Pillars – Pathways to Inclusive Labour Markets

Report

The Impact of Technological Change on Immigration and Immigrants

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The Impact of Technological Change on Immigration and Immigrants*

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We study the effects of technological change on immigration flows as well as the labor market outcomes of migrants versus natives. We analyse and compare the effects of two different automation technologies: Industrial robots and artificial intelligence. We exploit data provided by the Industrial Federation of Robotics as well as online job vacancy data on Germany, a highly automated economy and the main destination for migrants in Europe. We apply an instrumental variable strategy and identify how robots decrease the wage of migrants across all skill groups, while neither having a significant impact on the native population nor immigration flows. In the case of AI, we determine an increase in the wage gap as well as the unemployment gap of migrant and native populations. This applies to the low-, medium- and high-skilled and is indicative of migrants facing displacement effects, while natives might benefit from productivity and complementarity effects. In addition, AI leads to a significant inflow of immigrants. Policymakers should devote special attention to the migration population when designing mitigation policies in response to technological change to avoid further increases in inequality between migrants and natives.

JEL— F22, J15, J61, J78, O15, O33

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1 Introduction

Scientists continue to invent, build and implement technologies that can perform human tasks. These technologies are often based on automation, with robots and artificial intelligence (AI) representing two examples. For instance, the number of installed industrial robots increased by 85 percent between 2014 and 2019 worldwide (IFR, 2021). With more than 2.7 million robots installed in 2019 we have come a long way since *Unimate*; the first industrial robot patented in 1954. The adoption of robots has revolutionized the manufacturing sector, but their usage is starting to become more common also in other sectors such as the service sector. One example is the adoption of robots in nursing homes in Japan (Eggleston et al., 2021). More recently, new forms of automation technologies, such as AI, which are able to perform not only manual human tasks but mental ones, have started to emerge. One example is the implementation of *chatbots*, a technology that can hold real conversations with humans based on AI. In fact, the use of chatbots increased by more than 400 percent between 2006 and 2020 (Adamopoulou and Moussiades, 2020). The picture is even more staggering when we look at the evolution of AI technologies in general. The Artificial Intelligence Index Report 2021 by the University of Stanford finds that the number of peer-reviewed AI publications grew almost twelve-fold between 2000 and 2019 (Entwood et al., 2021).

AI could revolutionize how nearly all economic sectors function around the globe. However, the skills needed to work with AI is scarce. In the late 90s, McKinsey detected a severe shortage of equipped labor among US companies and predicted a so-called *War for Talent* (Chambers et al., 1998). Many have now reused this phrase in reference to the skill shortage observed within the recent Tech Revolution (Whysall et al., 2019). Firms in Germany, for example, take an average of six months to fill tech positions (Anderson et al., 2020), while tech companies pay high salaries for AI specialists (Tarki, 2021). These high salaries could bear testimony to skill shortages.

At the same time, the adoption of robots and AI has raised concerns about how they might affect labor markets and jobs. Certain human tasks could be entirely replaced by technologies and jobs may become redundant. Several papers have studied the effect of robots and AI on labor markets in several different countries, with differing results. In particular migrants at the lower end of the skill spectrum might be affected by potentially negative effects of technological change. This is because they tend to have worse language skills, less access to local networks, labor market institutions and information about the need to adapt their skill-set. Studying the labor market implications of automation for migrants and natives separately can therefore help us to better understand the underlying drivers of diverging effects under technological change. On the other hand, migrants might be more flexible and more willing to switch sectors, jobs and locations. They could therefore mitigate the effects of technological change on the local population.

This paper first studies whether automation technologies increase or decrease the demand for labor from abroad. Second, we study whether automation technologies have different effects on the immigrant workforce, in particular along the skill distribution.

To study the effects of technological change on immigration, we focus on two forms of automated technologies: manual robots (industrial robots) and mental robots (artificial intelligence). We look at these two technologies, as one mainly replaces manual tasks while the other predominantly replaces mental ones. We exploit data provided by the Industrial Federation of Robotics (IFR) on the operational stock of industrial robots, as well as Burning Glass data (BGD) on Online Job Vacancies (OJV) to measure the demand for AI-related skills. We focus on Germany, as it is one of the main robot adopters worldwide, and has been subject to large immigration flows during recent decades. We conduct our analysis at the local labor market level and take advantage of the industry structure of 403 German counties to apply a shift-share instrument. Our identification strategy relies on the assumption that robot exposure at the industry level is exogenous and not correlated with labor demand. However, the adoption of robotics could be subject to domestic industry-specific demand shocks. To address this endogeneity concern, we conduct an instrumental variable strategy. We instrument robot adoption in Germany by robot adoption in three leading Asian countries: Japan, South Korea and Taiwan. Similarly, we instrument the AI-related skill demand in Germany by a leading country that is not part of the EU or EEA: Switzerland. We use Switzerland in this case, as we only have data available for European countries. To measure labor market outcomes of migrants and natives as well as immigration flows, we exploit German matched employer-employee social security data. In addition to conducting analyses at the county-level, we use the panel-data structure of this dataset to follow individuals over time and study their labor market responses to technological change.

We find that robot adoption has no significant impact on immigrant inflows, whereas AI-related skill demands do. Additionally, robots create a wage gap between migrants and natives for all skill-groups. Similarly, local labor markets with elevated AI skill demands report a wage decrease for migrants and increase for natives as well as increased unemployment rates for migrants, but not for natives. While natives seem to benefit from technological change, migrants experience adverse effects. This could be evidence of productivity and complementarity effects for natives, but displacement effects for migrants. These findings would be in line with a theoretical framework, in which firms see automation technologies and migrants as substitutes, and move away from cheap labor from abroad in favor of even cheaper technologies.

When breaking this down by sector, we identify a decrease in the migrant share of those working in the manufacturing sector. This could be evidence of migrants moving towards other sectors in response to robotization. The overall negative effect of AI on migrants seems to be driven by negative spill-over effects on the least exposed sectors. There are no negative labor market effects on migrants in the most exposed sectors. In general, technological change increases the likelihood of migrants from certain skill groups working in communication-intensive tasks; this could be evidence of complementarities due to new technologies in these tasks. Still, migrants are less likely than natives to switch sectors as a response to robots and AI, which could indicate discriminatory effects or a lack of important access to information and labor market institutions. When analyzing the effect of AI on internal migration, migrants are more likely to migrate inside Germany as a response to AI. This could be connected to suggestive evidence showing that migrants from non-AI-heavy sectors seem to move into AI-heavy sectors.

Our paper contributes to the literature studying the labor market effects of automation. Graetz and Michaels (2018) show that the adoption of industrial robots in 17 countries increased productivity and had no overall effect on employment, whereas it reduced the employment share of low-skilled workers. Acemoglu and Restrepo (2018), on the other hand, determine negative effects on employment and wages for the US. In Germany, robots displace workers in the manufacturing sector, but these effects are mitigated by parallel employment creation in the service sector (Dauth et al., 2019). In France, firms implementing robots experience productivity increases at the expense of non-adopting competitors, leading to negative employment effects (Acemoglu et al., 2020a). On the effect of AI, Acemoglu et al. (2020b) find that AI has not yet had any significant aggregate labor market effects, while Webb (2019) predicts decreased inequality through replacement effects on the high-skilled. In contrast to that, Felten et al. (2019) show that AI could exacerbate inequality as it leads to an increase in wages of high-skilled occupations. Finally, Alekseeva et al. (2021) document an increased skill demand of AI in the US and a wage premium for these jobs.

This paper is closely connected to four papers tying the topic of technological change to migration economics. Basso et al. (2020) study the effect of computerization on immigration. They show that newly arrived immigrants specialize in manual service occupations and immigrants attenuate job and wage polarization facing natives owing to computerization. Recent work by Hanson (2021) finds that foreign-born workers have accounted for more than half of the job growth in AI-related occupations since 2000. Hanson (2021) shows that an increase in the supply of high-skilled immigrants leads to an increase of AI in local labor markets. Work by Beerli et al. (2021) study the effect of ICT adoption in the local labor market on immigrant inflows to Switzerland. They show that a higher exposure to ICT leads to a significant inflow of high-skilled immigrants.

While we are interested in the effect of technological change on immigration and migrants, there are a number of papers that have looked at the reverse. For Germany, Danzer et al. (2020) study the effect of immigrant inflows on innovation, and find that it reduces innovation. This especially applies to industries with many low-skilled workers. Hunt and Gauthier-Loiselle (2010) find that immigrants patent at double the rate of natives, Peri and Sparber (2011) show that immigration influences the specialization of the native population and research by Lewis (2011) suggests that firms could see low skilled migrants and automation machinery as substitutes.

Our paper contributes to this literature by comparing the effects of two related technologies: manual and mental robots. To the best of our knowledge, we are the first to study the effect of industrial robots and AI on immigration flows as well as labor market outcomes of migrants versus natives. While a large number of papers have studied the effect of immigrants on innovation, there is very little evidence with respect to this direction of causality as well as the subgroup of automation technologies; such as AI and robotics. Additionally, we focus on an economy that is highly relevant to the underlying technology under investigation: Germany. Lastly, we apply a number of innovative and large-scale databases to answer our underlying research question.

Our findings have several important policy implications. Firstly, we find that industrial robots and AI increase the overall wage of natives, but decrease it for migrants. This means that policymakers should devote special attention to the migration population when designing mitigation policies in response to technological change; this could avoid further increases in inequality between migrants and natives. Next, our paper shows that, in the case of AI, the negative effects on migrants are completely driven by the least exposed sectors. When combining this evidence with the fact that there is an inflow of new migrants into these sectors, policymakers should revise the labor market conditions of these migrants. Next, migrants are less likely to switch sectors as a response to robots and AI. Therefore, policymakers should ensure that migrants have equal access to labor market institutions and information about the need to adapt their skill-set in response to technological change. Finally, our diverging effects of AI and robots show that it is not possible to generalize the impact of technological change and that differentiated analyses are needed to fully understand its impact. On a general note, our results speak against migrants and natives being skill-type perfect substitutes.

The paper is structured as follows. Section 2 provides descriptive statistics that provide an overview of recent trends in the technologies under consideration and describes the datasets used in this paper. Section 3 outlines our empirical strategy and section 4 presents our main results. Section 5 looks at the underlying mechanisms behind these results by restricting the analysis to different economic sectors and conducting panel-data analysis of individuals. Section 6 provides robustness checks and section 7 concludes.

2 Descriptive Statistics, Data Sources, and Theoretical Rationale

The following section provides an overview of recent trends in the adoption of robotics and AI as well as immigration, the datasets used in this paper, and finally the theoretical framework of the paper.

2.1 Recent Trends in Robotics and AI

Figure 1 shows the number of industrial robots installed worldwide over time. The picture shows that the speed with which we have adopted robots has increased over time. Similarly, Figure 2 plots the number of AI-related patents and scientific publications over time. Especially since 2014, both technologies have experienced strong increases.

Figure 1: Global operational stock of industrial robots over time

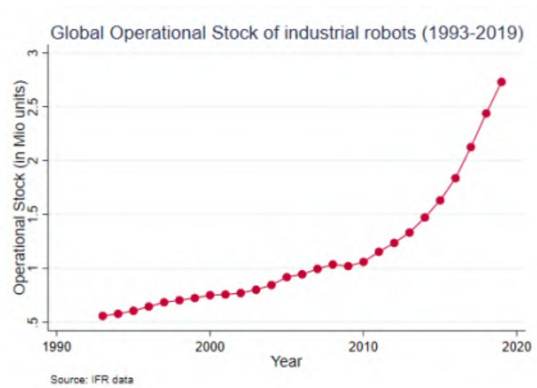
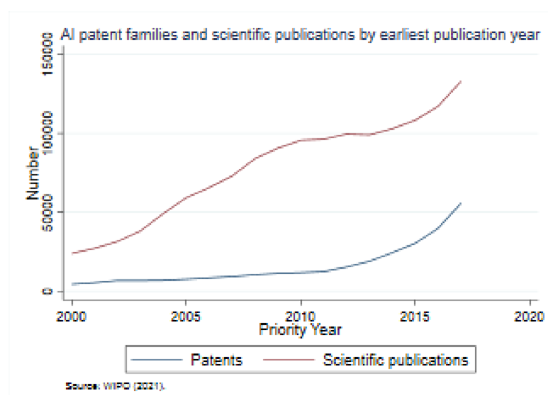


Figure 2: No. of AI-related patents and scientific publications over time



When analyzing robot adoption by region, Figure 3 shows that China is intensifying its implementation of industrial robots. While the growth rate of robot adoption between 2000 and 2019 was 234 percent in the US and 175 percent in Europe, it was over 84,000 percent in China, with 0.8 million industrial robots in 2019 (see Figure 3). Similarly, the number of AI-related patent applications has increased for the three economic players over time, with China catching up with the US by 2014 (see Figure 4). While the number of applications increased by 3.5 for the US and 2.9 for Europe, the number of AI-related patent applications in China in 2014 was more than 23 times the one observed for the year 2000.

This increase in the number of AI-related patents was associated with an increase in the demand of AI-related skills. The increase in absolute terms was greatest for Germany, followed by France (see Figure A11). Figure A13 plots the share of AI-related skill demand in the overall skill demand in selected European countries for the period 2014 to 2020. The overall share of AI-related skills is low with around 0.1 percent across all countries under consideration. Moreover, German-speaking countries report the highest share, together with the Netherlands. Switzerland is in the lead. When conducting the same

Figure 3: Global operational stock of industrial robots over time

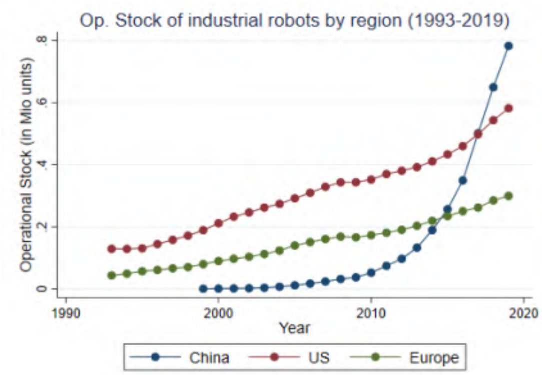
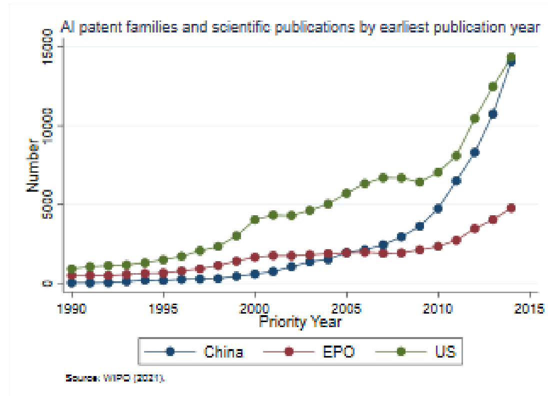


Figure 4: No. of AI-related patent applications over time



analysis for the share of OJV requiring at least one AI-related skill, the picture is similar, although the share is slightly higher, with around 0.4 percent in 2014 and 0.6 percent in 2020 for Germany.

Still, severe skill shortages are observed in the area of robotics and artificial intelligence. Metz (2017) note that Big Tech companies pay huge salaries for scarce AI talent. And a report by Anderson et al. (2020) concludes that Europe faces a dearth of AI talent. As an example, firms in Germany spent on average six months filling tech positions (Anderson et al., 2020). Additionally, the growth rates of robot adoption and AI was higher than the growth rates in ICT graduates. While robot adoption in Europe grew by 42 percent between 2014 and 2019, the number of ICT graduates grew by 26 percent, from 58,079 in 2014 to 72,942 in 2019 (see Figure A8). The number of graduates from Electronics and Automation, which also encompasses robotics, grew by even less. The number of graduates was 54,563 in 2015 and 58,837 in 2019, a growth of only eight percent.

2.2 Germany's Role in Automation

Germany is the fourth largest economy in the world when measured by GDP. Its industrial sector (including manufacturing) accounts for 26.5 percent of GDP in 2020 while the service sector constitutes for 63.3 percent and the primary sector for 0.7 percent of GDP in 2020 (The World Bank, 2021). Germany is the fourth largest manufacturing economy in the world and the country's manufacturing sector accounted for 18 percent of its GDP in 2020. It is the third largest exporter worldwide, after the US and China. Germany mainly exports motor vehicles, accounting for 15.5 percent of exports, followed by machinery (14.6 percent) and chemical products (9.3 percent) (Statistisches Bundesamt, 2021). Its main trading partners are China, the Netherlands and the US.

Along with the importance of the industrial sector for the German economy, there is a long history of automation. In fact, Germany is the most automated economy in Europe, when measured by industrial robots. Figure 5 shows that Germany is among the top five countries worldwide in terms of installed industrial robots. It is the major player among European countries, even when measuring the stock of industrial robots per employees (see Figure 6). In 2019 alone, Germany installed more than 22,000 industrial robots. In comparison, the US installed around 33,000 and China 139,859 industrial robots in the same year. Figure A7 shows that robot exposure is largest for the manufacturing sector.

Figure 5: Operational Stock of robots in 2019, Top 15 economies

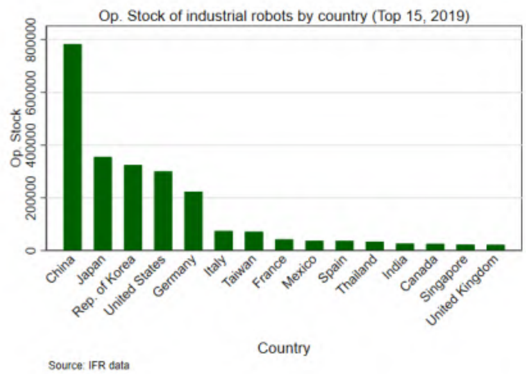
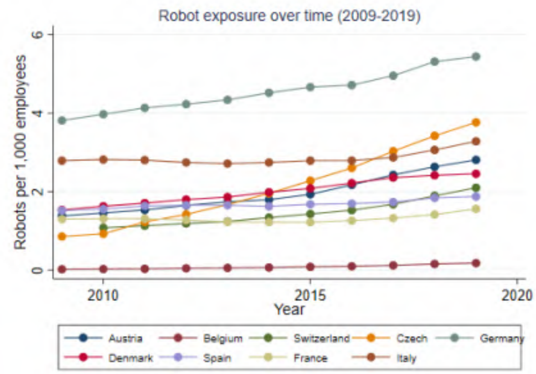


Figure 6: Operational Stock of robots (per 1,000 employees) over time in European countries



A similar picture emerges when analyzing Germany's role in the production of Artificial Intelligence. Figure 7 shows that Germany is among the Top 10 Artificial Intelligence producers in 2017, when measured by the number of patent filings (OECD, 2021). The country filed 400 AI patents in 2017, and was the largest player in the European market until 2016, when the UK caught up with Germany (see Figure 8). In comparison, the US filed 6,728 patents in 2017 and China 1,674.

Figure 7: AI Patent filings in 2017, Top 15 economies

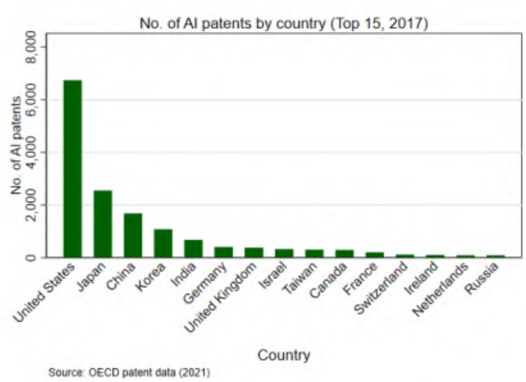
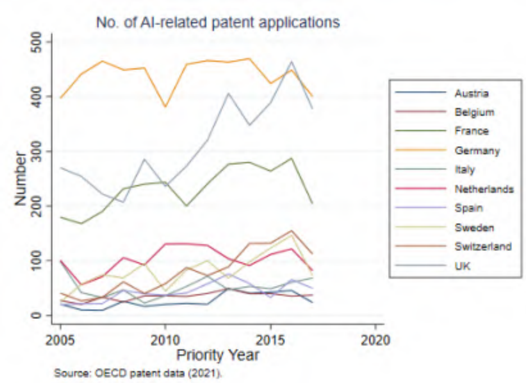


Figure 8: AI Patent Filings in European countries over time



2.3 Germany's Recent Trends in Migration

Germany is a migration recipient country and has been for many years. The annual influx of foreign-born citizens to Germany was over half a million between 2000 and 2013, and surpassed one million for the period 2013 to 2019. Figure A2 plots the immigrant inflow over time. At the same time, Germany has been subject to constant outflows of foreign-born citizens, but also native-born (see Figure A3 for details). For most years, the country's migration balance has been largely positive, with a balance fluctuating between 127,000 and 1.1 million since 2010. Germany has been the main migrant-receiving country among OECD countries, overtaking the US in 2012, in terms of yearly inflows (see Figure A4).

