Advances in Digital Technologies in Europe and their Local Labor Market Effects

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Abstract

How digital technologies will reshape labor markets, and how their impact differs from prior waves of technological change, is a key question. To shed light on this question we develop new measures for the advancement of AI and robotics technologies in Europe using Natural Language Processing techniques on patent data from the European Patent Office. Robotics technology has taken off earlier but is mainly concentrated in manufacturing industries. AI technologies, in turn, have grown very recently but diffuse into a broader range of industries. Combining the patent-based measures with administrative data on establishments in Germany, we investigate the employment and wage responses of local labor markets using a shift-share design. For robots, we find negative employment effects, especially in manufacturing. AI has negative employment effects in manufacturing but positive effects in services. Robots replace mostly low-skilled workers both inside and outside of manufacturing. AI, in turn, has negative employment effects for medium-skilled workers in manufacturing, but positive employment effects outside of manufacturing.

1 Introduction

The Fourth Industrial Revolution has dramatically improved the technical capabilities of artificial intelligence (AI), enabling machines to perform and learn tasks at human-like levels of capability in domains including translation and visual image recognition (Pratt, 2015; Schwab, 2016). Improvements in underlying techniques such as machine- or deep learning open up new possibilities for applications in AI, which may be used in a wide variety of industries (Brynjolfsson et al., 2018). Similarly, robots have been diffusing in the economy and further advances in AI could act as a catalyst for robots to become smarter, less dependent on human guidance and thereby more efficient. There is widespread belief that both technologies will reshape the way we work and live.

How robots and AI impact labor demand and labor market outcomes and who benefits and loses from these changes is far from clear, however. From a theoretical perspective, technologies may have three main effects on labor demand. There is a direct displacement effect as machines (or algorithms) take over some tasks previously performed by humans, which reduces the demand for labor that is a substitute to the new technology. At the same time, the technology by being more productive also enhances the productivity of remaining workers that are complementary to the new technology. As a result, the demand for their services actually increases. The third effect arises because new technologies often create entirely new job profiles and hence, additional labor demand (Acemoglu and Restrepo, 2018 2019). The net effect could be positive, zero or negative depending on the size of the three channels for a specific technology and the incentives to adopt the technology – including the costs of different types of labor.

This paper analyzes the impact of AI and robotics technologies on local labor market outcomes in Germany. A key challenge is how to capture the advancement and diffusion of digital technologies in the economy. Our approach builds on patent data from Europe to learn about the advancement of AI or robotics technologies over the past three decades. Patents are exclusive rights of use for novel solutions to technical problems. In exchange for these exclusive rights, all patent applications are published, revealing technical details of the invention. Hence, patents are a natural candidate for measuring technological progress and frequently serve as proxies for innovation. Especially in emerging technologies such as AI, new patents can be seen as a shift in the technological frontier, which increases the possibilities for firms to adopt this new technology in their production processes. In sum, patents are proxies for the new knowledge created in a particular technology and hence, provide a good source of information on how the technological frontier advances.[1]

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[1]Griliches (1990) and Moser (2005 2013) provide thorough discussions of the benefits and limitations of using

Our measures build on the European Patent Office's PATSTAT database, which includes patent applications and grants for all EPO member countries. Applying text mining and natural language processing, we extract patents related to AI and robotics based on patent codes and keyword searches in the patent titles and abstracts. To track which industries potentially apply the new knowledge created, we link the patents to industries that might make use of them by applying a probabilistic concordance scheme developed by Lybbert and Zolas (2014).[2] Our new patent-based measures enable us to track the diffusion of robotics and AI technologies across and within industries in Europe over almost three decades.

We match our patent-based measures to administrative data of establishments from Germany. Our unit of analysis is the local economy. We calculate the exposure of the local labor market to AI and robot technology by exploiting the local industry structure and the cumulative knowledge creation in a certain technology. Our empirical strategy builds on a shift-share design where we leverage the growth in knowledge in a certain technology with the initial industry shares in the local labor market. Using this shift-share design, we show that a growth in AI and robotics technologies reduces local employment. We find no effect on overall wages in the local economy. We explore further in which industries or for which workers we observe adjustments. For robots, we find negative employment effects, especially in manufacturing. AI has negative employment effects in manufacturing but positive effects in services. Robots replace mostly low-skilled workers both inside and outside of manufacturing. AI, in turn, has negative employment effects for medium-skilled workers in manufacturing, but positive employment effects outside of manufacturing.

We contribute to the literature in at least three ways. First, we provide new measures for the importance of new digital technologies in the workplace. Many studies have used broad measures such as firms' R&D expenditure or investments in information and communication technologies (ICT) (Bloom et al., 2014; Bresnahan et al., 2002; Caroli and van Reenen, 2001). The disadvantage is that it is difficult to track advances in specific digital technologies here. Other studies use direct measures on specific technologies such as the number of robots installed in broad industries (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020; Dauth et al., 2021) or by firms (Koch et al., 2019; Acemoglu et al., 2020; Dixon et al., 2020; Bonfiglioli et al., 2020). The drawback here is that these measures are available only for a limited set of technologies and, in the case of robots, for a

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patent data.

[2]Lybbert and Zolas (2014) match keywords from the description of patents to keywords extracted from the definition of industries according to SITC and ISIC codes. Then, they construct a probability match of IPC/CPC code classes to industries based on the amount of keyword matches obtained.

small number of industries only. Our measures allow characterizing the advancement of two specific digital technologies for a broad set of industries over the past three decades.

Another approach uses occupation-level measures constructed from information on tasks performed on the job. Earlier research relied on experts (Frey and Osborne, 2017) or crowd workers (Brynjolfsson et al., 2018) to assess the potential of digital technologies for replacing labor. These measures provide a snapshot of how automation could replace tasks and possibly occupations in the future. Yet, because these measures are cross-sectional, they tell us little about the dynamics of the digital transformation over a certain period. Furthermore, Arntz et al. (2017) demonstrate that expert assessments overstate automation potentials as they do not account for the heterogeneity and shifts in task usage within occupations. Firms might reshuffle the set of tasks performed in a job or add new tasks in response to automation of some tasks. Likewise, workers may specialize in tasks that cannot be easily automated to avoid displacement, for instance. Most importantly, these measures are silent about the potential of digital technologies to enhance productivity or create new tasks and occupations.

Most closely related to us are studies based on patents, which have long been used in the innovation literature to proxy innovation (Griliches, 1990) and technology diffusion (Jaffe et al., 1993). Patent meta-data, such as citation counts or the location and identity of inventors have been used frequently (Hall et al., 2001; Acemoglu et al., 2014; Bell et al., 2018) in innovation research. More recently, researchers have gone beyond the sheer number of patents and analyzed the actual text of patent documents (see Bessen and Hunt, 2007, for an early example). A few studies have generated patent-based measures of automation potentials (Mann and Püttmann, 2021) though they often focus on the industry that produces the knowledge rather than the industry that implements that knowledge in its production process (Dechezleprêtre et al., 2020; Montobbio et al., 2020). Very recently, authors have combined patent data with information on tasks performed on the job to quantify the automation potential of digital technologies (Felten et al., 2019; Webb, 2020). Like other occupation-level measures, these are cross-sectional and focus on the replacement of labor through automation - abstracting from the evolution of new tasks, for instance.

Our measures, in turn, characterize the evolution and diffusion of two major technologies, AI and robotics, that will shape the economy for decades to come. Moreover, these technologies may replace some workers, but also raise the productivity of other workers or even result in the reorganization of work and the emergence of new tasks. Hence, our evidence is not limited to identifying the automation effect of digital technologies. In addition, our measures go beyond the

actual usage of new technologies in industries, but capture the evolving technological frontier. And finally, our measures reflect the diffusion of digital technologies in Europe, which has experienced another dynamic in digital technologies than the United States. Europe, and in particular France and Germany, are leaders in the adoption of robotics technology; at the same time, they lag behind the United States and China in the development and provision of AI technologies.

Second, empirical studies on the labor market effects of digital technologies have largely focused on the diffusion of robots in the manufacturing sector. The results differ widely ranging from negative (Acemoglu and Restrepo, 2020), close to zero (Graetz and Michaels, 2018) or even positive employment effects (Dauth et al., 2021). Firm-level evidence, in contrast, indicates that adopters of robotics technology are not only more productive, but also grow after adoption and outperform their competitors within the same industry (Acemoglu et al., 2020; Alderucci et al., 2021; Benmelech and Zator, 2022; Koch et al., 2019). The empirical evidence for AI technologies is very scarce and shows few links between AI technology measures, employment or wages by industry or occupation (Acemoglu et al., 2021).

Third, we complement previous studies that focus on the effects of technologies such as AI on tasks in occupations (Brynjolfsson et al., 2018; Felten et al., 2018; Webb, 2020; Gregory et al., 2022). Recently, Webb (2020) proposed new measures of time-invariant exposure of occupations to three different technologies: information technology, robots and AI. However, the measure is based on US patent and occupational data and therefore not easily transferable to European data. Also, it is a static measure that does not provide variation of time. Similarly, Autor et al. (2022) generate measures of the evolution of new tasks from O*Net to track their impact on workers' careers. As for Webb, the proxies for technological change cover the U.S. and vary at the occupational level, which are not easily transferable to our context.

The paper proceeds as follows. In the next section, we present our patent-based measures and explain how we identify AI and robotics patents in the PATSTAT database. We describe in detail how we link patents to industries and how we measure industry-level exposure to AI and robotics technology. Section 3 shows descriptive evidence on our patent measures and compares them to existing proxy variables such as data on the installation of robots, on investment in ICT capital and on AI-related job vacancies. In Section 4, we provide a brief theoretical background to explain the main effects of labor substitution, enhancement and task creation. In Section 5 we introduce our administrative labor market data from Germany and discuss the empirical strategy to identify the employment and wage effects of exposure to digital technologies as measured by our patent data. In

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Section 6, we present our results on overall employment and wage effects as well as on the effects in manufacturing and services. Section 7 presents robustness checks for the results and finally, Section 8 discusses the implications of our findings and concludes.

2 Patent-based Measures of AI and Robotics for Europe

We construct measures of the technological opportunities of artificial intelligence and robotics using patent data from the European Patent Office (EPO). Our approach proceeds in three steps. First, we prepare the PATSTAT data for applying text analysis to the title and abstract describing each patent. In the second step, we use natural language processing techniques and the IPC/CPC codes to identify patents in robotics and AI technologies. In the final step, we match those patents to the industries that are most likely to use of them.

2.1 European Patent Data

We use data from the World Patent Statistical Database (PATSTAT) as of 2019, which contains detailed bibliographical and technical information on all patents filed in 86 countries. We focus on patents granted by the European Patent Office (EPO) between 1990 and 2018. Important innovations are patented in all major patent offices and any invention a firm wants to have protected in the European market will be patented at the EPO even if the innovation occurred abroad. Our data contain a total of about 7 million patent documents, which are identified by 3.5m unique application ids.[3] Of the 7 million documents, 5 million are patent applications and about 2 million are patent grants. The patent documents include the title and abstract of each patent, the name, company and location of the inventor, the dates of application and grant of the patent. The technical content of a patent is characterized by its IPC or CPC codes, which are assigned by highly specialized experts, the patent examiners. The older IPC and newer CPC frameworks are very detailed with several thousand entries.

We analyze the titles and abstract of patents to determine whether the patent describes an innovation in the field of AI or robotics technologies.[4] Though each patent document includes a title, abstracts are missing in about 30% of the patent grants (670,000 cases) we extracted. Rather

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[3]The smaller number of unique applications reflects the fact that most patents have multiple entries in the PAT-STAT database, one for the patent application, others for revisions and yet another for the patent grant if the patenting process was successful.

