Technological Change and Immigration - A race for talent or of displaced workers[*]

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We study the effect of technological change on immigration flows as well as the labor market outcomes of migrants versus non-migrants. We look at two different automation technologies: Industrial robots and artificial intelligence. For this purpose, we take advantage of data provided by the Industrial Federation of Robotics as well as online job vacancy data. Our research focuses on Germany, a highly automated economy and the main migration receiving country among OECD countries. We find that automation technologies decrease the wage of the migrant population, while it increases it for natives. This holds for the low-, middle- and high-skilled and is indicative of migrants facing displacement effects, while natives might benefit from productivity and complementarity effects. Robotics does not impact overall immigration flows, but leads to a decrease in the migrant share in the manufacturing sector. AI has a positive effect on immigrant inflows. Policy makers should make sure that technological change does not exacerbate discriminatory structures and inequalities, that migrants have equal access to labor market institutions and relevant information related to technological change, and that companies can compete globally in the search for scarce talent.

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1 Introduction

Scientists continue to invent, build and implement technologies which can perform human tasks. 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, was patented in 1954. The adoption of robots has revolutionized the manufacturing sector, but their usage is starting to conquer other sectors such as the service sector. One example is the adoption of robots in nursing homes in Japan (Eggleston et al., 2021). And more recently, new forms of robots, 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 which is able to have real conversations with humans based on Artificial Intelligence (AI). In fact, the usage of chatbots has increased by more than 400 percent between 2006 and 2020 (Adamopoulou and Moussiades, 2020). And the picture is even more staggering when having a 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 by almost 12 times between 2000 and 2019 (Entwood et al., 2021).

Automation brings along important benefits for companies. Experts and policy makers have observed a race between countries to win the automation competition and are convinced that AI could revolutionize the functioning of nearly all economic sectors around the globe. But as often with technological change, talent is scarce. In the late 90s, McKinsey detected a severe shortage of equipped labour 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, spend on average 6 months to fill tech positions (Anderson et al., 2020), while Tech companies pay horrendous salaries for AI specialists (Tarki, 2021). It is therefore straightforward to ask how technological change and immigration interact. Our first research question is whether automated technologies have brought us a global race for talent and whether increased technological change increases immigration flows.

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 fully replaced by technologies and jobs might become redundant. Several papers have studied the effect of robots and AI on labor markets in several different countries, with differing results. Migrants might be especially affected by potentially negative effects of technological change, as 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 of technological change. On the other hand, migrants might be more flexible and more willing to switch sectors and jobs. They might therefore mitigate the effects of technological change on the local population. The second research question we address in this paper is about how technological change affects the labor market outcomes of migrants versus natives.

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 take advantage of 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 globally 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. 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 not forming part of the EU or EEA: Switzerland. To measure labor market outcomes of migrants and natives as well as immigration flows we make use of the German matched employer-employee social security data. In addition to conducting analyses at the county-level we take advantage of 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 flows, but AI-related skill demands do. Additionally, robotics 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 elevated unemployment rates for migrants, but not for natives. This has important equity implications. Technological change could lead to increased inequalities between the migrant and native population, something that policy makers might need to consider. 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.

When breaking this down by sector, we find a decrease in the migrant share of those working in the manufacturing sector. This could be evidence of migrants moving towards other sectors as a 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 of certain skill groups to work in communication-intensive tasks, which 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 evidence of discriminatory effects or them lacking important access to information and labor market institutions.

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, but reduced the employment share of low-skilled workers. Acemoglu and Restrepo (2018), on the other hand, find negative effects on employment and wages for the US. In Germany, robots displace workers in the manufacturing sector, but these effects are mitigated through parallel employment creation in the service sector (Dauth et al., 2019). In France, firms that adopt 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 any significant aggregate labor market effects, while Webb (2019) predicts inequality decreases through replacement effects on the high-skilled. In contrast to that, Felten et al. (2019) show that AI might exacerbate inequality as it leads to an increase in the wages of high-skilled occupations. Finally, Alekseeva et al. (2021) document an increase in the skill demand of AI in the US and a wage premium for these jobs.

The paper at hand is closely related to three 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 that immigrants attenuate the job and wage polarization faced by the native-born from 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 local labor market on immigrant inflows in Switzerland. They show that a higher exposure to ICT leads to a significant inflow of high-skilled immigrants. Our work also contributes to the literature studying the effect of migration on innovation. Several scholars have studied the effect of migration on technological change. 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 might see low skilled migrants and automation machinery as substitutes.

Our paper contributes to this literature through comparing the effects of two related technologies: Manual and mental robots. To the best of our knowledge we are the first ones to study the effect of industrial robots on immigration flows as well as labor market outcomes of migrants versus natives. We are also the first ones to study the effect of AI on these outcome variables. While a large number of papers have studied the effect of immigrants on innovation, there is only scarce 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 a economy 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. First of all, policy makers that intend to attract talent should make sure that migration policies are not too rigid. Additionally, in order to avoid further increases in inequality, they should pay special attention to the migration population when designing mitigation policies in response to technological change. Lastly, countries should make sure that migrants have equal access to labor market institutions and information about the need to adapt their skill-set in response to technological change.

The paper is structured as follows. Section 2 provides descriptive statistics that give 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 through restricting the analysis to different economic sectors and conducting panel-data analysis of individuals. Lastly, section 6 concludes.

2 Descriptive Statistics and Data Sources

The digital revolution and automation techniques are not a new phenomenon, having its origins in the 1950s. Between 1969 and 1989 the internet and home computers conquered our society, while between 1989 and 2005 the World Wide Web and Web 1.0 revolution took place. This was followed by the Web 2.0, social media, smartphones and digital TVs from 2005 on-wards. In parallel, manual and virtual automation techniques were developed. The following section gives an overview of recent trends in the adoption of robotics and AI as well as the datasets at use in this paper.

2.1 Recent trends in robotics and AI

Figure 1 shows the number of installed industrial robots worldwide over time. The picture shows that the rhythm 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. The exponential increase observed for this technology is even more marked than the one for industrial robots. Especially since 2014 AI technologies have been on the rise.

