuperscript{8}, but their prevalence is low. Based on IFR data we can see that usage of robots in Germany is highly correlated with usage of robots in other countries, although in some important industries - such as automotive or chemical manufacturing - Germany seems to have higher robotization rates.

Digital technologies are more popular and more homogeneously distributed across industries. Technologies related to IT enhancements of business processes, such as big data analytics or cloud computing, are prevalent across many industries and their rates of usage is high. Technologies related to networks and communications between machines (e.g. Internet of Things) are less prevalent and tend to be concentrated in ICT and manufacturing sectors, although the contrast is not as stark as in the case of robots. In the EU KLEMS data software and databases capital is highest in sectors like ICT and finance. The stock of capital is lower in Germany than in other countries, but this is partially due to different reporting methods causing a level shift - when we examine changes in the capital stock between 2005 and 2015 (which are used in the empirical analysis) the values are very similar (see Figure A3 in the Appendix).

Usage of technology varies by geographical area, even after controlling for industry. Figure 3 shows the intensity of digitization and automation adoption across Germany. The measure is an average of firm assessments of adoption relative to other firms in the sector and hence it is not driven by industry composition, but rather by other factors affecting technology adoption, such as proximity of R&D centers, technological spillovers and labor market conditions.

Usage of technologies also varies by firm characteristics, see Fig 4. Large firms are more likely to report using robots and digital technologies. Firms with high levels of adoption are also more productive, which can be partially explained by the fact that their workforce is more skilled. Interestingly, high-adopters have also been growing faster in the last 5

\textsuperscript{8}Robots in IAB-EP are broadly defined as “program controlled means of production requiring indirect human intervention”; establishments outside of manufacturing reporting some usage of robots defined in such a way include e.g. airport services firms.
years. Hence, the naïve firm-level regression does not support the hypothesis that technology reduces employment. Clearly, however, such a conclusion is premature because technology adoption is endogenous and faster growing firms are likely faster to adopt new technologies.

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.

3 Theoretical Framework

To guide the empirical analysis, I introduce a model of firm’s decisions regarding technology adoption and inputs choice in the face of labor and capital costs/constraints. I model firm’s adoption decision in the spirit of Davies (1979) - firm decides whether or not to adopt the new technology by comparing benefits and costs of adoption. The benefits depend on the cost of labor and capital, but the shape of this dependence is different for different types of technology. The firm production function I employ is similar to task-based model of Acemoglu and Autor (2011) and related to pioneering work of Zeira (1998). Similar approach was recently employed by Acemoglu and Restrepo (2018b) to model automation. While this modeling choice is common for me and them, the focus is different - while they propose an endogenous growth model and model automation in general equilibrium, I consider a firm decision problem where prices are treated as given and highlight not only the automation process, but also the part of technological progress which complements labor.

Firm produces output by combining a continuum of tasks in the unit interval \([0,1]\) in the Cobb-Douglas form:

\[ Y = A \cdot \exp \left[ \int_{0}^{1} a \cdot \ln y(i) di \right] \tag{1} \]

where \( a < 1 \), i.e. firm faces decreasing returns to scale and sells its product on a competitive market with price of output equal to 1. Alternatively, \( Y \) can be interpreted as firm’s revenue and \( a \) as a way of capturing the downward-sloping demand function for firm’s product. \( A \) is a firm-specific productivity parameter. Different tasks represent different parts of the production process. For example, car manufacturer needs to perform welding, painting, design, marketing etc. to produce and sell a car.

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9 Cobb-Douglas form is chosen to simplify the exposition. Allowing for different elasticity of substitution between tasks does not change the main intuition of the model, formalized in Proposition 1.
Each task \( i \) can be produced by capital/machines or by labor and has the following production function:

\[
y(i) = \alpha_K(i)k(i) + \alpha_L(i)l(i)
\]  

(2)

Vector \( \alpha(i) = [\alpha_K(i), \alpha_L(i)] \) represents technology. For each \( i \) it determines the productivity of capital and labor at task \( i \). Terms \( k(i) \) and \( l(i) \) represent the amounts of capital and labor assigned to the production of task \( i \) (chosen by the firm).

Firm can hire labor paying cost \( w \) and rent capital at rate \( r \), which are exogenously given. For simplicity, in the model input markets are perfectly competitive and scarcity of labor and capital is represented by high labor costs (potentially coming from high search costs) or high rental price. However, I interpret these forces more broadly as labor and capital scarcity. That is, high labor cost in the model represents a tight local labor market - which in reality may manifests itself not only through high wages but also through high search costs and difficulties in finding suitable workers. High cost of capital in the model may represent also financial constraints, i.e. difficulties in obtaining credit.

Firm maximizes profits \( Y - rK - wL \) by choosing inputs \( K, L \) and assigning them to tasks (for each \( i \) choosing \( k(i), l(i) \)). Because capital and labor are perfect substitutes within a single task, whenever \( \alpha_K(i)/r \) (cost-adjusted capital productivity) is higher than \( \alpha_L(i)/w \), task \( i \) will be performed by capital (automated). Figure 5 demonstrates the determination of the automation threshold \( R \) under an arbitrary new technology - tasks in the interval \( [0, R] \) are performed by capital, while remaining tasks are performed by labor\(^{10} \). The Figure shows that the decision whether capital or labor performs given task depends on the interplay of costs and productivity of labor and capital.

What is the total labor demand of the firm? Using features of Cobb-Douglas production function one can derive\(^{11} \) the expression for firm’s profit:

\(^{10}\)For simplicity I assume that tasks are ordered in such a way that \( \alpha_K \) is decreasing in \( i \) and \( \alpha_L \) is weakly increasing; this assumption is inconsequential since the symmetry of all tasks implies that only the mass of automated tasks matters, not their index

\(^{11}\)The firm maximizes profits:

\[
\max_{l,k,R} \text{Exp} \left\{ \int_0^R a \cdot \ln[\alpha_K(i)k(i)]di + \int_R^1 a \cdot \ln[\alpha_L(i)l(i)]di \right\} - w \int_0^1 l(i)di - r \int_R^0 k(i)di
\]

Cobb-Douglas production function with symmetric tasks is characterized by equal expenditures on each task: \( p(i)y(i) = p(i')y(i') \), where \( p(i) \) denotes the price of one unit of task \( i \) (e.g. one widget). For two tasks produced by labor we therefore have \( p(i)\alpha_L(i)l(i) = p(i')\alpha_L(i')l(i') \). At the same time, the (hourly) wage of workers employed in each tasks is the same, and hence \( p(i) = w/\alpha_L(i) \). This implies that \( l(i) = l(i') \) for each 2 tasks performed by labor and similarly \( k(i) = k(i') \) for each 2 tasks performed by capital. Moreover, for each task performed by labor and each task performed by capital we have \( l(i) = k(i') \frac{r}{w} \). We can therefore write \( L = l(1 - R) \)
\[ \Pi = A \left( \frac{L}{1 - R} \right)^a \exp \left\{ \int_0^R \ln[\alpha_K(i) \frac{w}{r}] di + \int_R^1 \ln[\alpha_L(i)] di \right\}^a - w \frac{L}{1 - R} \quad (3) \]

Let us denote \( \theta = \exp(\int_0^R \ln[\alpha_K(i) \frac{w}{r}] di + \int_R^1 \ln[\alpha_L(i)] di) \) (notice that \( \theta \) captures overall productivity). Profit maximization implies that total labor demand equals:

\[ L = (1 - R) \left( \frac{Aa\theta^a}{w} \right)^{\frac{1}{1-a}} \quad (4) \]

**Different Effects of Technological Change.** Improvements in technology can be viewed as changes to the productivity schedule \( \alpha(i) = [\alpha_K(i), \alpha_L(i)] \). These changes, combined with prices of capital and labor, determine the value of \( R \) and \( \theta \), which govern the substitution and productivity effects of technology. Increases in \( \alpha_K \) generally increase both \( R \) and \( \theta \). Intuitively, increase in productivity of machines increases the set of tasks which are automated and at the same time rises overall productivity. Notice, however, that increase in both parameters does not need to be strict. If \( \alpha_K \) increases for tasks \( i < R \), that is those which are already automated, there is no change in automation threshold \( R \), but there is an increase in productivity \( \theta \). If \( \alpha_K \) increases for tasks \( i \gg R \) but the increase is small, so that \( \frac{\alpha_K}{w} > \frac{\alpha_L}{r} \) still holds for all \( i > R \), there is no impact on \( R \) nor on \( \theta \).

Increases in \( \alpha_L \) generally reduce automation threshold \( R \) but increase productivity \( \theta \). While empirically less relevant, an increase in labor productivity for \( i < R \) may lead to deautomation of some tasks, i.e. decrease in \( R \). More plausibly, however, \( \alpha_L \) increases for tasks \( i > R \), rising \( \theta \). This effect can be thought of labor-augmenting technological change.

Overall, technological change is a combination of: 1) automation, i.e. changes in \( R \), coming from changes in the relative productivity of capital, \( \alpha_K \), and labor, \( \alpha_L \); 2) labor-augmenting technological change, coming from increases in \( \alpha_L \) for \( i > R \); 3) productivity effect of capital improvements, i.e. increases in \( \alpha_K \) which increase \( \theta \) (possibly without influencing \( R \)). The intensity of these 3 channels can vary across industries and technology classes and can lead to different technology adoption patterns and different employment effects.

**Adoption and Labor Scarcity.** Consider now the firm’s decision whether or not to adopt new technology. For simplicity, let us assume that current technology is such that machines are not productive \( (\alpha_K(i) \equiv 0) \) and productivity of labor does not vary across tasks (productivity is normalized to 1, i.e. \( \alpha_L(i) \equiv 1 \); notice that Eq. 4 then implies that labor demand under current technology equals \((\frac{a}{w})^{\frac{1}{1-a}}\)). The firm is contemplating adopting
new technology with arbitrary characteristics $\alpha' = [\alpha'_L, \alpha'_K]$. While this is not necessary in the model, in empirically relevant scenario $\alpha' > \alpha$, i.e. new technology is unambiguously better. However, the adoption (which means obtaining access to $\alpha'$) has a fixed cost $C(r)$ (which may depend on the cost of capital the firm faces, $r$) and hence firm decides whether or not they want to pay it and produce using $\alpha'$ or stick with old technology and produce using $\alpha$. They will adopt new technology if and only if the cost of adoption $C(r)$ is lower than the increase in profits which can be attained, i.e. will maximize:

$$\Delta \Pi = \rho [\Pi_1 - \Pi_0 - C(r)] \quad (5)$$

where $\rho \in \{0, 1\}$ represents the decision to adopt. How does labor scarcity, represented by high $w$, affect the adoption? The adoption would be increasing in labor scarcity if and only if above function was supermodular in adoption and wages. Under appropriate differentiability assumptions, supermodularity corresponds to:

$$\frac{d^2(\Delta \Pi)}{d\rho dw} \geq 0 \quad (6)$$

It can be shown\footnote{\textsuperscript{12} $d^2(\Delta \Pi)_{\rho dw} \geq 0$ is true if and only if $\frac{d(\Pi_1 - \Pi_0)}{dw} \geq 0$. Substituting expressions for optimal labor demand from Eq. 4, $\Pi_1 - \Pi_0$ can be expressed as:}

$$\Pi_1 - \Pi_0 = A \left( \frac{Aa\theta^n}{w} \right)^{\frac{\theta}{\theta - n}} - w \left( \frac{Aa\theta^n}{w} \right)^{\frac{\theta}{\theta - n}} - A \left( \frac{Aa}{w} \right)^{\frac{\theta}{\theta - n}} + w \left( \frac{Aa}{w} \right)^{\frac{\theta}{\theta - n}} = w^{\frac{\theta}{\theta - n}} A \left\{ \begin{array}{l} a \frac{\theta}{\theta - n} - a \frac{\theta}{\theta - n} \left( \theta \frac{\theta}{\theta - n} - 1 \right) \\ h_1 > 0 \\ h_2 > 0 \end{array} \right\} \left( 1 - R \right)$$