[4]Following the patent literature, we do not use the full text of the patent description or claims. These texts are written by patent lawyers in generic language to increase the protective scope of a patent.

than dropping patents with missing abstract, we impute the abstract specifying the technical content of a patent by using the concept of patent families. Patents belong to a narrow patent family, which contains all documents of patents covering the same technical content or to an extended patent family, which combines patents covering a similar technical content. A patent family is defined based on patents with the same (detailed or slightly broader) IPC/CPC codes. As the patent classification of technologies is very detailed, the technical content is very similar even within an extended patent family. We first assign missing abstracts an abstract from the narrow patent family; if that was not successful, we use an abstract from the extended patent family instead. Overall, we are able to impute about 450,000 abstracts with these steps of which only 45,262 abstracts are based on the extended patent family. We drop the remaining patents with missing abstracts after imputation.

A patent can be filed at the EPO in one of the three official languages English, French and German. Patents filed in another language need to provide a translation into one of the official ones. While patent claims are published in all three languages, abstract and patent description are published in the official language the patent was filed in. For our purpose, we restrict attention to documents with an abstract in English as other languages are not compatible with our keyword search.[5] To perform the text search on the sample of patents, we convert all patent abstracts and titles to text corpora. We then pre-process the text as follows: we convert all text to lower cases; then remove numbers, special characters, punctuation and stop words. We then strip the text of any blanks and white spaces. Finally, we extract word stems and divide the text into *tokens*.

2.2 Identifying Patents in Robotics and AI

To identify patents related to robotics and AI technologies, we use a combination of patent classification codes (IPC/CPC) and keyword searches of the patent titles and abstracts. The technology for robotics is well defined. According to the ISO 8373 definition, a robot is an "actuated mechanism programmable in two or more axes with a degree of autonomy, moving within its environment, to perform intended tasks". Robots are further grouped into industrial or service robots based on their intended application. We identify robotics patents if they belong to the CPC code B25J9: "Programme-controlled manipulators" or if they match a keyword search conducted over the titles

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[5]PATSTAT typically records the language of the abstract but this information is missing for about 250,000 patent documents. We use natural language processing to identify the language of the abstract for documents missing that information. We then drop all documents that do not contain any information in English, which reduces our sample by only 7%.

and abstracts of all patents. A patent is then classified as a match for robotics if one or more keyword tokens match with tokens of the text corpora of titles and abstracts.

Unlike robotics, Artificial intelligence is a very broad concept and there are several important underlying technologies. We can identify AI patents in our data by a few IPC/CPC codes that are directly connected to a specific AI technology or sub-field, such as machine learning, neural networks or fuzzy logic. Examples include the code G06N7/046 'Computer systems based on specific mathematical models - implementation by means of a neural network' or the code H04N21/4662 'Selective content distribution, e.g. interactive television or video on demand - characterized by learning algorithms'. In the first step, we select all patents with a IPC/CPC code that is directly related to AI technology using a list of AI-specific IPC/CPC codes from the World Intellectual Property Organization (2019).

There are only a small number of IPC/CPC codes for software and algorithms and most AI-related inventions are not identified by these codes. Many AI innovations are patented if their purpose is to solve a specific technical problem. As a result, AI innovations are often embedded in patent applications for innovations in other technology fields. Examples are speech and image recognition, two of the most important applications of AI technologies. One example for such an embedded innovation is the case of level 4 and 5 autonomous driving, which relies heavily on image recognition through artificial intelligence. To identify such patents, we conduct a keyword search over the titles and abstracts of all remaining patents. The list of keywords we use is a synthesis from the World Intellectual Property Organization (2019) and Baruffaldi et al. (2020). Examples of keywords include machine learning, natural language processing, fuzzy logic or decision tree.[6] The keyword list is pre-processed using the same steps as for the patent documents. A patent is classified as a match for AI technologies if one or more keyword tokens match with tokens of the text corpora of titles and abstracts. Figures A1 and A2 in the appendix show examples for a robot and an AI patent application with highlighted keyword matches in their title and abstract fields. A general pattern is that patent titles often include specific techniques such as neural networks while more general technological concepts such as artificial intelligence or machine learning are more likely to appear in the abstract instead.

For technologies in robotics, our search yields 14,235 patent documents of which 92% contain one or more of the keywords and 8% are included based on the CPC code 'B25J9'. Among these

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[6]Our keyword list is shorter than the list used in World Intellectual Property Organization (2019) in order to reduce false positives. Their keyword list includes keywords like network, algorithm, logic or boost, which can potentially be found in many patents that are unrelated to AI technologies.

documents, around 11,000 are actual applications or grants; the remainder contain supplementary information to existing applications.[7] For AI technologies, the combined approach of codes and keyword search yields 10,311 AI patent documents of which 90% contain on or more of the AI-specific keywords and 10% are included purely on their CPC codes. After excluding supplementary documents, we are left with around 7,000 applications and grants.

Panel (A) of Figure 1 shows the evolution of robotics patent grants and applications between 1990 and 2018. Robot patents show a first peak in the mid-1990s and then again in the late 2000s. Patent applications for robotics continue to grow throughout the whole time period. Panel (B) in Figure 1 shows that AI patent grants start to emerge in the mid-1990s but remain at low levels until 2018. In contrast, patent applications for AI technologies start to grow strongly after 2015 and especially in 2017 and 2018.

To show in which broad sectors of the economy AI and robotics patents play a role, we aggregate patents to broader technology classes. We use a mapping of the more recent IPC codes at the 4-digit level to thirty-five technology classes developed by Schmoch (2008).[8] We then aggregate the thirty-five technology classes into five broad sectors: Electrical engineering, Mechanical engineering, Instruments, Chemistry and Other fields. Instruments include optical instruments, control technology and medical technology. Chemicals include pharmaceuticals, biotechnology, food and materials. Other includes many consumption goods like furniture, games but also civil engineering.

Appendix figure A3 shows that robotics technology is heavily concentrated in mechanical engineering (see Panel (A)). Since 2010, robotics patents have become more prevalent in the sector "Instruments and other fields", which points to new applications beyond mechanical engineering and industrial robots. The picture looks very different for AI patents (shown in Panel (B)): AI technologies are most prominent in electrical engineering, but have recently become more important in instruments.

2.3 Technological Opportunities in Robotics and AI at the Industry Level

The final step is to match the patents to the industries that adopt and use the evolving technological opportunities of AI and robotics in their production processes. This matching step is crucial as it will define how exposed particular industries are to the evolving possibilities of AI and robotics

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[7]Such supplementary documents can be corrections to existing applications or supporting material such as search reports.

[8]We prefer this classification over the one in Hall et al. (2001) because the latter is much older and thus less accurate in capturing recent developments in AI and robotics technologies.

innovations. We rely on a walkover between CPC codes and 4-digit ISIC industry codes from Lybbert and Zolas (2014).[9] A key advantage over older concordance schemes developed by Kortum and Putnam (1997) or Silverman (2002) is that it is better able to capture recent developments in AI and robotics technologies. In contrast to concordance schemes that focus on the industry of innovation (Dorner and Harhoff, 2018), our walkover identifies the industries in which the new technological opportunities are likely to be used in production.

The basic idea of the concordance scheme is to use the description of an industry from the official classification to find a concordance with the content of a patent. The keywords describing the activity in a certain industry are then used to search for patents that contain these keywords. The result is a list of patents with their IPC/CPC codes and the industries matched on keywords. The match frequency is then used to calculate a probabilistic weight for each industry. The weight is based on Bayes rule taking into account the number of possible codes and how often a code is matched to an industry.[10]

Appendix table A1 shows in the top panel the 4-digit industries with the highest number of AI patents. AI related patents are heavily used in the manufacturing of ICT, but also in machinery and measuring equipment. Interestingly, AI patents are also important in the music and film industry (see ISIC codes 5912 and 5920 in appendix table A1). The table further reports for each industry the share of patent grants in AI. The average share of AI patents across all industries is 0.21%, which indicates that AI has so far contributed only a small share of the overall patents used in an industry. Yet, industries with a high total number of AI patents also have a high share of AI patents, with the exception of medical and dental practice activities. Hence, AI plays an important role in these industries not only in absolute terms but also relative to other innovations. Among the industries without any AI patents, we find many services like real estate, care, tourism but also early childhood education and farming. Similarly to the case of AI patent grants, the bottom panel of appendix table A1 shows the industries with the highest number of robotics patent grants. As we would expect, the industries with most robotic patents are in manufacturing with the exception of "2592 Treatment and coating of metals". Further, all industries except "2620 Manufacture of computers and peripheral equipment" are robot intensive in absolute and relative terms as their share of robotic grants is higher than the average of 0.32% across all industries. Based on the number of patents

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[9]see also Goldschlag et al. (2019) for further walkovers to industry and trade classification schemes.

[10]The hybrid probability weight we use adjusts the weights upward for specific codes that are strongly linked to particular industries. The rationale for this reweighting is that matches with high specificity in a certain technology class may indicate particularly important linkages to certain industries compared to broad technologies that match to many different industries.

used, we construct measures reflecting the evolution of AI and robotics technology at the industry level. We interpret patents as shifting the technological frontier, which improves existing or opens up entirely new possibilities in production. As such, industries with a strong growth in patents are treated as relatively more exposed to these new technological opportunities than industries where the new digital technologies are not used as intensively.

3 Descriptive Evidence on Patent Measures in Europe

Our patent-based measures describe technological opportunities of robotics and AI that may or may not be heavily used by firms. To check whether the technological opportunities laid down in patents are used by firms in the industries assigned, we relate them to industry-level proxies for technological change previously used in the literature. More specifically, we compare robotics patents to data on industry-level robot installations. For AI patents, we compare them to industry-level investments in ICT capital and the prevalence of AI skills in online job vacancies. As new technologies embodied in patents take time to be adopted and diffuse in the economy, we allow for a time gap of three years between the timing of the patent grant and an industry's exposure and potential adoption to it. Hence, a patent granted in 1990 can have a measurable impact on innovation and the associated capital investment or skill demand at the earliest in 1993.

3.1 Robotics Patents and Robot Installations

To validate our patent-based measures on robotics technology, we use information from the International Federation of Robotics (IFR) (International Federation of Robotics, 2020). The IFR data track the installation and stock of robots in around fifty countries. The dataset contains a count of annual robot installations by broad industries mostly in manufacturing and an estimate of the annual stock of robots. We use the information on robots installed in European countries to ensure that the data cover the same set of countries as contained in the European Patent Convention. Our patent data is available at the 4-digit level and hence, much more detailed than the industry classification used in the IFR data, which contains information on thirteen industries in manufacturing (food and beverages; textiles including apparel; wood and furniture; paper and printing; plastics and chemicals; minerals; basic metals; metal products; industrial machinery; electronics; automotive; shipbuilding and aerospace; and miscellaneous manufacturing including production of jewelry and toys) and on six other broad sectors (agriculture, forestry and fishing; mining; utilities; construc-

tion; education, research and development; services). We therefore aggregate our patent data to the 2-digit level and match these to the IFR classification. About 30 percent of robots are not classified into one of the nineteen IFR industries though this share declines over time. Following Acemoglu and Restrepo (2020), we allocate unclassified robots to industries in the same proportions as in the classified data. Figure 2 shows a strong positive correlation between patents in robotics technology and robot installations three years later (both measured in logs). The grey area represents the 95% confidence intervals. Both patent applications and patent grants are positively correlated with robotics patents across industries.

3.2   AI Patents, ICT Capital and AI Job Vacancies

To validate our measure of AI patents, we compare it to two imperfect proxies: investments in ICT equipment and the importance of AI skills in online job vacancy data. The data for ICT equipment come from the EU-KLEMS database and are available by country and industry between 1995 and 2015.[11] We again focus on European countries, which includes the EU member states and the UK. All countries in the sample are also members of the European Patent Convention and are hence provided patent protection by the EPO. Industries in the EU-KLEMS database are available at the 2-digit level though some industries are combined. We define overall ICT investments as the sum of investments in information technology equipment, in communication technology equipment and in software and databases, all measured in 2010 prices. The link between AI and ICT is likely weaker than for patents in robotics and robot installations as not all investments in ICT capital need to be AI-related; and not all AI innovations are part of ICT equipment and software – a smart washing machine being one example. Panel A of figure 3 shows that there is a weak positive correlation between AI patent applications and ICT investments, while there is strong correlation between AI grants and ICT investments.