Figure 1: **Global operational stock of industrial robots over time**

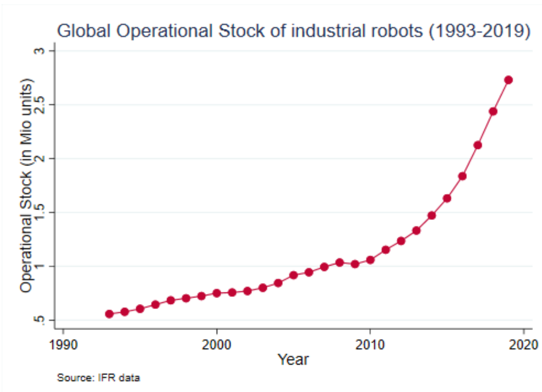
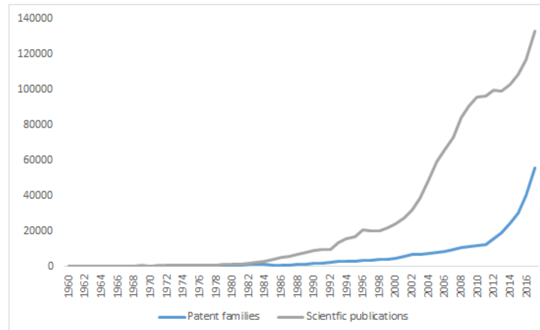


Figure 2: **No. of AI-related patents and scientific publications over time**



When analyzing robot adoption by region, Figure 3 shows that China is ramping up 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, standing at 0.8 million industrial robots in 2019 (see Figure 3). Similarly, the number of AI-related patent applications has increased for the 3 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.

Figure 3: **Global operational stock of industrial robots over time**

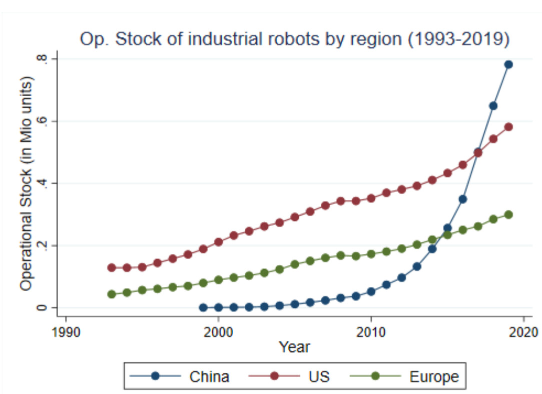
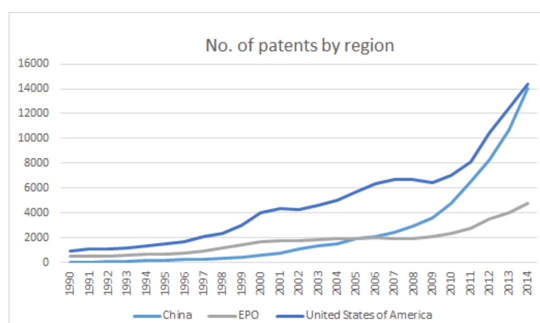


Figure 4: **No. of AI-related patent applications over time**



This increase in the number of AI-related patents has led to an increase in the demand of AI-related skills. The increase in absolute terms was largest for Germany, followed by France (see Figure A10). Figure A12 plots the share of AI-related skill demand in the overall skill demand in selected European countries for the period 2014-2020. The overall share of AI-related skills is low with around 0.1 percent across all countries under consideration. Moreover, the German-speaking countries report the highest share, together with the Netherlands. Switzerland is leading the list. When conducting the same 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). And indeed, when comparing the growth rates of robot adoption and AI to growth rates in ICT graduates, the picture is staggering. 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 A7). The number of graduates from Electronics and Automation, which also covers robotics, grew by even less. The number of graduates was 54,563 in 2015 and 58,837 in 2019, a growth of 8 percent only.

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) makes up for 26.5 percent of GDP in 2020 while the service sector accounts 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 accounts for 18 percent of its GDP in 2020. It is the third largest exporter globally, 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 comes a long history of automation. In fact, Germany in the most automated economy in Europe, when measured by industrial robots. Figure 5 shows that Germany is among the top 5 countries worldwide in terms of installed industrial robots. It is the mayor 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 A6 shows that robot exposure is largest for the manufacturing sector.

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

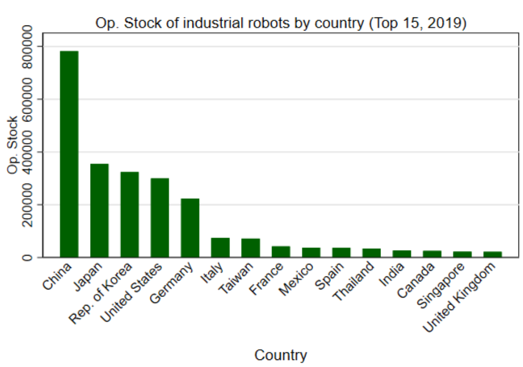
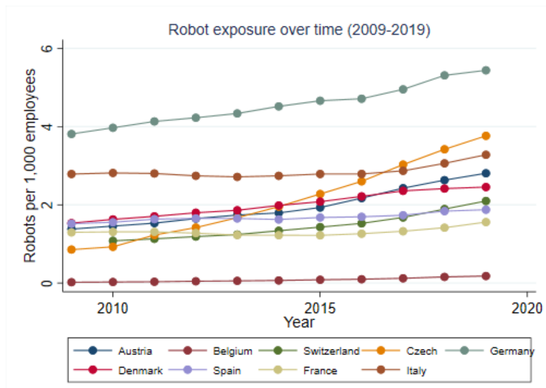


Figure 6: **Operational Stock of robots over time in European countries**



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 has been 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**

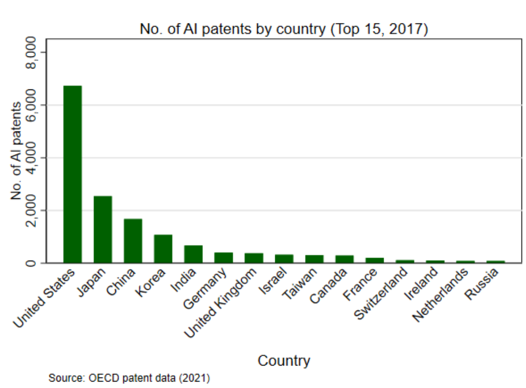
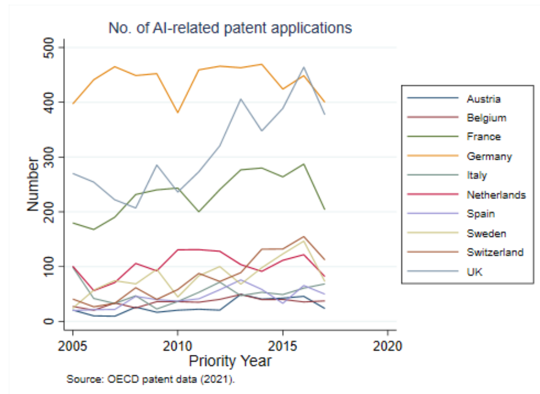


Figure 8: **AI Patent Filings in European countries over time**



2.3 Germany and recent trends in migration

Germany is a migration receiving country and has been so for many years. The yearly influx of foreign-born to Germany was above half a million from 2000 to 2013 and surpassed one million for the period 2013 to 2019. Figure A1 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 A2 for details). The country's migration balance has been largely positive for most years, with a balance fluctuating between 127,000 and 1.1 million since 2010. Germany has been the main migrant-receiving country among the OECD countries, overtaking the US in 2012 (see Figure A3).