The derivative of this expression with respect to wage equals (notice that $\frac{d\theta}{dw} = \frac{R}{w}$):

$$\frac{d(\Pi_1 - \Pi_0)}{dw} = h_1 h_2 \left[ - \frac{a}{1 - a} w^{\frac{\theta}{\theta - n}} (\theta \frac{\theta}{\theta - n} - 1) + w^{\frac{\theta}{\theta - n}} a \frac{\theta}{1 - a} \frac{\theta - 1}{\theta} R \theta \right] = -H \left[ (1 - R) \theta \frac{\theta}{\theta - n} - 1 \right]$$

where $H = -h_1 h_2 \frac{a}{1 - a} w^{\frac{\theta}{\theta - n}} > 0$. Therefore, technology adoption is increasing in labor scarcity if and only if

$$(1 - R) \cdot \theta \frac{\theta}{\theta - n} - 1 < 0$$

Intuitively, the adoption of technology is increasing in labor scarcity if technology mostly substitutes labor. If new technology reduces the demand for labor, firms which face highest labor cost (which could possibly come from high search costs) are most likely to adopt. Conversely, if technology mostly complements labor, i.e. labor productivity increases and it is optimal to hire more workers after technology is adopted, firms which face the lowest labor cost are most likely to adopt.
**Employment Change.** How would the quantity of labor demanded change if firm adopted the new technology? We can simply compare labor demand (given by Eq. 4) under new technology with arbitrary parameters $\alpha' = [\alpha'_L, \alpha'_K]$ to labor demand under the current technology with parameters $\alpha_K(i) \equiv 0$ and $\alpha_L(i) \equiv 1$ (continuing to assume it for simplicity). The change in employment is given by:

$$\Delta\%L = (1 - R) \cdot \theta^{\frac{a}{1-a}} - 1 \quad (8)$$

The adjustment of employment after the adoption can be decomposed into two parts. First, when productivity of machines ($\alpha'_K$) is large relatively to productivity of labor ($\alpha'_L$), some tasks are more efficiently performed by machines and thus get automated ($R$ increases). This is the substitution effect, which reduces the demand for labor. Second, when productivity of machines or labor increases, the firm experiences increase in productivity and increases its production and the demand for inputs. This is the productivity effect, which increases demand for labor. Which of these two effects dominates is an empirical question.

**Connecting Employment Change and Labor Scarcity Effect.** Suppose that we are interested in learning about unknown characteristics of new technology and in particular about the extent to which it substitutes labor versus complements it by increasing the productivity. Suppose also that we observe both firms’ adoption decisions, as well as information about their employment change and about labor costs they face. Then because both condition 7 and equation 8 contain the same expression, we can learn about the characteristics of new technology in two ways: by analyzing how labor scarcity affects adoption and by studying how adoption affects employment change.

**Proposition 1.** Technology adoption is higher when firm faces labor scarcity if and only if total employment decreases after technology is adopted. This is the case when substitution effect dominates over productivity effect, i.e. when

$$
\text{Substitution Effect} \cdot \exp\left\{ \int_0^R \ln[\alpha_K(i)\frac{w}{R}]di + \int_R^1 \ln[\alpha_L(i)]di \right\}^{\frac{a}{1-a}} - 1 < 0
\text{Productivity Effect}

$$

This proposition provides a motivation for the empirical analysis in which I analyze both how labor scarcity affects technology adoption as well as how technology affects employment. Both parts shed light on the same, unknown technology characteristics, which generate substitution and productivity effects.

Online Appendix presents additional theoretical results. I formalize an intuitive result that financial constraints impede the adoption of technology if and only if there is any tech-
nological progress embodied in machines or if adoption itself requires capital expenditures. I also present an extension of the model in which I consider different worker groups, corresponding e.g. to different skill groups. I show that the change in the share of workers of each type depends both on the changes in labor productivity as well as the degree to which tasks performed by different workers get automated.

4 Labor Scarcity and Technology Adoption

This section analyzes how availability of labor influences firm investment in digitization and automation. As formalized in Proposition 1, the shape of this relationship depends on the features of the technology. If the technology purely substitutes existing workers, then scarcity of labor should increase the investment. If technology is purely complementing existing workers, then scarcity of labor should have the opposite effect. I regress technology adoption on labor scarcity and demonstrate that the average effect is positive, consistent with substitution effect. I use various approaches, including instrumenting labor scarcity with aging, to address endogeneity concerns. Finally, I perform heterogeneity analysis which reveals that effect of labor scarcity significantly varies by industry and workforce characteristics.

4.1 Basic Results

The analysis in this section uses a cross-section of firms from IAB Establishment Panel. Basic specification is the OLS regression:

\[ Technology_i = \beta \cdot LaborScarcity_i + \gamma \cdot I_j + \phi \cdot Z_i + e_i \]  

(9)

The dependent variable is a measure of digitization and automation, which 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. I also employ alternative measure, such as binary indicator of adoption being above median and interaction of this indicator with investment share in sales being above median. \( I_j \) denotes set of industry fixed effects which correspond to 2-digit classification based on NACE Rev. 2 (see Online Appendix for the complete list of industries). \( Z_i \) contains set of firm-level controls. In the main specification I control for firm size 5 (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

13Both effects can clearly coexist even within a single industry. In retail, for example, introduction of self-checkout is a clear example of labor-substituting technology. Smartphone applications collecting customer shopping patterns, on the other hand, complement the work provided by data analysts and marketing specialists.
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 reduces sample size and thus I choose the main specification to be parsimonious but present results which demonstrate that including additional controls does not meaningfully change the magnitudes of the coefficients. An important potential control is area fixed effect, since part of the variation in labor scarcity is common for all firms in the area. I present the results both with and without area fixed effects. Standard errors in the main specification are clustered on industry level.

The main independent variable, Labor Scarcity, is defined in four different ways. First, firm’s own declaration that they have difficulties finding workers (main measure). Second, the indicator for declared demand for new hires being higher than actual hires that the firm has made. Third, capacity constraints measure which equals 1 if the firm declares that they cannot increase the production without hiring new workers. Fourth, for a subset of firms which declare abandoning planned project related to product or process innovation, a measure which equals 1 if among reasons for abandonment the firm lists “lack of qualified personnel”. Around 40% of firms in my sample report difficulties with finding workers (see Table A1). All measures are defined based on answers to 2014 survey (except for the fourth measure, which is an average of responses for 2009-2015 period), which predates the technology-adoption measure by 2 years. Lagging the independent variable is a first attempt to circumvent the reverse causality problem but the results would remain similar if I used measures from 2016 (see Table A3).

Table 2 presents the estimates of equation 9 with different measures of labor scarcity. Columns 1-7 present the results with adoption measure being a continuous assessment of adoption from the survey; columns 8-12 present the results for adoption measure which interacts above-median adoption assessment with above-median capital expenditures (share in total sales). 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. This result suggests that on average across firms, marginal worker is substituted, rather than complemented by the new technology. The magnitudes suggested by different measures are similar: changing labor constraints measure from 0 to 1 increases technology adoption by 10-15% of standard deviation. Inclusion of area fixed effects, in columns 4 and 12, slightly decreases the magnitude of the effect, consistent with part of the variation in labor scarcity being driven by area-level characteristics. However, even when those characteristics are purged off, significant variation across firms remains and is related to technology adoption.

Table A2 in the Appendix shows that the estimate remains similar after including addi-
tional controls such as profitability, past employment growth, establishment age and management and ownership characteristics. Basic labor scarcity measures are defined based on data from 2014, but table A3 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 come from years earlier than 2010. Table A5 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 which takes value 1 if a firm reports high labor costs as one of their staffing problems. Because in a competitive market scarcity should be manifested as high costs, it might be surprising at first. However, German labor market has many rigidities in the process of wage setting, including sectoral- and firm-specific collective agreements. It could be the case that a firm is willing to hire another worker at a higher wage, but doing so would require rising the compensation for all existing workers performing similar tasks, which may be prohibitively expensive. There exists a positive relationship between adoption and the demand for further training. While there are many ways of interpreting this relationship, one possibility is that firms which have difficulties finding suitable workers are also forced to hire employees which need to be intensely trained.

One weakness of my digitization and automation measure is that it is only available in one 2-year time period (I treat 2016 and 2017 jointly and do not analyze the time-series variation between these 2 years given the short period and technology measures not being directly comparable) and hence it measures the stock of technology as opposed to its change. While I do not observe my digitization and automation adoption variable in the past, and thus constructing the natural measure of change is not possible, Table A4 presents the results of a specification which attempts to approximate the analysis of technology changes. Using the information about computer equipment from 2001-07 I compute firms’ technological sophistication in the past. I then use it as a control variable and to create a synthetic measure of changes in technology. Both approaches confirm that digitization and automation adoption in 2016/17 is accelerated by labor scarcity.

4.2 Addressing Endogeneity Concerns

Table 2 demonstrates that the positive relationship between labor scarcity and technology adoption is robust to using various measures of both variables but the results are subject to important endogeneity concerns. First, there is a concern about reverse causality: a firm which adopted new, sophisticated technology may have troubles finding workers because skills
required to operate the technology are scarce. This concern is to some extent mitigated by using lagged measures of labor scarcity but it nonetheless remains valid. Second, there is a concern about omitted variables: firms which adopt new technology more intensely may be different in a way which 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.

I take couple of steps to address these concerns. I start by using labor scarcity measure which is not specific to the firm but which 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. However, local productivity shocks may affect both the labor market and the output market: when local economy is booming, the demand for goods sold locally is high and it is hard to find workers, because unemployment is low. High demand, in turn, may lead to higher technology adoption. To deal with this scenario, I limit sample of my firms to those who export 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.

Nonetheless, some threats to identification remain. For example, some areas may have better access to information and expertise about technology because they have more universities or other research institutes. This can cause bias if presence of these institutions is positively correlated with labor scarcity. To alleviate this type of concerns, I use a specific part of variation in labor scarcity which comes from aging of the workforce. When older workers retire and there are few young workers in the local area, it is harder to fill vacancies. I instrument labor scarcity with the change in the share of older workers in the last decade. The main factor driving differences in aging are fertility decisions made many years ago which are unlikely to be strongly related to today’s technology adoption. While this approach alleviates previous worries, some concerns may still remain. In particular, linking back to previous example, the coefficient of labor scarcity may be upward biased if places with e.g. more universities are also places which have aged the most. Certain threats to validity of the instrument are related to migration, even though it is likely too small to drive the results and would bias my estimates towards zero (see Online Appendix). To alleviate this concern I use predicted aging based on the age distribution of population in 2004. Another concern could be related to product market effects of aging, i.e. firms can adopt new technologies because the age structure of their customers makes it more attractive. Again, this concern probably
biases my estimates downward, because we typically expect younger customers to be more technology-savvy and thus aging should discourage firms from adopting new technologies. Nonetheless, I alleviate this concern by estimating my 2SLS specification in the subsample of exporters.

**Labor Scarcity in the Local Area.** Following the discussion of endogeneity concerns, I substitute firm-level measures of labor scarcity with measures defined on the local area level. The equation I estimate is:

\[
Technology_i = \tilde{\beta} \cdot \text{Labor Scarcity}_a + \tilde{\gamma} \cdot I_j + \tilde{\phi} \cdot X_i + e_i \tag{10}
\]

Labor scarcity is measured in two ways. First measure, analogously to firm-level analysis, is a share of firms in the area which declare difficulties finding workers.\(^{14}\) The geographical variation in labor scarcity index is presented in Figure A7. Second measure is local unemployment rate from German Statistical Office. The analysis is performed with ca. 400 districts, but it is robust to using ca. 100 larger areas (Raumordnungsregionen) instead.

