The Effects of Industrial Robots on U.S. Local Labor Markets

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Introduction

Rapid advances in new technologies are poised to shape the future of labor markets, fueling concerns that the automation of labor through robots and artificial intelligence is going to displace millions of workers in the near future (Brynjolfsson and McAfee, 2014, Susskind, 2020). Although technological change is also creating millions of new occupations (Autor et al., 2021), skill mismatches are likely to prevent displaced workers from performing these jobs (Jaimovich et al., 2020, Restrepo, 2015). This is an issue with profound implications, since displaced workers may leave the labor market to seek alternative sources of income (Ford, 2015).

This thesis investigates the effects of the introduction of industrial robots – one of the leading automation technologies of the last decades – on US local labor markets. Pioneering work of Acemoglu and Restrepo (2020) has shown that industrial robots have negative effects on employment and wages of workers in the US. This finding has been the starting point for a broad stream of research studying the impact of robots on different aspects of individuals' professional and private lives, providing evidence that progress in automation technologies is not only shaping labor markets, but societies as a whole. In particular, robots have been shown to affect voting behavior (Anelli et al., 2019), physical and mental health (Gihleb et al., 2022), job reshoring (Bonfiglioli et al., 2020, Faber, 2020), family and fertility behavior (Anelli et al., 2021), and internal migration flows (Faber et al., 2022). However, little is known about how these effects are spreading across the population, and where workers who have been displaced from the labor market end up. These questions are addressed in the three chapters of this thesis.

The first chapter studies how the introduction of industrial robots has affected the employment prospects across demographic groups, focusing on the development of the gender and the race/ethnicity employment gap. I find that robots have decreases employment among all demographic groups, but relatively more for men and racial/ethnic minorities than for women and whites, contributing to the secular decline in the gender employment gap, but increasing the race/ethnicity employment gap. These effects are driven by the persistent occupational segregation in the US labor market, as men and minorities are over-represented in blue-collar jobs which require physical skills that can be easily automated. Although robots are mostly adopted in the manufacturing sector, I find that their adverse effects spill over also to local service industries, in particular for Blacks and

Hispanics.

The second chapter investigates the margins of adjustment of workers after they get displaced by the introduction of industrial robots. I show that almost eight percent of the non-participants respond by enrolling in college, 10.5 percent claim disability benefits, and 40 percent retire early. The residual non-participants rely on income from their household members or live off their savings. These margins differ with the socio-demographic characteristics of individuals. My results further show that the rising disability take-up has been fueled by a deterioration of non-participants' health conditions, including self-reported health issues and hospitalization rates related to severe mental disorders and substance abuse.

The third chapter analyzes the link between automation and education in more detail. I find that the exposure to robots increases enrollment rates in community colleges. This finding goes beyond the effect on non-participation, including also individuals who are unemployed or employed part-time. Graduation rates of enrolled students are not affected significantly by the shock. However, I observe a shift in graduations towards more applied fields, such as Computer Science and Engineering. I show that these results are driven by low-skilled individuals who invest in human capital as a form of self-insurance against the risks of automation (due to lower opportunity costs of schooling), rather than due to increases in the college wage premium, as supposed by the skill-biased technological change literature.

Chapter 1

From Blue to Steel-Collar Jobs: The Decline in Employment Gaps?

1.1 Introduction

Technological progress in robotics and artificial intelligence is poised to shape the future of labor markets, fueling concerns that advances in automation are going to displace millions of workers in the coming years (Brynjolfsson and McAfee, 2014, Susskind, 2020). Despite the growing importance of these technologies, little is known about how their effects are spreading across the population and how they affect labor market outcomes across demographic groups. This paper addresses this policy-relevant question by investigating the impact of industrial robots, one of the leading automation technologies of the last decades, on gender and race/ethnicity employment differentials in the US labor market.

Industrial robots are machines that can be programmed to autonomously perform blue-collar work in the manufacturing sector. Between 1993 and 2014, the stock of robots in the US has increased by more than 180,000 units, displacing thousands of workers from so-called "steel-collar jobs" (Acemoglu and Restrepo, 2020).[1] Whether and why their introduction has had a different impact on the employment prospects of men, women, whites and non-whites remains an open question.

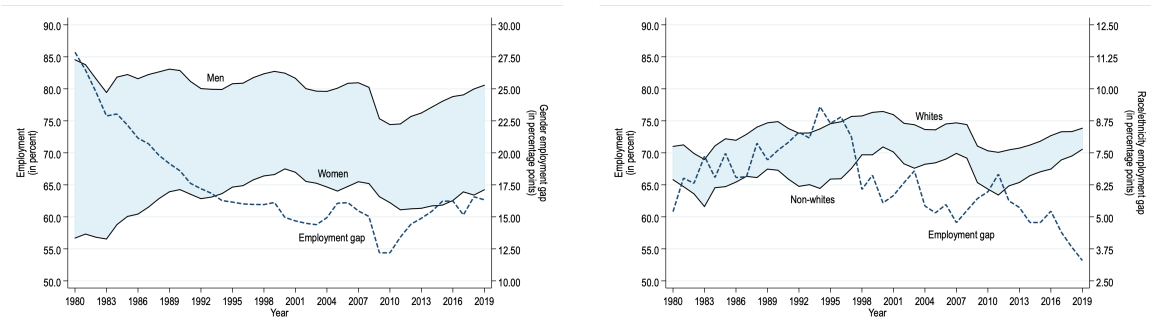
Demographic-specific employment rates have fluctuated substantially since the 1980s. As documented in Figure 1.1, the gender and the race/ethnicity employment gap have both experienced a secular decline, but still persist in recent years. These trends follow from decades of declining employment among men and increasing employment among women (Goldin, 2006), as well as the fact that employment levels among racial/ethnic minorities have been slowly catching up with those

[1] The term "steel-collar jobs" was first coined in the early 1980s to refer to the increasing threat of industrial robots to blue-collar jobs in US manufacturing, since robots are well suited to perform these jobs and steel is one of the main materials from which they are made.

Figure 1.1: Trends in employment

Panel A: Gender

Panel B: Race and ethnicity



Notes: This figure illustrates employment rates and gaps by gender and race/ethnicity in the US between 1980 and 2019 using data from the Annual Social and Economic Supplement (ASEC) of the Current Population Survey (CPS) (Flood et al., 2020). To correct for secular demographic change which has influenced employment rates since the 1980s, I fix the age and education profile of the population at its levels in 1980. Specifically, I build employment rates within subgroups of the population using 5-year age groups (25-29 years, 30-34 years, 35-39 years, ...) and two education groups (with and without a college education) for each year and compute the aggregate employment rate as a weighted average of these rates, keeping the subgroup population shares constant at their 1980 levels.

of whites since the 1990s.[2] In addition, the US labor market is also characterized by a persistent industrial and occupational segregation across demographic groups. In particular, men and non-white workers are more likely to be employed in blue-collar manufacturing jobs, which exposes them to a higher risk of automation through robots. Women and white workers, on the other hand, are often employed in occupations that require more cognitive and less physical skills, which are more difficult to automate (Acemoglu and Autor, 2011). I document these patterns using data from the US Census and the American Community Survey (ACS) matched with occupational data from the Dictionary of Occupation Titles (DOT).

To investigate the impact of robots on the employment prospects of different demographic groups, I match Census and ACS data with industry-level data about the adoption of robots from the International Federation of Robotics (IFR). I conduct a local labor market level analysis using commuting zones (CZs) as proxies for US local labor markets (Tolbert and Sizer, 1996). Following Acemoglu and Restrepo (2020), I build a measure of robot exposure using a shift-share approach that interacts baseline industry employment shares within local labor markets with the introduction of robots in the US. Identification builds on the assumption that advances in robotics vary by industry and expose local labor markets differently based on their industrial composition of employment.

[2] I use the terms "racial and ethnic minorities" and "non-whites" interchangeably. These include Blacks, Hispanics, Asians, American Indian, Alaska Natives and other not elsewhere classified races.

I account for endogeneity concerns from domestic demand shocks and identify robot adoption that is driven by exogenous advances in robotics using an instrumental variables strategy. The shift component is instrumented using the simultaneous adoption of robots in Europe and the share component uses plausibly exogenous industry employment shares that precede the introduction of industrial robots in the 1980s.

In line with Acemoglu and Restrepo (2020), I show that robot exposure has decreased employment and wages in the US labor market, but I find significant heterogeneity in the effect across demographic groups. First, I find that one additional robot per thousand workers displaces men more than twice as often as women, decreasing local employment rates by 2.34 and 1.04 percentage points, respectively, and contributing to the secular decline in the gender employment gap.[3] This effect is driven by workers without a college education who are employed in steel-collar jobs (i.e. blue-collar manufacturing jobs). I find that college-educated workers are also negatively affected in their employment prospects by the use of robots, but that the effect is smaller and does not differ significantly by worker gender.

Although a narrowing employment gap appears to be beneficial for the achievement of gender equality, it is important to consider that this effect is driven by an employment loss that is relatively larger for men than for women, an outcome that is far from desirable. This finding is also visible in the analysis of the impact of robots on wages, with men experiencing a decline in their average wage level which exceeds that of women by almost 0.35 percent, as documented also in Ge and Zhou (2020).

Second, I find that robots widen the race and ethnicity employment gap, slowing its secular decline. Specifically, I show that one additional robot per thousand workers decreases the local employment rate of whites by 1.16 percentage points and that of racial/ethnic minorities by 2.87 percentage points. In other words, the impact of robots on employment is about two-and-a-half times stronger for non-whites than for whites, a result borne by Black and Hispanic workers and that does not depend on whether they were born in the US or abroad. These findings are again driven by blue-collar workers without a college education.

[3] Displaced workers are individuals who do not find a job or who lost their job directly or indirectly due to the adoption of robots. The repeated cross-sectional nature of the data does not allow me to disentangle direct from indirect displacement effects of robots, since I am tracing local labor markets rather than the career trajectories of individual workers.

Although industrial robots are primarily used in the manufacturing sector, their impact on the labor market is not limited to these industries. This result is likely to follow from a reduction in manufacturing employment which contracts aggregate demand in the local economy, decreasing also the demand for labor in industries that are not directly affected by the shock (Acemoglu and Restrepo, 2020, Faber et al., 2022, Helm, 2020).

Interestingly, I find no significant differences in the negative effect of robot exposure on manufacturing employment by race and ethnicity, but I do find differences in how the effect spills over to the local service sector, where minorities suffer from greater employment losses relative to whites. This result could be fueled by two channels. First, displaced manufacturing workers who are white are more likely to be re-employed in the service sector than non-whites due to a comparative skill advantage in these jobs (Kletzer, 1991). Second, the labor market effects of robots cannot be explained using observables and might be the result of discrimination against minorities in these jobs (Bertrand and Mullainathan, 2004).

Finally, I show that, despite robots are widening the employment gap, they are decreasing the race/ethnicity wage gap by 1.28 percent. This result is due to a decline in the average wage level of white workers, while the wages of non-whites are unaffected by robot exposure. A plausible explanation for this result is again that middle-skilled white workers who have been displaced by robots are more likely to be re-employed in low-paying service sector jobs, contributing to the increasing job polarization of the US labor market (Autor and Dorn, 2013), while Blacks and Hispanics are more likely to drop out of the labor force (Lerch, 2020), leaving their average wages unaffected.

To pin down the mechanism through which the introduction of robots affects employment across demographic groups, I use a simple Roy model with heterogeneous individuals and endogenous job sorting in which workers compete with robots in the execution of tasks (Roy, 1951). Based on the patterns observed in the data, robots are relative substitutes of brawn labor, in which men have a comparative advantage, and they are relative complements to brain labor, in which racial/ethnic minorities have a comparative disadvantage.[4]

[4] Men have a biologically rooted comparative advantage in physical skills compared to women (Ngai and Petrongolo, 2017, Rendall, 2017), while racial and ethnic minorities suffer from persistent discrepancies in educational attainment caused by generations of labor market discrimination, giving them a comparative disadvantage in cognitive skills compared to whites (Alesina et al., 2001, Altonji and Blank, 1999, Cook, 2014, Derenoncourt, 2022, Derenoncourt et al., 2022).

The model shows that as robot capital accumulates, firms demand less brawn labor, since robots become a relatively cheaper substitute of human labor (displacement effect), and they demand more brain labor, since robots complement human labor in these tasks (productivity effect). The impact of robots on employment is ambiguous and depends on which of these two effects prevails.[5] Nevertheless, the model shows that robots unambiguously reduce the gender employment gap and increase the race/ethnicity employment gap, because women benefit from a stronger productivity effect than men and non-whites suffer from a larger displacement effect than whites.

The rest of the paper is organized as follows. Section 1.2 presents the related literature. Section 1.3 describes the data. Section 1.4 presents the identification strategy. Section 1.5 shows the empirical results. Section 1.6 discusses the mechanism through which robots affect the demand for human skills and the employment gaps. Section 1.7 concludes.

1.2 Literature

This paper contributes to the growing number of studies on the disruptive effects of technological progress on the labor market and the demand for human skills. The debate over the influence of the use of new technologies on the occupational structure has long been dominated by the assumption that technological change favors highly skilled occupations (Goldin and Katz, 2009, Katz and Murphy, 1992, Krueger, 1993). Recent evidence argues, however, that labor markets are instead experiencing an increasing job polarization, suggesting that new technologies are primarily displacing workers employed in middle-skill occupations (Acemoglu, 1999, Goos et al., 2009, Goos and Manning, 2007). This finding stems from the fact that automation is increasingly taking over jobs with a large routine task content, but that it is not yet able to perform jobs that require creative, problem-solving and coordination skills (Acemoglu and Autor, 2011, Autor and Dorn, 2013, Autor et al., 2003).

At the same time, rapid advances in robotics and artificial intelligence are fueling concerns that technological change could displace millions of workers from the labor market in the coming years (Brynjolfsson and McAfee, 2014, Ford, 2015, Frey and Osborne, 2017). In line with these concerns, Acemoglu and Restrepo (2020) show that the introduction of industrial robots in the US

[5] The empirical results show that the displacement effect outweighs the productivity effect among all demographic groups.

has decreased aggregate employment and wages between 1993 and 2007. They estimate that each additional robot adopted in a local labor market has displaced about six workers. Among others, robots have been shown to affect also voting behavior (Anelli et al., 2019), physical and mental health (Gihleb et al., 2022), job reshoring (Bonfiglioli et al., 2020, Faber, 2020), family and fertility behavior (Anelli et al., 2021), and internal migration flows (Faber et al., 2022). However, little is known about how their effects are distributed across the population, and about their implications for the increasing inequality in the labor market.[6]

Related to this paper, recent work by Ge and Zhou (2020) studies the effect of robots on pay differences between men and women in the US. The authors find that the adoption of robots decreases average wages and that the reduction is stronger for men than for women, narrowing the gender wage gap.[7] These findings are in line with Bacolod and Blum (2010) and Yamaguchi (2018), who argue that the gender gap is strongly influenced by the relative price of the skills in which men and women have a comparative advantage. Although this is not the main focus on the paper, I briefly replicate their results on the gender wage gap and further analyze how the introduction of robots has affected the race/ethnicity wage gap. To my knowledge, this is the first study that analyzes the impact of automation on wage inequality by race and ethnicity.

Despite the insightful results on gender pay differences, the heterogeneous impact of robots on the extensive margin of employment of men and women remains unclear. Anelli et al. (2021) address this question when investigating the effect of robots on marital status and fertility behavior, but they do not find significant differences in the impact on employment by gender in the short term. This result is likely to follow from the fact that labor markets need some time to adjust to the shock. This paper departs from their work as it explores the long-term impacts of robotics on the gender employment gap and, based on the industrial and occupational segregation observed in the data, investigates the mechanism through which the adoption of industrial robots affects employment

[6] The adverse effects of robots on employment are less visible in European countries (including countries with high robot intensity such as Germany and Italy), where the displacement of low-skilled manufacturing workers is almost fully compensated by the employment growth in other jobs (Dauth et al., 2021, Dottori, 2020, Graetz and Michaels, 2018). However, even if there are no aggregate effects in these countries, technological change may still affect the composition of labor markets, as many of the newly created jobs are unlikely to be performed by the displaced workers due to a skill mismatch.

[7] This trend is different among European countries, where robots have a positive effect on wages of medium- and high-skill jobs in which women are usually under-represented (Aksoy et al., 2021, Pavlenkova et al., 2021). This result is not surprising given the fact that the adoption of robots in European countries is mainly causing a reallocation of human labor across industries and occupations with negligible effects on aggregate employment, with the exception of France (Acemoglu et al., 2020, Bonfiglioli et al., 2020).

opportunities for men and women.

Also related to this paper, Acemoglu and Restrepo (2020) show that the adverse long-term effects of robots on employment are larger for men, but they do not analyze the underlying mechanism that leads to this result either. This paper further adds to this literature by analyzing the heterogeneous impact of industrial robots on employment across race and ethnicity groups, an important issue that has not been studied so far.[8]

I also contribute to the literature that studies the determinants of labor market inequalities by gender, race and ethnicity. In the US, employment and wage gaps are declining since the implementation of the Civil Right Act in 1964, but they are still highly persistent. A vast body of the literature argues that inequalities persist because of discriminatory reasons (see Guryan and Charles (2013) for a review) and labor supply factors (Altonji and Blank, 1999, Blau and Kahn, 2017, Marianne, 2011). However, recent evidence suggests that also demand-side factors, such as the rise of the service economy, are increasingly important determinants of the existence and development of pay differences and employment gaps (Ngai and Petrongolo, 2017, Petrongolo and Ronchi, 2020).

A striking example is the rise of white-collar jobs in the service sector through the diffusion of information and communication technologies (ICT). The transition towards these occupations has favored the employment opportunities of women, reducing substantially the gender employment gap (Bacolod and Blum, 2010, Beaudry and Lewis, 2014, Black and Spitz-Oener, 2010, Blau, 1998, Cortes et al., 2020, Olivetti and Petrongolo, 2016, Weinberg, 2000). This trend may not persist in the future though, since these jobs are also increasingly threatened by the risks of automation (Brussevich et al., 2019, Chuan and Zhang, 2021, Ge and Zhou, 2020). I contribute to this literature by providing evidence on the impact of industrial robots, an increasingly important demand-side factor which is poised to shape the composition of labor markets, on the secular decline of the employment gaps in the US, both by gender and race/ethnicity.

[8] To date, there is only descriptive evidence about the over-representation of Blacks and Hispanics in jobs at the lower end of the skill distribution (Couch and Daly, 2002, King, 1992), suggesting that these workers may be more exposed to the adverse effects of automation than whites in the coming decades (Cook et al., 2019, Muro et al., 2019).

1.3 Data

This section describes the main data sources along with a set of summary statistics on secular trends in robot adoption and the occupational and industrial segregation of the US labor market.

1.3.1 Industrial robots

I obtain data about the adoption of robots from the International Federation of Robotics (IFR, 2018). The IFR is a survey that collects data on the shipment and operational stock of industrial robots by country, industry and year ranging back to 1993 for 50 countries.[9]

Industrial robots are machines that can be programmed to autonomously perform several manual tasks (such as assembly, material handling, packing and welding) without the intervention of a human worker. The IFR defines them as "automatically controlled, reprogrammable, multipurpose manipulators, programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications" (IFR, 2018, p.29). They do not include conveyor belts, cranes or elevators, since these machines do not meet this definition.

Between 1993 and 2014, the stock of industrial robots in the US has increased by about 1.58 robots per thousand workers (roughly 180,000 units), corresponding to five times its level in 1993. According to the IFR, these values are expected to grow even more in coming years (IFR, 2018, pp.535–540).

The IFR breaks down the stock of operational robots according the International Standard Industrial Classification (ISIC), Fourth Revision, and provides consistent data for six broad industries outside of the manufacturing sector and 13 industries within the manufacturing sector. Table 1.1 illustrates the distribution of robots across these industries for the US and for Europe. The growth rate of the stock of robots at the industry level is computed as the difference in the stock of robots in terms of industry employment in 1993:

$$\frac{R^i_{j,14} - R^i_{j,93}}{L^i_{j,93}} \tag{1}$$

where $R^i_{j,t}$ is the stock of robots in industry j of country i at time t, and $L^i_{j,93}$ is the employment

[9] These data are praised for their reliability, but they include also some limitations that are addressed in Appendix A1.

level in 1993.

Table 1.1: Descriptive statistics: Industrial robots

	Robots in the US per thousand workers		Robots in EU7 countries per thousand workers		Employment in thousands
	1993	Δ_{14-93}	1993	Δ_{14-93}	1993
	[1]	[2]	[3]	[4]	[5]
	Panel A: High robot-intensive manufacturing				
Automotive	24.25	82.69	18.2	57.12	1111
Basic Metals	1.39	5.37	0.84	7.34	712
Electronics	2.01	10.99	2.34	3.31	2868
Food and Beverages	1.02	4.62	0.38	8.93	1862
Metal Products	1.69	6.51	6.91	11.13	1689
Plastics and Chemicals	1.80	7.43	2.85	16.04	2205
	Panel B: Low robot-intensive manufacturing				
Industrial Machinery	0.39	1.52	3.01	6.18	1541
Minerals	0.04	0.58	0.60	3.64	558
Miscellaneous	0.49	11.66	2.56	2.93	690
Paper and Printing	0.00	0.10	0.19	0.83	2467
Shipbuilding and Aerospace	0.02	0.44	0.73	2.18	1111
Textiles	0.00	0.05	0.24	0.88	1848
Wood and Furniture	0.00	0.12	1.14	2.75	1048
	Panel C: Non-manufacturing				
Agriculture	0.00	0.03	0.00	0.18	2552
Construction	0.00	0.02	0.00	0.11	7108
Education and Research	0.00	0.04	0.03	0.33	12636
Mining	0.00	0.05	0.23	1.36	763
Services	0.00	0.00	0.00	0.00	84776
Utilities	0.00	0.02	0.00	0.25	745

Notes: This table illustrates the number of industrial robot units adopted in the United States and the average robot adoption among seven European countries (Denmark, Finland, France, Italy, Spain, Sweden and the United Kingdom) by year and industry. Panel A reports the count of robots in the six manufacturing industries with the largest adoption of robots between 1993 and 2014. Panel B reports the count of robots in the remaining manufacturing industries. Panel C reports the count of robots for the six other sectors. Columns 1 and 3 report the stock robots per thousand workers in 1993. Columns 2 and 4 report the change in the stock of robots between 1993 and 2014 per thousand workers in 1993. Column 5 reports the number of workers by industry in 1993 in the US.

The statistics show that robots are mainly adopted in a subset of industries of the manufacturing sector, including Automotive, Basic Metals, Electronics, Food and Beverages, Metal Products, and Plastics and Chemicals. I refer to these industries as "High Robot-Intensive Manufacturing" industries. I refer to manufacturing industries which adopt less robots in their production processes as "Low Robot-Intensive Manufacturing" industries. These industries include Industrial Machinery, Minerals, Paper and Printing, Shipbuilding and Aerospace, Textiles, Wood and Furniture, and miscellaneous manufacturing. Finally, I group the six residual sectors into "Non-Manufacturing" industries. These industries adopt only few robots in their production compared to manufacturing industries. They include Agriculture, Construction, Education and Research, Mining, Services and

Utilities.

1.3.2 Employment

To measure changes in the local labor market structure contemporaneous to the introduction of industrial robots, I obtain data on employment and relevant socio-demographic characteristics from the decennial US Census samples for 1970, 1980, 1990 and 2000, and the American Community Survey (ACS) for the years 2007 and 2014.[10] These datasets are publicly provided by the Integrated Public Use Microdata Series (IPUMS) and are repeated cross-sectional surveys that include between 1 and 5 percent of the US population (Ruggles et al., 2019). They provide a rich set of information on each sampled individual, including gender, race, ethnicity, age, education, employment, industry, occupation, income, and the county group of residence.

I restrict my sample to the non-institutionalized civilian population between 25 and 64 years of age and aggregate the counts to 722 Commuting Zones (CZs) that cover all metropolitan and rural areas of the US mainland, acting as proxies of US local labor markers (Tolbert and Sizer, 1996). CZs represent economically relevant regions for local labor markets and are formed by clusters of counties with strong commuting ties within the area and weak commuting ties across CZs (Autor and Dorn, 2013).[11]

I use these data to measure employment rates of different demographic groups and compute employment gaps by gender and race/ethnicity at the local labor market level:

$$EG_{c,t}^{(M,W)} = E_{c,t}^{M} - E_{c,t}^{W} \tag{2}$$

where $E_{c,t}^{g} = L_{c,t}^{g}/N_{c,t}^{g}$ is the employment rate (employment count divided by the working-age population) of demographic group $g \in \{M, W\}$ in CZ c at time t. In case of the gender employment gap, M and W represent men and women, while they represent whites and non-whites for the race/ethnicity employment gap. Racial and ethnic minorities (non-whites) include Blacks, Hispanics, Asians, American Indian or Alaska Natives, and other (not elsewhere classified) races.

[10] I follow the literature and increase the sample size of the ACS samples using data from the 3-year sample of 2006-2008 and the 5-year sample of 2012-2016.

[11] The IPUMS provide county groups or Public Use Microdata Areas as lowest geographic units. I follow Autor and Dorn (2013) and aggregate data at the CZ level using a crosswalk which provides a probabilistic matching of sub-state geographic units in US Census Public Use Files to CZs.

Table 1.2: Summary statistics: Employment

	All		1st quartile		4th quartile	
	1990	Δ_{14-90}	1990	Δ_{14-90}	1990	Δ_{14-90}
	[1]	[2]	[3]	[4]	[5]	[6]
			Panel A: Gender			
Men	84.3	-4.46	83.8	-4.14	84.4	-4.73
Women	66.0	1.64	65.4	1.23	65.8	2.32
Gender gap	18.3	-6.10	18.3	-5.37	18.6	-7.06
			Panel B: Race and ethnicity			
White	76.7	-1.42	76.3	-2.17	76.4	-0.83
Non-white	68.8	0.94	70.0	1.01	67.2	0.99
Race and ethnicity gap	7.89	-2.37	6.22	-3.18	9.13	-1.82
Observations	722	722	181	181	180	180

Notes: This table illustrates average employment rates for men, women, whites, and non-whites, and average employment gaps by gender and race/ethnicity. Columns 1, 3 and 5 show values in 1990, and Columns 2, 4 and 6 show changes between 1990 and 2014, weighted by CZ population in 1990. Columns 1 and 2 reports averages over all 722 CZs in the sample. Columns 3 to 6 split the sample into quartiles according to the CZ's exposure to robots between 1993 and 2014, reporting averages for the first and the fourth quartile.

Table 1.2 reports summary statistics of the main employment variables for 1990 and their changes between 1990 and 2014. Columns 1 and 2 report averages over all 722 US CZs in the sample, while the remaining two column pairs split CZs according to their exposure to industrial robots, reporting averages for the first (least exposed) and fourth (most exposed) quartile.

In general, men and whites have higher employment rates than women and racial/ethnic minorities. At the beginning of the 1990s, the employment gaps were 18.3 and 7.89 percentage points respectively. However, both gaps declined by roughly one third during my sample period. In CZs that are more exposed to the adoption of robots, the decline of the gender employment gap has been larger, while it has been smaller for the race/ethnicity employment gap.[12]

Figure A1 in the Appendix provides information about the distribution of the employment gaps across US local labor markets. Specifically, the gender gap is particularly large in Texas and in CZs of the northern part of the Jell-O Belt (especially in Idaho and Utah), while the race and ethnicity gap is largest in states of the northern part of the Wheat Belt (Minnesota, North Dakota and South Dakota).[13]

Table A1 further decomposes the employment rate of racial and ethnic minorities between Blacks, Hispanics, Asians, American Indian or Alaska Natives, and other races, providing details on their

[12] The values of Columns 4 and 6 are statistically different at the 1 percent level.

[13] Figure A2 also shows the distribution of the population of non-whites across CZs. The highest shares of non-whites are in states of the Sun Belt, including Arizona, Florida, New Mexico, Mississippi, South Carolina, and Texas.

relative contribution to the group of non-whites in 1990. Blacks account for 37.6 percent of the racial and ethnic minority group (11.4 percent in the total population), Hispanics account for 41.8 percent (12.6 percent), Asians account for 14.6 percent (4.4 percent), American Indian or Alaska Natives account for 2.1 percent (0.6 percent), and other not elsewhere classified races account for 3.9 percent (1.2 percent). Moreover, the table shows that in 1990 the employment rates of all groups were between 68 and 72 percent (similar to the group's average). Until 2014, employment of Blacks and American Indian/Alaska Natives has decreased, while employment of Hispanics, Asians, and the residual group experienced an increase of about 1.5 percentage points.

1.3.3 Occupational and industrial segregation

Besides the existence of employment gaps, the US labor market is characterized by a persistent industrial and occupational segregation of workers who belong to different demographic groups, exposing them differently to the risks of automation through industrial robots.

The IFR provides information about the industry composition of the stock of robots, but it does not provide detailed data about the occupations in which they are deployed. As defined previously, industrial robots can be programmed to perform manual tasks, such as assembly and welding. Based on this definition, I investigate the relative exposure of workers to the introduction of robots at the occupational level by measuring the manual (brawn) and cognitive (brain) task content of occupations.

I measure the task intensity of labor using information on the skill requirements of jobs at detailed occupation level from the Dictionary of Occupational Titles (DOT, 1977). The DOT is a survey administered by the US Department of Labor performed on a random sample of workers to accurately collect information about the task content of jobs (Autor et al., 2003).

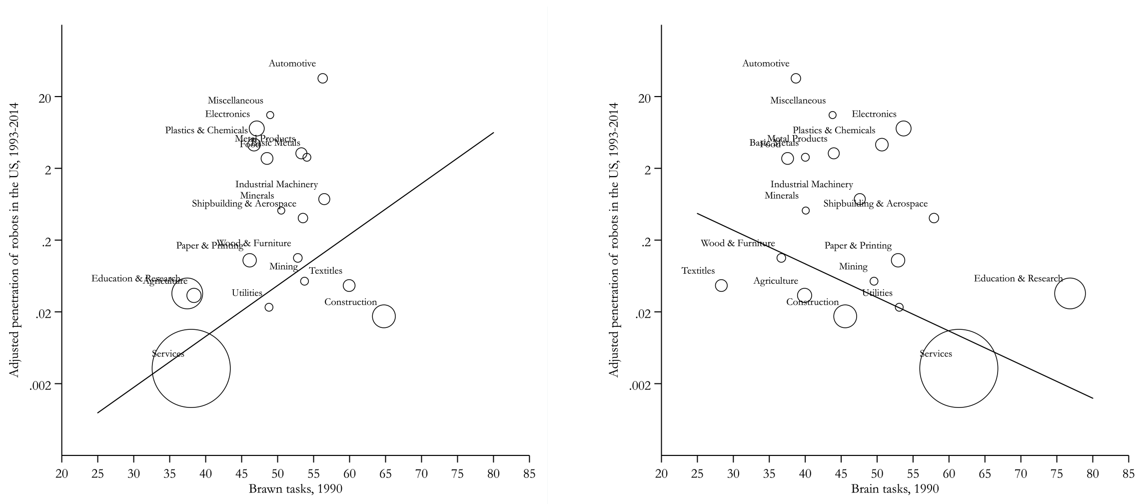
To extrapolate the relevant task content of occupations, I follow Ge and Zhou (2020) in defining an occupation's brawn task intensity based on five scores which measure the workload of manual tasks of jobs: (i) eye, hand and foot coordination, (ii) motor coordination, (iii) finger dexterity, (iv) manual dexterity, and (v) physical strength. The brain task intensity of occupations is based on temperaments which require cognitive and social skills: (i) quantitative reasoning, language, and verbal and numerical aptitude, (ii) direction, control and planning for activity, (iii) interpreting feeling, ideas, facts in terms of personal viewpoint, (iv) influencing people in their opinions, attitudes or judgment about ideas or things, (v) making generalizations, evaluations, or decisions based on sensory or judgmental criteria, (vi) making generalization, judgments, or decisions based on measurable or verifiable criteria, (vii) and dealing with people beyond giving and receiving instructions.

This information is used to compute brawn and brain task measures from averages of the relevant DOT variables and are standardized using the percentile values of their ranks in the 1970 employment distribution, a decade before the introduction of industrial robots in the US. These measures are then matched with 315 occupations from the Census.

Based on the occupational distribution within industries, I use these data to build measures of the brawn and brain task-intensity of IFR industries.[14] Figure 1.2 illustrates the relationship between robot exposure and brawn task intensity (Panel A) and brain task intensity (Panel B) at the industry level. Unsurprisingly, industrial robots are adopted more in manufacturing industries with a large brawn task content and less in industries that are intensive in brain tasks, suggesting that they are more substitutable for brawn skills than for brain skills.

Figure 1.2: Industries and job tasks: Brawn versus brain

Panel A: Brawn　　　　　Panel B: Brain



Notes: This figure illustrates the relationship between the growth in the (log) stock of robots per thousand workers at the IFR industry level between 1993 and 2014 (see Equation 1) and the brawn and brain task content in these industries. The task content at the industry level is expressed as the mean standardized task content of occupations within each industry weighted by the industry's occupational employment in 1990.

[14] Every IFR industry is composed by a set of occupations, each of which has been assigned a score for its brawn and brain task intensity. I compute brawn and brain task measures at the industry level using the weighted average of the occupation scores within each industry. I use employment at the occupation level as weights.

I use this evidence to identify the relative exposure to robots of census occupations. For this purpose, I use a double median split of the standardized measures of brawn and brain task intensity of jobs and build four occupation groups with common task characteristics. Although occupations combine elements from each task category and task intensity varies among occupations within these broad groups, they capture the central tendencies of the data (Acemoglu and Autor, 2011).

The first group includes occupations that are both brawn and brain task intensive (e.g. mechanical engineers). I refer to them as "Skill-Intensive" occupations. The second group includes "White-Collar" occupations that are intensive in brain tasks, but require only few brawn skills (e.g. secretaries). The third group includes "Blue-Collar" occupations that are intensive in brawn tasks and need only few brain skills (e.g. structural metal workers).[15] These are the occupations which, according to Figure 1.2, should be most exposed to the adoption of industrial robots. Finally, I refer to occupations that do not require particular brawn or brain skills as "Low-Skill" occupations (e.g. household cleaners and servants).

To identify the industrial and occupational segregation in the labor market, Figure 1.3 breaks down employment within industry and occupation groups by the demographic characteristics of workers. Panel A reports the results by gender and Panel B by race/ethnicity.

Results show that men are employed more often in blue-collar occupations of the manufacturing sector (also referred to as steel-collar jobs) than women, suggesting that they are more likely to be exposed to the risks of automation through robots. While there is no clear over-representation or under-representation of racial and ethnic minorities across industries, there is evidence of significant segregation by race and ethnicity across occupations. In particular, non-whites are employed more often in blue-collar and low-skills jobs, and they are under-represented in brain task-intensive occupations, exposing them to a larger risk of displacement through industrial robots.

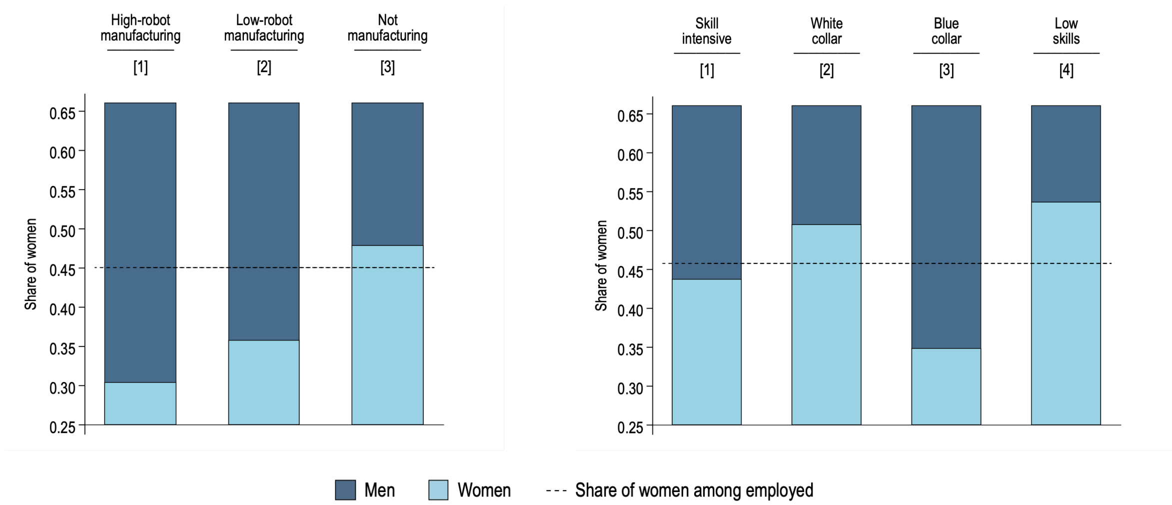
A list of occupations with the highest and lowest occupation shares by gender and race/ethnicity is illustrated in Table A2. Additionally, Table A3 decomposes the summary statistics on employment rates and gaps from Table 1.2 by industries and occupations, showing similar results about the industrial and occupational segregation of the US labor market by gender and race/ethnicity as

[15] For instance, Table A2 in the Appendix shows that the brawn and brain task intensities of structural metal workers are at the 67 and the 25 percentile of the distribution.

Figure 1.3: Industrial and occupational segregation

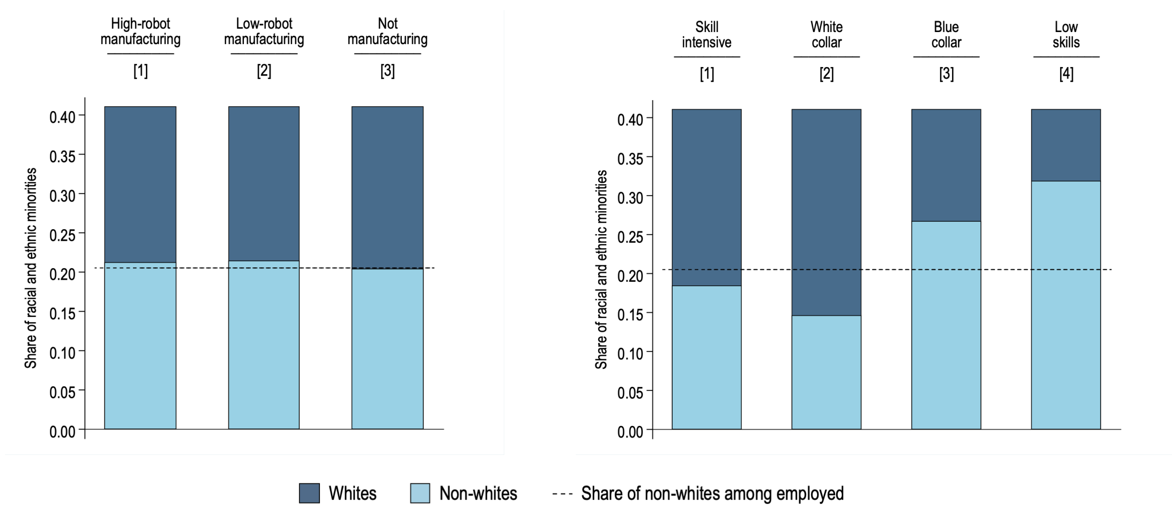
Panel A: Gender

Panel A1: Industry Panel A2: Occupation



Panel B: Race and ethnicity

Panel B1: Industry Panel B2: Occupation



Notes: This figure illustrates the shares of women and non-whites within industry and occupation groups in 1990. The share of a demographic group is computed as the number of workers who belong to this group divided by total employment in the industry or occupation. The dashed line shows the overall share of women and non-whites among employed workers. If a colored bar intersects the dashed line, the demographic group is over-represented in the industry or occupation group. If it does not, it is under-represented.

Figure 1.3.[16]

[16] Table 1.2 complements the results from Figure 1.3 without correcting for relative employment rates of demographic groups. This does not always make the size of the industrial and occupational segregation in the labor market obvious at first glance, since one needs first to correct for demographic-specific employment rate differentials.

1.4 Identification strategy

I estimate the effect of the introduction of industrial robots on employment across demographic groups using a stacked first-difference specification with 722 CZs and three time periods (1993-2000, 2000-07, 2007-14).[17] The key estimating equation is given by:

$$\Delta \mathrm{E}^{g}_{c,(t_0,t_1)} = \beta^{g}\, \text{US robot exposure}_{c,(t_0,t_1)} + \mathbf{X}'_{c,(t_0,t_1)}\mathbf{\Gamma}^{g} + \varepsilon^{g}_{c,(t_0,t_1)} \tag{3}$$

where $\Delta \mathrm{E}^{g}_{c,(t_0,t_1)}$ is the change in the employment rate among working-age individuals of demographic group $g \in \{M, W\}$ in CZ c between year t_0 and t_1. I test for significant differences in the impact of robots on employment across demographic groups using changes in the employment gaps:

$$\Delta \mathrm{EG}^{(M,W)}_{c,(t_0,t_1)} = \beta^{(M,W)}\, \text{US robot exposure}_{c,(t_0,t_1)} + \mathbf{X}'_{c,(t_0,t_1)}\mathbf{\Gamma}^{(M,W)} + \varepsilon^{(M,W)}_{c,(t_0,t_1)} \tag{4}$$

where $\Delta \mathrm{EG}^{(M,W)}_{c,(t_0,t_1)} = \Delta \mathrm{E}^{M}_{c,(t_0,t_1)} - \Delta \mathrm{E}^{W}_{c,(t_0,t_1)}$, such that $\beta^{(M,W)} = \beta^{M} - \beta^{W}$.