Figure 9: **Immigrant Inflow by skill-group**

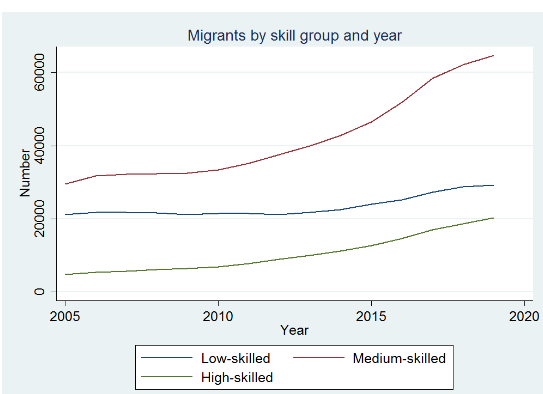


Figure 10: **Immigrant Inflow by Sector**

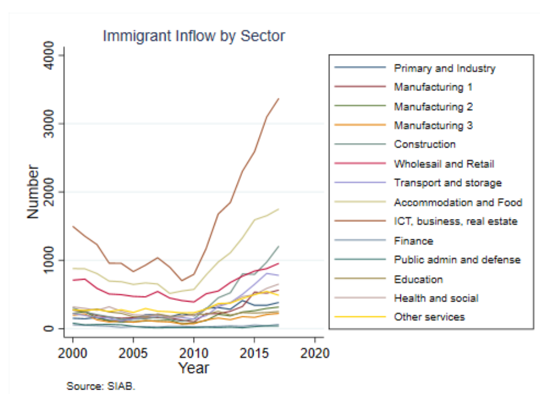


Figure 9 plots the immigrant inflow to Germany over time by skill group. There has been a constant increase of immigrants for each of the skill-groups, but the increase has been largest for the medium-skilled. Moreover, when looking at the immigrant inflow by economic sector, Figure 10 shows that the 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 A5). The migrant share is largest 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 Data sets at use

We make use of several different datasets in order to address the underlying research question. We measure technological change through two different datasets. First of all, 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 shows 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 take advantage of 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 and 2020. The data covers nearly the full universe of OJV in Germany, as it also pulls information from the country's public employment agencies.

Figure A9 shows that skill demand registered in OJV has doubled over time in Germany, from 31 million to 62 million. This could be due to economic growth but also an increased movement of job adds to the virtual space. It could also mean that jobs have become more complex over time and require a larger variety of skills. Figure A11 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 just due to economic growth. The number of AI-related skill demand registered in OJV has increased by 130 percent between 2014 and 2020, from 26,381 to 59,968 (see Figure A10). The share of AI-related skill demand in all skill demand is therefore still extremely low with 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 Labour Market Biographies (SIAB). The SIAB is a 2 % sample of the population of the Integrated Employment Biographies (IEB) of the IAB. The SIAB covers the employment histories of 1,940,69 individuals, and their employment biographies are

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

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

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 on-wards), 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 in principle (Cramer, 1985). It covers 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 yearly observations per individual.

Table 1 gives an overview of the main variables under consideration 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 (Middle-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 (Middle-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 (middle-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 (middle-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 (Middle-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 (Middle-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 Women 2004	402	.489217	.0394597	.3231241	.5844898
Share of middle-skilled 2004	402	.7496725	.0464956	.5925203	.8546042
Share of high-skilled 2004	402	.0953953	.0421964	.0263158	.2666236
Share of <35 in 2004	402	.3203929	.0307194	.21625	.4124424
Share of 35-54 in 2004	402	.5377275	.0303162	.4237918	.65875
Share of part-time 2004	402	.3055813	.0438054	.1544594	.479564
Share in manufacturing 2004	401	.2447619	.1031095	.0246305	.6248705
Share in ICT 2004	401	.020063	.0184684	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

Source: SIAB, Eurostat and IFR data.

3 Empirical Strategy

3.1 The effect of industrial robots

To estimate the effect of robot adoption on immigration demand as well as the labor market outcomes of migrants versus natives we follow the approach by Acemoglu and Restrepo, 2018 and analyze the effect of robot exposure at the level of local labor markets. We therefore aggregate the SIAB data at the commuting zone level. As the data provided by the IFR is only reported at the national level we apply a shift-share instrument to proxy robot exposure at the local level r, similar to Dauth, Eppelsheimer, et al., 2020. We consider the period of 2005 to 2019. We construct our main explanatory variable as follows:

$$\Delta \hat{\text{robots}}_r = \sum_{i \in I} \frac{\text{emp}_{ir}}{\text{emp}_r} \times \frac{\Delta \text{robots}_i}{\text{emp}_i} \text{ , with I=34} \tag{1}$$

The term $\frac{\Delta\text{robots}_i}{\text{emp}_i}$ is the difference in robot counts between 2019 and 2005 over the employment in the respective industry in 2004. We proxy the industry 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 first calculate the difference in the robotic operational stock between 2019 and 2005 for each industry. We then divide this number by the number of employed people in each industry in 2004. As a second step, we multiply the resulting scaled difference in robot counts by the share of people employed in a certain industry in a certain commuting zone (CZ) in the base year 2004.

We follow Dauth, Eppelsheimer, et al., 2020 and run the following regression:

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

We regress our outcome variable of interest on the change of robot exposure. We control for demographic characteristics at the CZ-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 the 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. To account for part-time workers, we additionally weight the part-time workers with a weight of 0.5.

We consider several outcome variables of interest: The cumulative immigrant inflow and outflow between 2005 and 2019, the percentage change in the migrant share for this same period, the percentage change in the unemployment rate as well as the percentage change in daily wages of migrants and natives. We conduct our analysis for the population as a whole, but also for three different skill groups: The high-, medium- and low-skilled workers.

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, closely following the methodology proposed by Acemoglu and Restrepo, 2018. We use robot installations from Japan, South Korea and Taiwan as our instrumental variables. We choose 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 10 countries with the largest number of robot installations in 2019. Figure A13 shows the robot exposure per 1,000 employees over time in all three countries compared to Germany. South Korea has been outperforming Germany since 2009 in its robot adoption, while Taiwan outpaced it in 2013 and Japan in 2015. All countries are therefore a good option as they are leading in robot adoption. Additionally, through 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 the industry-level in Switzerland. The coefficient is positive and significant and the F-statistic is well above 10.

