Robots, AI and Immigration - A race for talent or of displaced workers*

Yvonne Giesing† Britta Rude‡

March 9, 2022

We study the effect of technological change on immigration flows as well as the labor market outcomes of previous migrants versus natives. 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 one of the main migration receiving countries among OECD countries. We apply an instrumental variable strategy and find that robots decrease the wage of migrants across all skill groups, while having no significant impact on the native population nor immigration flows. In the case of AI we find an increase in the wage gap and also unemployment gap of the migrant and native population. In addition, AI leads to a significant inflow of immigrants. 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. Policymakers should pay special attention to the migration population when designing mitigation policies in response to technological change in order to avoid further increases in inequality between migrants and natives.

JEL— F22, J15, J61, J78, O15, O33

*We thank Michele Battisti, Oliver Falck, Ilpo Kauppinen, Nadzeya Laurentsyeva, Panu Poutvaara, Ariell Reshef, Luca Stella and participants of the ASSA Annual Meeting 2022 and several other seminars for helpful comments and suggestions. We thank the LMU-ifo Economics & Business Data Center for providing access to the IFR data. This project received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement number 101004703. The data access to the SIAB was provided via on-site use at the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB) and subsequently remote data access.

†Contact: giesing@ifo.de, ifo Institute - Leibniz Institute for Economic Research at LMU Munich, LMU Munich and CESifo.

‡Contact: rude@ifo.de, ifo Institute - Leibniz Institute for Economic Research at the LMU Munich, LMU Munich and CESifo.

1 Introduction

Scientists continue to invent, build and implement technologies which can perform human tasks. These technologies are often based on automation, and robots and AI are one example. 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 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 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 high salaries for AI specialists (Tarki, 2021). These high salaries could be evidence of 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 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. Especially migrants at the lower end of the skill spectrum might be 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.

Our first research question is whether automated technologies result in an increase in immigration flows due to skill shortages, or if firms replace cheap labor from abroad by these technologies. Additionally, we would like to analyze if the labor market effects as well as the impact on immigration flows differ from each other, based on these characteristics. We are especially interested in the effects on different skill groups.

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 one mainly replaces mental ones. 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. 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 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, 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 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. These findings would be in line with a theoretical framework, in which firms see automation technologies and migrants as substitutes, and substitute away from cheap labor from abroad towards even cheaper technologies.

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 hint towards 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 of 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, 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 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 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. For Germany, Danzer et al., 2020 study the effect of immigrant inflows on innovation, and find that it reduces innovation. This holds especially for industries with many low-skilled workers. 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, we find that industrial robots and AI increase the overall wage of natives, but decreases it for migrants. This means that policymakers should pay special attention to the migration population when designing mitigation policies in response to technological change in order 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 is 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 recommendable for policymakers to 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 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. Lastly, 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 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, data sources, and theoretical rational

The following section gives an overview of recent trends in the adoption of robotics and AI as well as immigration, the datasets at use in this paper, and finally the theoretical rational of the paper at hand.

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**

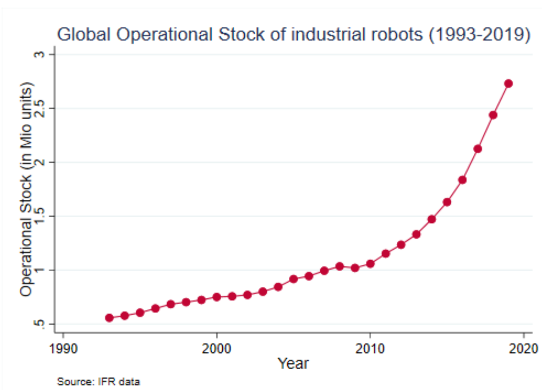
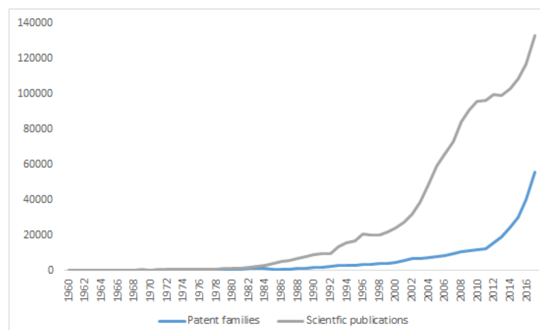


Figure 2: **No. of AI-related patents and scientific publications over time**



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.

This increase in the number of AI-related patents came along with an increase in the demand of AI-related skills. The increase in absolute terms was largest 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 2014-2020. The overall share of AI-related skills is low with around

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

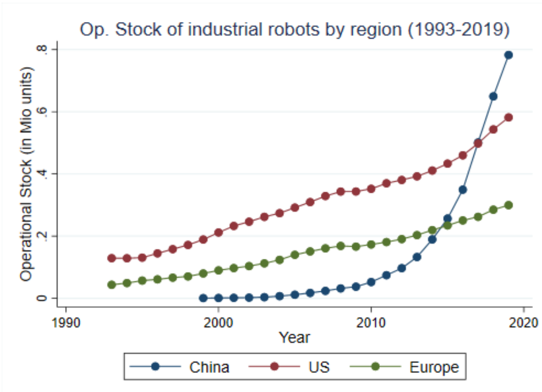
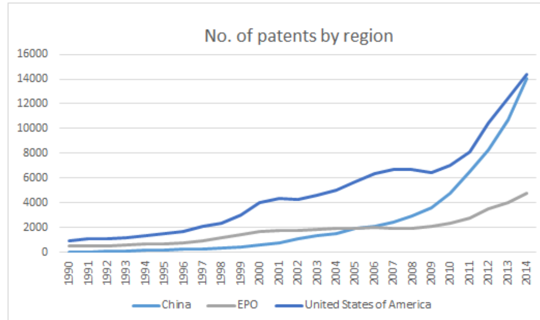


Figure 4: **No. of AI-related patent applications over time**



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). 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 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 A7 shows that robot exposure is largest for the manufacturing sector.