Alternatively, we use information on the prevalence of AI skills in online job vacancies as another proxy for the diffusion of AI in an industry. To construct this measure, we use data on online job vacancies from Lightcast between 2018 and 2021. We then select all job postings that mention at least one AI-related skill as a requirement. We follow Alekseeva et al. (2021) in the definition of AI skills and include the full list of keywords in the search for AI job vacancies. This list includes key AI techniques such as neural networks, deep learning or machine vision. Panel B of figure 3

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[11]See Stehrer et al. (2019) for details on the methodology of KLEMS and Stehrer and Adarov (2019) for empirical results on ICT and productivity growth. For an earlier release of KLEMS see Timmer et al. (2007).

shows a positive correlation between the number of job ads with AI skills and the number of AI patents granted in 2-digit (ISIC) industries for Germany [12]. Hence, patents do not only encourage investments in tangible and intangible capital embodying AI technology but also raise the demand for workers who can use and apply AI technology.

4   Theoretical Mechanisms

How technological change in general and digital technologies more specifically affect local labor markets is far from clear and depends on a variety of factors. We build our hypotheses on two theoretical models developed by Acemoglu and Restrepo (2018 2020). In these models, the impact of technologies on tasks performed on the job, and in consequence on occupations and local labor markets, is modeled as technology automating certain tasks while at the same time creating new tasks. This contrasts previous generations of models that interpret the impact of technology on labor markets as skill-augmenting (Autor et al., 2003; Autor and Dorn, 2013), which leads to a polarization of employment.

Acemoglu and Restrepo (2018) incorporate displacement effects (tasks within occupations get automated), productivity effects (remaining workers get more productive) and a reorganization effect of tasks (task structure of occupations changes as new tasks are created) following the introduction of a new technology. The underlying assumption is that automation technologies are adopted with the goal of cost-effectively replacing human labor in the production process.

Advances in technologies have two effects: They shift the frontier of tasks that can possibly be automated outwards and second, they introduce new tasks which are more complex and therefore more labor-intensive than previous tasks. These two effects run against each other, and which effects outweighs the other in the end depends on the technology considered and on the task structure of production for the final good.

At the regional level, as modeled in Acemoglu and Restrepo (2020), the mechanisms of automation and task creation are similar. Output in each industry is produced by a combination of tasks performed by either robots (capital) or human labor. Robots can automate the same tasks in an industry over all commuting zones. Tasks that are not (yet) able to be performed by robots are performed by human labor.

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[12]We correlate the number of job vacancies that require AI skills in 2021 to AI patents granted in 2018, thereby again allowing for a time lag of 3 years for technology adoption.

The impact of an increase in the use of automation technology on labor is made up of three effects. There is a direct negative displacement effect on labor in the industry-commuting zone cell that increases robot use. There is a positive productivity effect on labor as lower production costs lead to more labor demand in non-automated tasks in all industries. And last, there is a composition effect as industries with higher robot use expand which raises the demand for labor from their non-automated tasks.

A-priori, it is unclear which effect outweighs the others. However, Acemoglu and Restrepo (2020) show that automation which induces large cost savings, and therefore large increases in productivity, raises aggregate labor demand as the productivity effect outweighs the displacement effect. In turn, automation with small cost savings leads to a decrease in labor demand as the negative displacement and income effects outweigh the productivity effect.

Based on the theoretical model and the empirical findings for the US in Acemoglu and Restrepo (2020), we expect robot exposure to have a negative employment effect in local labor markets. For AI technology, we expect the automation component to be weaker than for robotics, which leads us to expect positive employment effects through increased productivity and the creation of new tasks.

5 Data and Empirical Strategy for Local Labor Market Analysis

With our measures of AI and robotics technologies in hand, we now turn to an analysis of their consequences in the labor market. In particular, we merge our industry-level measures of technological opportunities to plant-level data from Germany. We first describe the data, followed by a discussion of the theoretical framework we build our hypotheses on, and the estimation strategy we apply.

5.1 Administrative Establishment-level Data

We use administrative data from the German Establishment History Panel (BHP), a 50% random sample of all establishments with at least one employee covered by the social security system in Germany (see Ganzer et al., 2020, for more details). The social security data cover around 80% of the German labor force excluding civil servants, military personnel and the self-employed. Our plant sample spans the years from 1990 to 2018. We match our measures of AI and robot technolo-

gies, which vary by detailed industry and year, to the establishment data by the detailed (3-digit) industry.[13]

The data include detailed information on the socio-economic composition of the workforce by age, gender and skill in each establishment. We distinguish three skill groups - low, medium and high skilled - based on the highest qualification obtained. High-skilled workers are workers who have graduated from a college or university. Medium-skilled workers have completed a vocational training program or obtained the university entrance certificate after high school (*Abitur*). Low-skilled workers have lower qualifications or no qualifications at all. In the raw data, the education variable is missing for about 9% to 37% of the observations depending on the year. We use imputation procedures to fill in missing education information, which reduces missings to less than 1% (see Fitzenberger et al., 2005). We further distinguish three broad age groups (20-34, 35-49 and 50-64). We also expect that digital technologies affect some occupational groups more than others. To analyze who might benefit and who might lose, we use information on the occupational structure in the plants (e.g. the share of simple manual jobs, clerks, technicians, skilled manual labor, engineers, professionals and managers) and on the type of employment contracts used (e.g. fixed-term contract, temporary worker).

Finally, we also observe establishment wages. As is common in social security records, wages are right-censored at the highest level of earnings that are subject to social security contributions. Wages are imputed based on the imputation procedure of Gartner (2005). We observe the wage distribution characterized by the 25th, 50th and 75th percentile wage. The wage information is available for full-time workers, by the three skill groups and by gender.

We aggregate the plant-level data to the district level and explore how advances in robotics and AI technology affect local labor markets. In total, there are 401 districts (*Kreise*) in Germany. The main outcome variables are changes in employment (defined as Δ *log employment* or % $\Delta employment$) and wages (measured as Δ *log wages*) at the district level between 1993 and 2018 as well as for several sub-periods (1993-1998, 1999-2005, 2006-2011 and 2012-2018). Table 1 reports summary statistics.

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[13]We use a crosswalk provided by EU RAMON to convert the ISIC rev. 4 classification of our patent measures to the European NACE rev. 2 classification, which is equivalent to the German industry classification (WZ08) at the 3-digit level.

5.2 Estimation Strategy

To identify the impact of robotics and AI technologies in the labor market, we rely on a shift-share design (Bartik, 1993). Shift-share designs have become popular to study the impact of trade and technology shocks on local labor markets. In our context, the approach combines a 'shift' variable, which captures the overall technological knowledge potentially used in an industry, and a 'share' variable to proxy for how much a local labor market is possibly affected by the new technology.

Cumulative Knowledge Creation in AI and Robotics: We define the 'shift variable' by exploiting our patents in robotics or AI. More specifically, we sum all patents used in an industry over our sample period to reflect the cumulative nature of knowledge creation codified in patents. The overall sum over our sample period (1990-2018) reflects the additional knowledge of emerging technologies created between 1990 and 2018. This cumulative measure traces the long-run knowledge creation in each technology and we use the following measure:

$$TotPat_i^c = \sum_{1990}^{2018} Log(1 + Pat_{i,t}^c) \tag{1}$$

where $c = (Robotics, AI)$ denotes the technology considered, i stands for the industry and t for year. The measure $TotPat_i^c$ reflects the total accumulation of new knowledge in technology c to be used in industry i; it accounts for the relative importance of patents in different industries since the logarithm of patents puts less weight on industries with many patents.

To investigate the influence of digital technologies on the labor market, we characterize each local labor market by its industry structure in the base year. We choose 1993 as our base year as this is the first year when reliable labor market data is available for East Germany.

Our key independent variable, i.e. the local exposure to the technological innovations in robotics or AI, is then defined as the interaction between initial employment shares in industry i and region r ('shares') and the evolution in AI and robotics technologies in industry i over time ('shift'). The exposure measure using the long-run accumulation of knowledge in AI and robotics is thus calculated as:

$$Exposure_r^c = \sum_{i=1}^{I} \left(\frac{Emp_{i,r}^{1993}}{Emp_r^{1993}} * TotPat_i^c \right) \tag{2}$$

where r denotes the local labor market and i the 3-digit industry. The first term $(\frac{Emp_{ir}^{1993}}{Emp_r^{1993}})$ measures initial employment shares in industry i in the base year (1993). The second term, $TotPat_i^c$, captures

the growth in AI or robotics patents as a proxy of the technological opportunities in industry i.[14].

Figure 4 shows the geographic variation in exposure to robotics and AI patents where exposure is constructed as the combination of initial industry shares and the overall growth in patent grants between 1990 and 2018 (according to equation 2). Most notably, there is a marked difference between East and West Germany as districts in West Germany are much more likely to be exposed to both AI and robotics than districts in East Germany. More districts are exposed to robotics technology than AI technologies, which might in part reflect the wider diffusion of robotics technology in industries esp. in the manufacturing sector. AI on the other hand has diffused less broadly geographically and is concentrated on districts in the South and West of Germany.

To investigate the impact of digital technologies on local labor markets, we estimate models of the following form:

$$\Delta Y_r = \beta Exposure_r^c + \gamma_1 \Delta Trade_r + \gamma_2 \Delta ICT_r + \delta' X_r + \theta_I + \alpha_R + \epsilon_r \tag{3}$$

where ΔY_r denotes the local employment or wage changes between 1993 and 2018 and $Exposure_r^c$ characterizes the district's overall exposure to AI or robot technologies over this period. We control for the local structure of the workforce by including controls for employment shares by age, skill group and gender (X_r) as well as employment shares by broad (1-digit) industry (θ_I); all are measured in the base year. We further include dummies for the broad region (North, East, South, West), α_R. To control for potential confounding effects of international trade, we adjust for changes in net exports per worker ($\Delta Trade_r$). To control for other technology-driven changes in labor demand, we further include a variable for general investments in ICT capital per worker (ICT_r).

Our main parameter of interest is β, which measures how employment or wages in districts exposed to AI and robotics technologies change relative to districts less exposed to the new technologies. Note that β combines any direct effect on plants in industries highly exposed to the new technologies, adjustments in wages, and potential local spillover effects on plants linked to exposed industries through input-output linkages or local multiplier effects in the same region.

Exploiting the Panel Dimension of Knowledge Creation: The measure in equation (1) varies across industries only. To incorporate the dynamic development of the two technologies over

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[14]We find very similar results if we use the sum over three years (1990-1992 and 2016-2018) to calculate the long-run growth in patents instead.

time, we define the following panel measures:

$$Pat_{i,P}^c = \sum_{s \in P} Log(1 + Pat_{i,s}^c) \tag{4}$$

where P denotes the sub-periods 1990-1998, 1990-2005, 1990-2011, 1990-2018. The measure in equation (4) reflects the cumulative knowledge creation in each period. Hence, the shift variable is now the cumulative sum of patent grants between 1990 and the end of the period e.g. the sum from 1990 to 1998 for the first period and likewise for the other periods. The measures in equation (4) take on four values for each industry.

The panel exposure of a local labor market is then defined accordingly:

$$Exposure_{r,t}^c = \sum_{i=1}^{I} \left(\frac{Emp_{i,r}^{1993}}{Emp_r^{1993}} * Pat_{i,t}^c \right) \tag{5}$$

where r and t now indicate that exposure varies by both district and time. The source of the time variation is the accumulation of patents that varies across districts, as before, but also within districts over time.

Exploiting the panel dimension of our data, we then estimate models of the following form:

$$\Delta Y_{r,t} = \beta Exposure_{r,t} + \gamma_1 \Delta Trade_{r,t} + \gamma_2 \Delta ICT_{r,t} + \delta' X_{r,t} + \theta_I + \alpha_r + e_{r,t} \tag{6}$$

Here, $\Delta Y_{r,t}$ are changes in employment and wages in each sub-period.[15] As before, our main parameter of interest is β, which captures the impact of exposure to AI and robotics on the local labor market. α_r denote district fixed effects, which control for a district-specific linear trend in employment or wages. All other variables are measured as before. The inclusion of region fixed effects implies that the coefficient on the exposure measure (β) in equation 6 is identified from shifts in exposure to the two technologies within a district while controlling for overall employment trends in the region. Standard errors are clustered at the district level.