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

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

Standard errors in parentheses

Source: IFR Robotics data

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

Figure 11 maps the robot exposure for the period 2005-2019 at the county level. While certain counties report a high exposure to robots, others have implemented very little robots over time in relation to their employed population. There is also considerable variation in the overall cumulative immigration inflow over time, as documented in Figure 12. The Western and Southern regions of Germany report a higher immigrant inflow as the Eastern parts of the country.

Figure 11: **Robot exposure by county (2005-2019)**

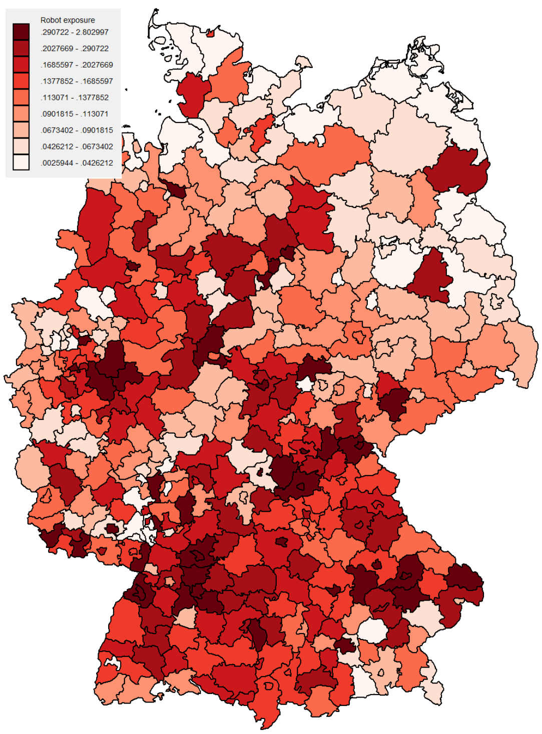
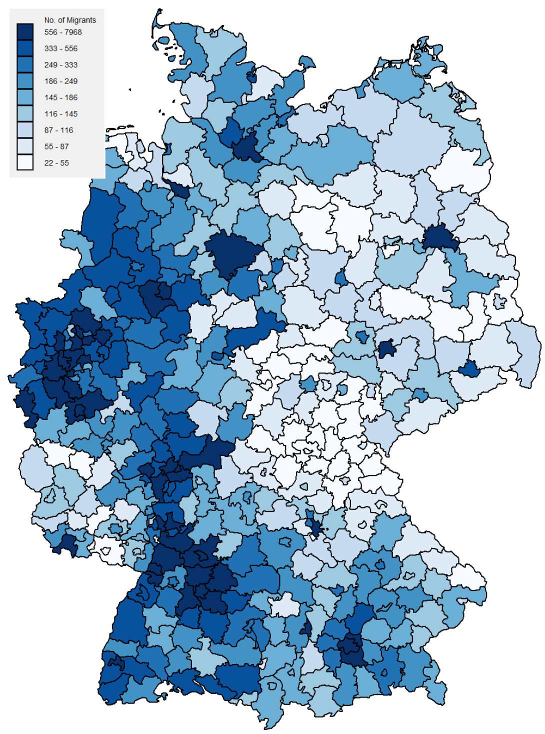


Figure 12: **Cummulative immigrant inflow by county (2005-2019)**



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 markets' demand for AI-related skills. We conduct a keyword search on terms relevant to AI in order 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 give 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 therefore 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 2014-2020, which does not form part of the European Union nor the European Economic Area. Switzerland therefore follows its own migration policies. Additionally, Switzerland is among the ten leading countries in Artificial Intelligence worldwide, according to the Nature Index, 2021. Figure A14 shows the share of AI-related skill demand over time in both countries. It becomes clear from the figure that Switzerland has a higher share of AI-related skill demand than Germany. We again take advantage of 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. Differently from 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:

$$Y_r j = \alpha X'_{rj} + \beta_1 \times \mathrm{A\hat{I}}_{rj} + \beta_2 \times \mathrm{tr\hat{a}de}_{rj} + \varphi_{REGrj} + \epsilon_r \tag{4}$$

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 instead of looking at changes over time, we estimate the effect on yearly values of the 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 10.

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.

[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**

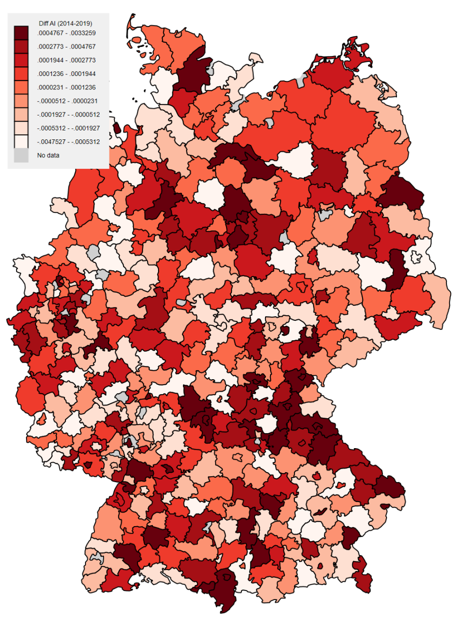
	Germany
AI-related skill demands (Switzerland)	0.194***
	(0.0423)
Adj. R-squared	0.0629
F-statistic	21.10
N	711

Standard errors in parentheses

Source: BGD (2014-2020). Year fixed-effects included.

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

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



4 Results

4.1 Industrial Robots

We do not detect any significant effects of robot adoptions on overall immigrant inflows, outflows or migrant shares, for neither of the skill groups (see Table A1 to A4). When analyzing the effect on labor market outcomes of migrants versus non-migrant, robot adoption decreases the unemployment rate of middle-skilled migrants significantly, but this effect becomes insignificant under the instrumental variable strategy (see Table 4). Still, robots have adverse effects on the employed migrant population. Table 5 shows that, while robot adoption increases the wage of natives of all skill-groups, it decreases it for migrants of all skill-groups. It therefore creates a wage gap between migrants and natives.

Table 4: **Robot exposure and perc. change in unemployment rate at the CZ-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

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

Table 5: **Robot exposure and perc. change in daily wage by skill-level at the CZ-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

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

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. The results suggest that migrants, on the other hand, do not benefit from those. There could be several reasons for that. First of all, migrants might 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, shows the importance of social networks for the economic integration of refugees. And Lochmann et al. (2019) give 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 headscarfes, for example (Weichselbaumer, 2016).

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 see migrants as cheap alternatives to local labor costs (Walia, 2010). The same applies to robots. The increasing adoption of robots might then lead to an increased competition between migrants and robots. This could be another explanation of the observed decrease in wages for migrants due to robotics.

The observed decrease in the unemployment rate of middle-skilled migrants could be explained by skill complementarities of technological change. There is evidence of skill complementarities of broadband internet adoption in Norway, for example (Akerman et al., 2015). The adoption of robots also creates the need for new tasks, such as their supervision or operation. Our results suggest that this task creation has positive effects on middle-skilled migrants' employment share. The mainly insignificant overall effects on unemployment in Germany are in line with findings by Dauth, Eppelsheimer, et al. (2020).