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

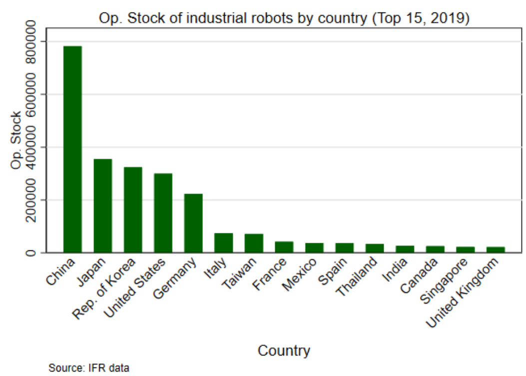
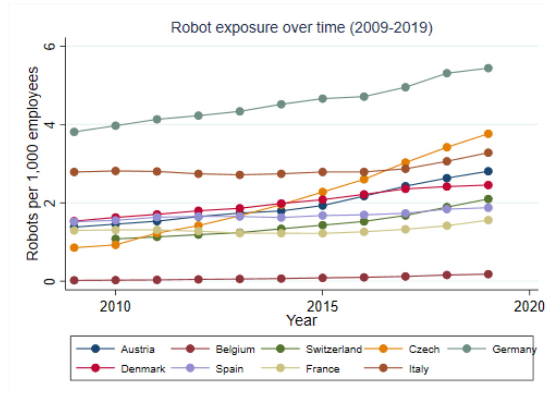


Figure 6: **Operational Stock of robots (per 1,000 employees) over time in European countries**



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 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**

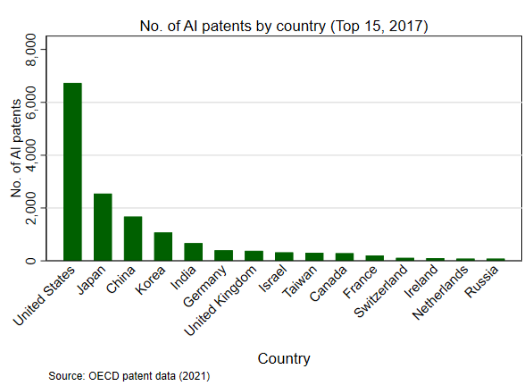
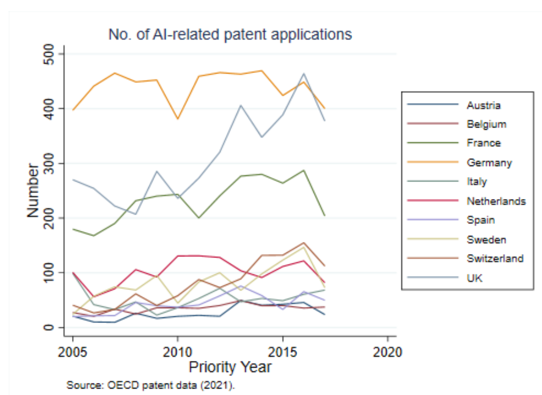


Figure 8: **AI Patent Filings in European countries over time**



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 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). 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, in terms of yearly inflows (see Figure A4).

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

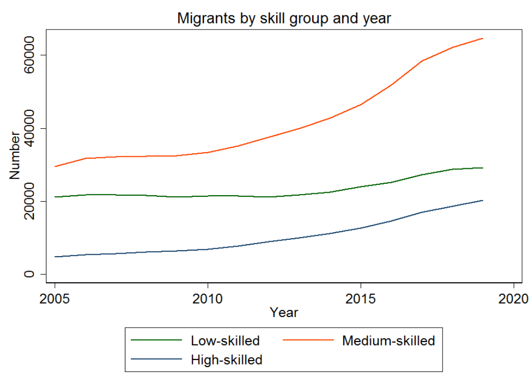


Figure 10: **Immigrant Inflow by Sector**

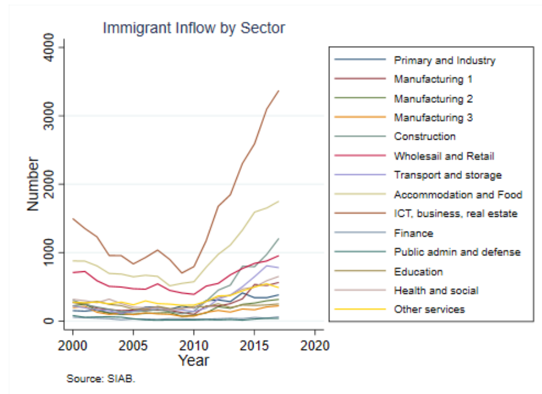


Figure 9 plots the immigrant inflow to Germany over time by skill group. There has been a constant increase of immigrants for each of the skill-groups, but the increase has been largest for the medium-skilled. Moreover, when looking at the immigrant inflow by economic sector, Figure 10 shows that the 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 A6). 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

[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.

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 A10 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 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 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 A11). 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 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. The unit of observation is the county.

2.5 Theoretical Rational

This paper is based on different theoretical rationals. We, first of all, rely on insights by 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. Consequently, there is a contraction in the number of tasks, which leads to a downward pressure on wages. At the same time, there is a productivity effect. This productivity effect evolves due to the substitution of expensive labor by cheaper capital. As a consequence, firms 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 if 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 rationals. First of all, similarly to robots and AI, migrants can substitute or complement natives (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). This is another rational for the paper at hand, as the question arises on if firms substitute cheap labor from abroad by cheap automated technologies. We would then expect to see a contraction in the immigrant inflow in those skill-groups most affected by the automated technologies under investigation in this paper. Similarly, in case automation leads to an inflow of complementing migrants, one might wonder if the productivity effects on the unaffected native skill groups, which can arise through technological change, are even larger. In addition, for most OECD countries, there is 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 of natives from the same skill group (Borjas, 2003). This is another rational for our research question, as it motivates the 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 there-through might mitigate the effects of technological change on natives. The greater willingness to migrate internally is due to the fact that migrants already assumed the high fix-costs of migration in the past. We take this into consideration by looking at the effect of technological change on the probability to switch counties for migrants and natives separately (see section 5).