Figure 9: Immigrant Inflow by skill-group

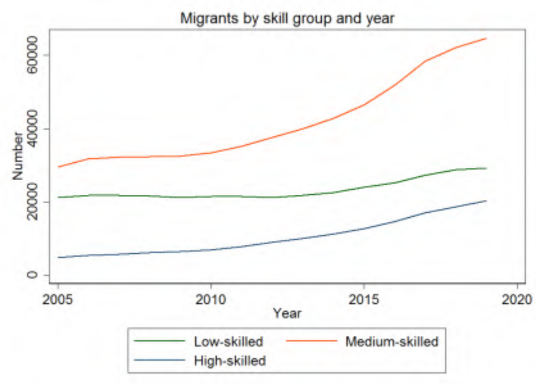
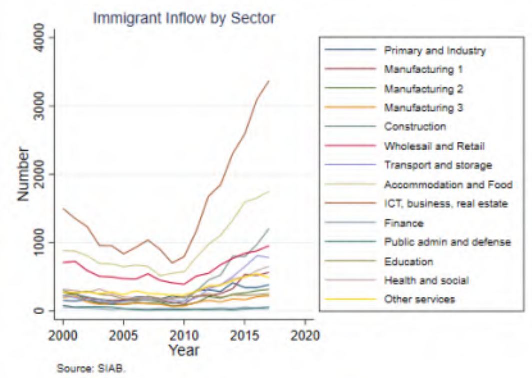


Figure 10: Immigrant Inflow by Sector



Note: The graphs shows the immigrant inflow by skill groups and economic sectors. We follow the IAB's definition of migrants, which is based on the citizenship. This means that a person is identified as a migrant as soon as they do not hold a German citizenship. The inflow is identified via the first observation of a foreigner in the SIAB data. The skill level is based on the imputed educational variable included in the SIAB. The low skilled have neither vocational training nor a university degree. The middle skilled have vocational training and the high skilled hold a degree from a university or university of applied science. The sector variable captures the economic activity in accordance with the WZ08 classification, grouped into 14 broad categories. The graph shows data from the SIAB, which is a 2 % sample of all individuals with an entry in the Integrated Employment Biographies (IEB).

Figure 9 plots the immigrant inflow to Germany over time by skill group. There has been a constant increase of immigrants for each of the skill-groups, but the increase has been largest for the medium-skilled. Moreover, when looking at the immigrant inflow by economic sector, Figure 10 shows that the inflow has been largest for the ICT and business services sector. The second largest increase of foreign-born is to the accommodation and food service sector. Importantly, the migrant share is above five percent for all sectors except the Financial Services Sector and the Public Administration and Defense sector (see Figure A6). The migrant share is greatest for the Accommodation and Food sector (nearly 30 percent), followed by the Construction and the ICT, Business and Real Estate as well as Transport and Storage sector (all above 15 percent).

2.4 Theoretical Rationale

This paper is based on different theoretical rationales. Firstly, we rely on insights from a model developed by Acemoglu and Restrepo (2018). They derive three effects of robotics. First of all, robots lead to a displacement effect. This displacement effect is based on a replacement of certain tasks traditionally performed by labor through technology. This means there is a contraction in the number of tasks, leading to downward pressure on wages. At the same time, there is a productivity effect. This productivity effect evolves due to expensive labor being substituted by cheaper capital. Firms thus increase their demand for labor in the tasks that are not yet automated, a so-called complementarity effect. The overall labor market effect of automated technologies depends on whether the productivity and complementarity effect outweighs the displacement effect. The same effects interact with each other when looking at Artificial Intelligence (Acemoglu et al., 2020b).

When applying this framework to the migrant and native population, one should consider additional theoretical rationales. First of all, similarly to robots and AI, migrants can substitute or complement native s (Battisti et al., 2018). An inflow of low-skilled migrants, for example, might complement native workers from a certain skill group (such as the high-skilled), but substitute those from the same skill group (such as the low-skilled native population). That is another rationale for this paper, as the question arises whether firms substitute cheap labor from abroad with cheap automated technologies. We would then expect to see a decline in the immigrant inflow in those skill-groups most affected by automated technologies investigated in this paper. Similarly, if automation leads to an inflow of complementing migrants, we might wonder if productivity effects on the unaffected native skill groups, which may arise due to technological change, are even greater. In addition, most OECD countries exhibit a wage gap between migrants and natives due to differences in labor productivity as well as outside options of natives (Battisti et al., 2018). We build upon this evidence by asking if these differences in labor productivity or outside options create a differing impact of technological change on migrants versus natives. Moreover, ex ante differences in labor productivity could increase through automation. We investigate these potential channels empirically in this paper.

Additionally, similarly educated migrants with different levels of experience might not be perfect substitutes for natives from the same skill group (Borjas, 2003). This is another rationale for our research question, as it motivates differentiation between migrants and natives when studying labor market effects of technological change. Moreover, migrants might be more willing to migrate internally than natives (Borjas, 2001), and thus mitigating the effects of technological change on natives. The greater willingness to migrate internally is because migrants already assumed the high fixed costs of migration in the past. We take this into account by looking at how technological change influences the probability of migrants and natives switching counties in each case 5).

2.5 Data Sets in Use

We make use of several different datasets in order to address the underlying research question. We measure technological change with two different datasets. Firstly, we make use of data provided by the Industrial Federation of Robotics on the installation and operational stock of industrial robots.[1] The data is available at the country-industry level and for the period 1994 to 2020. It reveals the number of newly installed industrial robots as well as the operational stock of already installed robots per year, country and industry. The data is available at one-digit industry codes for the non-manufacturing sectors and at the two or partly three-digit level for the manufacturing sector.

Next, we harness Online Job Vacancy data provided by Burning Glass. The data is available for ten European countries for the period 2014-2020.[2] For each job vacancy we have information about the NUTS-3-region the job add refers to, the respective economic sector (at the 2-digit-level), the occupation (at the 4-digit-level) as well as all skills mentioned in the job vacancy (at the ESCO-level-3). We also have the official description of each of these skills provided by the European Commission. Our analysis is based on a total number of 58,314,588 job vacancies in Germany for the period 2014 to 2020. Our analysis is based on a total number of 58,314,588 job vacancies in Germany for the period 2014 and 2020. The data covers virtually the entire spectrum of OJV in Germany, as it also extracts information from

[1] The IFR collects this data for a large number of countries using a survey of robot suppliers, covering more than 90 per cent of the world's robot market. The definition of a robot in this dataset is "automatically controlled, reprogrammable, and multipurpose machines" (IFR, 2016). This means that robots are machines that do not require a human operator and can be programmed to perform a variety of manual tasks.

[2] These countries are Austria, Belgium, Denmark, France, Germany, Luxemburg, the Netherlands, Norway, Sweden and Switzerland.

the country's public employment agencies.

Figure A10 shows that skill demand in Germany registered in OJV has doubled over time, from 31 million to 62 million. This could be due to economic growth but also to job adds being increasingly transferred the virtual space. It could also mean that jobs have become more complex over time and require a larger variety of skills. Figure A12 plots the number of OJV in Germany per year. While there has been a steady increase between 2015 and 2018, the number of online job adds fell below the level of 2018 in 2019 and 2020. This would mean that the observed increase in overall skill demand is not only as a result of economic growth. The number of AI-related skill demand registered in OJV increased by 130 percent between 2014 and 2020, from 26,381 to 59,968 (see Figure A11). The share of AI-related skill demand in all skill demand is therefore still extremely low at 0.1 percent in 2020.

We measure the labor market outcomes of immigrants and the native population in Germany using administrative individual-level spell data provided by the Institute for Employment Research (IAB) (Antoni et al., 2021). We use the Sample of Integrated Labor Market Biographies (SIAB). The SIAB is a two percent sample of the population of the Integrated Employment Biographies (IEB) of the IAB. The SIAB encompasses the employment histories of 1,940,69 individuals, and their employment biographies are documented in a total of 72,225,126 lines of data. Of these, 12.7 percent of observations (a total of 7.5 million data entries) are related to non-German nationalities.

The SIAB contains information on the following individuals: employees covered by social security (including marginal part-time employees from 1999 onwards), benefit recipients, job-seekers, as well as participants in active labor market policies. The SIAB covers all white-and blue-collar workers as well as apprentices as long as they are not exempt from social security contributions. This means that civil servants, self-employed persons and regular students are not recorded in the SIAB (Cramer, 1985). It comprises information on the following topics: the employee history, benefit recipient history, unemployment benefit recipient history, the job seeker history and information on participation in employment and training measures. We prepare the SIAB dataset closely following the methodology proposed by Dauth, Eppelsheimer, et al. (2020) in order to create a dataset in panel-format with annual observations per individual.

We follow the SIAB's definition of a migrant, which is based on the citizenship an individual holds in each year. We construct the immigrant inflow per year and county through aggregating the number of observations an immigrant is observed for the first time in the SIAB data. The skill level is based on the imputed educational variable included in the SIAB. The low skilled have neither vocational training nor a university degree. The middle skilled have vocational training and the high skilled hold a degree from a university or university of applied science. The sector variable captures the economic activity in accordance with the WZ08 classification, grouped into 14 broad categories.

We construct several control variables based on data from the SIAB as well as Eurostat and Comtrade. We control for basic labor market characteristics in our pre-treatment period 2004. More specifically, we control for the share of women, middle-skilled, high-skilled, those younger than 35 and aged 35-54, the share of part-time worker, as well as the share of workers in the manufacturing sector. We additionally control for a county's exposure to ICT as well as trade. The ICT and trade exposure variables are constructed via the shift-share instrument (see section 3 for the details). The original ICT variable is at the national-industry level and represents the value of computer software and databases in million Euros. The original trade variable is at the national-industry level and represents the trade value in Euros.

Table 1 provides an overview of the main variables considered in this paper.

Table 1: Descriptive table of main variables of interest

	N	Mean	Standard Dev.	Min	Max
Immigrant Inflow	402	290.709	550.7139	22	7968
Imm. Inflow (High-skilled)	402	51.24129	129.806	3	1972
Imm. Inflow (Medium-skilled)	402	151.0224	272.7884	9	4079
Imm. Inflow (Low-skilled)	402	84.68408	142.9582	4	1691
Immigrant Outflow	402	1.646766	4.148683	0	63
Imm. Outflow (High-skilled)	402	.2014925	.6600066	0	8
Imm. Outflow (Medium-skilled)	402	.9079602	2.519547	0	41
Imm. Outflow (Low-skilled)	402	.5149254	1.257804	0	12
Difference in unemployment rate (Non-migrant)	402	-.0246579	.0126249	-.069333	.00161
Difference in unemployment rate (Low-skilled non-migrant)	402	-.0327217	.0327294	-.1428571	.0433333
Difference in unemployment rate (Medium-skilled non-migrant)	402	-.0245083	.0131668	-.0795248	.0087214
Difference in unemployment rate (High-skilled non-migrant)	402	-.0133969	.0207048	-.0967742	.0454545
Difference in unemployment rate (Migrant)	401	-.0402964	.0622387	-.452381	.0833333
Difference in unemployment rate (Low-skilled migrant)	402	-.003102	.0139268	-.0707402	.0625
Difference in unemployment rate (Medium-skilled migrant)	402	-.0006246	.0026019	-.0116141	.0061892
Difference in unemployment rate (High-skilled migrant)	402	.0006686	.0063288	-.05	.0280374
Pct. change in daily wage	403	10.11622	6.448483	-28.50497	34.87538
Pct. change in migrant daily wage	402	8.047142	42.20394	-81.21874	355.6371
Pct. change in non-migrant daily wage	403	11.94946	6.314409	-9.346504	37.33421
Pct. change in income	403	30.54663	6.846435	-13.90737	68.47502
Pct. change in migrant income	402	29.59618	48.17743	-63.13544	423.708
Pct. change in non-migrant income	403	32.48462	6.557794	9.162827	74.25886
Pct. change in yearly labor earnings (Non-migrants)	403	14.33619	10.61179	-23.03249	182.5034
Pct. change in yearly labor earnings (Low-skilled migrants)	382	25.71007	100.3223	-84.53728	1167.658
Pct. change in yearly labor earnings (Medium-skilled migrants)	396	24.2519	312.5652	-66.54087	6088.281
Pct. change in yearly labor earnings (High-skilled migrants)	341	26.298	163.2595	-87.15948	2003.878
Pct. change in yearly labor earnings (Low-skilled non-migrants)	402	19.43951	26.63032	-32.07589	265.8091
Pct. change in yearly labor earnings (Medium-skilled non-migrants)	403	9.218668	9.774381	-63.04432	154.1482
Pct. change in yearly labor earnings (High-skilled non-migrants)	402	2.746858	16.93573	-31.21652	197.6927
Share of women 2004	402	.489217	.0394597	.3231241	.5844898
Share of medium-skilled 2004	402	.7496725	.0464956	.5925203	.8546042
Share of high-skilled 2004	402	.0953953	.0421964	.0263158	.2666236
Share of aged <35 in 2004	402	.3203929	.0307194	.21625	.4124424
Share of aged 35-54 in 2004	402	.5377275	.0303162	.4237918	.65875
Share of part-time 2004	402	.3055813	.0438054	.1544594	.479564
Share in manufacturing 2004	402	.2445977	.1030258	.0246305	.6248705
Share in ICT 2004	402	.0200683	.0184462	0	.1317073
ICT exposure	403	.0190358	.0025622	0	.0351929
Trade exposure	403	1862496	664482.9	0	5193728
No. of people	403	66891.47	154184.4	333	2688145
Employed (weighted)	402	1294.26	1640.083	226.5	19628.5
Robot exposure (Op. Stock)	403	.320462	2.849223	.0025944	57.1441
Robot exposure IV (Op. Stock)	403	.4650611	1.444664	-25.47161	8.558339
Observations	403				

Notes: The table shows the summary statistics of the underlying dataset at the county (NUTS-3) level for the period 2005-2018, as well as for the year 2004 (the pre-treatment period) in the case of control variables. We follow the IAB's definition of migrants, which is based on the citizenship. This means that a person is identified as a migrant as soon as they do not hold a German citizenship. The inflow is identified via the first observation of a foreigner in the SIAB data. The skill level is based on the imputed educational variable included in the SIAB. The low skilled have neither vocational training nor a university degree. The middle skilled have vocational training and the high skilled hold a degree from a university or university of applied science. The sector variable captures the economic activity in accordance with the WZ08 classification, grouped into 14 broad categories. The shares refer to the respective shares in the overall SIAB population. The ICT, trade, and robot exposure variables are constructed via the shift-share instrument (see section 3 for the details). The original ICT variable is at the national-industry level and represents the value of computer software and databases in million Euros. The original robots variable is at the national-industry level and represents the number of industrial robots installed. The original trade variable is at the national-industry level and represents the trade value in Euros. Source: SIAB, Eurostat, Comtrade and IFR data.

3 Empirical Strategy

3.1 The Effect of Industrial Robots

We analyze the effect of robot exposure at the level of local labor markets. We therefore aggregate our SIAB data at the county level. We consider the period of 2005 to 2018 due to data availability. To estimate the effect of robot adoption on immigration demand as well as labor market outcomes of migrants versus natives, we follow the approach by Acemoglu and Restrepo (2018) and apply a shift-share instrument. Simply analyzing the impact of an increased exposure to robots through linear regressions could bias our estimates, as locations with more exposure to robots might systematically differ on unobservable characteristics from those with less exposure to robots.

An additional challenge is that the data provided by the IFR on robot adoption is only reported at the national level. As a result, we apply a shift-share instrument to proxy robot exposure at the local level r through industry shares in each county, similar to Dauth, Eppelsheimer, et al. (2020). This means that we construct our main explanatory variable as follows:

$$\Delta \hat{\text{robots}}_r = \sum_{i \in I} \frac{\text{emp}_{ir}}{\text{emp}_r} \times \frac{\Delta \text{robots}_i}{\text{emp}_i} \text{ , with I=28} \tag{1}$$

The term $\frac{\Delta \text{robots}_i}{\text{emp}_i}$ is the difference in robot counts in a respective industry between 2018 and 2005 over employment in the respective industry in 2004. This means that we first calculate the difference in the robotic operational stock between 2018 and 2005 for each industry. We then divide this number by the number of employed people in each industry in 2004. As the robotics data is only available at the national level, we proxy the county level exposure to robotics via the employment share of each respective industry in each region in 2004 ($\frac{\text{emp}_{ir}}{\text{emp}_r}$). emp_{ir} is the number of employed people in region r in industry i in our base year in 2004. emp_r is the number of employed people in region r in our base year in 2004. We then multiply the resulting scaled difference in robot counts by the share of people employed in a particular industry in a certain county in the base year 2004. We fix industry shares to the pre-treatment period by convention (Goldsmith-Pinkham et al., 2020).

We follow Dauth, Eppelsheimer, et al. (2020) and conduct the following regression:

$$\Delta Y_r = \alpha X_r' + \beta_1 \times \Delta \hat{\text{robots}}_r + \beta_2 \times \Delta \hat{\text{trade}}_r + \beta_3 \times \Delta \hat{\text{ICT}}_r + \varphi_{REGr} + \epsilon_r \tag{2}$$

We regress our outcome variable of interest on the change of robot exposure. This means that we follow a differential exposure design. We control for demographic characteristics at the county-level in 2004 (the female share, the overall share of different skill-groups and the share of workers belonging to different age groups). We also control for regional dummies at the Federal State (NUTS-1) level and cluster our standard errors at geographic level of our analysis (the NUTS-3 level). We additionally control for the difference in ICT equipment as well as trade exposure at the local labor market. We weight our regression by the number of people observed in each local labor market.

Our identification strategy relies on the assumption that robot exposure at industry level is exogenous and not correlated with labor demand. However, the adoption of robotics could be subject to domestic industry-specific demand shocks. To address this endogeneity concern we conduct an instrumental variable strategy; this closely follows the methodology proposed by Acemoglu and Restrepo (2018). We use robot installations from Japan, South Korea and Taiwan as our instrumental variables. We select these countries as they are non-European and therefore not subject to the same unobservable shocks to migration as European counterparts would be. Additionally, they are major players in robotics worldwide. All three countries were among the ten countries with the largest number of robot installations in 2018. Figure A14 demonstrates the robot exposure per 1,000 employees over time in all three countries compared to Germany. South Korea has been outperforming Germany in its robot adoption since 2009, while Taiwan outperformed it in 2013 and Japan in 2015. All countries are therefore a good option as they lead in robot adoption. Additionally, by combining three different countries, the empirical strategy becomes more robust to individual country-level shocks. Table 2 shows the first-stage results at the industry level. For the first stage, we simply regress robot adoption, meaning the difference in the operational stock of robots during the period under consideration, at the industry-level in Germany on robot adoption at industry-level in our three instrument countries. The coefficient is positive and significant and the F-statistic is well above ten.

Table 2: First-stage: Difference in robot counts by industry

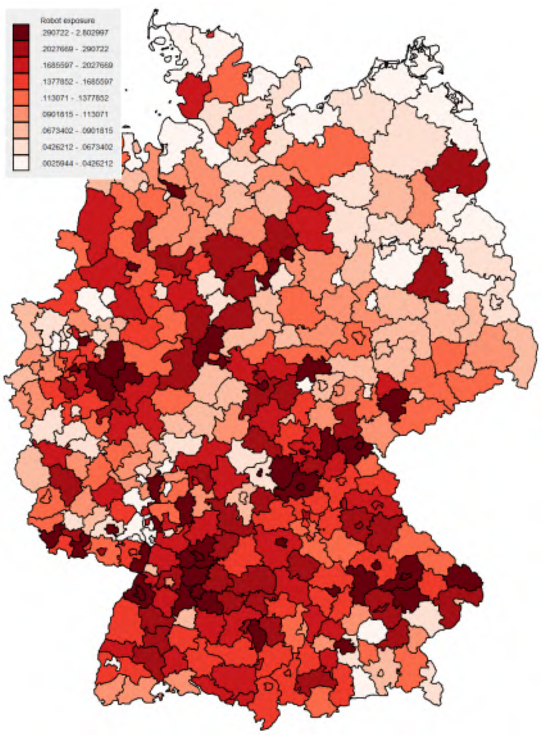
	Robot exposure (DE)
Difference in robot count (KR, JP, TW)	0.223***
	(0.0335)
Constant	1303.9
	(1725.4)
Adj. R-squared	0.548
F-statistic	44.43
N	34

Notes: The table shows the first stage results using robot adoption in Korea (KR), Japan (JP), and Taiwan (TW) as an instrument for robot adoption in Germany (DE). We define robot adoption as the difference in the number of installed robots between 2005 and 2018. The unit of observation is the sector level. We use the IFR classification of sectors, which is close to the ISIC Rev4 sector classification. These classification can be matched to the SIAB sector classification via crosswalks. This results in a number of observations of 34. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

We consider several outcome variables of interest: the cumulative immigrant inflow and outflow between 2005 and 2018, the percentage change in migrant share for this same period, the percentage change in unemployment rate as well as the percentage change in migrants' and natives' daily wages. We conduct our analysis for the population as a whole, but also for three different skill groups: the high-, medium- and low-skilled workers. In the case of daily wages and unemployment, we restrict our data to the migrant and native level and include an interaction term in order to analyze if the effect of robotics differs by nationality.

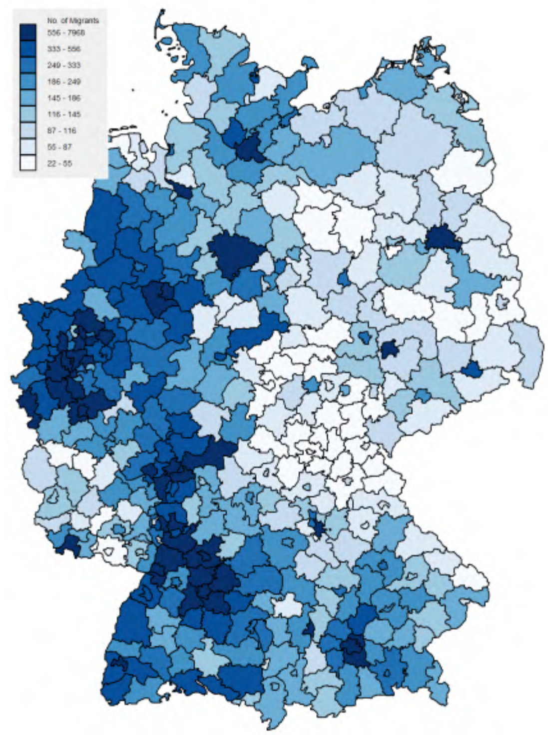
Figure 11 maps the robot exposure for the period 2005 to 2018 at county level. While certain counties report high exposure to robots, others have implemented very little robots over time in relation to their employed population. The overall cumulative immigration inflow over time also varies greatly, as documented in Figure 12. The Western and Southern regions of Germany report a higher immigrant inflow than Eastern parts of the country.