To account for potential sources of bias that might confound the estimates of the labor market effect of robots, I include state fixed effects, year dummies interacted with nine census-division fixed effects, and a vector of time-invariant regional characteristics and economic variables, including the industrial and occupational composition of employment, socio-demographic characteristics, and the demographic composition of industries and occupations within CZs in 1990.[18] I keep CZ characteristics constant to avoid contamination by endogenous adjustments in the structure of local labor markets in response to robot adoption. I further control for pre-existing trends in employment of men, women, whites and non-whites between 1970 and 1990, and for structural labor market shocks that are contemporaneous to the introduction of robots in the US, including the China trade shock, as defined in Autor et al. (2013), the adoption of personal computers (PC) and IT capital intensity, as defined in Acemoglu and Restrepo (2020), and routine-biased technological change (RBTC), as defined in Autor and Dorn (2013). Further details about covariates are provided in Table A4 and in Appendix A1.

[17] Note that in the 1990s the IPUMS includes only data from the 1990 Census. For comparability across periods, I rescale the 1990-2000 period to a 7-year equivalent change.

[18] Census divisions are administrative divisions of the US territory in nine broad groups of states: New England, Middle Atlantic, South Atlantic, East North Central, East South Central, West North Central, West South Central, Mountain and Pacific.

I build measures of US robot exposure at the CZ level from Equations 3 and 4 using a shift-share approach. Following Acemoglu and Restrepo (2020), I match industry-level data on robot adoption from the IFR with employment counts from the Census:

$$\text{US robot exposure}_{c,(t_0,t_1)} = \sum_{j \in J} \ell^{90}_{c,j} \left[\frac{R^{US}_{j,t_1} - R^{US}_{j,t_0}}{L^{US}_{j,90}} - g^{US}_{j,(t_0,t_1)} \frac{R^{US}_{j,t_0}}{L^{US}_{j,90}} \right] \tag{5}$$

The term in brackets (shift component) is a measure of industrial robot density, computed as the US wide change in the stock of robots in industry $j \in J$, relative to its workforce in 1990, and adjusted for the adoption of robots that is driven by overall industry output growth, $g^{US}_{j,(t_0,t_1)} = \Delta \ln(Y^{US}_{j,t})$.[19] The industry-level shock is apportioned across local labor markets using CZs' industry employment shares, $\ell^{90}_{c,j} = L^{90}_{c,j}/L^{90}_{c}$ (share component). The baseline employment shares are kept constant to avoid endogeneity and serial correlation across periods of my stacked first-difference specification.

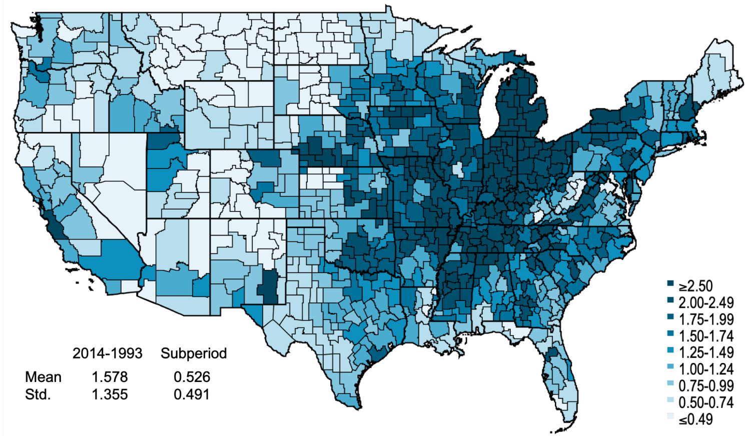
Figure 1.4 illustrates the distribution of US robot exposure across CZs between 1993 and 2014. The figure shows that the Midwest of the country is significantly more exposed to the adoption of industrial robots, in particular the local labor markets of the Rust Belt (i.e. parts of Indiana, Michigan and Ohio). This result follows from the specialization of these areas in the industrial sector, including steel-making and automobile manufacturing industries, in which robots have been heavily deployed in the production process. Some of these CZs experienced an increase of up to 11 robots per thousand workers between the early 1990s and the mid-2010s, exceeding the national average of 1.578 by more than seven times.[20] The average US robot exposure per sample period (seven years) is equal to 0.526 robots per thousand workers, with a standard deviation of 0.491.

Identification builds on the assumption that advances in robotics vary by industry and expose local labor markets differently depending on the industrial composition of employment. However, US firms could also adopt robots in response to domestic industry-specific shocks which influence also the demand for labor. For instance, positive demand shocks might induce US firms to raise both capital and employment, biasing the estimates of the impact of robots on labor demand upwards. To

[19] I obtain US data on employment and output at the industry level from the Integrated Industry-Level Production Account (KLEMS) of the Bureau of Economic Affairs (BEA, 2021). I use comparable data for several European countries from the EU KLEMS database (Jägger, 2017) to construct the instrument of my IV strategy (see Equation 6).

[20] In Appendix A3, I perform a set of robustness checks that exclude these CZs from the analysis, showing that the effect of robots on employment across different demographic groups is not solely driven by these areas.

Figure 1.4: US robot exposure at the CZ level between 1993 and 2014



Notes: This figure illustrates the distribution of US robot exposure at the CZ level between 1993 and 2014. Means and standard deviations (std.) are represented for the full sample period (1993-2014) and as averages of the subperiods (1993-2000, 2000-07, 2007-14).

address the endogeneity concern and identify robot adoption that is driven by exogenous advances in robotics (supply shock), I apply an IV strategy and instrument the shift component of Equation 5 using contemporaneous changes in the stock of robots in seven European countries with a comparable adoption of robots as the US:

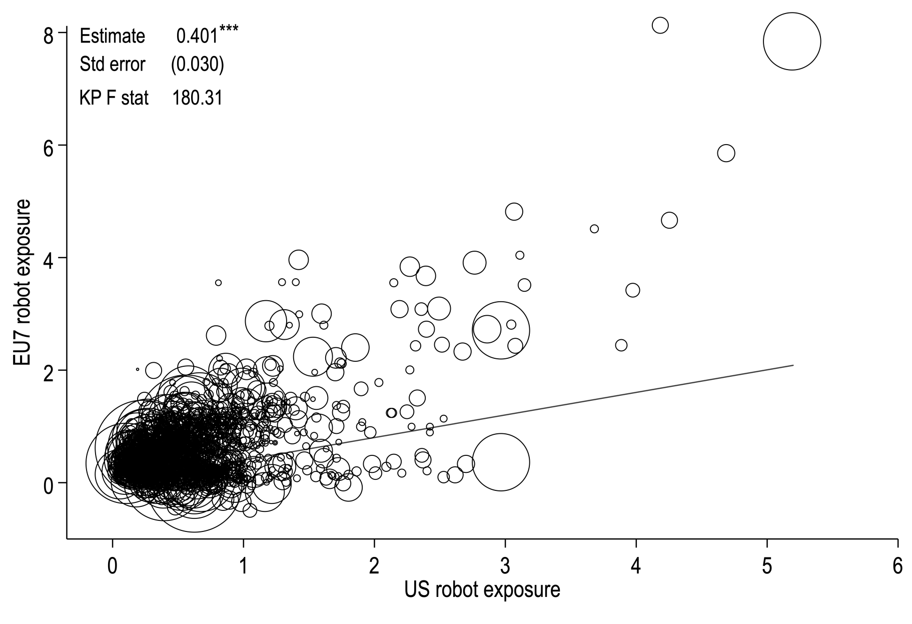
$$\text{EU7 robot exposure}_{c,(t_0,t_1)} = \sum_{j \in J} \ell^{70}_{c,j} \frac{1}{7} \sum_{i \in EU7} \left[\frac{R^i_{j,t_1} - R^i_{j,t_0}}{L^i_{j,90}} - g^i_{j,(t_0,t_1)} \frac{R^i_{j,t_0}}{L^i_{j,90}} \right] \tag{6}$$

where $R^i_{j,t}$ is the stock of robots in country $i \in EU7$ at time t in industry j. $EU7$ countries include Denmark, Finland, France, Italy, Spain, Sweden and the United Kingdom. The share component uses (plausibly exogenous) employment shares from 1970 to focus on the industrial composition of employment that precedes the introduction of industrial robots, which started in the 1980s (Acemoglu and Restrepo, 2020).[21]

The IV strategy aims at identifying the labor market effects of exogenous improvements in robotics available to US firms. The strategy relies on the assumptions that the adoption of robots in European countries is positively related to the adoption of robots in the US, but that it is not directly affecting US labor market conditions. Figure 1.5 shows that there is a strong positive correlation between the adoption of robots in the US and the seven European countries, supporting

[21] Appendix A3 provides a set of robustness checks using alternative constructions of the shift-share measure, including different combinations of countries, different employment shares, and by excluding the adjustment term. The results of the empirical analysis are robust to these changes.

Figure 1.5: First-stage: Robots in the US and in Europe



Notes: This figure illustrates the first-stage relationship between US robot exposure and EU7 robot exposure at the CZ level. Each circle represents a CZ in one of the three sample periods. The size is proportional to the employment level in 1990. The black line displays the fitted values from the first-stage regression:

$$\text{US robot exposure}_{c,(t_0,t_1)} = \alpha\,\text{EU7 robot exposure}_{c,(t_0,t_1)} + \mathbf{X}'_{c,(t_0,t_1)}\mathbf{\Gamma} + \nu_{c,(t_0,t_1)}$$

The slope of the line is equal to $\hat{\alpha} = 0.401$. The standard error of the estimate is equal to 0.03. The Kleibergen-Paap F statistic is 180.31. Standard error are robust against heteroskedasticity and allow for clustering at the state level. Regressions include the full battery of controls, they are weighted by CZ population in 1990. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level. Table A5 reports standardized first-stage estimates using different specifications. The (non-standardized) estimates of this figure correpond to Column 6. To standardize coefficients, one has to divide them by the standard deviation of 0.491 (Figure 1.4).

the relevance condition (the Kleibergen-Paap F statistic is well above 10). While I cannot test for the exclusion restriction to hold, I perform a set of robustness checks of my identification strategy, controlling for international product market competition between Europe and the US, as well as pre-trends in local labor market conditions.[22] The results are reported in Appendix A3. I do not find evidence of a violation of the exclusion restriction through these potential sources of bias.[23]

[22] International product market competition may violate the exclusion restriction, as the rapid adoption of robots in Europe could have made European firms more competitive than their US peers, unveiling a possible causal link with US labor market conditions. The instrument purposely does not include the countries with the world's heaviest adoption of industrial robots, i.e. South Korea, Germany, and Japan, since they are also among the main trading partners of the US and could directly affect US labor market conditions through their national adoption of robots. Appendix A3 stresses this assumption further and drops also the UK, Italy and France, using an instrument which includes only countries with the lowest trade engagement with the US (Denmark, Finland, Spain and Sweden). The results are unaffected (although noisier), and provide evidence in support of the exclusion restriction.

[23] The exogeneity of the shares should strengthen further the confidence that the instrument is exogenous (Goldsmith-Pinkham et al., 2020).

1.5 Results

This section presents the empirical results about the labor market impact of robots on employment across demographic groups, and explores the influence of socio-demographic characteristics, industries and occupations in the determination of the effects.

1.5.1 Robots and employment

I start the analysis by presenting the impact of industrial robots on employment using Equations 3 and 4. The OLS and IV estimates are reported in Table 1.3. Coefficients are standardized and represent the estimated effect of a one standard deviation increase in US robot exposure on the change in the respective employment rate and employment gap in percentage points. Regressions include the full battery of controls and are weighted by the CZ population in 1990. Standard errors allow for arbitrary clustering at the state level.[24]

Results show that robots decrease employment across all demographic groups.[25] The absolute size of OLS estimates is smaller than that of IV estimates, since US robot adoption is likely to be correlated with omitted demand shocks that bias the estimates of the underlying effect upwards.

Panel A shows that a one standard deviation increase in robot exposure decreases the local employment rate of men by 1.15 percentage points and the employment rate of women by 0.51 percentage points. In other words, employment rates decrease by 2.34 and 1.04 percentage points for each additional robot per thousand workers.[26] This result shows that men are losing their job more than twice as often as women, suggesting that the introduction of robots has contributed to the decrease of the gender employment gap. On the other hand, Panel B shows that a one standard deviation increase in robot exposure has decreased employment among racial and ethnic

[24] As outlined in Cadena and Kovak (2016), when examining outcomes across labor markets of different sizes, efficient weights must consider individuals' sampling weights to account for inherent heteroskedasticity. They also show that optimal weights are strongly correlated with initial population sizes of the unit of reference. Here, it is important to note that there are two sources of heteroskedasticity in the distribution of the population of different demographic groups. First, CZs strongly differ in their population size. Second, CZs differ in the shares of racial and ethnic minorities in the local population (see Figure A2). I examine the role of weights in Appendix A3.

[25] Table A5 shows that estimates are not significantly affected by the sequential inclusion of covariates.

[26] This computation follows from the de-standardization of the estimates to obtain the effect of one additional robot per thousand workers using the standard deviation reported in Figure 1.4 (e.g. $1.148/0.491 = 2.34$). To obtain estimates of the effect of the introduction of industrial robots between 1993 and 2014, I multiply these estimates with the average increase in the stock of robots from Figure 1.4 (e.g. $2.34 \times 1.578 = 3.7$). Appendix A2 compares and discusses the magnitude of these estimates with the findings of Acemoglu and Restrepo (2020).

Table 1.3: The effect of robots on employment

	Panel A: Gender		
	Men	Women	Gap
	[1]	[2]	[3]
	Panel A1: OLS estimates		
US robot exposure	-0.468***	-0.178*	-0.291***
	(0.144)	(0.090)	(0.096)
	Panel A2: IV estimates		
US robot exposure	-1.148***	-0.507**	-0.644***
	(0.243)	(0.189)	(0.166)
Observations	2166	2166	2166
	Panel B: Race and ethnicity		
	Whites	Non-whites	Gap
	[1]	[2]	[3]
	Panel B1: OLS estimates		
US robot exposure	-0.186***	-0.587***	0.400**
	(0.066)	(0.200)	(0.153)
	Panel B2: IV estimates		
US robot exposure	-0.569***	-1.415***	0.846***
	(0.097)	(0.315)	(0.276)
Observations	2166	2166	2166
Covariates:	✓	✓	✓

Notes: This table presents OLS and IV estimates of the effect of US robot exposure on employment rates and gaps by gender and race/ethnicity at the CZ level. Changes are expressed in percentage points of the working-age population of the respective demographic group and are multiplied by 100. Independent variables are standardized to have mean zero and standard deviation of one. There are three time periods and 722 CZs. All regressions include state fixed effects, time-varying division fixed effects, pre-trends in employment of men, women, whites and non-whites between 1970 and 1990, controls for the adoption of PCs, IT capital intensity and RBTC, exposure to Chinese imports, demographic characteristics (share of Blacks, Hispanics, women, population with less than a college degree, three age groups (25-34, 35-44 and 45-54 years), and the logarithmic population), the industry (employment share in construction, manufacturing, mining, research, service and utilities) and occupation composition of employment (employment share in offshorable, skill-intensive, white-collar, blue-collar and low-skill jobs) of CZs in 1990, and the composition of industry and occupation employment by gender and race/ethnicity of CZs in 1990. Standard errors are robust against heteroskedasticity and allow for clustering at the state level. Regressions are weighted by CZ population in 1990. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

minorities about two-and-a-half times as much as for whites, 1.41 and 0.57 percentage points respectively (2.87 and 1.16 percentage points for each additional robot per thousand workers), widening the race/ethnicity employment gap. These results show that each additional robot per thousand workers has decreased the gender employment gap by 1.30 percentage points and has increased the race/ethnicity employment gap by 1.72 percentage points, slowing its secular decline.

Table A6 in the Appendix shows that the effects are economically and statistically significant already before the start of the Great Recession. This finding suggests that the alteration of labor market conditions during this period of time is not driving my results.[27] Table A7 further shows that robots affect labor force participation gaps in the same direction as they do with the employment gaps. Interestingly, women are not leaving the labor force in response to robot exposure, implying that changes in the gender labor force participation gap are driven by changes in the labor force participation of men (Lerch, 2020).

Table A8 compares the labor market impact of robots with the impact of the China trade shock from Autor et al. (2013) and other technology shocks that are contemporaneous to the introduction of industrial robots, including PC adoption and IT capital intensity (Acemoglu and Restrepo, 2020), and RBTC (Autor and Dorn, 2013). These shocks are part of the vector of covariates of Equations 3 and 4.[28] I find that also the China trade shock has contributed to the decrease of the gender employment gap, but to a smaller extent than robots, and that the estimate is not statistically significant to the exclusion of the Great Recession period (2007-14).[29] On the other hand, RBTC appears to increase the gender employment gap, although this estimate is not particularly robust either. I do not find evidence of the trade shock and RBTC having affected the employment gap by race and ethnicity. However, I find that the exposure to PCs has increased the gap to a similar extent as robots, because of a reduction in employment among non-whites, but no significant change in the employment rate of whites. This finding suggests that the adverse impact of new technologies on racial and ethnic disparities could not be limited to the introduction of industrial robots.

1.5.2 Socio-demographic characteristics

Table 1.4 decomposes the previous effects of robots on employment by socio-demographic characteristics of workers, including education (college and non-college educated workers) and age (25-34, 35-44, 45-54 and 55-64 years). The employment rates from Table 1.3 are the result of the weighted sum of socio-demographic specific employment rates, $E^{g,s}_{c,t}$:

$$E^{g}_{c,t} = \sum_{s} \frac{N^{g,s}_{c,t}}{N^{g}_{c,t}} \frac{L^{g,s}_{c,t}}{N^{g,s}_{c,t}} = \sum_{s} \frac{N^{g,s}_{c,t}}{N^{g}_{c,t}} E^{g,s}_{c,t} \tag{7}$$

[27] Note, however, that the estimate on the gender employment gap almost halves in size (from -0.644 to -0.343), due to a smaller impact of robots on employment of men before 2007.

[28] Appendix A1 provides details about the construction of these shocks.

[29] This specification mimics the sample period used in Autor et al. (2013), 1993-2000 and 2000-07. Similar to their results, I find that import exposure decreases employment of men and women, but without significant differences by gender.

where $E_{c,t}^{g,s}$ is the employment rate in CZ c at time t among individuals from demographic group g with characteristics s. Panel A illustrates the estimates by gender and Panel B by race and ethnicity.

Table 1.4: The effect of robots on employment by socio-demographic characteristics

	Panel A: Gender							
	Race and ethnicity		Education		Age			
	Whites	Non-whites	College degree	Less than college	25-34 years	35-44 years	45-54 years	55-64 years
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
	Panel A1: Employment rate of men							
US robot exposure	-0.897***	-1.804***	-0.403***	-1.445***	-1.329***	-0.964***	-1.006***	-1.250***
	(0.120)	(0.421)	(0.113)	(0.318)	(0.327)	(0.246)	(0.230)	(0.229)
	Panel A2: Employment rate of women							
US robot exposure	-0.250**	-1.039***	-0.470***	-0.530**	-0.244	-0.503**	-0.578***	-0.525**
	(0.108)	(0.291)	(0.146)	(0.221)	(0.204)	(0.244)	(0.167)	(0.203)
	Panel A3: Employment gap							
US robot exposure	-0.647***	-0.766**	0.067	-0.915***	-1.085***	-0.461**	-0.428**	-0.725***
	(0.127)	(0.361)	(0.187)	(0.190)	(0.308)	(0.211)	(0.171)	(0.201)
Observations	2166	2166	2166	2166	2166	2166	2166	2166
	Panel B: Race and ethnicity							
	Gender		Education		Age			
	Men	Women	College degree	Less than college	25-34 years	35-44 years	45-54 years	55-64 years
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
	Panel B1: Employment rate of whites							
US robot exposure	-0.897***	-0.250**	-0.426***	-0.622***	-0.512***	-0.506***	-0.439***	-0.690***
	(0.120)	(0.108)	(0.082)	(0.108)	(0.139)	(0.146)	(0.064)	(0.109)
	Panel B2: Employment rate of racial and ethnic minorities							
US robot exposure	-1.804***	-1.039***	-0.729**	-1.611***	-1.262***	-1.381***	-1.665***	-1.150***
	(0.421)	(0.291)	(0.299)	(0.365)	(0.375)	(0.409)	(0.338)	(0.337)
	Panel B3: Employment gap							
US robot exposure	0.908**	0.789***	0.303	0.989***	0.750**	0.875**	1.226***	0.459
	(0.358)	(0.282)	(0.302)	(0.300)	(0.299)	(0.414)	(0.314)	(0.360)
Observations	2166	2166	2166	2166	2166	2166	2166	2166
Covariates:	✓	✓	✓	✓	✓	✓	✓	✓

Notes: This table presents IV estimates of the effect of US robot exposure on employment rates and gaps by gender and race/ethnicity at the CZ level. Columns decompose the outcomes by demographics, education and age groups. Changes are expressed in percentage points of the working-age population of the respective demographic group and are multiplied by 100. Independent variables are standardized to have mean zero and standard deviation of one. There are three time periods and 722 CZs. All regressions include state fixed effects, time-varying division fixed effects, pre-trends in employment of men, women, whites and non-whites between 1970 and 1990, controls for the adoption of PCs, IT capital intensity and RBTC, exposure to Chinese imports, demographic characteristics (share of Blacks, Hispanics, women, population with less than a college degree, three age groups (25-34, 35-44 and 45-54 years), and the logarithmic population), the industry (employment share in construction, manufacturing, mining, research, service and utilities) and occupation composition of employment (employment share in offshorable, skill-intensive, white-collar, blue-collar and low-skill jobs) of CZs in 1990, and the composition of industry and occupation employment by gender and race/ethnicity of CZs in 1990. Standard errors are robust against heteroskedasticity and allow for clustering at the state level. Regressions are weighted by CZ population in 1990. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Results show that the adverse impact of robots is strongest for non-white men and weakest for white women. I further find that the effects are significantly larger for individuals without a college degree, in particular for men and non-whites, and that the impact on these individuals is driving the results on the employment gaps from Table 1.3. Although workers with a college degree experience also a negative impact of robots, there are no significant differences by gender and race/ethnicity, leaving the employment gaps among college-educated workers almost unchanged.

The effect of robots on the employment gaps is relatively stable and persistent across age groups. By gender, the effect is lowest between 35 and 54 years, when the effect on male workers is slightly smaller. By race/ethnicity, it has a peak between 45 and 54 years, when the impact on racial and ethnic minorities is strongest, and drops from the age of 55 years.

It is also important to consider that racial and ethnic minorities are a fairly heterogenous group of individuals, which includes Blacks, Hispanics, American Indian, Alaska Natives, and Asians, among others. For this purpose, Table 1.5 disaggregates this broad group and analyzes whether the impact of robots differs across narrower race/ethnicity subgroups. Panel A reports estimates of the effect of robot exposure on the employment rates of whites, Blacks, Hispanics and other races (including American Indian, Alaska Natives, Asians, or other, not elsewhere classified, races), while Panel B reports estimates on the employment gaps.[30]

I find that the effect of robots is strongest for Hispanics and Blacks, followed by other races, and whites. As a consequence, robot exposure has increased mostly the employment gaps between whites and Hispanics, and between whites and Blacks. The employment gap between Blacks and Hispanics has not been affected significantly, suggesting that the impact of robots on employment is similar among these two groups. Moreover, I find that the employment gap between other races and Blacks or Hispanics has increased, while it has not changed significantly with whites.

Table 1.6 further decomposes the groups of whites and racial/ethnic minorities from Table 1.3 between US natives and immigrants. Panel A shows that robots have decreased employment among all demographic groups (although estimated imprecisely for white immigrants), but relatively more for non-whites. This result is also visible in Panel B, which reports estimates of the impact of robots on the employment gaps between natives and immigrants, showing that they increase the

[30] As shown in Table A1, Blacks account for about 38 percent of the group of racial/ethnic minorities, Hispanics account for nearly 42 percent, and other races account for about 20 percent.

Table 1.5: The effect of robots on employment: Whites, Blacks, Hispanics, and other races

	Panel A: Employment rates			
	Whites	Blacks	Hispanics	Other races
	[1]	[2]	[3]	[4]
US robot exposure	-0.569***	-1.724***	-2.023***	-0.951***
	(0.097)	(0.436)	(0.385)	(0.318)
Observations	2166	2166	2166	2166
	Panel B: Employment gaps			
	Whites	Blacks	Hispanics	Other races
	[1]	[2]	[3]	[4]
1) Whites				
US robot exposure	–			
2) Blacks				
US robot exposure	1.156***	–		
	(0.390)			
3) Hispanics				
US robot exposure	1.454***	0.298	–	
	(0.374)	(0.461)		
4) Other races				
US robot exposure	0.383	-0.777***	-1.071***	–
	(0.275)	(0.245)	(0.349)	
Observations	2166	2166	2166	
Covariates:	✓	✓	✓	✓

Notes: This table presents IV estimates of the effect of US robot exposure on employment rates and gaps by race/ethnicity at the CZ level. Columns decompose workers between whites, Blacks, Hispanics and other races (including American Indian or Alaska Natives, Asians, and other not elsewhere classified races). Changes are expressed in percentage points of the working-age population of the respective demographic group and are multiplied by 100. Independent variables are standardized to have mean zero and standard deviation of one. There are three time periods and 722 CZs. All regressions include state fixed effects, time-varying division fixed effects, pre-trends in employment of men, women, whites and non-whites between 1970 and 1990, controls for the adoption of PCs, IT capital intensity and RBTC, exposure to Chinese imports, demographic characteristics (share of Blacks, Hispanics, women, population with less than a college degree, three age groups (25-34, 35-44 and 45-54 years), and the logarithmic population), the industry (employment share in construction, manufacturing, mining, research, service and utilities) and occupation composition of employment (employment share in offshorable, skill-intensive, white-collar, blue-collar and low-skill jobs) of CZs in 1990, and the composition of industry and occupation employment by gender and race/ethnicity of CZs in 1990. Standard errors are robust against heteroskedasticity and allow for clustering at the state level. Regressions are weighted by CZ population in 1990. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

race/ethnicity employment gap, independently on whether white or non-white workers were born in the US or abroad.

1.5.3 Occupations and industries

As shown in Section 1.3, men and racial and ethnic minorities are over-represented in blue-collar occupations that are more susceptible to the risks of automation through industrial robots. In this section, I investigate to which extent US labor market segregation drives the impact of robots on

Table 1.6: The effect of robots on employment: The origin of workers by race and ethnicity

	Panel A: Employment rates			
	Natives		Immigrants	
	Whites	Non-whites	Whites	Non-whites
	[1]	[2]	[3]	[4]
US robot exposure	-0.578***	-1.262***	-0.360	-1.114***
	(0.101)	(0.261)	(0.351)	(0.313)
Observations	2166	2166	2166	2166
	Panel B: Employment gaps			
	Native whites Native non-whites	Native whites Non-white immigrants	White immigrants Native non-whites	White immigrants Non-white immigrants
	[1]	[2]	[3]	[4]
US robot exposure	0.684***	0.536*	0.902**	0.754*
	(0.249)	(0.299)	(0.378)	(0.435)
Observations	2166	2166	2166	2166
Covariates:	✓	✓	✓	✓

Notes: This table presents IV estimates of the effect of US robot exposure on employment rates and gaps by race/ethnicity at the CZ level. Columns decompose workers between natives and immigrants. Changes are expressed in percentage points of the working-age population of the respective demographic group and are multiplied by 100. Independent variables are standardized to have mean zero and standard deviation of one. There are three time periods and 722 CZs. All regressions include state fixed effects, time-varying division fixed effects, pre-trends in employment of men, women, whites and non-whites between 1970 and 1990, controls for the adoption of PCs, IT capital intensity and RBTC, exposure to Chinese imports, demographic characteristics (share of Blacks, Hispanics, women, population with less than a college degree, three age groups (25-34, 35-44 and 45-54 years), and the logarithmic population), the industry (employment share in construction, manufacturing, mining, research, service and utilities) and occupation composition of employment (employment share in offshorable, skill-intensive, white-collar, blue-collar and low-skill jobs) of CZs in 1990, and the composition of industry and occupation employment by gender and race/ethnicity of CZs in 1990. Standard errors are robust against heteroskedasticity and allow for clustering at the state level. Regressions are weighted by CZ population in 1990. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

the employment gaps by breaking down workers by occupation groups (skill-intensive, white-collar, blue-collar and low-skill workers, see Section 1.3 for details):

$$E^{g}_{c,t} = \sum_{o} \frac{L^{g,o}_{c,t}}{N^{g}_{c,t}} \tag{8}$$

where $L^{g,o}_{c,t}$ is the employment count of demographic group g in occupation group o. I repeat this exercise by industry group (high robot-intensive manufacturing, low robot-intensive manufacturing and non-manufacturing industries) to analyze the effect of robots on employment also from an industrial perspective. The results are presented in Table 1.7. Panel A illustrates the results by gender and Panel B by race and ethnicity.

I find that robot exposure is significantly narrowing the gender employment gap through a reduction in employment of men in blue-collar jobs. Women are not affected in their employment

Table 1.7: The effect of robots on employment by occupation and industry

	Panel A: Gender						
	Occupation				Industry		
	Skill intensive	White collar	Blue collar	Low skills	High robot-intensive	Low robot-intensive	Non-manufac-turing
	[1]	[2]	[3]	[4]	[5]	[6]	[7]
	Panel A1: Employment rate of men						
US robot exposure	-0.245***	-0.146**	-0.627***	-0.041	-0.627***	0.018	-0.551***
	(0.055)	(0.068)	(0.135)	(0.054)	(0.122)	(0.053)	(0.182)
	Panel A2: Employment rate of women						
US robot exposure	-0.013	-0.250***	-0.039	-0.052	-0.144***	0.077**	-0.448***
	(0.043)	(0.087)	(0.067)	(0.065)	(0.043)	(0.032)	(0.149)
	Panel A3: Employment gap						
US robot exposure	-0.232***	0.104	-0.588***	0.011	-0.483***	-0.058	-0.103
	(0.047)	(0.081)	(0.095)	(0.065)	(0.092)	(0.037)	(0.166)
Observations	2166	2166	2166	2166	2166	2166	2166
	Panel B: Race and ethnicity						
	Occupation				Industry		
	Skill intensive	White collar	Blue collar	Low skills	High robot-intensive	Low robot-intensive	Non-manufac-turing
	[1]	[2]	[3]	[4]	[5]	[6]	[7]
	Panel B1: Employment rate of whites						
US robot exposure	-0.089**	-0.162**	-0.197***	-0.018	-0.346***	0.048	-0.270***
	(0.037)	(0.066)	(0.050)	(0.034)	(0.051)	(0.053)	(0.078)
	Panel B2: Employment rate of racial and ethnic minorities						
US robot exposure	-0.099	-0.290**	-0.830***	-0.080	-0.490**	0.042	-0.962***
	(0.101)	(0.113)	(0.195)	(0.112)	(0.220)	(0.061)	(0.263)
	Panel B3: Employment gap						
US robot exposure	0.010	0.128	0.632***	0.062	0.144	0.007	0.692***
	(0.111)	(0.135)	(0.179)	(0.115)	(0.180)	(0.079)	(0.254)
Observations	2166	2166	2166	2166	2166	2166	2166
Covariates:	✓	✓	✓	✓	✓	✓	✓

Notes: This table presents IV estimates of the effect of US robot exposure on employment rates and gaps by gender and race/ethnicity at the CZ level. Columns decompose the outcomes by industry and occupation groups. Changes are expressed in percentage points of the working-age population of the respective demographic group and are multiplied by 100. Independent variables are standardized to have mean zero and standard deviation of one. There are three time periods and 722 CZs. All regressions include state fixed effects, time-varying division fixed effects, pre-trends in employment of men, women, whites and non-whites between 1970 and 1990, controls for the adoption of PCs, IT capital intensity and RBTC, exposure to Chinese imports, demographic characteristics (share of Blacks, Hispanics, women, population with less than a college degree, three age groups (25-34, 35-44 and 45-54 years), and the logarithmic population), the industry (employment share in construction, manufacturing, mining, research, service and utilities) and occupation composition of employment (employment share in offshorable, skill-intensive, white-collar, blue-collar and low-skill jobs) of CZs in 1990, and the composition of industry and occupation employment by gender and race/ethnicity of CZs in 1990. Standard errors are robust against heteroskedasticity and allow for clustering at the state level. Regressions are weighted by CZ population in 1990. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

prospects in these jobs. The adverse effects of robots, however, are not limited to blue-collar occupations, but spill over also to skill-intensive and, in particular for women, to white-collar jobs.

Although this effect might seem surprising at first, it has to be considered that the employment reduction in the certain occupations and sectors could contract aggregate demand in the local economy, decreasing also the demand for labor in jobs that are not directly affected by the shock (Acemoglu and Restrepo, 2020, Faber et al., 2022, Helm, 2020).

At the industry level, I find that changes in the gender employment gap are driven by the manufacturing industries with the heaviest adoption of robots. The effect is again not limited to these industries, but spills over also to non-manufacturing industries, decreasing employment both among men and women, but without significant differences by gender.

Panel B shows that also in case of the race/ethnicity employment gap robot exposure decreases employment relatively more for racial and ethnic minorities in blue-collar occupations. Again, the effect spills over to skill-intensive and white-collar occupations, but in similar proportions by race and ethnicity. At the industry level, I find that robots decrease employment in high robot-intensive industries without significant differences between whites and non-whites. However, I do find substantial differences in how the effect spills over to non-manufacturing industries, in which non-whites suffer from greater employment losses than whites. These spillovers are likely to be the main driver of the effect of robots on the overall race/ethnicity employment gap.

Table A9 in the Appendix breaks down the effect of robots on the race/ethnicity employment gap in non-manufacturing sectors from Column 7 of Table 1.7 into individual sectors, showing that it is driven by worse employment prospects for non-white workers in the service sector.[31] This result could be fueled by two channels (which cannot be disentangled at the local labor market level). First, displaced whites are more likely to be re-employed in the service sector due to a comparative advantage in brain skills (Kletzer, 1991).[32] Second, the labor market impact of robots goes beyond broad composition effects, which cannot be explained using observables. For instance, the spillover effect of robots on the employment of racial and ethnic minorities in the service sector could be fueled by non-observable factors such as discrimination against Black and Hispanic workers in these

[31] Column 7 of Panel B shows that the employment rate of racial and ethnic minorities in non-manufacturing industries decreases by more than 0.96 percentage points relative to less than 0.27 for whites. This effect appears implausibly strong at first glance. However, it has to be considered that these results are expressed in percentage points of the population of reference. While the proportional loss of jobs among non-whites is large, the magnitude of the loss in absolute terms is similar across racial and ethnic groups, as illustrated in Table A10. This result follows from the fact that the population of reference of non-whites is much smaller than the population of whites. For instance, in 1990 the average share of racial and ethnic minorities in the US was about 15 percent, and increased up to 23 percent in 2014.

[32] Figure 1.3 shows that the service sector is the second largest brain task-intensive sector after education and research.

jobs (Bertrand and Mullainathan, 2004).

Table A11 provides further evidence of the spillover channel by decomposing US robot exposure (right-hand side of Equation 4) into industry groups to estimate their effects separately.[33] Results show that the adverse effects of robots originate indeed in the manufacturing sector (high and low robot-intensive industries), but then spill over heterogeneously by race and ethnicity to the service sector. The adoption of robots in the service sector, on the other hand, has no detectable direct effects on the race/ethnicity employment gap.

1.5.4 Robots and wages

After discussing exhaustively the impact of robots on employment, this section shows how their adoption has affected wages. For this purpose, I use the natural logarithm of the average wages by demographic group at the CZ level. The wage gap is defined as the difference in log-wages between two groups:

$$WG_{c,t}^{(M,W)} = \ln(\omega_{c,t}^{M}) - \ln(\omega_{c,t}^{W}) \tag{9}$$

I estimate the effect of robots on wages using regressions analogous to Equations 3 and 4. The results are illustrated in Table 1.8.

The impact of robots on the gender wage gap have already been addressed in previous studies. In particular, Acemoglu and Restrepo (2020) and Ge and Zhou (2020) show that robot exposure has decreased wages of both genders, but relatively more for men. According to Ge and Zhou (2020), one additional robot per thousand workers decreases the gender wage gap by roughly 0.3 percent, suggesting that the introduction of robots has contributed to the secular decline in the gap. I find a similar result in Panel A. Specifically, I also find that robots decrease wages of men more than for women, and estimate that each additional robot per thousand workers decreases the gender wage gap by 0.348 percent (-0.171/0.491), suggesting that advances in robotics move the gender wage gap and the gender employment gap in the same direction.

In Panel B, I analyze the heterogeneous effect of robots on wages by race and ethnicity. This is a question that has not been addressed by previous research, and whose answer is not as straightforward. In fact, I find that robot exposure is actually decreasing the race and ethnicity wage gap,

[33] Note that Table 1.7 decomposes only the left-hand side variable of Equation 4.

Table 1.8: The effect of robots on wages

	Panel A: Gender		
	Men	Women	Gap
	[1]	[2]	[3]
US robot exposure	-0.359***	-0.188***	-0.171*
	(0.078)	(0.061)	(0.089)
Observations	2166	2166	2166
	Panel B: Race and ethnicity		
	Whites	Non-whites	Gap
	[1]	[2]	[3]
US robot exposure	-0.587***	0.040	-0.627*
	(0.191)	(0.163)	(0.338)
Observations	2166	2166	2166
Covariates:	✓	✓	✓

Notes: This table presents IV estimates of the effect of US robot exposure on wages and wage gaps by gender and race/ethnicity at the CZ level. Changes are expressed as natural logarithms and are multiplied by 100. Independent variables are standardized to have mean zero and standard deviation of one. There are three time periods and 722 CZs. All regressions include state fixed effects, time-varying division fixed effects, pre-trends in employment of men, women, whites and non-whites between 1970 and 1990, controls for the adoption of PCs, IT capital intensity and RBTC, exposure to Chinese imports, demographic characteristics (share of Blacks, Hispanics, women, population with less than a college degree, three age groups (25-34, 35-44 and 45-54 years), and the logarithmic population), the industry (employment share in construction, manufacturing, mining, research, service and utilities) and occupation composition of employment (employment share in offshorable, skill-intensive, white-collar, blue-collar and low-skill jobs) of CZs in 1990, and the composition of industry and occupation employment by gender and race/ethnicity of CZs in 1990. Standard errors are robust against heteroskedasticity and allow for clustering at the state level. Regressions are weighted by CZ population in 1990. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

while increasing the employment gap (Table 1.3). This result is caused by a drop in the average wage level among white workers, while average wages of non-whites are not affected by the adoption of robots.

A plausible explanation for this finding is that, after being displaced by robots, middle-skill white workers are more likely to be re-employed in low-skill jobs than Blacks and Hispanics (Kletzer, 1991), decreasing the average wage level among whites. This supposition is in line with the rising job polarization of the labor market caused by automation technologies (Autor and Dorn, 2013). On the other hand, middle-skill non-white workers who have been displaced are more likely to drop out of the labor force (Lerch, 2020), leaving average wages among racial and ethnic minorities unaffected.[34] This finding is also in line with the cross-industry spillover effects documented in the previous section.

[34] Figure A3 shows that middle-skill occupations are most susceptible to automation through industrial robots. The exit of workers employed in these occupations from the labor market, therefore, does not affect significantly the mean of the wage distribution.

1.6 Conceptual framework

The empirical analysis shows that there is significant segregation in the US labor market. In particular, Figure 1.3 shows that men are employed more often in jobs that are intensive in brawn tasks, including skill-intensive and blue-collar jobs, and that racial and ethnic minorities are employed more often in jobs that do not require much brain skills, such as blue-collar and low-skill jobs. Based on these pattern in the data, this section uses a simple Roy model with heterogeneous workers and endogenous job sorting to exposit the mechanism through which the adoption of robots affects the demand for human skills and employment across demographic groups (Roy, 1951). The model builds on Autor et al. (2003), but extends their framework by using workers with different demographic characteristics and by allowing them to choose whether to supply labor or not, a necessary condition to study the effects of automation on the employment gaps.

I consider a production model with two task inputs, manual and non-manual tasks, that are used to produce an output good Y in a competitive labor supply-demand framework in a closed economy. Tasks can be carried out by three factor inputs. Manual tasks (A) can be carried out by brawn labor, L_A, or they can be automated through the adoption of robot capital, R. Non-manual tasks (B) can be carried out only by brain labor, L_B (they cannot be automated). The production of goods combines both types of labor and robot capital, measured in efficiency units, using the following technology:

$$Y_t = \left(R_t^\rho + L_{A,t}^\rho\right)^{\frac{\beta}{\rho}} L_{B,t}^{1-\beta} \tag{10}$$

with $\beta, \rho \in (0,1)$ and $\beta < \rho$. In this simple setting, robot capital is an imperfect substitute of L_A and a relative complement to L_B. The elasticity of substitution between manual and non-manual tasks is equal to 1, while the elasticity of substitution between robot capital and brawn labor is $\frac{1}{1-\rho} > 1$. Perfect competition in the economy implies that in equilibrium labor is paid its marginal productivity. The first order conditions of the production function with respect to labor inputs provide the following endogenous labor demand functions:

$$\omega_{A,t} = \beta\left(R_t^\rho + L_{A,t}^\rho\right)^{\frac{\beta}{\rho}-1} L_{A,t}^{\rho-1} L_{B,t}^{1-\beta} \tag{11}$$

$$\omega_{B,t} = (1-\beta)\left(R_t^\rho + L_{A,t}^\rho\right)^{\frac{\beta}{\rho}} L_{B,t}^{-\beta} \tag{12}$$

where ω_A and ω_B are the respective labor wages per efficiency unit.