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 and consider the period of 2005 to 2018. The data provided by the IFR is only reported at the national level. Due to this, we apply a shift-share instrument to proxy robot exposure at the local level r, 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 between 2018 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 ($\frac{\text{emp}_{ir}}{\text{emp}_r}$), multiplied by robots per employees. 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 2018 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:

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

We regress our outcome variable of interest on the change of robot exposure. 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.

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 2018. Figure A14 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 our three instrumental countries. 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)
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

Standard errors in parentheses

Source: IFR Robotics data

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

We consider several outcome variables of interest: The cumulative immigrant inflow and outflow between 2005 and 2018, the percentage change in 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. In the case of daily wages and unemployment, we collapse our data to the migrant and native level and include an interaction term in order to analyze if the effect of robotics differ by nationality.

Figure 11 maps the robot exposure for the period 2005-2018 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 than the Eastern parts of the country.

Figure 11: **Robot exposure by county (2005-2018)**

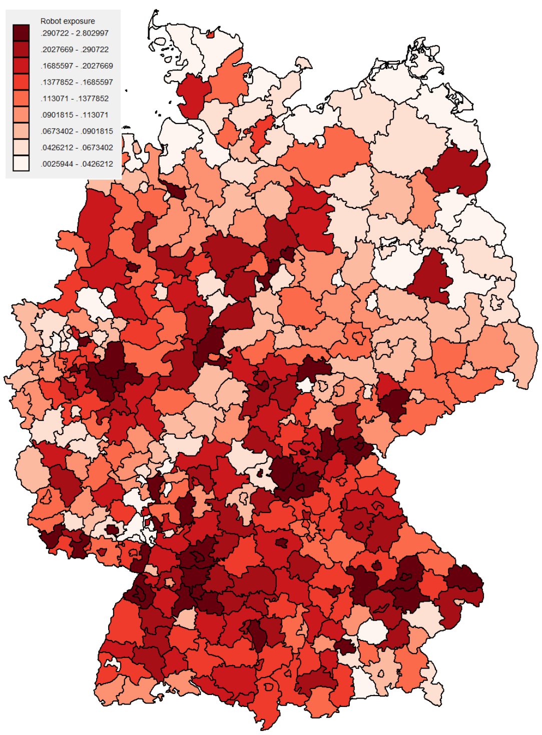
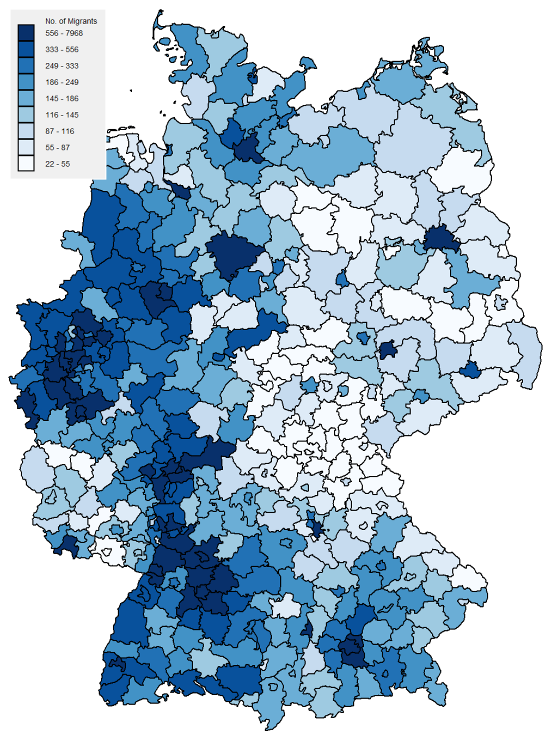


Figure 12: **Cumulative immigrant inflow by county (2005-2018)**



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, at least with respect to 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. 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:

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

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 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.

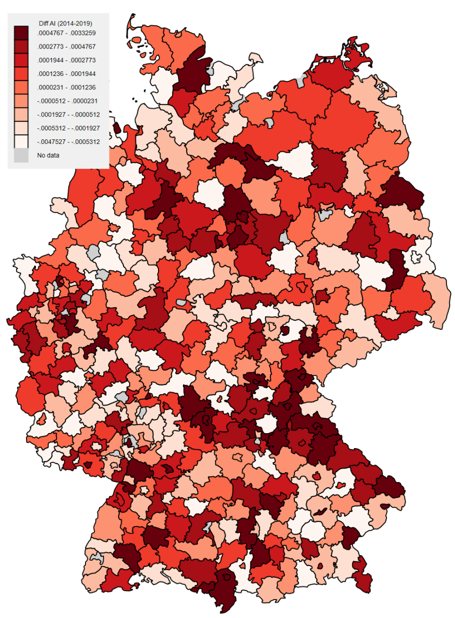
[4]This is also due to data constraints as job vacancy data is only available for recent years for Germany and Switzerland.

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 none of the skill groups (see Table 4 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 5). Still, robots have adverse effects on the employed migrant population. Table 6 shows that, while robot adoption increases the wage of natives of all skill-groups, it decreases it for migrants of all skill-groups.

Table 4: **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. Standard errors are clustered at the nuts-3 level.
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 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.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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 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

Table 6: **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.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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. 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 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).

To shed some more light on the above hypotheses, we divide our analysis by sectors (see Annex A1.2). In the case of robotics, 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 find that robot adoption leads to a decrease in the migrant share of middle-skilled migrants in the manufacturing sector (see Table 7). 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. We do not find any significant effect on the aggregate of all other sectors.