For the shift-share design to be valid requires that either the employment shares or the shift (here, the growth in patents) have to be exogenous (Goldsmith-Pinkham et al., 2018; Borusyak et al., 2018). It is important to stress that, in our setting, the growth in knowledge as codified in patents is measured at the European level. Hence, we consider how AI patents produced and patented in e.g. Finland impact local labor markets in Germany. In addition, we estimate the effect for firms *using* patents in the production of goods and services, not for firms producing the patents. It is highly unlikely that the employment conditions and wage levels of firms using the

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[15]Hence, for the first sub-period, for instance, the dependent variables are changes in employment or wages between 1993 and 1998.

knowledge codified in a patent have an impact on the likelihood or timing of patenting an invention in AI or robotics technology. Both conditions suggest it is reasonable to assume that the shift variable is exogenous to local labor market conditions of using firms. We will provide evidence on the employment shares below after presenting our main results.

A remaining concern of our estimation approach is that there could be differential labor market shocks in regions with industries that are exposed to greater advances in robotics and AI than other regions. A possible concern is that industry-specific demand shocks might lead to higher usage of AI and robotics in some industries than in others. A carmaker who is exposed to smart driving technology might implement electric vehicles faster if there is negative shock to the production of fuel cars or some problem in the supply of parts, for instance. To mitigate that concern, we control in our estimation for trade flows and investments in ICT. In addition, we also control in our panel estimation in equation (6) for district-specific trends to capture any differential trajectories on the labor demand or supply side.

Adão et al. (2019) point out that regions with similar industry structures (and hence, similar initial industry shares) are likely to be subject to similar technology- or demand-driven shocks. Hence, their error terms are likely to be correlated. To account for this spatial correlation, we calculate standard errors by clustering by regional industry shares.

6   AI and Robotics Technologies and Local Labor Markets

6.1   Employment and Wages in the Local Economy

We start out with estimating the long-term influence of AI and robotics technologies on local labor markets according to equation (3). The dependent variables are long-term changes in employment and wages between 1993 and 2018; the key independent variables are the local exposure to AI and robot technologies as defined by equation (2).

Table 2 shows the results for log employment changes in Panel A. The first two columns report estimates for exposure to AI technologies, while columns (3) to (4) report the results for robotics technologies separately. In column (5), we include both exposure measures to AI and robotics technologies simultaneously to see how a set of digital technologies like AI affects labor market outcomes conditional on exposure to robotics technology. The first specification (in columns (1) and (3)) controls for the skill, age, gender and industry structure of the local labor market as well as for broad regions. The second specification (in columns (2), (4) and (5)) adds changes in net exports

and changes in ICT investments to the specification in order to control for other demand-side forces through international trade and other technological advancement.

The long-run cumulative effect of exposure to AI technologies has increased local employment irrespective of the set of control variables included. Based on the specification in column (2), a one standard deviation change in the local exposure to AI raises local employment by around 3 percentage points over the 1993-2018 period. Exposure to robots, in contrast, seems to have had little long-run impact on overall local employment as the estimates fail to reach statistical significance.

Local economies that employ robotics technology might also be very active in the use and diffusion of AI technologies in production processes. An example is the car industry where robots have been heavily used in the actual production of vehicles, while AI technologies play an important role in the development of smart and self-driving vehicles. We could have regional economies with a weak industrial base but a strong, prosperous service sector. As robots are mostly used in manufacturing, these regions could be little exposed to robotics technology but at the forefront of using AI technologies. The correlation between the exposure measures in AI and robotics is only around 0.54; as such, we have a lot of independent variation in each local exposure measure.

Including both exposure measures simultaneously, we still find that AI technologies encourage employment growth over the long-run, while robotics has little effect (see column (5) in table 2). We find few effects on average wages in the region. Panel B of Table 2 shows that exposure to AI and robotics has no statistically significant impact on local wages over the 1993-2018 period. Our long-run results are in line with existing evidence on robot installations in Germany (Dauth et al., 2021). This congruence is important as our local exposure measure is based on patents rather than the number of robots installed. The advantage of our patent-based measure is that exposure is available for a much broader set of industries, including many outside manufacturing.

One concern with our estimation results in table 2 is that employment and wage changes are identified from variation across local labor markets only (see equation 3). Yet, local economies that are very exposed to one or both technologies might have different wage and employment trajectories than regions that are less exposed. If the adoption of technologies is in part motivated by competitive pressure from international markets and trade, labor demand changes are likely to differ between more and less exposed districts, for instance. Moreover, the dynamics of the two technologies might vary over time: robotics technologies diffused much earlier into the manufacturing sector, while AI technologies have spread more recently but diffused into more sectors in the economy.

To address these issues, we exploit the panel structure of our data. In particular, we measure our outcome variables in four sub-periods: 1993-1998, 1999-2005, 2006-2011 and 2012-2018. The dependent variables are now log employment or wage changes within each sub-period. The shift variable now measures the accumulation of knowledge in the two technologies until the end of each sub-period relative to 1990, the first year patents are recorded in our data (according to equation (5)). For a given district, the change in exposure is now higher in a period where a lot of knowledge has been created and diffused into the economy.

Table 3 shows the panel results for our baseline specifications (in columns (1)-(3)). To address the concerns that labor markets with more exposure have a different employment or wage trajectory than local labor markets with little exposure, we further include district fixed effects, which allow for district-specific trends in employment and wages (in column (4) to (6)). All specifications include the full set of demographic, regional and industry controls as well as demand-side changes as in previous tables.

The panel estimates without district fixed effects show the same pattern: AI technologies seem to increase local employment, while robotics technologies seem to replace labor and reduce local employment. The fact that AI and robotics technologies have opposing signs for employment changes over the long-run is important for the discussion on the digital transition. Given the scarcity of empirical results on AI, the public but also academic debate is often based on existing results for robots technology that are available for several advanced countries (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020; Dauth et al., 2021).

The picture changes if we allow for district-specific time trends. Columns (4)-(6) suggest that trend breaks of employment tend to be negative in local labor markets highly exposed to AI or robotics technologies. To gauge the size of these effects, we use the estimates including both technologies in column (6) and consider a one standard deviation change in local exposure. These calculations indicate a modest reduction in employment: A one standard deviation increase in AI exposure would reduce employment by 1.1 percentage points, while an increase in robot exposure by a standard deviation reduces local employment by 1.8 percentage points. For wages, the results shown in Panel B of Table 3 are very similar to the observed impact over the total period: the economic effect is small and most do not reach statistical significance.

These overall effects on local labor markets suggest that a flexible specification that controls for district-specific labor market trajectories shows that both technologies have an automation potential that is not compensated by productivity or innovation effects, at least not at the local labor market

level. We next turn to the question how the two technologies have impacted jobs and workers in manufacturing and the service sector.

6.2 Manufacturing versus Services

Beyond the overall effects on the local labor market, we would expect that robotics technology has a stronger effect in the manufacturing sector where robots have been most heavily used. In contrast, robots are not much used in the service sector; any impact we see on service sector employment would thus emerge from an indirect effect through sectoral mobility or sector-specific job creation or destruction by firms. In contrast, AI technologies might have diffused into both sectors though the direction of their effect is a-priori unclear. The impact in each sector depends on at least three factors: how much tasks in each sector are susceptible to automation through AI technologies; how strong the offsetting forces of increased productivity and creation of new tasks are; and how attractive the adoption of AI technologies is in each sector, which depends, among others, on the price of labor.

To investigate this empirically, we re-estimate equation 5 where the dependent variables are now employment or wages changes in the manufacturing sector and outside of manufacturing, which mostly covers the service sector. The panel estimates for employment changes are shown in table 4. Columns (1) to (3) do not include district fixed effects, while columns (4) to (6) add them.

If we analyze AI and robotics technologies in isolation, we see that both technologies replace labor in the manufacturing sector (see Panel A of table 4) reflecting their substantial automation potential. Robot exposure decreases local employment by roughly 6.6 percentage points based on a standard deviation change in exposure. Once we condition on AI exposure (see column (6)), exposure to robotics technologies reduces local employment by around 3.5 points. AI exposure reduces local employment in manufacturing by around 4 percentage points. The advancement of both technologies is therefore likely to hit areas with a strong industrial base especially hard.

Outside of manufacturing, the situation is different (see Panel B of table 4). AI technologies create employment in the service sector irrespective of whether we include district fixed effects or not (see column (3) and (6)) once we control for robot exposure in the local labor market. Robot exposure, in turn, reduces employment in the service sector across all specifications. The effect is about half the negative employment effect in manufacturing. One explanation for the employment decline outside of manufacturing is that robots, by destroying jobs in the local economy, but not raising wages, reduce the demand for local goods and services.

Do we see any differential effect on wages in manufacturing and outside of it – despite the fact that we saw no impact on average local wages? We report the results for wage changes based on the same panel specifications as for employment changes in appendix table A3. As for average wages, we find few effects of the two technologies on manufacturing wages. Outside of manufacturing, AI exposure tends to reduce wages. Together with the employment growth of AI outside of manufacturing, our results indicate that AI technologies create mostly low-wage jobs. For robotics technologies, wages tend to increase outside of manufacturing, though the effect vanishes if we allow for district-specific wage trends.

6.3 Effects by Worker Skill

We next investigate which workers might be most affected by the employment shifts in manufacturing and outside of it. Do robots mostly replace low-skilled jobs, but create new jobs further up the skill distribution with few net effects on the total number of jobs? And do AI technologies replace jobs further up the skill distribution as some have claimed? To shed light on these questions, we study employment changes in manufacturing and services for three different skill groups: low-skilled (without a vocational degree), medium-skilled (with a vocational degree) and high-skilled workers (with a college or university degree).

We again use our panel specification from equation (6) using both the baseline and allowing for district-specific effects in employment trajectories. The results in Panel A of Table 5 show robotics technology primarily automates manufacturing jobs of low-skilled workers. Based on the estimates in column (4), an increase of robot exposure by one standard deviation leads to a decline in low skill manufacturing employment of around 8.1 percentage points. Interestingly, AI technologies destroy manufacturing jobs further up the skill distribution: employment of medium-skilled workers decreased by almost 10 percentage points if AI exposure would increase by a standard deviation.

Outside of manufacturing, the pattern looks quite different. Here, AI technologies create more jobs up the skill ladder: a one standard deviation increase raises high-skilled employment outside of manufacturing by 2.9 percentage points. Effects for medium- and low-skilled workers are much smaller and typically do not reach statistical significance. Exposure to robotics reduces employment outside of manufacturing for all skill groups but esp. for the low- and medium-skilled (with employment declines of around 4 and 1.5 percentage points, respectively).

Overall, these results indicate that high-skilled workers seem to benefit from AI technologies. Medium-skilled workers actually see their job prospects endangered by both AI and robotics tech-

nologies. Low-skilled workers, in turn, are mostly harmed by the diffusion of robotics technologies as their job prospects decline strongly both within and outside of manufacturing. These results, which have not been documented so far, show that the diffusion of digital technologies has sizable distributional consequences and hence, potential implications for training and other policies to support the transition into the digital era.

Our findings paint a nuanced picture of the impact of different digital technologies on the labor market. Robots with their strong automation potential of routinized jobs have different effects than AI technologies, which seem to replace workers higher up the skill distribution. When discussing the economic consequences and policy implications of the digital transition, it is therefore important not to draw conclusions on evidence from just one technology and extrapolate it to another.