Robots are produced and competitively supplied each period using the following technology $R_t = Y_{R,t}\frac{e^{\delta t}}{\theta}$, where $Y_{R,t}$ is the amount of the final output allocated to produce robots, $\theta = e^{\delta}$ is an efficiency parameter, and productivity increases at rate $\delta > 0$ (Autor and Dorn, 2013).[35] The price of robots, which is given by $p_t = \theta e^{-\delta t}$, is falling exogenously over time due to technical advances.[36] This is the causal force of the model. From here on, I omit time subscripts.

Labor is supplied by a unit continuum of individuals $i \in [0, 1]$ who are endowed with skills in both tasks, $\xi_i = [x_{A,i}, x_{B,i}]$.[37] Skills are distributed independently and identically over all individuals according to a density function $f(x_{A,i}, x_{B,i})$ with support over $x_{j,i} \in [\varepsilon_j, 1 + \varepsilon_j]$, where ε_j is sufficiently small and $j = \{A, B\}$.[38]

Price-taking workers are equipped with one unit of labor supply and, given their skill endowment and labor wages, choose the employment allocation that maximizes their income:

$$U_i(\boldsymbol{\omega}, \boldsymbol{x}) = \max\{\omega_A x_{A,i}, \omega_B x_{B,i}, \omega_N\} \tag{13}$$

They may supply labor by choosing between L_A, L_B or any convex combination of the two, or, alternatively, they may choose not to supply any labor and consume one unit of leisure, earning exogenous non-labor income ω_N. Hence, workers supply:

$$\begin{cases} \text{Brawn labor if } x_{A,i} > \overline{x}_A \text{ and } x_{B,i} < x^*_{B,i} \\ \text{Brain labor if } x_{A,i} > \overline{x}_A \text{ and } x_{B,i} > x^*_{B,i} \text{ or if } x_{A,i} < \overline{x}_A \text{ and } x_{B,i} > \overline{x}_B \\ \text{No labor if } x_{A,i} < \overline{x}_A \text{ and } x_{B,i} < \overline{x}_B \end{cases} \tag{14}$$

where $\overline{x}_A = \frac{\omega_N}{\omega_A}$, $\overline{x}_B = \frac{\omega_N}{\omega_B}$, $x^*_{B,i} = \frac{\omega_A}{\omega_B} x_{A,i}$. Individuals choose brawn labor if they have sufficient brawn skills, they supply brain labor if they have enough brain skills, and they do not supply any

[35] This assumption implies that robot capital fully depreciates in each period or, in other words, that the flow of services provided by robots is continuously paid its rental price as these services are consumed (Autor and Dorn, 2013).

[36] In the first period ($t = 1$), one unit of Y_R can be used to produce one efficiency unit of R ($1 = \frac{e^{\delta}}{\theta}$). Competition guarantees that the real price of robot capital (per efficiency unit) is equal to marginal (and average) cost: $p_t = \theta e^{-\delta t}$. Productivity increases at rate $\delta > 0$ due to technological progress.

[37] It is important to draw a distinction between skills and tasks. Tasks are units of work activity that produce output, while skills are a worker's stock of capabilities for performing tasks in exchange for wages (Autor, 2013).

[38] As shown below, $\varepsilon_A \in [0, \overline{x}_A)$ and $\varepsilon_B \in (\overline{x}_B - 1, 0]$.

labor if they are not particularly skilled in either task. The model abstracts from involuntarily unemployment so that labor markets clear.

The shares of individuals who are employed in brawn and brain labor and those who are not employed are given by:

$$N_A = \int_{\overline{x}_A}^{1+\varepsilon_A} \int_{\varepsilon_B}^{x^*_{B,i}} f(x_{A,i}, x_{B,i}) dx_{B,i} dx_{A,i} \tag{15}$$

$$N_B = \int_{\varepsilon_A}^{\overline{x}_A} \int_{\overline{x}_B}^{1+\varepsilon_B} f(x_{A,i}, x_{B,i}) dx_{B,i} dx_{A,i} + \int_{\overline{x}_A}^{1+\varepsilon_A} \int_{x^*_{B,i}}^{1+\varepsilon_B} f(x_{A,i}, x_{B,i}) dx_{B,i} dx_{A,i} \tag{16}$$

$$N_N = \int_{\varepsilon_A}^{\overline{x}_A} \int_{\varepsilon_B}^{\overline{x}_B} f(x_{A,i}, x_{B,i}) dx_{B,i} dx_{A,i} \tag{17}$$

where $N_N = 1 - N_A - N_B$.[39] I quantify aggregate labor supplies by summing over workers' skill endowments in efficiency units:

$$L_A = \int_{\overline{x}_A}^{1+\varepsilon_A} \int_{\varepsilon_B}^{x^*_{B,i}} x_{A,i} f(x_{A,i}, x_{B,i}) dx_{B,i} dx_{A,i} \tag{18}$$

$$L_B = \int_{\varepsilon_A}^{\overline{x}_A} \int_{\overline{x}_B}^{1+\varepsilon_B} x_{B,i} f(x_{A,i}, x_{B,i}) dx_{B,i} dx_{A,i} + \int_{\overline{x}_A}^{1+\varepsilon_A} \int_{x^*_{B,i}}^{1+\varepsilon_B} x_{B,i} f(x_{A,i}, x_{B,i}) dx_{B,i} dx_{A,i} \tag{19}$$

In equilibrium, wages adjust such that labor supply (Equations 18 and 19) equals labor demand (Equations 11 and 12).

Suppose now that there are two types of individuals in equal proportions, let's say men, M, and women, W, and that men hold a biologically rooted comparative advantage in brawn skills (Pitt et al., 2012, Rendall, 2017). The comparative advantage is given by a right-shift of the support over the distribution of brawn skills:

$$x^g_{A,i} \in [\varepsilon^g_A, 1 + \varepsilon^g_A] \quad \forall g \in \{M, W\} \tag{20}$$

where $\varepsilon^M_A > \varepsilon^W_A = 0$ and $\varepsilon_B = 0$ for both genders.

Separately, suppose that non-whites have a comparative disadvantage in brain skills due to

[39] To ensure that $N_A > 0$, $N_B > 0$ and $N_N > 0$, it must hold that $\varepsilon_A < \overline{x}_A$ and $\overline{x}_B \leq 1 + \varepsilon_B$. Moreover, ω_N must be sufficiently small, i.e. $\omega_N < \min\{\omega_A, \omega_B\}$ is always true, such that not all workers with $\varepsilon_j = 0$ choose non-employment over labor ($L_A = 0$ or $L_B = 0$). Finally, starting from $t = 1$ the wage per efficiency unit of brain labor has to be larger than the wage of brawn labor, $\omega_B = \omega_A + \mu$ with $\mu > 0$. This assumption ensures a well-defined solution of the model and is based on patterns observed in the data which show that, on average, white-collar labor is paid more than blue-collar labor (see Figure A4).

persisting discrepancies in the educational achievement caused by generations of labor market discrimination against racial and ethnic minorities (Alesina et al., 2001, Altonji and Blank, 1999, Cook, 2014, Derenoncourt, 2022, Derenoncourt et al., 2022). The comparative disadvantage is given by a left-shift of the support over the distribution of brain skills, i.e. $\varepsilon_B^{NW} < \varepsilon_B^{WH} = 0$ and $\varepsilon_A = 0$ for whites and non-whites.

These assumptions follow from the empirical evidence provided in Figure 1.3, which shows that men are employed more often in brawn task-intensive occupations and non-whites are employed more often in occupations with less brain tasks, and are in line with the notion that workers sort into jobs according to their comparative skill advantage (Bacolod and Blum, 2010, Yamaguchi, 2018).

Proposition 1 *The comparative advantage of men in brawn skills and the comparative disadvantage of non-whites in brain skills imply that they are over-represented in brawn labor, that men have a higher employment rate than women, and that non-whites have a lower employment rate than whites.*

Using demographic-specific forms of Equation 17 and by computing the difference in the employment rates, it is straightforward to show that both the gender and the race/ethnicity employment gap are positive:

$$EG^{(M,W)} = (1 - N_N^M) - (1 - N_N^W) = \int_0^{\varepsilon_A^M} \int_0^{\overline{x}_B} f(x_{A,i}, x_{B,i}) dx_{B,i} dx_{A,i} > 0 \tag{21}$$

$$EG^{(WH,NW)} = (1 - N_N^{WH}) - (1 - N_N^{NW}) = \int_0^{\overline{x}_A} \int_{\varepsilon_B^{NW}}^{0} f(x_{A,i}, x_{B,i}) dx_{B,i} dx_{A,i} > 0 \tag{22}$$

The full proof of Proposition 1 is provided in Appendix A4, which shows also that men are employed more often in brawn task-intensive jobs than women, and that non-whites are employed less often in brain task-intensive jobs than whites, reflecting the empirical evidence from Figure 1.3.

Let's now focus on the impact of an increase in robots on employment by gender and race/ethnicity through an exogenous drop in the price of robot capital. As robots become a relatively cheaper production input, firms decrease their demand of brawn labor, lowering wages ω_A. As a consequence, brawn workers with sufficiently high brain skills are better off by moving to brain labor, while less skilled workers become non-employed. I define the transition from brawn labor to non-employment as the "displacement effect" of robots.

At the same time, the inflow of robot capital more than offsets the decrease in brawn labor, yielding a net increase in the intensity of the manual task input in firms' production (it becomes cheaper to produce with capital). This condition boosts the productivity of brain labor, raising wages ω_B, and inducing even more workers to reallocate their labor supply from brawn labor to brain labor. Moreover, some previously non-employed individuals might also join the workforce and supply brain labor, if they have enough brain skills. I refer to this effect as the "productivity effect".

Theoretically, the overall effect of robots on employment is ambiguous and depends on the relative size of the displacement and the productivity effect (see Appendix A4). The empirical analysis shows that in the US labor market the displacement effect dominates the productivity effect among all demographic groups (see Table 1.3). The model, however, unambiguously shows that, independently of the aggregate employment effect:

Proposition 2 *The comparative advantage of men in brawn skills and the comparative disadvantage of non-whites in brain skills imply that the adoption of robot capital reduces the gender employment gap and increases the race/ethnicity employment gap.*

This proposition follows from the fact that women benefit more from the productivity effect of robots than men:

$$\frac{\partial EG^{(M,W)}}{\partial p} = -\int_0^{\varepsilon_A^M} f(x_{A,i}, \overline{x}_B) \frac{\overline{x}_B}{\omega_B} \frac{\partial \omega_B}{\partial p} dx_{A,i} > 0 \tag{23}$$

and because non-whites suffer from a larger displacement effect than whites:

$$\frac{\partial EG^{(WH,NW)}}{\partial p} = -\int_{\varepsilon_B^{NW}}^0 f(\overline{x}_A, x_{B,i}) \frac{\overline{x}_A}{\omega_A} \frac{\partial \omega_A}{\partial p} dx_{B,i} < 0 \tag{24}$$

Note that $\frac{\partial R}{\partial p} < 0$. These results show that robots decrease the gender employment gap, since more women join the labor force to work in white-collar jobs than men. On the other hand, the race/ethnicity employment gap increases because non-white workers are displaced more often from blue-collar jobs than whites. The full proof of Proposition 2 is again provided in Appendix A4.

1.7 Conclusion

The adoption of industrial robots has already been shown to have displaced thousands of US workers over the last decades (Acemoglu and Restrepo, 2020). However, little is known about how these technologies are shaping the composition of the labor force, and how they affect inequality across demographic groups. This paper investigates this issue and analyzes how the effects of robots are spreading across the population, focusing on gender and race/ethnicity employment differentials in the US labor market.

Results show that robot exposure decreases employment with substantial differences across demographic groups. Between 1993 and 2014, the introduction of industrial robots has decreased local employment rates of men and women by 3.7 and 1.6 percentage points, contributing to the secular decline in the gender employment gap. At the same time, it has decreased employment of whites and non-whites by 1.8 and 4.5 percentage points, slowing the secular decline in the race/ethnicity employment gap.

These findings are driven by the over-representation of male and non-white workers in blue-collar occupations as a result of their comparative advantage in physical skills. Using a simple task-based model, I show that women benefit more from the productivity effect of robots than men (although it is offset by the displacement effect), and that racial/ethnic minorities suffer from a larger displacement effect than whites. These forces unambiguously narrow the gender employment gap and widen the race/ethnicity employment gap.

Despite their predominance in the manufacturing sector, the labor market impacts of robots are not confined to these industries. In fact, I find significant spillover effects to the service sector, in particular for Blacks and Hispanics. Finally, I show that the introduction of robots has narrowed both the gender and the race/ethnicity wage gap. These results follow from wages of men having decreased more than those of women, and wages of whites having decreased, while average wages of non-whites have not been affected by robot exposure.

Appendix A

A1 Data

This section discusses the data sources and the construction of the variables.

A1.1 Current Population Survey

Figure 1.1 illustrates employment rates and gaps across demographic groups using data from the Annual Social and Economic Supplement (ASEC) of the Current Population Survey between 1980 and 2019 (Flood et al., 2020). These data are publicly available at IPUMS and include monthly repeated cross-sectional surveys. The frequency with which these data are collected comes at the expense of the scale of the survey, making it representative at the national level, but not at the CZ level. I use these data in Figure 1.1 to trace the development of employment across demographic groups in the US on a yearly basis. In the empirical analysis, however, I use data from the US Census and the ACS.

A1.2 Industrial robots

IFR data on industrial robots are praised for their reliability, but they include also some limitations. First, a fraction of the stock of industrial robots is not attributed to any industry and is referred to as "unclassified". I attribute unclassified robots proportionally to an industry's share of total classified robots for each year (Graetz and Michaels, 2018). Second, up to 2011, the IFR provides data on the operational stock of robots only for North America as a whole, which includes the United States, Canada and Mexico. This aggregation introduces noise, but is not a major concern for the identification of US robot adoption, since the Unites States account for more than 90 percent of the North American market and the IV strategy purges this type of measurement error (Acemoglu and Restrepo, 2020). Third, the stock of robots by industry going back to the 1990s is only available for a subset of European countries: Denmark, Finland, France, Germany, Italy, Norway, Spain, Sweden, and the United Kingdom. The IFR provides data on the total stock of robots in North America from 1993, but it does not provide industry breakdowns until 2004. For these years, I attribute the aggregate number of robots to industries proportionally to their shares of the total stock in 2004. I use the same procedure to impute the stock of robots for Denmark, for which the industry breakdown starts in 1996.

A1.3 Import exposure

China – I follow Autor et al. (2013) in using a shift-share approach to measure the exposure of local labor markets to imports from China. I interact CZs' industry employment shares in the manufacturing sector prior to the admission of China to the World Trade Organization in 2001 with the growth in product trade flows from China to the US. Since US imports from China may also be endogenous to demand shocks, I use a similar identification strategy to Equation 6 and exploit plausibly exogenous variation in the trade shock by instrumenting the shift component with trade flows from China to other industrialized countries with a similar trade development as the US:

$$\text{Import exposure}_{c,(t_0,t_1)} = \sum_{j \in J} \frac{1}{8} \sum_{i \in OT8} \ell^{90}_{c,j} \Delta IM^{i}_{j,(t_0,t_1)} \tag{25}$$

where $\Delta IM^{i}_{j,(t_0,t_1)}$ is the change in industry $j \in J$ imports from China in thousand dollars per worker of country $i \in OT8$, which includes Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland. I keep the baseline employment shares constant to avoid endogeneity and serial correlation concerns.

To build this measure, I collect product-level data at the six-digit Harmonized System (HS) on Chinese imports from the UN Comtrade Database (UN Comtrade, 2019) which I match with industry employment shares from the 1991 County Business Patterns (CBP, 2019). The CBP classifies industry employment according to the Standard Classification System (SIC) until 1997 and according to the North American Industry Classification System (NAICS) afterwards. These systems are more detailed than the industrial classification system used in the IPUMS. I use crosswalks from Autor et al. (2013) to convert SIC and NAICS manufacturing industries and six-digit HS product-level trade data to 392 four-digit SIC industries. I construct the import penetration measure by matching local employment shares with converted product-level trade data on imports from China. For confidentiality reasons, county-industry observations with few cases are reported as ranges. In reconstructing these data, I follow Acemoglu et al. (2016).

Europe – I build a measure of international product market competition from Europe using a shift-share approach as described in the previous section. The share component is the same as in Equation 25, while the shift component does not account for imports from China, but for average trade flows from Denmark, Finland, France, Italy, Spain, Sweden and the United Kingdom (EU7 countries) to the US from UN Comtrade. Since US imports are again subject to endogeneity concerns, I instrument imports to the US with trade flows from Europe to Canada, an industrialized country with a comparable trade engagement with European countries as the US, but whose import intensity is less likely to be affected by US domestic shocks than the US itself.

A1.4 Technology shocks

I account for technology shocks other than industrial robots using shift-share measures of the adoption of PCs and IT capital intensity, and a measure of routine task-intensity at the CZ level in 1990.

Exposure to PCs – I measure PC adoption at the CZ level following Acemoglu and Restrepo (2020). The measure is computed by interacting the share of workers using a computer in each industry from the 1993 Current Population Survey (shift component) with CZ baseline employment shares from the Census (share component). Ge and Zhou (2020) show that computer capital in the 1990s is a strong predictor of subsequent computer adoption.

IT capital intensity – I use a measure of IT capital intensity from Acemoglu and Restrepo (2020). The measure is computed by interacting the industry share of IT investments in 1992 from the Annual Survey of Manufactures (ASM, 2020) (shift component) with baseline CZ employment shares from the Census (share component). Industry data are available for 4-digit SIC87 manufacturing industries.

Routine-biased technological change – I build a measure of RBTC using the share of routine task-intensive employment in a local labor market in 1990. For this purpose, I match the classification of occupational routine task-intensity from Autor and Dorn (2013) with employment data from the Census and compute the corresponding employment shares at the CZ level.

A1.5 CZ characteristics

I construct time-invariant controls for CZ characteristics from the 1990 Census, which include demographic characteristics, the industrial and occupational composition of employment, and the demographic-specific composition of workers within industries and occupations.

Demographics of the population – These controls include the population share of women, Blacks, Hispanics, college-educated individuals, and three age groups (25-34, 35-44 and 45-54 years), as well as the log-population in 1990. Shares are computed in terms of the total population in the CZ.

Industry and occupation – These controls include the employment share in the construction, education and research, manufacturing, mining, services, and utilities industry, as well as the share of offshorable, skill-intensive, white-collar, blue-collar and low-skill occupations in 1990. I use a measure of offshorability of occupations from Autor and Dorn (2013). Shares are computed in terms of total employment in the CZ.

Demographics of employment – These covariates control for the initial composition of employment of women and racial/ethnic minorities within industries (high robot-intensive manufacturing and low-robot intensive manufacturing) and occupations (skill-intensive, white-collar and blue-collar). I compute these measures as the number of women (non-whites) who are employed in industry or occupation j divided by total employment in j. This measure is also used to represent the industrial and occupational segregation of the US labor market in Figure 1.3.

A2 Comparison with Acemoglu and Restrepo (2020)

The results of this paper account for partial equilibrium effects of robot adoption and do not consider aggregate effects resulting from cross-CZ spillovers that could influence the gender- or race/ethnicity-specific demand for labor in other areas. A parametric model to quantify the general equilibrium effects of robots on employment is presented in Acemoglu and Restrepo (2020), although it does not allow to differentiate for demographic-specific cross-CZ effects either.

It is worth noting that the magnitude of the employment estimates of this paper are larger than those reported in Acemoglu and Restrepo (2020), since the authors are not exploring variation in US robot exposure within states, but within census divisions. However, as demographic-specific labor market outcomes are highly heterogeneous across US states, it is critical to account for systematic differences across these areas in this type of analysis.

To compare the consistency of my results with Acemoglu and Restrepo (2020), Table A12 reports estimates of the effect of robots on employment rates and gaps, controlling only for time-varying division fixed effects, the vector of time-invariant regional characteristics and economic variables, pre-trends and structural labor market shocks contemporaneous to the introduction of robots from Equations 3 and 4. This specification does not include state fixed effects.

Results show that the relative size of the effects by gender and race/ethnicity is similar to that in Table 1.3, even when excluding state fixed effects (despite changes in the absolute size). Using this specification, the results on the overall population (Column 1) are similar to the finding of Acemoglu and Restrepo (2020), i.e. that each industrial robot reduces local employment by six workers (3.3 workers when accounting for general equilibrium effects across CZs).

Based on this result, my findings suggest that each robot displaces four men and two women or, when looking at differences by race/ethnicity, 3.6 whites and 2.4 non-whites. These values are illustrated in Table A13, which reports estimates of the impact of robots on employment by demographic groups as shares of the total local population.

A3 Robustness checks

This section performs a set of robustness checks in support of the identification strategy and of my preferred specification. I report results for the overall population and the population without a college education, which is driving my results.

A3.1 Product market competition

A concern that I need to address is that the adoption of robots in Europe is influencing US labor market conditions through increased product market competition, violating the exclusion restriction of my IV strategy. Although I cannot rule out this possibility, I can show that it is rather unlikely that my results are driven by this causal link.

In Table A14, I estimate the labor market impact of robots on the employment gaps when controlling for international competition on the product market using a shift-share measure of US imports from Europe à la Autor et al. (2013), as defined in Appendix A1. Between the mid-1990s and 2014, trade flows from Europe to the US have increased substantially. This increase is mainly driven by a rise in imports of manufacturing goods that is positively related to the introduction of robots in Europe (Figure A5, Panel A). Since US imports could be subject to domestic shocks that affect also local labor demand (demand shocks), I account for endogeneity of imports by using trade flows from Europe to Canada, a country with a comparable trade engagement with European countries as the US (Figure A5, Panel B). My estimates are not significantly affected by the inclusion of these additional controls.

In a second approach, I omit from the instrument the European countries with the largest trade engagement with the US, namely the UK, Italy and France. By including only countries that are less likely to impact US labor market conditions through product market competition because of their national adoption of robots, the results lose some precision (because of the heavier exposure of the instrument to labor market shocks in Nordic countries and in Spain), but remain statistically significant at conventional levels. These findings suggest that my estimates are unlikely to be driven by higher product market competition through the heavier utilization of robots in Europe.

A3.2 Pre-trends

The secular decline in the gender and the race/ethnicity employment gap raises the concern that changes in the employment gaps and the adoption of industrial robots are driven by some common factors. For instance, changes in the employment gaps and the adoption of robots could both stem from a labor market's industrial composition of employment. In this case, my estimates could confound the impact of robot exposure with pre-existing local labor market trends. I account for this concern in my preferred specification by controlling for past changes in the employment gaps between 1970 and 1990 and the employment composition of industries and occupations by gender and race/ethnicity in 1990.

I report estimates of pre-trends in employment of men, women, whites and non-whites between 1970 and 1990 in Table A15. There is no evidence of pre-trends affecting subsequent employment by gender. However, I do find that increases in employment of whites between 1970 and 1990 decrease the race/ethnicity employment gap between 1990 and 2014, and that increases in employment of non-whites widen it (although to a smaller extent). Nevertheless, Table A5 shows that there is no evidence of these pre-trends confounding the estimated effect of industrial robots on the employment gaps (see sequential inclusion of controls).

A3.3 Weights

Figure A2 in the Appendix shows that there is substantial variation in the distribution of racial and ethnic minorities in the US, with the largest concentration in states of the Sun Belt because of their proximity to Mexico and the Caribbean islands. Table A16 examines the role of population weights and the geographic distribution of non-whites for the determination of the effect of robots on changes in the race/ethnicity employment gap.

I start by estimating Equations 3 and 4 using as regression weights the initial population of non-whites in the CZ. The size of the estimates is larger than in my preferred specification, suggesting that the effect is likely to emerge from labor markets with a larger population of racial and ethnic minorities. Column 2 estimates the effect of robots on the employment gaps without any weights. The results are not economically nor statistically significant, since CZs with a small population of non-whites receive too much weight. Column 3 restricts the sample to CZs with a large population of racial and ethnic minorities (see Panel B of Figure A2) and repeats the exercise of the previous column, showing that the results specific to these CZs are similar to my preferred specification's estimates in Table 1.3.[40] This finding suggests that my main results are indeed driven by CZs with a sufficiently large population of racial and ethnic minorities, and that this effect is captured by the population weight of my preferred specification.

The homogeneous distribution of men and women across labor markets does not expose my results to the above mentioned concerns. As illustrated in Panel B of Table A16, the estimates of the labor market effect of robots on the gender employment gap are economically and statistically significant across all specifications, independently of the regression weights.

[40] I perform a double median split and select the 275 CZs with a population of non-whites and a share of the non-white population above the US local labor market median, as shown in Figure A2.

A3.4 Shift-share measure

Table A17 shows that the exact construction of the shift-share measure is not affecting my results. Panels A1, A2, B1 and B2 report estimates with a different mix of European countries used in the construction of the instrument. Panels A3 and B3 report estimates using an instrument with baseline employment shares from 1990, $\ell_{c,j}^{90}$, rather than those from 1970. Panels A4 and B4 report estimates using measures that omit the adjustment for industry growth, $g_{j,(t_0,t_1)} \frac{R_{j,t_0}}{L_{j,90}}$. The estimates are not significantly different from my preferred specification's results.

A3.5 Exclusion of CZs

Table A18 excludes a set of outlying CZs with the heaviest adoption of robots. Panels A1 and B1 report estimates when excluding the area around Detroit (MI), which is the CZ with the largest exposure to robots, while Panels A2 and B2 exclude CZs in the top 1 percentile of the distribution of robot exposure during my sample period. The results lose some precision, because most of the identification is coming from CZs in the Rust Belt (see Figure 1.4), but they are not significantly different from my baseline results, especially for individuals without a college degree. These findings suggest that my results are not solely driven by the subset of CZs with the largest adoption of robots.

A3.6 Covariates and CZ trends

Table A19 shows that unobserved heterogeneity does not alter my results. Panels A1 and B1 include covariates of CZ characteristics at the beginning of each subperiod (1990, 2000 and 2007) instead of covariates from 1990. Panels A2 and B2 use a more demanding specification and include CZ fixed effects (CZ trends). Using both specifications, the results are quantitatively and qualitatively significant at conventional levels.

A4 Conceptual framework: Proofs

In this part of the Appendix, I provide proofs and further results of the equilibrium labor market impact of robots on the demand for human skills and the employment gaps.

The model presents a basic production function which combines labor (brawn labor, L_A, and brain labor, L_B) and robot capital, R, to produce an output good Y (Equation 10). The perfectly competitive environment implies that input factors are paid their marginal productivity (Equations 11 and 12). Robot capital is produced and competitively supplied each period using the following technology, $R_t = Y_{R,t}\frac{e^{\delta t}}{\theta}$, where $Y_{R,t}$ is the amount of the final output allocated to produce robots and $e^{\delta(t-1)}$ is the total factor productivity (Autor and Dorn, 2013). That is, firms can sell their output good Y at the normalized price of 1 or they can invest a share of their production, Y_R, in the production of robot capital at price p:

$$\pi_t = Y_{R,t} - p_t R_t \tag{26}$$

Taking the first order condition of Equation 26 with respect to $Y_{R,t}$ gives:

$$\frac{\partial \pi_t}{\partial Y_{R,t}} = 1 - p_t \frac{e^{\delta t}}{\theta} = 0 \tag{27}$$

which solves to $p_t = \theta e^{-\delta t}$.

Labor is supplied by a unit continuum of individuals who are endowed with independently and identically distributed skills on two input tasks, $f(x_{A,i}, x_{B,i})$ with support $x_{j,i} \in [\varepsilon_j, 1+\varepsilon_j]$, where $j = \{A, B\}$, $\varepsilon_A \in [0, \overline{x}_A)$ and $\varepsilon_B \in (\overline{x}_B - 1, 0]$.

Workers want to maximize their income and may supply labor by choosing between brawn labor, brain labor or any convex combination of the two, or they may choose not to supply any labor and consume one unit of leisure. These assumptions imply that workers choose tasks according to their comparative advantage, given their skills and equilibrium wages. The share of individuals who supply labor is determined by Equations 15 and 16, while the share of individuals who is not employed is given by Equation 17. Labor supplies are determined by Equations 18 and 19. In equilibrium, wages adjust such that labor demand and labor supply are equal.

Figure A6 illustrates the distribution of individuals in N_A, N_B and N_N graphically in a two-dimensional space in which every point designates the endowment of brawn and brain skills $(x_{A,i}, x_{B,i})$ of an individual i. The yellow area denotes the share of individuals who are employed in brawn labor, the green area those who are employed in brain labor and the blue area those who are not employed.

According to Proposition 1, the comparative advantage of men in brawn skills implies that they are employed more often in brawn labor and that women opt more often for non-employment. Moreover, whites are employed more often in brain labor, given their comparative advantage in brain skills, and racial/ethnic minorities opt more often for non-employment. Therefore, the gender employment gap and the race/ethnicity employment gap are both positive.

I prove the first part of the proposition by supposing that men have a comparative advantage in brawn skills, $\varepsilon_A^M > 0$, $\varepsilon_A^W = 0$ and $\varepsilon_B = 0$. The gender employment gap, expressed as the difference between the employment rate of men and the employment rate of women, can be computed using gender-specific forms of Equation 17:

$$EG^{(M,W)} = (1 - N_N^M) - (1 - N_N^W) = \int_0^{\varepsilon_A^M} \int_0^{\overline{x}_B} f(x_{A,i}, x_{B,i}) dx_{B,i} dx_{A,i} > 0 \tag{28}$$

The positive sign of this expression suggests that the employment rate of men is higher than the employment rate of women. Panel A of Figure A6 shows that men have the same support over the distribution of brain skills as women ($\varepsilon_B = 0$), but on average they hold more brawn skills ($\varepsilon_A^M > \varepsilon_A^W$), such that in equilibrium women opt more often for non-employment.[41] Note that Equation 28 denotes the density of the population in the bottom left rectangle (light blue area) of Figure A6. The comparative advantage implies also that in equilibrium men are employed more often in brawn task-intensive jobs:

$$EG_A^{(M,W)} = N_A^M - N_A^W = \int_0^{\varepsilon_A^M} \int_0^{x_{B,i}^*} f(x_{A,i}, x_{B,i}) dx_{B,i} dx_{A,i} > 0 \tag{29}$$

To compute the employment gap by race and ethnicity, I assume that non-whites have a comparative disadvantage in brain skills, i.e. $\varepsilon_B^{NW} < 0$, $\varepsilon_B^{WH} = 0$ and $\varepsilon_A = 0$. The comparative advantage of whites in brain skills implies that a higher proportion of them supplies brain labor in equilibrium:

$$EG_B^{(WH,NW)} = N_B^{WH} - N_B^{NW} = \int_0^1 \int_{\varepsilon_B^{NW}}^0 f(x_{A,i}, x_{B,i}) dx_{B,i} dx_{A,i} > 0 \tag{30}$$

[41] The claim that fewer men opt for non-employment works with any skill distribution function which assumes that men have a comparative advantage in brawn skills, conditional on men and women having the same skill density between $[\varepsilon_A, 1]$.

Using Equation 17, the computation of the race and ethnicity employment gap is straightforward:

$$EG^{(WH,NW)} = (1 - N_N^{WH}) - (1 - N_N^{NW}) = \int_0^{\overline{x}_A} \int_{\varepsilon_B^{NW}}^0 f(x_{A,i}, x_{B,i}) dx_{B,i} dx_{A,i} > 0 \tag{31}$$

Panel B of Figure A6 shows that if non-whites have the same support over the distribution of brawn skills ($\varepsilon_A = 0$), but on average they hold less brain skills ($\varepsilon_B^{NW} < \varepsilon_B^{WH}$), they are employed less often in brain task-intensive jobs, and in equilibrium they have a lower employment rate than whites.

To sum up, as stated in Proposition 1, Equations 28 and 29 show that the comparative advantage of men in brawn skills implies that in equilibrium they are employed more often in brawn labor and that the gender employment gap is positive. Moreover, Equations 30 and 31 show that the comparative advantage of whites in brain skills implies that they are employed more often in brain labor and that the race/ethnicity employment gap is positive too. ■

From Equation 27, we know that the price of robots decreases over time due to exogenous technological progress, increasing robot capital in the production of output good Y. An increase in the adoption of robots has adverse effects on the demand for labor and, through changes in wages, also on the labor supply.

To understand the mechanism through which the adoption of robots influences the demand of labor in the economy, I compute the components of the following equations, showing the partial derivatives of brawn and brain labor with respect to the price of robots:

$$\frac{\partial L_A}{\partial p} = \frac{\partial L_A}{\partial \omega_A}\frac{\partial \omega_A}{\partial p} + \frac{\partial L_A}{\partial \omega_B}\frac{\partial \omega_B}{\partial p} \tag{32}$$

$$\frac{\partial L_B}{\partial p} = \frac{\partial L_B}{\partial \omega_A}\frac{\partial \omega_A}{\partial p} + \frac{\partial L_B}{\partial \omega_B}\frac{\partial \omega_B}{\partial p} \tag{33}$$

I start with the computation of the partial derivatives of L_A and L_B with respect to labor wages:

$$\begin{aligned} \frac{\partial L_A}{\partial \omega_A} = &- \left[\frac{\partial}{\partial \overline{x}_A} \int_{\overline{x}_A}^{1+\varepsilon_A} \left(\int_{\varepsilon_B}^{x_{B,i}^*} x_{A,i} f(x_{A,i}, x_{B,i}) dx_{B,i} \right) dx_{A,i} \right] \frac{\overline{x}_A}{\omega_A} + \\ &+ \int_{\overline{x}_A}^{1+\varepsilon_A} (x_{A,i})^2 f(x_{A,i}, \overline{\omega} x_{A,i}) \frac{1}{\omega_B} dx_{A,i} > 0 \end{aligned} \tag{34}$$

where $\overline{\omega} = \frac{\omega_A}{\omega_B}$ such that $x_{B,i}^* = \overline{\omega} x_{A,i}$.

$$\frac{\partial L_A}{\partial \omega_B} = -\int_{\overline{x}_A}^{1+\varepsilon_A} (x_{A,i})^2 f(x_{A,i}, \overline{\omega} x_{A,i}) \frac{\overline{\omega}}{\omega_B} dx_{A,i} < 0 \tag{35}$$

$$\begin{aligned} \frac{\partial L_B}{\partial \omega_A} = & -\int_{\overline{x}_B}^{1+\varepsilon_B} x_{B,i} f(\overline{x}_A, x_{B,i}) \frac{\overline{x}_A}{\omega_A} dx_{B,i} - \\ & - \left[\frac{\partial}{\partial \overline{x}_A} \int_{\overline{x}_A}^{1+\varepsilon_A} \left(\int_{x^*_{B,i}}^{1+\varepsilon_B} x_{B,i} f(x_{A,i} x_{B,i}) dx_{B,i} \right) dx_{A,i} \right] \frac{\overline{x}_A}{\omega_A} - \\ & - \int_{\overline{x}_A}^{1+\varepsilon_A} (x_{A,i})^2 f(x_{A,i}, \overline{\omega} x_{A,i}) \frac{\overline{\omega}}{\omega_B} dx_{A,i} < 0 \end{aligned} \tag{36}$$

The positive term in the second line of Equation 36 is outweighed by the other terms.

$$\begin{aligned} \frac{\partial L_B}{\partial \omega_B} = & \int_{\varepsilon_A}^{\overline{x}_A} f(x_{A,i}, \overline{x}_B) \frac{(\overline{x}_B)^2}{\omega_B} dx_{A,i} + \\ & + \int_{\overline{x}_A}^{1+\varepsilon_A} (x_{A,i})^2 f(x_{A,i} \overline{\omega} x_{A,i}) \frac{\overline{\omega}^2}{\omega_B} dx_{A,i} > 0 \end{aligned} \tag{37}$$

These equations show that the supply of brawn (brain) labor increases as brawn (brain) wages increase and decreases if brain (brawn) wages increase.

Next, I compute changes in equilibrium wages in response to an increase in the price of robots. Taking total differentials of Equations 11 and 12, I obtain that:

$$\frac{\partial \omega_A}{\partial p} = -\frac{\left(\frac{\beta}{\rho} - 1\right) \rho R^{\rho-1} L_B}{\left(R^\rho + L_A^\rho\right) \left[\left(\frac{\beta}{\rho} - 1\right) \frac{\rho L_A^{\rho-1} L_B}{R^\rho + L_A^\rho} \frac{\partial L_A}{\partial \omega_A} + (\rho - 1) \frac{L_B}{L_A} \frac{\partial L_A}{\partial \omega_A} + (1-\beta) \frac{\partial L_B}{\partial \omega_A} - \frac{L_B}{\omega_A} \right]} \frac{\partial R}{\partial p} > 0 \tag{38}$$

$$\frac{\partial \omega_B}{\partial p} = -\frac{\beta R^{\rho-1}}{\left(R^\rho + L_A^\rho\right) \left[\frac{\beta L_A^{\rho-1}}{R^\rho + L_A^\rho} \frac{\partial L_A}{\partial \omega_B} - \frac{\beta}{L_B} \frac{\partial L_B}{\partial \omega_B} - \frac{1}{\omega_B} \right]} \frac{\partial R}{\partial p} < 0 \tag{39}$$

because of $0 < \beta < \rho < 1$, $\frac{\partial R}{\partial p} < 0$ and Equations 34 to 37. Inserting Equations 34 to 39 in Equations 32 and 33 already shows that, as the price of robots falls, in equilibrium, the demand for brawn labor decreases and the demand for brain labor increases:

$$\begin{aligned}\frac{\partial L_A}{\partial p} =& -\left[\frac{\partial}{\partial \overline{x}_A}\int_{\overline{x}_A}^{1+\varepsilon_A}\left(\int_{\varepsilon_B}^{x^*_{B,i}} x_{A,i} f(x_{A,i}, x_{B,i}) dx_{B,i}\right) dx_{A,i}\right]\frac{\overline{x}_A}{\omega_A}\frac{\partial \omega_A}{\partial p}+ \\ &+\int_{\overline{x}_A}^{1+\varepsilon_A}(x_{A,i})^2 f(x_{A,i}, \overline{\omega} x_{A,i})\frac{1}{\omega_B}\left[\frac{\partial \omega_A}{\partial p}-\overline{\omega}\frac{\partial \omega_B}{\partial p}\right] dx_{A,i} > 0\end{aligned} \tag{40}$$

$$\begin{aligned}\frac{\partial L_B}{\partial p} =& \int_{\varepsilon_A}^{\overline{x}_A} f(x_{A,i}, \overline{x}_B)\frac{(\overline{x}_B)^2}{\omega_B}\frac{\partial \omega_B}{\partial p} dx_{A,i}- \\ &-\int_{\overline{x}_B}^{1+\varepsilon_B} x_{B,i} f(\overline{x}_A, x_{B,i})\frac{\overline{x}_A}{\omega_A}\frac{\partial \omega_A}{\partial p} dx_{B,i}- \\ &-\int_{\overline{x}_A}^{1+\varepsilon_A}(x_{A,i})^2 f(x_{A,i}, \overline{\omega} x_{A,i})\frac{\overline{\omega}}{\omega_B}\left[\frac{\partial \omega_A}{\partial p}-\overline{\omega}\frac{\partial \omega_B}{\partial p}\right] dx_{A,i}- \\ &-\left[\frac{\partial}{\partial \overline{x}_A}\int_{\overline{x}_A}^{1+\varepsilon_A}\left(\int_{x^*_{B,i}}^{1+\varepsilon_B} x_{B,i} f(x_{A,i}, x_{B,i}) dx_{B,i}\right) dx_{A,i}\right]\frac{\overline{x}_A}{\omega_A}\frac{\partial \omega_A}{\partial p} < 0\end{aligned} \tag{41}$$

since the positive term in the fourth line of Equation 41 is outweighed by the other terms. This result follows from the fact that there is a more than offsetting increase in the demand for manual tasks in the form of robot capital (since it becomes relatively cheaper) which increases the productivity of brain labor (and therefore its wage), raising its equilibrium level.

Following the procedure outlined above, we can show that the share of workers who supply brawn labor decreases. These workers are either reallocating their labor supply towards brain labor, as the relative wage $\frac{\omega_B}{\omega_A}$ increases, or they opt for non-employment, as also $\frac{\omega_N}{\omega_A}$ increases.

$$\begin{aligned}\frac{\partial N_A}{\partial p} =& -\left[\frac{\partial}{\partial \overline{x}_A}\int_{\overline{x}_A}^{1+\varepsilon_A}\left(\int_{\varepsilon_B}^{x^*_{B,i}} f(x_{A,i}, x_{B,i}) dx_{B,i}\right) dx_{A,i}\right]\frac{\overline{x}_A}{\omega_A}\frac{\partial \omega_A}{\partial p}+ \\ &+\int_{\overline{x}_A}^{1+\varepsilon_A} x_{A,i} f(x_{A,i}, \overline{\omega} x_{A,i})\frac{1}{\omega_B}\left[\frac{\partial \omega_A}{\partial p}-\overline{\omega}\frac{\partial \omega_B}{\partial p}\right] dx_{A,i} > 0\end{aligned} \tag{42}$$

Note again that $\frac{\partial R}{\partial p} < 0$. Panels A2 and B2 of Figure A6 show how the decrease in brawn wages makes brain labor and non-labor income relatively more attractive to workers, who respond by moving away from brawn task-intensive jobs.