Table 7: **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.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4.2 Artificial Intelligence

In the case of artificial intelligence, we find a significant and positive impact on immigrant inflows (see Table 8). This could point towards skill shortages arising as a consequence of artificial intelligence and firms covering them from abroad. Surprisingly, the effect of AI on immigration flows is positive across all skillg groups. In terms of labor market effects, we find a positive impact on the unemployment rate of migrants across all skill groups (see Table 9). This is not the case for the native population. Additionally, it decreases the wage of migrants across the board, but not natives (see Table 10). 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 8: **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*
	(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

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

Table 9: **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 8 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 show that this also applies the other way around, meaning that an increase in AI leads to an increase in immigrants.

Table 10: **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.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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.

In order to analyze the possible channels behind the observed results, we again conduct a subsector analysis. 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 12). 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 11). 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 A23). AI does not seem to influence unemployment rates significantly (see Table A22).

Table 11: **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.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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 14), but this time the demand seems to be covered from abroad, as AI positively impacts immigrant inflows (see Table 13). 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

Table 12: **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.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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.

Table 13: **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 14: **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.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5 Mechanisms

In order to analyze some of the mechanisms behind the results we outlined before, we take advantage of the panel-data structure of the SIAB and follow individuals over time. We then observe three outcomes of interest along the worklife of each individual: 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 can help to analyze if the observed adverse effects on migrants are because of them being less adaptive than natives, due to factors such as discriminatory structures or a lack of relevant job market information.

5.1 The probability to switch sectors

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 15). Importantly, robotics also decreases the native population's probability to switch sector, but 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 the decrease in the middle-skilled migrant share.

Table 15: **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 16: **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.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Similarly to what we found for industrial robots, migrants are less likely than natives to switch sectors when exposed to AI (see Table 16). The effect is significant for high- and middle-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 to take 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 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 17). Robots have 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.

Table 17: **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 18: **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.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

[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.

In the case of AI, middle- and low-skilled migrants are more likely to work in language-intensive, culture-specific services as shown in Table 18. 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 for them to work in these areas. There are no significant effects of this kind on the high-skilled migrant population. This might be due to them absorbing some of the complex tasks created through and with AI technologies.

5.3 The probability for internal migration

Another form of adapting ones behavior as a response to technological change is internal migration. Employees might need to relocate inside of 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 to migrate inside of Germany.

Table 19: **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 20: **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 any significant impact of robotics on individuals' probability to migrate internally (see Table 19). In the case of AI, the probability increases significantly for natives but not for the migrant population. When breaking this further down by skill groups, we find that AI increases the probability to move 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 stands in contrast to theoretical predictions, such as Borjas (2001). Borjas, 2001 predicts that migrants are more mobile internally, 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 Conclusion

The paper at hand analyzes the effect of automation on immigration flows and labor market outcomes of migrants already residing in Germany 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, 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 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. When analyzing the effect of AI on internal migration, migrants are more likely to migrate inside of 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. First of all, we find that industrial robots and AI increase the overall wage of natives, but decreases it for migrants. This means that policymakers should pay special attention to the migration population when designing mitigation policies in response to technological change in order 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 is 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 recommendable for policymakers to 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 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. Lastly, 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.

References

Acemoglu, Daron, Claire Lelarge, and Pascual Restrepo (2020a). "Competing with robots: Firm-level evidence from france". *AEA Papers and Proceedings*. Vol. 110, pp. 383–88.

Acemoglu, Daron and Pascual Restrepo (2018). "The race between man and machine: Implications of technology for growth, factor shares, and employment". *American Economic Review* 108 (6), pp. 1488–1542.

Acemoglu, Daron et al. (2020b). *AI and jobs: Evidence from online vacancies*. Tech. rep. National Bureau of Economic Research.

Adamopoulou, Eleni and Lefteris Moussiades (2020). "Chatbots: History, technology, and applications". *Machine Learning with Applications* 2, p. 100006.

Alekseeva, Liudmila et al. (2021). "The demand for AI skills in the labor market". *Labour Economics*, p. 102002.

Anderson, Julia, Paco Viry, and Guntram B Wolff (2020). "Europe has an artificial-intelligence skills shortage". *Bruegel-Blogs*.

Antoni, Manfred et al. (2021). *Weakly anonymous Version of the Sample of Integrated Labour Market Biographies (SIAB) – Version 7519 v1*. Tech. rep. Institut für Arbeitsmarkt-und Berufsforschung (IAB), Nürnberg [Institute for ...

Basso, Gaetano, Giovanni Peri, and Ahmed S Rahman (2020). "Computerization and immigration: Theory and evidence from the United States". *Canadian Journal of Economics/Revue canadienne d'économique* 53 (4), pp. 1457–1494.

Battisti, Michele et al. (2018). "Immigration, search and redistribution: A quantitative assessment of native welfare". *Journal of the European Economic Association* 16 (4), pp. 1137–1188.

Beerli, Andreas, Ronald Indergand, and Johannes S Kunz (2021). *The supply of foreign talent: How skill-biased technology drives the location choice and skills of new immigrants*. Tech. rep. GLO Discussion Paper.

Borjas, George J (2001). "Does immigration grease the wheels of the labor market?" *Brookings papers on economic activity* 2001 (1), pp. 69–133.

— (2003). "The labor demand curve is downward sloping: Reexamining the impact of immigration on the labor market". *The quarterly journal of economics* 118 (4), pp. 1335–1374.

Chambers, Elizabeth G et al. (1998). "The war for talent". *The McKinsey Quarterly* (3), p. 44.

Chiacchio, Francesco, Georgios Petropoulos, and David Pichler (2018). *The impact of industrial robots on EU employment and wages: A local labour market approach*. Tech. rep. Bruegel working paper.