Figure 11: Robot exposure by county (2005 to 2018)



Notes: The map shows the counties' exposure to industrial robots. We proxy robot exposure by employing the Bartik instrument. This means that we first take the difference of the operational stock of industrial robots in a respective industry between 2005 and 2018. We then multiply this difference by the sectoral employment shares in each county in 2004. Darker shaded areas indicate a greater exposure to robot adoption, while lighter areas indicate a lower exposure. Source: SIAB data.

Figure 12: Cumulative immigrant inflow by county (2005 to 2018)



Notes: The map shows the cumulative immigrant inflow into a county during the period 2005 and 2018. We identify the immigrant inflow by aggregating the number of times a migrant appears for the first time in the SIAB per year. Darker areas indicate a larger exposure to immigrant inflows, while lighter areas indicate a lower exposure. Source: SIAB data.

3.2 The Effect of Artificial Intelligence

To measure the effect of artificial intelligence on migration flows and labor market outcomes of migrants versus natives, we construct a variable equal to a local labor market's demand for AI-related skills. We conduct a keyword search on terms relevant to AI to detect all online job vacancies demanding AI-related skills in the Burning Glass dataset described above. We rely on keywords defined by Acemoglu et al. (2020b) and Chiarello et al. (2021).[3] As soon as one of these keywords forms part of an ESCO-skill or its description, we assign it a value of one. We then calculate the share of these skills within all skill demand in a local labor market.

We face similar endogeneity concerns as in the case of robots and thus apply an instrumental variable strategy. In the case of AI, we instrument the AI-related skill demand in Germany with the one in Switzerland. We choose Switzerland as it is the only country among the ten countries, for which data is available in Europe for 2014 to 2020, and which is neither part of the European Union nor the European Economic Area. Switzerland therefore follows its own migration policies, at least regarding migration from outside the European Union. Additionally, Switzerland is among the ten leading countries in Artificial Intelligence worldwide, according to the Nature Index, 2021. Figure A15 shows the share of AI-related skill demand over time in both countries. From the figure it becomes clear that Switzerland has a higher share of AI-related skill demand than Germany. We again exploit the local industry structure of labor markets and construct our shift-share instrument as detailed below:

$$\mathrm{A\hat{I}}_{rj} = \sum_{i \in I} \frac{\mathrm{emp}_{irj}}{\mathrm{emp}_{rj}} \times AI_{ij} \text{ , with I=86} \tag{3}$$

where emp_{irj} is the number of employees in industry I, labor market r and year j. emp_{rj} is the number of employees in labor market r and year j, AI_{ij} is the share of AI-related skill demand in all skill demand for industry i and year j. Unlike our analysis for industrial robots we conduct our analysis at the yearly level as the application of AI technologies is more of a recent phenomenon and we are interested in the short-term effects.[4] We run the following regression:

$$Y_{rj} = \alpha X'_{rj} + \beta_1 \times \mathrm{A\hat{I}}_{rj} + \beta_2 \times \widehat{\mathrm{trade}}_{rj} + \varphi_{REGrj} + \epsilon_r \tag{4}$$

We control for the same variables as in the case of robots, but do not consider the adoption of ICT technologies. We consider the same outcome variables as in the case of robots, but rather than looking at changes over time, we estimate the effect on yearly values of immigrant inflow and outflow, migrant share, unemployment rate and daily wage. Table 3 shows the first-stage results. The coefficient is positive and significant and the F-statistic is over ten.

Figure 13 shows the difference in the share of AI-related skill demand. While some counties report negative growth rates, others have experienced a difference in the share of AI-related skill demand of up to 0.003.

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[3] These terms are Artificial Intelligence, Machine Learning, Decision Support System, Speech Recognition, Natural Language Processing, Computational Linguistics, Speech Recognition, Virtual Machine, Deep Learning, Biometrics, Neural Networks, Computer Vision, Machine Vision, Virtual Agents, Image Recognition, Data Mining, Pattern Recognition, Object Recognition, AI ChatBot, Text Mining, Support Vector Machines, Unsupervised Learning, Image Processing, Mahout, Recommender Systems, SVM, Random Forests, Latent Semantic Analysis, Sentiment Analysis, Opinion Mining, Latent Dirichlet Allocation, Predictive Models, Kernel Methods, Keras, Gradient boosting, OpenCV, Xgboost, Libsvm, Word2Vec, Chatbot, Machine Translation, Sentiment Classification.

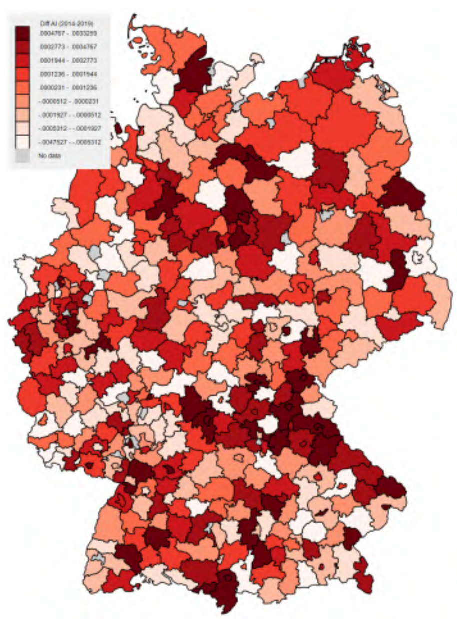
[4] This is also due to data constraints as job vacancy data is only available for recent years for Germany and Switzerland.

Table 3: First-stage: Exposure to AI-related skill demands by sector

	Germany
AI-related skill demands (Switzerland)	0.194^{***}
	(0.0423)
Adj. R-squared	0.0629
F-statistic	21.10
N	711

Notes: The table shows the first stage results using AI-related skill demand in Switzerland for AI-related skill demand in Germany. The unit of observation is the year-sector level. We consider economic sectors at the ESCO 2-digit level. This results in a number of observations of 711. We define the AI-related skill demand as the share of job vacancies mentioning the keywords identifying AI. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Source: BGD (2014-2020).

Figure 13: Difference in the share of AI-related skill demand at the county level (2014 to 2019)



Notes: The map shows the difference in the demand for AI-related skills between 2014 and 2019 in a respective county. We define the AI-related skill demand as the share of job vacancies mentioning the keywords identifying AI. The unit of analysis is the county level. Darker colors indicate that there has been an increase in the demand for AI-related skills, while brighter colors indicate that there has been a decrease in the demand for AI-related skills. Source: Burning Glass Data (2014-2019).

4 Results

In the following we present our results. We first focus on the impact of industrial robots and then investigate the effect of AI. For each technology, we first report our findings on immigrant inflows. Second, we show results for labor market outcomes of migrants and natives. Lastly, we investigate if our overall results are driven by the most or least exposed sectors.

4.1 Industrial Robots

Table 4 reports the results for the impact of robot exposure on immigrant inflows. We first present the coefficients from running simple linear regressions, and then the ones from our instrumental variable specification. We first show the results for all immigrants and then for high-, middle- and low-skilled immigrants.

The table makes clear that an increase in robot exposure does not lead to a significant increase in immigrant inflows at the county level. This is the case for all skill groups. Repeating these regressions using the difference in the migrant share at the county level as an outcome variable confirms our results (see Table to A4). This could mean that the installment of industrial robots does not lead to skill shortage, which firms cover by recruiting these skills from abroad.

We next investigate if robot adoption affects migrants who are already in Germany differently from natives on different labor market outcomes. To do so, we interact the robot adoption in a respective county with a dummy variable which is equal to one if the outcome variable refers to the migrant population, and zero otherwise. Table 5 shows that robot adoption significantly decreases the unemployment rate of medium-skilled migrants when running simple linear regression (see Column 5). The observed decrease in the unemployment rate of medium-skilled migrants could be explained by skill complementarities of technological change. This means that the adoption of robots creates the need for new tasks, such as their supervision or operation. Our results suggest that this task creation has positive effects on medium-skilled migrants' employment share. Still, the effect becomes insignificant when applying the shift-share instrument (see Column 6). The largely insignificant overall effects on unemployment in Germany are in line with findings by Dauth, Eppelsheimer, et al. (2020).

If robot adoption adversely affects the employment outcomes of migrants - instead of becoming unemployed - they could also leave the country. This is why we, in addition, analyze the impact of robots on migrant outflows. We do not find any evidence in favor of robots leading to a significant migrant outflow (see Table A3).

Table 6 shows that robots have adverse effects on the wage of the employed migrant population. the table shows that, while robot adoption increases the wage of natives from all skill-groups, it decreases it for migrants of all skill-groups. The literature shows that robots can increase labor productivity (see Graetz and Michaels, 2018 or Acemoglu and Restrepo, 2018). This might explain the observed wage increase for natives. Our results suggest that migrants, on the other hand, do not benefit from those. There could be several reasons for that. Firstly, migrants could have less access to information about the need to adapt their skill-set as a response to technological change. This could be due to language barriers, less access to local networks, or discriminatory structures. Work by Martén et al. (2019), for example, demonstrates the importance of social networks for integrating refugees into the economy. And Lochmann et al. (2019) provide evidence of the positive effect of language training on labor force participation. Others have shown that there are discriminatory effects in job applications as a response to headscarves, for example (Weichselbaumer, 2016). These discriminatory effects could worsen the adverse effects of robots on migrants.

Additionally, even without considering technological change, scholars have shown that immigrants are subject to downskilling, also in Germany (Elsner and Zimmermann, 2016). Technological change could worsen this trend. Moreover, firms might consider migrants as cheap alternatives to local labor costs (Walia, 2010). The same applies to robots. The increasing adoption of robots could then lead to increased competition between migrants and robots. This might be another explanation of the observed decrease in wages for migrants due to robotics.

Table 4: Robot exposure and perc. change in immigrant inflow by skill-groups at the county-year-level (2005-2018)

	All (OLS)	All (IV)	High-skilled(OLS)	High-skilled (IV)	Medium-skilled (OLS)	Medium-skilled (IV)	Low-skilled (OLS)	Low-skilled (IV)
Robot exposure (Op. Stock)	-10.33	-1763.7	-4.658	-464.1	-9.533	-732.4	4.008	-550.8
	(204.0)	(1749.4)	(46.73)	(445.8)	(91.33)	(728.8)	(64.67)	(559.0)
Constant	10864.1*	6262.0	2235.8	1029.9	4954.5*	3057.1	3582.5*	2126.4
	(5099.8)	(4394.7)	(1263.5)	(1083.3)	(2204.4)	(1923.2)	(1598.8)	(1372.6)
Federal States fixed-effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.908	0.873	0.915	0.876	0.924	0.900	0.842	0.779
N	401	401	401	401	401	401	401	401

Notes: Robot exposure (Op. Stock) is the exposure of a county to industrial robots measured via the shift share instrument. The unit of observation is the county (NUTS-3). The immigrant inflow is the cumulative immigrant inflow into a respective county during the period 2005 and 2018. We identify the immigrant inflow by aggregating the number of times a migrant appears for the first time in the SIAB per year. The skill level is based on the imputed educational variable included in the SIAB. The low skilled have neither vocational training nor a university degree. The middle skilled have vocational training and the high skilled hold a degree from a university or university of applied science. Standard errors are in parentheses and clustered at the nuts-3 level. We control for the following variables: The share of women in the SIAB population and county, the share of young- and middle-aged workers, the share of part-time workers, the share of middle- and high-skilled workers, the share of workers in the manufacturing sector, in the information and communication sector. We also create a shift-share instrument for a county's exposure to information and communication technology as well as trade, using data from EUROSTAT as well as COMTRADE. We control for federal states (NUTS-1) fixed effects. We weight each cell by the respective population in a county. Source: IFR Robotics data and SIAB data. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 5: Robot exposure and perc. change in unemployment rate at the county-year-level

	All (OLS)	All (IV)	High-skilled(OLS)	High-skilled (IV)	Medium-skilled (OLS)	Medium-skilled (IV)	Low-skilled (OLS)	Low-skilled (IV)
Migrant	-1.483	-1.438	31.59	39.21	47.08***	48.75***	12.20	11.92
	(2.107)	(2.744)	(19.98)	(25.94)	(6.540)	(8.175)	(6.333)	(7.336)
Robot exposure (Op. Stock)	0.132	9.387	2.194	-68.93	-13.48	-20.81	16.41	-10.15
	(4.298)	(12.47)	(22.30)	(100.6)	(11.11)	(35.36)	(13.27)	(32.66)
Migrant*Robots	-6.360	-6.523	36.90	-14.17	-25.74**	-34.68	-26.06	-25.51
	(4.170)	(9.843)	(71.75)	(74.68)	(9.789)	(21.44)	(21.75)	(34.66)
Constant	74.75	100.0	126.8	30.67	-191.1	-223.6	693.9**	636.3**
	(81.55)	(86.02)	(304.6)	(306.5)	(249.2)	(285.1)	(212.2)	(228.2)
Federal States fixed-effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.107	0.102	0.179	0.154	0.164	0.162	0.0906	0.0838
N	727	727	431	431	688	688	642	642

Notes: Robot exposure (Op. Stock) is the exposure of a county to industrial robots measured via the shift share instrument. The unit of observation is the county-migrant combination. This means that there are two lines of data for each county, one showing the average change in the unemployment rate for migrants in the manufacturing sector in a respective county during the period 2005 and 2018, and the other one showing the average change in the unemployment rate for natives in the manufacturing sector. The skill level is based on the imputed educational variable included in the SIAB. The low skilled have neither vocational training nor a university degree. The middle skilled have vocational training and the high skilled hold a degree from a university or university of applied science. Standard errors are in parentheses and clustered at the NUTS-3 level. We control for the following variables: The share of women in the SIAB population and county, the share of young- and middle-aged workers, the share of part-time workers, the share of middle- and high-skilled workers, the share of workers in the manufacturing sector, in the information and communication sector. We also create a shift-share instrument for a county's exposure to information and communication technology as well as trade, using data from EUROSTAT as well as COMTRADE. We control for federal states (NUTS-1) fixed effects. We weight each cell by the respective population in a county. Source: IFR Robotics data and SIAB data. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

To shed some more light on the above research questions, we divide our analysis into sectors (see Annex A1.2). We look at the manufacturing and service sectors, as well as all the aggregate of all other sectors not belonging to these two sectors. We are especially interested in the dynamics taking place in the manufacturing sector, as this is the most exposed sector.

Table 7 shows the results for the migrant share in the manufacturing sector. We find that robot adoption results in a decrease in the migrant share of medium-skilled migrants in the manufacturing sector. This could be evidence of medium-skilled migrants from the manufacturing sector switching to other sectors due to otherwise negative effects from robot adoption. It could also be due to migrants leaving Germany. To investigate this possibility, we analyze the impact of robot adoption on immigrant outflows. Table A11 shows that there is no evidence in favor of this mechanism. While the coefficient on middle-skilled migrants is significant and positive (Column 5), it becomes insignificant when employing

Table 6: Robot exposure and perc. change in daily wage by skill-level at the county-year-level

	High-skilled(OLS)	High-skilled (IV)	Medium-skilled (OLS)	Medium-skilled (IV)	Low-skilled (OLS)	Low-skilled (IV)
Migrant	10.76	13.72*	-0.631	0.283	7.477	11.75*
	(5.902)	(5.749)	(3.117)	(3.633)	(4.178)	(5.568)
Robot exposure (Op. Stock)	8.955	-1.821	12.73**	9.490*	22.62***	12.79
	(7.758)	(11.70)	(4.666)	(4.816)	(5.780)	(7.307)
Migrant*Robots	-21.29**	-41.31*	-17.15**	-22.10*	-27.89***	-50.72**
	(6.894)	(16.66)	(5.285)	(10.84)	(6.812)	(17.53)
Constant	22.81	15.16	6.377	-0.118	-239.1	5.384
	(216.3)	(15.63)	(97.33)	(3.075)	(171.6)	(4.797)
Federal States fixed-effect	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.0569	0.0198	0.0961	0.0897	0.253	0.235
N	741	741	796	796	782	782

Notes: Robot exposure (Op. Stock) is the exposure of a county to industrial robots measured via the shift share instrument. The unit of observation is the county-migrant combination. This means that there are two lines of data for each county, one showing the average percentage change of daily wages for migrants in a respective county during the period 2005 and 2018, and the other one showing the average percentage change of daily wages for natives. The skill level is based on the imputed educational variable included in the SIAB. The low skilled have neither vocational training nor a university degree. The middle skilled have vocational training and the high skilled hold a degree from a university or university of applied science. Standard errors are in parentheses and clustered at the nuts-3 level. We control for the following variables: The share of women in the SIAB population and county, the share of young- and middle-aged workers, the share of part-time workers, the share of middle- and high-skilled workers, the share of workers in the manufacturing sector, in the information and communication sector. We also create a shift-share instrument for a county's exposure to information and communication technology as well as trade, using data from EUROSTAT as well as COMTRADE. We control for federal states (NUTS-1) fixed effects. We weight each cell by the respective population in a county. Source: IFR Robotics data and SIAB data. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

our instrumental variable strategy. In addition, we find that robot adoption has no significant effects on employees' employment or wages in the manufacturing sector (see Table A12 and Table A13).

There are no significant effects on employment outcomes in the service sector Moreover, we do not find any significant effects on outcomes in the aggregate of all other sectors (see Table A14 to A18). This could be due to employees moving between different economic sectors as a response to robots. These movements could then mitigate otherwise negative effects. Furthermore, robot adoption does also not seem to influence immigrant inflows into or outflows from the service sector or the aggregate of all other sectors.

Table 7: Robot exposure and perc. change in migrant share (manufacturing) by skill-groups at the county-year-level

	All (OLS)	All (IV)	High-skilled(OLS)	High-skilled (IV)	Medium-skilled (OLS)	Medium-skilled (IV)	Low-skilled (OLS)	Low-skilled (IV)
Robot exposure (Op. Stock)	-59.52**	-94.89	-61.44	25.86	-52.91**	-35.71*	-50.35	-22.46
	(21.78)	(72.10)	(34.68)	(44.10)	(18.07)	(16.04)	(39.18)	(24.94)
Constant	-1079.1	-1230.6	-70.70	-30.74	-171.4	26.52	-816.4	66.90
	(549.1)	(725.4)	(862.4)	(23.58)	(395.3)	(27.09)	(590.4)	(51.22)
Federal States fixed-effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.416	0.414	0.179	0.146	0.414	0.342	0.156	0.0736
N	367	367	210	210	342	342	311	311

Notes: Robot exposure (Op. Stock) is the exposure of a county to industrial robots measured via the shift share instrument. The unit of observation is the county. The outcome variable is the change in the migrant share in the manufacturing sector of a respective county. The migrant share is defined as the number of migrants over the total SIAB population in the manufacturing sector in a respective county. The skill level is based on the imputed educational variable included in the SIAB. The low skilled have neither vocational training nor a university degree. The middle skilled have vocational training and the high skilled hold a degree from a university or university of applied science. Standard errors are in parentheses and clustered at the NUTS-3 level. We control for the following variables: The share of women in the SIAB population and county, the share of young- and middle-aged workers, the share of part-time workers, the share of middle- and high-skilled workers, the share of workers in the manufacturing sector, in the information and communication sector. We also create a shift-share instrument for a county's exposure to information and communication technology as well as trade, using data from EUROSTAT as well as COMTRADE. We control for federal states (NUTS-1) fixed effects. We weight each cell by the respective population in a county. Source: IFR Robotics data and SIAB data. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Lastly, in order to study the implications of robots on sector employment, we analyze the impact of robot exposure on the percentage change in the number of employed in the three sectors under consideration in this paper. Table 8 shows the results. Robots lead to a negative percentage change in the number of employed over time, which is more pronounced for migrants than for natives.