Columns 1-5 of Table 3 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 digitization and automation adoption. Moving local labor constraints index from 10th percentile to 90th percentile increases adoption by around 10% of its standard deviation. Local labor constraints index is negatively related to local unemployment rate and indeed there is a negative relationship between unemployment and technology adoption. However, with area-level clustering this relationship is not significant in the full sample, which might be the case because of large differences in structural unemployment across Germany.\(^ {15}\)

Local area conditions affect firms through local labor market, but they may also affect it through the output market. To mitigate this concern I estimate equation (10) using only the sample of firms exporting significant share of their production, i.e. at least 20%. This reduces the sample size significantly but the results, presented in columns 3 and 4 of Table 3, confirm the positive relationship between labor scarcity and adoption of digitization and automation. This relationship is significant both for local index of labor constraints and for local unemployment rate. These results show that the demand channel likely does not explain my findings.

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\(^{14}\)I employ leave-one-out procedure: for each firm in the sample I exclude its own declaration when calculating local averages. Therefore, denoting the variable with subscript \(a\) slightly abuses the notation.

\(^{15}\)While in general labor constraint index is negatively correlated with unemployment, large parts of Germany - especially in the East - have high unemployment rate and at the same time high share of firms complaining about difficulties in finding workers; this is caused by the structural mismatch of labor supply and labor demand.
Instrumenting Labor Scarcity with Aging. While local area labor market conditions are exogenous to the firm (ignoring endogenous firm location decision), it still might be the case that unobservable characteristics of firms differ by area in a way which is correlated with labor scarcity, even after controlling for industry. To further alleviate the endogeneity concerns, I instrument local labor scarcity with aging patterns in the local area. German society is aging rapidly and its fertility rate, around 1.4 in the last decade, is one of the lowest in the world. The total population was decreasing since 2003, although recent influx of immigrants have actually reversed this trend. With the median age of 47, 3rd highest in the world, aging is commonly considered to cause shortages of workers (Börsch-Supan, 2003). Figure A8 in the Appendix presents the evolution of the share of older workers over time and shows that it is accompanied by an upward trend in labor constraints declarations.

I use the differences in the intensity of aging across local areas to isolate part of variation in labor scarcity driven by demographics. I define aging as the change in the share of workers above 55 in the entire workforce and compute it using the information on the age composition from Establishment History Panel. This data set contains personnel records of half of all the German establishments and allows to calculate the share of workers above 55 per area with large precision. The retirement age in Germany is now slightly above 65 years but early retirement schemes allow many workers to retire earlier, depending on their work experience (e.g. at 60). The instrument is supposed to capture the fact that when there are relatively fewer young workers and many workers nearing retirement, finding a new worker is difficult.

Column 6 of Table 3 uses of the fact that I observe age composition and declarations about staffing problems for several years and shows that aging is related to more difficulties in finding workers even after controlling for firm and year fixed effects. Interestingly, a simple cross-sectional correlation between labor constraints and share of older workers has negative sign. Of course places with many older people are very different from places with many younger people and hence not taking into consideration these fixed differences obscures the real impact of aging.

Column 6 may be interpreted as a conceptual first stage, but it is not the same as actual first stage presented in the upper part of column 7. Because my measures of digitization and automation are only available in 2016/17, the 2SLS regression has to be cross-sectional. This precludes the usage of firm or area fixed effects and requires a different specification. I instrument labor constraints today with the change in share of workers above 55 between 2004 and 2014 and with labor constraints index in 2004. The results of the first stage regression are presented in column 2: the local-area change in the share of older workers in the last decade positively and significantly predicts labor constraints today. The F-statistic is 5.8 and indicates that the relationship between instruments and labor scarcity measure is
significant, although the value of the statistic is below the common rule-of-thumb for weak instrument assessment.

The results of second stage regression are presented in the lower part of column 7. There is positive and significant relationship between labor scarcity, instrumented with aging, and adoption of digitization and automation, which confirms the findings from previous specifications and suggests that the relationship is causal. As discussed in section 4.2, OLS coefficient may suffer from both downward and upward bias. While the IV coefficient is larger than OLS, suggesting that the downward bias may be more pronounced, the confidence interval is large enough to accommodate bias of different direction and hence I do not draw strong conclusions regarding the true sign of the bias. Column 8 presents the coefficients from IV regression where predicted aging is used instead of observed aging. I use age distribution by local labor market region in 2004, obtained from German Statistical office, and construct predicted change in the share of workers above 55. I assume that individuals who were between 55 and 65 years old in 2004 are no longer in the workforce in 2014, while individuals who were between 15 and 25 in 2004 are in the workforce by 2014. Predicted aging is strongly correlated with actual aging but eliminates the part of aging which comes from migration. Using predicted aging as an instrument confirms the results - the coefficient becomes a bit larger and more significant, and first stage becomes stronger. Column 9 presents the coefficients from IV regression estimated on the subsample of exporters. While the small sample prevents me from obtaining significant estimates, the coefficient remains positive and of similar magnitude as in the main sample, suggesting the demand considerations related to aging are unlikely to drive the results.

### 4.3 Heterogeneity of Labor Scarcity Effect

The results presented so far suggest that substitution effect dominates over the productivity effect on average, but average result may masks heterogeneous impact of different technologies in different industries. Figure 6 shows the results of specification from Eq. 9 modified by adding an interaction of labor scarcity (main measure, difficulties in finding workers) with 10 broad industry groups (see Online Appendix for details on industry group definition). Panel A reveals that the aggregate positive relationship hides significant heterogeneity across industries. Industries like manufacturing or utilities display significant, positive relationship, consistent with the idea that recent technological progress there is labor-substituting. At the same time, industries such as finance or professional services see either significant negative relationship between labor scarcity and technology adoption, or an effect close to zero, consistent with the view that recent technological progress there is complementing labor. Im-
portantly, industries such as retail and wholesale trade or hospitality - which are responsible for large part of employment - display clear positive relationship, consistent with substitution effect.

Panel B of Figure 6 provides further details about the heterogeneity, showing the effects on two alternative dependent variables: digitization and automation defined separately (using the measures from 2017 IAB-EP interacted with adoption intensity from 2016). Robots drive the substitution pattern in manufacturing and agriculture but play no significant role in other industries. The effect of digitization is responsible for substitution in industries such as trade or hospitality and for complementarity in industries such as finance or education and health.

These results highlight the importance of considering broad set of technologies and allowing for heterogeneous relationship of technology and labor across industries. Recent literature (Acemoglu and Restrepo, 2018c; Dauth et al., 2018) analyzes industrial robots in manufacturing and shows that they can reduce employment. However, the current wave of technological change involves also other technologies which affect different industries differently. In most industries substitution effect of technology dominates and hence the overall employment problem is still a potential concern. At the same time, however, complementarity effect of technology seems to dominate in selected industries and hence facilitation of workers’ movement between sectors may be even more important challenge related to technological change.

Another dimension of heterogeneity is related to different types of jobs or different skill levels of workers. Table 4 presents the results of Eq. 9 modified by adding interactions of labor scarcity with the share of administrative and non-administrative and skilled and unskilled workers in the firm. Columns 1 and 2 demonstrate that labor scarcity accelerates adoption of technology especially when a firm employs many non-administrative workers. Columns 5 and 6 present similar analysis for ICT technologies in years 2001-02, where the opposite pattern is visible. This suggests that recent technology is affecting workers outside of office jobs, contrary to ICT technology in the early 2000s, which mainly affected administrative workers. Columns 3 and 4 show that labor scarcity accelerates technology adoption particularly when a firm employs many unskilled workers. This suggests that the substitution effect of new technologies is most pronounced for unskilled workers and hence the technologies are skill-biased.
5 Impact of Technology on Employment

This section studies how digitization and automation affect firms’ employment. I regress 10-year changes in total employment on measures of technological change, defined on industry-area level, controlling for industry and area fixed effects. I find that automation significantly reduces employment, while digitization insignificantly increases it on average. However, aggregate results hide significant heterogeneity across industries: employment decreases in high- vs low-adoption areas in industries such as manufacturing, mining, construction, retail or hospitality, but increase in industries such as IT, finance or education and health. Consistent with Proposition 1, these findings paint the same picture of the technology as the analysis of adoption patterns in section 4.

The two sections can be therefore viewed as alternative approaches to identifying unknown characteristics of the technology. At the same time, however, both bring unique value. Adoption analysis cannot inform us how technology affects patterns of firms entry or exit and is of partial equilibrium type. The employment analysis, performed at the industry-area level, can take these patterns into account and moves one step towards general equilibrium analysis. More precisely, it captures any employment change at the industry-area cell level, although it still cannot capture the employment changes in the whole industry, whole local area or in the whole economy. While I can perform analysis at the industry-level, the ability to cleanly identify the effects of technology is then limited.

Methodology. The naive approach to studying the effects of automation and digitization would regress change in outcome variable in the last 10 years on the measure of digitization and automation from IAB Establishment Panel. This approach, however, suffers from several concerns which might lead to unwarranted conclusions. First, the decision to adopt technology is endogenous and related to many characteristics of the firm. In particular, firms which are growing are more likely to adopt new technology and hence regressing e.g. employment change on technology adoption will not reveal the true causal effect of technology (see section 2.3 for evidence). Second, the adoption measure is only available at the end of the period and hence measures an end-of-period stock as opposed to actual change. Third, the technology measure is not absolute, but relative to other firms in the sector - the analysis would therefore ignore any variation in technology adoption across industries and give the same weight to across-firm differences in every industry. Fourth, since the technology adoption is measured only at the end of the period, firm exits cannot be properly taken into account. To deal with these concerns I employ alternative specification and measures of digitization and automation. For digitization, I use stock of software and databases capital per worker from
EU KLEMS database. For automation, I use number of robots per 1000 workers, based on robot shipments data from International Federation of Robotics. Both measures are at the country-industry-year level. The variation in these measures across industries can be used to analyze the employment effects of technology, as demonstrated by Graetz and Michaels (2018) and Acemoglu and Restrepo (2018c). 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 correlated with technology adoption - independently of any transformations which researcher can apply. Therefore I combine the variation in technology across industries with variation in adoption levels across local areas. Doing this allows me to look within 2-digit industry and identify the effect of technology by comparing firms in high-adoption areas to those in low-adoption areas. The geographic variation in adoption is captured by local area\textsuperscript{16} measures of intensity of digitization and automation adoption, computed as average of firm-level measures from IAB Establishment Panel.

I use data from BHP (Establishment History Panel) - an administrative data set with information on 50\% of all German establishments - and aggregate employment information to industry X area level, which is a natural choice given the desire to properly take into account firm entry and exit and that the variation in independent variables is at the area-industry level. My main empirical specification is:

\[
\Delta Y_{a,j} = \beta_R \cdot (\Delta \text{Robots}_{j} \cdot \text{Adoption}_a) + \beta_D \cdot (\Delta \text{Digitization}_{j} \cdot \text{Adoption}_a) + \phi I_j + \xi A_a + \epsilon_{a,j} \quad (11)
\]

This is a long differences specification with all changes in the above equation, denoted by $\Delta$, 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 industry, respectively. $\Delta \text{Robots}_{j}$ is the change in number of robots per 1000 workers used in a given industry, coming from International Federation of Robotics data. $\Delta \text{Digitization}_{j}$ is the change in software and databases capital stock per worker in a given industry, coming from EU KLEMS data. Because of changes in reporting which happened in 2014/15, I use 2004-2014 change in digitization. $\text{Adoption}_a$ is a measure of digitization and automation adoption in area $a$. In the basic specification, this is an indicator of intensity of adoption being above median. Intensity of adoption is the average of firms’ declarations from the IAB Establishment Panel. It is a measure which is relative to other firms in the sector and hence

\textsuperscript{16}Area in this section is defined using spatial planning regions (ROR, Raumordnungsregionen), constructed by 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.
it is not driven by industry composition of the area. The independent variables include vectors of industry fixed effects $I_j$ and area fixed effects $A_a$. In the basic specification I weight all the observations with 2005 level of employment.