Chiarello, Filippo et al. (2021). "Towards ESCO 4.0–Is the European classification of skills in line with Industry 4.0? A text mining approach". *Technological Forecasting and Social Change* 173, p. 121177.

Cramer, Ulrich (1985). "Probleme der genauigkeit der beschäftigtenstatistik". *Allgemeines Statistisches Archiv* 69, pp. 56–68.

Danzer, Alexander, Carsten Feuerbaum, and Fabian Gaessler (2020). "Labor supply and automation innovation". *Max Planck Institute for Innovation & Competition Research Paper* (20-09).

Dauth, Wolfgang, Johann Eppelsheimer, et al. (2020). "Preparing the sample of integrated labour market biographies (SIAB) for scientific analysis". *Journal for Labour Market Research* 54 (1), pp. 10–1.

Dauth, Wolfgang et al. (2019). "The adjustment of labor markets to robots". *Journal of the European Economic Association*.

Eggleston, Karen, Yong Suk Lee, and Toshiaki Iizuka (2021). *Robots and Labor in the Service Sector: Evidence from Nursing Homes*. Tech. rep. National Bureau of Economic Research.

Elsner, Benjamin and Klaus F Zimmermann (2016). "Migration 10 years after: EU enlargement, closed borders, and migration to Germany". *Labor migration, EU enlargement, and the great recession*. Springer, pp. 85–101.

Entwood, Jim et al. (2021). "Artificial Intelligence Index Report 2021".

Felten, Edward, Manav Raj, and Robert Channing Seamans (2019). "The effect of artificial intelligence on human labor: An ability-based approach". *Academy of Management Proceedings*. Vol. 2019. 1. Academy of Management Briarcliff Manor, NY 10510, p. 15784.

Graetz, Georg and Guy Michaels (2018). "Robots at work". *Review of Economics and Statistics* 100 (5), pp. 753–768.

Hanson, Gordon H (2021). *Immigration and Regional Specialization in AI*. Tech. rep. National Bureau of Economic Research.

Hunt, Jennifer and Marjolaine Gauthier-Loiselle (2010). "How Much Does Immigration Boost Innovation?" *American Economic Journal: Macroeconomics* 2 (2), pp. 31–56. DOI: 10.1257/mac.2.2.31.

IFR (2021). *World Robotics Report 2020)*. https://ifr.org/ifr-press-releases/news/record-2.7-million-robots-work-in-factories-around-the-globe. Accessed: 2021-7-7.

Lewis, Ethan (May 2011). "Immigration, Skill Mix, and Capital Skill Complementarity*". *The Quarterly Journal of Economics* 126 (2), pp. 1029–1069. ISSN: 0033-5533. DOI: 10.1093/qje/qjr011. eprint: https://academic.oup.com/qje/article-pdf/126/2/1029/5289078/qjr011.pdf.

Lochmann, Alexia, Hillel Rapoport, and Biagio Speciale (2019). "The effect of language training on immigrants' economic integration: Empirical evidence from France". *European Economic Review* 113, pp. 265–296.

Martén, Linna, Jens Hainmueller, and Dominik Hangartner (2019). "Ethnic networks can foster the economic integration of refugees". *Proceedings of the National Academy of Sciences* 116 (33), pp. 16280–16285.

Metz, Cade (2017). "Tech giants are paying huge salaries for scarce AI talent". *The New York Times* 22.

Mitaritonna, Cristina, Gianluca Orefice, and Giovanni Peri (2017). "Immigrants and firms' outcomes: Evidence from France". *European Economic Review* 96, pp. 62–82.

Nature Index (2021). *Top 25 countries/territories in artificial intelligence*. https://www.natureindex.com/supplements/nature-index-2020-ai/tables/countries. Accessed: 2021-12-28.

OECD (2021). *OECD.stats.Patents by technology*. https://stats.oecd.org/Index.aspx?DataSetCode=PATS_IPC. Accessed: 2021-12-23.

Ottaviano, Gianmarco IP, Giovanni Peri, and Greg C Wright (2018). "Immigration, trade and productivity in services: Evidence from UK firms". *Journal of International Economics* 112, pp. 88–108.

Paserman, M Daniele (2013). "Do high-skill immigrants raise productivity? Evidence from Israeli manufacturing firms, 1990-1999". *IZA Journal of Migration* 2 (1), pp. 1–31.

Peri, GIOVANNI and CHAD Sparber (2011). "Highly Educated Immigrants and Native Occupational Choice". *Industrial Relations: A Journal of Economy and Society* 50 (3), pp. 385–411. DOI: https://doi.org/10.1111/j.1468-232X.2011.00643.x. eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1468-232X.2011.00643.x.

Statistisches Bundesamt (2021). *The main German export product: motor vehicles.* https://www.destatis.de/EN/Themes/Economy/Foreign-Trade/trading-goods.html;jsessionid=7FE117F758F72D99447C29275 live741. Accessed: 2021-12-23.

Tarki, Atta (2021). *How Tech's Trillion-Dollar War For Talent Will Forever Redefine Business Strategy.* https://www.forbes.com/sites/forbesbusinesscouncil/2021/02/22/how-techs-trillion-dollar-war-for-talent-will-forever-redefine-business-strategy/?sh=3b732c6b2498. Accessed: 2021-12-24.

The World Bank (2021). *World Bank Data.* https://data.worldbank.org/. Accessed: 2021-12-23.

Walia, Harsha (2010). "Transient servitude: Migrant labour in Canada and the apartheid of citizenship". *Race & Class* 52 (1), pp. 71–84.

Webb, Michael (2019). "The impact of artificial intelligence on the labor market". *Available at SSRN 3482150.*

Weichselbaumer, Doris (2016). "Discrimination against female migrants wearing headscarves".