Table 8: Robot exposure and perc. change in the number of employed by economic sector at the county-year-level

	Manu (OLS)	Manu (IV)	Service (OLS)	Service (IV)	All other (OLS)	All other (IV)
Migrant	115.6***	129.0***	217.3***	227.6***	288.8***	298.9***
	(21.07)	(27.85)	(18.63)	(23.07)	(21.63)	(30.78)
Robot exposure (Op. Stock)	8.464	-70.10	26.39	49.27	-33.10	50.33
	(20.88)	(79.75)	(22.35)	(78.86)	(28.09)	(111.3)
Migrant*Robots	-92.25**	-164.5*	-2.511	-58.75	-68.80	-123.8
	(33.60)	(75.87)	(54.31)	(74.66)	(55.58)	(134.0)
Constant	-1172.7	-1483.2	-1070.3**	-1088.7**	-1334.0	-1190.0
	(640.2)	(847.3)	(372.7)	(418.7)	(707.5)	(778.4)
Federal States fixed-effect	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.248	0.234	0.421	0.420	0.365	0.363
N	765	765	798	798	743	743

Notes: Robot exposure (Op. Stock) is the exposure of a county to industrial robots measured via the shift share instrument. The unit of observation is the county-migrant combination. This means that there are two lines of data for each county, one showing the average percentage change of the number of employed migrants in a respective county during the period 2005 and 2018, and the other one showing the average percentage change of the number of employed natives. The skill level is based on the imputed educational variable included in the SIAB. The low skilled have neither vocational training nor a university degree. The middle skilled have vocational training and the high skilled hold a degree from a university or university of applied science. Standard errors are in parentheses and clustered at the nuts-3 level. We control for the following variables: The share of women in the SIAB population and county, the share of young- and middle-aged workers, the share of part-time workers, the share of middle- and high-skilled workers, the share of workers in the manufacturing sector, in the information and communication sector. We also create a shift-share instrument for a county's exposure to information and communication technology as well as trade, using data from EUROSTAT as well as COMTRADE. We control for federal states (NUTS-1) fixed effects. We weight each cell by the respective population in a county. Source: IFR Robotics data and SIAB data. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

4.2 Artificial Intelligence

In the case of artificial intelligence, we identify a significant and positive impact on immigrant inflows (see Table 9). This could point towards skill shortages arising from artificial intelligence and firms covering them from abroad. Surprisingly, the effect of AI on immigration flows is positive across all skill groups. In terms of labor market effects, we determine a positive impact on the unemployment rate of migrants across all skill groups (see Table 10). This is not the case for the native population. Additionally, it decreases the wage of migrants across the board, but not natives (see Table 11). In fact, AI increases natives' wages. This deviates from findings from the US, where AI did not lead to any aggregated labor market effects (Acemoglu et al., 2020b). This could be due to the different time period under consideration, the different industry structure of the German economy, or due to the German welfare system and rigid labor market institutions, which might protect a large share of the population against negative effects of AI. In fact, others have explained the differing results of robot adoption on labor market outcomes observed between the US and Europe through these factors (Chiacchio et al., 2018).

Our results testify to the productivity and complementarity effects for natives, from which migrants do not benefit. They might compete with AI technologies, while natives might complement and benefit from them. Similar to our rational for industrial robots, it could also be evidence of migrants having less access to labor market institutions, networks and information about the role of AI. AI-related skill demand has significant effects on the inflow of low-, medium- and high-skilled migrants, too (see Table 9 to A21). This is in line with previous research, showing that technological change can lead to an inflow of immigrants (Beerli et al., 2021). Hanson (2021) shows that an increase in the supply of high-skilled immigrants leads to an increase of AI in local labor markets. We demonstrate that this also applies conversely, meaning that an increase in AI leads to an increase in immigrants.

Table 9: AI skill demands and immigrant inflow by skill-groups at the county-year-level

	All (OLS)	All (IV)	High-skilled(OLS)	High-skilled (IV)	Medium-skilled (OLS)	Medium-skilled (IV)	Low-skilled (OLS)	Low-skilled (IV)
AI skill demand	142507.5*	436984.0*	44822.5*	121382.3	61148.1*	191488.1*	35458.4*	122724.2*
	(64943.9)	(190492.4)	(21996.4)	(63566.3)	(28752.7)	(79640.6)	(15603.9)	(47879.0)
Constant	331.6**	78.68	73.43**	-6.552	165.0**	61.92	92.30***	21.88
	(107.3)	(182.4)	(26.73)	(53.85)	(54.20)	(85.65)	(27.64)	(44.34)
Federal States fixed-effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.786	0.257	0.800	0.229	0.775	0.256	0.746	0.285
N	2406	2406	2406	2406	2406	2406	2406	2406

Notes: AI skill demands are measured via the share of job vacancies mentioning AI-related expressions in the total number of job vacancies. The immigrant inflow is the yearly inflow into a specific county. We identify the immigrant inflow by aggregating the number of times a migrant appears for the first time in the SIAB per year. The skill level is based on the imputed educational variable included in the SIAB. The low skilled have neither vocational training nor a university degree. The middle skilled have vocational training and the high skilled hold a degree from a university or university of applied science. Standard errors are in parentheses and clustered at the nuts-3 level. We control for the following variables: The share of women in the SIAB population and county, the share of young- and middle-aged workers, the share of part-time workers, the share of middle- and high-skilled workers, the share of workers in the manufacturing sector, in the information and communication sector. We also create a shift-share instrument for a county's exposure to information and communication technology as well as trade, using data from EUROSTAT as well as COMTRADE. We control for federal states (NUTS-1) fixed effects. We weight each cell by the respective population in a county. The period under consideration is 2014 to 2019, as the Burning Glass data is only available from 2014 onwards. Source: Burning Glass data and SIAB data. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 10: AI skill demands and unemployment at the county-year-level

	All (OLS)	All (IV)	High-skilled(OLS)	High-skilled (IV)	Medium-skilled (OLS)	Medium-skilled (IV)	Low-skilled (OLS)	Low-skilled (IV)
Migrant	0.0126***	0.0109*	-0.0194***	-0.0285***	-0.0245***	-0.0378***	-0.0446***	-0.0828***
	(0.00271)	(0.00517)	(0.00157)	(0.00382)	(0.00198)	(0.00384)	(0.00405)	(0.00764)
AI	-4.319*	-23.36***	-6.344**	-20.44***	-5.663**	-16.34***	-24.40***	-58.67***
	(2.086)	(6.205)	(2.234)	(5.676)	(2.131)	(4.480)	(4.756)	(9.095)
Migrant*AI	-5.575	-2.710	9.021**	24.41***	13.89***	36.67***	49.38***	114.6***
	(4.324)	(8.570)	(2.884)	(6.793)	(3.731)	(6.877)	(7.433)	(13.42)
Constant	0.0275***	0.0425***	0.0226***	0.0323***	0.0350***	0.0411***	0.0688***	0.0893***
	(0.00703)	(0.00903)	(0.00355)	(0.00487)	(0.00412)	(0.00490)	(0.00772)	(0.00968)
Federal States fixed-effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.202	0.193	0.564	0.559	0.789	0.779	0.361	0.328
N	4812	4812	4812	4812	4812	4812	4812	4812

Notes: AI skill demands are measured via the share of job vacancies mentioning AI-related expressions in the total number of job vacancies. The outcome variable is the unemployment rate. In this case, we only consider the unemployment rate in the most exposed sector. The skill level is based on the imputed educational variable included in the SIAB. The low skilled have neither vocational training nor a university degree. The middle skilled have vocational training and the high skilled hold a degree from a university or university of applied science. Standard errors are in parentheses and clustered at the nuts-3 level. We control for the following variables: The share of women in the SIAB population and county, the share of young- and middle-aged workers, the share of part-time workers, the share of middle- and high-skilled workers, the share of workers in the manufacturing sector, in the information and communication sector. We also create a shift-share instrument for a county's exposure to information and communication technology as well as trade, using data from EUROSTAT as well as COMTRADE. We control for federal states (NUTS-1) fixed effects. We weight each cell by the respective population in a county. The period under consideration is 2014 to 2019, as the Burning Glass data is only available from 2014 onwards. Source: Burning Glass data and SIAB data. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 11: AI skill demands and daily wages by skill-level at the county-year-level

	High-skilled(OLS)	High-skilled (IV)	Medium-skilled (OLS)	Medium-skilled (IV)	Low-skilled (OLS)	Low-skilled (IV)
Migrant	-17.65**	40.06**	4.243	42.94***	19.32***	42.00***
	(6.085)	(14.78)	(2.411)	(6.285)	(1.924)	(5.435)
AI	103019.9***	312155.8***	46279.8***	152040.8***	23957.0***	84883.8***
	(8721.7)	(23146.1)	(4420.2)	(14902.9)	(2955.4)	(9248.6)
Migrant*AI	-45872.9***	-144412.0***	-43571.7***	-109640.5***	-23393.6***	-62115.3***
	(10510.3)	(25584.1)	(4680.7)	(11309.3)	(3682.0)	(9744.2)
Constant	362.1***	203.7***	148.1***	70.08***	78.23***	33.35**
	(27.72)	(28.48)	(12.11)	(13.56)	(9.652)	(10.84)
Federal States fixed-effect	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.564	0.478	0.755	0.637	0.423	0.299
N	4800	4800	4812	4812	4795	4795

Standard errors in parentheses

Source: BGD and SIAB data. 2014-2019.

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

Notes: AI skill demands are measured via the share of job vacancies mentioning AI-related expressions in the total number of job vacancies. The outcome variable is the daily wage. The skill level is based on the imputed educational variable included in the SIAB. The low skilled have neither vocational training nor a university degree. The middle skilled have vocational training and the high skilled hold a degree from a university or university of applied science. Standard errors are in parentheses and clustered at the nuts-3 level. We control for the following variables: The share of women in the SIAB population and county, the share of young- and middle-aged workers, the share of part-time workers, the share of middle- and high-skilled workers, the share of workers in the manufacturing sector, in the information and communication sector. We also create a shift-share instrument for a county's exposure to information and communication technology as well as trade, using data from EUROSTAT as well as COMTRADE. We control for federal states (NUTS-1) fixed effects. We weight each cell by the respective population in a county. The period under consideration is 2014 to 2019, as the Burning Glass data is only available from 2014 onwards. Source: Burning Glass data and SIAB data. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Our results could mean that these new skill demands are highly specialized and cannot be covered by the internal labor supply. Employers then satisfy their demand by importing these skills from abroad. It could also mean that migrants already in Germany move into these new skill demand areas and employers cover the vacancies they leave with new labor from abroad.

In order to analyze the possible channels behind the observed results, we conduct a sub-sector analysis. Similar to the analysis for robot adoptions, we analyze the effect of AI on the most exposed sectors, namely the ICT sector, public administration and defense, mining and quarrying as well as professional, scientific and technical activities. We find that labor markets more exposed to AI are characterized by an increase in migrant share within the population that forms part of the most exposed sectors for all skill groups (see Table 13). This illustrates skill shortages in these sectors and immigrants capturing these shortages. The skill shortages seem to be captured mainly by migrants already residing in Germany, as the effect on immigrant inflows is insignificant (see Table 12). AI increases wages for natives working in the most exposed sectors across the board, but in the case of migrants the effect is only significant for the medium-skilled (see Table A23). AI does not seem to influence unemployment rates to a great extent (see Table A22).

Table 12: AI skill demands and immigrant inflow (most exposed sectors) by skill-groups at the county-year-level

	All (OLS)	All (IV)	High-skilled(OLS)	High-skilled (IV)	Medium-skilled (OLS)	Medium-skilled (IV)	Low-skilled (OLS)	Low-skilled (IV)
AI skill demand	16161.6*	10395.2	8712.2	5511.8	5814.2	2245.9	1695.1*	3018.3
	(7244.8)	(33116.1)	(4472.7)	(20434.0)	(2984.5)	(8215.7)	(682.7)	(4340.9)
Constant	2.898	-11.99	1.936	-6.654	0.310	-2.918	0.606	-2.567
	(4.288)	(13.41)	(2.646)	(8.375)	(1.896)	(3.984)	(0.673)	(1.699)
Federal States fixed-effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.859	0.212	0.827	0.204	0.838	0.200	0.817	0.220
N	2406	2406	2406	2406	2406	2406	2406	2406

Notes: The economic sectors most exposed to AI are the ICT sector, public administration and defense, mining and quarrying as well as professional, scientific and technical activities. The least exposed sectors are all other sectors. AI skill demands are measured via the share of job vacancies mentioning AI-related expressions in the total number of job vacancies. The immigrant inflow is the yearly inflow into a specific county. We identify the immigrant inflow by aggregating the number of times a migrant appears for the first time in the SIAB per year. The skill level is based on the imputed educational variable included in the SIAB. The low skilled have neither vocational training nor a university degree. The middle skilled have vocational training and the high skilled hold a degree from a university or university of applied science. Standard errors are in parentheses and clustered at the nuts-3 level. We control for the following variables: The share of women in the SIAB population and county, the share of young- and middle-aged workers, the share of part-time workers, the share of middle- and high-skilled workers, the share of workers in the manufacturing sector, in the information and communication sector. We also create a shift-share instrument for a county's exposure to information and communication technology as well as trade, using data from EUROSTAT as well as COMTRADE. We control for federal states (NUTS-1) fixed effects. We weight each cell by the respective population in a county. The period under consideration is 2014 to 2019, as the Burning Glass data is only available from 2014 onwards. Source: Burning Glass data and SIAB data. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 13: AI skill demands and perc. change in migrant share (most exposed sectors) by skill-groups at the county-year-level

	All (OLS)	All (IV)	High-skilled(OLS)	High-skilled (IV)	Medium-skilled (OLS)	Medium-skilled (IV)	Low-skilled (OLS)	Low-skilled (IV)
AI skill demand	81.46***	348.4***	99.97***	343.3***	47.86***	256.9***	117.1***	589.3***
	(12.34)	(41.86)	(16.41)	(59.40)	(10.14)	(35.91)	(30.37)	(95.62)
Constant	0.0566***	-0.140***	0.0663**	-0.112**	0.0359**	-0.108***	0.0722	-0.269***
	(0.0150)	(0.0278)	(0.0242)	(0.0390)	(0.0128)	(0.0261)	(0.0437)	(0.0768)
Federal States fixed-effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.635	0.200	0.445	0.170	0.518	0.130	0.210	.
N	2406	2406	2400	2400	2406	2406	2279	2279

Notes: The economic sectors most exposed to AI are the ICT sector, public administration and defense, mining and quarrying as well as professional, scientific and technical activities. The least exposed sectors are all other sectors. AI skill demands are measured via the share of job vacancies mentioning AI-related expressions in the total number of job vacancies. The outcome variable is the migrant share. The migrant share is defined as the number of people in the SIAB with foreign nationality over the total SIAB population. In this case, we restrict the migrant share to the least exposed sector. The skill level is based on the imputed educational variable included in the SIAB. The low skilled have neither vocational training nor a university degree. The middle skilled have vocational training and the high skilled hold a degree from a university or university of applied science. Standard errors are in parentheses and clustered at the nuts-3 level. We control for the following variables: The share of women in the SIAB population and county, the share of young- and middle-aged workers, the share of part-time workers, the share of middle- and high-skilled workers, the share of workers in the manufacturing sector, in the information and communication sector. We also create a shift-share instrument for a county's exposure to information and communication technology as well as trade, using data from EUROSTAT as well as COMTRADE. We control for federal states (NUTS-1) fixed effects. We weight each cell by the respective population in a county. The period under consideration is 2014 to 2019, as the Burning Glass data is only available from 2014 onwards. Source: Burning Glass data and SIAB data. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

To study spillover effects on the less exposed sectors, we also analyze outcomes of those forming part of these sectors. We again observe an increase in the migrant share of migrants across all skill groups (see Table 15), but this time the demand seems to be covered from abroad; since AI positively impacts immigrant inflows (see Table 14). This could mean that migrants leave less exposed sectors to take on jobs in more exposed sectors, and that employers compensate for this through attracting newly arrived migrants. AI also leads to wage decreases for migrants, which is not the case for natives (see Table A25). This could mean that employers pay newly arrived migrants less money. Additionally, the unemployment rate increases for migrants among all skill groups, while it decreases for natives (see Table A24). This is proof of complementarity and productivity effects for natives, but displacement effects for migrants and confirms our hypothesis of how technological change has discriminatory effects on the migrants population.

Table 14: AI skill demands and immigrant inflow (least exposed sectors) by skill-groups at the county-year-level

	All (OLS)	All (IV)	High-skilled(OLS)	High-skilled (IV)	Medium-skilled (OLS)	Medium-skilled (IV)	Low-skilled (OLS)	Low-skilled (IV)
AI skill demand	137897.8*	496045.1**	38843.4*	126297.7**	61264.8*	227584.1**	36611.2*	139714.2**
	(61964.8)	(161763.7)	(18802.3)	(48848.1)	(28248.0)	(70504.3)	(15946.5)	(42784.7)
Constant	280.5*	77.37	54.51*	1.444	144.2*	55.36	81.21**	19.62
	(109.1)	(147.8)	(24.47)	(39.88)	(56.42)	(70.60)	(29.05)	(38.00)
Federal States fixed-effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.771	0.242	0.782	0.223	0.763	0.237	0.734	0.262
N	2406	2406	2406	2406	2406	2406	2406	2406

Notes: The economic sectors most exposed to AI are the ICT sector, public administration and defense, mining and quarrying as well as professional, scientific and technical activities. The least exposed sectors are all other sectors. AI skill demands are measured via the share of job vacancies mentioning AI-related expressions in the total number of job vacancies. The immigrant inflow is the yearly inflow into a specific county. We identify the immigrant inflow by aggregating the number of times a migrant appears for the first time in the SIAB per year. The skill level is based on the imputed educational variable included in the SIAB. The low skilled have neither vocational training nor a university degree. The middle skilled have vocational training and the high skilled hold a degree from a university or university of applied science. Standard errors are in parentheses and clustered at the nuts-3 level. We control for the following variables: The share of women in the SIAB population and county, the share of young- and middle-aged workers, the share of part-time workers, the share of middle- and high-skilled workers, the share of workers in the manufacturing sector, in the information and communication sector. We also create a shift-share instrument for a county's exposure to information and communication technology as well as trade, using data from EUROSTAT as well as COMTRADE. We control for federal states (NUTS-1) fixed effects. We weight each cell by the respective population in a county. The period under consideration is 2014 to 2019, as the Burning Glass data is only available from 2014 onwards. Source: Burning Glass data and SIAB data. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 15: AI skill demands and perc. change in migrant share (least exposed sectors) by skill-groups at the county-year-level

	All (OLS)	All (IV)	High-skilled(OLS)	High-skilled (IV)	Medium-skilled (OLS)	Medium-skilled (IV)	Low-skilled (OLS)	Low-skilled (IV)
AI skill demand	65.66***	576.4***	12.36	229.6***	66.33**	574.6***	121.7***	1040.1***
	(18.49)	(54.98)	(12.52)	(38.63)	(21.16)	(62.52)	(30.20)	(98.68)
Constant	0.233***	-0.225**	0.0516	-0.171***	0.236***	-0.212**	0.596***	-0.239
	(0.0482)	(0.0780)	(0.0359)	(0.0500)	(0.0502)	(0.0803)	(0.0815)	(0.134)
Federal States fixed-effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.627	.	0.417	0.0420	0.601	.	0.565	.
N	2406	2406	2406	2406	2406	2406	2406	2406

Notes: The economic sectors most exposed to AI are the ICT sector, public administration and defense, mining and quarrying as well as professional, scientific and technical activities. The least exposed sectors are all other sectors. AI skill demands are measured via the share of job vacancies mentioning AI-related expressions in the total number of job vacancies. The outcome variable is the migrant share. The migrant share is defined as the number of people in the SIAB with foreign nationality over the total SIAB population. In this case, we restrict the migrant share to the least exposed sector. The skill level is based on the imputed educational variable included in the SIAB. The low skilled have neither vocational training nor a university degree. The middle skilled have vocational training and the high skilled hold a degree from a university or university of applied science. Standard errors are in parentheses and clustered at the nuts-3 level. We control for the following variables: The share of women in the SIAB population and county, the share of young- and middle-aged workers, the share of part-time workers, the share of middle- and high-skilled workers, the share of workers in the manufacturing sector, in the information and communication sector. We also create a shift-share instrument for a county's exposure to information and communication technology as well as trade, using data from EUROSTAT as well as COMTRADE. We control for federal states (NUTS-1) fixed effects. We weight each cell by the respective population in a county. The period under consideration is 2014 to 2019, as the Burning Glass data is only available from 2014 onwards. Source: Burning Glass data and SIAB data. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

5 Mechanisms

In order to analyze some of the mechanisms behind the above-described results, we exploit the panel-data structure of the SIAB and follow individuals over time. We then observe three outcomes of interest during each individual's working life: their probability to switch sectors, their probability to take on communication-intensive tasks, as well as their probability to migrate internally. We believe that these outcomes may help analyze whether the observed adverse effects on migrants are due to them being less adaptive than natives, emanating from factors such as discriminatory structures or a lack of relevant job market information.

5.1 The Probability of Switching Sectors

We study if technological change affects migrants' probability to switch sectors differently than in the case of natives. In order to do this, we follow the individuals registered in the SIAB over time and create a dummy variable as soon as an individual switches sectors. We then run the same regression as above, but with the probability of switching sectors as an outcome variable. Since migrants might have less access to local networks, information and labor market institutions, we would expect them to be less reactive to technological change than natives. And indeed, we find that they are less likely to switch sectors as a response to robot adoption than natives, but the effect is only significant for the high-skilled (see Table 16). Importantly, robotics also decreases the native population's probability of switching sectors, whereas the decrease is larger for middle-skilled migrants. This could be due to these migrants leaving the German labor market, which would be in line with a decrease in the medium-skilled migrant share.