**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 across time is included in the dependent variable, which is the change in employment). The treatment is the change in digitization and automation intensity at the industry level and the treated group are firms in high-adoption areas, while control group are firms in low-adoption areas. The identifying assumption is that absent technological change, the difference between 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 propensity to adopt technology. Two independent forces are pushing firms to adopt the technology: the first is large technological change in the industry, the second is being located in high-adoption area. Looking at firms in industries with large technological change which are located in high-adoption areas and partialling out the effect of industry alone and area alone should therefore allow me to isolate the effect of technology.

To intuitively understand the specification, consider an example of two industries - car manufacturing and paper manufacturing - with two firms in each of them. Let us assume that there is a large technological change in car manufacturing, but negligible technological change in paper manufacturing. In each industry, one firm is located in high-adoption area (assumed to be around Munich), the other in an area with negligible adoption level (around Berlin). Suppose we are interested in learning how technology affects employment. To calculate this effect we need to compare how change in employment differs between Munich and Berlin firms in car manufacturing. The observed difference is a combination of the "technology effect" and of the "location effect". Comparing Munich and Berlin firms within paper industry - which has negligible technological change and therefore "technology effect" is negligible - allows us to compute "location effect". Assuming that this effect does not systematically differ across industries, this allows us to back out the "technology effect" in the car industry.

**Endogeneity.** Changes in robots density and digitization intensity in Germany may be endogenous. For example, when German firms in a given industry face large demand, they may be adopting more robots and digital technologies and at the same time increasing employment - in this case my estimates of employment effect would be biased upwards. While in my specification the technology coefficient is identified using within-industry variation and
thus the concern is less severe, 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 exogenous variation in technology, I follow the approach of Autor et al. (2013) and Acemoglu and Restrepo (2018c) and use changes in robot density and software and databases capital in a group of other European countries. I present both the reduced form estimates with technology abroad as the independent variable and IV estimates in which I use technology abroad to instrument the domestic technological change.

Differences in adoption across local areas are not random and can be correlated with various other factors affecting employment. I do not assume that high- and low-adoption areas are similar except for the levels of technology adoption. Instead, I include area fixed effects with the goal of capturing all area-specific factors other than technology. The key identifying assumption is that the effect of these factors does not systematically vary across industries. For example, I allow for the presence of many universities in the area to affect employment, but I assume that it will affect employment in each industry in a similar way.

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 technology. Nonetheless, the former assumption can still be violated. Most plausible concern is related to agglomeration effects differentially affecting different industries. High-skill industries may prefer to be located in selected business hubs more than manufacturing firms. The existence of these preferences alone does not pose a problem to my 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 high-skill services (which have high digitization) employment increases, while manufacturing employment (which has high robotization) decreases in high-adoption areas.

While this is a possible concern, it is unlikely to explain the whole set of results presented in this paper. In particular, employment effects hold also when controlling for past employment changes, and hence are unlikely to be driven by differential employment trends across industry-area pairs. Moreover, section 4 shows that technology adoption overall is higher in areas with more labor scarcity. If these characteristics identify “business hubs” which are attracting most productive firms in high-skill services industries, we should see positive relationship between technology adoption and labor scarcity for high-skill services.

\[\text{Both for robots and digitization I use 6 other countries but the group is different because of data availability. For robots, it includes France, Italy, Denmark, Netherlands, Sweden and United Kingdom. For software and databases capital, the group includes France, Italy, Belgium, Netherlands, Finland and Austria.}\]
- but we see the opposite. In addition, the analysis of adoption patterns across Germany (Fig. 3) 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 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 of employment effects analysis. I estimate equation 11 with dependent variable being the percentage change in employment between 2005 and 2015. The results for main specification, presented in column 3, show that robotization has 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. The effect of digitization is positive, but insignificant in the main specification. When a continuous measure of adoption is used instead (column 4), effect of robots is still negative and significant, while effect of digitization remains positive and becomes significant. Interestingly, naive approach on regressing employment change on area- or industry-level measures of technological change (column 1 or 2) shows very different results and highlights the necessity to properly take into account other industry-level changes.

The intensity of automation and digitization in Germany may be endogenous. To deal with this concern, I estimate an alternative specification in which instead of using domestic change in technology I use change in technology abroad (column 5) or instrument domestic changes with the changes abroad (column 6). Both results confirm the negative and significant effect of automation and positive but insignificant effect of digitization. Consistent with expectations, the coefficients of employment effect are lower, suggesting that endogeneity concerns can indeed to some extent bias the coefficients upwards.

Columns 7-10 analyze alternative periods. The signs of the coefficients and main conclusion remain unchanged, although in the recent period negative effect of robotization is more evident, while positive effect of digitization is significant between 2005 and 2010.

Table A6 presents the results which confirm robustness of the main findings and contain additional details. The main result is robust to alternative measures of adoption, excluding 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 first stage of the IV regressions as well as the results of analogous regression for wages. Digitization increases wages while automation does not have significant effects.

Heterogeneity. The results presented in Table 5 show average effects of technology but Figure 6 suggests that they may be hiding important heterogeneity across industries. To shed
more light on across industry heterogeneity, I computed differences in employment changes between high- and low-adoption areas across industries. These differences, demeaned and aggregated to 10 industry groups, are presented in Figure 7. The Figure presents differences between areas in the 4th and 1st quartiles of adoption. The differences between above and below median areas show similar pattern, but the estimates are less precise. The difference in employment effects between high- and low-adoption areas is consistently negative for industries in which robots are present, i.e. mining, manufacturing and construction and utilities. However, the difference is of mixed sign in industries in which digitization is playing some role. While some industries, including IT or finance, experience positive employment change when moving from low- to high-adoption, others industries - like trade and hospitality - see negative employment change. This result confirms the findings presented in Figure 6. Consistent with Proposition 1, in industries in which labor scarcity increases the adoption of technology, the employment effect of technology is negative, while in industries in which labor scarcity decreases the adoption, the employment effect is positive.

6 Additional Results

6.1 Financial Constraints and Technology Adoption

This section completes the analysis of determinants of technology adoption by studying the role of financial constraints. As shown in Table 1, technology adoption is associated with higher investment. This investment can be impeded if a firm faces financial constraints, understood as difficulties in accessing the capital. While it is natural to expect that this mechanism is also relevant for investment in digitization and automation, it is not clear how important it is given that many new technologies - cloud computing, software-as-a-service type of programs - may not require capital investment.

Measures. My measures of financial constraints come from IAB Establishment Panel. Because majority of firms in this data are private, and because the data is collected for different purposes, many traditional accounting variables (e.g. measures of liabilities) are not available. Instead, however, in selected years firms are explicitly asked about financial constraints, which is an interesting advantage of this data set. The survey explicitly asks firms if in the last year they had difficulties in obtaining credit and, if the answer is positive, asks for more detailed answer (credit application rejected, credit volume decreased, credit costs increased). I use binary variable coded as 1 if firm reports difficulties in obtaining credit as my first measure of financial constraints. In addition, firms report size of their investment in a given year, together with the sources of financing. In selected years, each firm which
reports non-zero investment is asked what share of expenditures was financed by equity and
debt (and separately government subsidies), based on which I calculate leverage measure
defined as the share of debt in total investment. Unfortunately, these financial variables
are part of Additional Modules of the IAB Establishment Panel and are not available after
2010. I will therefore use the lagged measures which may introduce downward bias into
my analysis because they may have limited power in explaining the cumulative level of
investment in 2016-17. I will complement these measures with another variable which is
available every 2 years (last time in 2015) but only for a subset of firms. The variable is
deﬁned for a subset of ﬁrms which declare abandoning planned project related to product
or process innovation, and takes value of 1 if among reasons for abandonment the ﬁrm lists
“lack of financing sources” (note that this is different than another reason which can be listed,
“costs too high”), and 0 otherwise.

Table 6 presents the results. Column 1 shows that there is a signiﬁcant, negative rela-
tionship between ﬁnancial constraints and adoption of digitization and automation. Column
2 conﬁrms the negative relationship between ﬁnancial constraints and digitization and au-
tomation adoption using an alternative measure based on reasons for abandoning investment.
The magnitude of the coefﬁcient are similar, even though measure from column 1 was based
on declarations from 2008. It is consistent with the view that ﬁnancial constraints are persis-
tent and that the current level of technology adoption stems from investment decisions made
in the last several years. Columns 3 and 4 shows that ﬁrms with higher leverage have lower
levels of adoption, consistent with both the fact that high debt may decrease the ability to
borrow more and with the possibility that investment in new technologies is ill-suited for
debt ﬁnancing, perhaps because of its intangible character in many cases.

Comparison of columns 2 and column 7 in Table 2 unveils an interesting contrast between
ﬁnancial and labor constraints. The sample in both cases consists of the same subset of ﬁrms
which declare abandoning an investment in an innovative project. When the ﬁrm declares
that the reason for abandoning the investment was lack of access to ﬁnance, it has lower levels
of digitization and automation (which may directly result from abandoning the innovative
project, possibly involving new technologies). Yet, when the ﬁrm declares that the reason for
abandoning the investment was lack of qualiﬁed personnel, it has higher levels of automation
and digitization.

Endogeneity. The evidence presented in columns 1-4 of Table 6 can suffer from endo-
genisty concerns, similar to those discussed in section 4.2. To some extent, these concerns
are less severe, e.g. the reverse causality is rather implausible in the case of ﬁnancial con-
straints. Nonetheless, to alleviate these concerns, I follow Huber (2018) and use the lending
cut of Commerzbank as an exogenous shock to availability of credit. For historical reasons,
some areas in Germany had larger share of firms with relationship to Commerzbank than others. When in the course of financial crisis Commerzbank significantly limited lending because of losses they suffered in their international trading activities, ability to obtain credit decreased in areas more exposed to the bank. In my data, being located in an area more exposed to Commerzbank is indeed related to higher probability of firms reporting difficulties in obtaining credit in years 2009-2015, but is uncorrelated with financial constraints in 2008. Using area-level exposure to Commerzbank as an instrument for area-level average difficulties in obtaining financing (2009-15) confirms the negative effect of financial constraints on technology adoption. In addition, Table A7 in the Appendix shows the results of the main specification after including additional controls, which also alleviates the concern that financial constraints are only capturing other firm characteristics.

Columns 6-9 of Table 6 confirm that financial constraints impede technology adoption not only in manufacturing, where capital-intensive robots are ubiquitous, but also in other industries, where many new technologies, e.g. cloud computing, are explicitly designed to limit capital investment. Even though smaller sample size prevents me from obtaining significant estimates in all specifications, coefficients are consistently negative and significant results are obtained both within and outside of manufacturing.

6.2 Technology and Skill Level

New technology may affect not only the total employment level but also the skill level of the workforce. In theory, the existence and direction of the skill bias of the technology is ambiguous, as formalized in Proposition 3 (Online Appendix). On the one hand, new technologies are commonly thought to substitute low skilled workers and complement high skilled workers. This assumption is explicitly built into the model of Acemoglu and Restrepo (2018b) and is consistent with (Graetz and Michaels, 2018) who show that higher usage of robots is associated with lower low skill employment. An extensive literature on ICT revolution points to the polarization effect on employment - share of low and high skilled workers increases at the expense of middle skilled workers. At the same time, artificial intelligence is often thought to threaten also high skilled workers - performing tasks such as credit application approval - for which labor input can be strongly decreased thanks to advances in big data analytics and machine learning.

I define educational structure based on the skill level information from the administrative data records. For each firm, number of workers in low, medium and high education group is reported every year. The groups are based on German educational system and are defined as follows: low skilled include workers without vocational qualifications; medium skilled
include workers with vocational education but no higher degree; high skilled workers include employees with university degree or applied university degree (Fachhochschule). In the data, around 12% of workers are low skilled, 73% medium skilled and remaining 15% high skilled.