Whysall, Zara, Mike Owtram, and Simon Brittain (2019). "The new talent management challenges of Industry 4.0". *Journal of Management Development.*

Additional Graphs and Tables

A1.1 Additional Graphs

Figure A2: **Immigrant inflow to Germany over time**

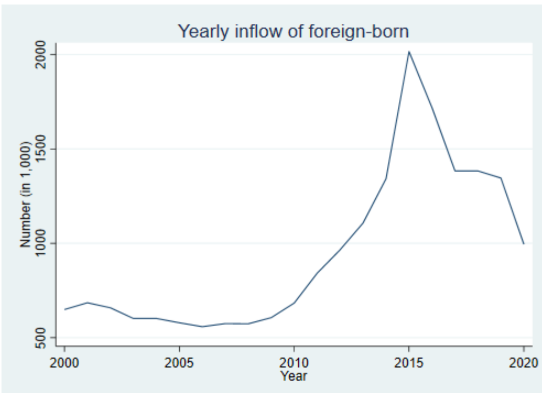


Figure A3: **Outflow of German and non-German residents over time**

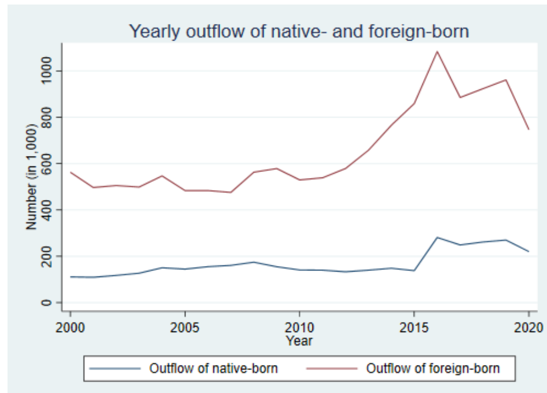


Figure A4: **Immigrant inflow to main OECD countries**

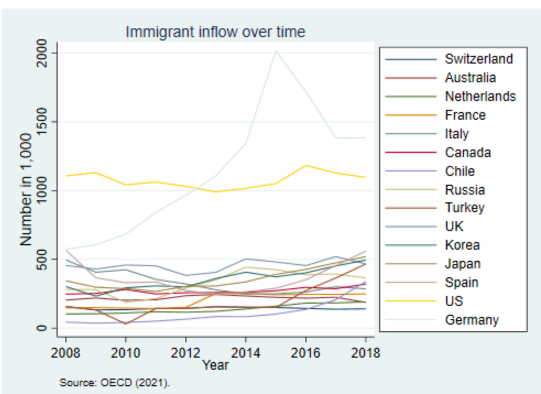


Figure A5: **Native workers by skill group over time**

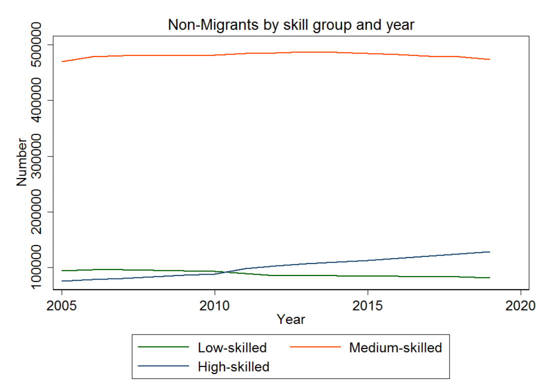


Figure A6: **Migrant Share by economic sector in 2005 and 2017**

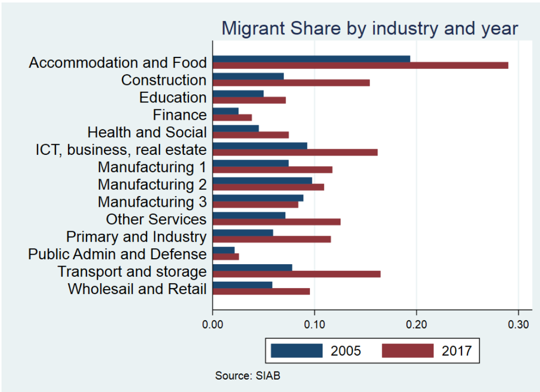


Figure A7: **Robot exposure by industry in Germany**

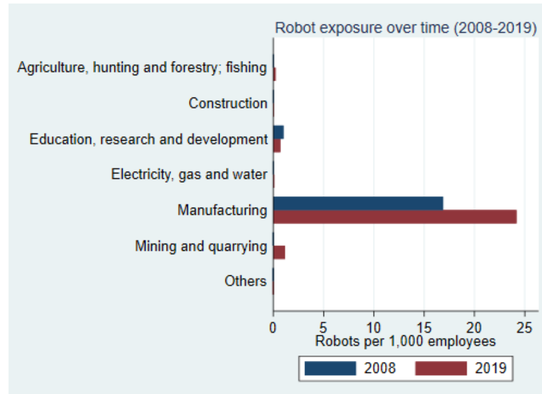


Figure A8: **ICT and Automation Graduates in Germany**

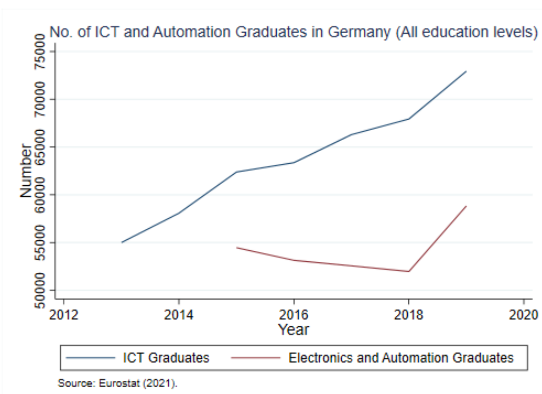


Figure A9: **ICT Graduates in Germany by education level**

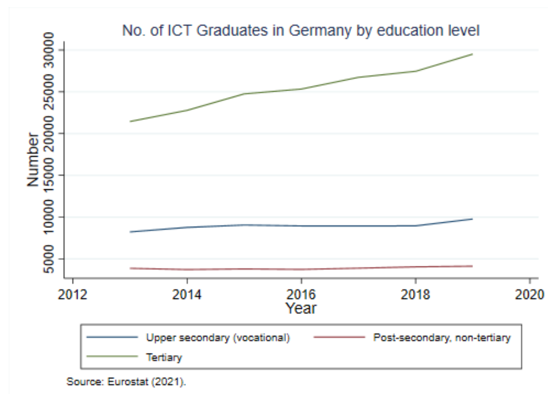


Figure A10: **Number of skills in demand over time by selected European countries**