4.2 Artificial Intelligence

We find that AI increases the unemployment rate of migrants across all skill groups (see Table 6). This is not the case for the native population. Additionally, it decreases the wage of migrants across the board, but not natives (see Table 7). In fact, AI increases the natives' wages. This is different 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).

Table 6: **AI skill demands and unemployment at the CZ-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

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

Our results are indicative of 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. Also, similar to our rational for industrial robots, it could be evidence of migrants having less access to labor market institutions, networks and information about the role of AI. AI-related skill demand additionally has significant effects on the inflow of low-, medium- and high-skilled migrants (see Table A15 to A17). This is in line with previous research, showing that technological change can lead

Table 7: **AI skill demands and daily wages by skill-level at the CZ-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.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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 show that this also applies the other way around, meaning that an increase in AI leads to an increase in immigrants.

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

5 Mechanisms

5.1 Industrial Robots

The adoption of industrial robots mainly takes place in the manufacturing sector. This is why in this subsector analysis, we analyze the effect of robot adoption on the manufacturing sector only. We run the same regressions as in section 3 but restrict our outcome variables to the manufacturing sector. To analyze spillover effects on the service sector, we additionally analyze the effect of robot adoption on migration flows and labor market outcomes of migrants as well as natives in the service sector. We find that robot adoption leads to a decrease in the migrant share of middle-skilled migrants in the manufacturing sector (see Table A11). This could be evidence of middle-skilled migrants from the manufacturing sector switching to other sectors due to otherwise negative effects they would experience by robot adoption. Robot adoption has no significant employment or wage effects of employees in the manufacturing or service sector. This could be due to employees moving between different economic sectors as a response to robots. These movements could then mitigate otherwise negative effects.

Next, we study if technological change affects migrants' probability to switch sectors differently than natives' probability. 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 to switch sectors as an outcome variable. Due to the fact that migrants could 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 A26).

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 comes into mind if this mechanism is also in place when analyzing the effect of technological change on labor market outcomes. This question is of interest 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 overall more likely to work in these language-intensive, culture-specific services, following an elevated exposure to industrial robots (see Table A28). For the high-skilled, robotics increases the likelihood of migrants to work in LR and LHR services, while it has no such effect on the low- or medium-skilled. This could be due to high-skilled migrants moving into 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.

5.2 Artificial Intelligence

Similarly to the analysis for robot adoptions, we analyze the effect of AI on the most exposed sectors, which are the ICT sector, public administration and defense, mining and quarrying as well as professional, scientific and technical activities. We find that labor markets with a higher exposure to AI are characterized by an increase in the migrant share within the population forming part of the most exposed sectors for all skill groups (see Table A19). This could be evidence of skill shortages in these sectors and immigrants capturing these shortages. The skill shortages seem to be captured mainly by migrants who are already residing in Germany, as the effect on immigrant inflows is insignificant (see Table A18). AI increases the 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 A21). AI does not seem to influence unemployment rates significantly (see Table A20).

To study spillover effects on the less exposed sectors, we additionally analyse 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 A23), but this time the demand seems to be covered from abroad, as AI positively impacts immigrant inflows (see Table A22). This could mean that migrants are leaving less exposed sectors to take on jobs in more exposed sectors, and that employers compensate for this through attracting newly arrived migrants. AI does also lead 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 evidence of complementarity and productivity effects for natives, but displacement effects for migrants and confirms our hypothesis of discriminatory effects of technological change on the non-native population.

Similarly to what we found for industrial robots, migrants are less likely than natives to switch sectors when exposed to AI (see Table A27). Additionally, migrants are more likely to work in language-

[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.

intensive, culture-specific services as shown in Table A27. Different from robots, AI has the capacity to replace services, as for example recruiting activities, and these findings could be evidence of migrants complementing tasks being replaced by these new technologies. While they probably were less likely to occupy these tasks without AI, AI makes it easier to them to work in these areas. There are no significant effects of this kind on the high-skilled migrant population.

6 Conclusion

The paper at hand analyzes the effect of automation on immigration flows and labor market outcomes of migrants versus 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 could have important inequality implications.

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 as well as the unemployment rate and wages of migrants versus natives. We apply our research question to the context of Germany as it is one of the leading automation economies and one of the main receivers of immigrants in recent decades. We study the effects of technological change on three different skill groups: The low-, middle- and high-skilled.

We find that robot adoption has no significant impact on immigrant flows, but AI-related skill demands do. Additionally, robotics 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 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 evidence of productivity and complementarity effects for natives, but displacement effects for migrants.

When breaking this down by sector, we find a decrease in the migrant share of those 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 of certain skill groups to work in communication-intensive tasks, which 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 indicative of discriminatory effects or them lacking important access to information and labor market institutions.

Our paper has several important policy implications. First of all, policy-makers should carefully evaluate if migrants have the same access to local labor market institutions, networks and information about the need to adapt their skill-set as a response to technological change as natives. All these factors could play an important role in the adverse effects of automation technologies outlined in this paper. Mitigating them through, for example, language courses, targeted welfare programs or policies addressing the social integration of migrants, can decrease inequalities evolving as a consequence of technological change between migrants and natives. Lastly, they should evaluate if migration policies are too rigid when it comes to the employment of scarce talent and analyze how to better attract the best talent.

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Additional Graphs and Tables