Table 7 presents the results of educational structure analysis. I estimate equation 11 and use 10-year change in the share of low-, medium- and high-skill workers as my dependent variables. The table shows that both digitization and automation are associated with skill upgrading, even though the significance of coefficients appears in different columns for the two technologies and for digitization the results are only significant when technology abroad is used as a proxy for technological change. These results are consistent with the findings from Table 4, which suggest that the substitution effect of new technologies affects mostly unskilled workers (in Table 4 workers are classified based on whether they performed skilled or unskilled occupation, as opposed to the actual level of education used in Table 7).

If digitization and automation require new skills, not possessed by firm’s existing workers, firms can adapt not only by hiring better educated workers but also by training its existing employees. While the second solution may not always be feasible (certain skills might be very hard to acquire or require many years of education), its advantage is that it allows firm to retain existing workers which have valuable experience and firm-specific human capital. Also, if particular technology requires skills which are specific to the firm (e.g. because a digital system installed in the firm is unique), internal training might be the only way to acquire necessary skills.

Panel B of Table 7 analyzes measures of training intensity coming from IAB Establishment Panel. Each firm reports how many workers took part in training activities in the last year and checks what type of training methods were used (external or internal courses, symposium, on the job training etc.). Based on this information I construct a share of workers who underwent training and number of training methods used and calculate average of these two variables between 2005 and 2015. Using these variables as a dependent variable, I estimate an equation analogous to 11, but at the firm-level and with firm-level measure of adoption:

$$\Delta Y_i = \beta'_R \cdot (\Delta Robots_j \cdot Adoption_i) + \beta'_D \cdot (\Delta Digitization_j \cdot Adoption_i) + \phi' I_j + \xi' A_a + \epsilon_i \quad (12)$$

In this specification, instead of interacting industry-level changes in technology with area-level adoption propensity, I directly interact technological change with firm adoption measure. This allows me to measure the technology with less noise but requires availability of firm-level adoption measure (and thus can be used only in a subsample of firms from IAB Establishment Panel; however training intensity is also observed only for those firms) and
may suffer from endogeneity concerns, requiring more caution when interpreting the results.

There is a positive and significant association of adoption and training intensity. Firms which adopt the technology are training more workers and use more training methods. This increase in training is especially pronounced for industries which have high levels of digitization and is not significantly higher for industries with high levels of automation. These results suggest that new technologies do require new skills and training existing workers is a significant part of the process of adaptation to new technology. The training, however, seems to be used mostly in case of digital technologies.

6.3 Technology and Number and Size of Firms

Employment effects of technology may not affect all firms equally. Instead, they may mask both changes in employment in existing firms as well as firm creation and destruction. Table 8 analyzes the effect of technology on number of firms and average firm size in the area-industry cell. Robotization decreases number of firms in the area and insignificantly increases firm size. Digitization has the opposite effect - it seems to increase number of firms in the area and decrease average firm size. This is consistent with the fact that robots are most useful for firms with large scale of the production. At the same time, it is consistent with the notion that modern digital technologies such as cloud computing may be available also to small firms and hence they may reduce barriers to entry in some sectors. It is worth remembering that compared to other publicly available data sets (e.g. Compustat), the data used in this paper contains many small, private establishments. Therefore even though some technological forces may lead to increasing concentration among the very large firms (as evidenced by the example of Google and other similar firms), among smaller establishments the effect of digitization appears to be the opposite.

6.4 Technology and Productivity

In this section I study how technology adoption affects labor productivity. While in the basic theoretical framework technology typically leads to productivity improvements, in reality productivity gains from technology adoption are not always evident. In 1987 Robert Solow famously said that “You can see the computer age everywhere but in the productivity statistics”, which succinctly captures the concept of productivity paradox - an observed slowdown in productivity growth in the 1980s despite rapid adoption of IT technologies. The possible return of this paradox, i.e. lack of productivity gains from IT investment in

\[ \text{Because otherwise it would not be adopted. However, in a richer dynamic model it is possible to observe that technology adoption decreases initial productivity, but increases it in the future.} \]
recent decade, is discussed by Acemoglu et al. (2014), while Brynjolfsson et al. (2019) discuss a similar paradox in the context of artificial intelligence.

In my data, productivity can only be observed for establishments surveyed in IAB Establishment Panel. While equation 11 can be estimated using only these firms, the smaller sample size combined with the fact that proxying for technology usage with local area adoption necessarily introduces noise makes it difficult to obtain precise estimates. To deal with this problem, I employ analogous specification which makes direct use of firm-level technology adoption declarations, see Eq. 12.

Table 9 presents the results. Higher adoption of robots at the firm-level is associated with productivity increase (column 2) but the effect of digital technologies is insignificant. Using industry-level measures of technological change confirms the positive effect of robots, both when using variation across industries (column 4) or when relying on within-industry variation across firms with different levels of adoption (column 5). The findings are the same also when weighting observations by initial employment (column 6) and when using value added per worker instead of sales (column 7). One extra robot per 1000 workers increases labor productivity by 3% in high-adoption firms compared to low-adoption firms. Interestingly, the effect of digitization is significant only in column 5, but not in column 6, which is weighted by employment. This may suggest that digitization increases productivity to a limited extent and the gains are concentrated in small establishments.

7 Conclusions

The main contribution of this paper is to inform the debate on automation, AI and other digital technologies and their impact on the economy. While numerous countries and organizations are devoting a lot of attention to the new technology, the debate often remains at a superficial level and is based on anecdotes and futuristic visions. This paper provides empirical evidence based on rich firm-level data on a broad set of technologies for a complete set of industries.

The adoption of the last wave of technological change - digitization and automation - is typically increased by labor scarcity, suggesting that these technologies substitute workers on average. Consistent with that, the new technologies typically reduce employment. These effects, however, significantly vary across industries, worker types and technology classes. Average effects are driven by industries such as manufacturing, retail or hospitality, but in industries such as finance or education and health technology seems to complement workers and leads to increased employment. As a result, the main challenge of responding to technological change will be not the overall decline in the number of available jobs, but rather
the necessity to facilitate workers’ transition between different sectors.

The fact that technology adoption is driven by labor scarcity means that machines are not necessarily stealing workers’ jobs, even in sectors where substitution dominates. Instead, their adoption could be a response to the lack of workers. In addition, to the extent that they do displace some workers, they do so in places where jobs are most abundant.

Future research could contribute to the debate by using an alternative measure of technology which is available at the firm level and at many points in time. While such data sets are becoming available for industrial robots, it is important to consider broader set of technologies which are often referred to as AI. Doing this for the entire economy might be difficult but analysis within particular industries may generate important insights which can be then generalized to other industries as well. The growing interest in the topic and the fact that many organizations, including US Census, are starting to collect more data on digitization and automation, suggests that in the future we can hope to see further studies which combine rich data with convincing research design and improve our understanding of the relationship between technological change and economic outcomes. Moreover, the results of this paper suggest that reallocation of workers between sectors is an important challenge associated with periods of technological change and future research on this topic could be very fruitful.
References


Figures and Tables

Figure 1: Firm-Level and Industry-Level Measures of Technology
Left panel presents the relationship between robot density at the industry level and the intensity of dealings with digitization and automation based on firm-level data. Each dot represents one of 2-digit industries (see Online Appendix for the list). Robot density is defined as standardized logarithm of 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. Digitization and automation is the average of firms’ responses to part A of the digitization and automation question from IAB Establishment Panel (how intensively have you dealt with it so far, scale 1-10). Right panel presents the relationship between software & databases capital stock at the industry level and intensity of dealings with digitization and automation based on firm-level data. Software and databases capital stock is standardized natural logarithm of per-worker software & database capital stock from EU KLEMS.
Figure 2: Digitization and Automation Usage by Industry Group

Panel A. Robots and Digitization based on IAB Establishment Panel

The graph shows the frequency with which technologies are used, based on firm-level responses from 2017 IAB Establishment Panel. On the left, share of firms declaring use of “means of production requiring indirect human intervention” (robots, CNC machines) is shown. On the right, the graph presents the share of firms which use digital technologies related to IT-based optimization of business processes (big data, cloud computing) and networking and data exchange between facilities or processes. For data confidentiality reasons the exact value of robot usage for ICT and Finance was censored - the value is below 0.1 and the Figure shows it as 0.05.

Panel B. Robots and Digitization based on IFR and EU KLEMS data

The upper graph shows number of robots per 1000 workers in Germany and 6 other European countries by industry, based on data from International Federation of Robotics. The bottom graph shows the stock of software and databases capital, in thousands of Euros per worker, based on EU KLEMS data.
Figure 3: Geographic Distribution of Digitization and Automation Adoption
The map presents values of digitization and automation adoption index from 2016 IAB Establishment Panel, mapped by district. However, for data confidentiality reasons, presented values were computed on the spatial planning regions (RORs) level - each ROR contains ca. 4 districts. The index is the average of firms’ responses to a question about the intensity of digitization and automation 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 4: Digitization and Automation Usage and Firm Characteristics
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 digitization and automation adoption. High-adopting firms are larger and typically have been growing faster, although the pattern is not monotone. 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 5: Productivity of Labor and Capital Across Tasks Under New and Old Technology

The graph shows cost-adjusted productivity of labor and capital for different tasks for an example of technology parameters before and after technological change. For simplicity, it is assumed that the initial technology has machines which are not productive ($\alpha_K(i) \equiv 0$) and labor is uniformly productive in all tasks ($\alpha_L = 1$ and, also for simplicity, $w = 1$, and hence $\alpha_L(i) w \equiv 1$). For new technology, labor productivity schedule is assumed to be weakly increasing in task index $i$ and capital productivity is decreasing in task index. Under old technology, all tasks are performed with labor and the quantity of labor demanded is determined by productivity which is equal to 1. Under new technology, point $R$ marks the limit of capital-labor substitution. For tasks in the interval $[0, R]$, $\alpha_K(i)/r$ (cost-adjusted capital productivity) is higher than $\alpha_L(i)/w$ and hence they are performed by capital. For the remaining tasks, $\alpha_K(i)/r$ is lower than $\alpha_L(i)/w$ and hence the tasks are performed by labor. Quantity of capital and labor is determined by productivity parameter $\theta$ which is an average of the upper-envelope of new productivity curves.
Figure 6: Labor Scarcity Effect by Industry

Panel A. Digitization and Automation Adoption
The figure presents coefficients from the regression of digitization and automation adoption (main measure of adoption intensity from IAB-EP 2016) on labor scarcity interacted with indicators for 10 industry groups. The positive coefficients indicate that labor scarcity increases adoption of the technology (and hence substitution effect dominates), while negative coefficients indicate that labor scarcity impedes the adoption (and hence productivity effect dominates).