Table 16: Robot exposure and the probability to switch sectors

	All (OLS)	All (IV)	High-skilled(OLS)	High-skilled (IV)	Medium-skilled (OLS)	Medium-skilled (IV)	Low-skilled (OLS)	Low-skilled (IV)
Migrant	0.0671***	0.0696***	0.0794***	0.0874***	0.0716***	0.0735***	-0.000844	0.000123
	(0.00675)	(0.00972)	(0.00669)	(0.00854)	(0.00768)	(0.0108)	(0.00651)	(0.00934)
Robot exposure (Op. Stock)	-0.399***	-0.836***	-0.494**	-1.079**	-0.372***	-0.771***	-0.378***	-0.799***
	(0.113)	(0.248)	(0.156)	(0.353)	(0.103)	(0.222)	(0.0983)	(0.225)
Migrant*Robots	-0.0662*	-0.0903	-0.0773**	-0.153**	-0.0708*	-0.0857	-0.0482	-0.0569
	(0.0318)	(0.0508)	(0.0255)	(0.0566)	(0.0335)	(0.0514)	(0.0353)	(0.0520)
Constant	0.101	1.005	0.136	1.361	0.121	0.965	-0.0270	0.745
	(0.270)	(0.570)	(0.460)	(0.968)	(0.234)	(0.494)	(0.248)	(0.506)
Federal States fixed-effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.126	0.0899	0.164	0.104	0.126	0.0916	0.0902	0.0675
N	9865642	9865642	1557376	1557376	6958648	6958648	1349617	1349617

Standard errors in parentheses
Source: IFR Robotics data and SIAB data.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 17: AI-related skill demands and the probability to switch sectors

	All (OLS)	All (IV)	High-skilled(OLS)	High-skilled (IV)	Medium-skilled (OLS)	Medium-skilled (IV)	Low-skilled (OLS)	Low-skilled (IV)
Migrant	0.0563***	-0.0248	0.0714***	0.187***	0.0593***	0.134***	-0.00941**	-0.0802
	(0.00177)	(0.0641)	(0.00458)	(0.0334)	(0.00171)	(0.0287)	(0.00310)	(0.0644)
AI	-0.00688***	-0.802**	0.00273	0.0917	-0.00933***	-1.058***	-0.0106**	-0.666
	(0.00169)	(0.258)	(0.00335)	(0.266)	(0.00173)	(0.255)	(0.00327)	(0.398)
Migrant*AI	0.0190***	1.037	-0.00462	-0.677*	0.0151	-2.910*	0.0284***	1.662
	(0.00465)	(0.991)	(0.00898)	(0.273)	(0.0104)	(1.310)	(0.00773)	(1.457)
Constant	-0.735***	0.361***	-0.899***	0.267***	-0.676***	0.355***	-0.734***	0.402***
	(0.154)	(0.0247)	(0.239)	(0.0403)	(0.134)	(0.0186)	(0.155)	(0.0288)
Federal States fixed-effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.0951	.	0.121	.	0.0951	.	0.0709	.
N	9865642	4177551	1557376	757587	6958648	2885919	1349617	534044

Standard errors in parentheses
Source: IFR Robotics data and BGD. 2014-2019.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Similar to what we found for industrial robots, migrants are less likely than natives to switch sectors when exposed to AI (see Table 17). The effect is significant for high- and medium-skilled migrants as well as high-skilled natives. The more adverse effects of AI on migrants could therefore be explained by them having less access to relevant information on how to adapt their skill set as a response to technological change.

5.2 The Probability of Taking on Communication-Intensive Tasks

Additionally, the literature shows that natives move into language-intensive, culture-specific services tasks when migrants arrive (see for example Mitaritonna et al., 2017, Ottaviano et al., 2018 and Paserman, 2013). The question arises as to whether this mechanism is also in place when analyzing the effect of technological change on labor market outcomes. This question is interesting as it might be more difficult to automate tasks, which require a high level of communication skills and cultural knowledge and sensitivity. We follow Ottaviano et al., 2018 and define a set of legal and related (LR)[5] as well as language and human resources (LHR)[6] services.

We find that high-skilled migrants are generally more likely to work in these language-intensive, culture-specific services, following an elevated exposure to industrial robots (see Table 18). Robots have no such effect on the low- or medium-skilled. This could be due to high-skilled migrants taking on these tasks as a response to technological change, as they might be more likely to have the necessary skills to do so. In the case of natives, there are significant effects on the medium-skilled.

Table 18: Robot exposure and communication-intensive occupations

	All (OLS)	All (IV)	High-skilled(OLS)	High-skilled (IV)	Medium-skilled (OLS)	Medium-skilled (IV)	Low-skilled (OLS)	Low-skilled (IV)
Migrant	-0.0436***	-0.0436***	-0.0455***	-0.0476***	-0.0323***	-0.0312***	-0.0541***	-0.0549***
	(0.00308)	(0.00339)	(0.00520)	(0.00573)	(0.00395)	(0.00429)	(0.00457)	(0.00453)
Robot exposure (Op. Stock)	0.0127	0.00771	0.00835	-0.0150	0.0165**	0.0204**	0.00831	0.00270
	(0.00703)	(0.00460)	(0.0111)	(0.0143)	(0.00621)	(0.00641)	(0.00547)	(0.00938)
Migrant*Robots	0.00321	0.00300	0.0227	0.0359**	-0.00722	-0.0138	0.0129	0.0184
	(0.00925)	(0.00721)	(0.0126)	(0.0126)	(0.00946)	(0.00992)	(0.0109)	(0.0111)
Constant	-0.193***	-0.183***	-0.287***	-0.241**	-0.205***	-0.212***	0.0973**	0.106***
	(0.0442)	(0.0427)	(0.0747)	(0.0826)	(0.0395)	(0.0398)	(0.0298)	(0.0317)
Federal States fixed-effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.00424	0.00424	0.00524	0.00516	0.00340	0.00340	0.00892	0.00892
N	9865642	9865642	1557376	1557376	6958648	6958648	1349617	1349617

Standard errors in parentheses
Source: IFR Robotics data and SIAB data.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 19: AI-related skill demands and communication-intensive tasks

	All (OLS)	All (IV)	High-skilled(OLS)	High-skilled (IV)	Medium-skilled (OLS)	Medium-skilled (IV)	Low-skilled (OLS)	Low-skilled (IV)
Migrant	-0.0482***	-0.0764	-0.0465***	-0.118	-0.0397***	-0.0541*	-0.0512***	-0.0896*
	(0.00336)	(0.0460)	(0.00563)	(0.138)	(0.00350)	(0.0218)	(0.00437)	(0.0382)
AI	-0.0283***	0.727***	0.00374	0.425***	-0.0637***	0.779***	0.0222	0.590***
	(0.00672)	(0.0705)	(0.00706)	(0.113)	(0.00682)	(0.139)	(0.0116)	(0.145)
Migrant*AI	0.0644**	0.934	0.0333	0.586	0.0672***	1.191*	0.00520	1.927*
	(0.0223)	(0.604)	(0.0319)	(0.892)	(0.00938)	(0.588)	(0.0206)	(0.821)
Constant	-0.168***	0.101***	-0.266***	0.160***	-0.175***	0.0956***	0.118***	0.0909***
	(0.0389)	(0.00714)	(0.0665)	(0.0217)	(0.0357)	(0.0104)	(0.0290)	(0.0109)
Federal States fixed-effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.00474	.	0.00531	.	0.00562	.	0.00915	.
N	9865642	4177551	1557376	757587	6958648	2885919	1349617	534044

Standard errors in parentheses
Source: IFR Robotics data and BGD. 2014-2019.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In the case of AI, medium- and low-skilled migrants are more likely to work in language-intensive, culture-specific services as shown in Table 19. Unlike robots, AI has the capacity to replace services, for example by recruiting activities, and these findings could provide evidence of migrants complementing tasks that are being replaced by these new technologies. While they were probably less likely to occupy

[5]This group includes accounting, controlling and auditing; tax consultancy; legal services, jurisdiction and other officers of the court.

[6]This group includes human resource management and personnel services; cultural and recreational services; publishing services; media and information services; public relations; health services.

these tasks without AI, AI makes it easier for them to work in these areas. There are no significant effects of this kind on the high-skilled migrant population. This could be due to them absorbing some of the complex tasks created through and with AI technologies.

5.3 The Probability of Internal Migration

Another form of adapting behavior as a response to technological change is internal migration. Employees might need to relocate inside Germany due to shifting working opportunities as a response to technological change. We therefore construct a dummy variable, which is equal to one, as soon as the county of residence changes from one year to the other. We then analyze the impact of robotics as well as AI on this dummy variable, representing an individual's probability of migrating inside of Germany.

Table 20: Robot exposure and internal migration

	All (OLS)	All (IV)	High-skilled(OLS)	High-skilled (IV)	Medium-skilled (OLS)	Medium-skilled (IV)	Low-skilled (OLS)	Low-skilled (IV)
Migrant	-0.00541*	-0.00599**	-0.00802**	-0.00840***	-0.0000314	-0.000722	-0.0212***	-0.0219***
	(0.00226)	(0.00219)	(0.00254)	(0.00237)	(0.00232)	(0.00226)	(0.00313)	(0.00306)
Robot exposure (Op. Stock)	0.00507	-0.00324	0.00560	-0.00188	0.00376	-0.00209	0.00911	-0.00511
	(0.00376)	(0.00359)	(0.00356)	(0.00368)	(0.00276)	(0.00285)	(0.00812)	(0.00685)
Migrant*Robots	-0.00164	0.00185	-0.00117	0.00123	-0.00131	0.00281	0.00233	0.00681
	(0.00789)	(0.00743)	(0.0108)	(0.00953)	(0.00578)	(0.00601)	(0.0133)	(0.0114)
Constant	-0.0768**	-0.0604**	-0.0670*	-0.0519*	-0.0379*	-0.0262	-0.190***	-0.166***
	(0.0238)	(0.0206)	(0.0289)	(0.0254)	(0.0175)	(0.0160)	(0.0359)	(0.0304)
Federal States fixed-effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.00241	0.00236	0.00221	0.00218	0.00190	0.00187	0.00546	0.00537
N	9865642	9865642	1557376	1557376	6958648	6958648	1349617	1349617

Standard errors in parentheses
Source: IFR Robotics data and SIAB data.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 21: AI-related skill demands and internal migration

	All (OLS)	All (IV)	High-skilled(OLS)	High-skilled (IV)	Medium-skilled (OLS)	Medium-skilled (IV)	Low-skilled (OLS)	Low-skilled (IV)
Migrant	-0.00590*	0.0534**	-0.00904***	0.0494	-0.000310	0.0359***	-0.0203***	0.0403
	(0.00238)	(0.0183)	(0.00209)	(0.0426)	(0.00212)	(0.00996)	(0.00324)	(0.0211)
AI	0.00193	0.292***	-0.00248	0.110*	-0.00104	0.201**	0.0109**	0.515***
	(0.00146)	(0.0414)	(0.00316)	(0.0513)	(0.000769)	(0.0669)	(0.00355)	(0.0618)
Migrant*AI	0.00585*	-0.696*	0.00577	-0.407	-0.0000800	-0.543	0.000672	-1.175
	(0.00240)	(0.302)	(0.00637)	(0.287)	(0.00312)	(0.341)	(0.00161)	(0.602)
Constant	-0.0665***	0.00949***	-0.0554*	0.0418***	-0.0302*	0.0123*	-0.172***	0.0176***
	(0.0185)	(0.00280)	(0.0237)	(0.00838)	(0.0136)	(0.00491)	(0.0278)	(0.00380)
Federal States fixed-effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.00241	.	0.00221	.	0.00189	.	0.00559	.
N	9865642	4177551	1557376	757587	6958648	2885919	1349617	534044

Standard errors in parentheses
Source: IFR Robotics data and BGD. 2014-2019.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

We do not find a significant impact of robotics on individuals' probability to migrate internally (see Table 20). In the case of AI, the probability increases significantly for natives but not for the migrant population. When breaking this down further into skill groups, we find that AI increases the probability of moving inside of Germany for natives across all skill groups. This could be connected to our hypotheses about migrants having less access to relevant information about technology induced changes in the labor market and the need to move towards other counties. It lies in contrast to theoretical predictions, such as Borjas (2001). Borjas, 2001 predicts that migrants are more internally mobile, as they already accrued the high fixed costs of moving in the past. Our results could mean that the productivity gains experienced by natives through AI outweigh these fixed costs.

6 Robustness Checks

6.1 Alternative Measures of Immigrant Inflows

As a robustness check to our results we restrict the immigrant inflow to the immediately employed population only. As the Tables in Annex 1 shows, the results do not differ significantly from each other. In the case of AI, we additionally consider the cumulative immigrant inflow as an alternative outcome variable (see Table A20). The change in AI skill demands as a share of overall skill demand over the 5-year period did not significantly impact the cumulative immigrant flow across neither of the skill groups. What this tells us is that, while AI might change immigrant flows in the short-run, it does not impact the inflow in the middle-run.

6.2 Testing the Validity of the Shift-Share Instrument

6.2.1 Exogeneity of Initial Shares

Our research design relies on several important assumptions. Firstly, it relies on the assumption that initial shares are exogenous to changes in the error terms (Goldsmith-Pinkham et al., 2020). A potential identification threat would then be that the initial shares $\frac{\text{emp}_{ir}}{\text{emp}_r}$ are correlated with the change in the outcome variables (e.g. the percentage change in daily wages during the period 2005 to 2018). This is a concern as the Bartik instrument is the equivalent of using initial shares as multiple instruments in a weighted generalized methods of moment estimation. We can then understand the initial shares as instruments, and the industry growth rates as weights. If the initial shares were correlated with changes in the outcome variable, this would violate the exclusion restriction. One example would be if the initial employment structure is correlated with the unobservable tendency to discriminate against migrants, e.g. through being a more conservative county. This initial tendency to discriminate against migrants could then affect the observed percentage change in daily wages and bias our estimates.

We employ several tests to identify if our research design satisfies the shares assumption of exogenous industry exposure. We start by exploring if the industry shares in 2004 are correlated with average county characteristics in 2004. Table 22 shows the results. The table makes clear that most of the industry shares are correlated with at least one control variable. To give an example, those counties with a higher industry share of the third aggregated manufacturing sector, which covers the vehicle manufacturing sector, also have a higher share of high-educated workers. This means that we have to make sure that there are no other unobservable trends potentially affecting our outcome variables of interest, as for example the percentage change in daily wages for migrants, in the manufacturing sector in areas, which are more educated.

Table 22: Relationship between industry shares and characteristics

	Primary Sector	Manufacturing Sector (1)	Manufacturing Sector (2)	Manufacturing Sector (3)	Construction	Education	Other service activities
Female Share	-0.0195	0.166**	-0.212*	-0.368***	0.0665*	0.158***	1.478***
	(0.0327)	(0.0518)	(0.0841)	(0.0950)	(0.0332)	(0.0315)	(0.127)
Part-time Share	-0.0349*	-0.184***	-0.261***	-0.255***	-0.135***	0.00429	-0.908***
	(0.0158)	(0.0250)	(0.0405)	(0.0459)	(0.0160)	(0.0152)	(0.0615)
Share of low-skilled	0.0768*	0.132**	-0.0543	0.488***	0.232***	0.0236	-1.668***
	(0.0301)	(0.0478)	(0.0776)	(0.0877)	(0.0307)	(0.0291)	(0.118)
Share of high-skilled	0.0888	-0.291**	-0.718***	0.494**	0.167**	0.334***	-1.766***
	(0.0567)	(0.0899)	(0.146)	(0.165)	(0.0577)	(0.0547)	(0.221)
Constant	-0.0117	-0.0380	0.362***	-0.139	-0.111**	-0.0741*	1.722***
	(0.0352)	(0.0559)	(0.0909)	(0.103)	(0.0359)	(0.0340)	(0.137)
R-squared	0.254	0.502	0.358	0.366	0.655	0.539	0.726
N	324	326	325	326	326	326	326

Notes: The table shows the relationship between the initial industry shares and average county characteristics in 2004. Each Column represents a separate regression of the industry shares in a respective county and the controls presented in the table. The manufacturing (1) sector refers to the manufacture of food products, Manufacture of beverages, Retail sale of food, beverages and tobacco in specialised stores, Wood and Wood products, as well as other manufacturing. The manufacturing (2) sector refers to the manufacture of coke and refined petroleum products, chemical and pharmaceutical products, as well as rubber and plastics, and of basic metals and fabricated metal products. The manufacturing (3) sector refers to the manufacture of computer, electronic and optical products, electrical equipment, mechanical engineering, and vehicle manufacturing. We weight each county by its population in 2004. Standard errors are in parentheses. Source: SIAB data. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

6.3 Parallel Trend Assumption

Figure 1 shows that the adoption of robots was gradual and took place constantly over time. This means that there is no clear pre-treatment period in our setting. It is therefore not possible to test for parallel trends without further assumptions. Additionally, the IFR data is only available from 1993 onwards.

7 Conclusion

This paper analyzes the effect of automation on immigration flows and labor market outcomes of migrants already residing in Germany as opposed to natives. This is an important research question as policy makers could mitigate the effect of technological change through adjustments in their migration policies. Additionally, it may have important implications on inequality.

We use a shift-share instrument to study the impact of two automation technologies, industrial robots as well as artificial intelligence, on immigrant inflows and outflows alongside the unemployment rate and wages of migrants versus natives. We specifically focus on these two automation technologies, as one mainly replaces mental tasks (AI), while the other mainly replaces physical tasks (robots). We apply our research question to the context of Germany since it is one of the leading automation economies and one of the main recipients of immigrants over recent decades. We study the effects of technological change on three different skill groups: the low-, medium- and high-skilled.

We find that robot adoption has no significant impact on immigrant flows, whereas AI-related skill demands do. Additionally, robotics creates a wage gap between migrants and natives for all skill groups. Similarly, an increase in AI skill demands leads to a wage decrease for migrants and increase for natives as well as elevated unemployment rates for migrants, but not natives. This has important equity implications. Technological change could lead to increased inequalities between the migrant and native population, something that policy makers should try to mitigate. While natives seem to benefit from technological change, migrants experience adverse effects. This could be proof of productivity and complementarity effects for natives, but displacement effects for migrants.

When breaking this down according to sector, we find a decreased share of migrants working in the manufacturing sector. This could be evidence of migrants moving towards other sectors as a response to robotization. Movements between sectors could also explain why there are no overall significant effects on labor market outcomes by robots. The overall negative effect of AI on migrants seems to be driven by negative spill-over effects on the least exposed sectors. There are no negative labor market effects on migrants in the most exposed sectors. In general, technological change increases the likelihood of migrants from certain skill groups working in communication-intensive tasks. This could be evidence of complementarities through new technologies in these tasks. Still, migrants are less likely than natives to switch sectors as a response to robots and AI, which could be testimony to discriminatory effects or them lacking important access to information and labor market institutions. When analyzing the effect of AI on internal migration, migrants are more likely to migrate inside Germany as a response to AI. This could be connected to suggestive evidence showing that migrants from non-AI-heavy sectors seem to move into AI-heavy sectors.

Our findings have several important policy implications. Firstly, we determine that industrial robots and AI increase the overall wage of natives, but decrease it for migrants. This means that policymakers should devote special attention to the migration population when designing mitigation policies in response to technological change so as to avoid further increases in inequality between migrants and natives.

Next, our paper shows that, in the case of AI, the negative effects on migrants are completely driven by the least exposed sectors. When combining this evidence with the fact that there is an inflow of new migrants into these sectors, it is recommended that policymakers revise the labor market conditions of these migrants. Next, migrants are less likely to switch sectors as a response to robots and AI. Therefore, countries should ensure that migrants have equal access to labor market institutions and information about the need to adapt their skill set in response to technological change. Finally, our diverging effects of AI and robots reveal that it is not possible to generalize the impact of technological change and that differentiated analyses are needed to fully understand its impact. Generally,, our results speak against migrants and natives being skill-type perfect substitutes.