7 Robustness Checks

We conduct a series of robustness checks in order to provide additional evidence on the stability of the results we find. First, we show the robustness of our shift-share exposure measures by excluding German inventors. Next, we include tests of the validity of our instrument following Borusyak et al. (2018) and adjust standard errors using the method proposed by Adão et al. (2019)

7.1 Excluding German inventors

In our main specification of the shift-share instrument, we include all patents filed at the EPO over the sample period. This also includes patents filed by German inventors. However, there might be concerns that patenting in Germany is endogenously related to local labor market conditions and therefore threatens the exogeneity assumption of the shift variable. To test for this, we construct a separate measure of exposure to AI and robotics that excludes all patents filed by German inventors. The share of German patents among all patents filed is 11% for AI and 14% for robotics patents. We drop these patents and continue to construct the district-level exposure measures in the same way as before. Running the same set of regressions as previously, but using the new exposure measure, we find that our results are largely robust to the exclusion of German patents. The results can be found in tables A4 to A7 in the appendix.

8 Conclusion

We develop new measures for the advancement of robotics and AI technologies in Europe applying natural language processing on patent data from the European Patent Office. Our measures for robotics are strongly correlated with robot installations but are available for more industries in manufacturing as well as outside manufacturing compared to existing data on industrial robots. Our measure for AI technologies show a positive, but weaker correlation with ICT capital. They are also positively related to AI-related job vacancies. Overall, knowledge in robotics technology has been more prominent over the 1990-2018 period, but has diffused into a small set of industries in Germany. The patenting of knowledge in AI technologies, in turn, has only picked up since 2015 but has started to diffuse into more industries.

We then use our new measures to explore the labor market consequences of the new technologies. Using a shift-share approach and data on local labor markets in Germany, we find that exposure to AI and robotics technologies reduce local employment with few effects on local wages. Most importantly, the small average effects mask considerable heterogeneities across sectors of the economy: employment declines are much more pronounced in manufacturing than in the service sector. We also investigate what happens if we control for both types of digital technologies simultaneously. These conditional estimates indicate that AI technologies have stronger negative employment effects in manufacturing, while districts with high robot exposure see employment declines in both manufacturing and services.

Finally, we investigate how different skill groups are affected by the new technologies. We find that high-skilled workers tend to benefit from the diffusion of AI technologies, while medium-skilled workers see their job prospects decline through both technologies. Low-skilled workers are hit hardest by the diffusion of robotics technology, which replaces low-skilled jobs both within and outside the manufacturing sector.

Our results for robotics are consistent with earlier evidence using installations as direct measure of robot diffusion in manufacturing (Dauth et al., 2021) that finds negative employment effects. However, in our setting, these negative effects are not compensated for by increasing employment in services. The consistency of results for the two measures provides additional support for our approach to proxy the advancement of digital technologies using patent data. For AI, our approach provides a novel measure at the industry level over three decades, which complements recent attempts to quantify the future automation potential at the occupation level.

Unlike previous studies that consider both AI and robotics as automation technologies (see Mann and Püttmann (2021) for example), we find considerable differences in the labor market effects of the two technologies, especially if we consider differences across sectors and skill groups. The most likely explanation is that they are used differently in production and thereby vary in the way they substitute for or enhance human labor. In this context, the impact of robots is stronger labor-replacing than that of AI, which tends to increase non-manufacturing employment.

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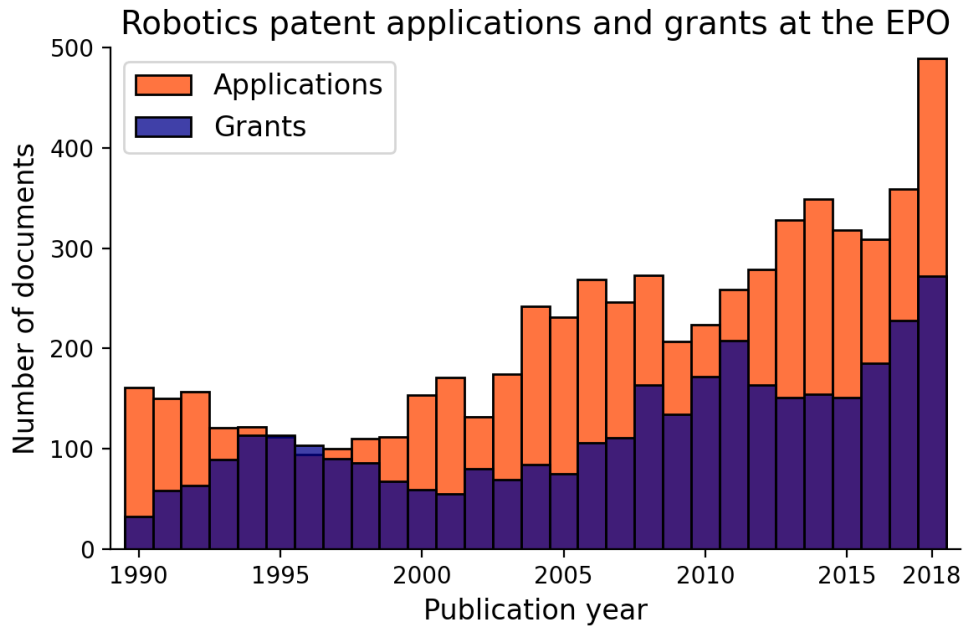
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Figure 1: Number of Patents in AI and Robotics, 1990-2018

(a) Robotics Patents

Robotics patent applications and grants at the EPO

(b) AI Patents

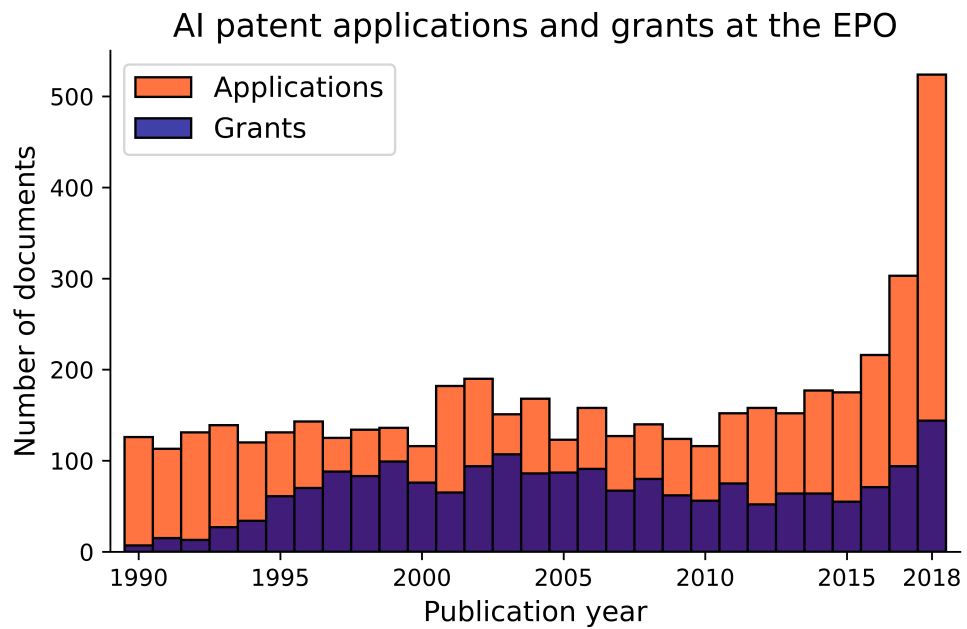AI patent applications and grants at the EPO

Figure 2: Correlation of Robotics Patents with Robot Installations, 1990-2018
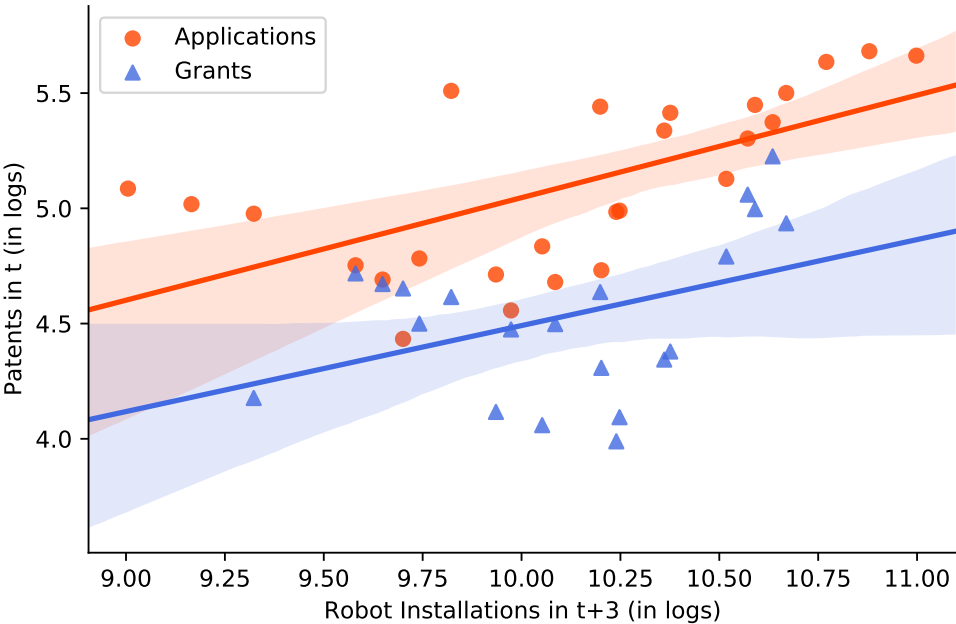
Figure 3: Correlation of AI Patents, ICT Investments and AI Job Vacancies

(a) AI patents and ICT Investments
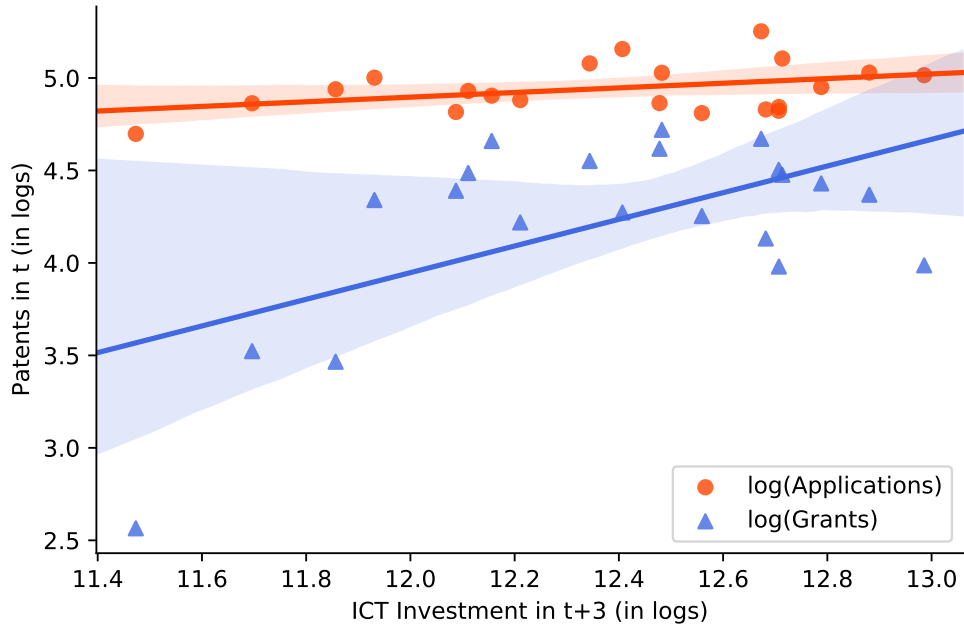
(b) AI patents and AI Skills in Online Job Ads
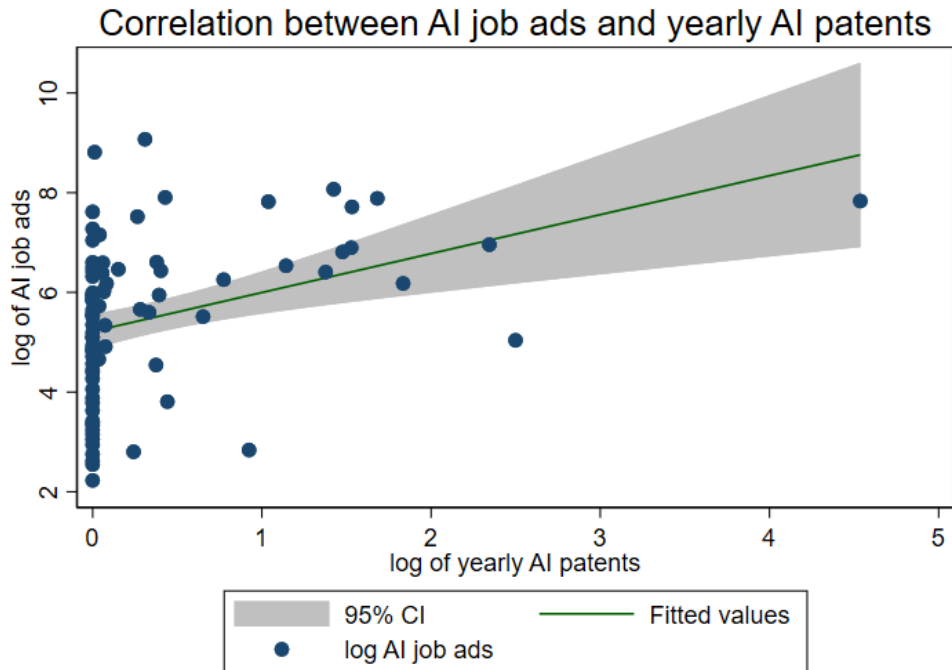
Figure 4: Regional Exposure to AI and Robotics in 2018