Panel B. Digitization and Automation Separately
The figure presents coefficients from the regression of technology measures on labor scarcity interacted with indicators for 10 industry groups. Automation is defined as the interaction of the main measure of intensity of adoption (from IAB-EP 2016) with indicator for using robots (from IAB-EP 2017) and considering them at least somewhat important (≥3 on 1-5 scale). Digitization is defined analogously, but with measures of digital technologies (data and networks).
Figure 7: Employment Effects of Technology by Industry

The figure presents the difference in 2005-2015 employment change between high- and low-adoption areas for different industry groups. High-adoption area is defined as area in the 4th quartiles of adoption, while low-adoption area is defined as area in the 1st quartile of adoption. Adoption index is an area-level average of firm-level declarations of digitization and automation adoption from IAB-EP. The estimates are obtained by regressing industry-level differences between high- and low-adoption areas on indicators for 10 industry groups, weighting the observation by number of areas. Details of assignment to industry groups are presented in the Appendix. The whiskers represent 5% confidence intervals for the coefficients.
Table 1: Digitization and Automation: Summary Statistics and Relation to Other Variables

Panel A: Summary Statistics

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<th>MEDIAN</th>
<th>P75</th>
<th>NUM OBS</th>
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<td>5</td>
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<td>and Digitization C (adoption)</td>
<td>5.72</td>
<td>2.68</td>
<td>4</td>
<td>6</td>
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Panel B: Relation to Other Variables

$Y = \text{Adoption of Automation and Digitization}$

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| 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 digitization and automation from IAB Establishment Panel (wave 2016, part C). Independent variables are binary indicators of usage of different technology classes coming from wave 2017 of the IAB Establishment Panel, share of gross investment in sales; firm assessment of their equipment age and share of R&D workers in the total employment. Industry fixed effects are included as a control variable. (*) denotes significance at 10% level, (**) at 5% level and (***) at 1% level.
Table 2: OLS Regression of Digitization and Automation Adoption on Labor Scarcity

<table>
<thead>
<tr>
<th>Basic Specification</th>
<th>Alternative Measures of Labor Scarcity</th>
<th>Alternative Measure of Technology</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( Y = \text{Digitization and Automation Adoption} )</td>
<td>( Y = \text{High Adoption} \times \text{High Investment} )</td>
</tr>
<tr>
<td></td>
<td>(1) (2) (3) (4) (5) (6) (7)</td>
<td>(8) (9) (10) (11) (12)</td>
</tr>
<tr>
<td>Hard to Find Workers</td>
<td>0.307*** 0.285*** 0.372*** 0.260***</td>
<td>0.066*** 0.065***</td>
</tr>
<tr>
<td></td>
<td>(0.072) (0.076) (0.105) (0.070)</td>
<td>(0.011) (0.013)</td>
</tr>
<tr>
<td>Demand for Hiring &gt; Hired</td>
<td>0.180**</td>
<td>0.085***</td>
</tr>
<tr>
<td></td>
<td>(0.083)</td>
<td>(0.015)</td>
</tr>
<tr>
<td>Can't Increase Sales without New Staff</td>
<td>0.361***</td>
<td>0.039***</td>
</tr>
<tr>
<td></td>
<td>(0.083)</td>
<td>(0.016)</td>
</tr>
<tr>
<td>Investment Prevented By Lack of Personnel</td>
<td>0.381**</td>
<td>0.077**</td>
</tr>
<tr>
<td></td>
<td>(0.159)</td>
<td>(0.034)</td>
</tr>
<tr>
<td>N</td>
<td>7469 5855 3479 7469 7449 6260 1431</td>
<td>5781 5771 5615 1191 5781</td>
</tr>
<tr>
<td>Industry FE</td>
<td>✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓</td>
<td></td>
</tr>
<tr>
<td>Size</td>
<td>✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓</td>
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</tr>
<tr>
<td>Profits &amp; Growth</td>
<td>✓ ✓</td>
<td>✓</td>
</tr>
<tr>
<td>Firm Type</td>
<td>✓ ✓</td>
<td>✓</td>
</tr>
<tr>
<td>Area FE</td>
<td>✓ ✓</td>
<td>✓</td>
</tr>
</tbody>
</table>

Dependent variable in columns 1-7 is the digitization and automation 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 which 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 which 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 10% level, (**) at 5% level and (***) at 1% level.
Table 3: Digitization and Automation and Labor Scarcity: Addressing Endogeneity Concerns

<table>
<thead>
<tr>
<th></th>
<th>Labor Scarcity in Local Area</th>
<th>Instrumenting Scarcity with Aging</th>
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</thead>
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<tr>
<td></td>
<td>Full Cross-Section</td>
<td>Exporters</td>
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<td></td>
</tr>
<tr>
<td>$Y = \text{Labor Constraints Index (Area Level)}$</td>
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<td></td>
</tr>
<tr>
<td>Local</td>
<td>-4.955***</td>
<td></td>
</tr>
<tr>
<td>Unemployment</td>
<td>(1.438)</td>
<td></td>
</tr>
<tr>
<td>% Workers &gt; 55</td>
<td>0.688*</td>
<td>1.497***</td>
</tr>
<tr>
<td>[in local market]</td>
<td>(0.420)</td>
<td>(0.722)</td>
</tr>
<tr>
<td>Δ % Workers &gt;55</td>
<td>-0.019</td>
<td>-0.060***</td>
</tr>
<tr>
<td>[in local market]</td>
<td>(0.038)</td>
<td>(0.028)</td>
</tr>
<tr>
<td>$Y = \text{Hard to Find Workers (Firm Level)}$</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$Y = \text{Digitization and Automation Adoption}$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Labor Constraints Index</td>
<td>0.688*</td>
<td>1.497***</td>
</tr>
<tr>
<td>[Area Level]</td>
<td>(0.420)</td>
<td>(0.722)</td>
</tr>
<tr>
<td>Local</td>
<td>-0.019</td>
<td>-0.060***</td>
</tr>
<tr>
<td>Unemployment</td>
<td>(0.038)</td>
<td>(0.028)</td>
</tr>
<tr>
<td>Hard To Find Workers</td>
<td>4.150**</td>
<td>5.245**</td>
</tr>
<tr>
<td>(1.985)</td>
<td>(2.090)</td>
<td>(2.473)</td>
</tr>
<tr>
<td>N</td>
<td>13109</td>
<td>10220</td>
</tr>
<tr>
<td>Industry FE</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Size</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Firm FE</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>Year FE</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>IV</td>
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</tr>
<tr>
<td>Aging</td>
<td>Pred. Aging</td>
<td>Aging</td>
</tr>
<tr>
<td>F-Stat</td>
<td>5.80</td>
<td>6.38</td>
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</table>

Dependent variable in column 1 (top panel) is district-level average of “Hard to Find Workers” declarations, excluding the firm’s own declaration (leave one out). Dependent variable in columns 2-5 (bottom panel) is the digitization and automation adoption measure from IAB Establishment Panel. In column 6, dependent variable is firm’s own declaration about difficulties finding workers. In columns 7-9 2SLS results are presented. In the top panel first stage regressions are presented and the dependent variable is firm’s declaration about difficulties finding workers. In the bottom panel, second stage regressions are presented and the dependent variable is firm’s technology adoption. Independent variable in row 1 and 6 is local district-level unemployment rate. In row 2, the independent variable is district-level share of workers above 55 in the workforce, while row 3 contains change in this share between 2004 and 2014. This change is used as an instrument together with 2004 level of labor constraints in the area, which proxies for unobserved fixed characteristics of the area. Independent variables in row 5 and 7 are measures of difficulties in finding workers, on area- and firm-level, respectively. In columns 4, 5 and 9 the sample is limited to firms which in the last year (2016) exported at least 20% of their production. All columns include industry (2-digit) and firm size quintiles fixed effects. (*) denotes significance at 10% level, (**) at 5% level and (***) at 1% level.
Table 4: Technology and Labor Scarcity: Worker Type Heterogeneity

<table>
<thead>
<tr>
<th></th>
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</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Hard to Find</td>
<td>0.296***</td>
<td>0.140</td>
</tr>
<tr>
<td></td>
<td>(0.089)</td>
<td>(0.109)</td>
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<tr>
<td>Workers % Admin</td>
<td>0.038</td>
<td>1.301**</td>
</tr>
<tr>
<td></td>
<td>(0.205)</td>
<td>(0.646)</td>
</tr>
<tr>
<td>% Non-Admin X HFW</td>
<td>0.337*</td>
<td>-1.212**</td>
</tr>
<tr>
<td></td>
<td>(0.179)</td>
<td>(0.524)</td>
</tr>
<tr>
<td>% Unskilled X HFW</td>
<td>0.785***</td>
<td>-0.193</td>
</tr>
<tr>
<td></td>
<td>(0.189)</td>
<td>(0.573)</td>
</tr>
<tr>
<td>% Skilled X HFW</td>
<td>-0.423**</td>
<td>-0.185</td>
</tr>
<tr>
<td></td>
<td>(0.194)</td>
<td>(0.567)</td>
</tr>
<tr>
<td>N</td>
<td>6626</td>
<td>6626</td>
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<tr>
<td>Industry FE</td>
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<td>✓</td>
</tr>
<tr>
<td>Size</td>
<td>✓</td>
<td>✓</td>
</tr>
</tbody>
</table>

Dependent variable in columns 1-4 is adoption of digitization and automation from IAB Establishment Panel. Dependent variable in columns 5-8 is the average investment in Information and Communication technologies in 2001-02. Independent variable is firm-level indicator of difficulties in finding workers, interacted with the employment share of administrative and non-administrative workers (rows 2 and 3) and of unskilled and skilled workers (rows 5 and 6). The two classifications and based on occupational structure of the firm reported in 12 occupational groups. Since some occupational groups are difficult to classify, shares of the two groups (admin and non-admin or skilled and unskilled) do not sum to 1. Difficulties in finding workers are measured in 2014 for digitization and automation adoption and in 1999 for ICT investment. Each specification includes firm size fixed effects and industry fixed effects. Standard errors are clustered on the industry level. (*) denotes significance at 10% level, (**) at 5% level and (***) at 1% level.
### Table 5: Employment Effects of Technology

<table>
<thead>
<tr>
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</thead>
<tbody>
<tr>
<td></td>
<td>Naive Basic</td>
<td>Basic Technology Abroad</td>
<td>Basic Specification</td>
<td>Basic Specification</td>
<td>Basic Specification</td>
</tr>
<tr>
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<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
</tr>
<tr>
<td>Adoption</td>
<td>1.894</td>
<td>-0.022</td>
<td>-0.357*</td>
<td>-0.544*</td>
<td>-0.185</td>
</tr>
<tr>
<td></td>
<td>(0.0134)</td>
<td>(0.328)</td>
<td>(1.204)</td>
<td>(0.194)</td>
<td>(0.298)</td>
</tr>
<tr>
<td>Robots</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Digitization</td>
<td>-1.674</td>
<td>0.756</td>
<td>0.700</td>
<td>0.746**</td>
<td>1.054</td>
</tr>
<tr>
<td></td>
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<td></td>
</tr>
<tr>
<td>Robots X</td>
<td></td>
<td>-0.357*</td>
<td>-0.544*</td>
<td>-0.185</td>
<td>-0.768**</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.194)</td>
<td>(0.298)</td>
<td>(0.157)</td>
<td>(0.379)</td>
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<tr>
<td>Adoption P(50)</td>
<td></td>
<td></td>
<td></td>
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<td>Digitization X</td>
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<td>Adoption P(50)</td>
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<td>Robots X</td>
<td>-0.278**</td>
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<td></td>
<td></td>
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<td></td>
<td>(0.113)</td>
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</tr>
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<td>Adoption (cont.)</td>
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<tr>
<td>Digitization X</td>
<td></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Adoption (cont.)</td>
<td></td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Robots Abroad X</td>
<td>-0.635**</td>
<td>-0.325</td>
<td>-0.970**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.308)</td>
<td>(0.285)</td>
<td>(0.324)</td>
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</tr>
<tr>
<td>Adoption P(50)</td>
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<td>Digitization Abroad X</td>
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<td>Adoption P(50)</td>
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<td>Robots Abroad X</td>
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<tr>
<td>Cragg-Donald F-Stat</td>
<td></td>
<td></td>
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</tr>
</tbody>
</table>

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 change in number of robots per 1000 workers on industry level in Germany - and digitization - measured as stock of Software and Databases capital per worker (in thousands of dollars) in Germany - and their interactions with indicators of a firm being located in high technology adoption area. The analysis is conducted on the industry X area level (2-digit industry; ROIs/commuting zones). The local indicator for adoption (which is used in rows labeled Adoption (cont.)) is defined based on area-level average of responses to digitization and automation 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 and digitization abroad are defined analogously to German measures, except they are averages for several other European countries. Column 5 presents their reduced form relationship to employment change, while column 6 presents Instrumental Variable regression in which robots abroad and digitization abroad, interacted with adoption, serve as instruments. The first stage of the IV specification is presented in the Appendix. All regressions, except column 1 and 2, 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: Digitization and Automation Adoption and Financial Constraints