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Additional Graphs and Tables

A1.1 Additional Graphs

Figure A2: Immigrant inflow to Germany over time

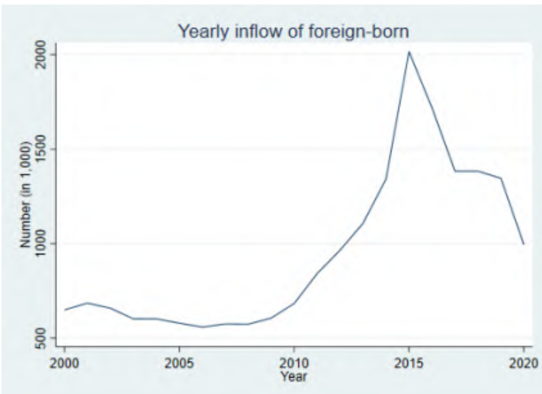


Figure A3: Outflow of German and non-German residents over time

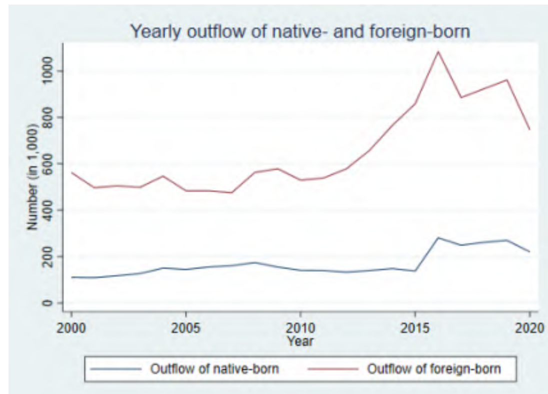


Figure A4: Immigrant inflow to main OECD countries

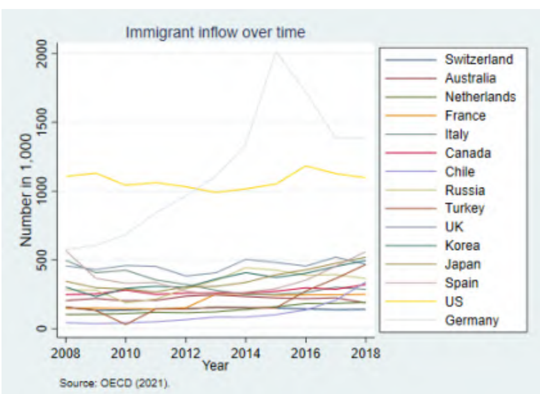


Figure A5: Native workers by skill group over time

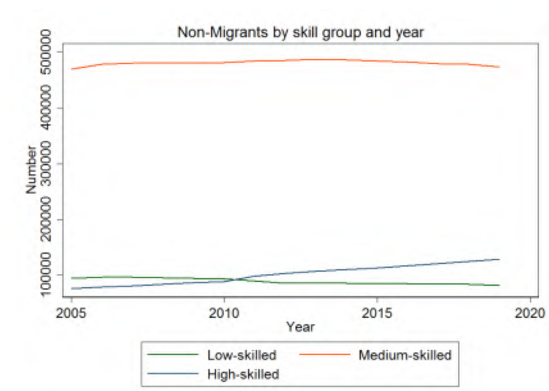


Figure A6: Migrant Share by economic sector in 2005 and 2017

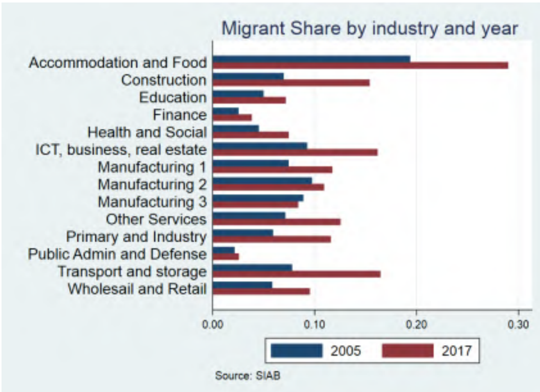


Figure A7: Robot exposure by industry in Germany

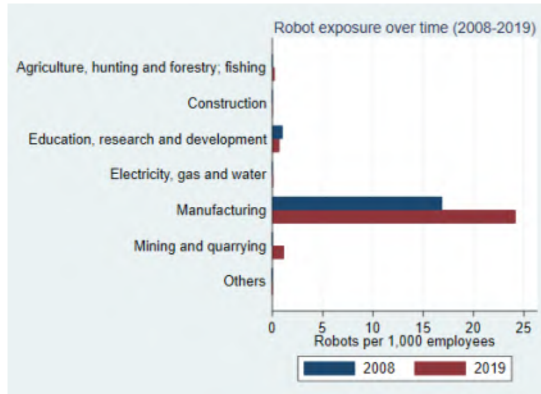


Figure A8: ICT and Automation Graduates in Germany

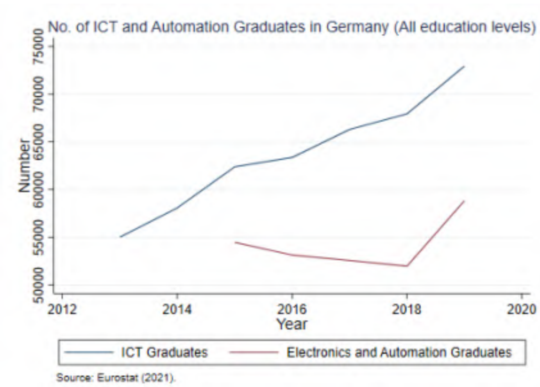


Figure A9: ICT Graduates in Germany by education level

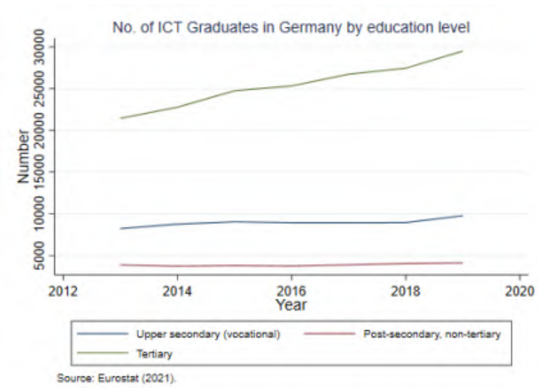


Figure A10: Number of skills in demand over time by selected European countries

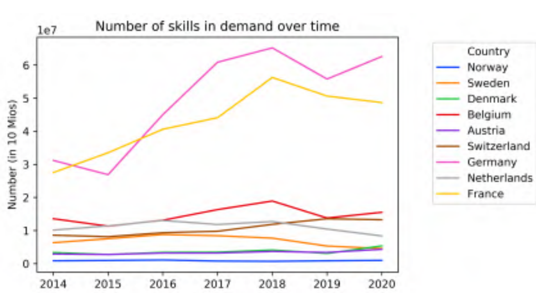


Figure A11: Number of AI-related skill demand over time by selected European countries

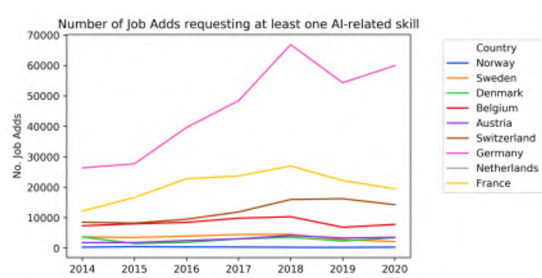


Figure A12: Number of OJV in Germany over time

Figure A13: Share of AI-related skill demand over time by selected European countries

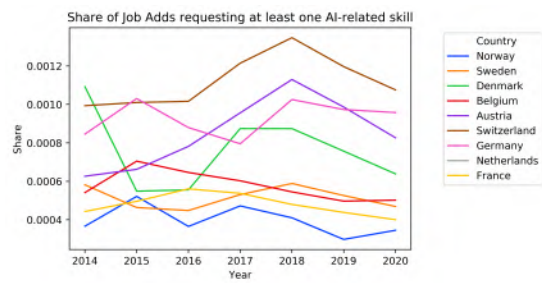


Figure A14: Robot exposure in Germany and instrumental countries

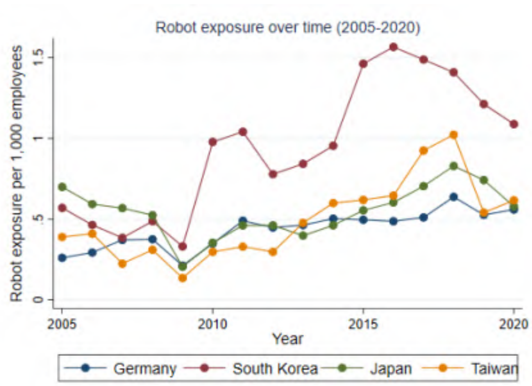


Figure A15: AI-related skill demand in Germany and Switzerland

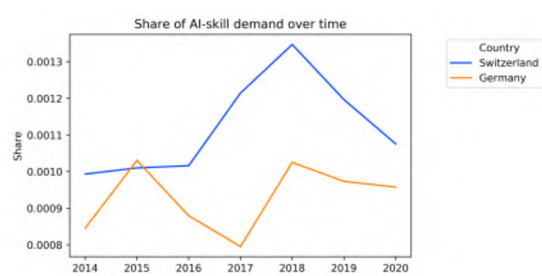
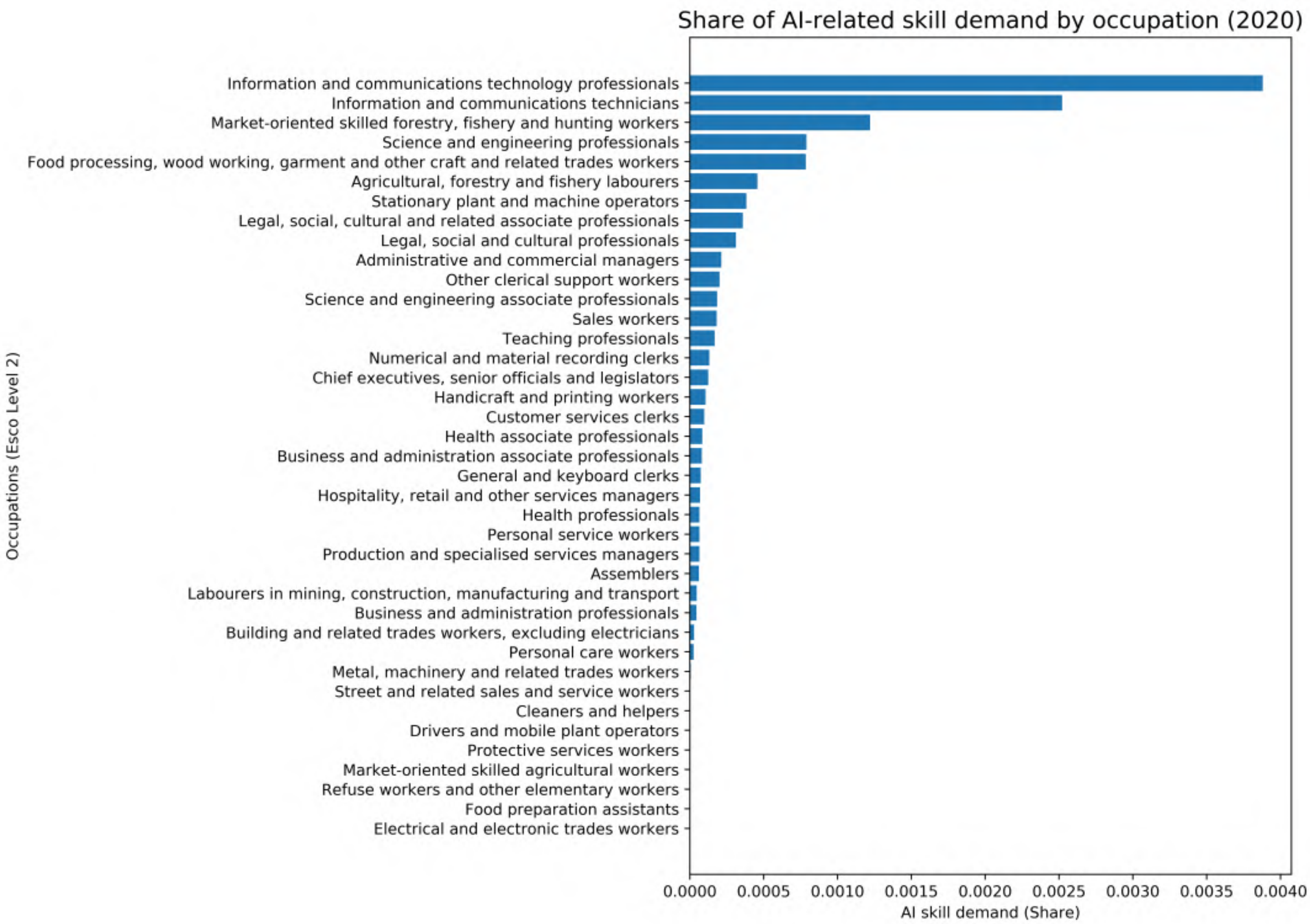
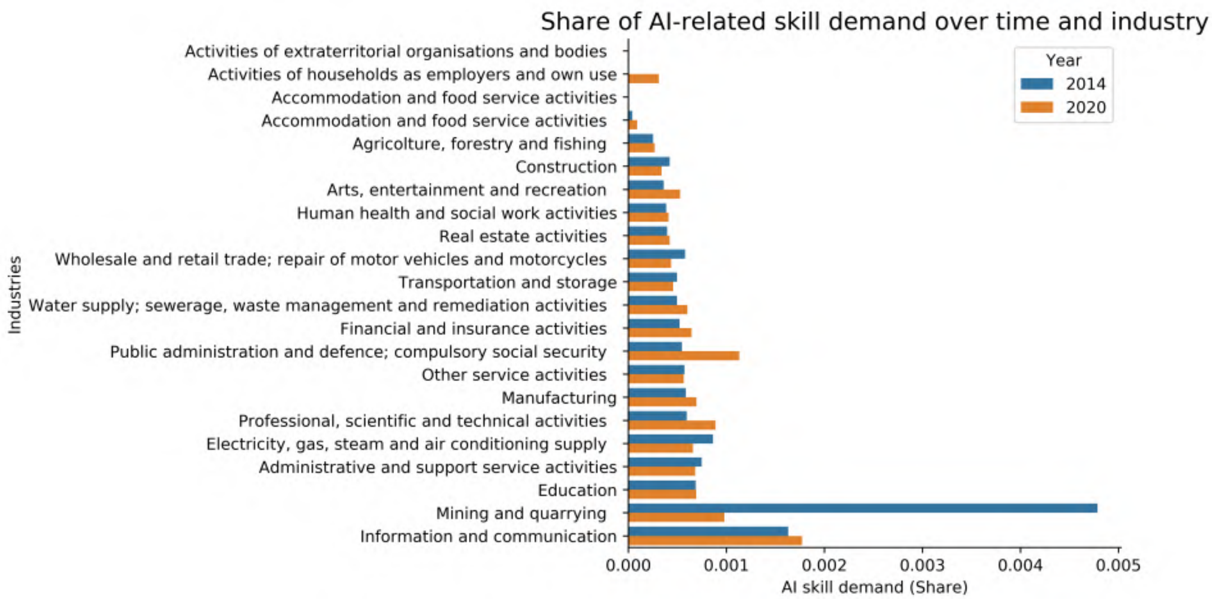


Figure A16: Share of AI skill demand in overall skill demand by occupation



Source: BGD (2020)

Figure A17: Share of AI skill demand in overall skill demand by sector



A1.2 Additional Tables

A1.2.1 Robots (Overall)

Table A2: Robot exposure and perc. change in immigrant inflow (employed) by skill-groups at the county-year-level

	All (OLS)	All (IV)	High-skilled(OLS)	High-skilled (IV)	Medium-skilled (OLS)	Medium-skilled (IV)	Low-skilled (OLS)	Low-skilled (IV)
Robot exposure (Op. Stock)	-28.26	-1694.7	-4.658	-464.1	-28.26	-1694.7	-0.693	-536.4
	(163.7)	(1606.0)	(46.73)	(445.8)	(163.7)	(1606.0)	(57.40)	(530.3)
Constant	8560.7	4186.8	2235.8	1029.9	8560.7	4186.8	3123.8*	1717.7
	(4498.6)	(3878.5)	(1263.5)	(1083.3)	(4498.6)	(3878.5)	(1482.7)	(1278.1)
Federal States fixed-effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.842	0.764	0.915	0.876	0.842	0.764	0.775	0.674
N	401	401	401	401	401	401	401	401

Notes: Robot exposure (Op. Stock) is the exposure of a county to industrial robots measured via the shift share instrument. The unit of observation is the county (NUTS-3). The immigrant inflow is the cumulative immigrant inflow into a respective county during the period 2005 and 2018. We identify the immigrant inflow by aggregating the number of times a migrant appears for the first time in the SIAB per year. In this case, we restrict the inflow to those who are immediately employed once they appear in the SIAB. The skill level is based on the imputed educational variable included in the SIAB. The low skilled have neither vocational training nor a university degree. The middle skilled have vocational training and the high skilled hold a degree from a university or university of applied science. Standard errors are in parentheses and clustered at the nuts-3 level. We control for the following variables: The share of women in the SIAB population and county, the share of young- and middle-aged workers, the share of part-time workers, the share of middle- and high-skilled workers, the share of workers in the manufacturing sector, in the information and communication sector. We also create a shift-share instrument for a county's exposure to information and communication technology as well as trade, using data from EUROSTAT as well as COMTRADE. We control for federal states (NUTS-1) fixed effects. We weight each cell by the respective population in a county. Source: IFR Robotics data and SIAB data. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A3: Robot exposure and perc. change in immigrant outflow by skill-groups at the county-year-level

	All (OLS)	All (IV)	High-skilled(OLS)	High-skilled (IV)	Medium-skilled (OLS)	Medium-skilled (IV)	Low-skilled (OLS)	Low-skilled (IV)
Robot exposure (Op. Stock)	-0.491	-5.636	-0.144	-0.0569	0.134	-2.462	-0.470	-3.079
	(1.187)	(7.018)	(0.122)	(0.503)	(0.690)	(3.544)	(0.545)	(3.594)
Constant	78.78**	65.28**	4.253	4.481	46.01**	39.19**	27.32*	20.47
	(29.09)	(24.27)	(3.259)	(3.543)	(15.12)	(12.56)	(13.45)	(12.02)
Federal States fixed-effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.933	0.928	0.895	0.895	0.949	0.945	0.790	0.769
N	401	401	401	401	401	401	401	401

Notes: Robot exposure (Op. Stock) is the exposure of a county to industrial robots measured via the shift share instrument. The unit of observation is the county (NUTS-3). The immigrant outflow is the cumulative immigrant outflow from a respective county during the period 2005 and 2018. We identify the immigrant outflow by aggregating the number of times a migrant appears for the last time in the SIAB per year. The skill level is based on the imputed educational variable included in the SIAB. The low skilled have neither vocational training nor a university degree. The middle skilled have vocational training and the high skilled hold a degree from a university or university of applied science. Standard errors are in parentheses and clustered at the nuts-3 level. We control for the following variables: The share of women in the SIAB population and county, the share of young- and middle-aged workers, the share of part-time workers, the share of middle- and high-skilled workers, the share of workers in the manufacturing sector, in the information and communication sector. We also create a shift-share instrument for a county's exposure to information and communication technology as well as trade, using data from EUROSTAT as well as COMTRADE. We control for federal states (NUTS-1) fixed effects. Source: IFR Robotics data and SIAB data. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A4: Robot exposure and perc. change in migrant share by skill-groups at the county-year-level

	All (OLS)	All (IV)	High-skilled(OLS)	High-skilled (IV)	Medium-skilled (OLS)	Medium-skilled (IV)	Low-skilled (OLS)	Low-skilled (IV)
Robot exposure (Op. Stock)	-24.22	-30.82	-40.83	-58.93	-19.73	2.850	56.40	-100.9
	(24.18)	(93.25)	(41.13)	(44.32)	(31.60)	(40.09)	(35.12)	(57.86)
Constant	-1544.2**	-1561.6*	-39.54	135.2**	-1397.9	103.7***	-1255.2	100.6***
	(526.4)	(607.4)	(814.3)	(42.89)	(730.0)	(18.25)	(822.5)	(26.02)
Federal States fixed-effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.626	0.626	0.241	0.154	0.512	0.468	0.523	0.488
N	401	401	340	340	395	395	381	381

Notes: Robot exposure (Op. Stock) is the exposure of a county to industrial robots measured via the shift share instrument. The unit of observation is the county. The outcome variable is the change in the migrant share in a respective county. The migrant share is defined as the number of migrants over the total SIAB population in a respective county. The skill level is based on the imputed educational variable included in the SIAB. The low skilled have neither vocational training nor a university degree. The middle skilled have vocational training and the high skilled hold a degree from a university or university of applied science. Standard errors are in parentheses and clustered at the NUTS-3 level. We control for the following variables: The share of women in the SIAB population and county, the share of young- and middle-aged workers, the share of part-time workers, the share of middle- and high-skilled workers, the share of workers in the manufacturing sector, in the information and communication sector. We also create a shift-share instrument for a county's exposure to information and communication technology as well as trade, using data from EUROSTAT as well as COMTRADE. We control for federal states (NUTS-1) fixed effects. We weight each cell by the respective population in a county. Source: IFR Robotics data and SIAB data. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

A1.2.2 Robots (Service Sector)

Table A5: Robot exposure and perc. change in immigrant inflow by skill-groups (Service Sector) at the county-year-level

	All (OLS)	All (IV)	High-skilled(OLS)	High-skilled (IV)	Medium-skilled (OLS)	Medium-skilled (IV)	Low-skilled (OLS)	Low-skilled (IV)
Robot exposure (Op. Stock)	94.56	-1775.6	17.30	-474.0	38.68	-712.3	37.22	-570.5
	(225.0)	(1707.5)	(53.98)	(441.8)	(96.63)	(692.0)	(72.55)	(556.4)
Constant	9591.4*	6158.4	2051.4	1149.6	4270.8*	2892.3	3164.9*	2049.3
	(4469.7)	(3759.4)	(1122.4)	(940.4)	(1889.3)	(1605.2)	(1422.2)	(1192.1)
Federal States fixed-effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.910	0.872	0.924	0.887	0.925	0.898	0.846	0.778
N	401	401	401	401	401	401	401	401

Notes: Robot exposure (Op. Stock) is the exposure of a county to industrial robots measured via the shift share instrument. The unit of observation is the county (NUTS-3). The immigrant inflow is the cumulative immigrant inflow into the service sector of a respective county during the period 2005 and 2018. We identify the immigrant inflow by aggregating the number of times a migrant appears for the first time in the service sector in the SIAB data per year. The skill level is based on the imputed educational variable included in the SIAB. The low skilled have neither vocational training nor a university degree. The middle skilled have vocational training and the high skilled hold a degree from a university or university of applied science. Standard errors are in parentheses and clustered at the nuts-3 level. We control for the following variables: The share of women in the SIAB population and county, the share of young- and middle-aged workers, the share of part-time workers, the share of middle- and high-skilled workers, the share of workers in the manufacturing sector, in the information and communication sector. We also create a shift-share instrument for a county's exposure to information and communication technology as well as trade, using data from EUROSTAT as well as COMTRADE. We control for federal states (NUTS-1) fixed effects. We weight each cell by the respective population in a county. Source: IFR Robotics data and SIAB data. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A6: Robot exposure and perc. change in migrant share (Service Sector) by skill-groups at the county-year-level