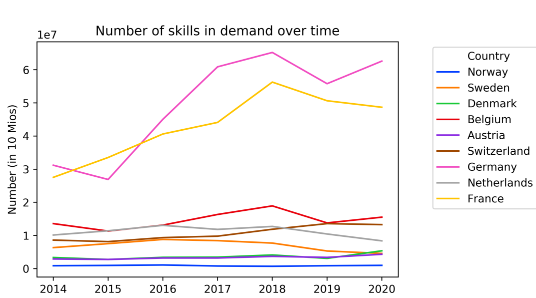


Figure A11: **Number of AI-related skill demand over time by selected European countries**

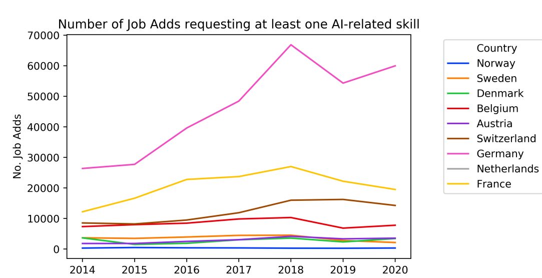


Figure A12: **Number of OJV in Germany over time**

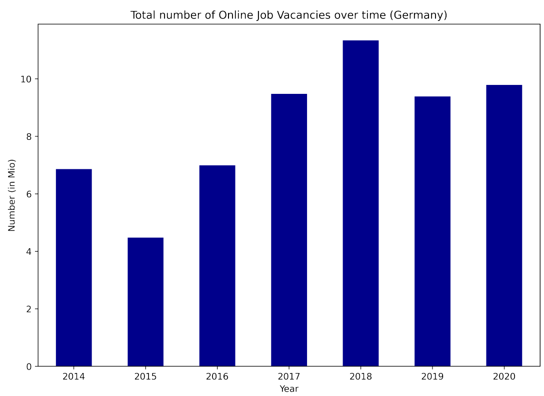


Figure A13: **Share of AI-related skill demand over time by selected European countries**