A0.1 Additional Graphs

Figure A1: **Immigrant inflow to Germany over time**

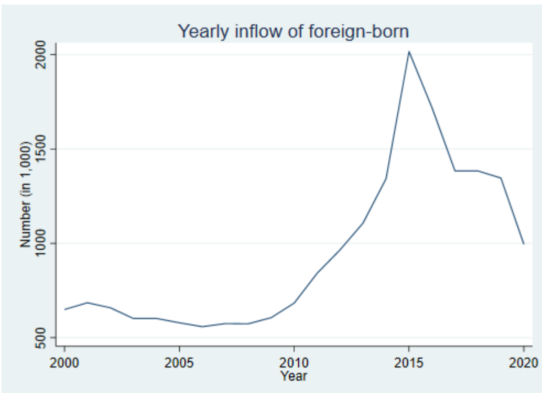


Figure A2: **Outflow of German and non-German residents over time**

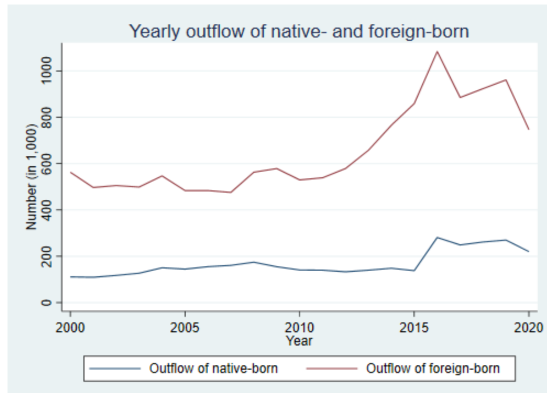


Figure A3: **Immigrant inflow to main OECD countries**

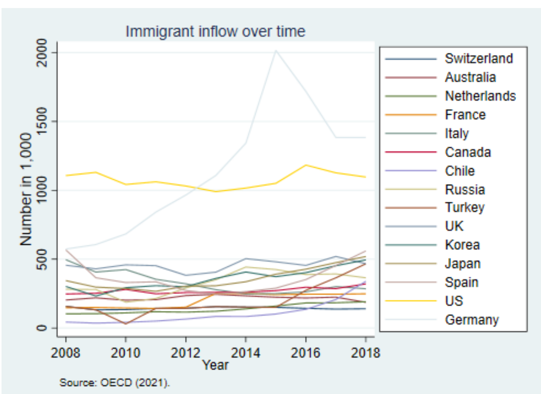


Figure A4: **Import of services to Germany over time**

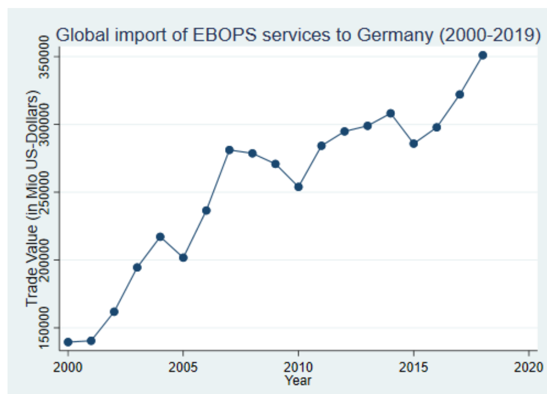


Figure A5: **Migrant Share by economic sector in 2005 and 2017**

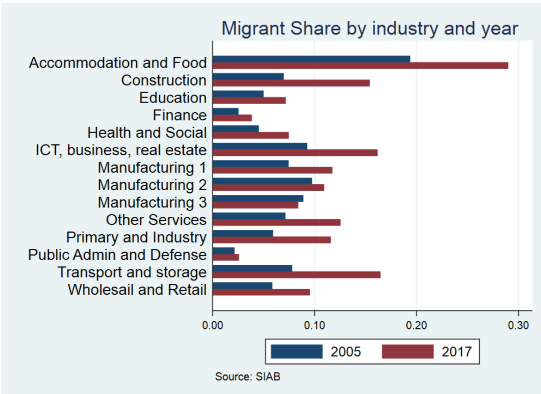


Figure A6: **Robot exposure by industry in Germany**

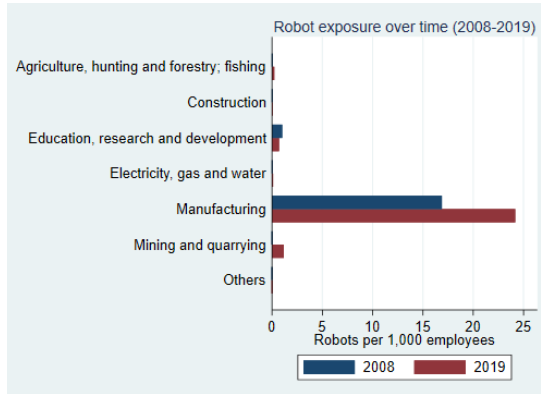


Figure A7: **ICT and Automation Graduates in Germany**

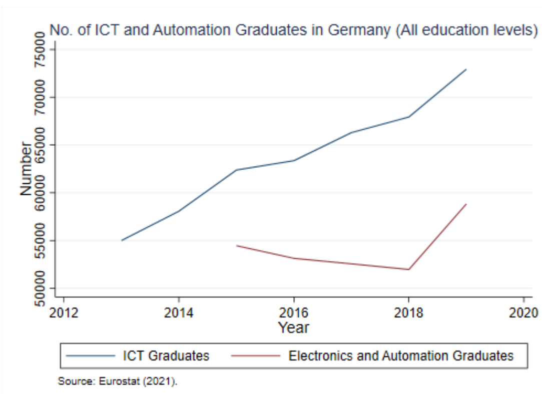


Figure A8: **ICT Graduates in Germany by education level**

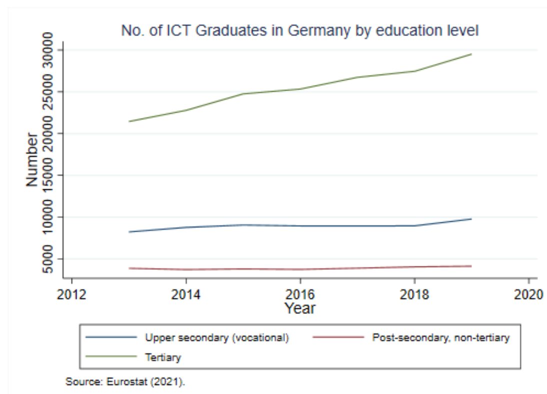


Figure A9: **Number of skills in demand over time by selected European countries**

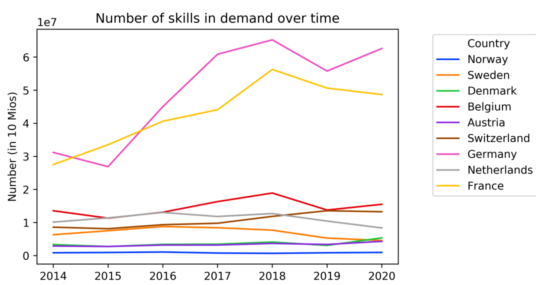


Figure A10: **Number of AI-related skill demand over time by selected European countries**

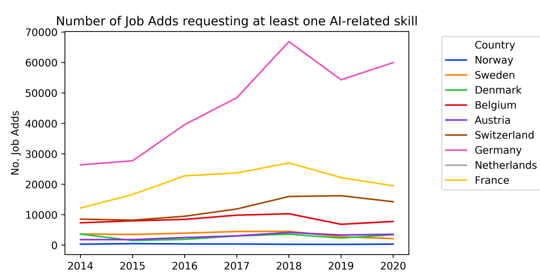


Figure A11: **Numer of OJV in Germany over time**

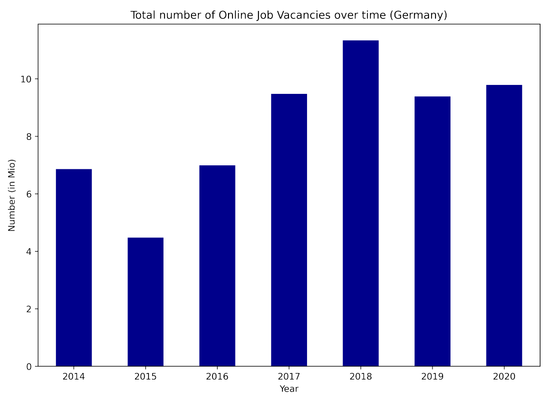


Figure A12: **Share of AI-related skill demand over time by selected European countries**