<table>
<thead>
<tr>
<th>Y = Automation &amp; Digitization Adoption</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
<th>(9)</th>
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<td></td>
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<tr>
<td>Difficulties in Obtaining Credit</td>
<td>-0.640*</td>
<td>-0.676**</td>
<td>-0.782*</td>
<td>-0.578</td>
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<tr>
<td>(0.327)</td>
<td>(0.295)</td>
<td>(0.392)</td>
<td>(0.434)</td>
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<tr>
<td>Investment Prevented</td>
<td>-0.549***</td>
<td></td>
<td>-0.360</td>
<td>-0.576**</td>
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<tr>
<td>Can't Obtain Financing</td>
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<tr>
<td>(area-level average)</td>
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<td>✓</td>
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<tr>
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<td>CB</td>
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<td></td>
<td></td>
<td>4.23</td>
<td></td>
<td></td>
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</tr>
</tbody>
</table>

Dependent variable in all columns is the digitization and automation adoption measure from IAB Establishment Panel. Independent variables are firms' reported difficulties in obtaining credit; declarations of abandoning innovative project because of inability to access financing; share of debt in the financing of capital expenditures; and local area share of firms abandoning the innovative project because of inability to access financing. The last independent variable is instrumented in column 5 with quartile of area-level dependence on Commerzbank (based on Huber (2018)). Each specification includes firm size quintiles fixed effects and industry fixed effects. Standard errors are clustered on the industry level, except for column 5, where they are clustered on area and industry level. (*) denotes significance at 10% level, (**) at 5% level and (***) at 1% level. Columns 1-5 show results for the full sample. Columns 6-9 show results for manufacturing and non-manufacturing industries separately.
## Table 7: Effects of Technology on Skill Structure and Training

### Panel A: Skill Structure

<table>
<thead>
<tr>
<th>Y = Δ% Low-Skilled</th>
<th>Y = Δ% Medium-Skilled</th>
<th>Y = Δ% High-Skilled</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Adoption</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Robots X Adoption</td>
<td>-0.029</td>
<td>-0.027</td>
</tr>
<tr>
<td></td>
<td>(0.035)</td>
<td>(0.033)</td>
</tr>
<tr>
<td>Digitization X Adoption</td>
<td>-0.113</td>
<td>0.045</td>
</tr>
<tr>
<td></td>
<td>(0.097)</td>
<td>(0.210)</td>
</tr>
<tr>
<td>Robots Abroad X</td>
<td>-0.002</td>
<td>-0.068</td>
</tr>
<tr>
<td>Adoption &gt; P(50)</td>
<td>(0.061)</td>
<td>(0.051)</td>
</tr>
<tr>
<td>Digitization Abroad X</td>
<td>0.050*</td>
<td>0.018</td>
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<tr>
<td>Adoption &gt; P(50)</td>
<td>(0.027)</td>
<td>(0.072)</td>
</tr>
<tr>
<td>N</td>
<td>5268</td>
<td>5268</td>
</tr>
<tr>
<td>Area FE</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Industry FE</td>
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<td>✓</td>
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### Panel B: Training

<table>
<thead>
<tr>
<th>Y = % Workers Trained</th>
<th>Y = # Training Measures</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
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<tr>
<td>Adoption</td>
<td>1.352***</td>
</tr>
<tr>
<td></td>
<td>(0.316)</td>
</tr>
<tr>
<td>Robots X Adoption</td>
<td>0.053</td>
</tr>
<tr>
<td></td>
<td>(0.061)</td>
</tr>
<tr>
<td>Digitization X Adoption</td>
<td>0.335***</td>
</tr>
<tr>
<td></td>
<td>(0.119)</td>
</tr>
<tr>
<td>N</td>
<td>983</td>
</tr>
<tr>
<td>Area FE</td>
<td>✓</td>
</tr>
<tr>
<td>Industry FE</td>
<td>✓</td>
</tr>
<tr>
<td>Firm Controls</td>
<td>✓</td>
</tr>
<tr>
<td>Lagged Dep. Var.</td>
<td>✓</td>
</tr>
</tbody>
</table>

Dependent variables in the top panel are changes in the share of low-, medium- and high-skill workers for a given industry X area cell expressed in percentage points. The analysis is conducted on the industry X area level (2-digit industry; ROHs/commuting zones). Independent variables are interactions of average industry-level robotization - measured as change in number of robots per 1000 workers - and digitization - measured as stock of Software and Databases capital per worker (in thousands of dollars) - in several European countries, excluding Germany, with indicators of a firm being located in high technology adoption area. The local indicator for adoption is defined based on area-level average of responses to Automation and Digitization adoption question from IAB Establishment Panel (measured in 2016) and is defined as having the adoption indicator above median. All regressions include industry and area fixed effects and are weighted using employment levels from 2005. The analysis in the bottom panel is conducted on the establishment level. Dependent variable in columns 1-3 is the average share of workers undergoing any training between 2005 and 2015 in percentage points; dependent variable in column 4-6 is the average number of training methods in use reported by the firm in 2005-2015. The independent variable is the digitization and automation adoption measure from IAB Establishment Panel and its interaction with 2005-2015 changes in number of robots per 1000 workers and in stock of software and databases capital per worker on industry level. Columns 1, 3, 4 and 6 also include values of dependent variable in the earlier period, i.e. between 1995 and 2000. All regressions include industry and area fixed effects. (*) denotes significance at 10% level, (**) at 5% level and (***) at 1% level. Standard errors, reported in parentheses, are two-way clustered by area and industry (upper panel) or clustered by industry (lower panel).
Table 8: Effects of Technology on the Number and Size of Establishments

<table>
<thead>
<tr>
<th></th>
<th>Y = ∆log(Number of Firms)</th>
<th>Y = ∆Avg Firm Size</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Robots X</td>
<td>-0.0017***</td>
<td></td>
</tr>
<tr>
<td>Adoption &gt; P(50)</td>
<td>(0.0006)</td>
<td></td>
</tr>
<tr>
<td>Digitization X</td>
<td>0.0065**</td>
<td></td>
</tr>
<tr>
<td>Adoption &gt; P(50)</td>
<td>(0.0031)</td>
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</tr>
<tr>
<td>Robots Abroad X</td>
<td>-0.0033***</td>
<td></td>
</tr>
<tr>
<td>Adoption &gt; P(50)</td>
<td>(0.0006)</td>
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<tr>
<td>Digitization Abroad X</td>
<td>0.0023**</td>
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<tr>
<td>Adoption &gt; P(50)</td>
<td>(0.0011)</td>
<td></td>
</tr>
</tbody>
</table>

N 5269 5269 5269 5269

Area FE √ √ √ √

Industry FE √ √ √ √

Dependent variable in columns 1-2 is the change in the logarithm of number of firms in the industry-area cell. Dependent variable in columns 3-4 is the change in average number of employees per firm in industry-area cell between 2005 and 2015. The analysis is conducted on the industry X area level (2-digit industry; ROIs/commuting zones). Independent variables are robotization - measured as change in number of robots per 1000 workers on industry level in Germany - and digitization - measured as stock of Software and Databases capital per worker (in thousands of dollars) in Germany - and their interactions with indicators of a firm being located in high technology adoption area. The local indicator for adoption is defined based on area-level average of responses to digitization and automation adoption question from IAB Establishment Panel (measured in 2016). High adoption area is defined as having the adoption indicator above median. Robots abroad and digitization abroad are defined analogously to German measures, except they are averages for several other European countries. All regressions 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 9: Effects of Technology on Labor Productivity

<table>
<thead>
<tr>
<th></th>
<th>Y=%ΔSales per Worker</th>
<th></th>
<th>Y=ΔVA p.Wrk</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>Adoption</td>
<td>1.325</td>
<td>(1.013)</td>
<td></td>
</tr>
<tr>
<td>Adoption X</td>
<td></td>
<td>3.328*</td>
<td>(1.769)</td>
</tr>
<tr>
<td>Has Robots</td>
<td></td>
<td>0.534</td>
<td></td>
</tr>
<tr>
<td>Adoption X</td>
<td></td>
<td></td>
<td>(0.882)</td>
</tr>
<tr>
<td>Robots</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Digitization</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ΔRobots X</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Adoption&gt;P(50)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ΔDigitization X</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Adoption&gt;P(50)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>N</th>
<th>1364</th>
<th>1364</th>
<th>1364</th>
<th>2223</th>
<th>1364</th>
<th>1364</th>
<th>1398</th>
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</thead>
<tbody>
<tr>
<td>Weights</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
</tr>
</tbody>
</table>

The analysis is conducted on the establishment level. Dependent variable in columns 1-6 is the relative change in labor productivity (sales per worker) between 2005 and 2015 in percentage points. Dependent variable in column 7 is the relative change in value added per worker. The independent variable “Adoption” is firm-level measure of the intensity of digitization and automation adoption from IAB Establishment Panel (wave 2016). Adoption X Has Robots and Adoption X Has Digit Tech is the adoption measure indicator interacted with binary indicators for using robots and using digital technologies (from 2017 wave of the IAB Establishment Panel). Robots and Digitization, respectively, denote 2005-2015 changes in number of robots per 1000 worker and in stock of software and databases capital per worker on industry level and their interactions with firm-level adoption measure. They are interacted with high adoption variable - binary indicator of firm-level adoption being above median. All regressions include industry fixed effects. Standard errors, reported in parentheses, are clustered by industry. All observations are weighted equally, except for column 6, where firm-level employment in 2005 is used as weights. (*) denotes significance at 10% level, (**) at 5% level and (***) at 1% level.
Appendix Figures and Tables

Figure A1: Digitization and Automation Adoption: Summary Statistics by Industry Group
The figure presents summary statistics for the intensity of digitization and automation adoption from IAB Establishment Panel (part C - intensity of adoption on scale from 1 to 10) by broad industry groups. 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: Evolution of Robotization and Digitization for Germany and Other Countries
The figure shows the evolution of robot density (number of robots per 1000 workers) and of digitization (stock of software and databases capital per worker, in tho. Euro) in Germany and other European countries. Both for robots and digitization I 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 A3: Changes in Robotization and Digitization in 2005-2014/15 for Germany and Other Countries

The figure shows the 2005-2015 change of robot density (number of robots per 1000 workers) and 2004-2014 change of digitization (stock of software and databases capital per worker, in thou. Euro) in Germany and other European countries. Both for robots and digitization I 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: Digitization and Automation Usage and Other Firm Characteristics

The graph shows the relationship between Digitization and Automation adoption and various firm characteristics: introducing product innovation in the last year, establishment being part of multi-establishment firm, establishment having foreign owner, and being part of public firm. All variables come from IAB Establishment Panel.
Figure A5: Digitization and Automation Usage and Wages
The graph shows the relationship between Digitization and Automation 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.
Figure A7: Geographic Distribution of Labor Scarcity
The map presents values of labor scarcity index, mapped by district. However, for data confidentiality reasons, the index is computed on the spatial planning regions (RORs) level - each ROR contains ca. 4 districts. The index is the average of firms’ responses to a question about the difficulties in finding workers from 2014 wave of IAB Establishment Panel. The response are binary and ROR-level fraction of firms which respond positively (i.e. who say that they have difficulties finding workers) varies between 0.15 and 0.65.