	All (OLS)	All (IV)	High-skilled(OLS)	High-skilled (IV)	Medium-skilled (OLS)	Medium-skilled (IV)	Low-skilled (OLS)	Low-skilled (IV)
Robot exposure (Op. Stock)	27.42	19.08	-46.09	-60.91	64.60	44.60	81.16*	-140.3
	(35.16)	(120.2)	(48.61)	(71.13)	(48.51)	(46.57)	(38.85)	(76.90)
Constant	-1429.0**	-1444.1*	-1078.8	180.7***	-604.1	110.1***	-548.0	113.2***
	(548.5)	(588.6)	(1360.9)	(51.43)	(633.9)	(27.61)	(794.3)	(28.38)
Federal States fixed-effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.556	0.556	0.199	0.132	0.475	0.425	0.510	0.450
N	397	397	308	308	384	384	370	370

Notes: Robot exposure (Op. Stock) is the exposure of a county to industrial robots measured via the shift share instrument. The unit of observation is the county. The outcome variable is the change in the migrant share in the service sector of a respective county. The migrant share is defined as the number of migrants over the total SIAB population in the service sector in a respective county. The skill level is based on the imputed educational variable included in the SIAB. The low skilled have neither vocational training nor a university degree. The middle skilled have vocational training and the high skilled hold a degree from a university or university of applied science. Standard errors are in parentheses and clustered at the NUTS-3 level. We control for the following variables: The share of women in the SIAB population and county, the share of young- and middle-aged workers, the share of part-time workers, the share of middle- and high-skilled workers, the share of workers in the manufacturing sector, in the information and communication sector. We also create a shift-share instrument for a county's exposure to information and communication technology as well as trade, using data from EUROSTAT as well as COMTRADE. We control for federal states (NUTS-1) fixed effects. We weight each cell by the respective population in a county. Source: IFR Robotics data and SIAB data. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A7: Robot exposure and perc. change in immigrant outflow (Service Sector) by skill-groups at the county-year-level

	All (OLS)	All (IV)	High-skilled(OLS)	High-skilled (IV)	Medium-skilled (OLS)	Medium-skilled (IV)	Low-skilled (OLS)	Low-skilled (IV)
Robot exposure (Op. Stock)	-0.372	-7.326	-0.128	-0.298	0.188	-2.360	-0.423	-4.669
	(1.240)	(7.173)	(0.131)	(0.508)	(0.749)	(3.341)	(0.533)	(3.968)
Constant	64.57**	51.81*	5.734	5.422	37.70**	33.02**	19.90	12.10
	(24.89)	(21.60)	(3.221)	(3.363)	(12.62)	(11.17)	(11.47)	(10.38)
Federal States fixed-effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.925	0.914	0.916	0.916	0.938	0.934	0.767	0.700
N	401	401	401	401	401	401	401	401

Notes: Robot exposure (Op. Stock) is the exposure of a county to industrial robots measured via the shift share instrument. The unit of observation is the county (NUTS-3). The immigrant outflow is the cumulative immigrant outflow from the service sector a respective county during the period 2005 and 2018. We identify the immigrant outflow by aggregating the number of times a migrant appears for the last time in the service sector in the SIAB per year. The skill level is based on the imputed educational variable included in the SIAB. The low skilled have neither vocational training nor a university degree. The middle skilled have vocational training and the high skilled hold a degree from a university or university of applied science. Standard errors are in parentheses and clustered at the nuts-3 level. We control for the following variables: The share of women in the SIAB population and county, the share of young- and middle-aged workers, the share of part-time workers, the share of middle- and high-skilled workers, the share of workers in the manufacturing sector, in the information and communication sector. We also create a shift-share instrument for a county's exposure to information and communication technology as well as trade, using data from EUROSTAT as well as COMTRADE. We control for federal states (NUTS-1) fixed effects. Source: IFR Robotics data and SIAB data. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A8: Robot exposure and perc. change in unemployment rate (Services Sector) at the county-year-level

	All (OLS)	All (IV)	High-skilled(OLS)	High-skilled (IV)	Medium-skilled (OLS)	Medium-skilled (IV)	Low-skilled (OLS)	Low-skilled (IV)
Migrant	-4.487	-3.916	20.75	23.73	39.64***	38.06***	10.61	9.101
	(2.535)	(3.404)	(19.43)	(24.71)	(7.321)	(8.348)	(7.221)	(8.531)
Robot exposure (Op. Stock)	4.876	-9.942	11.91	-83.65	-7.184	-12.13	22.97	-23.48
	(5.404)	(16.44)	(25.48)	(106.1)	(9.935)	(28.42)	(19.36)	(45.07)
Migrant*Robots	-7.029	-10.31	53.41	31.28	-20.66	-11.20	-37.55	-28.48
	(6.040)	(14.20)	(78.54)	(80.41)	(16.85)	(28.75)	(21.63)	(31.97)
Constant	22.12	-9.979	-164.3	-238.1	-306.6	-308.6	769.0***	692.8**
	(123.4)	(124.6)	(312.4)	(307.0)	(242.0)	(250.1)	(222.2)	(228.4)
Federal States fixed-effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.125	0.114	0.186	0.153	0.230	0.230	0.107	0.0934
N	685	685	396	396	633	633	572	572

Standard errors in parentheses

Source: IFR Robotics data and SIAB data.

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

Notes: Robot exposure (Op. Stock) is the exposure of a county to industrial robots measured via the shift share instrument. The unit of observation is the county-migrant combination. This means that there are two lines of data for each county, one showing the average change in the unemployment rate for migrants in the manufacturing sector in a respective county during the period 2005 and 2018, and the other one showing the average change in the unemployment rate for natives in the manufacturing sector. The skill level is based on the imputed educational variable included in the SIAB. The low skilled have neither vocational training nor a university degree. The middle skilled have vocational training and the high skilled hold a degree from a university or university of applied science. Standard errors are in parentheses and clustered at the NUTS-3 level. We control for the following variables: The share of women in the SIAB population and county, the share of young- and middle-aged workers, the share of part-time workers, the share of middle- and high-skilled workers, the share of workers in the manufacturing sector, in the information and communication sector. We also create a shift-share instrument for a county's exposure to information and communication technology as well as trade, using data from EUROSTAT as well as COMTRADE. We control for federal states (NUTS-1) fixed effects. We weight each cell by the respective population in a county. Source: IFR Robotics data and SIAB data. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A9: Robot exposure and perc. change in daily wage (Service Sector) by skill-level at the county-year-level

	High-skilled(OLS)	High-skilled (IV)	Medium-skilled (OLS)	Medium-skilled (IV)	Low-skilled (OLS)	Low-skilled (IV)
Migrant	63.73	74.20^{*}	6.761	5.540	21.18^{***}	20.60^{**}
	(33.39)	(36.44)	(3.874)	(4.099)	(4.978)	(6.393)
Robot exposure (Op. Stock)	-11.08	64.45	8.466	8.693	10.50	4.093
	(29.90)	(55.64)	(4.740)	(5.446)	(7.681)	(8.610)
Migrant*Robots	12.48	-62.18	-5.761	0.548	-10.75	-7.882
	(47.17)	(68.40)	(5.920)	(10.37)	(8.711)	(17.72)
Constant	361.3	4.877	-57.80	0.758	-381.7^{*}	15.57^{*}
	(1087.4)	(27.94)	(131.0)	(3.460)	(185.2)	(6.721)
Federal States fixed-effect	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.0420	0.0333	0.0874	0.0771	0.187	0.161
N	709	709	785	785	771	771

Notes: Robot exposure (Op. Stock) is the exposure of a county to industrial robots measured via the shift share instrument. The unit of observation is the county-migrant combination. This means that there are two lines of data for each county, one showing the average percentage change of daily wages for migrants in the manufacturing sector in a respective county during the period 2005 and 2018, and the other one showing the average percentage change of daily wages for natives in the manufacturing sector . The skill level is based on the imputed educational variable included in the SIAB. The low skilled have neither vocational training nor a university degree. The middle skilled have vocational training and the high skilled hold a degree from a university or university of applied science. Standard errors are in parentheses and clustered at the nuts-3 level. We control for the following variables: The share of women in the SIAB population and county, the share of young- and middle-aged workers, the share of part-time workers, the share of middle- and high-skilled workers, the share of workers in the manufacturing sector, in the information and communication sector. We also create a shift-share instrument for a county's exposure to information and communication technology as well as trade, using data from EUROSTAT as well as COMTRADE. We control for federal states (NUTS-1) fixed effects. We weight each cell by the respective population in a county. Source: IFR Robotics data and SIAB data. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

A1.2.3 Robots (Manufacturing Sector)

Table A10: Robot exposure and perc. change in immigrant inflow (manufacturing) by skill-groups at the county-year-level

	All (OLS)	All (IV)	High-skilled(OLS)	High-skilled (IV)	Medium-skilled (OLS)	Medium-skilled (IV)	Low-skilled (OLS)	Low-skilled (IV)
Robot exposure (Op. Stock)	-3.709	-77.66	-0.926	-41.82	-2.493	-22.74	0.0503	-13.84
	(12.77)	(102.3)	(3.474)	(43.75)	(5.605)	(33.07)	(4.136)	(27.21)
Constant	1027.6^{**}	714.1	259.0	85.64	418.6^{**}	332.7^{*}	352.8^{**}	293.9^{**}
	(387.1)	(369.8)	(147.5)	(143.4)	(139.8)	(147.6)	(115.5)	(110.6)
Federal States fixed-effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.901	0.887	0.797	0.708	0.930	0.926	0.835	0.825
N	401	401	401	401	401	401	401	401

Notes: Robot exposure (Op. Stock) is the exposure of a county to industrial robots measured via the shift share instrument. The unit of observation is the county (NUTS-3). The immigrant inflow is the cumulative immigrant inflow into the manufacturing sector of a respective county during the period 2005 and 2018. We identify the immigrant inflow by aggregating the number of times a migrant appears for the first time in the manufacturing sector in the SIAB data per year. The skill level is based on the imputed educational variable included in the SIAB. The low skilled have neither vocational training nor a university degree. The middle skilled have vocational training and the high skilled hold a degree from a university or university of applied science. Standard errors are in parentheses and clustered at the nuts-3 level. We control for the following variables: The share of women in the SIAB population and county, the share of young- and middle-aged workers, the share of part-time workers, the share of middle- and high-skilled workers, the share of workers in the manufacturing sector, in the information and communication sector. We also create a shift-share instrument for a county's exposure to information and communication technology as well as trade, using data from EUROSTAT as well as COMTRADE. We control for federal states (NUTS-1) fixed effects. We weight each cell by the respective population in a county. Source: IFR Robotics data and SIAB data. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A11: Robot exposure and perc. change in immigrant outflow (manufacturing) by skill-groups at the county-year-level

	All (OLS)	All (IV)	High-skilled(OLS)	High-skilled (IV)	Medium-skilled (OLS)	Medium-skilled (IV)	Low-skilled (OLS)	Low-skilled (IV)
Robot exposure (Op. Stock)	0.338*	0.536	-0.0180	0.240	0.373**	-0.770	-0.0155	1.074
	(0.159)	(0.908)	(0.0310)	(0.168)	(0.119)	(1.112)	(0.121)	(0.625)
Constant	17.53**	18.37***	-0.930	0.165	11.78**	6.933	6.673*	11.29*
	(5.424)	(5.011)	(0.834)	(1.134)	(4.060)	(4.593)	(3.318)	(4.755)
Federal States fixed-effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.835	0.834	0.447	0.393	0.771	0.710	0.603	0.502
N	401	401	401	401	401	401	401	401

Notes: Robot exposure (Op. Stock) is the exposure of a county to industrial robots measured via the shift share instrument. The unit of observation is the county (NUTS-3). The immigrant outflow is the cumulative immigrant outflow from the manufacturing sector in a respective county during the period 2005 and 2018. We identify the immigrant outflow by aggregating the number of times a migrant appears for the last time in the SIAB per year. The skill level is based on the imputed educational variable included in the SIAB. The low skilled have neither vocational training nor a university degree. The middle skilled have vocational training and the high skilled hold a degree from a university or university of applied science. Standard errors are in parentheses and clustered at the nuts-3 level. We control for the following variables: The share of women in the SIAB population and county, the share of young- and middle-aged workers, the share of part-time workers, the share of middle- and high-skilled workers, the share of workers in the manufacturing sector, in the information and communication sector. We also create a shift-share instrument for a county's exposure to information and communication technology as well as trade, using data from EUROSTAT as well as COMTRADE. We control for federal states (NUTS-1) fixed effects. Source: IFR Robotics data and SIAB data. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A12: Robot exposure and perc. change in unemployment rate (manufacturing) at the county-year-level

	All (OLS)	All (IV)	High-skilled(OLS)	High-skilled (IV)	Medium-skilled (OLS)	Medium-skilled (IV)	Low-skilled (OLS)	Low-skilled (IV)
Migrant	-4.396	-2.517	-10.70	9.396	-7.974	-6.198	-9.598	-9.896
	(5.866)	(7.423)	(24.65)	(28.92)	(5.410)	(6.360)	(11.06)	(13.68)
Robot exposure (Op. Stock)	-11.15	-18.79	20.59	19.40	-10.72	32.99	-30.62	-25.37
	(8.443)	(26.77)	(28.24)	(63.46)	(7.216)	(25.50)	(19.36)	(31.11)
Robots*Migrants	4.772	-2.641	121.8	34.21	6.293	-0.576	5.400	7.150
	(9.102)	(17.59)	(117.0)	(102.8)	(9.670)	(15.72)	(26.53)	(42.37)
Constant	130.1	75.86	678.5	658.5	76.93	274.6	-112.9	-101.4
	(186.9)	(181.2)	(546.1)	(495.7)	(147.7)	(191.0)	(314.0)	(312.4)
Federal States fixed-effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.0493	0.0452	0.480	0.473	0.0678	0.0161	0.121	0.121
N	611	611	197	197	550	550	445	445

Notes: Robot exposure (Op. Stock) is the exposure of a county to industrial robots measured via the shift share instrument. The unit of observation is the county-migrant combination. This means that there are two lines of data for each county, one showing the average change in the unemployment rate for migrants in the manufacturing sector in a respective county during the period 2005 and 2018, and the other one showing the average change in the unemployment rate for natives in the manufacturing sector. The skill level is based on the imputed educational variable included in the SIAB. The low skilled have neither vocational training nor a university degree. The middle skilled have vocational training and the high skilled hold a degree from a university or university of applied science. Standard errors are in parentheses and clustered at the NUTS-3 level. We control for the following variables: The share of women in the SIAB population and county, the share of young- and middle-aged workers, the share of part-time workers, the share of middle- and high-skilled workers, the share of workers in the manufacturing sector, in the information and communication sector. We also create a shift-share instrument for a county's exposure to information and communication technology as well as trade, using data from EUROSTAT as well as COMTRADE. We control for federal states (NUTS-1) fixed effects. We weight each cell by the respective population in a county. Source: IFR Robotics data and SIAB data. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A13: Robot exposure and perc. change in daily wage (manufacturing) by skill-level at the county-year-level

	High-skilled(OLS)	High-skilled (IV)	Medium-skilled (OLS)	Medium-skilled (IV)	Low-skilled (OLS)	Low-skilled (IV)
Migrant	0.549	-3.392	13.03	18.58	7.219	12.21
	(9.356)	(13.21)	(13.32)	(17.40)	(7.525)	(9.414)
Robot exposure (Op. Stock)	38.99	-63.14	5.707	29.28	11.84	11.45
	(24.07)	(53.18)	(16.34)	(30.94)	(14.77)	(11.41)
Robots*Migrants	-7.190	6.546	-0.560	-28.91	-19.03*	-43.97
	(14.56)	(34.18)	(9.213)	(24.25)	(9.624)	(25.16)
Constant	495.4	6.992	331.0	-12.84	-115.7	10.28
	(613.2)	(16.96)	(388.8)	(10.50)	(253.8)	(11.01)
Federal States fixed-effect	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.0353	0.00944	0.0653	0.0583	0.0802	0.0743
N	597	597	735	735	699	699

Notes: Robot exposure (Op. Stock) is the exposure of a county to industrial robots measured via the shift share instrument. The unit of observation is the county-migrant combination. This means that there are two lines of data for each county, one showing the average percentage change of daily wages for migrants in the manufacturing sector in a respective county during the period 2005 and 2018, and the other one showing the average percentage change of daily wages for natives in the manufacturing sector . The skill level is based on the imputed educational variable included in the SIAB. The low skilled have neither vocational training nor a university degree. The middle skilled have vocational training and the high skilled hold a degree from a university or university of applied science. Standard errors are in parentheses and clustered at the nuts-3 level. We control for the following variables: The share of women in the SIAB population and county, the share of young- and middle-aged workers, the share of part-time workers, the share of middle- and high-skilled workers, the share of workers in the manufacturing sector, in the information and communication sector. We also create a shift-share instrument for a county's exposure to information and communication technology as well as trade, using data from EUROSTAT as well as COMTRADE. We control for federal states (NUTS-1) fixed effects. We weight each cell by the respective population in a county. Source: IFR Robotics data and SIAB data. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

A1.2.4 Robots (All other Sector)

Table A14: Robot exposure and perc. change in immigrant inflow (all other sectors) by skill-groups at the county-year-level

	All (OLS)	All (IV)	High-skilled(OLS)	High-skilled (IV)	Medium-skilled (OLS)	Medium-skilled (IV)	Low-skilled (OLS)	Low-skilled (IV)
Robot exposure (Op. Stock)	-0.935	-159.1	-1.241	-9.773	-1.378	-103.8	1.264	-44.32
	(19.01)	(156.7)	(1.723)	(9.914)	(11.73)	(100.5)	(5.739)	(45.71)
Constant	451.1	225.6	26.62	14.46	297.9	151.9	128.9	63.91
	(304.6)	(292.2)	(26.86)	(28.63)	(189.4)	(180.9)	(92.11)	(87.31)
Federal States fixed-effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.884	0.847	0.919	0.911	0.897	0.861	0.735	0.665
N	401	401	401	401	401	401	401	401

Notes: Robot exposure (Op. Stock) is the exposure of a county to industrial robots measured via the shift share instrument. The unit of observation is the county (NUTS-3). The immigrant inflow is the cumulative immigrant inflow into all sectors but the manufacturing and service sector of a respective county during the period 2005 and 2018. We identify the immigrant inflow by aggregating the number of times a migrant appears for the first time in all sectors but the manufacturing and service sector in the SIAB data per year. The skill level is based on the imputed educational variable included in the SIAB. The low skilled have neither vocational training nor a university degree. The middle skilled have vocational training and the high skilled hold a degree from a university or university of applied science. Standard errors are in parentheses and clustered at the nuts-3 level. We control for the following variables: The share of women in the SIAB population and county, the share of young- and middle-aged workers, the share of part-time workers, the share of middle- and high-skilled workers, the share of workers in the manufacturing sector, in the information and communication sector. We also create a shift-share instrument for a county's exposure to information and communication technology as well as trade, using data from EUROSTAT as well as COMTRADE. We control for federal states (NUTS-1) fixed effects. We weight each cell by the respective population in a county. Source: IFR Robotics data and SIAB data. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A15: Robot exposure and perc. change in migrant share (all other sectors) by skill-groups at the county-year-level

	All (OLS)	All (IV)	High-skilled(OLS)	High-skilled (IV)	Medium-skilled (OLS)	Medium-skilled (IV)	Low-skilled (OLS)	Low-skilled (IV)
Robot exposure (Op. Stock)	-75.78	347.7	-148.6	-108.5	-7.753	104.9	29.76	20.74
	(65.36)	(471.1)	(121.5)	(150.6)	(137.6)	(133.1)	(97.63)	(85.86)
Constant	-2280.6	-1623.6	690.5	47.71**	-790.5	215.4***	710.0	23.11
	(1440.4)	(1523.7)	(1540.3)	(17.64)	(1287.8)	(59.28)	(970.1)	(35.85)
Federal States fixed-effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.357	0.318	0.658	0.511	0.230	0.115	0.120	0.0710
N	343	343	73	73	318	318	254	254

Notes: Robot exposure (Op. Stock) is the exposure of a county to industrial robots measured via the shift share instrument. The unit of observation is the county. The outcome variable is the change in the migrant share in all sectors but the manufacturing and service sector of a respective county. The migrant share is defined as the number of migrants over the total SIAB population in all sectors but the manufacturing and service sector in a respective county. The skill level is based on the imputed educational variable included in the SIAB. The low skilled have neither vocational training nor a university degree. The middle skilled have vocational training and the high skilled hold a degree from a university or university of applied science. Standard errors are in parentheses and clustered at the NUTS-3 level. We control for the following variables: The share of women in the SIAB population and county, the share of young- and middle-aged workers, the share of part-time workers, the share of middle- and high-skilled workers, the share of workers in the manufacturing sector, in the information and communication sector. We also create a shift-share instrument for a county's exposure to information and communication technology as well as trade, using data from EUROSTAT as well as COMTRADE. We control for federal states (NUTS-1) fixed effects. We weight each cell by the respective population in a county. Source: IFR Robotics data and SIAB data. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A16: Robot exposure and perc. change in immigrant outflow (all other sectors) by skill-groups at the county-year-level