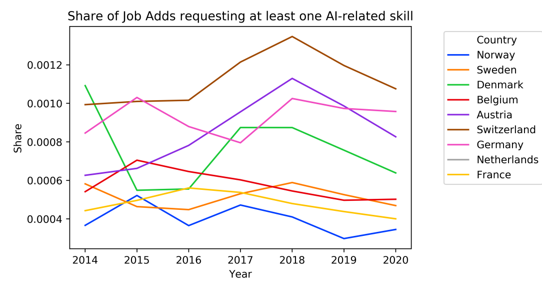


Figure A13: **Robot exposure in Germany and instrumental countries**

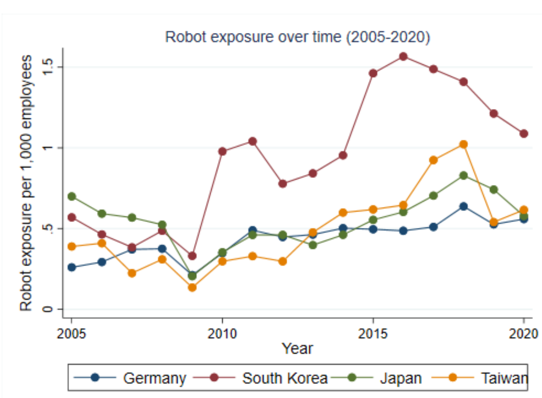


Figure A14: **AI-related skill demand in Germany and Switzerland**

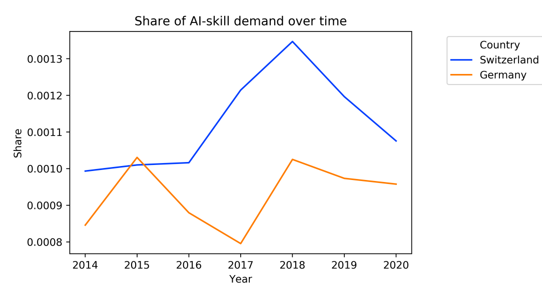
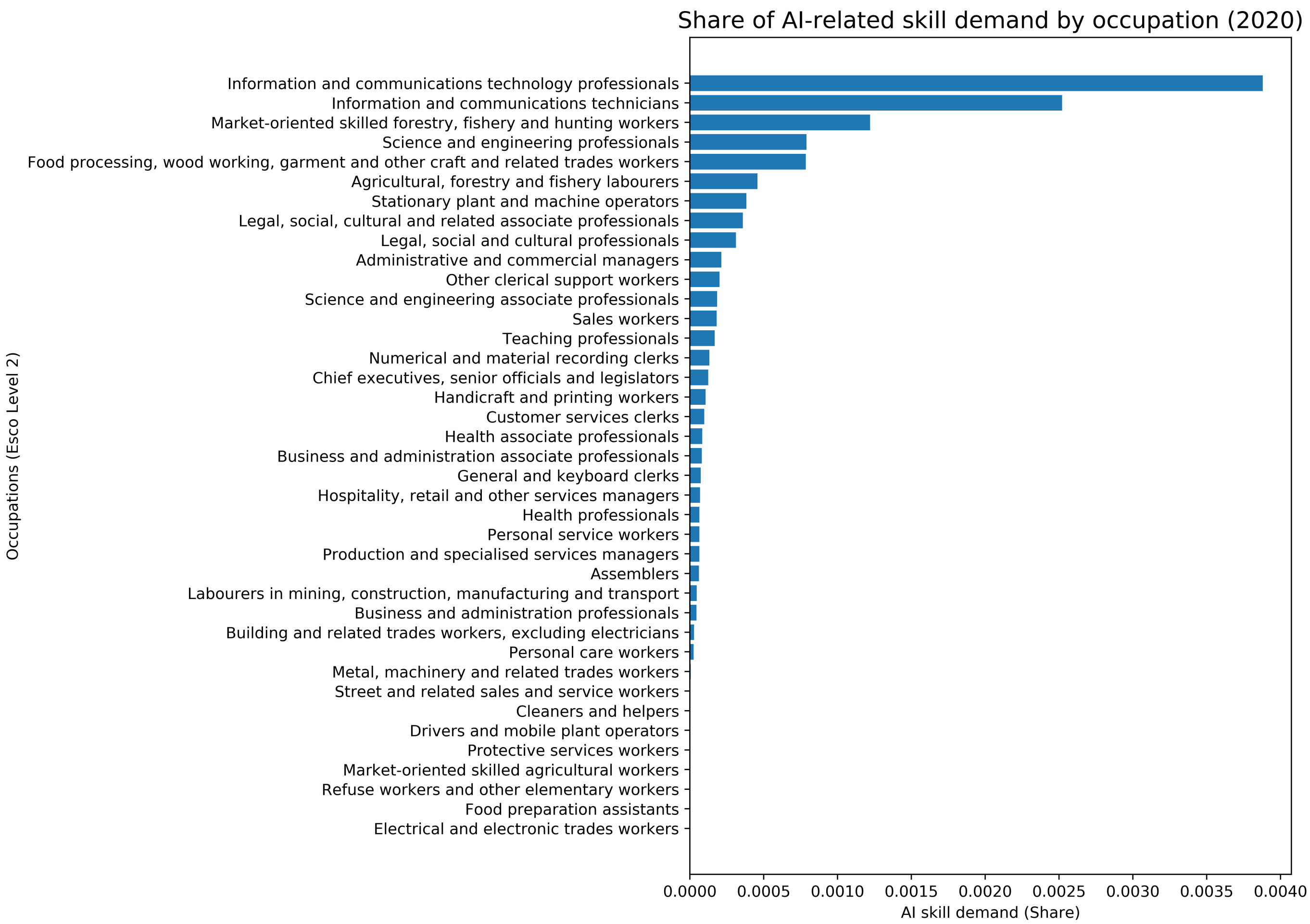
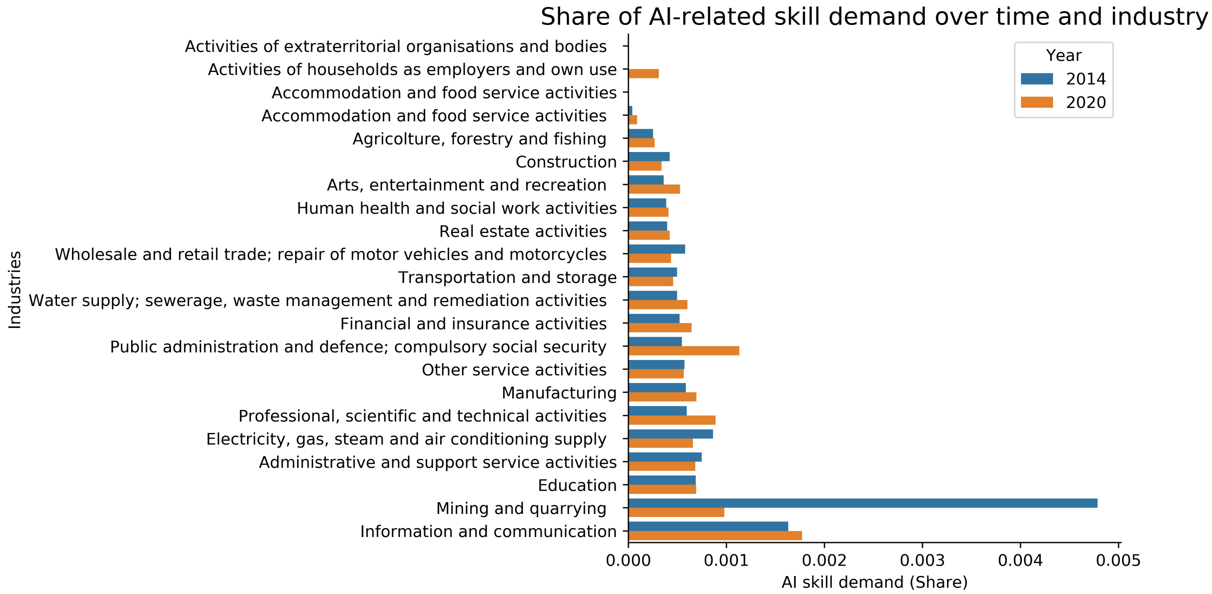