(a) AI exposure
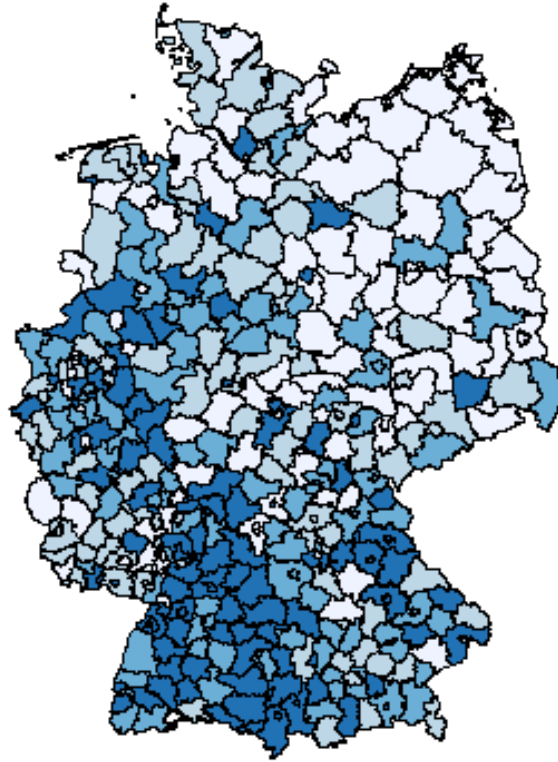
(b) Robot exposure
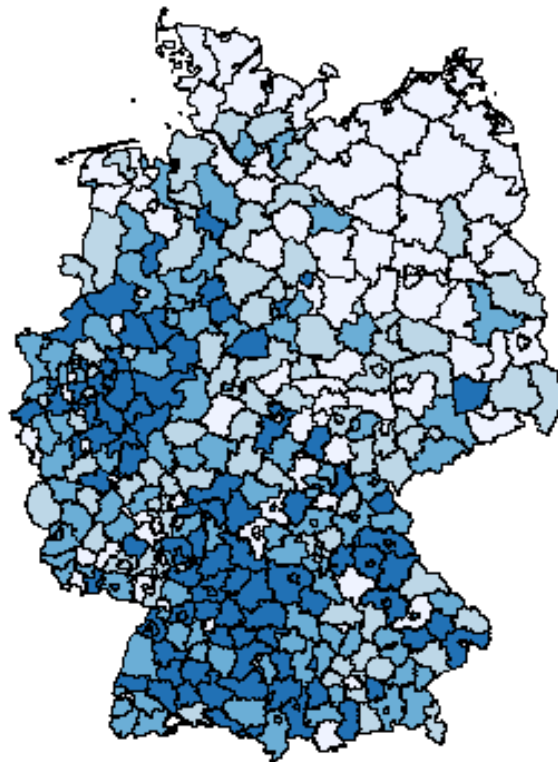
Table 1: Local Labor Market Characteristics and Exposure Measures

	Obs	Mean	Std. Dev.	Min	Max
Outcome variables:					
Δ Log Employment	401	-0.5317	0.8632	-3-4593	1.5946
Δ Log Daily Wages	401	0.4853	0.0970	0.2594	0.8871
Exposure Measures:					
Δ AI Exposure (log)	401	3.1013	2.5634	.3372	20.3104
Δ Robot Exposure (log)	401	8.6630	7.8316	.3149	54.7126
Control variables:					
Manufacturing Employment (1993)	401	0.2797	0.1686	0.0185	0.8896
High-skilled Workers (1993)	401	0.0773	0.0535	0.0155	0.4126
Medium-skilled Workers (1993)	401	0.7332	0.0507	0.4703	0.8773
Low-skilled Workers (1993)	401	0.1792	0.0537	0.0617	0.3569
% Female Employment (1993)	401	0.4220	0.0778	0.1282	0.6377
% Young Workers (1993)	401	0.3975	0.0392	0.2846	0.5346
% Prime-Aged Workers (1993)	401	0.3488	0.0301	0.2770	0.4381
% Older Workers 50-64 (1993)	401	0.2033	0.0286	0.1094	0.2744
Δ Net exports	401	0.7584	0.2411	0.7308	0.8768
Δ ICT investment	401	0.2527	0.0268	0.1854	0.3950

Notes: The outcome and exposure measures are measured at the district level and calculated as log changes between 1993 and 2018. The exposure measures are a shift-share variable consisting of two components: the shift variable denotes the cumulative number of patents in robotics and AI technologies used in a certain industry. The information on patents is extracted from EPO data using natural language processing techniques. The share variable is the employment share of an industry in the district in 1993. All control variables are measured at the district level and refer to 1993. Young workers are between 25 and 24 years of age; prime-aged workers between 35 and 49 years of age; and older workers between 50 and 64 years of age.

Table 2: Long Differences Estimates of Exposure to AI and Robotics Technologies on Employment and Wages

Panel A: Employment Changes

	(1)	(2)	(3)	(4)	(5)
ΔAI Exposure	0.0104**	0.0105**			0.0155***
	(0.00452)	(0.00452)			(0.00572)
ΔRobot Exposure			0.000929	0.000905	-0.00351
			(0.00205)	(0.00204)	(0.00258)
Δ Net exports	No	Yes	No	Yes	Yes
Δ ICT investment	No	Yes	No	Yes	Yes
Demographic controls	Yes	Yes	Yes	Yes	Yes
Industry shares	Yes	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes	Yes
Observations	401	401	401	401	401

Panel B: Wage Changes

	(1)	(2)	(3)	(4)	(5)
ΔAI Exposure	0.000162	0.000175			-0.000837
	(0.00169)	(0.00168)			(0.00232)
ΔRobot Exposure			0.000482	0.000471	0.000709
			(0.000811)	(0.000806)	(0.00108)
Δ Net exports	No	Yes	No	Yes	Yes
Δ ICT investment	No	Yes	No	Yes	Yes
Demographic controls	Yes	Yes	Yes	Yes	Yes
Industry shares	Yes	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes	Yes
Observations	401	401	401	401	401

Notes: The table reports estimates from equation (3) where the dependent variables are log employment changes between 1993 and 2018 in Panel A and log wage changes between 1993 and 2018 in Panel B. The exposure measures are shift share variables as defined in equation (2). Demographic controls include the share of female workers, the share of high-, medium- and low-skilled workers, the share of young, prime-aged and older workers and the industry shares at the one-digit level. All demographic control variables refer to 1993. Δ Net exports is the change in net exports between 1993 and 2018 at the one-digit industry level, adjusted by the total wage bill. Δ ICT is the change in ICT investment per worker between 1993 and 2018 at the one-digit industry level. Region dummies refer to broad regions (North, South, East, West). Standard errors are reported in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

Table 3: Panel Estimates of AI and Robotics Technologies on Employment and Wages

Panel A: Employment Changes

	(1)	(2)	(3)	(4)	(5)	(6)
ΔAI Exposure	-0.000389		0.00309	-0.0131**		-0.00623*
	(0.00163)		(0.00211)	(0.00295)		(0.00356)
ΔRobot Exposure		-0.00137	-0.00233**		-0.00634***	-0.00425**
		(0.000863)	(0.00114)		(0.00143)	(0.00174)
Δ Net exports	Yes	Yes	Yes	Yes	Yes	Yes
Δ ICT investment	Yes	Yes	Yes	Yes	Yes	Yes
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry employment shares	Yes	Yes	Yes	Yes	Yes	Yes
District FE	No	No	No	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1604	1604	1604	1604	1604	1604

Panel B: Wage Changes

	(1)	(2)	(3)	(4)	(5)	(6)
ΔAI Exposure	-0.00132		-0.00267*	-0.00239		-0.000648
	(0.00108)		(0.00138)	(0.00223)		(0.00288)
ΔRobot Exposure		0.0000798	0.000904		-0.00129	-0.00107
		(0.000527)	(0.000667)		(0.000955)	(0.00123)
District FE	No	No	No	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes	Yes	Yes
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry employment shares	Yes	Yes	Yes	Yes	Yes	Yes
Δ Net exports	Yes	Yes	Yes	Yes	Yes	Yes
Δ ICT investment	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1604	1604	1604	1604	1604	1604

Notes: The table reports estimates from equation (6) where the dependent variables are log employment changes in four sub-periods in Panel A and log wage changes in Panel B. The exposure measures are shift share variables as defined in equation (5). Demographic controls include the share of female workers, the share of high-, medium- and low-skilled workers, the share of young, prime-aged and older workers and the industry shares at the one-digit level. All demographic control variables refer to the first year of the respective sub-period. Δ Net exports is the change in net exports at the one-digit industry level, adjusted by the total wage bill. Δ ICT is the change in ICT investment per worker at the one-digit industry level. Region dummies refer to broad regions (North, South, East, West). Standard errors are clustered at the district level and are reported in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

Table 4: Employment Effects in Manufacturing and Services

Panel A: Manufacturing Employment

	(1)	(2)	(3)	(4)	(5)	(6)
ΔAI Exposure	-0.00350		-0.00380	-0.0361***		-0.0224**
	(0.00519)		(0.00466)	(0.00105)		(0.0110)
ΔRobot Exposure		-0.000973	0.000199		-0.0160***	-0.00845
		(0.00282)	(0.00298)		(0.00526)	(0.00607)
District FE	No	No	No	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes	Yes	Yes
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry employment shares	Yes	Yes	Yes	Yes	Yes	Yes
Δ Net exports	Yes	Yes	Yes	Yes	Yes	Yes
Δ ICT investment	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1604	1604	1604	1604	1604	1604

Panel B: Non-Manufacturing Employment

	(1)	(2)	(3)	(4)	(5)	(6)
ΔAI Exposure	-0.000808		0.00382*	-0.00231		0.00459
	(0.00150)		(0.00205)	(0.00292)		(0.00432)
ΔRobot Exposure		-0.00192***	-0.00309***		-0.00273**	-0.00426**
		(0.00106)	(0.00163)		(0.00243)	(0.00403)
District FE	No	No	No	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes	Yes	Yes
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry employment shares	Yes	Yes	Yes	Yes	Yes	Yes
Δ Net exports	Yes	Yes	Yes	Yes	Yes	Yes
Δ ICT investment	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1604	1604	1604	1604	1604	1604

Notes: The table reports estimates from equation (6) where the dependent variables are log employment changes in four sub-periods in Manufacturing in Panel A and outside of Manufacturing in Panel B. The exposure measures are shift share variables as defined in equation (5). Demographic controls include the share of female workers, the share of high-, medium- and low-skilled workers, the share of young, prime-aged and older workers and the industry shares at the one-digit level. All demographic control variables refer to the first year of the respective sub-period. Δ Net exports is the change in net exports at the one-digit industry level, adjusted by the total wage bill. Δ ICT is the change in ICT investment per worker at the one-digit industry level. Region dummies refer to broad regions (North, South, East, West). Standard errors are clustered at the district level and are reported in parentheses. Significance levels: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 5: Employment Effects by Skill Level and Broad Sector