The share of brain workers increases, since a fraction of workers who were previously employed in brawn labor reallocates towards brain task-intensive jobs (see previous equation) and some non-employed individuals enter the workforce to supply brain labor, as $\frac{\omega_N}{\omega_B}$ decreases.

$$
\begin{aligned}
\frac{\partial N_B}{\partial p} = &\int_{\varepsilon_A}^{\overline{x}_A} f(x_{A,i}, \overline{x}_B)\frac{\overline{x}_B}{\omega_B}\frac{\partial \omega_B}{\partial p}dx_{A,i} - \\
&- \int_{\overline{x}_B}^{1+\varepsilon_B} f(\overline{x}_A, x_{B,i})\frac{\overline{x}_A}{\omega_A}\frac{\partial \omega_A}{\partial p}dx_{B,i} - \\
&- \int_{\overline{x}_A}^{1+\varepsilon_A} x_{A,i} f(x_{A,i}, \overline{\omega} x_{A,i})\frac{1}{\omega_B}\left[\frac{\partial \omega_A}{\partial p} - \overline{\omega}\frac{\partial \omega_B}{\partial p}\right]dx_{A,i} - \\
&- \left[\frac{\partial}{\partial \overline{x}_A}\int_{\overline{x}_A}^{1+\varepsilon_A}\left(\int_{x^*_{B,i}}^{1+\varepsilon_B} f(x_{A,i}, x_{B,i})dx_{B,i}\right)dx_{A,i}\right]\frac{\overline{x}_A}{\omega_A}\frac{\partial \omega_A}{\partial p} < 0
\end{aligned}
\tag{43}
$$

The positive term in the fourth line of Equation 43 is outweighed by the other terms.[42]

Altogether, robots could increase or decrease aggregate employment depending on whether the displacement effect or the productivity effect prevails:

$$
\begin{aligned}
\frac{\partial N_N}{\partial p} = &- \int_{\varepsilon_B}^{\overline{x}_B} f(\overline{x}_A, x_{B,i})\frac{\overline{x}_A}{\omega_A}\frac{\partial \omega_A}{\partial p}dx_{B,i} - \\
&- \int_{\varepsilon_A}^{\overline{x}_A} f(x_{A,i}, \overline{x}_B)\frac{\overline{x}_B}{\omega_B}\frac{\partial \omega_B}{\partial p}dx_{A,i} \lesseqgtr 0
\end{aligned}
\tag{44}
$$

or simply:

$$
\frac{\partial N_N}{\partial p} = 1 - \frac{\partial N_A}{\partial p} - \frac{\partial N_B}{\partial p} \lesseqgtr 0 \tag{45}
$$

Despite the ambiguous effect of robot adoption on employment, robots clearly reduce the gender employment gap:

$$
\frac{\partial EG^{(M,W)}}{\partial p} = - \int_{0}^{\varepsilon_A^M} f(x_{A,i}, \overline{x}_B)\frac{\overline{x}_B}{\omega_B}\frac{\partial \omega_B}{\partial p}dx_{A,i} > 0 \tag{46}
$$

Analogously, using Equation 31, it can be shown that the adoption of robots is widening the race

[42] This result is visible from changes in the areas of the shapes in Figure A6, where the share of brain workers, N_B, is formed by a rectangle and a trapezoid. The shift of $\overline{x}_A$ to the left decreases the rectangle (second term) and at the same time increases the trapezoid (fourth term), without affecting the area of N_B. This, however, is going to change with shifts in $x^*_{B,i}$ and $\overline{x}_B$.

and ethnicity employment gap:

$$\frac{\partial EG^{(WH,NW)}}{\partial p} = -\int_{\varepsilon_B^{NW}}^{0} f(\overline{x}_A, x_{B,i}) \frac{\overline{x}_A}{\omega_A} \frac{\partial \omega_A}{\partial p} dx_{B,i} < 0. \tag{47}$$

These results emerge from one of three scenarios. First, robots reduce male (non-white) employment more than female (white) employment. Second, robots increase male (non-white) employment less than female (white) employment. Third, robots reduce male (non-white) employment and increase female (white) employment. The empirical analysis shows that US labor markets experience the first scenario.

One could also investigate which scenario occurs theoretically by assuming a closed form solution for the skill distribution, $f(x_{A,i}, x_{B,i})$, as well as values for the exogenous parameters ω_N, ρ, β and ε_j^g with $j \in \{A, B\}$ and $g \in \{(M, W), (WH, NW)\}$.

To sum up, as stated in Proposition 2, Equations 46 and 47 show that an increase in the adoption of robots in the production of output Y decreases the gender employment gap and increases the race/ethnicity employment gap. ■

These findings come along with a decrease (increase) in the gender (race/ethnicity) employment gap in brawn labor as robot capital increases:

$$\frac{\partial EG_A^{(M,W)}}{\partial p} = \int_0^{\varepsilon_A^M} x_{A,i} f(x_{A,i}, \overline{\omega} x_{A,i}) \frac{1}{\omega_B} \left[\frac{\partial \omega_A}{\partial p} - \overline{\omega} \frac{\partial \omega_B}{\partial p} \right] dx_{A,i} > 0 \tag{48}$$

$$\frac{\partial EG_A^{(WH,NW)}}{\partial p} = -\int_{\varepsilon_B^{NW}}^{0} f(\overline{x}_A, x_{B,i}) \frac{\overline{x}_A}{\omega_A} \frac{\partial \omega_A}{\partial p} dx_{A,i} < 0 \tag{49}$$

where $EG_A^{(M,W)} = N_A^M - N_A^W$. Conversely, the adoption of robots generates an ambiguous effect on the gender employment gap in brain labor:

$$\begin{aligned} \frac{\partial EG_B^{(M,W)}}{\partial p} = &-\int_0^{\varepsilon_A^M} f(x_{A,i}, \overline{x}_B) \frac{\overline{x}_B}{\omega_B} \frac{\partial \omega_B}{\partial p} dx_{A,i} - \\ &- \int_0^{\varepsilon_A^M} x_{A,i} f(x_{A,i}, \overline{\omega} x_{A,i}) \frac{1}{\omega_B} \left[\frac{\partial \omega_A}{\partial p} - \overline{\omega} \frac{\partial \omega_B}{\partial p} \right] dx_{A,i} \lesseqgtr 0 \end{aligned} \tag{50}$$

where $EG_B^{(M,W)} = N_B^M - N_B^W$ and does not influence the race and ethnicity employment gap in brain labor (Equation 30):

$$\frac{\partial EG_B^{(WH,NW)}}{\partial p} = 0 \tag{51}$$

Example using a uniform skill distribution – I provide an illustrative example of the impact of robots on the employment gaps using a uniform skill distribution, $f(x_{A,i}, x_{B,i}) = 1$. To keep the notation simple, I focus on the gender case and assume that $\varepsilon_B = 0$. The shares of workers (Equations 15 and 16) and of non-employed individuals (Equation 17) simplify to:

$$N_A = \frac{1}{2}\overline{\omega}\Big[(1+\varepsilon_A)^2 - (\overline{x}_A)^2\Big] \tag{52}$$

$$N_B = 1 - \overline{x}_B(\overline{x}_A - \varepsilon_A) - \frac{1}{2}\overline{\omega}\Big[(1+\varepsilon_A)^2 - (\overline{x}_A)^2\Big] \tag{53}$$

$$N_N = \overline{x}_B(\overline{x}_A - \varepsilon_A) \tag{54}$$

with $\varepsilon_A < \overline{x}_A$ and $\omega_B > \omega_N + \frac{1}{2}\omega_A$ to ensure that $N_B > 0$ and $N_N > 0$. Using Equation 54, we can again compute the gender employment gap (Equation 21):

$$EG^{(M,W)} = N_N^W - N_N^M = \varepsilon_A^M \overline{x}_B > 0 \tag{55}$$

Analogously, the employment rates of whites and non-whites are equal to $1 - \overline{x}_A(\overline{x}_B - \varepsilon_B)$ and the race/ethnicity employment gap is given by:

$$EG^{(WH,NW)} = -\varepsilon_B^{NW} \overline{x}_A > 0 \tag{56}$$

where $\varepsilon_B = 0$ for whites and $\varepsilon_B < 0$ for non-whites.

To compute the effect of the adoption of robots on employment, I need to define again all components of Equations 32 and 33. Let's start with the computation of the brawn and brain labor supply (Equations 18 and 19):

$$L_A = \frac{1}{3}\varpi\Big[(1+\varepsilon_A)^3 - (\overline{x}_A)^3\Big] \tag{57}$$

$$L_B = \frac{1}{2}\Big[1 - (\overline{x}_A - \varepsilon_A)(\overline{x}_B)^2 - \frac{1}{3}\varpi^2\big[(1+\varepsilon_A)^3 - (\overline{x}_A)^3\big]\Big] \tag{58}$$

Next, we take first derivatives of the labor supplies with respect to wages (as in Equations 34 to 37):

$$\frac{\partial L_A}{\partial \omega_A} = \frac{1}{3\omega_B}\Big[(1+\varepsilon_A)^3 + 2(\overline{x}_A)^3\Big] > 0 \tag{59}$$

$$\frac{\partial L_A}{\partial \omega_B} = -\frac{1}{3}\frac{\varpi}{\omega_B}\Big[(1+\varepsilon_A)^3 - (\overline{x}_A)^3\Big] < 0 \tag{60}$$

$$\frac{\partial L_B}{\partial \omega_A} = \frac{1}{2}\Big[\frac{\overline{x}_A(\overline{x}_B)^2}{\omega_A} - \frac{1}{3}\frac{\varpi}{\omega_B}\big[2(1+\varepsilon_A)^3 + (\overline{x}_A)^3\big]\Big] < 0 \tag{61}$$

$$\frac{\partial L_B}{\partial \omega_B} = \Big[\frac{(\overline{x}_B)^2}{\omega_B}(\overline{x}_A - \varepsilon_A) + \frac{1}{3}\frac{\varpi^2}{\omega_B}\big[(1+\varepsilon_A)^3 - (\overline{x}_A)^3\big]\Big] > 0 \tag{62}$$

where Equations 60 and 62 hold since $\varepsilon_A < \overline{x}_A$ and Equation 61 holds since $\omega_A > \omega_N$. The partial derivatives of wages with respect to the price of robot capital are the same as in Equations 38 and 39, since they depend on the distribution of skills only through Equations 59 to 62.

Using these equations, it is possible to compute the impact of an exogenous decline in the price of robots on the equilibrium levels of labor and employment:

$$\frac{\partial L_A}{\partial p} = \frac{\partial \omega_A}{\partial p}\Big[(1+\varepsilon_A)^3 + 2(\overline{x}_A)^3\Big]\frac{1}{3\omega_B} - \frac{\partial \omega_B}{\partial p}\Big[(1+\varepsilon_A)^3 - (\overline{x}_A)^3\Big]\frac{\varpi}{3\omega_B} > 0 \tag{63}$$

$$\begin{aligned}\frac{\partial L_B}{\partial p} = {} & \frac{\partial \omega_A}{\partial p}\Big[(\overline{x}_A)^2\overline{x}_B - \frac{1}{3}\varpi\big[2(1+\varepsilon_A)^3 + (\overline{x}_A)^3\big]\Big]\frac{1}{2\omega_B} + \\ & + \frac{\partial \omega_B}{\partial p}\Big[\overline{x}_B(\overline{x}_A - \varepsilon_A) + \frac{1}{3}\varpi^2\big[(1+\varepsilon_A)^3 - (\overline{x}_A)^3\big]\Big]\frac{1}{\omega_B} < 0\end{aligned} \tag{64}$$

$$\frac{\partial N_A}{\partial p} = \frac{\partial \omega_A}{\partial p}\left[(1+\varepsilon_A)^2 + (\overline{x}_A)^2\right]\frac{1}{2\omega_B} - \frac{\partial \omega_B}{\partial p}\left[(1+\varepsilon_A)^2 - (\overline{x}_A)^2\right]\frac{\overline{\omega}}{2\omega_B} > 0 \tag{65}$$

$$\begin{aligned}\frac{\partial N_B}{\partial p} = &-\frac{\partial \omega_A}{\partial p}\left[(1+\varepsilon_A)^2 - (\overline{x}_A)^2\right]\frac{1}{2\omega_B}+ \\ &+\frac{\partial \omega_B}{\partial p}\left[(1+\varepsilon_A)^2 - (\overline{x}_A)^2 + 2\frac{\overline{x}_B(\overline{x}_A - \varepsilon_A)}{\overline{\omega}}\right]\frac{\overline{\omega}}{2\omega_B} < 0\end{aligned} \tag{66}$$

$$\frac{\partial N_N}{\partial p} = \frac{\partial \omega_A}{\partial p}\left[-\overline{x}_A\overline{x}_B\right]\frac{1}{\omega_A} + \frac{\partial \omega_B}{\partial p}\left[(-\overline{x}_A + \varepsilon_A)\overline{x}_B\right]\frac{1}{\omega_B} \lesseqgtr 0 \tag{67}$$

where the signs of the equations hold as long as $\omega_N < \omega_A$ and $\varepsilon_A < \overline{x}_A$. Again, an increase in the stock of robots unambiguously reduces the gender employment gap:

$$\frac{\partial EG^{(M,W)}}{\partial p} = -\varepsilon_A^M \frac{\overline{x}_B}{\omega_B}\frac{\partial \omega_B}{\partial p} > 0 \tag{68}$$

and increases the race/ethnicity employment gap:

$$\frac{\partial EG^{(WH,NW)}}{\partial p} = \varepsilon_B^{NW} \frac{\overline{x}_A}{\omega_A}\frac{\partial \omega_A}{\partial p} < 0. \tag{69}$$

Results by gender are represented visually in Figure A7 in a 3-dimensional space, showing the impact of changes of robot capital and ρ on wages, labor quantities, employment and the employment gap.

Wages – The previous results focus on the mechanism through which an increase in robot capital affects the employment gaps. Interestingly, the effect of robots on employment depends on how it influences labor wages, raising the question of whether an increase in robot capital affects also the wage gap. The gender wage gap can be simply computed using Equations 11, 12, 18 and 19:

$$WG^{M,W} = \frac{\omega^M}{\omega^W} = \frac{\omega_A L_A^M + \omega_B L_B^M}{\omega_A L_A^W + \omega_B L_B^W} \tag{70}$$

where the gender-specific wage is determined by gender-specific labor supplies and marginal products of labor. Analogously, the race and ethnicity employment gap can be computed substituting men (M) with whites and women (W) with non-whites. Note that the wage gap considers only wages of employed individuals (ω_N is excluded, since it includes unemployment benefits, Social Security income, welfare assistance, etc.). To compute the effect of a decrease in the price of robot capital on Equation 70, one could use the results from Equations 38, 39, 40 and 41.

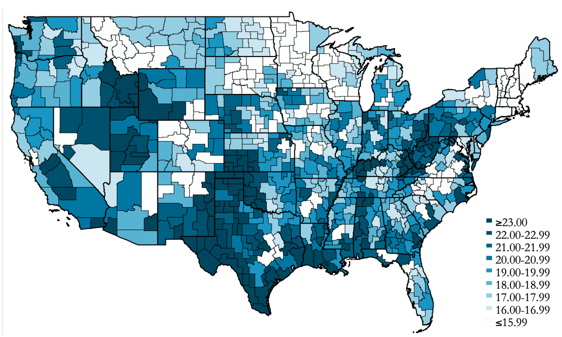
An increase in robot capital has an ambiguous effect on both ω^M and ω^W, since robots decrease the wage of brawn labor, ω_A, and increase the wage of brain labor, ω_B (and respectively affect labor supplies). I provide insights on how the adoption of robots affects wages across demographic groups in the empirical analysis. For a detailed theoretical illustration of the mechanism through which robot adoption affects the gender wage gap, see Ge and Zhou (2020).

A5 Additional figures and tables

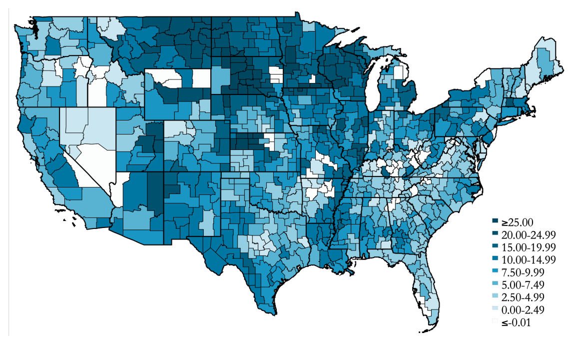
Figure A1: Employment gaps at the commuting zone level

Panel A: Employment gaps in 1990

Gender

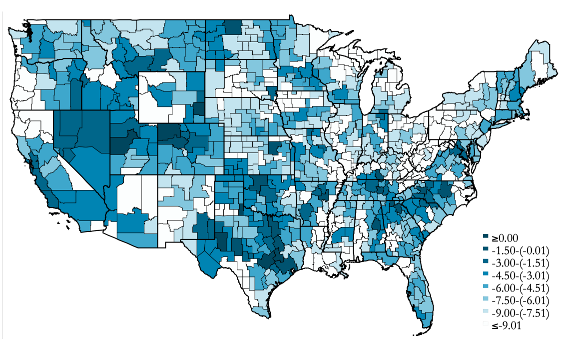


Race and ethnicity

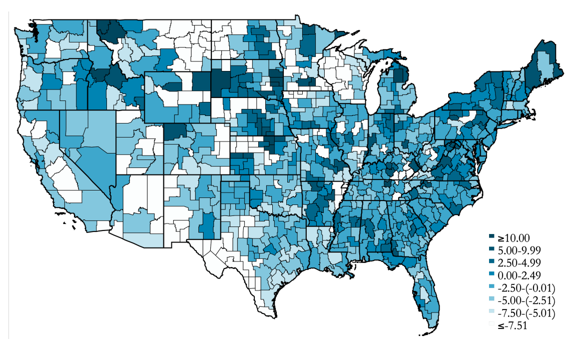


Panel B: Change in employment gaps between 1990 and 2014

Gender



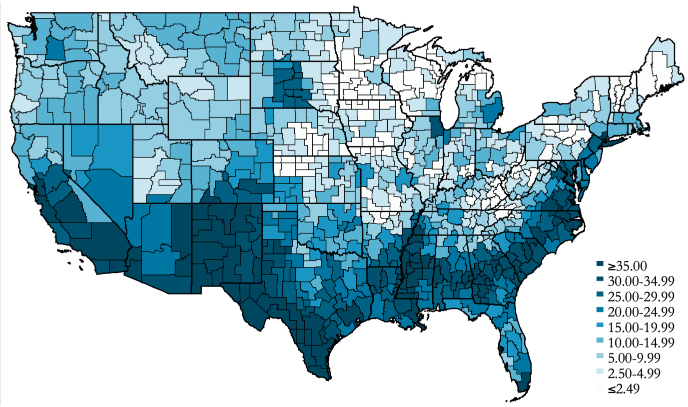
Race and ethnicity



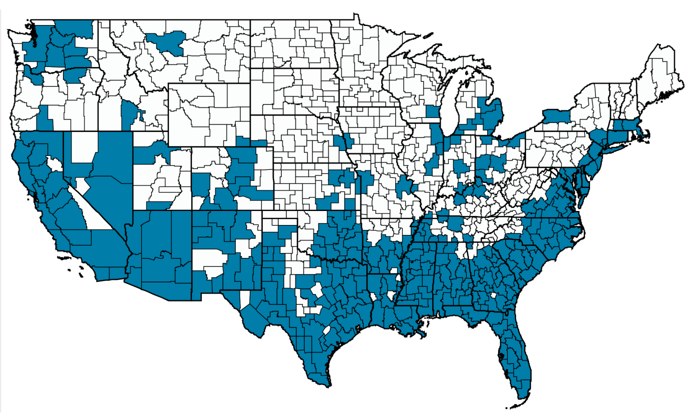
Notes: This figure illustrates the geographic distribution of the gender and race/ethnicity employment gap in 1990 and their changes between 1990 and 2014 at the CZ level, all multiplied by 100.

Figure A2: Racial and ethnic minorities at the commuting zone level in 1990

Panel A: Share of non-whites

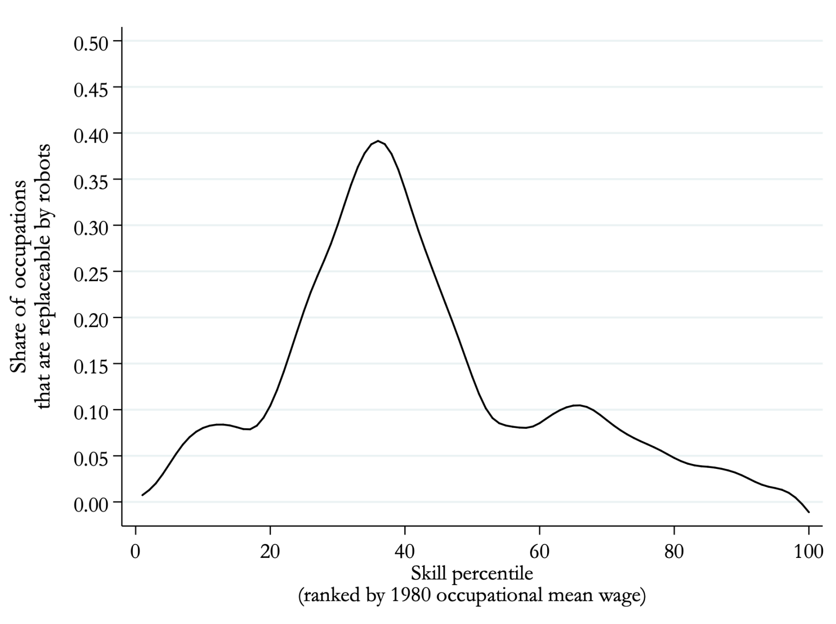


Panel B: Commuting zones with a large population of non-whites



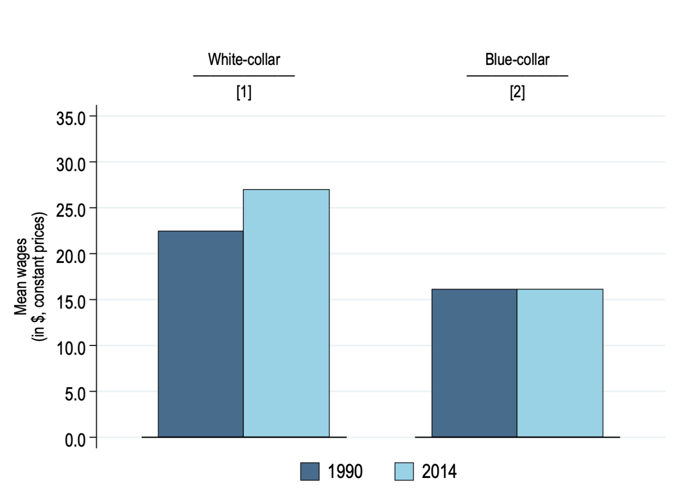
Notes: This figure illustrates the geographic distribution of non-whites in the US in 1990. Panel A shows the CZ share of non-whites multiplied by 100. Panel B shows the CZs with a population of non-whites and a share of non-whites both above the US local labor market median.

Figure A3: Robots along the skill distribution



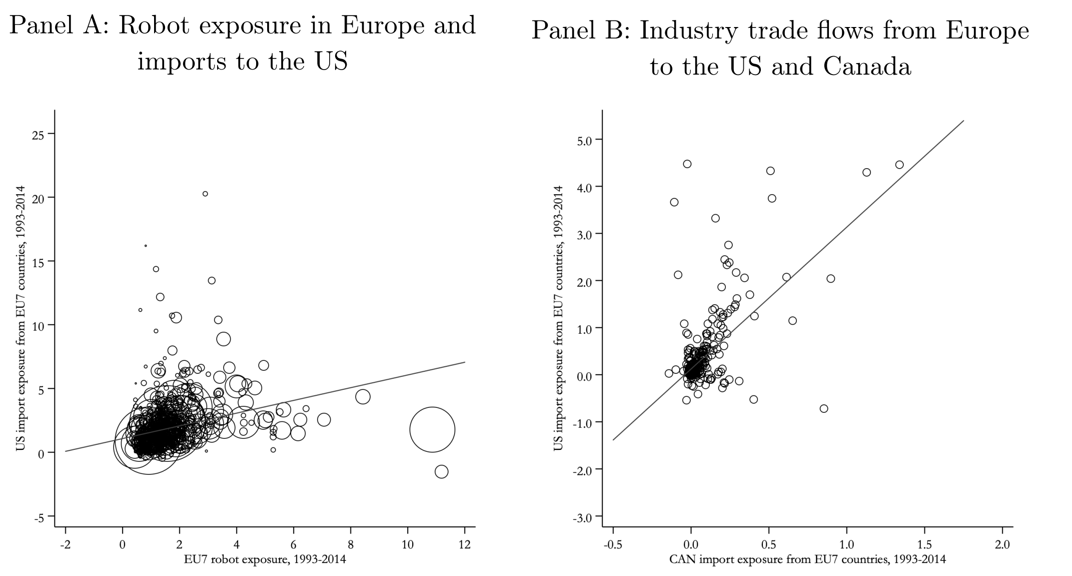
Notes: This figure illustrates the share of occupations that are replaceable by robots, as defined in Graetz and Michaels (2018), by occupational skill percentile. This is a modified version of Figure 4 in Autor and Dorn (2013).

Figure A4: Wages in white-collar and blue-collar occupations



Notes: This figure illustrates the average hourly wages in white-collar and in blue-collar occupations in 1990 and 2014, expressed in 2007 prices. Occupation groups are computed from a median split of the standardized measures of the brawn and brain task content of jobs. White-collar jobs include occupations that are brain task intensive and require only few brawn skills. Blue-collar jobs include occupations that are brawn task intensive and require only few brain skills.

Figure A5: Robot exposure in Europe and imports to the US and Canada

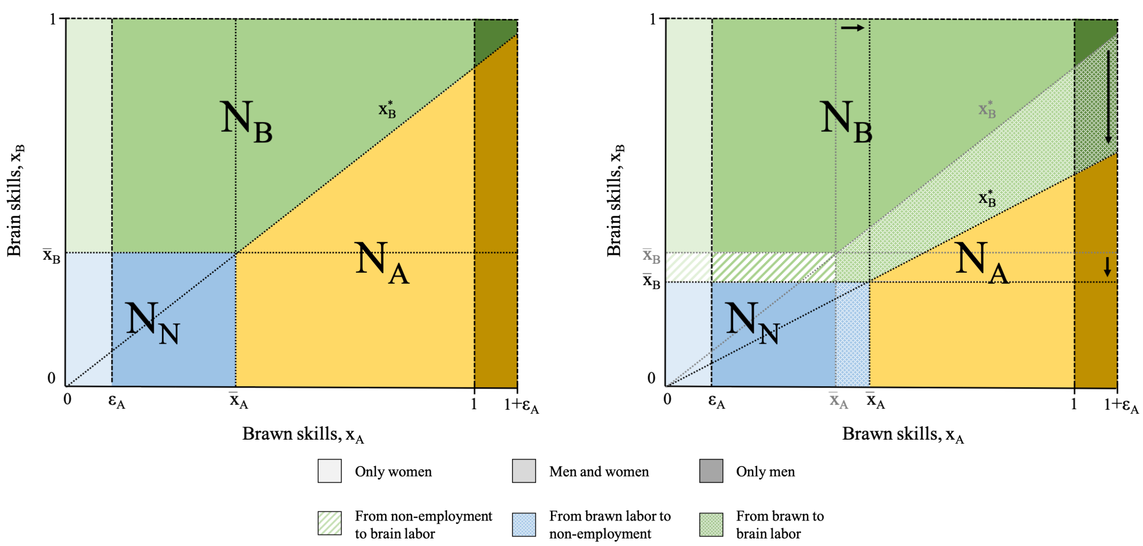


Notes: Panel A of this figure presents the unweighted correlation between robot exposure in seven European countries (Denmark, Finland, France, Italy, Spain, Sweden and the United Kingdom), as presented in Equation 6, and a shift-share measure of imports from these countries to the US. The size of the circles represent a labor market's size in terms of population in 1990. The solid line represents a prediction for US import exposure from European countries from a linear regression on robot exposure in Europe. Panel B presents the unweighted correlation between imports from the seven European countries to the US and Canada. Imports are represented by 392 SIC industry of the manufacturing sector in billions of US dollars in 2017 prices. For visual purposes, I omitt outlying industries with imports that exceed five billion US dollars in the US or three billion US dollars in Canada. These industries are ice cream and frozen desserts (2024), food preparations, nec (2099), hardwood dimension and flooring mills (2426), millwork (2431), pharmaceutical preparations (2834), petroleum refining (2911), women's handbags and purses (3171), primary nonferrous metals, nec (3339), electronic connectors (3678), motor vehicles and car bodies (3711), motor vehicle parts and accessories (3714), aircraft (3721), aircraft engines and engine parts (3724). The solid line represents a prediction for US import exposure from European countries from a linear regression on Canadian import exposure from European countries based on all 392 SIC industries of the manufacturing sector.

Figure A6: Robots and labor

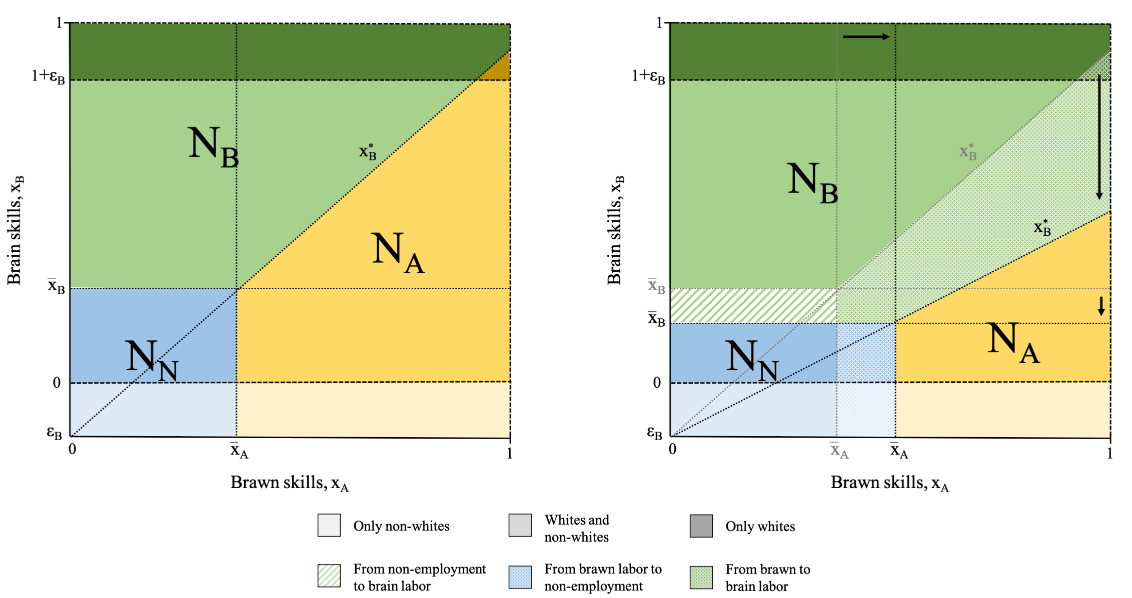
Panel A: Gender

Panel A1: Employment rates   Panel A2: The effect of robots



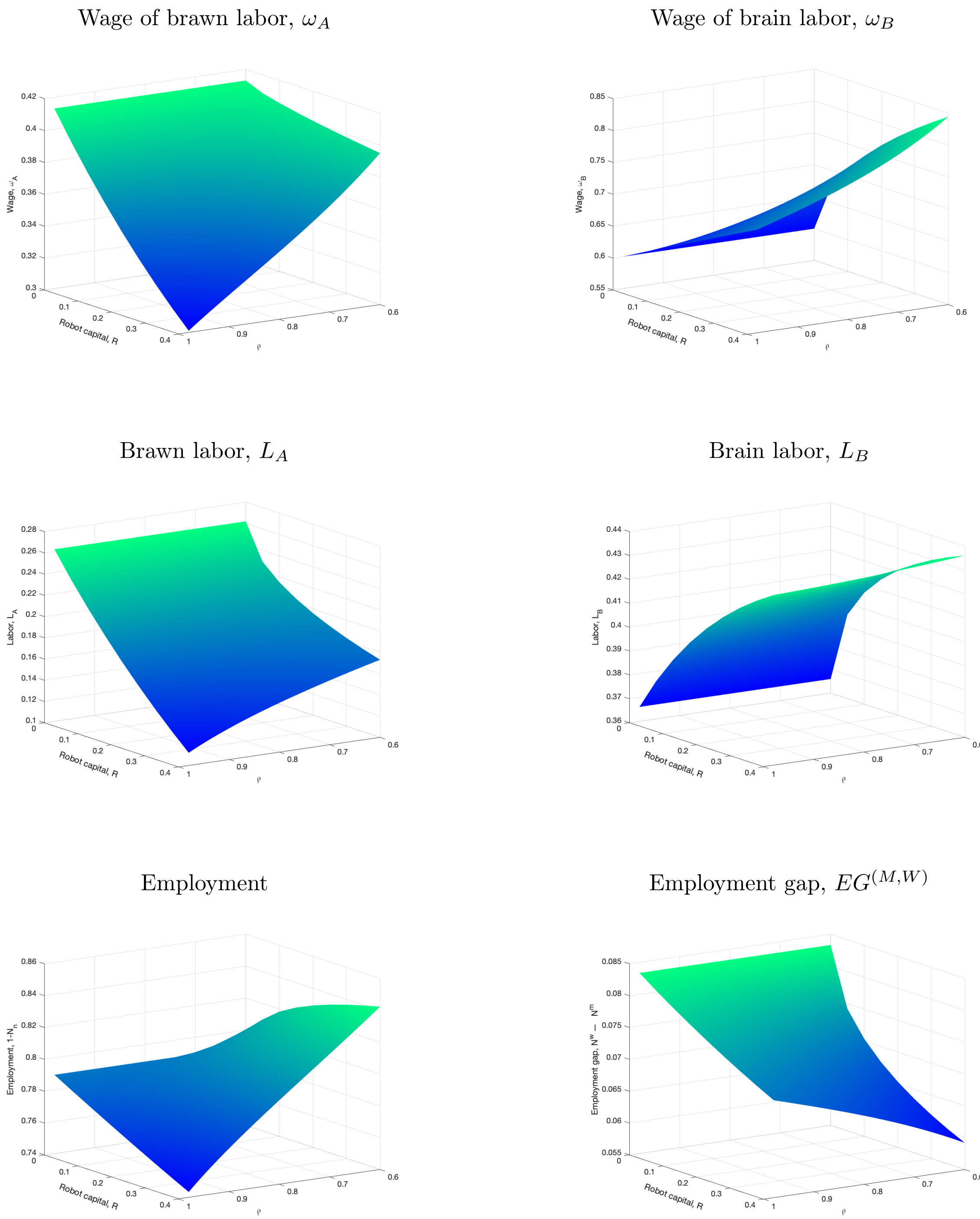
Panel B: Race and ethnicity

Panel B1: Employment rates   Panel B2: The effect of robots



Notes: This figure illustrates theoretically the impact of robots on employment outcomes across demographic groups. Panel A shows the results by gender and Panel B by race/ethnicity. Panels A1 and B1 illustrate the employment allocation by gender and race/ethnicity in equilibrium. N_A, N_B and N_N represent the share of individuals that supply brawn labor, brain labor and no labor. $\varepsilon_A > 0$ accounts for the comparative advantage of men in brawn skills, $\varepsilon_B < 0$ accounts for the comparative disadvantage of non-whites in brain skills, $\overline{x}_A = \frac{\omega_N}{\omega_A}$, $\overline{x}_B = \frac{\omega_N}{\omega_B}$ and $x^*_{B,i} = \frac{\omega_A}{\omega_B} x_{A,i}$. Panels A2 and B2 illustrate the effect of an exogenous decrease in the price of robot capital on relative wages and the equilibrium allocation of labor across these demographic groups.

Figure A7: Robots, elasticity of substitution and the gender employment gap



Notes: This figure illustrates the impact of changes in R (through changes in p) and ρ on equilibrium wages, labor, employment rates and gaps by solving for Equations 11, 12, 18 and 19. The model is calibrated using a uniform skill distribution with the following parameters: $\beta = 0.33$ (based on employment in blue-collar jobs in 1970), $\omega_N = 0.25$, $\varepsilon_A^M = 0.2$.

Table A1: Summary statistics: Racial and ethnic minorities

	Population rates		Employment rates					
	All	Minorities	All		1st quartile		4th quartile	
	1990	1990	1990	Δ_{14-90}	1990	Δ_{14-90}	1990	Δ_{14-90}
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Blacks	11.4	37.6	69.1	-1.8	72.6	-2.2	66.8	-0.9
Hispanics	12.6	41.8	71.2	1.4	72.3	1.2	70.3	1.5
Asians	4.4	14.6	71.6	1.7	71.4	2.1	72.0	1.0
American Indian or Alaska Natives	0.6	2.1	68.0	-5.3	68.8	-6.0	67.5	-4.2
Other	1.2	3.9	68.2	1.5	72.1	-0.8	66.3	1.5
Observations	722	722	722	722	181	181	180	180

Notes: This table illustrates average population and employment rates for Blacks, Hispanics, Asians, American Indian or Alaska Natives, and other not elsewhere classified races. Columns 1, 2, 3, 5 and 7 show values in 1990, and Columns 4, 6 and 8 show changes between 1990 and 2014 weighted by CZ population in 1990. Columns 1 reports the share of each subgroup in the population, while Columns 2 reports the share among racial and ethnic minorities. Columns 1 to 4 reports averages over all 722 CZs in the sample. Columns 5 to 8 split the sample into quartiles according to the CZ's exposure to robots between 1993 and 2014, reporting averages for the first and the fourth quartile.

Table A2: Occupations with the largest and smallest shares of non-whites and women

Racial and ethnic minorities					Women				
	%	Type	Brawn	Brain		%	Type	Brawn	Brain
	[1]	[2]	[3]	[4]		[5]	[6]	[7]	[8]
Panel A: Top 15 occupations					Panel A: Top 15 occupations				
Private household cleaners and servants	62.03	Low skill	32	5	Secretaries	98.98	White collar	48	88
Parking lot attendants	59.38	Low skill	1	13	Dental hygenists	98.33	White collar	20	53
Housekeepers, maids, butlers and related	53.58	Low skill	42	5	Kindergarten and earlier school teachers	98.21	White collar	45	64
Elevator operators	50.34	Blue collar	63	24	Dental assistants	97.52	White collar	3	60
Baggage porters	47.50	Low skill	36	28	Receptionists	96.96	Low skill	22	41
Materials movers	47.10	Low skill	41	6	Child care workers	96.58	Low skill	3	37
Garbage and recyclable material collectors	45.56	Low skill	23	1	Typists	95.38	Low skill	35	39
Textile sewing machine operators	45.53	Blue collar	83	7	Private household cleaners and servants	94.80	Low skill	32	5
Laundry workers	45.19	Low skill	49	1	Teacher's aides	94.62	White collar	4	59
Waiter's assistant	45.05	Low skill	1	13	Home economics instructors	94.52	White collar	38	100
Taxi cab drivers and chauffeurs	44.74	Skill intensive	87	55	Registered nurses	94.50	Skill intensive	65	84
Farm workers	44.21	Blue collar	50	18	Licensed practical nurses	93.85	Skill intensive	65	50
Tailors	44.04	Blue collar	92	37	Dressmakers and seamstresses	93.66	Blue collar	83	28
Graders and sorters in manufacturing	43.40	Blue collar	50	2	Bank tellers	93.54	Skill intensive	98	65
Vehicle washers and equipment cleaners	42.96	Low skill	21	2	Health record tech specialists	93.40	White collar	1	84
Panel B: Bottom 15 occupations					Panel B: Bottom 15 occupations				
Tool and die markers and die setters	7.71	Skill intensive	86	53	Automobile mechanics	1.87	Skill intensive	80	56
Psychology instructors	7.61	White collar	1	100	Structural metal workers	1.82	Blue collar	67	25
Lawyers	7.53	White collar	2	96	Excavating and loading machine operators	1.82	Blue collar	64	11
Other health and therapy	7.22	Skill intensive	87	94	Materials movers	1.71	Low skill	41	6
Veterinarians	7.17	Skill intensive	97	75	Operating engineers of construction equipm.	1.70	Blue collar	84	33
Optometrists	7.04	Skill intensive	91	69	Carpenters	1.64	Blue collar	89	45
Writers and authors	6.79	White collar	10	83	Mason, tilers, and carpet installers	1.59	Blue collar	81	31
Podiatrists	6.65	White collar	36	88	Roofers and slaters	1.44	Blue collar	91	27
Foresters and conservation scientists	6.52	Low skill	46	47	Electric power installers and repairers	1.44	Skill intensive	92	48
Dental hygenists	6.00	White collar	20	53	Plumbers, pipe fitters, and steamfitters	1.38	Blue collar	90	46
Geologists	5.44	Skill intensive	63	95	Railroad brake, coupler, and switch operators	1.36	Blue collar	65	23
History instructors	4.74	White collar	1	100	Concrete and cement workers	1.35	Blue collar	80	25
Sales engineers	4.62	White collar	39	94	Heating, air cond., and refrig. mechanics	1.22	Blue collar	67	42
Airplane pilots and navigators	4.60	Skill intensive	97	66	Paving, surfacing, tamping equipm. operators	1.07	Blue collar	91	23
Farmers (owners and tenants)	2.88	White collar	22	58	Heavy equipm. and farm equipm. mechanics	0.86	Blue collar	92	43

Notes: This table presents a set of occupations with the corresponding share of non-white and female workers, the percentile of the standardized brawn and brain task content in the distribution of occupations and the respective occupation group. Occupation groups are computed from a median split of the standardized measures of the brawn and brain task content of jobs. Skill-intensive jobs include occupations that are both brawn and brain task intensive. White-collar jobs include occupations that are brain task intensive and require only few brawn skills. Blue-collar jobs include occupations that are brawn task intensive and require only few brain skills. Low-skill jobs include occupations that do not require particular brawn or brain skills. Panel A shows the 15 occupations with the highest share of non-whites and women. Panel B shows the 15 occupations with the highest share of whites and men.