Figure A15: **Share of AI skill demand in overall skill demand by occupation**



Source: BGD (2020)

Figure A16: **Share of AI skill demand in overall skill demand by sector**



A0.2 Additional Tables

A0.2.1 Robots (Overall)

Table A1: **Robot exposure and perc. change in immigrant inflow by skill-groups at the CZ-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)	-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

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

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

Standard errors in parentheses
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 CZ-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

Standard errors in parentheses
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 CZ-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

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

A0.2.2 Robots (Service Sector)

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

Standard errors in parentheses
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 CZ-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

Standard errors in parentheses
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 CZ-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

Standard errors in parentheses
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 CZ-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.

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

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

Standard errors in parentheses

Source: IFR Robotics data and SIAB data.

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

A0.2.3 Robots (Manufacturing Sector)

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

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

Table A11: **Robot exposure and perc. change in migrant share (manufacturing) by skill-groups at the CZ-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

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

Table A12: **Robot exposure and perc. change in immigrant outflow (manufacturing) by skill-groups at the CZ-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

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

Table A13: **Robot exposure and perc. change in unemployment rate (manufacturing) at the CZ-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

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

Table A14: **Robot exposure and perc. change in daily wage (manufacturing) by skill-level at the CZ-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

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

A0.2.4 AI (Overall)

Table A15: **AI skill demands and immigrant inflow by skill-groups at the CZ-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*
	(67405.7)	(190492.4)	(22574.6)	(63566.3)	(30041.0)	(79640.6)	(16231.7)	(47879.0)
Constant	331.6**	78.68	73.43*	-6.552	165.0**	61.92	92.30**	21.88
	(118.9)	(182.4)	(29.37)	(53.85)	(59.95)	(85.65)	(30.88)	(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

Standard errors in parentheses

Source: BGD and SIAB Data. 2014-2019.

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

Table A16: **AI skill demands and immigrant inflow (employed) by skill-groups at the CZ-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*
	(67405.7)	(67405.7)	(190492.4)	(16231.7)	(47879.0)
Constant	331.6**	331.6**	78.68	92.30**	21.88
	(118.9)	(118.9)	(182.4)	(30.88)	(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

Standard errors in parentheses

Source: BGD SIAB Data. 2014-2019. Only for medium- and high-skilled due to small sample problem.

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

Table A17: **AI skill demands and perc. change in migrant share by skill-groups at the CZ-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

Standard errors in parentheses

Source: BGD and SIAB data. 2014-2019.

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

A0.2.5 AI (Most AI exposed economic sectors)

Table A18: **AI skill demands and immigrant inflow (most exposed sectors) by skill-groups at the CZ-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

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

Table A19: **AI skill demands and perc. change in migrant share (most exposed sectors) by skill-groups at the CZ-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

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

Table A20: **AI skill demands and unemployment (most exposed sectors) at the CZ-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

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

Table A21: **AI skill demands and daily wages (most exposed sectors) by skill-level at the CZ-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.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A0.2.6 AI (Least AI exposed economic sectors)

Table A22: **AI skill demands and immigrant inflow (least exposed sectors) by skill-groups at the CZ-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

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

Table A23: **AI skill demands and perc. change in migrant share (least exposed sectors) by skill-groups at the CZ-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

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

Table A24: **AI skill demands and unemployment (least exposed sectors) at the CZ-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

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

Table A25: **AI skill demands and daily wages (least exposed sectors) by skill-level at the CZ-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.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A0.2.7 Mechanisms

Table A26: **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 A27: **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.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A28: **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 A29: **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	-0.0567***	-0.118	-0.0517***	-0.0541*	-0.0544***	-0.0896*
	(0.00336)	(0.0460)	(0.00518)	(0.138)	(0.00280)	(0.0218)	(0.00370)	(0.0382)
AI	-0.0283***	0.727***		0.425***		0.779***		0.590***
	(0.00672)	(0.0705)		(0.113)		(0.139)		(0.145)
Migrant*AI	0.0644**	0.934	0.0450	0.586	0.00779	1.191*	0.0465*	1.927*
	(0.0223)	(0.604)	(0.0372)	(0.892)	(0.00874)	(0.588)	(0.0213)	(0.821)
AI skill demand			-6.928*		0.0714		-0.221	
			(2.952)		(1.851)		(1.863)	
Constant	-0.168***	0.101***	0.0773	0.160***	-0.0799**	0.0956***	-0.0129	0.0909***
	(0.0389)	(0.00714)	(0.0502)	(0.0217)	(0.0300)	(0.0104)	(0.0353)	(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	.	0.00524	.	0.00614	.	0.0102	.
N	9865642	4177551	718597	757587	2771945	2885919	510271	534044

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