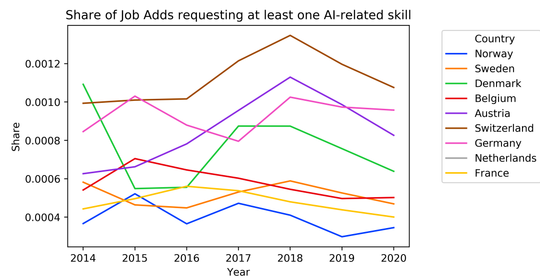


Figure A14: **Robot exposure in Germany and instrumental countries**

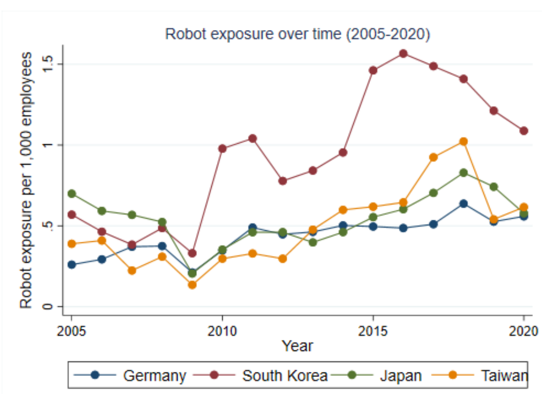


Figure A15: **AI-related skill demand in Germany and Switzerland**

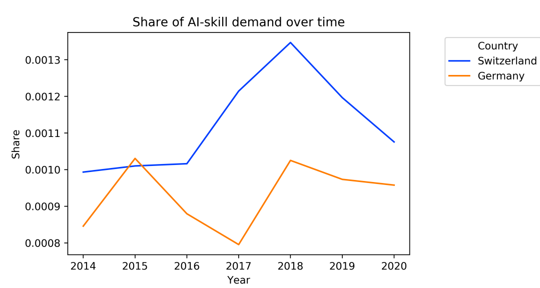
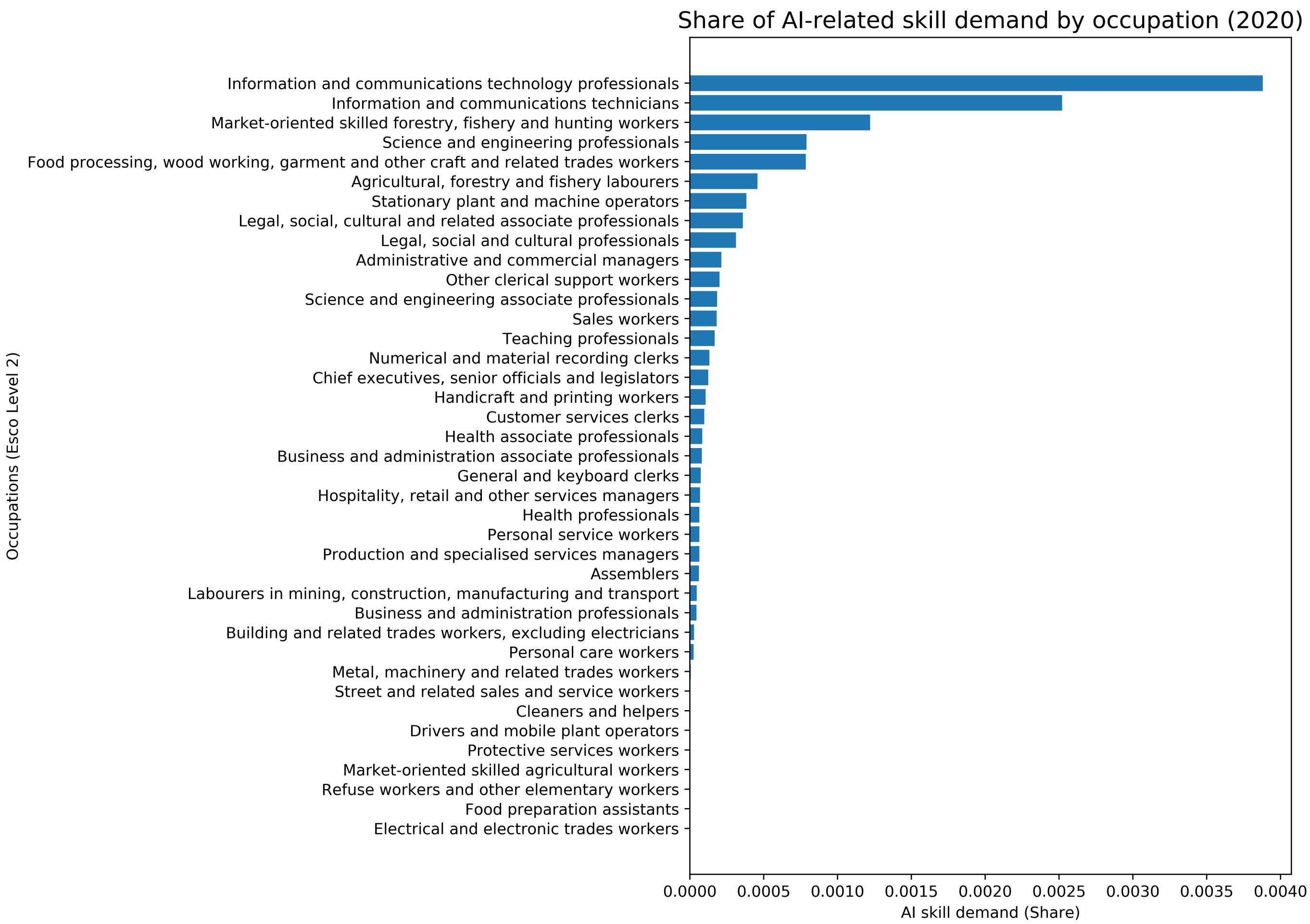
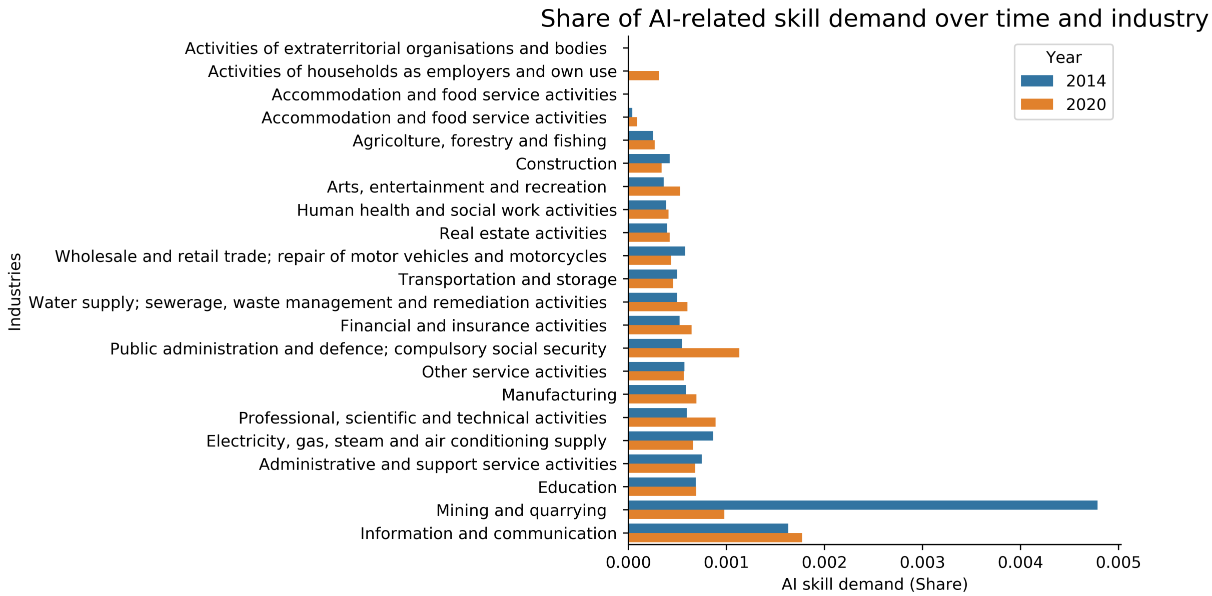


Figure A16: **Share of AI skill demand in overall skill demand by occupation**



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

A1.2.2 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.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A1.2.3 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 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 A12: **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 A13: **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.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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 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)	-0.935	-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

Standard errors in parentheses
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 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)	-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

Standard errors in parentheses
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 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)	0.0437	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

Standard errors in parentheses
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 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	-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

Standard errors in parentheses
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 CZ-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

Standard errors in parentheses
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 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*
	(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

Standard errors in parentheses

Source: BGD SIAB Data. 2014-2019.

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

Table A20: **AI skill demands and immigrant inflow by skill-groups at the CZ-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

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 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.

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

A1.2.6 AI (Most AI exposed economic sectors)

Table A22: **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 A23: **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.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A1.2.7 AI (Least AI exposed economic sectors)

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.

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