Table A3: Summary statistics: Employment by occupation and industry

	Occupation								Industry					
	Skill-intensive		White-collar		Blue-collar		Low-skill		High robot-int.		Low robot-int.		Non-manuf.	
	1990	Δ_{14-90}	1990	Δ_{14-90}	1990	Δ_{14-90}	1990	Δ_{14-90}	1990	Δ_{14-90}	1990	Δ_{14-90}	1990	Δ_{14-90}
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[14]
Panel A: Gender														
Men	13.3	-1.60	31.4	-0.12	24.1	-3.70	8.22	0.95	9.78	-2.70	9.39	-3.90	65.0	1.71
Women	9.86	2.55	30.9	1.34	12.2	-3.70	9.06	0.76	4.07	-1.20	4.99	-2.80	56.9	5.94
Gender gap	3.47	-4.20	0.53	-1.40	11.8	-0.00	-0.84	0.19	5.70	-1.50	4.40	-1.10	8.03	-4.20
Panel B: Race and ethnicity														
Whites	12.2	0.36	34.8	2.11	16.4	-4.30	7.38	-0.23	6.70	-2.00	7.05	-3.10	62.8	3.61
Non-whites	9.49	1.35	19.8	3.55	21.9	-4.50	12.2	0.75	7.64	-2.10	6.89	-3.40	54.2	6.78
Race and ethnicity gap	2.71	-0.99	15.0	-1.40	-5.40	0.23	-4.90	-0.98	-0.94	0.13	0.15	0.30	8.67	-3.10
Observations	722	722	722	722	722	722	722	722	722	722	722	722	722	722

Notes: This table illustrates employment rates and gaps of demographic groups by occupation and industry groups in 1990 and their changes between 1990 and 2014. Averages are weighted by the CZ population in 1990. Occupation groups are computed from a median split of the standardized measures of the brawn and brain task content of jobs. Skill-intensive jobs include occupations that are both brawn and brain task intensive. White-collar jobs include occupations that are brain task intensive and require only few brawn skills. Blue-collar jobs include occupations that are brawn task intensive and require only few brain skills. Low-skill jobs include occupations that do not require particular brawn or brain skills. As shown in Table 1.1, industry groups are created according to the relative adoption of industrial robots of industries. High robot-intensive manufacturing industries include the industries with the heaviest adoption of industrial robots. Low robot-intensive manufacturing industries include the remaining manufacturing industries, while non-manufacturing industries include all industries outside of the manufacturing sector.

Table A4: Summary statistics: Covariates

	All	US robot exposure 1993-2014 Q1	Q2	Q3	Q4
	[1]	[2]	[3]	[4]	[5]
Pre-trends					
Employment men	-5.09	-3.98	-5.0	-3.93	-6.25
Employment women	19.8	20.3	19.7	19.2	19.9
Employment whites	9.43	10.4	9.41	9.62	8.94
Employment non-whites	3.16	5.51	5.04	4.14	0.54
Labor market shocks					
Import exposure	3.61	1.70	3.34	4.34	5.06
PC exposure	44.8	44.5	44.8	44.2	45.3
IT capital	2.02	1.40	1.92	2.32	2.15
Routine task-intensity	35.0	33.6	35.1	35.1	35.4
Demographics					
Black	10.9	9.33	12.1	9.82	11.5
Hispanic	7.94	15.8	7.92	10.2	3.62
Women	51.1	50.9	51.3	50.7	51.4
Less educated	77.1	76.6	75.4	77.7	78.0
Log population	13.3	12.8	13.4	13.4	13.4
25-34 years	33.9	34.1	34.2	34.5	33.2
35-44 years	29.4	29.4	29.7	29.5	29.3
45-54 years	20.0	19.7	19.8	19.9	20.3
Industries					
Construction	6.24	7.72	6.17	6.24	5.73
Manufacturing	24.4	14.8	21.3	27.3	28.3
Mining	0.99	1.45	1.05	0.96	0.81
Research and education	1.91	1.89	1.98	1.76	1.96
Services	63.0	69.4	65.9	60.1	60.5
Utilities	1.49	1.59	1.46	1.40	1.52
Occupations					
Skill-intensive	16.1	17.0	16.2	15.5	16.2
White-collar	41.4	42.1	42.6	40.2	41.0
Blue-collar	28.3	26.1	27.1	30.1	29.0
Offshorable	37.2	37.2	38.0	37.4	36.6
Employment composition					
Women in high robot-intensive industries	30.8	31.9	32.3	32.2	28.7
Women in low robot-intensive industries	35.3	35.1	36.8	36.8	33.6
Non-whites in high robot-intensive industries	23.8	30.7	24.9	29.3	17.3
Non-whites in low robot-intensive industries	22.7	30.0	25.4	28.1	15.3
Women in skill-intensive occupations	47.3	47.5	47.3	46.2	47.8
Women in white-collar occupations	50.8	51.4	51.0	50.0	50.8
Women in blue-collar occupations	35.3	34.0	36.0	36.1	35.0
Non-whites in skill-intensive occupations	17.9	24.1	19.1	20.9	13.0
Non-whites in white-collar occupations	13.3	19.1	13.6	15.6	9.64
Non-whites in blue-collar occupations	29.2	38.1	31.2	35.2	21.0
Observations	722	181	180	181	180

Notes: This table illustrates averages of the covariates used in the main analysis. Column 1 reports averages over all 722 CZs in the sample. Columns 2 to 5 split the sample into four quartiles, accounting for a labor market's exposure to robots between 1993 and 2014. Pre-trends account for changes in employment of men, women, whites and non-whites between 1970 and 1990. Labor market shocks include the China trade shock, a measure of exposure to PCs, IT capital intensity and the share of workers who are employed in routine task-intensive occupations. Demographics, industries and occupations include measures of the population composition in 1990. The remaining variables report the employment composition by demographic group within industries and occupations in 1990.

Table A5: The effect of robots on the employment gaps and first-stage estimates

	[1]	[2]	[3]	[4]	[5]	[6]
	Panel A: Gender employment gap					
US robot exposure	-0.508***	-0.497***	-0.519***	-0.519***	-0.618***	-0.644***
	(0.141)	(0.143)	(0.144)	(0.144)	(0.158)	(0.166)
	Panel B: Race/ethnicity employment gap					
US robot exposure	0.640***	0.685***	0.687***	0.687***	0.804***	0.846***
	(0.232)	(0.221)	(0.225)	(0.225)	(0.268)	(0.276)
	Panel C: First-stage					
EU7 robot exposure	0.568***	0.565***	0.555***	0.555***	0.497***	0.478***
	(0.047)	(0.042)	(0.051)	(0.053)	(0.049)	(0.036)
Kleibergen-Paap F stat	146.98	177.31	119.76	107.91	103.18	180.31
Observations	2166	2166	2166	2166	2166	2166
Covariates:						
Region	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓
Pre-trends		✓	✓	✓	✓	✓
Computer & IT			✓	✓	✓	✓
Chinese imports				✓	✓	✓
Demographics					✓	✓
Occupations					✓	✓
Industries					✓	✓
Composition						✓

Notes: This table presents IV estimates of the effect of US robot exposure on employment gaps by gender and race/ethnicity and first-stage estimates at the CZ level adding covariates sequentially. Changes in Panel A and B are expressed in percentage points of the working-age population of the respective demographic group and are multiplied by 100. Independent variables are standardized to have mean zero and standard deviation of one. Panel C standardizes also the dependent variable. There are three time periods and 722 CZs. Column 1 includes only state fixed effects and time-varying division fixed effects. Column 2 includes also pre-trends in employment of men, women, whites and non-whites between 1970 and 1990. Column 3 controls for the adoption of PCs, IT capital intensity and RBTC. Column 4 includes the exposure to Chinese imports. Column 5 controls also for demographic characteristics (share of Blacks, Hispanics, women, population with less than a college degree, three age groups (25-34, 35-44 and 45-54 years), and the logarithmic population), the industry (employment share in construction, manufacturing, mining, research, service and utilities) and occupation composition of employment (employment share in offshorable, skill-intensive, white-collar, blue-collar and low-skill jobs) of CZs in 1990. Column 6 controls also for the initial composition of industry and occupation employment by gender and race/ethnicity in 1990. Standard errors are robust against heteroskedasticity and allow for clustering at the state level. Regressions are weighted by CZ population in 1990. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Table A6: Robots and employment: Exclusion of the Great Recession period (2007-14)

	Panel A: Gender		
	Men	Women	Gap
	[1]	[2]	[3]
US robot exposure	-0.695***	-0.357***	-0.343***
	(0.137)	(0.121)	(0.072)
Observations	1444	1444	1444
	Panel B: Race and ethnicity		
	Whites	Non-whites	Gap
	[1]	[2]	[3]
US robot exposure	-0.375***	-0.958***	0.583***
	(0.050)	(0.194)	(0.155)
Observations	1444	1444	1444
Covariates:	✓	✓	✓

Notes: This table presents IV estimates of the effect of US robot exposure on employment rates and gaps by gender and race/ethnicity at the CZ level. Changes are expressed in percentage points of the working-age population of the respective demographic group and are multiplied by 100. Independent variables are standardized to have mean zero and standard deviation of one. There are two time periods and 722 CZs. Time periods are 1990-2000 and 2000-07. All regressions include state fixed effects, time-varying division fixed effects, pre-trends in employment of men, women, whites and non-whites between 1970 and 1990, controls for the adoption of PCs, IT capital intensity and RBTC, exposure to Chinese imports, demographic characteristics (share of Blacks, Hispanics, women, population with less than a college degree, three age groups (25-34, 35-44 and 45-54 years), and the logarithmic population), the industry (employment share in construction, manufacturing, mining, research, service and utilities) and occupation composition of employment (employment share in offshorable, skill-intensive, white-collar, blue-collar and low-skill jobs) of CZs in 1990, and the composition of industry and occupation employment by gender and race/ethnicity of CZs in 1990. Standard errors are robust against heteroskedasticity and allow for clustering at the state level. Regressions are weighted by CZ population in 1990. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Table A7: Robots and labor force participation

	Panel A: Gender		
	Men	Women	Gap
	[1]	[2]	[3]
US robot exposure	-0.633***	-0.113	-0.520***
	(0.182)	(0.150)	(0.136)
Observations	2166	2166	2166
	Panel B: Race and ethnicity		
	Whites	Non-whites	Gap
	[1]	[2]	[3]
US robot exposure	-0.167*	-0.805***	0.638***
	(0.091)	(0.228)	(0.232)
Observations	2166	2166	2166
Covariates:	✓	✓	✓

Notes: This table presents IV estimates of the effect of US robot exposure on labor force participation rates and gaps by gender and race/ethnicity at the CZ level. Changes are expressed in percentage points of the working-age population of the respective demographic group and are multiplied by 100. Independent variables are standardized to have mean zero and standard deviation of one. There are three time periods and 722 CZs. All regressions include state fixed effects, time-varying division fixed effects, pre-trends in employment of men, women, whites and non-whites between 1970 and 1990, controls for the adoption of PCs, IT capital intensity and RBTC, exposure to Chinese imports, demographic characteristics (share of Blacks, Hispanics, women, population with less than a college degree, three age groups (25-34, 35-44 and 45-54 years), and the logarithmic population), the industry (employment share in construction, manufacturing, mining, research, service and utilities) and occupation composition of employment (employment share in offshorable, skill-intensive, white-collar, blue-collar and low-skill jobs) of CZs in 1990, and the composition of industry and occupation employment by gender and race/ethnicity of CZs in 1990. Standard errors are robust against heteroskedasticity and allow for clustering at the state level. Regressions are weighted by CZ population in 1990. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Table A8: The effect of labor market shocks on employment

	Panel A: Gender					
	Full sample			Exclude Great Recession		
	Men	Women	Gap	Men	Women	Gap
	[1]	[2]	[3]	[4]	[5]	[6]
EU7 robot exposure	-0.553***	-0.245***	-0.308***	-0.583***	-0.263*	-0.321***
	(0.104)	(0.079)	(0.085)	(0.154)	(0.133)	(0.065)
Import exposure	-0.328***	-0.141	-0.187***	-0.403***	-0.328**	-0.075
	(0.112)	(0.129)	(0.067)	(0.125)	(0.133)	(0.094)
PC exposure	0.002	0.057	-0.055	0.065	-0.020	0.085
	(0.081)	(0.059)	(0.050)	(0.070)	(0.084)	(0.069)
IT capital intensity	-0.022	-0.016	-0.006	0.034	-0.011	0.045
	(0.095)	(0.094)	(0.068)	(0.114)	(0.097)	(0.077)
Routine task-intensity	0.137	-0.072	0.209***	0.101	-0.047	0.148
	(0.083)	(0.092)	(0.061)	(0.097)	(0.112)	(0.096)
Observations	2166	2166	2166	1444	1444	1444
	Panel B: Race and ethnicity					
	Full sample			Exclude Great Recession		
	Whites	Non-whites	Gap	Whites	Non-whites	Gap
	[1]	[2]	[3]	[4]	[5]	[6]
EU7 robot exposure	-0.272***	-0.676***	0.404***	-0.266***	-0.713***	0.447***
	(0.039)	(0.135)	(0.126)	(0.059)	(0.210)	(0.164)
Import exposure	-0.147*	-0.298*	0.150	-0.291***	-0.352*	0.062
	(0.079)	(0.166)	(0.161)	(0.098)	(0.188)	(0.206)
PC exposure	0.084	-0.264***	0.348***	0.085	-0.486***	0.571***
	(0.064)	(0.093)	(0.075)	(0.061)	(0.148)	(0.151)
IT capital intensity	-0.022	-0.078	0.056	-0.037	0.088	-0.125
	(0.073)	(0.145)	(0.096)	(0.074)	(0.197)	(0.161)
Routine task-intensity	0.027	-0.015	0.042	-0.014	-0.097	0.083
	(0.072)	(0.137)	(0.105)	(0.080)	(0.187)	(0.179)
Observations	2166	2166	2166	1444	1444	1444
Covariates:	✓	✓	✓	✓	✓	✓

Notes: This table presents reduced form estimates of the effect of robot exposure, import exposure, PC adoption, IT capital intensity and routine task-intensity on employment rates and gaps by gender and race/ethnicity at the CZ level. Changes are expressed in percentage points of the working-age population of the respective demographic group and are multiplied by 100. Independent variables are standardized to have mean zero and standard deviation of one. There are three time periods and 722 CZs. All regressions include state fixed effects, time-varying division fixed effects, pre-trends in employment of men, women, whites and non-whites between 1970 and 1990, controls for demographic characteristics (share of Blacks, Hispanics, women, population with less than a college degree, three age groups (25-34, 35-44 and 45-54 years), and the logarithmic population), the industry (employment share in construction, manufacturing, mining, research, service and utilities) and occupation composition of employment (employment share in offshorable, skill-intensive, white-collar, blue-collar and low-skill jobs) of CZs in 1990, and the composition of industry and occupation employment by gender and race/ethnicity of CZs in 1990. Standard errors are robust against heteroskedasticity and allow for clustering at the state level. Regressions are weighted by CZ population in 1990. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Table A9: Robots and race/ethnicity employment gaps in non-manufacturing industries

	Agricul-ture	Construc-tion	Mining	Research and Education	Services	Utilities
	[1]	[2]	[3]	[4]	[5]	[6]
US robot exposure	0.068*	-0.003	-0.015	-0.043*	0.662***	0.029*
	(0.040)	(0.052)	(0.013)	(0.025)	(0.200)	(0.016)
Observations	2166	2166	2166	2166	2166	2166
Covariates:	✓	✓	✓	✓	✓	✓

Notes: This table presents IV estimates of the effect of US robot exposure on the employment gap by race/ethnicity at the CZ level. Columns decompose the outcomes by sectors outside of manufacturing. Changes are expressed in percentage points of the working-age population of the respective demographic group and are multiplied by 100. Independent variables are standardized to have mean zero and standard deviation of one. There are three time periods and 722 CZs. All regressions include state fixed effects, time-varying division fixed effects, pre-trends in employment of men, women, whites and non-whites between 1970 and 1990, controls for the adoption of PCs, IT capital intensity and RBTC, exposure to Chinese imports, demographic characteristics (share of Blacks, Hispanics, women, population with less than a college degree, three age groups (25-34, 35-44 and 45-54 years), and the logarithmic population), the industry (employment share in construction, manufacturing, mining, research, service and utilities) and occupation composition of employment (employment share in offshorable, skill-intensive, white-collar, blue-collar and low-skill jobs) of CZs in 1990, and the composition of industry and occupation employment by gender and race/ethnicity of CZs in 1990. Standard errors are robust against heteroskedasticity and allow for clustering at the state level. Regressions are weighted by CZ population in 1990. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Table A10: Robots and industry employment by race/ethnicity as a share of total population

	High robot-intensive		Low robot-intensive		Non-manufacturing	
	White	Non-white	White	Non-white	White	Non-white
	[1]	[2]	[3]	[4]	[5]	[6]
US robot exposure	-0.271***	-0.109***	0.042	0.002	-0.275***	-0.220*
	(0.056)	(0.029)	(0.045)	(0.017)	(0.094)	(0.121)
Observations	2166	2166	2166	2166	2166	2166
Covariates:	✓	✓	✓	✓	✓	✓

Notes: This table presents IV estimates of the effect of US robot exposure on employment rates by race/ethnicity at the CZ level. Columns decompose the outcomes between industry groups. Changes are expressed in percentage points of the overall working-age population and are multiplied by 100. Independent variables are standardized to have mean zero and standard deviation of one. There are three time periods and 722 CZs. All regressions include state fixed effects, time-varying division fixed effects, pre-trends in employment of men, women, whites and non-whites between 1970 and 1990, controls for the adoption of PCs, IT capital intensity and RBTC, exposure to Chinese imports, demographic characteristics (share of Blacks, Hispanics, women, population with less than a college degree, three age groups (25-34, 35-44 and 45-54 years), and the logarithmic population), the industry (employment share in construction, manufacturing, mining, research, service and utilities) and occupation composition of employment (employment share in offshorable, skill-intensive, white-collar, blue-collar and low-skill jobs) of CZs in 1990, and the composition of industry and occupation employment by gender and race/ethnicity of CZs in 1990. Standard errors are robust against heteroskedasticity and allow for clustering at the state level. Regressions are weighted by CZ population in 1990. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Table A11: Robots and race/ethnicity employment gap by industry

	High robot-intensive	Low robot-intensive	Non manufacturing
	[1]	[2]	[3]
Robots in high robot-intensive	0.070	0.012	0.327***
	(0.083)	(0.034)	(0.116)
Robots in low robot-intensive	0.066	-0.050	0.423***
	(0.056)	(0.045)	(0.155)
Robots in non-manufacturing	0.014	0.105*	0.197
	(0.077)	(0.054)	(0.226)
Observations	2166	2166	2166
Covariates:	✓	✓	✓

Notes: This table presents IV estimates of the effect of US robot exposure by industry group on the employment gap by race/ethnicity at the CZ level. Columns decompose the outcomes (employment) by industry group. Changes are expressed in percentage points of the working-age population of the respective demographic group and are multiplied by 100. Independent variables are standardized to have mean zero and standard deviation of one. There are three time periods and 722 CZs. All regressions include state fixed effects, time-varying division fixed effects, pre-trends in employment of men, women, whites and non-whites between 1970 and 1990, controls for the adoption of PCs, IT capital intensity and RBTC, exposure to Chinese imports, demographic characteristics (share of Blacks, Hispanics, women, population with less than a college degree, three age groups (25-34, 35-44 and 45-54 years), and the logarithmic population), the industry (employment share in construction, manufacturing, mining, research, service and utilities) and occupation composition of employment (employment share in offshorable, skill-intensive, white-collar, blue-collar and low-skill jobs) of CZs in 1990, and the composition of industry and occupation employment by gender and race/ethnicity of CZs in 1990. Standard errors are robust against heteroskedasticity and allow for clustering at the state level. Regressions are weighted by CZ population in 1990. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Table A12: Robots and employment: No state fixed effects

	Panel A: Gender			
	All	Men	Women	Gap
	[1]	[2]	[3]	[4]
US robot exposure	-0.588***	-0.794***	-0.392***	-0.408***
	(0.112)	(0.138)	(0.108)	(0.113)
Observations	2166	2166	2166	2166
	Panel B: Race and ethnicity			
	All	Whites	Non-whites	Gap
	[1]	[2]	[3]	[4]
US robot exposure	-0.588***	-0.439***	-1.026***	0.587***
	(0.112)	(0.060)	(0.188)	(0.174)
Observations	2166	2166	2166	2166
Covariates:	✓	✓	✓	✓

Notes: This table presents IV estimates of the effect of US robot exposure on employment rates and gaps by gender and race/ethnicity at the CZ level. Changes are expressed in percentage points of the working-age population of the respective demographic group and are multiplied by 100. Independent variables are standardized to have mean zero and standard deviation of one. There are three time periods and 722 CZs. All regressions include time-varying division fixed effects (but no state fixed effects), pre-trends in employment of men, women, whites and non-whites between 1970 and 1990, controls for the adoption of PCs, IT capital intensity and RBTC, exposure to Chinese imports, demographic characteristics (share of Blacks, Hispanics, women, population with less than a college degree, three age groups (25-34, 35-44 and 45-54 years), and the logarithmic population), the industry (employment share in construction, manufacturing, mining, research, service and utilities) and occupation composition of employment (employment share in offshorable, skill-intensive, white-collar, blue-collar and low-skill jobs) of CZs in 1990, and the composition of industry and occupation employment by gender and race/ethnicity of CZs in 1990. Standard errors are robust against heteroskedasticity and allow for clustering at the state level. Regressions are weighted by CZ population in 1990. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Table A13: Robots and employment: Shares of total population

	Panel A: Gender		
	All	Men	Women
	[1]	[2]	[3]
US robot exposure	-0.826***	-0.559***	-0.267***
	(0.202)	(0.132)	(0.096)
Relative contribution	100.0	67.7	32.3
Observations	2166	2166	2166
	Panel B: Race and ethnicity		
	All	Whites	Non-whites
	[1]	[2]	[3]
US robot exposure	-0.826***	-0.494***	-0.332**
	(0.202)	(0.144)	(0.165)
Relative contribution	100.0	59.8	40.2
Observations	2166	2166	2166
Covariates:	✓	✓	✓

Notes: This table presents IV estimates of the effect of US robot exposure on employment rates by gender and race/ethnicity at the CZ level and the relative contribution of each demographic group to the aggregate effect (in percent). Changes are expressed in percentage points of the total working-age population in the CZ and are multiplied by 100. Independent variables are standardized to have mean zero and standard deviation of one. There are three time periods and 722 CZs. All regressions include time-varying division fixed effects (but no state fixed effects), pre-trends in employment of men, women, whites and non-whites between 1970 and 1990, controls for the adoption of PCs, IT capital intensity and RBTC, exposure to Chinese imports, demographic characteristics (share of Blacks, Hispanics, women, population with less than a college degree, three age groups (25-34, 35-44 and 45-54 years), and the logarithmic population), the industry (employment share in construction, manufacturing, mining, research, service and utilities) and occupation composition of employment (employment share in offshorable, skill-intensive, white-collar, blue-collar and low-skill jobs) of CZs in 1990, and the composition of industry and occupation employment by gender and race/ethnicity of CZs in 1990. Standard errors are robust against heteroskedasticity and allow for clustering at the state level. Regressions are weighted by CZ population in 1990. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Table A14: Robots and employment: Product market competition from Europe

	Panel A: Gender					
	All			Less than college		
	Men	Women	Gap	Men	Women	Gap
	[1]	[2]	[3]	[4]	[5]	[6]
	Panel A1: Import competition in the US					
US robot exposure	-1.114***	-0.490***	-0.624***	-1.385***	-0.497**	-0.888***
	(0.231)	(0.177)	(0.160)	(0.302)	(0.206)	(0.179)
US imports from EU7	-0.113	-0.059	-0.054	-0.159	-0.088	-0.071
	(0.095)	(0.063)	(0.069)	(0.102)	(0.073)	(0.077)
	Panel A2: Import competition in Canada					
US robot exposure	-1.157***	-0.513***	-0.644***	-1.446***	-0.530**	-0.916***
	(0.243)	(0.190)	(0.166)	(0.318)	(0.221)	(0.190)
CAN imports from EU7	0.099	0.054	0.045	0.108	0.022	0.086
	(0.119)	(0.115)	(0.062)	(0.122)	(0.117)	(0.078)
	Panel A3: Include only countries with least trade with the US					
US robot exposure	-0.916***	-0.596*	-0.320**	-1.141***	-0.678*	-0.463***
	(0.318)	(0.328)	(0.130)	(0.417)	(0.380)	(0.165)
Observations	2166	2166	2166	2166	2166	2166
	Panel B: Race and ethnicity					
	All			Less than college		
	Whites	Non-whites	Gap	Whites	Non-whites	Gap
	[1]	[2]	[3]	[4]	[5]	[6]
	Panel B1: Import competition in the US					
US robot exposure	-0.573***	-1.348***	0.775***	-0.619***	-1.520***	0.901***
	(0.098)	(0.301)	(0.264)	(0.102)	(0.350)	(0.287)
US imports from EU7	0.011	-0.179	0.191*	-0.007	-0.244*	0.236**
	(0.049)	(0.115)	(0.105)	(0.047)	(0.123)	(0.107)
	Panel B2: Import competition in Canada					
US robot exposure	-0.569***	-1.417***	0.847***	-0.623***	-1.613***	0.990***
	(0.098)	(0.316)	(0.277)	(0.108)	(0.366)	(0.300)
CAN imports from EU7	0.066	0.140	-0.073	0.047	0.107	-0.060
	(0.105)	(0.173)	(0.121)	(0.097)	(0.175)	(0.145)
	Panel B3: Include only countries with least trade with the US					
US robot exposure	-0.537**	-1.132***	0.596*	-0.652***	-1.304***	0.653*
	(0.202)	(0.393)	(0.338)	(0.230)	(0.467)	(0.369)
Observations	2166	2166	2166	2166	2166	2166
Covariates:	✓	✓	✓	✓	✓	✓

Notes: This table presents IV estimates of the effect of US robot exposure on employment rates and gaps by gender and race/ethnicity at the CZ level. Changes are expressed in percentage points of the working-age population of the respective demographic group and are multiplied by 100. Independent variables are standardized to have mean zero and standard deviation of one. There are three time periods and 722 CZs. Panels A1 and B1 include a shift-share measure of US imports from the seven European countries included in the instrument. Panels A2 and B2 include a shift-share measure of Canadian imports from the seven European countries included in the instrument. Panels A3 and B3 report IV estimates using an instrument that includes only the four European countries with the lowest trade engagement with the US (Denmark, Finland, Spain and Sweden). Columns 1 to 3 report results for all individuals, while Columns 4 to 6 report results for individuals without a college degree. All regressions include state fixed effects, time-varying division fixed effects, pre-trends in employment of men, women, whites and non-whites between 1970 and 1990, controls for the adoption of PCs, IT capital intensity and RBTC, exposure to Chinese imports, demographic characteristics (share of Blacks, Hispanics, women, population with less than a college degree, three age groups (25-34, 35-44 and 45-54 years), and the logarithmic population), the industry (employment share in construction, manufacturing, mining, research, service and utilities) and occupation composition of employment (employment share in offshorable, skill-intensive, white-collar, blue-collar and low-skill jobs) of CZs in 1990, and the composition of industry and occupation employment by gender and race/ethnicity of CZs in 1990. Standard errors are robust against heteroskedasticity and allow for clustering at the state level. Regressions are weighted by CZ population in 1990. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Table A15: Robots and employment: Pre-trends

	Panel A: Gender		
	Men	Women	Gap
	[1]	[2]	[3]
US robot exposure	-1.148***	-0.507**	-0.644***
	(0.243)	(0.189)	(0.166)
Employment of men, 1970-1990	-0.041	-0.029	-0.009
	(0.041)	(0.030)	(0.024)
Employment of women, 1970-1990	0.037	0.006	0.032
	(0.040)	(0.032)	(0.030)
Employment of whites, 1970-1990	-0.024	0.026	-0.054
	(0.070)	(0.052)	(0.052)
Employment of non-whites, 1970-1990	0.001	0.006	-0.006
	(0.007)	(0.005)	(0.005)
Observations	2166	2166	2166
	Panel B: Race and ethnicity		
	Whites	Non-whites	Gap
	[1]	[2]	[3]
US robot exposure	-0.569***	-1.415***	0.846***
	(0.097)	(0.315)	(0.276)
Employment of men, 1970-1990	-0.001	-0.091	0.090*
	(0.024)	(0.059)	(0.048)
Employment of women, 1970-1990	0.050**	-0.010	0.060
	(0.025)	(0.050)	(0.042)
Employment of whites, 1970-1990	-0.054	0.117	-0.171**
	(0.042)	(0.094)	(0.078)
Employment of non-whites, 1970-1990	0.006	-0.025*	0.032**
	(0.005)	(0.015)	(0.012)
Observations	2166	2166	2166
Covariates:	✓	✓	✓

Notes: This table presents IV estimates of the effect of US robot exposure on employment rates and gaps by gender and race/ethnicity at the CZ level. Changes are expressed in percentage points of the working-age population of the respective demographic group and are multiplied by 100. US robot exposure has been standardized to have mean zero and standard deviation of one. Changes in the employment rates between 1970 and 1990 are demographic specific and are multiplied by 100. There are three time periods and 722 CZs. All regressions include state fixed effects, time-varying division fixed effects, pre-trends in employment of men, women, whites and non-whites between 1970 and 1990, controls for the adoption of PCs, IT capital intensity and RBTC, exposure to Chinese imports, demographic characteristics (share of Blacks, Hispanics, women, population with less than a college degree, three age groups (25-34, 35-44 and 45-54 years), and the logarithmic population), the industry (employment share in construction, manufacturing, mining, research, service and utilities) and occupation composition of employment (employment share in offshorable, skill-intensive, white-collar, blue-collar and low-skill jobs) of CZs in 1990, and the composition of industry and occupation employment by gender and race/ethnicity of CZs in 1990. Standard errors are robust against heteroskedasticity and allow for clustering at the state level. Regressions are weighted by CZ population in 1990. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Table A16: Robots and employment: Weights

	Panel A: Gender					
	All	Less than college	All	Less than college	All	Less than college
	[1]	[2]	[3]	[4]	[5]	[6]
	Panel A1: Employment rate of men					
US robot exposure	-1.662***	-2.091***	-1.015***	-1.216***	-1.309***	-1.370***
	(0.307)	(0.400)	(0.300)	(0.342)	(0.371)	(0.358)
	Panel A2: Employment rate of women					
US robot exposure	-0.753***	-0.812***	-0.124	-0.037	-0.767**	-0.730**
	(0.262)	(0.264)	(0.132)	(0.164)	(0.283)	(0.271)
	Panel A3: Employment gap					
US robot exposure	-0.909***	-1.279***	-0.890***	-1.179***	-0.542**	-0.640**
	(0.202)	(0.256)	(0.320)	(0.393)	(0.244)	(0.282)
Observations	2166	2166	2166	2166	825	825
	Panel B: Race and ethnicity					
	All	Less than college	All	Less than college	All	Less than college
	[1]	[2]	[3]	[4]	[5]	[6]
	Panel B1: Employment rate of whites					
US robot exposure	-0.658***	-0.750***	-0.516***	-0.528***	-0.691***	-0.606***
	(0.154)	(0.138)	(0.152)	(0.174)	(0.213)	(0.221)
	Panel B2: Employment rate of non-whites					
US robot exposure	-1.888***	-2.164***	-0.469	-0.640	-1.476***	-1.614***
	(0.365)	(0.435)	(0.382)	(0.457)	(0.395)	(0.425)
	Panel B3: Employment gap					
US robot exposure	1.230***	1.414***	-0.047	0.111	0.785**	1.008**
	(0.355)	(0.402)	(0.403)	(0.509)	(0.319)	(0.400)
Observations	2166	2166	2166	2166	825	825
Covariates:						
Division	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓
Computer & IT	✓	✓	✓	✓	✓	✓
Chinese imports	✓	✓	✓	✓	✓	✓
Demographics	✓	✓	✓	✓	✓	✓
Occupations	✓	✓	✓	✓	✓	✓
Industries	✓	✓	✓	✓	✓	✓
Non-white population weights	✓			✓		
Unweighted		✓	✓		✓	✓
Non-white CZs			✓			✓

Notes: This table presents IV estimates of the effect of US robot exposure on employment rates and gaps by gender and race/ethnicity at the CZ level. Changes are expressed in percentage points of the working-age population of the respective demographic group and are multiplied by 100. Independent variables are standardized to have mean zero and standard deviation of one. There are three time periods and 722 CZs in the first four columns and three time periods and 275 CZs in the last pair of columns. The latter restrict the sample to CZs with a population of non-whites and a share of non-whites above the respective local labor market median in 1990. Columns 1 to 3 report results for all individuals, while Columns 4 to 6 report results for individuals without a college degree. All regressions include state fixed effects, time-varying division fixed effects, pre-trends in employment of men, women, whites and non-whites between 1970 and 1990, controls for the adoption of PCs, IT capital intensity and RBTC, exposure to Chinese imports, demographic characteristics (share of Blacks, Hispanics, women, population with less than a college degree, three age groups (25-34, 35-44 and 45-54 years), and the logarithmic population), the industry (employment share in construction, manufacturing, mining, research, service and utilities) and occupation composition of employment (employment share in offshorable, skill-intensive, white-collar, blue-collar and low-skill jobs) of CZs in 1990, and the composition of industry and occupation employment by gender and race/ethnicity of CZs in 1990. Standard errors are robust against heteroskedasticity and allow for clustering at the state level. Regressions in Columns 1 and 4 are weighted by the population of non-whites in the CZ in 1990. Regressions in the remaining columns are unweighted. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Table A17: Robots and employment: Alternative construction of the instrument

	Panel A: Gender					
	All			Less than college		
	Men	Women	Gap	Men	Women	Gap
	[1]	[2]	[3]	[4]	[5]	[6]
	Panel A1: EU7 countries and Germany					
US robot exposure	-0.975***	-0.408***	-0.568***	-1.223***	-0.422**	-0.801***
	(0.212)	(0.141)	(0.148)	(0.280)	(0.170)	(0.172)
	Panel A2: EU5 countries (Acemoglu and Restrepo, 2020)					
US robot exposure	-1.254***	-0.627**	-0.627***	-1.567***	-0.682**	-0.885***
	(0.309)	(0.269)	(0.164)	(0.403)	(0.306)	(0.197)
	Panel A3: EU7 countries with $\ell_{j,c}^{90}$					
US robot exposure	-1.161***	-0.573***	-0.588***	-1.464***	-0.672***	-0.793***
	(0.250)	(0.198)	(0.161)	(0.334)	(0.242)	(0.203)
	Panel A4: EU7 countries without $g_{j,(t_0,t_1)} \frac{R_{j,t_0}}{L_{j,90}}$					
US robot exposure	-0.918***	-0.404**	-0.514***	-1.143***	-0.375**	-0.768***
	(0.179)	(0.151)	(0.166)	(0.226)	(0.166)	(0.184)
Observations	2166	2166	2166	2166	2166	2166
	Panel B: Race and ethnicity					
	All			Less than college		
	Whites	Non-whites	Gap	Whites	Non-whites	Gap
	[1]	[2]	[3]	[4]	[5]	[6]
	Panel B1: EU7 countries and Germany					
US robot exposure	-0.477***	-1.205***	0.728***	-0.528***	-1.368***	0.840***
	(0.074)	(0.279)	(0.245)	(0.087)	(0.322)	(0.265)
	Panel B2: EU5 countries (Acemoglu and Restrepo, 2020)					
US robot exposure	-0.631***	-1.566***	0.935***	-0.712***	-1.784***	1.073***
	(0.144)	(0.383)	(0.313)	(0.156)	(0.444)	(0.342)
	Panel B3: EU7 countries with $\ell_{j,c}^{90}$					
US robot exposure	-0.497***	-1.446***	0.950***	-0.597***	-1.627***	1.030***
	(0.107)	(0.319)	(0.276)	(0.122)	(0.381)	(0.310)
	Panel B4: EU7 countries without $g_{j,(t_0,t_1)} \frac{R_{j,t_0}}{L_{j,90}}$					
US robot exposure	-0.461***	-1.115***	0.654***	-0.468***	-1.272***	0.804***
	(0.097)	(0.260)	(0.231)	(0.097)	(0.293)	(0.250)
Observations	2166	2166	2166	2166	2166	2166
Covariates:	✓	✓	✓	✓	✓	✓

Notes: This table presents IV estimates of the effect of US robot exposure on employment rates and gaps by gender and race/ethnicity at the CZ level. Changes are expressed in percentage points of the working-age population of the respective demographic group and are multiplied by 100. Independent variables are standardized to have mean zero and standard deviation of one. There are three time periods and 722 CZs. Panels A1 and B1 report estimates using an instrument which includes seven European countries and Germany. Panels A2 and B2 report estimates using an instrument that includes only five European countries. I exclude Spain and the United Kingdom as in Acemoglu and Restrepo (2020). Panels A3 and B3 report estimates using an instrument with seven European countries, but US employment shares of 1990 instead of 1970. Panels A4 and B4 report estimates using an endogenous variable and an instrument of robot density without the adjustment term of industry growth. Columns 1 to 3 report results for all individuals, while Columns 4 to 6 report results for individuals without a college degree. All regressions include state fixed effects, time-varying division fixed effects, pre-trends in employment of men, women, whites and non-whites between 1970 and 1990, controls for the adoption of PCs, IT capital intensity and RBTC, exposure to Chinese imports, demographic characteristics (share of Blacks, Hispanics, women, population with less than a college degree, three age groups (25-34, 35-44 and 45-54 years), and the logarithmic population), the industry (employment share in construction, manufacturing, mining, research, service and utilities) and occupation composition of employment (employment share in offshorable, skill-intensive, white-collar, blue-collar and low-skill jobs) of CZs in 1990, and the composition of industry and occupation employment by gender and race/ethnicity of CZs in 1990. Standard errors are robust against heteroskedasticity and allow for clustering at the state level. Regressions are weighted by CZ population in 1990. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Table A18: Robots and employment: Exclude CZs with highest robot exposure

	Panel A: Gender					
	All			Less than college		
	Men	Women	Gap	Men	Women	Gap
	[1]	[2]	[3]	[4]	[5]	[6]
	Panel A1: Exclusion of Detroit area					
US robot exposure	-1.292***	-0.764*	-0.528*	-1.570**	-0.815	-0.755**
	(0.460)	(0.450)	(0.283)	(0.595)	(0.511)	(0.355)
Observations	2163	2163	2163	2163	2163	2163
	Panel A2: Exclusion of CZs in top 1 percentile					
US robot exposure	-1.561**	-1.019	-0.542	-1.888**	-1.009	-0.879*
	(0.646)	(0.746)	(0.390)	(0.828)	(0.853)	(0.454)
Observations	2142	2142	2142	2142	2142	2142
	Panel B: Race and ethnicity					
	All			Less than college		
	Whites	Non-whites	Gap	Whites	Non-whites	Gap
	[1]	[2]	[3]	[4]	[5]	[6]
	Panel B1: Exclusion of Detroit area					
US robot exposure	-0.614**	-1.688***	1.074**	-0.649**	-1.974***	1.325**
	(0.269)	(0.546)	(0.456)	(0.286)	(0.648)	(0.500)
Observations	2163	2163	2163	2163	2163	2163
	Panel B2: Exclusion of CZs in top 1 percentile					
US robot exposure	-0.781*	-1.772**	0.990	-0.771	-2.149**	1.378*
	(0.454)	(0.792)	(0.654)	(0.483)	(0.974)	(0.739)
Observations	2142	2142	2142	2142	2142	2142
Covariates:	✓	✓	✓	✓	✓	✓

Notes: This table presents IV estimates of the effect of US robot exposure on employment rates and gaps by gender and race/ethnicity at the CZ level. Changes are expressed in percentage points of the working-age population of the respective demographic group and are multiplied by 100. Independent variables are standardized to have mean zero and standard deviation of one. There are three time periods and 722 CZs. Panels A1 and B1 exclude Detroit from the sample. Panels A2 and B2 exclude the CZs in the top 1 percentile of US robot exposure between 1993 and 2014. Columns 1 to 3 report results for all individuals, while Columns 4 to 6 report results for individuals without a college degree. All regressions include state fixed effects, time-varying division fixed effects, pre-trends in employment of men, women, whites and non-whites between 1970 and 1990, controls for the adoption of PCs, IT capital intensity and RBTC, exposure to Chinese imports, demographic characteristics (share of Blacks, Hispanics, women, population with less than a college degree, three age groups (25-34, 35-44 and 45-54 years), and the logarithmic population), the industry (employment share in construction, manufacturing, mining, research, service and utilities) and occupation composition of employment (employment share in offshorable, skill-intensive, white-collar, blue-collar and low-skill jobs) of CZs in 1990, and the composition of industry and occupation employment by gender and race/ethnicity of CZs in 1990. Standard errors are robust against heteroskedasticity and allow for clustering at the state level. Regressions are weighted by CZ population in 1990. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Table A19: Robots and employment: Unobserved heterogeneity

	Panel A: Gender					
	All			Less than college		
	Men	Women	Gap	Men	Women	Gap
	[1]	[2]	[3]	[4]	[5]	[6]
	Panel A1: CZ characteristics at $t-1$					
US robot exposure	-0.985***	-0.415**	-0.570***	-1.244***	-0.449**	-0.795***
	(0.237)	(0.178)	(0.133)	(0.307)	(0.218)	(0.157)
	Panel A2: CZ fixed effects					
US robot exposure	-1.606***	-0.872***	-0.735***	-2.087***	-0.993***	-1.094***
	(0.304)	(0.259)	(0.190)	(0.382)	(0.307)	(0.220)
Observations	2166	2166	2166	2166	2166	2166
	Panel B: Race and ethnicity					
	All			Less than college		
	Whites	Non-whites	Gap	Whites	Non-whites	Gap
	[1]	[2]	[3]	[4]	[5]	[6]
	Panel B1: CZ characteristics at $t-1$					
US robot exposure	-0.479***	-1.229***	0.750***	-0.552***	-1.396***	0.845***
	(0.077)	(0.280)	(0.230)	(0.104)	(0.324)	(0.247)
	Panel B2: CZ fixed effects					
US robot exposure	-0.797***	-2.098***	1.301***	-0.930***	-2.470***	1.540***
	(0.104)	(0.372)	(0.305)	(0.150)	(0.407)	(0.313)
Observations	2166	2166	2166	2166	2166	2166
Covariates:	✓	✓	✓	✓	✓	✓

Notes: This table presents IV estimates of the effect of US robot exposure on employment rates and gaps by gender and race/ethnicity at the CZ level. Changes are expressed in percentage points of the working-age population of the respective demographic group and are multiplied by 100. Independent variables are standardized to have mean zero and standard deviation of one. There are three time periods and 722 CZs. Panels A1 and B1 use time-varying covariates. Panels A2 and B2 include CZ fixed effects. Columns 1 to 3 report results for all individuals, while Columns 4 to 6 report results for individuals without a college degree. All regressions include state fixed effects, time-varying division fixed effects, pre-trends in employment of men, women, whites and non-whites between 1970 and 1990, controls for the adoption of PCs, IT capital intensity and RBTC, exposure to Chinese imports, demographic characteristics (share of Blacks, Hispanics, women, population with less than a college degree, three age groups (25-34, 35-44 and 45-54 years), and the logarithmic population), the industry (employment share in construction, manufacturing, mining, research, service and utilities) and occupation composition of employment (employment share in offshorable, skill-intensive, white-collar, blue-collar and low-skill jobs) of CZs in 1990, and the composition of industry and occupation employment by gender and race/ethnicity of CZs in 1990. Standard errors are robust against heteroskedasticity and allow for clustering at the state level. Regressions are weighted by CZ population in 1990. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Chapter 2

Robots and Non-participation in the US: Where Have All the Workers Gone?