Panel A: Employment Changes in Manufacturing

	Low-skilled Workers (1)	Medium-skilled Workers (2)	High-skilled Workers (3)	Low-skilled Workers (4)	Medium-skilled Workers (5)	High-skilled Workers (6)
ΔAI Exposure	0.00513	-0.00465	-0.00734	-0.00226	-0.0240**	-0.0165
	(0.00631)	(0.00460)	(0.00120)	(0.0153)	(0.0105)	(0.0199)
ΔRobot Exposure	-0.00401	0.000357	-0.00120	-0.0194***	-0.00641	-0.0171
	(0.00360)	(0.00283)	(0.00465)	(0.00674)	(0.00553)	(0.0111)
District FE	No	No	No	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes	Yes	Yes
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry employment shares	Yes	Yes	Yes	Yes	Yes	Yes
Δ Net exports	Yes	Yes	Yes	Yes	Yes	Yes
Δ ICT investment	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1604	1604	1604	1604	1604	1604

Panel B: Employment Changes outside of Manufacturing

	Low-skilled Workers (1)	Medium-skilled Workers (2)	High-skilled Workers (3)	Low-skilled Workers (4)	Medium-skilled Workers (5)	High-skilled Workers (6)
ΔAI Exposure	0.000412	0.00352*	0.00867**	0.00202	0.00213	0.0162*
	(0.00295)	(0.00196)	(0.00366)	(0.00725)	(0.00390)	(0.00914)
ΔRobot Exposure	-0.000981	-0.00367***	-0.00323**	-0.00959***	-0.00360*	-0.00496
	(0.00130)	(0.000810)	(0.00146)	(0.00341)	(0.00184)	(0.00389)
District FE	No	No	No	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes	Yes	Yes
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry employment shares	Yes	Yes	Yes	Yes	Yes	Yes
Δ Net exports	Yes	Yes	Yes	Yes	Yes	Yes
Δ ICT investment	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1604	1604	1604	1604	1604	1604

Notes: The table reports estimates from equation (6) where the dependent variables are log employment changes by skill level in Manufacturing in Panel A and outside of Manufacturing in Panel B. The exposure measures are shift share variables as defined in equation (5). Demographic controls include the share of female workers, the share of high-, medium- and low-skilled workers, the share of young, prime-aged and older workers and the industry shares at the one-digit level. All demographic control variables refer to the first year of the respective sub-period. Δ Net exports is the change in net exports at the one-digit industry level, adjusted by the total wage bill. Δ ICT is the change in ICT investment per worker at the one-digit industry level. Region dummies refer to broad regions (North, South, East, West). Standard errors are clustered at the district level and are reported in parentheses. Significance levels: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

A   Additional Results

Table A1: Top Using Industries of AI and Robotics Patents

ISIC	Industry	AI Patents	% AI Grants in Industry
2620	Computers and peripheral equipment	582	1.49
2640	Consumer electronics	316	4.45
2630	Communication equipment	139	0.55
2817	Office machinery and equipment	138	2.00
2822	Metal-forming machinery and machine tools	74	0.86
2670	Optical instruments and photographic equipment	72	0.25
5912	Motion picture, video and television programme post-production activities	69	0.47
5920	Sound recording and music publishing activities	65	0.24
2651	Measuring, testing, navigating and control equipment	52	0.35
8620	Medical and dental practice activities	40	0.18
ISIC	**Industry**	**Robotics Patent**	**% Robotics Patents in Industry**
2814	Bearings, gears, gearing and driving elements	413	1.80
2822	Metal-forming machinery and machine tools	228	2.63
2651	Measuring, testing, navigating and control equipment	169	1.13
2750	Domestic appliances	148	1.15
2592	Treatment and coating of metals	138	1.89
2811	Engines and turbines	137	0.41
1050	Dairy products	137	4.93
2816	Lifting and handling equipment	117	0.82
2670	Optical instruments and photographic equipment	101	0.36
2620	Computers and peripheral equipment	97	0.24

Notes: The table reports the top ten four-digit industries using AI (top panel) and robotics patents (bottom panel). The second column reports the total number of patent grants used in the industry during the 1990-2018 period, while the last column reports the share of AI resp. robotics patents to all patents used in the industry.

Table A2: Industries with Strongest Growth in AI and Robotics Patents

ISIC	Industry	Growth in AI Patents
262	Manufacture of computers and peripheral equipment	5.76
264	Manufacture of consumer electronics	3.71
862	Medical and dental practice activities	3.70
263	Manufacture of communication equipment	3.53
267	Manufacture of optical instruments and photographic equipment	3.36
265	Manufacture of measuring, testing, navigating and control equipment; watches and clocks	3.26
592	Sound recording and music publishing activities	3.01
281	Manufacture of general-purpose machinery	2.76
282	Manufacture of special-purpose machinery	2.52
749	Other professional, scientific and technical activities	2.43
ISIC	**Industry**	**Growth in Robotics Patents**
862	Medical and dental practice activities	4.35
267	Manufacture of optical instruments and photographic equipment	3.36
262	Manufacture of computers and peripheral equipment	3.32
325	Manufacture of medical and dental instruments and supplies	3.00
105	Manufacture of dairy products	2.74
360	Water collection, treatment and supply	2.52
310	Manufacture of furniture	2.40
202	Manufacture of other chemical products	2.17
960	Other personal service activities	2.11
201	Manufacture of basic chemicals, fertilizers and nitrogen compounds, plastics and synthetic rubber	2.11

Notes: The table reports the top ten four-digit industries using AI (top panel) and robotics patents (bottom panel). The second column reports the total number of patent grants used in the industry during the 1990-2018 period, while the last column reports the share of AI resp. robotics patents to all patents used in the industry.

Table A3: Panel Estimates of Wage Effects in Manufacturing vs. Non-Manufacturing

Panel A: Manufacturing Wages

	(1)	(2)	(3)	(4)	(5)	(6)
ΔAI Exposure	-0.0000814		-0.000509	-0.00586*		-0.00401
	(0.00141)		(0.00172)	(0.00326)		(0.00422)
ΔRobot Exposure		0.000129	0.000285		-0.00249	-0.00115
		(0.000674)	(0.000839)		(0.000170)	(0.00224)
District FE	No	No	No	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes	Yes	Yes
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry employment shares	Yes	Yes	Yes	Yes	Yes	Yes
Δ Net exports	Yes	Yes	Yes	Yes	Yes	Yes
Δ ICT investment	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1604	1604	1604	1604	1604	1604

Panel B: Non-Manufacturing Wages

	(1)	(2)	(3)	(4)	(5)	(6)
ΔAI Exposure	-0.000926		-0.00268**	-0.00220		-0.00188
	(0.000817)		(0.00105)	(0.00153)		(0.00215)
ΔRobot Exposure		0.000348	0.00118***		-0.000829	-0.000201
		(0.000335)	(0.000436)		(0.000731)	(0.00103)
District FE	No	No	No	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes	Yes	Yes
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry employment shares	Yes	Yes	Yes	Yes	Yes	Yes
Δ Net exports	Yes	Yes	Yes	Yes	Yes	Yes
Δ ICT investment	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1604	1604	1604	1604	1604	1604

Notes: The table reports estimates from equation (6) where the dependent variables are log employment changes in four sub-periods in Panel A and log wage changes in Panel B. The exposure measures are shift share variables as defined in equation (5). Demographic controls include the share of female workers, the share of high-, medium- and low-skilled workers, the share of young, prime-aged and older workers and the industry shares at the one-digit level. All demographic control variables refer to the first year of the respective sub-period. Δ Net exports is the change in net exports at the one-digit industry level, adjusted by the total wage bill. Δ ICT is the change in ICT investment per worker at the one-digit industry level. Region dummies refer to broad regions (North, South, East, West). Standard errors are clustered at the district level and are reported in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

Table A4: R1: Long Difference Employment and Wage Effects excluding German patents

Panel A: Employment Changes

	(1)	(2)	(3)	(4)	(5)
ΔAI Exposure	0.0110**	0.0114**			0.0155**
	(0.00495)	(0.00493)			(0.00634)
ΔRobot Exposure			0.00120	0.00125	-0.00272
			(0.00292)	(0.00202)	(0.00255)
Δ Net exports	No	Yes	No	Yes	Yes
Δ ICT investment	No	Yes	No	Yes	Yes
Demographic controls	Yes	Yes	Yes	Yes	Yes
Industry shares	Yes	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes	Yes
Observations	401	401	401	401	401

Panel B: Wage Changes

	(1)	(2)	(3)	(4)	(5)
ΔAI Exposure	0.00169	0.00176			0.00192
	(0.00244)	(0.00239)			(0.00291)
ΔRobot Exposure			0.000364	0.000390	-0.0001
			(0.000938)	(0.000920)	(0.00113)
Δ Net exports	No	Yes	No	Yes	Yes
Δ ICT investment	No	Yes	No	Yes	Yes
Demographic controls	Yes	Yes	Yes	Yes	Yes
Industry shares	Yes	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes	Yes
Observations	401	401	401	401	401

Notes: The table reports estimates from equation (3) where the dependent variables are log employment changes between 1993 and 2018 in Panel A and log wage changes between 1993 and 2018 in Panel B. The exposure measures are shift share variables as defined in equation (2), excluding all patents by German inventors. Demographic controls include the share of female workers, the share of high-, medium- and low-skilled workers, the share of young, prime-aged and older workers and the industry shares at the one-digit level. All demographic control variables refer to 1993. Δ Net exports is the change in net exports between 1993 and 2018 at the one-digit industry level, adjusted by the total wage bill. Δ ICT is the change in ICT investment per worker between 1993 and 2018 at the one-digit industry level. Region dummies refer to broad regions (North, South, East, West). Standard errors are reported in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

Table A5: R2: Panel Employment and Wage Effects excluding German patents

Panel A: Employment Changes

	(1)	(2)	(3)	(4)	(5)	(6)
ΔAI Exposure	-0.000286		0.00338	-0.0139***		-0.00529
	(0.00175)		(0.00231)	(0.00330)		(0.00382)
ΔRobot Exposure		-0.00135	-0.00229*		-0.00639***	-0.00485***
		(0.000889)	(0.00118)		(0.00147)	(0.00178)
District FE	No	No	No	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes	Yes	Yes
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry employment shares	Yes	Yes	Yes	Yes	Yes	Yes
Δ Net exports	Yes	Yes	Yes	Yes	Yes	Yes
Δ ICT investment	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1604	1604	1604	1604	1604	1604

Panel B: Wage Changes

	(1)	(2)	(3)	(4)	(5)	(6)
ΔAI Exposure	-0.00000182		-0.000657	0.000568		0.00444*
	(0.00105)		(0.00128)	(0.00227)		(0.00254)
ΔRobot Exposure		0.000226	0.000410		-0.000875	-0.00217**
		(0.000512)	(0.000633)		(0.000913)	(0.00105)
District FE	No	No	No	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes	Yes	Yes
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry employment shares	Yes	Yes	Yes	Yes	Yes	Yes
Δ Net exports	Yes	Yes	Yes	Yes	Yes	Yes
Δ ICT investment	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1604	1604	1604	1604	1604	1604

Notes: The table reports estimates from equation (6) where the dependent variables are log employment changes in four sub-periods in Panel A and log wage changes in Panel B. The exposure measures are shift share variables as defined in equation (5), excluding all patents by German inventors. Demographic controls include the share of female workers, the share of high-, medium- and low-skilled workers, the share of young, prime-aged and older workers and the industry shares at the one-digit level. All demographic control variables refer to the first year of the respective sub-period. Δ Net exports is the change in net exports at the one-digit industry level, adjusted by the total wage bill. Δ ICT is the change in ICT investment per worker at the one-digit industry level. Region dummies refer to broad regions (North, South, East, West). Standard errors are clustered at the district level and are reported in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