Figure A8: Aging and Labor Scarcity in Germany
The graph presents the evolution of workforce aging and labor scarcity index. Aging is measured using the share of workers above 55 years among all workers. Labor scarcity index is the average of firms’ responses to question “Do you have troubles finding workers?” in different waves of IAB Establishment Panel (the question is not asked every year and hence no continuous series can be plotted; instead, linear fit is shown on the graph together with values for each available year). Because of changes in reporting in 1999, the values of share of workers above 55 before 1999 were adjusted to remove discontinuity (increased by 0.04).
Table A1: Summary Statistics of Selected Variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std Dev</th>
<th>P25</th>
<th>Median</th>
<th>P75</th>
<th>Num Obs</th>
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</thead>
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<tr>
<td>Investment (% sales)</td>
<td>6.81</td>
<td>24.80</td>
<td>0.5</td>
<td>2.37</td>
<td>6.55</td>
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<td>Investment (%)</td>
<td>0.33</td>
<td>0.47</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>7512</td>
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<tr>
<td>High Adoption</td>
<td>0.40</td>
<td>0.49</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>10391</td>
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<tr>
<td>Hard to Find Workers</td>
<td>0.40</td>
<td>0.11</td>
<td>0.35</td>
<td>0.39</td>
<td>0.47</td>
<td>14202</td>
</tr>
<tr>
<td>Hard to Find Workers (Area)</td>
<td>7.56</td>
<td>3.00</td>
<td>5.2</td>
<td>7.3</td>
<td>9.8</td>
<td>13109</td>
</tr>
<tr>
<td>Share of Workers &gt;55 (Area)</td>
<td>0.25</td>
<td>0.03</td>
<td>0.23</td>
<td>0.25</td>
<td>0.27</td>
<td>12761</td>
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<tr>
<td>Financial Constraints</td>
<td>0.04</td>
<td>0.18</td>
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<td>Debt/Other Sources</td>
<td>0.47</td>
<td>1.68</td>
<td>0</td>
<td>0</td>
<td>0</td>
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<tr>
<td>Number of Employees</td>
<td>106.8</td>
<td>853.3</td>
<td>4</td>
<td>14</td>
<td>59</td>
<td>14202</td>
</tr>
<tr>
<td>Share Unskilled</td>
<td>0.36</td>
<td>0.35</td>
<td>0.03</td>
<td>0.25</td>
<td>0.67</td>
<td>12141</td>
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<td>Share Admin</td>
<td>0.29</td>
<td>0.33</td>
<td>0.02</td>
<td>0.14</td>
<td>0.47</td>
<td>12141</td>
</tr>
<tr>
<td>Share Workers Trained</td>
<td>0.31</td>
<td>0.29</td>
<td>0.06</td>
<td>0.24</td>
<td>0.50</td>
<td>12160</td>
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<tr>
<td>Sales (mln Euro)</td>
<td>25.7</td>
<td>640.0</td>
<td>0.25</td>
<td>1.03</td>
<td>5.4</td>
<td>7874</td>
</tr>
<tr>
<td>Sales per Employee (tho Eur)</td>
<td>131</td>
<td>230</td>
<td>42</td>
<td>75</td>
<td>140</td>
<td>7874</td>
</tr>
<tr>
<td>∆%Sales Per Employee (2005-15)</td>
<td>28.9</td>
<td>97.4</td>
<td>-11.2</td>
<td>13.0</td>
<td>44.6</td>
<td>2223</td>
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<td>Employment (2015)</td>
<td>3154</td>
<td>561.5</td>
<td>283</td>
<td>1276</td>
<td>3503</td>
<td>5703</td>
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<tr>
<td>Robots (Ind)</td>
<td>4.1</td>
<td>18.7</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>5511</td>
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<tr>
<td>Digitization (Ind)</td>
<td>4.2</td>
<td>7.6</td>
<td>1.0</td>
<td>1.5</td>
<td>2.2</td>
<td>5640</td>
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<tr>
<td>∆%Employment (2005-15)</td>
<td>33.7</td>
<td>189.8</td>
<td>-6.2</td>
<td>14.2</td>
<td>43.4</td>
<td>5392</td>
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<tr>
<td>∆Robots (Ind)</td>
<td>0.84</td>
<td>4.79</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>5402</td>
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<tr>
<td>∆Digitization (Ind)</td>
<td>1.56</td>
<td>3.41</td>
<td>0.17</td>
<td>0.45</td>
<td>0.50</td>
<td>5535</td>
</tr>
<tr>
<td>Adoption (Area)</td>
<td>5.78</td>
<td>0.65</td>
<td>5.48</td>
<td>5.88</td>
<td>6.25</td>
<td>5642</td>
</tr>
<tr>
<td>% Low Skill</td>
<td>11.9</td>
<td>8.5</td>
<td>6.7</td>
<td>10.5</td>
<td>15.2</td>
<td>5655</td>
</tr>
<tr>
<td>% Medium Skill</td>
<td>72.8</td>
<td>13.9</td>
<td>66.7</td>
<td>75.8</td>
<td>81.8</td>
<td>5655</td>
</tr>
<tr>
<td>∆% Low Skill</td>
<td>-3.3</td>
<td>7.6</td>
<td>-5.6</td>
<td>-2.9</td>
<td>-0.6</td>
<td>5557</td>
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<tr>
<td>∆% Medium Skill</td>
<td>-1.1</td>
<td>9.7</td>
<td>-4.5</td>
<td>-0.6</td>
<td>0.3</td>
<td>5557</td>
</tr>
</tbody>
</table>

Summary statistics for technology measures are presented in Table 1. Variable 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 which combines survey declaration about automation and digitization adoption with information about firm investment: it equals 1 if both adoption and investment are above industry-wide median. Hard to find workers is a main measure of labor scarcity at the firm level (from 2014 IAB-EP). It is aggregated to district level to create area-level measure (with leave-one-out procedure). 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) in investment financing in 2008. Sales are in thousands Euro and are from 2015. Change in sales per employee is in relative terms and only available for a subset of firms for whom both 2005 and 2015 IAB Establishment Panel responses are observed. Employment count and change on industry-area level comes from BHP [Establishment History Panel]. Robots and their change is expressed in number of robots per 1000 workers and comes 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 Raumordnungregion (ROR/commuting zone) average of firm declarations about intensity of digitization and automation adoption from 2016 IAB Establishment Panel. Shares of low- and medium-skill workers are based on workers’ three educational groups reported in BHP data. High-skill workers are the remaining group, omitted for brevity.
Table A2: OLS Regression of Digitization and Automation Adoption on Labor Scarcity with Additional Control Variables

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
<th>(9)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Y = Automation and Digitization Adoption (2016)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hard to Find Workers</td>
<td>0.294***</td>
<td>0.301***</td>
<td>0.308***</td>
<td>0.299***</td>
<td>0.312***</td>
<td>0.347***</td>
<td>0.334***</td>
<td>0.396***</td>
<td>0.372***</td>
</tr>
<tr>
<td></td>
<td>(0.067)</td>
<td>(0.068)</td>
<td>(0.064)</td>
<td>(0.068)</td>
<td>(0.066)</td>
<td>(0.070)</td>
<td>(0.073)</td>
<td>(0.094)</td>
<td>(0.105)</td>
</tr>
<tr>
<td>N</td>
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<td>7346</td>
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<td>7469</td>
<td>7434</td>
<td>6590</td>
<td>6232</td>
<td>4419</td>
<td>3479</td>
</tr>
</tbody>
</table>

- 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 2, 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 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 A4: Semi Difference-in-Difference Approach: Including ICT Adoption in Early 2000s

<table>
<thead>
<tr>
<th></th>
<th>Y = Automation &amp; Digitization Adoption (2016)</th>
<th>Y = ΔTechnology (A&amp;D - Comp 01)</th>
<th>Y = ΔTechnology (A&amp;D - ICT01-07)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>Hard to Find Workers (2014)</td>
<td>0.315***</td>
<td>0.195***</td>
<td>0.317</td>
</tr>
<tr>
<td>Computers (2001)</td>
<td>0.072**</td>
<td>(0.073)</td>
<td>(0.285)</td>
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<tr>
<td>ICT Investment (2001-07)</td>
<td>0.158***</td>
<td></td>
<td>(0.026)</td>
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</table>

N 1351 2840 1351 2840

Industry FE √ √ √ √
Size √ √ √ √

In columns 1 and 2, specification analogous to column 1 from Table 2 is presented, but additional independent variables - decile of computer usage in 2001 and decile of ICT investment in 2001-07 period - are included. Using these variables reduces sample size because only selected firms were interviewed in past waves of the IAB Establishment Panel. Columns 3 and 4 present specification analogous to column 1 from Table 2, but with the dependent variable being the difference between intensity of 2016 digitization and automation adoption and the decile of computer usage in 2001 (column 3) or decile of ICT investment in 2001-07 (column 4).

Table A3: Persistence of the Labor Scarcity Effect

<table>
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<tr>
<th></th>
<th>Y = Automation and Digitization Adoption (2016)</th>
</tr>
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<tbody>
<tr>
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<tr>
<td>Hard to Find Workers (2016)</td>
<td>0.272***</td>
</tr>
<tr>
<td>Hard to Find Workers (2014)</td>
<td>0.308***</td>
</tr>
<tr>
<td>Hard to Find Workers (2012)</td>
<td>0.286***</td>
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<tr>
<td>Hard to Find Workers (2010)</td>
<td>0.225***</td>
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<tr>
<td>Hard to Find Workers (2008)</td>
<td>0.142</td>
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<td>Hard to Find Workers (2006)</td>
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<tr>
<td>Hard to Find Workers (2004)</td>
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<tr>
<td>N</td>
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<tr>
<td>Industry FE</td>
<td>√ √ √ √ √ √ √ √</td>
</tr>
<tr>
<td>Size</td>
<td>√ √ √ √ √ √ √ √</td>
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</table>

All columns present specification analogous to column 1 from Table 2, but with labor scarcity measures coming from different periods.
### Table A5: Other Staffing Problems

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<td>Too Many Employees</td>
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<td>High Labor Turnover</td>
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<td>Demand For</td>
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<td>Many Absences</td>
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</table>

All columns present specification analogous to column 1 from Table 2, 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 2016 IAB Establishment Panel. Standard errors are clustered on the industry level. (*) denotes significance at 10% level, (**) at 5% level and (***) at 1% level.
### Table A6: Robustness Checks of Employment Changes Regression and Additional Results

<table>
<thead>
<tr>
<th></th>
<th>Y = %Δ Employment</th>
<th>Y = Δ Average Wage</th>
<th>Y = Δ Robotization</th>
<th>Y = Δ Digitization</th>
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<tr>
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<tr>
<td>Robots X</td>
<td>-0.357**</td>
<td>-1.470***</td>
<td>-0.352*</td>
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<tr>
<td>Adoption &gt; P(50)</td>
<td>(0.194)</td>
<td>(0.440)</td>
<td>(0.195)</td>
<td>(0.380)</td>
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<td>Digitization X</td>
<td>0.756</td>
<td>-0.303</td>
<td>0.701</td>
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<td>Adoption &gt; P(50)</td>
<td>(0.464)</td>
<td>(0.919)</td>
<td>(0.461)</td>
<td>(0.489)</td>
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<tr>
<td>Robots Abroad X</td>
<td>-0.635**</td>
<td>-2.446***</td>
<td>-0.630**</td>
<td>-0.801**</td>
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<tr>
<td>Adoption &gt; P(50)</td>
<td>(0.308)</td>
<td>(0.562)</td>
<td>(0.309)</td>
<td>(0.392)</td>
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<td>Digitization Abroad X</td>
<td>0.179</td>
<td>-0.330</td>
<td>0.162</td>
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<tr>
<td>Adoption &gt; P(50)</td>
<td>(0.174)</td>
<td>(0.277)</td>
<td>(0.173)</td>
<td>(0.184)</td>
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<tr>
<td>Robots X</td>
<td>-0.635***</td>
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<td>Adoption &gt; P(75)</td>
<td>(0.134)</td>
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<td>Digitization X</td>
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<td>Robots Abroad X</td>
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<td>Adoption &gt; P(75)</td>
<td>(0.243)</td>
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</table>

N 5275 5275 5275 5275 5275 5275 5275 5275 5275 5275 5275 5275 5275
Area FE ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓
Industry FE ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓
F-Stat 30.26 163.57

The analysis 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 weighing 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 X 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 A7: Effect of Financial Constraints - Additional Controls

**Y = Automation and Digitization Adoption (2016)**

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<th>(6)</th>
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<td>difficulties in obtaining credit</td>
<td>-0.619**</td>
<td>0.634**</td>
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<td>-0.644**</td>
<td>-0.663**</td>
<td>-0.779**</td>
<td>-0.660**</td>
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<td>-0.818+</td>
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<td>Obtaining Credit</td>
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<td>(0.289)</td>
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</tr>
</tbody>
</table>

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 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.