2.1 Introduction

Advances in labor-replacing technologies are poised to shape the future of labor markets, fueling concerns that the automation of labor through robots and artificial intelligence is going to displace millions of workers in the years to come (Brynjolfsson and McAfee, 2014, Susskind, 2020).[43] This is an issue with profound implications, since information technologies are disrupting labor markets at an unprecedented speed, forcing displaced workers to leave the labor force and to seek alternative sources of income (Ford, 2015). Despite growing interest in the impact of new technologies on the labor market, little is known about how displaced workers adapt to automation. This paper investigates the margins of adjustment of workers after they get displaced by the introduction of industrial robots in the United States between 1993 and 2014, and offers first evidence about where these individuals end up, highlighting the need to design policies that facilitate the transition of the workforce to new jobs.

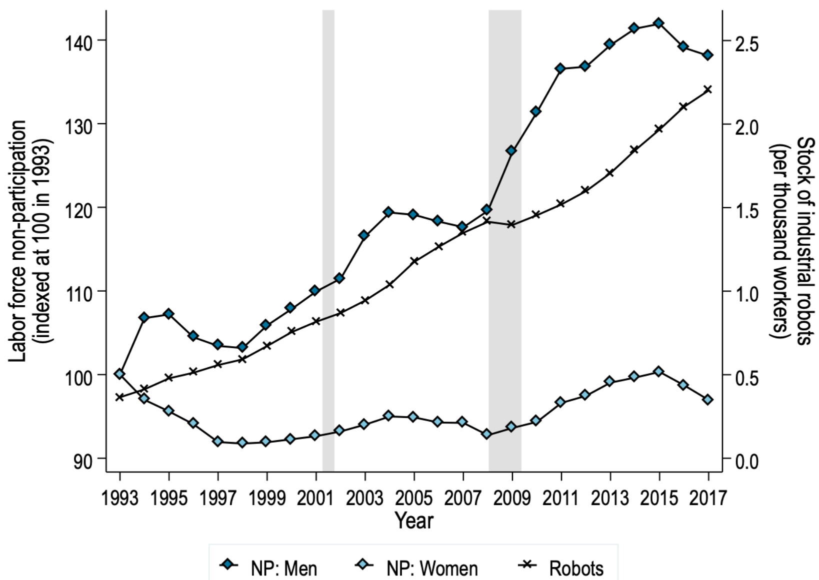
Industrial robots have been among the leading automation technologies of the last decades. The International Federation of Robotics (IFR) defines them as fully autonomous machines that can be programmed to perform various manual tasks without the intervention of a human worker. The astonishing advances in robotics in recent decades, along with a decline in their quality-adjusted prices, have led to a widespread adoption of robots in many countries, affecting the demand for labor (Graetz and Michaels, 2018). In the US, the stock of industrial has increased from less than half a robot to more than two robots per thousand workers (about 180,000 units) between 1993 and 2014, displacing thousands of workers from their jobs (Acemoglu and Restrepo, 2020).

Although technological change is also creating millions of new jobs (Autor et al., 2021), these

[43] Frey and Osborne (2017) project that 47 percent of total US employment is at high risk of automation in the next two decades, raising concerns about the future of work.

jobs often require the interplay of humans with machines, and may not be performed by workers who have been displaced by automation due to a skill mismatch (Restrepo, 2015). Displaced workers are therefore likely to become unemployed or to drop out of the labor force altogether (Grigoli et al., 2020, Jaimovich et al., 2020), unless they are endowed with easily redeployable human capital (Goldin and Katz, 2010).

Figure 2.1: Labor force non-participation and robots in the US



Notes: This figure illustrates the non-participation rate of men and women indexed at 100 at the start of the sample period (left axis), and the stock of industrial robots per thousand workers in the US (right axis). The number of workers used for the computation of the stock of robots is kept constant at its 1993 level. Labor force participation has been computed using data from the Current Population Survey.

Figure 2.1 shows that, while labor force participation among women has remained relatively stable over the past decades, the US have been experiencing a secular surge in the non-participation rate of men, which increased by more than 40 percent since the early 1990s (from 11 to 15 percent). The adoption of industrial robots in the labor market has been acknowledged to play a crucial role for labor force participation in the country (Abraham and Kearney, 2020), raising questions about where workers have gone in the aftermath of a displacement. In particular, how can they afford not to work? Do they leave the labor market temporary to acquire new skills that increase their labor market competitiveness? Do they drop out of the labor force permanently to retire early or claim disability benefits? Do they live off their parents' or their partner's income? Or are they just idle?

To identify the margins of adjustment of individuals, I use individual-level information about the labor force status and detailed socio-demographic characteristics of the US population from the Census and the American Community Survey (ACS), including college enrollment, disability take-up, early retirement, income, and their recent migration history. I match these data with industry-level data about the adoption of industrial robots from the IFR. I follow Acemoglu and Restrepo (2020) in constructing a plausibly exogenous measure of robot exposure at the local labor market level using a shift-share approach that interacts baseline industry employment shares within local labor markets, proxied by commuting zones (CZs, Tolbert and Sizer, 1996), with the adoption of robots in the US. Identification builds on the assumption that advances in robotics vary by industry and expose CZs differently based on their industrial composition of employment.

In line with Acemoglu and Restrepo (2020), I document that the introduction of robots has decreased US labor force participation. Estimates suggest that each additional robot drives four workers out of the local labor force.[44] I further show that this result is fully driven by men. Although women are also affected negatively in their job prospects, there is no evidence of robot exposure affecting their labor force participation rate.

The literature on regional shocks would expect workers' geographic mobility to be one of the key mechanisms through which labor markets adjust to local economic shocks (Blanchard and Katz, 1992, Howard, 2020). However, there is only limited support for this hypothesis in the context of industrial robots, as they reduce the inflow of individuals to exposed areas (affecting the behavior of prospective migrants), but they do not affect migration outflows from these CZs (Faber et al., 2022).[45] Nevertheless, this result raises the possibility that changes in the labor force participation rate reflect changes in the composition of local labor markets, rather than an increase in labor force dropouts. I account for this concern by restricting my analysis to the population of individuals born in the same US state to exclude individuals who have migrated across labor markets.[46] The results are economically and statistically unaffected when using the restricted sample, providing confidence in the interpretation of labor force participation changes reflecting changes in individuals' behavior

[44] Displaced workers are individuals who do not find a job or who lost their job directly or indirectly due to the adoption of robots. The repeated cross-sectional nature of the data does not allow me to disentangle direct from indirect displacement effects of robots, since I am tracing local labor markets rather than the career progression of individual workers.

[45] In line with this finding, Monras (2018), Foote et al. (2019), Yagan (2019) and Notowidigdo (2020) show that in recent decades internal migration does not constitute a primary margin of adjustment of displaced workers anymore.

[46] This result is far from perfect, as it cleans out only migration flows across US states. Unfortunately, the Census/ACS do not provide more granular information about the birthplace of individuals.

rather than changes in the composition of local labor markets.

To understand the underlying causes that drive individuals out of the labor market, it is important to take into account that robots might influence individuals' labor supply decisions differently based on their demographic characteristics. For instance, above a certain age, workers are more likely to retire early, when displaced by robots, instead of investing in additional human capital. For this purpose, I decompose the non-participating population into narrow age and education groups, and analyze their margins of adjustment separately. I also distinguish between whites and racial/ethnic minorities, since there are noteworthy differences in the adjustment margins of these individuals.

I find that young whites delay their labor market entry or temporarily leave the labor force to enroll in college. These individuals usually have already an undergraduate degree, and they enroll in graduate or professional schools to acquire additional skills to increase their competitiveness on the labor market. This result does not hold for young individuals belonging to minorities nor for older age groups, who are not investing in human capital as a margin of adjustment against robot exposure.

I instead find that middle-aged workers often enroll in Social Security Disability Insurance (SSDI) and claim disability benefits. This is the main margin of adjustment of whites aged between 35 and 44 years. These workers are unlikely to rejoin the labor force in the future, since only a small fraction of disability beneficiaries exits the program again (Liebman, 2015, Raut, 2017). I observe an increase in disability take-up also among racial/ethnic minorities, although this is not their primary adjustment margin.

The rising enrollment in SSDI is likely to be fueled by two channels. First, the labor market impact of robot exposure has a procyclical effect on workers' health (Schaller and Stevens, 2015), making them medically eligible for disability benefits (Frank et al., 2019). Second, displaced workers are misusing SSDI as an insurance against adverse shocks (Deshpande and Lockwood, 2021, Ford, 2015). While I cannot exclude the latter channel, I find that displaced prime-aged individuals who are exposed to robots do suffer from a deterioration of their physical and mental health. I do not find evidence of robot exposure affecting negatively the health condition of employed workers, suggesting that the labor market status is a crucial determinant of the impact of robots on health (Gihleb et al., 2022).

A plausible explanation for this result, which is supported by the data, is that for many US workers, the job loss is associated with losing health insurance. The inability to be treated by a doctor for cost reasons may substantially worsen the course of a disease (Lang et al., 2019) which, if neglected for too long, may become severe and require surgery, and eventually lead to a disability. In line with this mechanism, I find that robot exposure increases the hospitalization rates of patients with acute health issues, in particular those diagnosed with mental disorders that are common among disability beneficiaries, potentially justifying the rising disability take-up. I also find that robots increase the share of severe hospital admissions related to substance abuse, including alcohol, drug and tobacco abuse, which are often associated with mental disorders. These results are in line with the findings of Gihleb et al. (2022), who show that robots led to an increase in drug-related and alcohol-related deaths in the US.[47]

The impact of robots on non-participation becomes stronger with age. As the retirement age approaches, most of the displaced individuals drop out of the labor force and start claiming Social Security early retirement benefits or withdraw their pension plan income. In other words, they retire early.

Table 2.1 summarizes the relative contribution of the margins of adjustment discussed so far for the aggregate increase in non-participation. According to my estimates, almost eight percent of the non-participants enroll in college, 10.5 percent receive disability benefits, and nearly 40 percent retire early. These findings show that almost half of the non-participants do not fall in any of these categories, in particular among racial and ethnic minorities.

Table 2.1: Margins of adjustment of non-participants

College enrollment	Disability take-up	Early retirement	Reliance on household	Savings	Idle
[1]	[2]	[3]	[4]	[5]	[6]
7.7%	10.5%	39.3%	25.1%	14.3%	4.7%

Notes: This table illustrates the relative contribution of each margin of adjustment to the increase in non-participation after a displacement due to the introduction of robots. In terms of Equations 71, 72 and 73, each column reports the ratio between the coefficient of interest from a regression of the change in NP^{m}/ NP on robot exposure (and covariates). This clarification is useful when coming back to this table after reading the paper.

[47] Aside from the results on mental health problems related to substance abuse, Gihleb et al. (2022) focus on the impact of robots on workers (rather than on non-participants) and find that their adoption has reduced work-related injury rates, in particular at manufacturing firms. According to their estimates, between 2005 and 2011 the introduction of industrial robots saved the US economy $1.69 billion per year in injury costs.

I investigate two further (rather passive) margins of adjustment that may explain how displaced workers can afford not to work. First, I find that half of these non-participants live in households in which they can rely on income from other household members, such as their partner or their parents. This source of income is also important for non-participants who are enrolled in college. Second, a significant share of non-participants has earned some wage income in the previous 12 months, suggesting that they are likely to live off their savings, and that they have not been out of the labor force for too long. This could make them qualitatively more similar to unemployed individuals than to permanent labor force non-participants (Jones et al., 2002). These additional margins of adjustment are particularly popular among racial/ethnic minorities. Taken together with the previous results, they can explain where more than 95 percent of the displaced workers, who leave the labor force because of robots, end up.

The rest of the paper is organized as follows. Section 2.2 briefly summarizes the related literature. Section 2.3 describes the data. Section 2.4 presents the empirical strategy and challenges to identification. Section 2.5 reports results about the effect of robots on non-participation, while Section 2.6 investigates the margins of adjustment of displaced workers. Section 2.7 concludes.

2.2 Related literature

This paper contributes to the growing literature that studies the disruptive labor market impacts of automation. Although to date there is no general consensus on its aggregate implications on the labor market, the literature agrees on the fact that technological progress is rapidly changing the demand for skills and the nature of work (Acemoglu, 1999, Autor and Dorn, 2013, Goos et al., 2009, Goos and Manning, 2007, Katz and Murphy, 1992). Building on the stream of the literature that warns about the race of humans against machines (Acemoglu and Restrepo, 2018, Goldin and Katz, 2010), I investigate the question of where workers, who have presumably lost this race, end up. This paper further builds on the pioneering work by Acemoglu and Restrepo (2020), who show that industrial robots have reduced aggregate employment and wages in the US. I complement their work by providing a comprehensive assessment of the margins of adjustment of workers who leave the labor force because of robots, analyzing systematic differences in the adjustment across narrow demographic groups.

The adverse effects of robots on employment are less visible in Europe. In these countries, the displacement of workers from low-skill (Graetz and Michaels, 2018), routine task-intensive (De Vries et al., 2020) and manufacturing jobs (Dauth et al., 2021) has often been compensated by the employment growth in other occupations and industries.[48] However, it is important to account for the fact that even among European countries a fraction of the displaced workers may drop out of the labor force due to a skill mismatch with the newly created jobs (Grigoli et al., 2020), leaving open the question of where they end up, and suggesting that the findings of this paper are also interesting for Europe.

2.3 Data

This section describes the main data sources along with a set of descriptive statistics.

2.3.1 Industrial robots

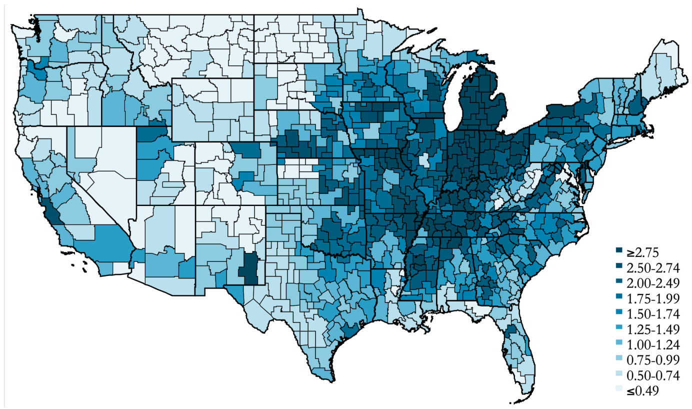
I obtain data on the adoption of robots from the International Federation of Robotics (IFR). The IFR is a survey that collects data about shipments and operational stocks of industrial robots by country, industry and year ranging back to 1993 for 50 countries. The IFR defines an industrial robot as an "automatically controlled, reprogrammable, multipurpose manipulator, programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications" (IFR, 2018, p.29). That is, industrial robots are machines that can be programmed to autonomously perform several manual tasks (e.g. assembly, material handling, packing and welding) without the intervention of a human worker. They are often designed as robotic arms and do not include conveyor belts, cranes or elevators, since these machines do not meet the above requirements.

The IFR breaks down the stock of operational robots according to the International Standard Industrial Classification (ISIC), Fourth Revision, and provides consistent data for six broad industries outside of the manufacturing sector (agriculture, forestry and fishing; construction; education, research and development; manufacturing; mining; utilities; and other non-manufacturing branches, such as services) and 13 industries within the manufacturing sector (automotive; basic metals; electronics; food and beverages; industrial machinery; metal products; minerals; paper and printing;

[48] These findings do not apply for France, as documented in Acemoglu et al. (2020) and Bonfiglioli et al. (2020).

plastics and chemicals; textiles; wood and furniture; other transport equipment (e.g. airplanes, locomotives and ships); and other manufacturing branches). These data are praised for their reliability and have been widely used in the literature. However, they include also some limitations that are addressed in Appendix B2.

Figure 2.2: US robot exposure at the CZ level



Notes: This figure illustrates the geographic distribution of US robot exposure (in robots per thousand workers) at the commuting zone level between 1993 and 2014.

Figure 2.1 shows that the stock of industrial robots has increased by about 1.5 robots per thousand workers in the US – a fivefold or roughly 180,000 units compared to its 1993 level. According to the International Federation of Robotics, this number is expected to grow even more in the future (IFR, 2018, pp.535-540). Industrial robots are mainly adopted in a subset of manufacturing industries, such as the automotive, electronic, plastic and chemical, and metal production industry (see Table B1 for details). This exposes the Midwest of the country significantly more to their deployment, especially the local labor markets of the Rust Belt (including the states of Indiana, Michigan and Ohio), due to their specialization in industrial manufacturing industries, a result that is visible in Figure 2.2.

2.3.2 Margins of adjustment

To measure long-term changes in local labor market outcomes contemporaneous to the introduction of industrial robots, I obtain data from the Integrated Public Use Microdata Series (IPUMS) of the decennial Census for 1970, 1980, 1990 and 2000, and the ACS for 2007 and 2014 (Ruggles et al., 2019).[49] These datasets are repeated cross-sectional surveys that include between 1 and 5 percent of the US population and provide a comprehensive set of information at the individual and household level, including the employment status, socio-demographic characteristics, income sources, and the place of residence of households and their members.[50]

An individual is considered to be out of the labor force if he or she is not employed and is not looking for work at the time the survey is conducted. Individuals are asked also about whether they have recently migrated, if they are attending school, they receive Social Security income, and their role in the household. I use these information in conjunction with their labor force status to determine the margins of adjustment of non-participants. I focus on the non-institutionalized population between 25 and 64 years of age. These individuals are above the usual full-time school age and below the full retirement age.[51]

I aggregate individual-level data at the labor market level using 722 Commuting Zones (CZs) that cover the entire US mainland and act as proxies of local labor markers (Tolbert and Sizer, 1996).[52] This aggregation allows me to build a measure of the labor force non-participation rate at the local labor market level:

$$\mathrm{NP}_{c,t} = \frac{L_{c,t}}{N_{c,t}} \tag{71}$$

where $L_{c,t}$ is the number of non-participants and $N_{c,t}$ is the working-age population in CZ c in year t. Then, I decompose the non-participation rate into population subgroups (using detailed information on individuals' socio-demographic characteristics) to identify the margins of adjustment of workers, when they drop out of the labor force:

$$\mathrm{NP}_{c,t} = \sum_m \mathrm{NP}^m_{c,t} = \sum_m \frac{L^m_{c,t}}{N_{c,t}} \tag{72}$$

[49] I follow the literature and increase the sample size of the ACS 2007 and 2014 samples using data from the 3-year sample of 2006-2008 and the 5-year sample of 2012-2016.

[50] Income sources include wages; Social Security income; business and farm income; welfare income (public assistance); or interest, dividend and rental income. Appendix B3 discusses the institutional background of the US Social Security and pension plan system, and points to some shortcomings in the data.

[51] In the US, the usual high school age goes from 14 to 18 years, while undergraduate college starts at 19 years until 22 to 23 years. The full retirement age starts at 66 or 67 years, depending on the year of birth.

[52] CZs represent economically relevant regions for labor markets and are formed by clusters of counties with strong commuting ties within CZs and weak commuting ties across CZs. The IPUMS provide county groups or Public Use Microdata Areas as lowest geographic units. Following Autor and Dorn (2013), I aggregate data at the CZ level using a crosswalk that provides a probabilistic matching of sub-state geographic units in US Census Public Use Files to CZs.

where $\text{NP}^m_{c,t}$ is the share of the population that is non-participant with margin of adjustment m (e.g. student, disability beneficiary, or early retiree).

Table 2.2: Descriptive statistics: Main variables

	All	US robot exposure 1993-2014 Q1	Q2	Q3	Q4
	[1]	[2]	[3]	[4]	[5]
Panel A: Labor force and margins of adjustment					
Men					
Non-participation rate (1990)	11.1	12.3	11.8	10.0	11.5
• Students	0.93	0.96	1.07	0.91	0.79
• Disability beneficiaries	1.35	1.53	1.35	1.20	1.52
• Early retirees	3.55	3.88	3.66	3.06	4.09
ΔNon-participation rate (1990-2014)	4.37	3.83	3.78	4.36	5.37
ΔNon-participation rate (1970-1990)	3.15	2.74	3.08	2.70	4.14
Women					
Non-participation rate (1990)	30.4	31.5	31.3	29.0	30.9
ΔNon-participation rate (1990-2014)	-2.70	-3.50	-2.90	-2.10	-3.20
Panel B: Robots and imports from China (1993-2014)					
US robot exposure	1.83	0.53	0.94	1.52	4.03
US import exposure	5.13	2.34	3.46	6.06	6.92
Panel C: Labor market covariates (1990)					
Demographics					
25–34 years	33.9	33.1	33.9	34.7	32.8
35–44 years	29.4	29.7	29.6	29.3	29.2
45–54 years	20.0	20.2	19.8	19.8	20.3
Black	10.9	12.1	11.2	11.5	9.19
White men	38.4	35.5	36.8	37.7	42.6
Hispanic	7.94	12.9	10.1	8.51	2.07
Women	51.1	51.1	51.2	51.0	51.3
Less than college	77.1	76.9	76.4	75.8	80.4
Log population	13.3	12.6	13.4	13.8	12.8
Same state of birth	54.8	40.5	49.4	54.9	67.5
Industries					
Construction	6.24	7.64	6.84	6.01	5.27
Manufacturing	24.4	12.7	19.0	26.5	32.7
Mining	0.99	2.93	1.29	0.55	0.54
Research	1.91	1.94	1.86	2.00	1.80
Services	63.0	69.8	67.0	62.1	56.6
Utilities	1.49	1.75	1.60	1.36	1.44
Occupations					
Offshorable	37.2	36.9	37.6	37.7	36.0
Routine	35.0	32.7	34.6	35.5	35.5
Observations	722	181	180	181	180

Notes: This table presents averages of the main variables used in the analysis, weighted by CZ population in 1990. Column 1 reports averages over all 722 CZs in the sample. Columns 2 to 5 split the sample into four quartiles, accounting for a labor market's exposure to robots between 1993 and 2014. Labor force participation indicators are expressed in terms of the working-age population of reference in the CZ, demographics are expressed in terms of the overall working-age population (except for log-population), and the industry and occupation covariates are expressed in terms of total CZ employment.

Table 2.2 shows that the US have been experiencing a significant rise in labor force non-participation of men over the last decades, increasing from 11.1 percent in 1990 to 15.3 percent in 2014 (a 40 percent increase). About eight percent of the non-participants are enrolled in college (0.93/11.1), one out of ten receives disability benefits from the SSDI, and almost one third receives some form of retirement income (pension plan income or Social Security early retirement benefits). Labor force non-participation of women decreased by 2.7 percentage points during this period of time (almost 10 percent).

Columns 2 to 5 split the sample into four quartiles based on a CZ's exposure to industrial robots and provide means of the main variables used in the analysis for the respective quartile. Results show that the increase in labor force participation of men is largest in CZs with a heavy utilization of industrial robots (5.37 percentage points), while there is no particular correlation between the decline in non-participation of women and robot exposure. Interestingly, male non-participation was already on an increasing trend since the 1970s in more exposed areas and, as illustrated in Panel B, these CZs are also highly exposed to import competition from China during my sample period. These observations highlight the potentially confounding impact of other ongoing labor market shocks, when analyzing the impact of industrial robots, especially in CZs that are intensive in the manufacturing industry (see Panel C), a threat to identification that I take into account in my empirical strategy.

2.3.3 Health

A potential margin of adjustment against robot exposure is disability enrollment. However, it is not clear whether an increase in disability take-up is associated with a deterioration in the health condition of displaced workers, or whether individuals are misusing the SSDI as a sort of permanent unemployment insurance. I investigate this question by supplementing labor market data with indicators on mental and physical health conditions at the CZ level from the Behavioral Risk Factor Surveillance System (BRFSS) of the Centers for Disease Control and Prevention (CDC) and the National Inpatient Sample (NIS) of the Healthcare Cost and Utilization Project (HCUP) for 1993, 2000, 2007 and 2011.[53]

The BRFSS is a health-related telephone survey that collects 400,000 adult interviews each

[53] After 2011, the BRFSS and NIS datasets do not provide geographic indicators that allow me to identify observations at the CZ level.

year on health-related risk behaviors, chronic health conditions, and the use of preventive services. For each individual, I have information on basic demographics, labor force status, self-reported health, smoking and drinking habits, body height and weight, physical activity, healthcare coverage and the use of healthcare services. Respondents are also asked about their physical and mental health condition, and report whether they suffered from physical illness or injuries, or from stress, depression or problems with emotions in the 30 days prior to the interview.

The NIS collects information on hospital stays each year using a 20-percent stratified sample of discharges from US community hospitals. For each discharge, I observe information on up to 15 diagnoses using classification codes from the International Classification of Diseases, Ninth Revision (ICD-9). I follow the Centers for Disease Control and Prevention (2009) and group ICD-9 codes into the most common causes of disability (arthritis and rheumatism; back and spine problems; circulatory system diseases; respiratory system diseases; mental disorders; and diabetes) and into other conditions that are not directly related to a disability. A detailed description of the data is provided in Appendix B2.

2.4 Empirical strategy

I estimate the effect of robots on the margin of adjustment of non-participants using a stacked first-difference specification with 722 CZs and three time periods (1993-2000, 2000-07, 2007-14).[54,55] The key estimating equation is given by:

$$\Delta \mathrm{NP}^{m}_{c,(t_0,t_1)} = \beta^m \,\text{US robot exposure}_{c,(t_0,t_1)} + \mathbf{X}'_{c,(t_0,t_1)}\mathbf{\Gamma}^m + \varepsilon^m_{c,(t_0,t_1)} \tag{73}$$

where $\Delta \mathrm{NP}^{m}_{c,(t_0,t_1)}$ is the change in the share of the population of CZ c that is non-participant with margin of adjustment m. To account for potential sources of bias that might confound the estimates of the labor market effect of robots, Equation 73 includes also year fixed effects, US Census

[54] Since I use data on labor market outcomes from the 1990 Census and health outcomes from the BRFSS and NIS that range only up to 2011, I rescale the 1990-2000 and 2007-11 periods to 7-year equivalent changes to achieve comparability across periods.

[55] It is documented that the 2000 Census measures lower employment levels than the CPS for that year, and the extent of this issue varies across geography. However, measurement error is unlikely to be correlated with the instrument, since, as described below, the exogenous shift-share measure of robot exposure uses employment shares of the 1970s. To address this issue further, I account for division × year fixed effects in all specifications, and I illustrate the main results using a long-difference specification from 1993 to 2014 in Appendix B4.

division trends, pre-existing trends in US labor force participation and manufacturing employment, a measure of the China trade shock (Autor et al., 2013), and a vector of start-of-sample-period regional characteristics and economic variables (gender, race, ethnicity, education, age, state of birth, population, industry and occupation composition).[56] I keep CZ characteristics constant at their 1990 levels to avoid contamination by endogenous adjustments in the structure of local labor markets in response to robot adoption. Further details about covariates are provided in Table 2.2 and in Appendix B2.

I build a measure of robot exposure at the CZ level using a shift-share approach. I follow Acemoglu and Restrepo (2020) and match industry-level data from the IFR with employment counts from the Census:

$$\text{US robot exposure}_{c,(t_0,t_1)} = \sum_{j \in J} \ell_{c,j}^{1990} \left[\frac{R_{j,t_1}^{US} - R_{j,t_0}^{US}}{L_{j,1990}^{US}} - g_{j,(t_0,t_1)}^{US} \frac{R_{j,t_0}^{US}}{L_{j,1990}^{US}} \right] \tag{74}$$

The term in brackets (shift-component) is a measure of industrial robot density, computed as the US wide change in the stock of robots in industry $j \in J$, relative to its workforce in 1990, and adjusted for the adoption of robots that is driven by overall industry output growth, $g_{j,(t_0,t_1)}^{US} = \Delta \ln(Y_{j,t}^{US})$.[57] The industry-level shock is apportioned across local labor markets using CZs' industry employment shares, $\ell_{c,j}^{1990} = L_{c,j}^{1990}/L_c^{1990}$. The baseline employment shares are kept constant to avoid endogeneity and serial correlation concerns across periods of my stacked first-difference specification.

Identification builds on the assumption that advances in robotics vary by industry and expose CZs differently depending on the industrial composition of employment. The adoption of robots, however, is likely to be correlated also with local labor market conditions that affect the demand for labor and, therefore, labor force participation rates. For instance, positive demand shocks might induce US firms to raise both capital and employment, biasing the estimates of the effect of robots on labor demand upwards.

To address the endogeneity concern and identify robot adoption that is driven by the supply

[56] Census divisions are administrative divisions of the US territory into nine groups of states: New England, Middle Atlantic, South Atlantic, East North Central, East South Central, West North Central, West South Central, Mountain and Pacific.

[57] The IFR estimates the operational stock of robots using the sum of robot installations in the previous 12 years. I stress this assumption in Appendix B4, and construct measures of the stock of robots based on yearly shipments using the perpetual inventory method at different depreciation rates.

channel, I instrument the shift-component of Equation 74 using contemporaneous changes in the stock of robots in seven European countries with a comparable adoption of robots as the US:

$$\text{EU7 robot exposure}_{c,(t_0,t_1)} = \sum_{j \in J} \ell_{c,j}^{1970} \frac{1}{7} \sum_{i \in EU7} \left[\frac{R^i_{j,t_1} - R^i_{j,t_0}}{L^i_{j,1990}} - g^i_{j,(t_0,t_1)} \frac{R^i_{j,t_0}}{L^i_{j,1990}} \right] \tag{75}$$

where $R^i_{j,t}$ is the stock of robots in country $i \in EU7$ at time t in industry j. $EU7$ countries include Denmark, Finland, France, Italy, Spain, Sweden and the United Kingdom.[58] The share-component uses (plausibly exogenous) employment shares from 1970 to focus on the industrial composition of employment that precedes the introduction of industrial robots, which started in the 1980s (Acemoglu and Restrepo, 2020).

The IV strategy aims at identifying the labor market effects of exogenous improvements in robotics available to US firms. The strategy relies on the assumptions that the adoption of robots in European countries is positively related to the adoption of robots in the US, but it is unrelated to domestic labor market conditions. The first condition can be easily verified (see first-stage results in Table 2.3), while I discuss possible threats to identification related to the exclusion restriction in Appendix B4. Reassuringly, the empirical results are robust and outlive a variety of tests, including checks for international product market competition from Europe, industry trends (Goldsmith-Pinkham et al., 2020), and labor market pre-trends.

2.5 Robots and non-participation

I start the analysis by presenting the impact of robot exposure on US labor force non-participation. Table 2.3 reports OLS and IV estimates, as well as first-stage results.[59] The coefficients are standardized and represent the estimated labor market effect of a one standard deviation increase in robot exposure.[60] Regressions are weighted by the 1990 CZ population and standard errors allow

[58] The instrument purposely does not include the countries with the world's heaviest adoption of industrial robots, namely South Korea, Germany, and Japan. These countries are also among the main trading partners of the US and could directly affect US labor market conditions through their national adoption of robots.

[59] Estimates of the effect of robot adoption on other labor market outcomes, including total employment, manufacturing employment and unemployment are reported in Table B2.

[60] A one standard deviation increase of US robot exposure corresponds roughly to its average increase during a sample period.

for arbitrary clustering at the state level.[61,62]

Table 2.3: Robots and non-participation

	Population				Men	Women
	[1]	[2]	[3]	[4]	[5]	[6]
	Panel A: OLS results					
US robot exposure	0.195**	0.191**	0.169***	0.092***	0.181***	0.006
	(0.076)	(0.073)	(0.056)	(0.034)	(0.035)	(0.035)
	Panel B: IV results					
US robot exposure	0.224**	0.242**	0.237***	0.192***	0.346***	0.045
	(0.093)	(0.095)	(0.085)	(0.063)	(0.072)	(0.062)
	Panel C: First-stage					
EU7 robot exposure	0.773***	0.792***	0.787***	0.740***	0.740***	0.740***
	(0.055)	(0.044)	(0.055)	(0.049)	(0.049)	(0.049)
Kleibergen-Paap F stat	197.7	326.4	115.4	117.6	117.6	117.6
Observations	2166	2166	2166	2166	2166	2166
Covariates:						
Divisions	✓	✓	✓	✓	✓	✓
Years	✓	✓	✓	✓	✓	✓
Pre-trends		✓	✓	✓	✓	✓
Chinese imports			✓	✓	✓	✓
Demographics				✓	✓	✓
Industries				✓	✓	✓
Occupations				✓	✓	✓

Notes: This table presents IV estimates of the effect of US robot exposure on the non-participation rate at the CZ level. Changes are expressed in percentage points of the working-age population and are multiplied by 100. Independent variables are standardized to have mean zero and standard deviation of one. There are three time periods and 722 CZs. Column 1 includes year dummies, nine census divisions and their interactions. Column 2 includes also changes in the non-participation rate and in the manufacturing employment rate between 1970 and 1990. Column 3 includes a measure of exposure to Chinese imports. Column 4 controls also for demographic (share of individuals aged between 25 and 34 years, 35 and 44 years, 45 and 54 years, the share of white men, Blacks, Hispanics, women, individuals born in the same US state of their current residency, and individuals with less than a college degree and logarithmic population), industry (shares of employment in the construction, manufacturing, mining, research, service and utilities sector) and occupation (share of offshorable and routine task-intensive occupations) characteristics of CZ in 1990. Columns 5 and 6 report estimates of the effect for men and women separately. Standard errors are robust against heteroskedasticity and allow for clustering at the state level. Regressions are weighted by CZ population in 1990. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Column 1 presents a baseline specification which accounts only for division-specific business cycles. The following columns include further covariates that might confound the labor market effect of robots. The IV coefficients are not affected neither in size nor in significance by the inclusion of these controls. The absolute size of OLS estimates is smaller than that of IV estimates across all specifications, since US robot adoption is likely to be correlated with omitted demand

[61] As outlined in Cadena and Kovak (2016), when examining outcomes across labor markets of different sizes, efficient weights must consider individuals' sampling weights to account for inherent heteroskedasticity. They show that optimal weights are strongly correlated with initial population sizes and therefore are well approximated by the initial population of a local labor market.

[62] In Appendix B4, I show that the results do not change when clustering at the industry level à la Borusyak et al. (2021), and at the division level to account for potential correlations across CZs resulting from other industry or region shocks.

shocks that bias the estimates towards zero.

In line with the findings of Acemoglu and Restrepo (2020), results show that robots have an adverse impact on US labor markets. On average, a one standard deviation increase in robot exposure decreases labor force participation by 0.192 percentage points, which translates into a decrease in the local labor force of about four workers for each additional robot.[63] In Column 5, I show that this effect is fully driven by men. The magnitude of this result suggests that the introduction of robots between 1993 and 2014 has had an impact on the labor force non-participation rate of men that is equivalent to about 18 percent of its secular increase.[64] Although women are affected negatively in their job prospects too (see Table B2), there is no evidence that robots are affecting their labor force participation rate.[65] In the subsequent analysis, I therefore focus on the margins of adjustment of men (Column 5).[66,67]

Migration – The literature on regional shocks would expect workers' geographic mobility to be one of the key channels through which labor markets adjust to local economic shocks (Blanchard and Katz, 1992, Howard, 2020). I address this potential margin of adjustment by analyzing the impact of the introduction of robots on internal migration flows across CZs in Table 2.4. Columns 3 and 4 show that robots trigger a significant reduction in the inflow of individuals to exposed areas both from outside and within the state (although the latter is noisily estimated). However, there is no evidence of them affecting migration outflows from these CZs (Columns 1 and 2). These findings suggest that internal migration does not constitute a margin of adjustment of workers who have been displaced (Foote et al., 2019, Notowidigdo, 2020, Yagan, 2019), but that robot exposure affects the behavior of prospective migrants (Faber et al., 2022, Monras, 2018).

This finding raises the possibility of robots changing the composition of the population in a CZ

[63] This number is obtained by de-standardizing the effect of robot exposure from Table 2.3 using the standard deviation of the variable expressed in robots per thousand workers from Table B17. This results in the estimated effect in terms of robots per thousand workers ($0.192/0.491 = 0.391$ percentage points). I use US population statistics from the IPUMS and robot adoption from the IFR to estimate the average effect of one additional robot on the size of the labor force.

[64] I compute this number by de-standardizing the coefficient from Column 5, and dividing it for the adjusted secular increase in labor force participation of men from Table 2.2 ($0.346/0.491 \times 1/4.37 \times 24/21$).

[65] Acemoglu and Restrepo (2020) analyze the effect of robot exposure on employment and wages, finding that they are fueled both by men and women. However, they do not investigate the gender-specific effects on non-participation which, as it turns out, are driven exclusively by men.

[66] The purpose of this paper is to investigate the margins of adjustment of workers who drop out of the labor force, with focus on partial equilibrium effects. For a discussion about the general equilibrium effects of robot exposure on non-participation, see Appendix B5.

[67] I provide a set of robustness checks in support of my preferred specification, including controls for industry trends, pre-trends, confounding labor market shocks, and alternative outcomes and covariates, in Appendix B4.