	All (OLS)	All (IV)	High-skilled(OLS)	High-skilled (IV)	Medium-skilled (OLS)	Medium-skilled (IV)	Low-skilled (OLS)	Low-skilled (IV)
Robot exposure (Op. Stock)	0.0437	0.898	-0.000102	-0.0611	-0.0230	1.084	0.0667	-0.125
	(0.154)	(0.850)	(0.0253)	(0.0740)	(0.120)	(1.086)	(0.107)	(0.507)
Constant	-0.209	1.008	0.185	0.0984	-0.206	1.371	-0.188	-0.461
	(2.302)	(2.308)	(0.250)	(0.268)	(1.528)	(1.692)	(1.953)	(1.986)
Federal States fixed-effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.886	0.877	0.648	0.645	0.902	0.880	0.749	0.745
N	401	401	401	401	401	401	401	401

Notes: Robot exposure (Op. Stock) is the exposure of a county to industrial robots measured via the shift share instrument. The unit of observation is the county (NUTS-3). The immigrant outflow is the cumulative immigrant outflow from all sectors but the manufacturing or service sector a respective county during the period 2005 and 2018. We identify the immigrant outflow by aggregating the number of times a migrant appears for the last time in all sectors but the manufacturing or service sector in the SIAB per year. The skill level is based on the imputed educational variable included in the SIAB. The low skilled have neither vocational training nor a university degree. The middle skilled have vocational training and the high skilled hold a degree from a university or university of applied science. Standard errors are in parentheses and clustered at the nuts-3 level. We control for the following variables: The share of women in the SIAB population and county, the share of young- and middle-aged workers, the share of part-time workers, the share of middle- and high-skilled workers, the share of workers in the manufacturing sector, in the information and communication sector. We also create a shift-share instrument for a county's exposure to information and communication technology as well as trade, using data from EUROSTAT as well as COMTRADE. We control for federal states (NUTS-1) fixed effects. Source: IFR Robotics data and SIAB data. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A17: Robot exposure and perc. change in unemployment rate at the county-year-level

	All (OLS)	All (IV)	High-skilled(OLS)	High-skilled (IV)	Medium-skilled (OLS)	Medium-skilled (IV)	Low-skilled (OLS)	Low-skilled (IV)
Migrant	-12.75*	-10.14	-1.658	-6.867	7.455	11.63	0.235	3.461
	(5.540)	(6.319)	(11.19)	(12.21)	(10.24)	(11.99)	(12.46)	(15.25)
Robot exposure (Op. Stock)	-12.91	-38.84	-7.137	-190.0	-8.890	-28.61	22.07	-34.66
	(9.398)	(21.73)	(68.30)	(108.0)	(13.19)	(26.60)	(16.60)	(33.35)
Robots*Migrants	9.855	-4.724	-53.91	-13.60	-0.150	-23.67	48.76	28.49
	(10.98)	(19.60)	(67.59)	(71.50)	(19.86)	(36.85)	(37.88)	(50.79)
Constant	-152.4	-206.8	-348.9	-619.3	-297.7	-349.6	-349.7	-450.1
	(177.8)	(178.9)	(478.7)	(425.4)	(285.6)	(285.8)	(392.1)	(390.8)
Federal States fixed-effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.0892	0.0728	0.249	0.122	0.0927	0.0830	0.135	0.102
N	547	547	119	119	504	504	336	336

Notes: Robot exposure (Op. Stock) is the exposure of a county to industrial robots measured via the shift share instrument. The unit of observation is the county-migrant combination. This means that there are two lines of data for each county, one showing the average change in the unemployment rate for migrants in all sectors but the manufacturing and service sector in a respective county during the period 2005 and 2018, and the other one showing the average change in the unemployment rate for natives in all sectors but the manufacturing and service sector. The skill level is based on the imputed educational variable included in the SIAB. The low skilled have neither vocational training nor a university degree. The middle skilled have vocational training and the high skilled hold a degree from a university or university of applied science. Standard errors are in parentheses and clustered at the NUTS-3 level. We control for the following variables: The share of women in the SIAB population and county, the share of young- and middle-aged workers, the share of part-time workers, the share of middle- and high-skilled workers, the share of workers in the manufacturing sector, in the information and communication sector. We also create a shift-share instrument for a county's exposure to information and communication technology as well as trade, using data from EUROSTAT as well as COMTRADE. We control for federal states (NUTS-1) fixed effects. We weight each cell by the respective population in a county. Source: IFR Robotics data and SIAB data. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A18: Robot exposure and perc. change in daily wage by skill-level at the county-year-level

	High-skilled(OLS)	High-skilled (IV)	Medium-skilled (OLS)	Medium-skilled (IV)	Low-skilled (OLS)	Low-skilled (IV)
Migrant	-19.63	8.400	5.791	3.023	27.00*	29.99*
	(17.66)	(21.36)	(5.558)	(7.047)	(12.07)	(13.70)
Robot exposure (Op. Stock)	10.97	10.34	12.73	-0.930	16.92	16.78
	(15.23)	(20.44)	(9.757)	(8.740)	(15.25)	(20.89)
Robots*Migrants	91.33	-95.81	-17.81	-3.183	-34.98	-54.41
	(71.66)	(101.4)	(12.15)	(31.50)	(18.26)	(33.82)
Constant	-765.0	11.22	-2.976	21.77	-161.8	1.850
	(484.1)	(19.21)	(140.9)	(12.54)	(415.4)	(17.15)
Federal States fixed-effect	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.0480	0.00665	0.0935	0.0713	0.108	0.0929
N	445	445	718	718	638	638

Notes: Robot exposure (Op. Stock) is the exposure of a county to industrial robots measured via the shift share instrument. The unit of observation is the county-migrant combination. This means that there are two lines of data for each county, one showing the average percentage change of daily wages for migrants in all sectors but the manufacturing and service sector in a respective county during the period 2005 and 2018, and the other one showing the average percentage change of daily wages for natives in all sectors but the manufacturing and service sector. The skill level is based on the imputed educational variable included in the SIAB. The low skilled have neither vocational training nor a university degree. The middle skilled have vocational training and the high skilled hold a degree from a university or university of applied science. Standard errors are in parentheses and clustered at the nuts-3 level. We control for the following variables: The share of women in the SIAB population and county, the share of young- and middle-aged workers, the share of part-time workers, the share of middle- and high-skilled workers, the share of workers in the manufacturing sector, in the information and communication sector. We also create a shift-share instrument for a county's exposure to information and communication technology as well as trade, using data from EUROSTAT as well as COMTRADE. We control for federal states (NUTS-1) fixed effects. We weight each cell by the respective population in a county. Source: IFR Robotics data and SIAB data. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

A1.2.5 AI (Overall)

Table A19: AI skill demands and immigrant inflow (employed) by skill-groups at the county-year-level

	All (OLS)	All (IV)	Medium-skilled (OLS)	Medium-skilled (IV)	Low-skilled (OLS)
AI skill demand	142507.5*	142507.5*	436984.0*	35458.4*	122724.2*
	(64943.9)	(64943.9)	(190492.4)	(15603.9)	(47879.0)
Constant	331.6**	331.6**	78.68	92.30***	21.88
	(107.3)	(107.3)	(182.4)	(27.64)	(44.34)
Federal States fixed-effect	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.786	0.786	0.257	0.746	0.285
N	2406	2406	2406	2406	2406

Notes: AI skill demands are measured via the share of job vacancies mentioning AI-related expressions in the total number of job vacancies. The immigrant inflow is the yearly inflow into a specific county. We identify the immigrant inflow by aggregating the number of times a migrant appears for the first time in the SIAB per year. In this case, we restrict the inflow to those who are immediately employed. The skill level is based on the imputed educational variable included in the SIAB. The low skilled have neither vocational training nor a university degree. The middle skilled have vocational training and the high skilled hold a degree from a university or university of applied science. Standard errors are in parentheses and clustered at the nuts-3 level. We control for the following variables: The share of women in the SIAB population and county, the share of young- and middle-aged workers, the share of part-time workers, the share of middle- and high-skilled workers, the share of workers in the manufacturing sector, in the information and communication sector. We also create a shift-share instrument for a county's exposure to information and communication technology as well as trade, using data from EUROSTAT as well as COMTRADE. We control for federal states (NUTS-1) fixed effects. We weight each cell by the respective population in a county. The period under consideration is 2014 to 2019, as the Burning Glass data is only available from 2014 onwards. Source: Burning Glass data and SIAB data. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A20: AI skill demands and immigrant inflow by skill-groups at the county-year-level (cumulative 5 years)

	All (OLS)	All (IV)	High-skilled(OLS)	High-skilled (IV)	Medium-skilled (OLS)	Medium-skilled (IV)	Low-skilled (OLS)	Low-skilled (IV)
AI	11.52	182.5	4.039	63.43	4.445	80.14	2.962	37.93
	(7.275)	(100.5)	(2.278)	(34.72)	(3.201)	(44.51)	(1.784)	(20.59)
Constant	2611.5***	-8460.7	596.9***	-3333.2	1316.9***	-3525.7	688.0***	-1555.9
	(666.0)	(6933.6)	(164.0)	(2387.0)	(336.5)	(3075.4)	(171.0)	(1425.0)
Federal States fixed-effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.812	.	0.836	.	0.808	.	0.774	.
N	401	401	401	401	401	401	401	401

Notes: AI skill demands are measured via the share of job vacancies mentioning AI-related expressions in the total number of job vacancies. The immigrant inflow is the cumulative inflow into a specific county for 2014-2019. We identify the immigrant inflow by aggregating the number of times a migrant appears for the first time in the SIAB during this period. The skill level is based on the imputed educational variable included in the SIAB. The low skilled have neither vocational training nor a university degree. The middle skilled have vocational training and the high skilled hold a degree from a university or university of applied science. Standard errors are in parentheses and clustered at the nuts-3 level. We control for the following variables: The share of women in the SIAB population and county, the share of young- and middle-aged workers, the share of part-time workers, the share of middle- and high-skilled workers, the share of workers in the manufacturing sector, in the information and communication sector. We also create a shift-share instrument for a county's exposure to information and communication technology as well as trade, using data from EUROSTAT as well as COMTRADE. We control for federal states (NUTS-1) fixed effects. We weight each cell by the respective population in a county. The period under consideration is 2014 to 2019, as the Burning Glass data is only available from 2014 onwards. Source: Burning Glass data and SIAB data. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A21: AI skill demands and perc. change in migrant share by skill-groups at the county-year-level

	All (OLS)	All (IV)	High-skilled(OLS)	High-skilled (IV)	Medium-skilled (OLS)	Medium-skilled (IV)	Low-skilled (OLS)	Low-skilled (IV)
AI skill demand	54.75^{**}	516.0^{***}	17.16	223.3^{***}	54.36^{**}	516.8^{***}	100.9^{***}	948.8^{***}
	(16.58)	(51.99)	(11.97)	(35.34)	(18.99)	(59.81)	(27.76)	(98.06)
Constant	0.243^{***}	-0.193^{*}	0.0726^{*}	-0.152^{**}	0.248^{***}	-0.181^{*}	0.610^{***}	-0.203
	(0.0439)	(0.0789)	(0.0357)	(0.0510)	(0.0456)	(0.0816)	(0.0762)	(0.138)
Federal States fixed-effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.638	0.00350	0.455	0.0778	0.611	.	0.569	.
N	2406	2406	2406	2406	2406	2406	2406	2406

Notes: AI skill demands are measured via the share of job vacancies mentioning AI-related expressions in the total number of job vacancies. The outcome variable is the migrant share. The migrant share is defined as the number of people in the SIAB with foreign nationality over the total SIAB population. The skill level is based on the imputed educational variable included in the SIAB. The low skilled have neither vocational training nor a university degree. The middle skilled have vocational training and the high skilled hold a degree from a university or university of applied science. Standard errors are in parentheses and clustered at the nuts-3 level. We control for the following variables: The share of women in the SIAB population and county, the share of young- and middle-aged workers, the share of part-time workers, the share of middle- and high-skilled workers, the share of workers in the manufacturing sector, in the information and communication sector. We also create a shift-share instrument for a county's exposure to information and communication technology as well as trade, using data from EUROSTAT as well as COMTRADE. We control for federal states (NUTS-1) fixed effects. We weight each cell by the respective population in a county. The period under consideration is 2014 to 2019, as the Burning Glass data is only available from 2014 onwards. Source: Burning Glass data and SIAB data. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

A1.2.6 AI (Most AI exposed economic sectors)

Table A22: AI skill demands and unemployment (most exposed sectors) at the county-year-level

	All (OLS)	All (IV)	High-skilled(OLS)	High-skilled (IV)	Medium-skilled (OLS)	Medium-skilled (IV)	Low-skilled (OLS)	Low-skilled (IV)
Migrant	0.0503^{**}	0.0835^{**}	-0.0141^{***}	-0.0138	-0.0124^{***}	-0.0102^{*}	-0.0185^{**}	-0.0339^{**}
	(0.0163)	(0.0277)	(0.00364)	(0.00789)	(0.00227)	(0.00408)	(0.00682)	(0.0123)
AI	19.07^{*}	16.86	-3.357	-12.53	-2.021	-7.093	13.10	-1.170
	(7.635)	(20.90)	(5.285)	(10.92)	(3.825)	(6.551)	(12.26)	(23.34)
Migrant*AI	-65.19^{*}	-120.3^{**}	-0.917	-1.490	0.328	-3.285	5.104	30.72
	(25.57)	(44.34)	(6.779)	(13.48)	(3.993)	(7.036)	(11.57)	(20.71)
Constant	-0.000957	0.00510	0.0149^{**}	0.0218^{**}	0.0184^{***}	0.0225^{***}	0.00407	0.0128
	(0.0165)	(0.0217)	(0.00508)	(0.00783)	(0.00336)	(0.00478)	(0.0101)	(0.0161)
Federal States fixed-effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.0237	0.0212	0.214	0.212	0.360	0.358	0.0726	0.0716
N	4220	4220	4812	4812	4812	4812	4705	4705

Notes: AI skill demands are measured via the share of job vacancies mentioning AI-related expressions in the total number of job vacancies. The outcome variable is the unemployment rate. In this case, we only consider the unemployment rate in the most exposed sector. The skill level is based on the imputed educational variable included in the SIAB. The low skilled have neither vocational training nor a university degree. The middle skilled have vocational training and the high skilled hold a degree from a university or university of applied science. Standard errors are in parentheses and clustered at the nuts-3 level. We control for the following variables: The share of women in the SIAB population and county, the share of young- and middle-aged workers, the share of part-time workers, the share of middle- and high-skilled workers, the share of workers in the manufacturing sector, in the information and communication sector. We also create a shift-share instrument for a county's exposure to information and communication technology as well as trade, using data from EUROSTAT as well as COMTRADE. We control for federal states (NUTS-1) fixed effects. We weight each cell by the respective population in a county. The period under consideration is 2014 to 2019, as the Burning Glass data is only available from 2014 onwards. Source: Burning Glass data and SIAB data. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A23: AI skill demands and daily wages (most exposed sectors) by skill-level at the county-year-level

	High-skilled(OLS)	High-skilled (IV)	Medium-skilled (OLS)	Medium-skilled (IV)	Low-skilled (OLS)	Low-skilled (IV)
Migrant	-27.59	-7.166	-53.92***	-88.10***	-14.54	-13.98
	(14.71)	(27.78)	(14.02)	(23.69)	(10.32)	(18.45)
AI	90095.1***	292630.2***	18835.9*	111260.5***	23907.1**	113038.0***
	(13234.3)	(35482.5)	(7471.8)	(17855.0)	(8494.9)	(20287.0)
Migrant*AI	-1468.1	-36501.8	61086.5*	116922.9**	29897.7	28000.3
	(23229.2)	(45029.5)	(23992.4)	(39926.8)	(15862.4)	(29879.6)
Constant	298.4***	146.3***	186.2***	111.4***	108.7***	39.88*
	(24.54)	(30.34)	(15.75)	(18.73)	(12.57)	(19.15)
Federal States fixed-effect	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.365	0.288	0.356	0.278	0.300	0.254
N	3465	3465	3713	3713	3141	3141

Standard errors in parentheses

Source: BGD and SIAB data. 2014-2019.

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

Notes: AI skill demands are measured via the share of job vacancies mentioning AI-related expressions in the total number of job vacancies. The outcome variable is the daily wage. In this case, we only consider the daily wage in the most exposed sector. The skill level is based on the imputed educational variable included in the SIAB. The low skilled have neither vocational training nor a university degree. The middle skilled have vocational training and the high skilled hold a degree from a university or university of applied science. Standard errors are in parentheses and clustered at the nuts-3 level. We control for the following variables: The share of women in the SIAB population and county, the share of young- and middle-aged workers, the share of part-time workers, the share of middle- and high-skilled workers, the share of workers in the manufacturing sector, in the information and communication sector. We also create a shift-share instrument for a county's exposure to information and communication technology as well as trade, using data from EUROSTAT as well as COMTRADE. We control for federal states (NUTS-1) fixed effects. We weight each cell by the respective population in a county. The period under consideration is 2014 to 2019, as the Burning Glass data is only available from 2014 onwards. Source: Burning Glass data and SIAB data. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

A1.2.7 AI (Least AI exposed economic sectors)

Table A24: AI skill demands and unemployment (least exposed sectors) at the county-year-level

	All (OLS)	All (IV)	High-skilled(OLS)	High-skilled (IV)	Medium-skilled (OLS)	Medium-skilled (IV)	Low-skilled (OLS)	Low-skilled (IV)
Migrant	0.0108***	0.00721	-0.0204***	-0.0313***	-0.0254***	-0.0402***	-0.0463***	-0.0871***
	(0.00275)	(0.00526)	(0.00176)	(0.00395)	(0.00206)	(0.00411)	(0.00419)	(0.00794)
AI	-5.065*	-25.22***	-6.617**	-22.36***	-5.427*	-16.20***	-26.07***	-60.65***
	(2.163)	(6.405)	(2.456)	(5.958)	(2.183)	(4.700)	(4.781)	(9.311)
Migrant*AI	-2.989	3.077	10.69***	29.38***	14.76***	40.12***	52.38***	122.1***
	(4.385)	(8.710)	(3.116)	(6.966)	(3.897)	(7.385)	(7.689)	(13.95)
Constant	0.0305***	0.0451***	0.0244***	0.0346***	0.0361***	0.0421***	0.0742***	0.0944***
	(0.00710)	(0.00904)	(0.00368)	(0.00509)	(0.00423)	(0.00514)	(0.00787)	(0.00971)
Federal States fixed-effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.191	0.183	0.525	0.518	0.777	0.767	0.347	0.312
N	4812	4812	4812	4812	481 ¿ 2	4812	4812	4812

Notes: AI skill demands are measured via the share of job vacancies mentioning AI-related expressions in the total number of job vacancies. The outcome variable is the unemployment rate. In this case, we only consider the unemployment rate in the least exposed sector. The skill level is based on the imputed educational variable included in the SIAB. The low skilled have neither vocational training nor a university degree. The middle skilled have vocational training and the high skilled hold a degree from a university or university of applied science. Standard errors are in parentheses and clustered at the nuts-3 level. We control for the following variables: The share of women in the SIAB population and county, the share of young- and middle-aged workers, the share of part-time workers, the share of middle- and high-skilled workers, the share of workers in the manufacturing sector, in the information and communication sector. We also create a shift-share instrument for a county's exposure to information and communication technology as well as trade, using data from EUROSTAT as well as COMTRADE. We control for federal states (NUTS-1) fixed effects. We weight each cell by the respective population in a county. The period under consideration is 2014 to 2019, as the Burning Glass data is only available from 2014 onwards. Source: Burning Glass data and SIAB data. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A25: AI skill demands and daily wages (least exposed sectors) by skill-level at the county-year-level

	High-skilled(OLS)	High-skilled (IV)	Medium-skilled (OLS)	Medium-skilled (IV)	Low-skilled (OLS)	Low-skilled (IV)
Migrant	-15.13*	49.53***	5.603*	45.64***	18.12***	38.47***
	(6.353)	(14.55)	(2.474)	(6.227)	(1.943)	(5.643)
AI	102320.3***	300522.6***	45881.0***	151354.8***	21163.8***	77361.5***
	(9446.2)	(28822.6)	(4405.7)	(14950.1)	(2794.6)	(9564.3)
Migrant*AI	-53120.7***	-163732.5***	-44144.4***	-112637.2***	-20100.8***	-54916.5***
	(10920.4)	(25040.3)	(4867.0)	(11285.7)	(3757.2)	(10162.2)
Constant	346.8***	206.9***	139.8***	66.46***	74.22***	35.00***
	(27.79)	(28.96)	(12.33)	(13.21)	(9.735)	(10.26)
Federal States fixed-effect	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.555	0.486	0.746	0.625	0.441	0.335
N	4800	4800	4812	4812	4795	4795

Standard errors in parentheses

Source: BGD and SIAB data. 2014-2019.

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

Notes: AI skill demands are measured via the share of job vacancies mentioning AI-related expressions in the total number of job vacancies. The outcome variable is the daily wage. In this case, we only consider the daily wage in the least exposed sector. The skill level is based on the imputed educational variable included in the SIAB. The low skilled have neither vocational training nor a university degree. The middle skilled have vocational training and the high skilled hold a degree from a university or university of applied science. Standard errors are in parentheses and clustered at the nuts-3 level. We control for the following variables: The share of women in the SIAB population and county, the share of young- and middle-aged workers, the share of part-time workers, the share of middle- and high-skilled workers, the share of workers in the manufacturing sector, in the information and communication sector. We also create a shift-share instrument for a county's exposure to information and communication technology as well as trade, using data from EUROSTAT as well as COMTRADE. We control for federal states (NUTS-1) fixed effects. We weight each cell by the respective population in a county. The period under consideration is 2014 to 2019, as the Burning Glass data is only available from 2014 onwards. Source: Burning Glass data and SIAB data. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.