Table A6: R3: Panel Employment Effects Manufacturing vs. Services excluding German patents

Panel A: Manufacturing Employment

	(1)	(2)	(3)	(4)	(5)	(6)
ΔAI Exposure	-0.00389		-0.00421	-0.0390***		-0.0221*
	(0.00552)		(0.00494)	(0.0119)		(0.0119)
ΔRobot Exposure		-0.000976	0.000202		-0.0159***	-0.00951
		(0.00292)	(0.00317)		(0.00553)	(0.00639)
District FE	No	No	No	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes	Yes	Yes
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry employment shares	Yes	Yes	Yes	Yes	Yes	Yes
Δ Net exports	Yes	Yes	Yes	Yes	Yes	Yes
Δ ICT investment	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1604	1604	1604	1604	1604	1604

Panel B: Non-Manufacturing Employment

	(1)	(2)	(3)	(4)	(5)	(6)
ΔAI Exposure	-0.000783		0.00405*	-0.00278		0.00417
	(0.00164)		(0.00223)	(0.00329)		(0.00496)
ΔRobot Exposure		-0.00189***	-0.00302***		-0.00268*	-0.00389*
		(0.000621)	(0.000846)		(0.00142)	(0.00204)
District FE	No	No	No	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes	Yes	Yes
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry employment shares	Yes	Yes	Yes	Yes	Yes	Yes
Δ Net exports	Yes	Yes	Yes	Yes	Yes	Yes
Δ ICT investment	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1604	1604	1604	1604	1604	1604

Notes: The table reports estimates from equation (6) where the dependent variables are log employment changes in four sub-periods in Panel A and log wage changes in Panel B. The exposure measures are shift share variables as defined in equation (5), excluding all patents by German inventors. Demographic controls include the share of female workers, the share of high-, medium- and low-skilled workers, the share of young, prime-aged and older workers and the industry shares at the one-digit level. All demographic control variables refer to the first year of the respective sub-period. Δ Net exports is the change in net exports at the one-digit industry level, adjusted by the total wage bill. Δ ICT is the change in ICT investment per worker at the one-digit industry level. Region dummies refer to broad regions (North, South, East, West). Standard errors are clustered at the district level and are reported in parentheses. Significance levels: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table A7: R4: Panel Employment Effects Manufacturing vs. Services by skill excluding German patents

Panel A: Employment Changes in Manufacturing

	Low-skilled Workers (1)	Medium-skilled Workers (2)	High-skilled Workers (3)	Low-skilled Workers (4)	Medium-skilled Workers (5)	High-skilled Workers (6)
ΔAI Exposure	0.00547	-0.00498	-0.00941	0.000688	-0.0226**	-0.0232
	(0.00693)	(0.00489)	(0.00747)	(0.0171)	(0.0111)	(0.0219)
ΔRobot Exposure	-0.00419	-0.000373	-0.00104	-0.0204***	-0.00767	-0.0162
	(0.00376)	(0.00299)	(0.00496)	(0.00698)	(0.00574)	(0.0119)
District FE	No	No	No	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes	Yes	Yes
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry employment shares	Yes	Yes	Yes	Yes	Yes	Yes
Δ Net exports	Yes	Yes	Yes	Yes	Yes	Yes
Δ ICT investment	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1604	1604	1604	1604	1604	1604

Panel B: Employment Changes outside of Manufacturing

	Low-skilled Workers (1)	Medium-skilled Workers (2)	High-skilled Workers (3)	Low-skilled Workers (4)	Medium-skilled Workers (5)	High-skilled Workers (6)
ΔAI Exposure	0.000926	0.00373*	0.00845**	0.00187	0.00162	0.0165
	(0.00314)	(0.00214)	(0.00403)	(0.00882)	(0.00424)	(0.0108)
ΔRobot Exposure	-0.00114	-0.00361***	-0.00270*	-0.00950***	-0.00338*	-0.00414
	(0.00131)	(0.000825)	(0.00152)	(0.00352)	(0.00182)	(0.00405)
District FE	No	No	No	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes	Yes	Yes
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry employment shares	Yes	Yes	Yes	Yes	Yes	Yes
Δ Net exports	Yes	Yes	Yes	Yes	Yes	Yes
Δ ICT investment	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1604	1604	1604	1604	1604	1604

Notes: The table reports estimates from equation (6) where the dependent variables are log employment changes in four sub-periods in Panel A and log wage changes in Panel B. The exposure measures are shift share variables as defined in equation (5), excluding all patents by German inventors. Demographic controls include the share of female workers, the share of high-, medium- and low-skilled workers, the share of young, prime-aged and older workers and the industry shares at the one-digit level. All demographic control variables refer to the first year of the respective sub-period. Δ Net exports is the change in net exports at the one-digit industry level, adjusted by the total wage bill. Δ ICT is the change in ICT investment per worker at the one-digit industry level. Region dummies refer to broad regions (North, South, East, West). Standard errors are clustered at the district level and are reported in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

Figure A1: Example of a robot patent document
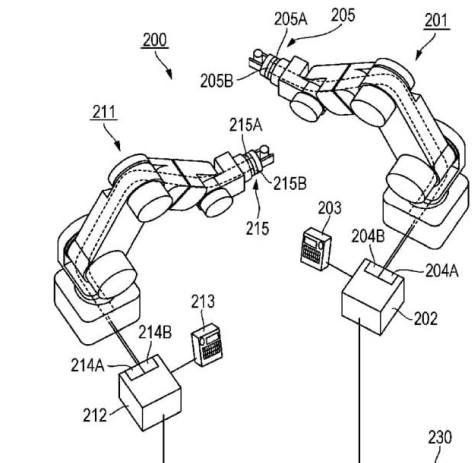with highlighted keyword matches

(19)

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(54)   **ROBOT APPARATUS**

(57)   A plurality of robot arms (201, 211, 301, 311) are each provided with indication devices (205, 215) that have indicators (205B, 215B) which indicate operability states of at least one other robot arm different from the robot arm on which the indication device is provided. Alternatively or in addition, the indication devices (205, 215) have indicators (205A, 215A) which indicate operability states of a respective robot arm upon which the indication devices are provided. Robot control devices (202, 212) which control operations of the robot arms communicate through a LAN (230) to share information regarding the states of the robot arms. Indication drive signals for the indication devices (205, 215) are generated based on states of servo control signals and/or brake control signals for the robot arms.

FIG. 1

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(19)

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Remarks:
   Amended claims in accordance with Rule 137(2)
   EPC.

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(54)   **Method and structure for a neural associative memory based on optimal ==Bayesian learning==**

(57)   This invention is in the field of ==machine learning== and neural associative memory. In particular the invention discloses a neural associative memory structure for storing and maintaining associations between memory address patterns and memory content patterns using a ==neural network==, as well as methods for storing and retrieving such associations. ==Bayesian learning== is applied to achieve non-linear learning.
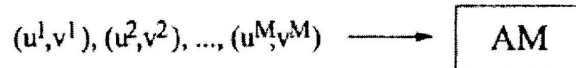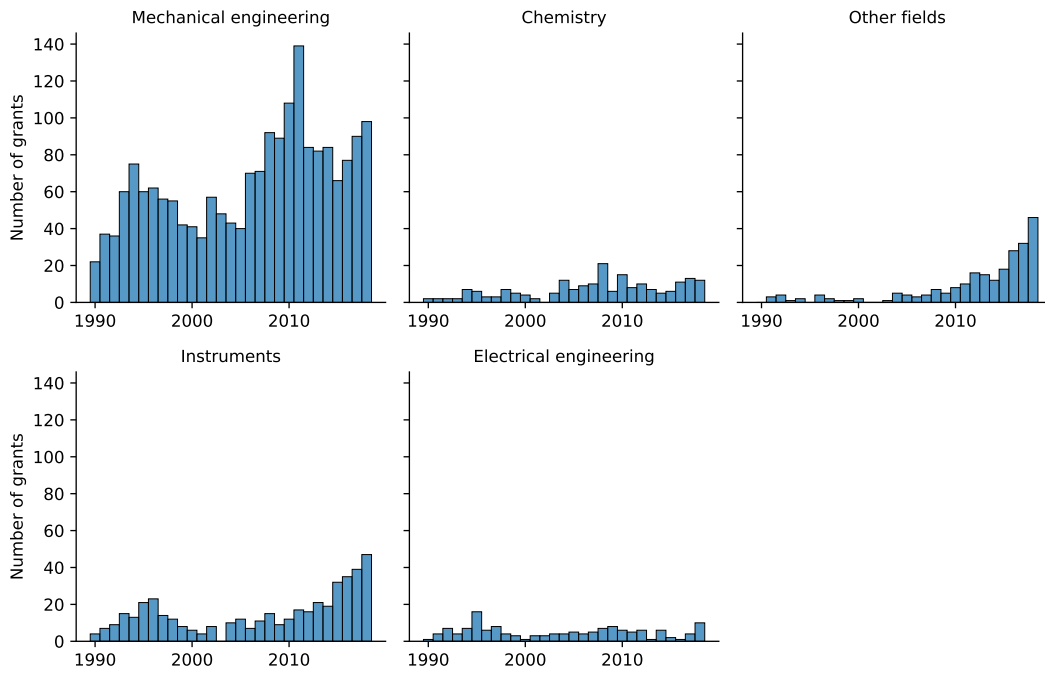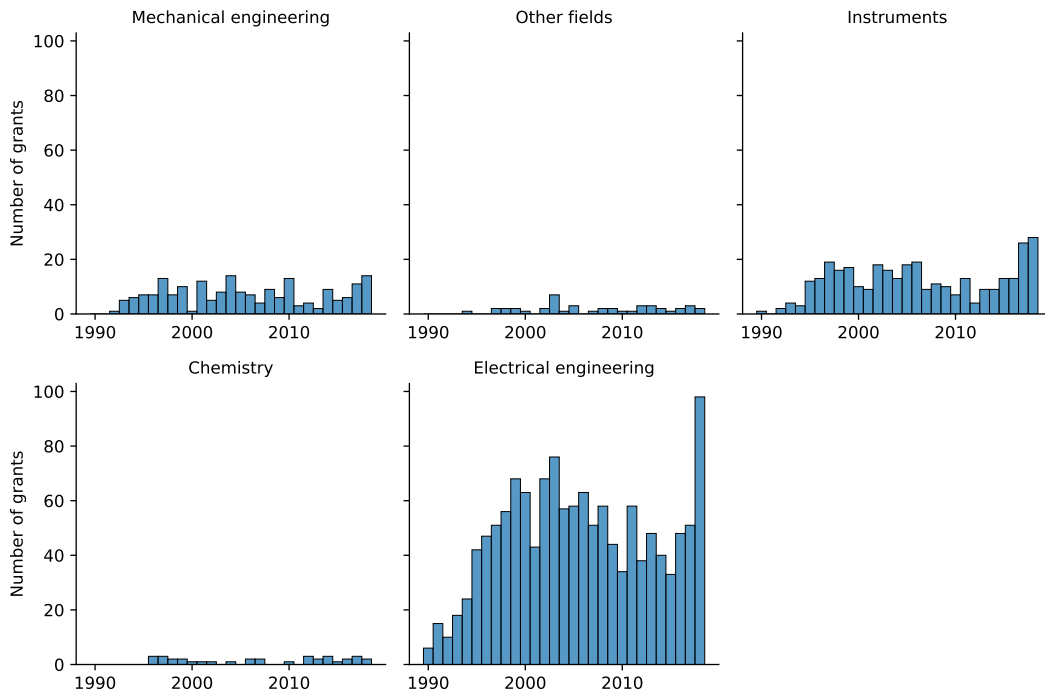
$$(u^1, v^1), (u^2, v^2), ..., (u^M, v^M) \longrightarrow \boxed{\text{AM}}$$

Fig. 1a

Figure A3: Evolution of Patents by Broad Technology Class

(a) Robotics Patents

(b) AI Patents

Notes: The figures show the number of patent grants in Robotics (Panel (A)) and AI (Panel (B)) in broad technology classes over time.