Table 2.4: Internal migration and non-participation by origin

	Migration				Non-participation		
	Outflows		Inflows		Birthplace		
	Same state	Other state	Same state	Other state	Same state	Other state	Foreign country
	[1]	[2]	[3]	[4]	[5]	[6]	[7]
US robot exposure	0.030 (0.101)	-0.048 (0.105)	-0.151* (0.076)	-0.133 (0.088)	0.299*** (0.049)	0.346*** (0.068)	0.399** (0.163)
Observations	2166	2166	2166	2166	2166	2166	2166
Covariates:	✓	✓	✓	✓	✓	✓	✓

Notes: This table presents IV estimates of the effect of US robot exposure on migration flows across CZs, both within and outside of the state, as well as non-participation rates by state of birth. I compute outflows (inflows) in Columns 1 and 2 (Columns 3 and 4) as the share of individuals who migrated away from (to) a CZ. The denominator equals the population in their CZ of residence before (after) moving. Note that the information about individuals' migration status changes over time. In particular, the Census asks whether a person changed its residence in the previous 5 years, while the ACS asks whether a person changed its residence in the previous year. I follow Molloy et al. (2011) in building measures of 5-year migration flows from the ACS by using four times the annual migration flow of a CZ. I compute non-participation rates in Columns 5, 6 and 7 as the number of non-participants of a particular group divided by the population of reference of this group. For instance, Column 5 is computed as the number of non-participants in a CZ born in the same state of their current residency divided by the population of the CZ born in the same state of their current residency. All regressions include the full battery of controls from my preferred specification. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

by mechanically increasing the share of non-participants through the lack of incoming workers. I account for this concern by restricting the population to individuals born in the same US state as their current residence (Column 5). This approach should provide more confidence in the interpretation of labor force participation changes reflecting changes in individuals' behavior rather than changes in the composition of local labor markets, since this sample of the population is not affected by internal migration flows (at least across states). Unfortunately, the Census/ACS do not provide more granular information about the birthplace of individuals.

Results show that the increase in non-participation among the share of the population that lives in its state of birth is not economically nor statistically different from my preferred specification's estimates. For completeness, Column 6 and 7 include also the labor force participation rates of individuals born in another US state or in a foreign country, showing that the introduction of robots has increased the non-participation rate among these groups in similar proportions.

Demographics – To understand the underlying causes that drive individuals out of the labor force (rather than to migrate), it is important to consider that robots might influence individuals' labor supply decisions differently based on their socio-demographic characteristics. For this purpose, I break down the estimated effect of robots on non-participation of men by race and ethnicity (whites and racial/ethnic minorities), age groups (25-34, 35-44, 45-54 and 55-64 years) and education levels (college-educated and less educated).[68] This is achieved by using an analogous decomposition exercise to Equation 72, but by using demographic groups $g \in G$ instead of margins of adjustment $m \in M$:

$$\mathrm{NP}_{c,t} = \sum_g \mathrm{NP}^g_{c,t} = \sum_g \frac{L^g_{c,t}}{N_{c,t}} \tag{76}$$

where $\mathrm{NP}^g_{c,t}$ is the share of the population that is non-participant with demographic characteristics g. Whites include individuals who, when asked about their race and ethnicity in the Census, report to be "White" and of no "Hispanic, Latino, or Spanish" origin. Racial and ethnic minorities include all demographic groups who are either not white (e.g. Blacks, Asians, American Indian and Alaska natives), or are of Hispanic, Latino, or Spanish origin.

Table 2.5: Robots and non-participation: Breakdown by demographics

	Whites				Racial and ethnic minorities			
	25-34	35-44	45-54	55-64	25-34	35-44	45-54	55-64
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
	Panel A: College degree or more							
US robot exposure	0.012***	0.004**	0.000	0.011	0.001	-0.000	-0.002	0.007***
	(0.003)	(0.002)	(0.003)	(0.008)	(0.004)	(0.003)	(0.003)	(0.002)
% of total effect ($\beta^g/\beta \times 100$)	3.46	1.15	0.00	3.17	0.29	0.00	-0.58	2.02
% of population ($N^g/N \times 100$)	6.76	7.73	4.55	3.04	1.27	1.18	0.65	0.31
	Panel B: Less than a college degree							
US robot exposure	0.010	0.018**	0.030***	0.094***	0.027	0.050*	0.047***	0.037***
	(0.007)	(0.008)	(0.010)	(0.009)	(0.029)	(0.025)	(0.012)	(0.011)
% of total effect ($\beta^g/\beta \times 100$)	2.88	5.19	8.64	27.09	7.78	14.41	13.54	10.66
% of population ($N^g/N \times 100$)	19.03	15.65	11.55	10.37	7.29	5.11	3.20	2.29
Observations	2166	2166	2166	2166	2166	2166	2166	2166
Covariates:	✓	✓	✓	✓	✓	✓	✓	✓

Notes: This table presents IV estimates of the effect of robot exposure on the male non-participation rate by education, age, and race/ethnicity. Percentages of the total effect are computed by dividing the estimates of the effect within each demographic subgroup by the estimates of the effect on the working-age population of men (Column 5 of Table 2.3). The key estimating equation is given by $\Delta\mathrm{NP}^g_{c,(t_0,t_1)} = \beta^g$ US robot exposure$_{c,(t_0,t_1)} + \mathbf{X}'_{c,(t_0,t_1)}\mathbf{\Gamma}^g + \varepsilon^g_{c,(t_0,t_1)}$, and includes the full battery of controls from my preferred specification. For convenience, in the following I also write down $\Delta\mathrm{NP}_{c,(t_0,t_1)}$ as $\Delta\mathrm{NP}_{c,t}$ for all superscripts g and m. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level. Average shares of population subgroups are computed for 1990. Between 1990 and 2014, the share of the population with a college degree, the share of racial/ethnic minorities, and the share of individuals between 55 and 64 years have increased.

Using my preferred specification, Table 2.5 illustrates the relative contribution of each group to the aggregate effect of robots on non-participation. Results show that the increase in non-participation is fueled in equal proportions by whites and racial/ethnic minorities (51.6 and 48.4

[68] The less educated group includes high school and undergraduate college dropouts, individuals who have achieved at most a high school diploma, and students that are enrolled in college, but who have not achieved an undergraduate degree.

percent), and that it is caused predominantly by less educated workers (only ten percent of the non-participants have a college degree). This result is in line with previous literature which argues that college-educated workers are often employed in occupations that require the use of communication and interpersonal skills that are more difficult to automate (Acemoglu and Autor, 2011). However, this effect is also mechanically small due to the relatively low share of the population with a college degree ($N^g_{c,t}/N_{c,t}$ never exceeds 32 percent in my sample period, with g being "college education"). The same reasoning applies to racial and ethnic minorities (who make up less than 36 percent of the population). Finally, the impact of robots on labor force dropouts increases (not monotonically among each group) with age (individuals aged between 55 and 64 years account for 40 percent of the overall increase in non-participation). Again, this result is likely to be subject to underlying composition effects, such as population aging, and due to older individuals having lower labor force participation rates.

To clean out these effects from my results, I analyze changes in the non-participation rate within population subgroups. This is achieved by multiplying and dividing $\mathrm{NP}^g_{c,t}$ by the population count of each demographic group $N^g_{c,t}$:

$$\mathrm{NP}^g_{c,t} = \frac{N^g_{c,t}}{N_{c,t}} \underbrace{\frac{L^g_{c,t}}{N^g_{c,t}}}_{\mathrm{NP}^{\dot{g}}_{c,t}} \tag{77}$$

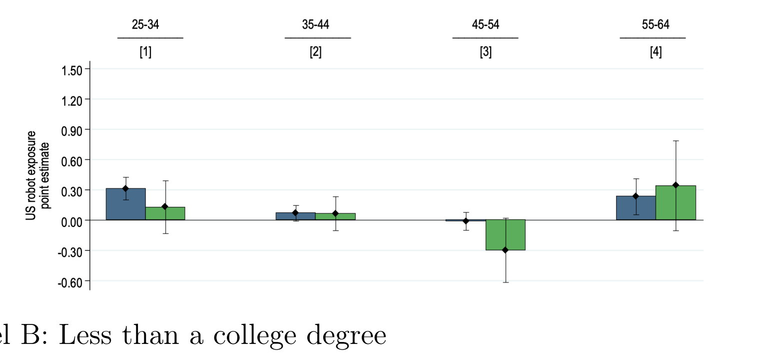
As a result, Equation 77 provides a measure of the non-participation rate within demographic groups, $\mathrm{NP}^{\dot{g}}_{c,t}$. The impact of robot exposure on demographic-specific non-participation rates is illustrated in Figure 2.3.[69]

When accounting for the relative population size of demographic groups, the adverse effect of robots on the non-participation rate of racial and ethnic minorities stands out. The increase is more than twice that of whites. This result follows from the fact these workers are often over-represented in blue-collar jobs with a high workload of manual tasks which are more susceptible to automation through industrial robots (Lerch, 2021). The only demographic group that seems to benefit from the adoption of robots are non-whites aged between 45 and 54 years. Figure B1 shows that the decrease in labor force non-participation of this group is associated with an increase in employment.

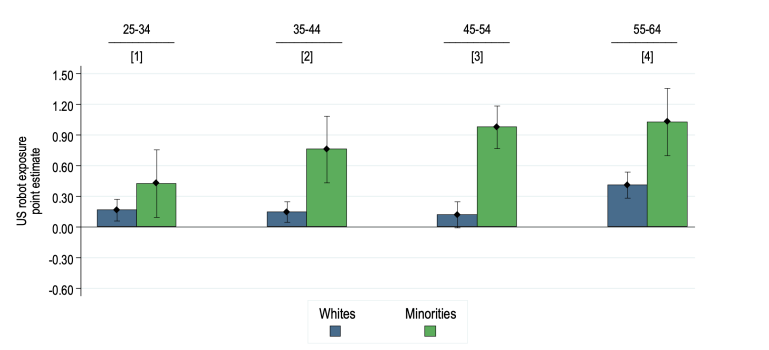
[69] For clarification, Table 2.5 shows that a one standard deviation increase in robot exposure increase the share of white non-participants with a college degree who are aged between 25 and 34 years in the total population by 0.012 percentage points, while Figure 2.3 shows that within the population group with these demographic characteristics, the non-participation rate increases by about 0.3 percentage points.

Figure 2.3: Robots and non-participation within demographic groups

Panel A: College degree or more



Panel B: Less than a college degree



Notes: This figure illustrates the IV point estimates of the effect of US robot exposure on non-participation by race/ethnicity, age and education ($\Delta \mathrm{NP}^{\hat{g}}_{c,t}$). Regressions include the full battery of controls from my preferred specification and are weighted by CZ population in 1990. Confidence intervals are at the 95% level.

2.6 Where have all the workers gone?

Let's now turn to the question of where individuals end up, when they leave the labor force after the introduction of robots. The following analysis uses Figure 2.3 to identify the margins of adjustment of non-participants that prevail within each demographic group.

2.6.1 College enrollment

A potential margin of adjustment, in particular among individuals in their early prime-age, is the accumulation of additional human capital through the enrollment in college. In fact, individuals may respond to negative labor demand shocks by enrolling in school due to lower opportunity cost of being out of the labor force. This question has also occupied the previous literature, which finds that adverse shocks have contributed to the rising high school graduation and college enrollment rates in the US.[70] Related to this paper, Di Giacomo and Lerch (2021) show that robot adoption has increased enrollment in US community colleges, and Dauth et al. (2021) show that robots have increased the share of college graduates in Germany, at the expense of the share of workers who completed an apprenticeship. Although these results provide important evidence that automation increases the level of education among young workers, the consequences that these educational choices have for the attachment to the labor force – and to which extent college enrollment contributes to the increase in non-participation – are still unclear.

This section addresses these questions by investigating whether the decline in labor force participation is fueled by individuals who leave the labor force temporarily or who delay their labor market entry to enroll in post-secondary education institutions. For this purpose, I apply the decomposition exercise from Equation 72 to the demographic-specific non-participation rate ($\mathrm{NP}_{c,t}^{\dot{g}}$) shown in Figure 2.3, and I differentiate between non-participants who are enrolled in school (m_1) and those who are not (m_0). Specifically,

$$\mathrm{NP}_{c,t}^{\dot{g}} = \mathrm{NP}_{c,t}^{\dot{g},m_1} + \mathrm{NP}_{c,t}^{\dot{g},m_0} \tag{78}$$

where $\mathrm{NP}_{c,t}^{\dot{g},m} = L_{c,t}^{g,m}/N_{c,t}^{g}$.

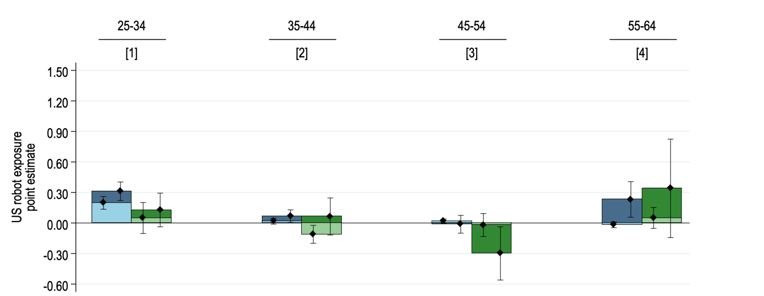
I define school enrollment as schooling which leads to a high school diploma, a college degree or a graduate degree. School attendance identifies whether an individual is completing a schooling degree or, after completing it, continues with a higher degree. It does not include enrollment in a trade or business school, company training, or tutoring unless the course would be accepted for credit at a regular college. Figure 2.4 illustrates the results.

I find that schooling is the main margin of adjustment for white non-participants who already have a college degree and who are aged between 25 and 34 years. These individuals are either delaying their labor market entry or they are temporarily leaving the labor force to enroll in graduate

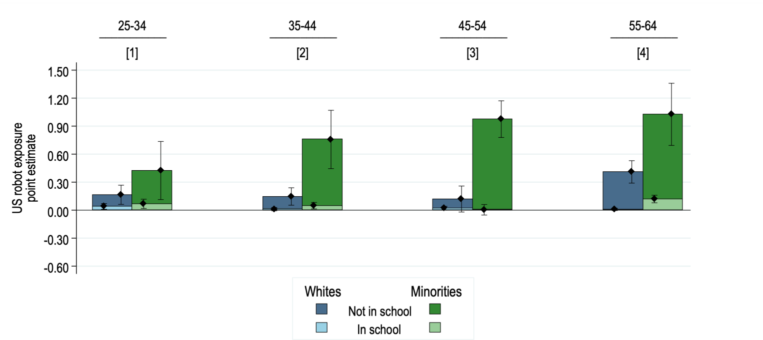
[70] In particular, research has focused on the impacts of business cycle fluctuations (Foote and Grosz, 2020, Weinstein, 2020), trade competition (Greenland and Lopresti, 2016) and immigration (Hickman and Olney, 2011, Hunt, 2017).

Figure 2.4: College enrollment

Panel A: College degree or more



Panel B: Less than a college degree



Notes: This figure illustrates the IV point estimates of the effect of US robot exposure on non-participation by age and education, and decomposes them by school enrollment ($\Delta \mathrm{NP}^{\dot{g},m}_{c,t}$). Regressions include the full battery of controls from my preferred specification and are weighted by CZ population in 1990. Confidence intervals of the estimates on non-participants who are enrolled in school (left CI) and those who are not in school (right CI) are at the 95% level.

or professional schools to increase their competitiveness in the labor market.[71] Figure B2 shows that they have been employed (at least some time) in the previous five years, but that they have not been working in the previous 12 months.

At this point, one may worry that students are moving across CZs to enroll in college, and hence that migrants may not have been affected by the shock in the college's CZ, but by the shock in the CZ in which they grew up. Di Giacomo and Lerch (2021) address this concern and show that the mobility of students is not affecting the results, and that the effect of robots on college enrollment

[71] Figure B2 shows that a minority of the non-participants are PhD or undergraduate students, while nobody is enrolled in high school. This result is fairly different from the findings of Di Giacomo and Lerch (2021), as it focuses exclusively on non-participants. According to their estimates, these individuals account for only one third of the overall increase in college enrollment due to the introduction of robots, with the remaining ones being either unemployed or employed in part-time jobs. Moreover, a significant share of their finding on community college enrollment stems from individuals aged between 19 and 24 years, who are not included in my population sample. Finally, their sample includes men and women, while the analysis of the margins of adjustment of workers focuses on men.

is driven by students who enroll in a school which is located in their CZ of origin.[72]

Although I observe also an increase in schooling among non-white and less educated non-participants, this effect is rather small and does not constitute their main margin of adjustment against robot exposure. Figures B2 and B3 show that a significant share of these individuals does not even have a high school diploma, and that the effect on schooling is driven by individuals who are likely to be pursuing a GED.[73]

Figure 2.4 further shows that there is no evidence of an increase in college enrollment after the age of 35 years. This finding suggests that this effect is limited to individuals in their early prime age, since they have the most to gain from additional human capital, given their long career horizon (and many of them not being financially independent). Older workers are instead leaving the labor force for reasons that are discussed in the next sections.

2.6.2 Disability take-up

There is evidence that labor demand shocks and poor labor market conditions are significantly affecting disability take-up in the US (e.g. Autor et al., 2013, Black et al., 2002, Maestas et al., 2015). The fraction of disability claims that is related to hard-to-verify impairments has risen substantially over the last decades (Autor and Duggan, 2003, Liebman, 2015), suggesting that SSDI could be misused as a sort of permanent unemployment insurance against adverse shocks (Deshpande and Lockwood, 2021, Ford, 2015).[74]

Other empirical work argues that poor labor market conditions could also have a direct impact on workers' health (Hollingsworth et al., 2017), and that poor health is one of the main reasons for individuals not to join the labor force (Krueger, 2017, Parsons, 1980a,b). Evidence shows that the high job insecurity during periods of poor labor market conditions and the exposure to trade shocks during the 2000s led to a substantial increase in mental health problems among working-age Americans (Adda and Fawaz, 2020, Lang et al., 2019, Pierce and Schott, 2018), with the strongest

[72] Table B3 also shows that the results are robust to the inclusion of controls that account for the local supply of educational institutions (e.g. public, non-profit and community colleges), which could confound the decision of individuals to leave the labor force to enroll in college in response to robot exposure.

[73] The General Educational Diploma (GED) is a high school equivalent diploma that is designed for individuals who have not completed high school. The GED can be used to apply to college or for a job resume, just like a traditional high school diploma.

[74] There is no general consensus on this result though. Mueller et al. (2016), for example, find no indication that the expiration of unemployment benefits has caused an increase in disability applications during the Great Recession period.

deterioration in health conditions among white males (Case and Deaton, 2015, 2017).[75]

This section investigates whether the decline in labor force participation is fueled by individuals who leave the labor force permanently to enroll in disability insurance, and analyzes whether robot exposure affects also workers' health conditions directly, increasing the share of the population that qualifies for SSDI. Acemoglu and Restrepo (2020) provide evidence of an increase in social benefits in exposed areas, including Social Security, TAA, and unemployment benefits. However, it remains unclear to which extent this increase is related to disability take-up of new non-participants, and how they are related to individuals' health conditions.

I start by breaking down the increase in non-participation from Figure 2.3 into non-participants who receive Social Security income (disability or retirement benefits), non-participants who exclusively withdraw income from their pension plans, and non-participants without any Social Security or pension plan income (these margins can be denominated with m_1, m_2 and m_0). This distinction allows me to identify the share of non-participants who respond to the automation shock by enrolling in disability insurance. Before 62 years of age, non-participants may claim Social Security income in form of disability benefits from the SSDI program.[76] After 62 years, they become eligible also for Social Security early retirement benefits. The point estimates of the effect of robots on the change in non-participation by income source, age and education level are illustrated in Figure 2.5.

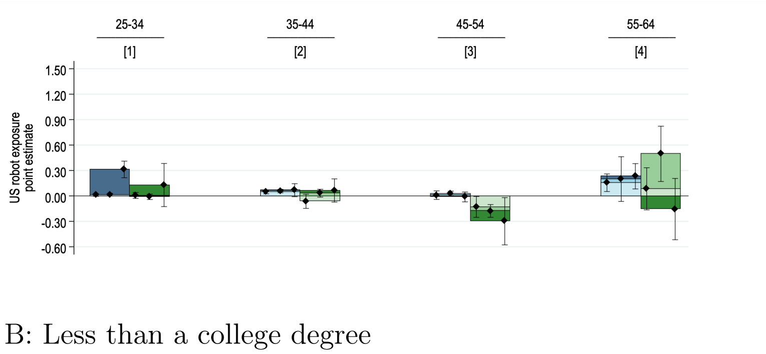
Let's first focus on middle-aged individuals. As we know from previous results, the impact of robots is weakest among white individuals in this age range. Although relatively small (but significant), the increase in non-participants with a college degree between 35 to 44 years is almost fully driven by SSDI beneficiaries. Interestingly, Figure B4 shows that only few of them claim also Supplemental Security Income (SSI), suggesting that even if they are not working anymore, based on their income and resources, they do not qualify for additional financial support from the Social

[75] These papers mostly use data from 1990 onward and find that poor labor market conditions and the job loss have a negative impact on people's mental health conditions (Browning and Heinesen, 2012, Eliason and Storrie, 2009, Sullivan and Von Wachter, 2009). In contrast, using US health data from the 1970s to the 1990s, scholars argue that the relationship between health problems and recessions is mostly countercyclical (Miller et al., 2009, Ruhm, 2000, 2003). These findings are expected to result from rising opportunity cost of time and less leisure time during economic upturns.

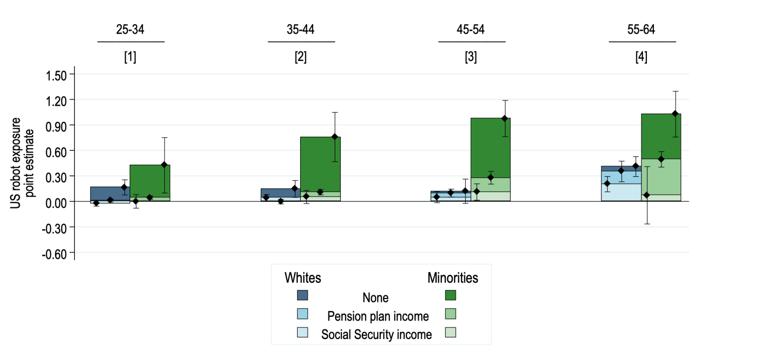
[76] To be precise, from the age of 60 years, widows or widowers may also claim Social Security survivor benefits. The adoption of robots could influence the number of survivor benefit recipients, if it affects the mortality rate of spouses of male non-participants. Since I find a weaker impact of robots on employment and an insignificant impact on labor force participation of women, I feel comfortable in excluding this potential causal link. Therefore, I assume that the change in Social Security beneficiaries before the age of 62 years reflects the change in disability benefit recipients. Appendix B3 provides further details on the Social Security system in the US.

Figure 2.5: Social Security and pension plan income

Panel A: College degree or more



Panel B: Less than a college degree



Notes: This figure illustrates the IV point estimates of the effect of US robot exposure on non-participation by age and education, and decomposes them by Social Security and pension plan income ($\Delta \text{NP}^{\hat{g},m}_{c,t}$). Regressions include the full battery of controls from my preferred specification and are weighted by CZ population in 1990. Confidence intervals for Social Security beneficiaries (left CI), pension plan income beneficiaries (middle CI), or for non-participants without any income from these sources (right CI) are at the 95% level.

Security Administration.

I find that also among less educated whites between 35 and 54 years there is a statistically significant increase in disability take-up. This margin of adjustment explains about one third of their increase in non-participation. Disability take-up seems to play a minor role for non-whites. Although a significant share of them is enrolling in disability insurance, this increase cannot explain the strong rise in non-participation of this demographic group. In contrast with the finding for whites, Figure B4 shows that a significant share of racial and ethnic minorities receives SSI, in particular less educated non-participants between 45 and 54 years.

From the age of 55 years, I observe a sharp increase in non-participants who receive Social Security or pension plan income. This increase reflects the fact that Social Security income includes early retirement benefits for individuals aged more than 62 years, and penalties on early withdrawals of pension plan income are often waived from the age of 55. I discuss these results in the next section, when analyzing the impact of robots on early retirement. Finally, I find that young non-participants do not enroll in disability insurance. This result is mainly driven by the fact that these workers have not paid enough Social Security taxes to be eligible for disability benefits.

The observed rise in disability take-up of prime-age workers after a displacement through robots may be fueled by two channels. First, SSDI acts as a sort of permanent unemployment insurance against the risks of automation and worse future job prospects. Second, adverse shocks affect the health condition of workers who, as a consequence, become eligible for disability benefits. While I cannot exclude that non-participants are misusing SSDI as an insurance against adverse labor market shocks (Deshpande and Lockwood, 2021), I show that the increase in disability take-up comes along with an increase in disability-related physical and mental impairments.

Health conditions – Table 2.6 reports estimates of the labor market effect of robot exposure on self-reported health conditions, smoking and drinking habits, physical shape, and access to healthcare services among non-employed individuals using data from the BRFSS. Table B4 reports the same health results for employed workers and the entire population.[77]

I find that the exposure to robots increases regular drinking behavior and decreases physical activity, raising the share of non-employed individuals who suffer from obesity, in particular among whites.[78] Overall, robot exposure is influencing negatively the self-perceived health of these individuals, and it is increasing the share of individuals who report a fair or bad health condition, as well as those who report persistent physical or mental health problems (although the latter effect

[77] I analyze the average health condition of individuals within (non-)employment groups for two reasons. First, an increase in non-participation may mechanically increase the share of the population who reports to suffer from health problems. However, I am primarily interested in the effect of robots on the health condition of these individuals. If robot exposure leads to a deterioration in individuals' physical and mental health condition that exacerbates the impact on health beyond the mechanical effect of losing a job (Sullivan and Von Wachter, 2009), this should be visible in the shares. Second, the negative effect of robots on displaced workers' health may not be visible when analyzing the average effect on the population, since it is offset by a positive effect on the health condition of workers who work along with robots. For example, Gihleb et al. (2020) show that robot adoption reduces work-related injuries in the manufacturing sector. For completeness and comparability with the previous results, I report estimates in per capita terms in Table B5. In line with the findings from Table 2.6, these results suggest that robot exposure increases the non-employment rate (unemployed and non-participants) of individuals who suffer from health issues (but they include also the composition effect of robots on non-participation). Unfortunately, the BRFSS does not explicitly distinguish between unemployed and non-participating individuals. Non-employed individuals include individuals who report to be out of work, unable to work, homemakers, students, and retirees.

[78] I consider regular drinkers as people who drink alcohol in at least five days per week.

Table 2.6: Health and access to healthcare services among non-employed

	Self-reported health			Smoking and drinking habits		Physical shape and activity		Access to healthcare services			
	No good health	Physical problems	Mental problems	Smoke	Drink	Obese	Regular exercise	Health coverage	Checkup last 12	Checkup too costly	Checkup more 24
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]
	Panel A: Whites										
US robot exposure	0.950**	0.977***	0.357	0.849	0.254***	0.840***	-1.563***	-1.174*	1.320	1.488**	0.897***
	(0.417)	(0.244)	(0.253)	(0.723)	(0.062)	(0.311)	(0.545)	(0.616)	(1.127)	(0.704)	(0.272)
	Panel B: Racial and ethnic minorities										
US robot exposure	-1.031*	0.336	0.003	-0.323	-0.046	0.496	-2.214**	1.635	4.352***	-1.698***	-0.447
	(0.600)	(0.503)	(0.451)	(0.376)	(0.059)	(0.670)	(0.962)	(1.425)	(1.570)	(0.391)	(0.306)
Observations	1238	1238	1238	1238	1238	1238	1238	1238	1238	1208	1238
Covariates:	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes: This table presents IV estimates of the effect of US robot exposure on the change in self-reported health, smoking and drinking habits, physical shape and exercises and access to healthcare services among non-employed individuals. Changes are expressed in percentage points of non-employed individuals and are multiplied by 100 ($\Delta \frac{L^{g,m}_{c,t}}{L^{g}_{c,t}}$). Column 1 reports individuals that report fair or poor health. Columns 2 and 3 report individuals that suffered from physical or mental problems in more than 14 days of the previous 30 days. Columns 4 and 5 report smokers and individuals that consume alcohol in at least five days per week. Column 6 reports individuals that suffer from obesity, i.e. a BMI of over 30. Column 7 reports individuals that did physical activity outside of the work environment in at least one day in the previous 30 days. Column 8 reports individuals with healthcare coverage. Column 9 reports individuals that had a medical checkup in the previous year (12 months). Column 10 reports individuals that could not visit a doctor when needed for cost reasons. Column 11 reports individuals that had no medical checkup in the previous two years (24 months). All regressions include the full battery of controls from my preferred specification. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

is estimated imprecisely).[79] Table B4, on the other hand, shows that the adoption of robots has no adverse effects on the self-perceived health of employed workers.

These findings suggest that the impact of robots on individuals' health depends on their employment status. Non-employed individuals are likely to suffer from a deterioration of their health condition, while physical and mental problems of employed workers are not significantly affected by their adoption (except for a slight reduction in physical problems among whites). Also at the aggregate population level, the impact of robots on health is negligible.[80]

In Figure B5, I decompose the health effects on non-employed individuals by age groups. I find that the increase in health issues among whites are driven by individuals aged between 35 and 44 years. For these individuals, also the effect on mental problems becomes statistically significant.

[79] I define people that suffer from persistent problems as people who report physical or mental problems in at least 14 days (two weeks) of the 30 days prior to the interview. Table B6 shows that the results are robust to an increase of the threshold up to 21 days, while the effect on persistent mental problems loses significance and becomes economically small as I lower the threshold to seven days.

[80] Gihleb et al. (2022) argue that at the population level there is a positive relationship between robot exposure and the number of days in which individuals report to suffer from mental health problems. This result differs fundamentally from (and complements) my findings. While Gihleb et al. (2022) show that, on average, individuals suffer from mental problems half a day longer in a months due to an increase in robot exposure by one standard deviation, I show that the share of non-employed individuals who report to suffer from persistent mental problems increases in exposed areas (but it does not increase at the population level). These individuals are the ones most likely to qualify for disability benefits.

This finding is in line with the previous result that disability take-up increases the most for non-participants in this age range.[81] Additionally, I observe an increase in mental problems among whites between 45 and 54 years, and an increase in physical health problems among individuals between 55 and 64 years. Although the effects among racial and ethnic minorities are estimated less precisely, there is evidence of robots increasing the share of individuals in their prime-age who suffer from physical problems, and the share of individuals between 25 and 34 years who struggle with mental disorders.

These results suggest that the negative impact of robots on the average health condition of non-employed individuals could justify the increase in disability take-up among whites. According to Table B5, almost eight in ten workers who have been displaced by robots suffer from persistent physical health problems, and four in ten displaced workers suffer from persistent mental health problems.[82] These findings are in line with the literature which finds a procyclical effect of adverse labor market shocks on workers' health, including firms' plant closures (Rege et al., 2009, Schaller and Stevens, 2015, Sullivan and Von Wachter, 2009), and the China trade shock (Adda and Fawaz, 2020, Lang et al., 2019).

The adoption of robots might affect workers' health conditions in two (not mutually exclusive) ways. First, workers who already suffer from health problems are less productive and are therefore more likely to be displaced by robots. These workers mechanically increase the share of non-employed individuals who suffer from health problems (Frank et al., 2019).[83] Second, the health condition of displaced workers deteriorates after a job loss (Sullivan and Von Wachter, 2009). This mechanism is likely to be reinforced by the fact that for many US workers, losing their job is associated with losing health insurance (Schaller and Stevens, 2015). In fact, Table 2.6 shows that robot exposure decreases the share of non-employed whites with healthcare coverage. This, in

[81] Note that the subjective self-reported health condition may not fully reflect the underlying real health condition, since non-participants who want to apply for disability benefits could have an incentive to over-report physical and mental health problems. The same reasoning may hold for disability beneficiaries with mild conditions who report to suffer from severe health problems for fear of losing eligibility. In the following, I address these concerns with more objective measures of the health condition of individuals using hospitalization data from the NIS.

[82] This result is expressed in population shares, similarly to Figures 2.4 and 2.5 ($\Delta \mathrm{NP}_{c,t}^{\dot{g},m}$).

[83] Frank et al. (2019) argue that workers affected by pre-existing mental disorders are predominantly employed in routine task-intensive occupations. Work is often beneficial to them and has a therapeutic effect that leads to better general well-being. However, these workers are also mostly exposed to the recent technological advances, since most of the tasks they used to carry out are at high risk of automation (Autor and Dorn, 2013, Jaimovich et al., 2020). The job loss could aggravate their health impairments and force them to leave the labor force, and eventually apply for disability benefits.

turn, increases the share of individuals who cannot afford to visit a doctor for cost reasons and who had no medical checkup in the previous two years (these results do not apply for racial and ethnic minorities, which are also not reporting to suffer from worse health in exposed areas). The inability to be treated by a doctor in case of need may substantially worsen individuals' health conditions which, if neglected for too long, may become severe and require surgical intervention, eventually leading to a disability. If this mechanism takes place, we should also observe a rise in the hospitalization rates with acute health problems in areas that are more exposed to robots, a question that I explore in the next paragraph.

To analyze the effect of robots on hospitalization by diagnosis and severity, I use data from the NIS. Table 2.7 summarizes the results on the impact of robots on the share of hospital admissions with a length of stay of more than seven days (they are most likely to be related to a severe health condition) and a disability-related diagnosis.[84,85] I use shares in terms of hospital admissions (rather than in per capita terms) because the sample of US community hospitals is changing from year to year, making a comparison of per capita values across years uninformative.

Results show that robots increase the share of admissions with an acute health condition and, in particular, that they increase the share of admissions diagnosed with mental disorders.[86] The rise in severe disability-related admissions is visible both among whites and racial and ethnic minorities (despite minorities not reporting to suffer from worse health in the BRFSS results from Table 2.6), with the estimates being larger among the first. Figure B6 shows again that the adverse effects of robots on health are strongest among prime-age individuals. Interestingly, I also find that robots increase the share of severe hospital admissions related to substance abuse, such as alcohol, drug

[84] The share of severe hospital admissions by diagnosis is calculated by dividing the count of hospital admissions with a length of stay of more than seven days and a particular diagnosis by the number of hospital admissions in a CZ in the year of reference. Appendix B2 provides more detailed information on the construction of the variables.

[85] I consider hospital admissions with a length of stay of more than seven days to be serious and hence to be more likely to be related to a disability. Table B7 shows that the estimates of the effect of robots on mental disorders do not differ significantly when lowering the length-of-stay threshold for acute health conditions to four days or when increasing it up to 14 days. Unfortunately, the NIS does not provide individual identifiers and therefore does not allow me to identify the hospitalization of individuals who suffer from disability-related health problems that require repeated short-term treatments.

[86] The increase in hospital admissions related to severe mental disorders suggests that robots increase the share of people suffering from mental disorders or that they worsen the general health condition of people who are already suffering from these disorders. The latter interpretation is in line with the finding in Frank et al. (2019) discussed in footnote 83.

Table 2.7: Hospital admissions with disability-related disorders

	All admissions	All disability-related admissions	Arthritis & rheu-matology	Back or spine problems	Ciculato-ry system diseases	Respira-tory system diseases	Mental disorders	Diabetes
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
				Panel A: Whites				
US robot exposure	1.212*	1.251**	0.492*	0.174	0.693	0.574*	1.615***	0.137
	(0.622)	(0.595)	(0.267)	(0.220)	(0.526)	(0.312)	(0.562)	(0.197)
				Panel B: Racial and ethnic minorities				
US robot exposure	0.522	0.660*	0.037	-0.370	0.236	0.295	1.356***	0.133
	(0.325)	(0.337)	(0.196)	(0.293)	(0.226)	(0.229)	(0.477)	(0.129)
Observations	469	469	469	469	469	469	469	469
Covariates:	✓	✓	✓	✓	✓	✓	✓	✓

Notes: This table presents IV estimates of the effect of US robot exposure on the share of hospital admissions with a length of stay of more than seven days and a diagnosis related to a cause of disability. Changes are expressed in percentage points of CZ hospital admissions multiplied by 100. Column 1 reports all admissions with a length of stay of more than seven days. Column 2 reports all disability-related admissions with a length of stay of more than seven days. Columns 3 to 8 report admissions diagnosed with arthritis or rheumatology, back or spine problems, circulatory system diseases, respiratory system diseases, mental disorders and diabetes with a length of stay of more than seven days. All regressions include the full battery of controls from my preferred specification. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

(in particular opioid) and tobacco abuse. These diagnoses are often related to mental disorders.[87]

These findings suggest that the increasing disability take-up in CZs that are more exposed to robots could be, at least partially, justified by a deterioration in individuals' health condition, when related to mental disorders. These disorders are, however, often hard to verify and leave some margin of error in the decision on whether to grant disability benefits, which could be misused by displaced workers whose real health condition does not prevent them from engaging in substantial gainful activity.[88] Therefore, I cannot exclude that SSDI may involuntarily act as a sort of permanent unemployment insurance against the risks of automation for some workers (Ford, 2015).

[87] Table B8 reports estimates of the effect of robots on the share of disability-related hospital admissions by diagnosis including all admissions, while Table B9 reports estimates of the effect of robots on the share of diagnoses which are not directly related to a disability. I find no evidence that robots are systematically affecting health outcomes of these individuals. These results suggest that the spectrum of the health impact of robots is more limited than the impact of international trade, which increases also hospitalizations related to external causes (e.g. injuries and suicide attempts), as well as organic and physical diseases with a similar magnitude as mental health problems (Adda and Fawaz, 2020).

[88] Predictors that are often used in the literature as hard evidence of mental disorders are suicides and suicide attempts (Harris and Barraclough, 1997). Table B9 shows that the labor market effect of robots on suicide attempts is neither economically relevant nor statistically significant at conventional levels. Hence, I cannot ignore the suspicion that a fraction of disability claimants is misusing the margin of error in the evaluation process of hard-to-verify impairments. In line with this result, Gihleb et al. (2022) also do not find evidence of robot exposure affecting the suicide rate in the US.

2.6.3 Early retirement

Firms often invest in job training programs of prime-age workers to keep up with technological progress (Bartel and Sicherman, 1998) and, even in case workers have been displaced, many of them reallocate towards other occupations in the labor market (Autor and Dorn, 2013, Dauth et al., 2021). This reasoning may not hold for older workers who are close to retirement though, as the career horizon in which they can make use of the acquired skills is relatively short, and their cognitive ability to keep up with technological progress declines with age (Mazzonna and Peracchi, 2012). In fact, above 55 years, most workers are eligible for some form of retirement income and retire early when facing labor-displacing technological progress (Ahituv and Zeira, 2011, Bartel and Sicherman, 1993, Burlon and Vilalta-Bufí, 2016, Peracchi and Welch, 1994), leaving the labor force permanently. This section investigates the impact of industrial robots on early retirement, and analyzes its contribution to the aggregate increase in non-participation.

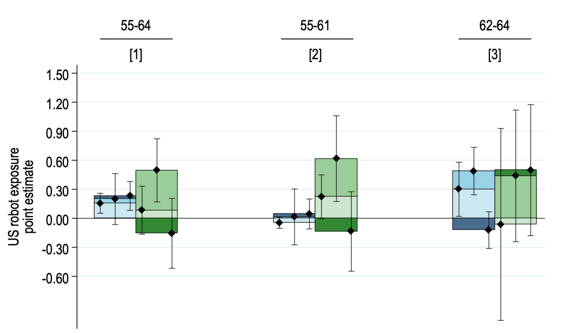
To identify the share of non-participants who retire early, I break down the group of older non-participants (55 to 64 years) into individuals aged between 55 and 61, and between 62 and 64 years. The first are not eligible for Social Security early retirement benefits, while the latter are. Figure 2.6 reports the point estimates of the labor market effect of robots on changes in the elderly non-participation rate by income source, age and education (similarly to Figure 2.5).

Results show that robots do not significantly affect the non-participation rate of college-educated whites between 55 and 61 years. This finding is in line with the trend observed for individuals aged between 45 and 54 years, and suggests that individuals between 45 and 61 years of age are least affected by the adoption of robots in their labor supply decision. The result is different when we look at individuals aged between 62 and 64 years. In fact, I find that robots have a strong impact on the non-participation rate of workers in their early retirement age, who leave the labor force to start claiming Social Security retirement benefits or pension plan income.

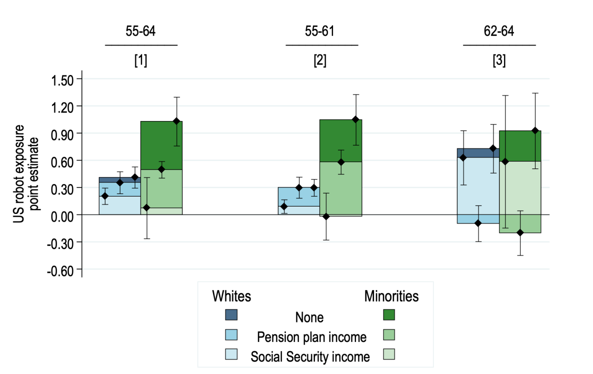
I find quite different results among racial and ethnic minorities. While robots are decreasing the non-participation rate of individuals between 45 and 54 years, as soon as they reach the age at which pension plans waive penalties on early withdrawals (this is usually at 55 years in case of employment termination), they leave the labor force and live off pension plan income. Interestingly, one third of these non-participants receives also disability benefits. The adverse effect of robots on

Figure 2.6: Social Security and pension plan income of older non-participants

Panel A: College degree or more



Panel B: Less than a college degree



Notes: This figure illustrates the IV point estimates of the effect of US robot exposure on non-participation by age and education, and decomposes them by Social Security and pension plan income ($\Delta \mathrm{NP}_{c,t}^{\dot{g},m}$). Regressions include the full battery of controls from my preferred specification and are weighted by CZ population in 1990. Confidence intervals for Social Security beneficiaries (left CI), pension plan income beneficiaries (middle CI), or for non-participants without any income from these sources (right CI) are at the 95% level.

non-participation persists beyond 62 years of age. Somewhat surprisingly, I do not find evidence of an increase in Social Security early retirement benefit claims, with all of the non-participants still living from pension plan income (note that confidence intervals are large due to the small sample size of this group).

Panel B shows the effects on less educated non-participants. I find that robot exposure increases the non-participation rate of whites already between 55 and 61 years, with a third of them receiving disability benefits and the remaining ones withdrawing pension plan income early. Similarly to Panel A, I find that robots have a strong positive effect on non-participation among individuals aged between 62 and 64 years, leading to a sharp increase in Social Security early retirement benefit claims.

As for prime-age workers, the effect of robots on less educated non-white non-participants is strong. I find that between the age of 55 and 61, almost two thirds of them withdraw their pension plan income early, while after the age of 62 (unlike more educated ones), most of them start to claim Social Security early retirement benefits.

To summarize, I show that robot exposure reduces labor force participation among older workers significantly, leading to a rise in premature retirement decisions. These individuals opt for early retirement and mainly live off disability benefits, pension plan income, and early retirement benefits.[89] The only exception are less educated non-white non-participants, with half of them receiving no income from either of these sources. I investigate further how they can afford not to work in the next section.

2.6.4 Alternative sources of income

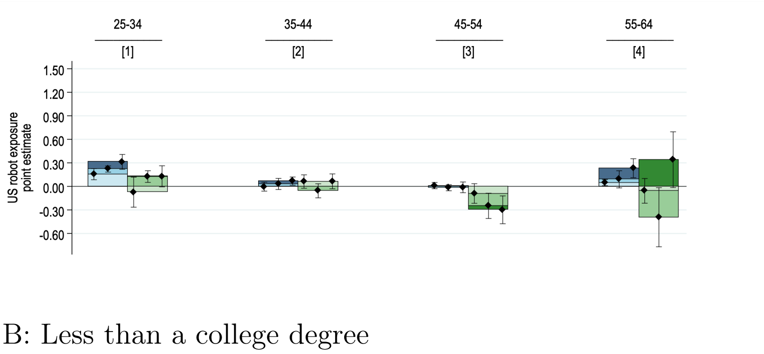
The previous results suggest that college enrollment, disability take-up and early retirement are among the main margins of adjustment of individuals who have been displaced by robots. This is the case especially for highly educated non-participants and for less educated white non-participants above the age of 45. However, a significant fraction of less educated non-participants, in particular among racial and ethnic minorities, does not fall in any of these categories (see Figure B8 for a joint representation of the margins of adjustment discussed to far). These workers account for almost half of the increase in the total non-participation rate. Therefore, it is important to investigate further where these workers have gone, and how can they afford not to work. The latter question is also interesting for individuals who enroll in college.

Reliance on household members – One possibility is that the labor force dropout of displaced men is compensated by the labor force participation of a family member (Lundberg, 1985, Ortigueira and Siassi, 2013). I investigate this channel by decomposing non-participants who are the head (or spouse) of their household and have a partner who is employed (m_1), non-participants who are not the head (or spouse) of the household (e.g. children, siblings, parents) (m_2) and therefore are likely to rely on the income of the household head (or spouse), and non-participants who are the

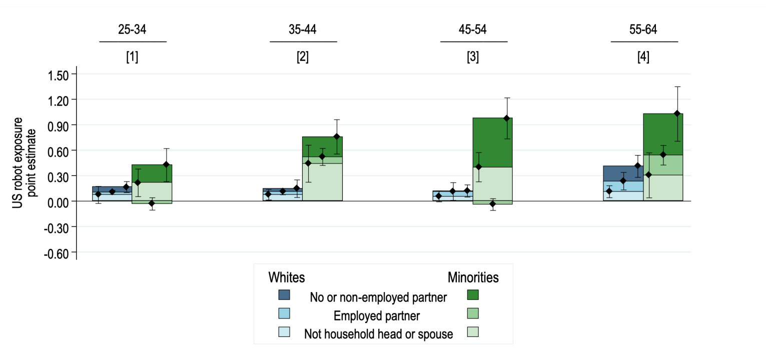
[89] I further check to which extent older workers who leave the labor force because of robots rely on these income sources and find that Social Security and pension plan income account for more than 90 percent of their total income (see Figure B7). This result supports the hypothesis that these workers are leaving the labor force permanently to retire early.

Figure 2.7: Income from household members

Panel A: College degree or more



Panel B: Less than a college degree



Notes: This figure illustrates the IV point estimates of the effect of US robot exposure on non-participation by age and education, decomposing them between household heads and spouses without a partner or with a non-employed partner, household heads and spouses with an employed partner, and other household members ($\Delta \mathrm{NP}^{\hat{g},m}_{c,t}$). Confidence for household heads and spouses without an employed partner (left CI), those with an employed partner (middle CI) and other household members (right CI) are at the 95% level.

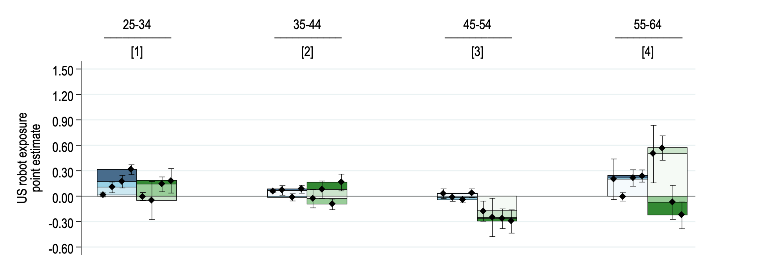
household head and do not have a partner or who are the household head (or spouse) and have a partner who is not employed (m_0). Figure 2.7 illustrates the results.

I find that the reliance on income from household members plays a crucial role for the increase in non-participation of less educated individuals from racial and ethnic minorities. Most of these individuals live in a household in which they are neither the head nor the spouse and therefore are likely to rely on the income from the respective household head (or spouse). I find similar results also for white non-participants, in particular for less educated ones and for those who are enrolled in college. There is also evidence of an increase in non-participation of household heads (or spouses) who rely on their partner's income, although this effect is smaller.

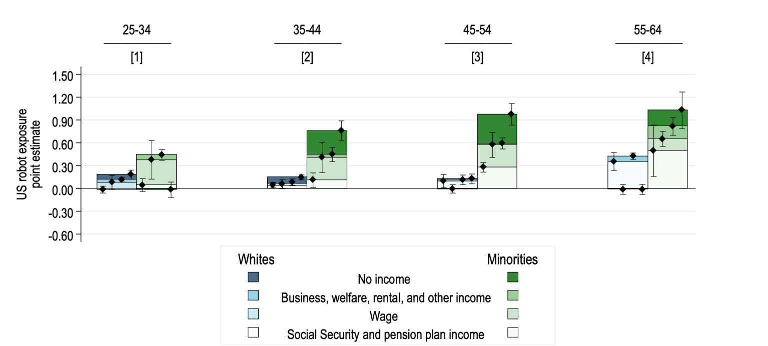
Wages, capital and welfare income – Another possibility for the absence of an active margin of adjustment of displaced workers is that they are still receiving some form of income after leaving the labor force, or that they are out of the labor force for a limited period of time and live off their savings. In Figure 2.8, I investigate this possibility by decomposing the non-participation rate by various sources of income that non-participants received (or earned) in the previous 12 months, including Social Security and pension plan income (same as in Figure 2.5) (m_1); wage income (m_2); business, rental, welfare, and other income (m_3). I denote non-participants without any income using m_0.

Figure 2.8: Personal income

Panel A: College degree or more



Panel B: Less than a college degree

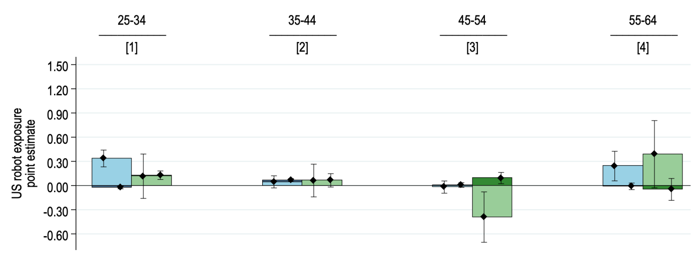


Notes: This figure illustrates the IV point estimates of the effect of US robot exposure on non-participation by age and education level, and decomposes them by source of income, including Social Security or pension plan income; wage income; business or farm income; welfare (public assistance) income; interest, dividend and rental income; and no income in the previous twelve months ($\Delta\text{NP}^{\dot{g},m}_{c,t}$). Regressions include the full battery of controls from my preferred specification and are weighted by CZ population in 1990. Confidence intervals for non-participants with Social security and pension plan income (left CI), wage income (middle-left CI), income from other sources (middle-right CI) and no income (right CI) are at the 95% level.

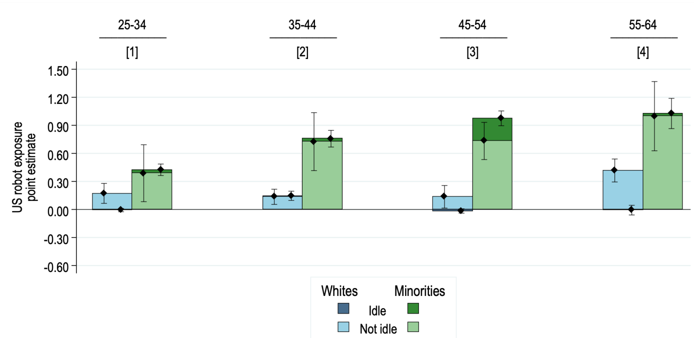
Results show that a considerable share of less educated non-participants, in particular prime-age individuals belonging to racial and ethnic minorities, earned some wage income in the last year, and therefore are likely to live off their savings. This finding suggests that these non-participants have not been out of the labor force for too long. These workers are likely to leave the labor force in the short-term because they are discouraged from worse job prospects, but they may join it again in the future, which makes them qualitatively more similar to unemployed individuals than to permanent labor force non-participants (Jones et al., 2002). Income from sources other than past employment and Social Security is limited (with some exceptions).

Figure 2.9: Idle non-participants

Panel A: College degree or more



Panel B: Less than a college degree



Notes: This figure illustrates the IV point estimates of the effect of US robot exposure on non-participation by age and education, and decomposes them into individuals who fall into at least one of the margins of adjustment discussed in this paper, and idle non-participants ($\Delta \text{NP}_{c,t}^{\dot{g},m}$). Regressions include the full battery of controls from my preferred specification and are weighted by CZ population in 1990. Confidence intervals for non-idle (left CI) and idle (right CI) non-participants are at the 95% level.

Idle – Finally, Figure 2.9 illustrates the share of non-participants including all (active and passive) margins of adjustment discussed in this paper and those who do not fall into any of these categories. I refer to the latter group as "idle" non-participants. Except for some idle individuals among racial and ethnic minorities aged between 45 and 54 years, all of the non-participants who have been displaced by robots are either students, disability beneficiaries, early retirees, they rely on income from their household members, or they live off their savings.

2.6.5 Relative contribution of adjustment margins

To conclude, we can use the results from Sections 2.6.1 to 2.6.4 to compute the relative contribution of each margin of adjustment for the increase in non-participation, as summarized in Table 2.1. To do so, Panel A of Table B27 in the Appendix reports estimates of the effect of robot exposure on non-participation as a share of the population subgroups, $\text{NP}_{c,t}^{m,\dot{g}}$ (as in Figures 2.4 to 2.9), while Panel B reports estimates as a share of the total population of men in a CZ, $\text{NP}_{c,t}^{m,g}$ (note from Equations 72 and 76 that $\text{NP}_{c,t} = \sum_m \sum_g \text{NP}_{c,t}^{m,g}$). The sum of the estimates from Panel B by margin of adjustment, divided by the estimated effect of robots on overall non-participation from Column 5 of Table 2.3, shows that almost eight percent of the non-participants enroll in college, 10.5 percent receive disability benefits, and nearly 40 percent retire early. Estimates further suggest that about half of all the non-participants live in a household in which their parents or the partner is employed, and almost one third have earned some wage or alternative form of income in the previous year.

While the first three margins of adjustment are mutually exclusive among each other, there are significant overlaps with the latter two margins. For example, students are usually not receiving any Social Security benefits, but they are likely to live in a household with at least one parent who is employed. Or, early retirees are unlikely to enroll in school, but they may have earned some wage income in the previous year (if they were employed) or have a partner who is still employed. Accounting only for the margins of adjustment of non-participants who are not enrolled in school, who do not receive any disability benefits, and who are not retired, I find that 25.1 percent of them rely on the income of other household members, and 14.3 percent live off their savings, suggesting that only 4.7 percent of the non-participants do not fall in any of the categories analyzed in this paper.

2.7 Conclusion

This paper investigates the margins of adjustment of US workers after they get displaced by industrial robots between 1993 and 2014, exploiting plausibly exogenous variation in robot exposure across local labor markets over time. To identify the underlying causes that drive workers out of the labor force, I decompose the working-age population into narrow groups based on their socio-demographic characteristics. I find that robots have an adverse effect on the labor force participation of men, but not of women. Results further show that the impact is concentrated among workers without a college degree, that it increases with age, and that it is strongest among racial and ethnic minorities.

Overall, each additional robots drives four workers out of the labor market. The margins of adjustment of these individuals include college enrollment (7.7 percent), disability take-up (10.5 percent), and early retirement (39.3 percent). Moreover, non-participants (in particular those who do not fall in any of these categories) often rely on income of their household members or live off their savings. The rising enrollment in SSDI comes along with robots affecting negatively workers' self-reported health conditions, and an increasing share of hospital admissions diagnosed with acute mental disorders.

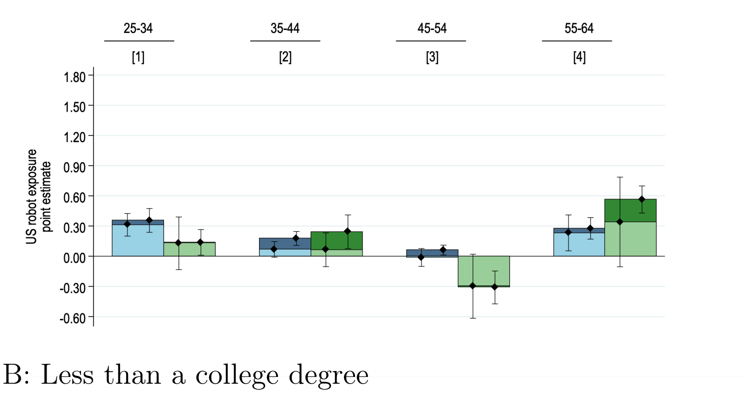
The rapid progress in automation technologies is likely to intensify the mismatch between the skill requirements of jobs and the skills of workers. As a result, workers may increasingly drop out of the labor force to seek alternative sources of income, unless they are endowed with redeployable human capital. These findings highlight the need for policymakers to design policies that facilitate the transition of the workforce to new jobs, and to improve the interplay between workers and machines through education and on-the-job training.

Appendix B

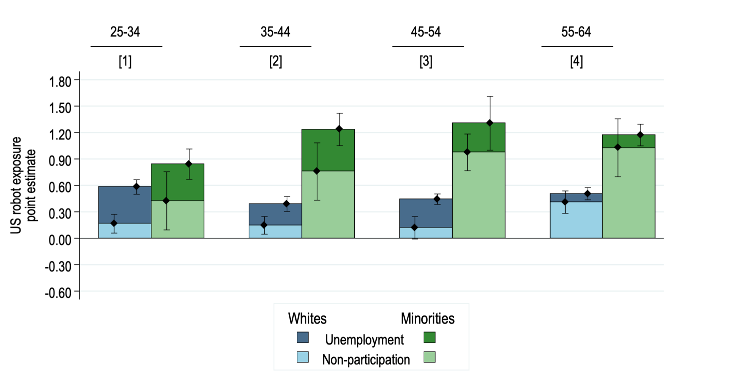
B1 Figures and tables

Figure B1: Robots, unemployment and non-participation

Panel A: College degree or more



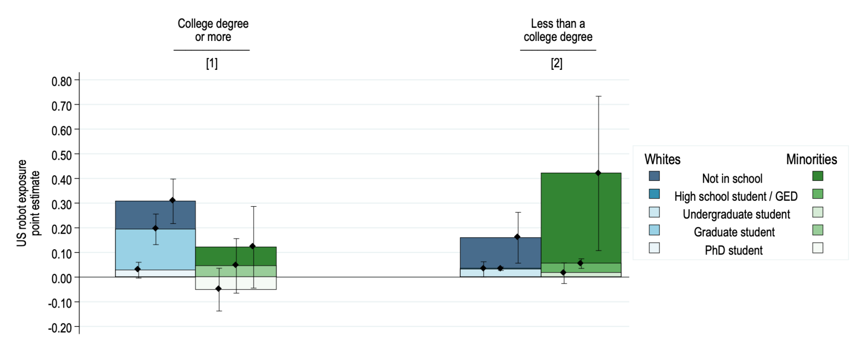
Panel B: Less than a college degree



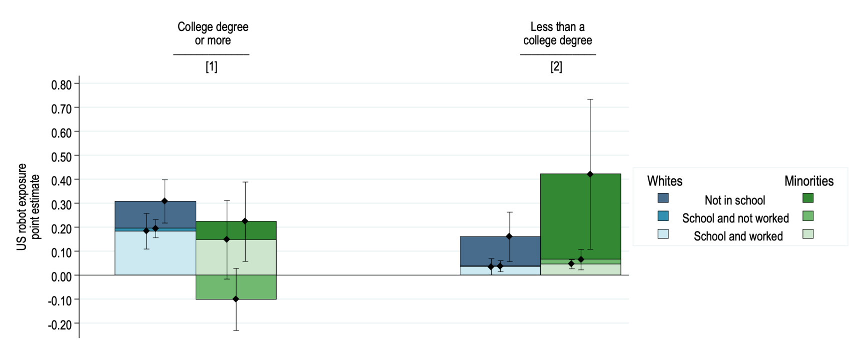
Notes: This figure illustrates the IV point estimates of the effect of US robot exposure on the change in the employment rate of men by age and education. Changes are expressed in percentage points of the population subgroup and are multiplied by 100. Independent variables are standardized to have mean zero and standard deviation of one. There are three time periods and 722 CZs. The figure decomposes the change in employment that flows into unemployment and non-participation. Analytically, $\mathrm{EP}^g_{c,t} = E^g_{c,t}/N^g_{c,t}$, $\mathrm{UP}^g_{c,t} = U^g_{c,t}/N^g_{c,t}$ and $\mathrm{NP}^g_{c,t} = L^g_{c,t}/N^g_{c,t}$, where $E^g_{c,t}$ is the number of employed, $U^g_{c,t}$ is the number of unemployed, $L^g_{c,t}$ is the number of non-participating individuals and $N^g_{c,t} = E^g_{c,t} + U^g_{c,t} + L^g_{c,t}$ is the number of individuals in age-education group g, in CZ c, at time t. By definition, $-\Delta\mathrm{EP}^g_{c,t} = \Delta\mathrm{UP}^g_{c,t} + \Delta\mathrm{NP}^g_{c,t}$. Note that, since the effect of robots on employment is negative, $-\Delta\mathrm{EP}^g_{c,t} > 0$. Panel A (Panel B) reports the point estimates of the effect of US robots robot exposure on the change in labor market outcomes among college-educated (less educated) individuals. Each column reports the point estimates for a different age group. Standard errors are robust against heteroskedasticity and allow for clustering at the state level. Regressions include the full battery of controls from my preferred specification and are weighted by CZ population in 1990. Confidence intervals of the effects on non-participation (left CI) and unemployment (right CI) are at the 95% level. Regressions include covariates of my preferred specification and are weighted by CZ population in 1990.

Figure B2: Detailed education level and work history of young non-participants

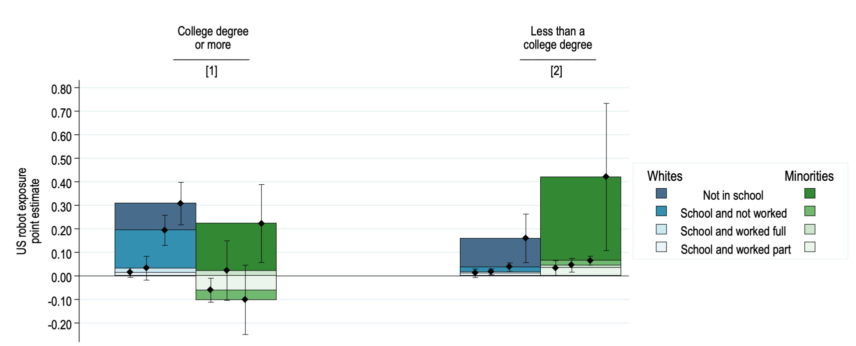
Panel A: Schooling in more detail



Panel B: Worked in previous 5 years

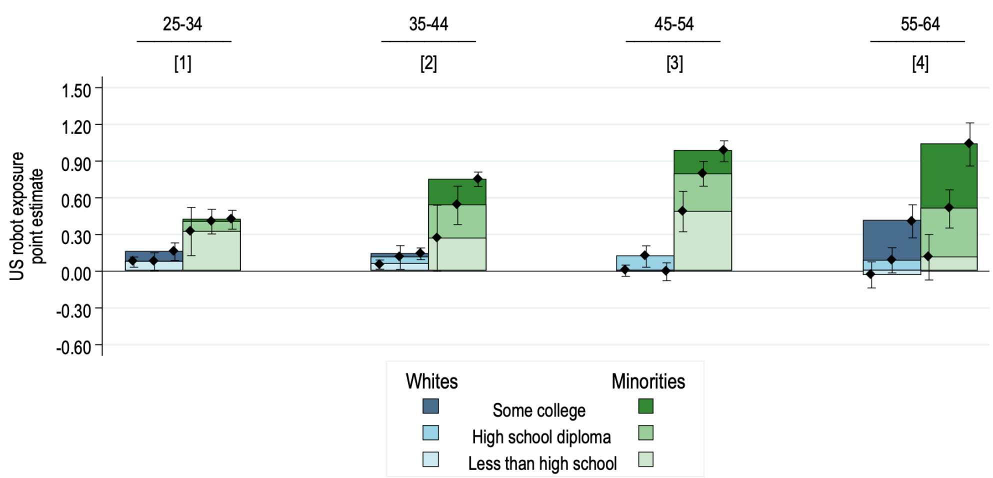


Panel C: Worked in previous 12 months



Notes: This figure illustrates the IV point estimates of the effect of US robot exposure on the non-participation rate of individuals between 25 and 34 years of age by education level, and decomposes school enrollment into detailed schooling (Panel A), working experience in the last five years (Panel B) and working experience in the last twelve months (Panel C). The latter differentiates also between part-time and full-time employment. I consider workers with an average working week of less than 30 hours (or less than 1560 hours a year) as being employed part time. Regressions include the full battery of controls from my preferred specification and are weighted by CZ population in 1990. Confidence intervals are at the 95% level.

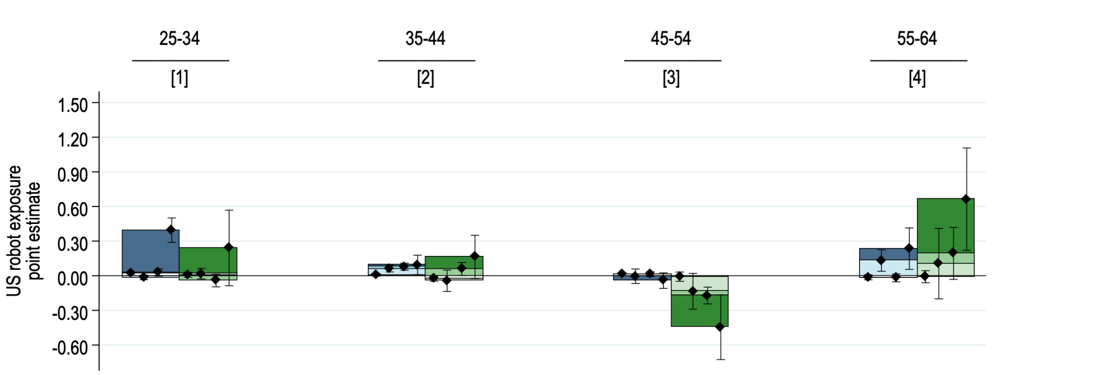
Figure B3: Robots and less educated non-participants



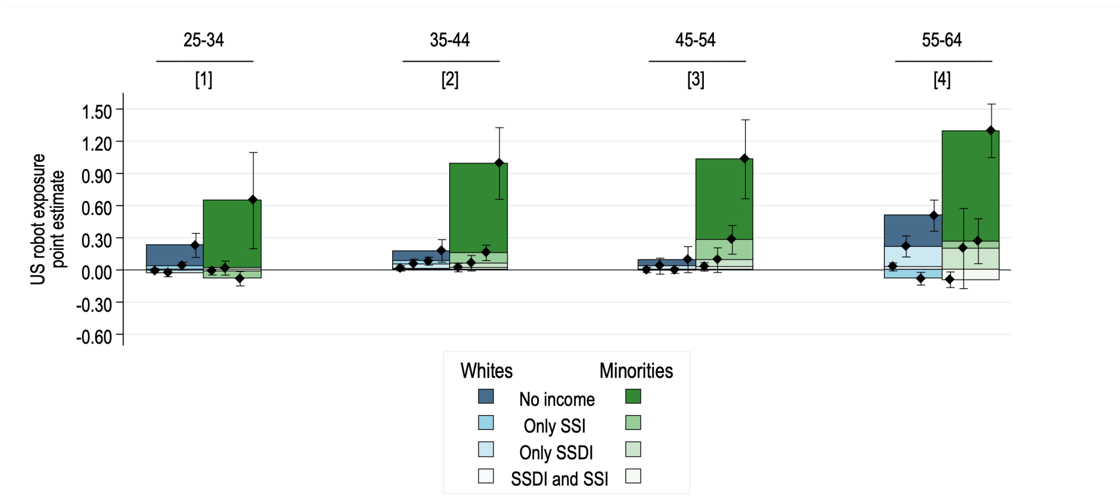
Notes: This figure illustrates the IV point estimates of the effect of US robot exposure on the change in the non-participation rate of men by age and education, focusing on individuals without a college degree: no high school degree, high school degree, some college. Changes are expressed in percentage points of the population without a college degree and are multiplied by 100. Independent variables are standardized to have mean zero and standard deviation of one. There are three time periods and 722 CZs. Standard errors are robust against heteroskedasticity and allow for clustering at the state level. Regressions include the full battery of controls from my preferred specification and are weighted by CZ population in 1990. Confidence intervals of the effects on non-nonparticipants without a high school degree (left CI), with a high school degree (middle CI) and with some college (right CI) are at the 95% level. Regressions include covariates of my preferred specification and are weighted by CZ population in 1990.

Figure B4: Supplemental Security Income

Panel A: College degree or more



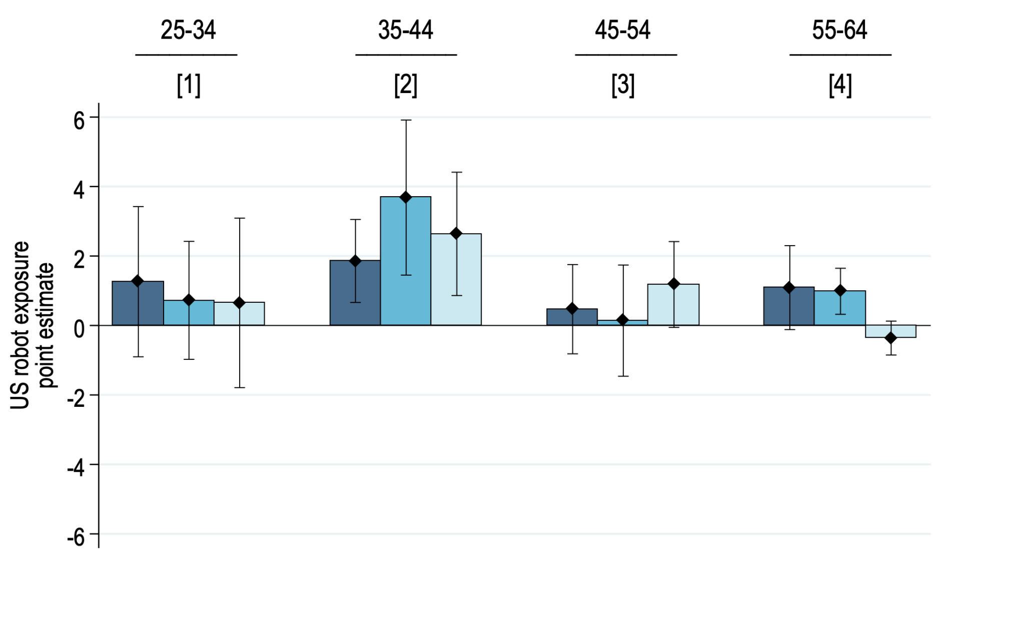
Panel B: Less than a college degree



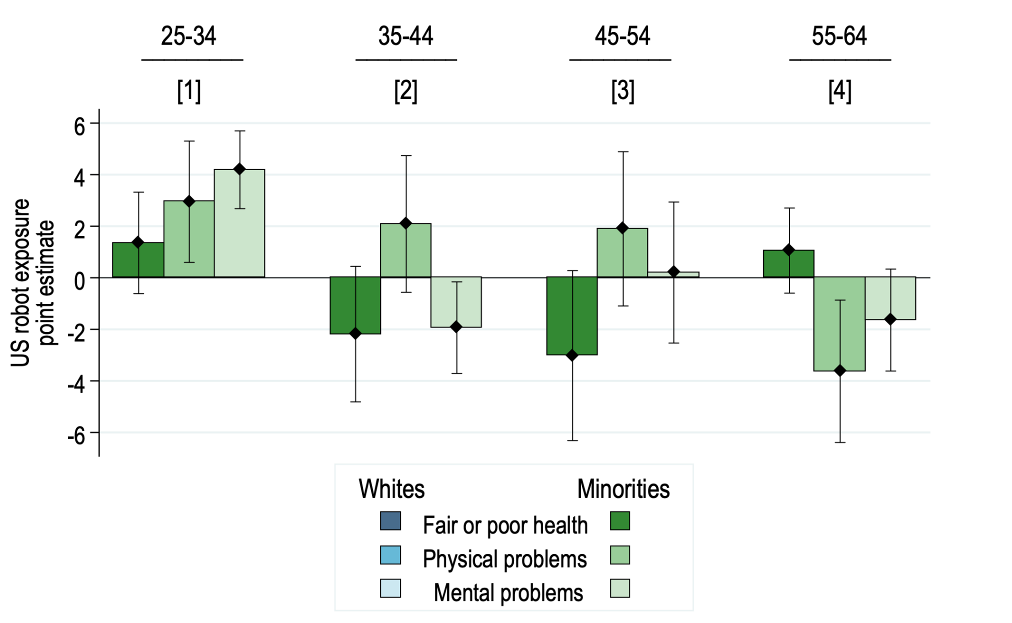
Notes: This figure illustrates the IV point estimates of the effect of US robot exposure on non-participation by age and education, and decomposes them by Social Security Disability Insurance (SSDI) income and Supplemental Security income (SSI) beneficiaries. Regressions include the full battery of controls from my preferred specification and are weighted by CZ population in 1990. Confidence intervals of the effects on non-participants with SSDI benefits and SSI (left CI), only SSDI benefits (middle-left CI), only SSI (middle-right CI) and no income (right CI) are at the 95% level. Regressions include covariates of my preferred specification and are weighted by CZ population in 1990.

Figure B5: Robots and health of non-employed by age

Panel A: Whites

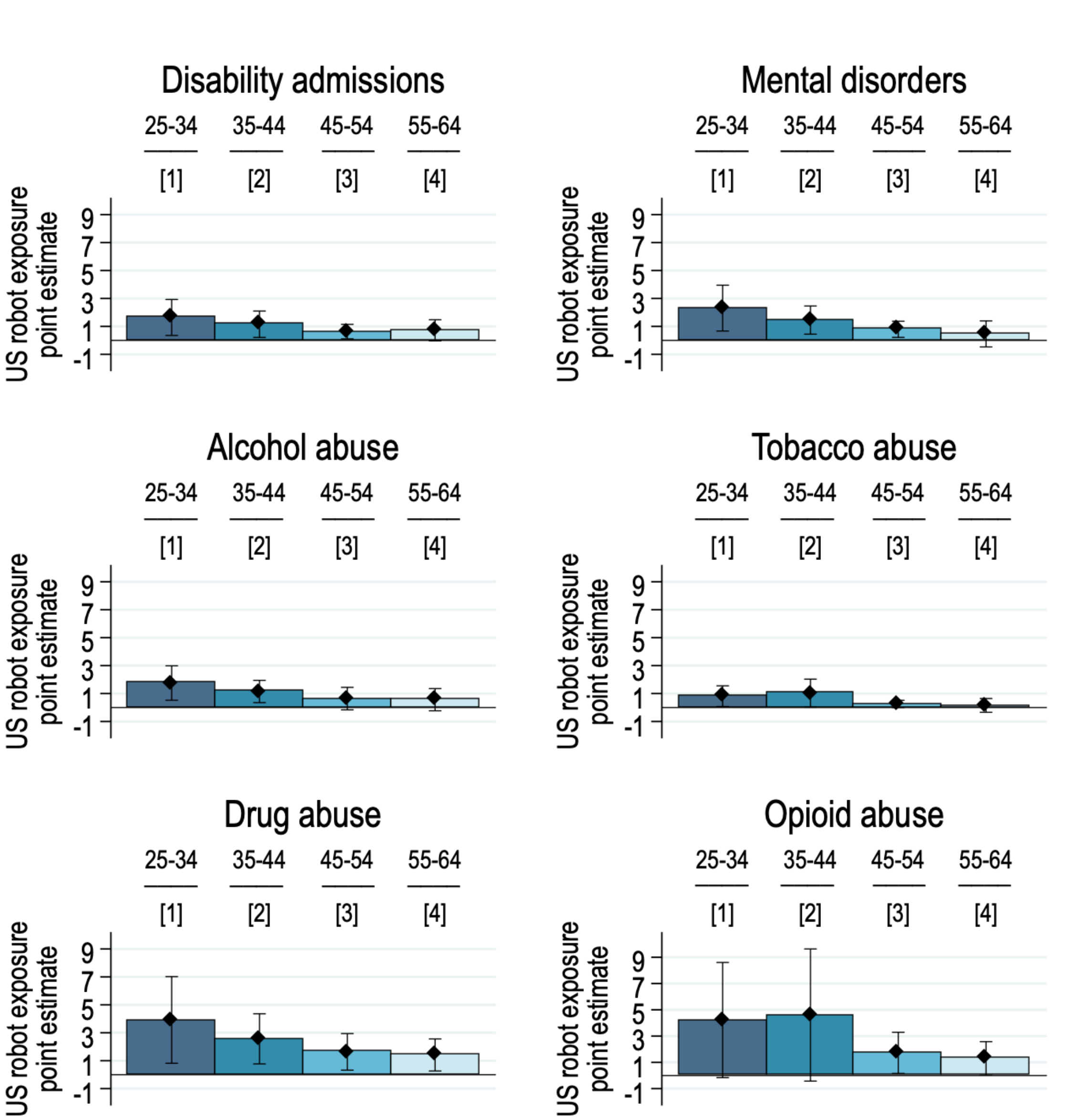


Panel B: Racial and ethnic minorities



Notes: This figure illustrates the IV point estimates of the effect of US robot exposure on the share of non-employed individuals that report a fair or poor health condition, and individuals that have suffered from physical or mental health problems in 14 days of the 30 days prior to the interview by age. Changes are expressed in percentage points of non-employed individuals of the respective age group and are multiplied by 100. Independent variables are standardized to have mean zero and standard deviation of one. Every bar reports the estimate for general health, physical health or mental health problems among non-employed individuals of a specific age group. Regressions include covariates of my preferred specification and are weighted by CZ population in the first period in which it appears in the sample. Confidence intervals are at the 95% level.

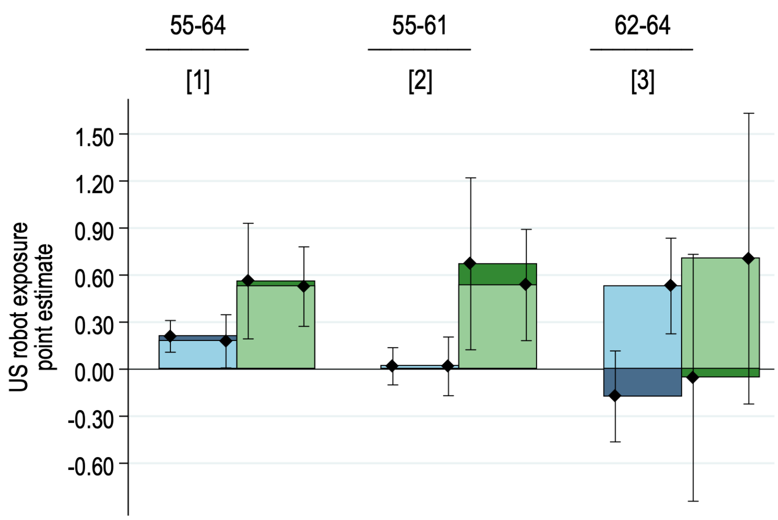
Figure B6: Hospital admissions with mental or respiratory disorders by age



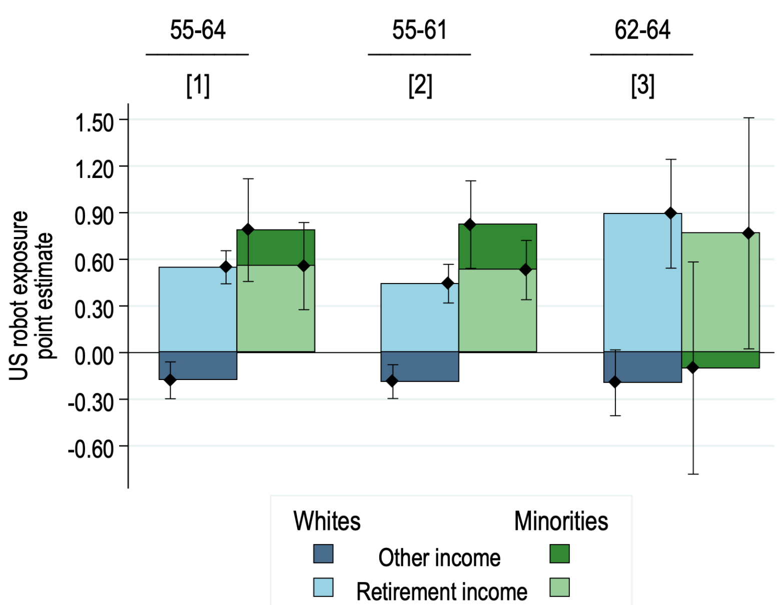
Notes: This figure illustrates the IV point estimates of the effect of US robot exposure on the share of hospital admissions with a length of stay of more than seven days by diagnosis and age. Changes are expressed in percentage points of total hospital admissions of the age group and are multiplied by 100. All variables are standardized to have mean zero and standard deviation of one. Every barplot reports the effect for a specific diagnosis for different age groups. Standard errors are robust against heteroskedasticity and allow for clustering at the state level. Regressions include covariates of my preferred specification and are weighted by CZ hospital admissions. Confidence intervals are at the 95% level.

Figure B7: Reliance on Social Security and pension plan income of older non-participants

Panel A: College degree or more



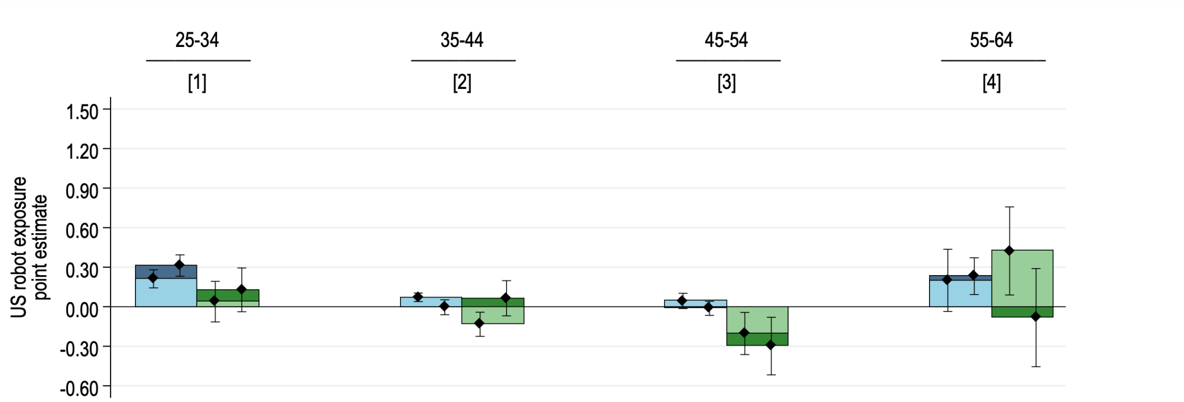
Panel B: Less than a college degree



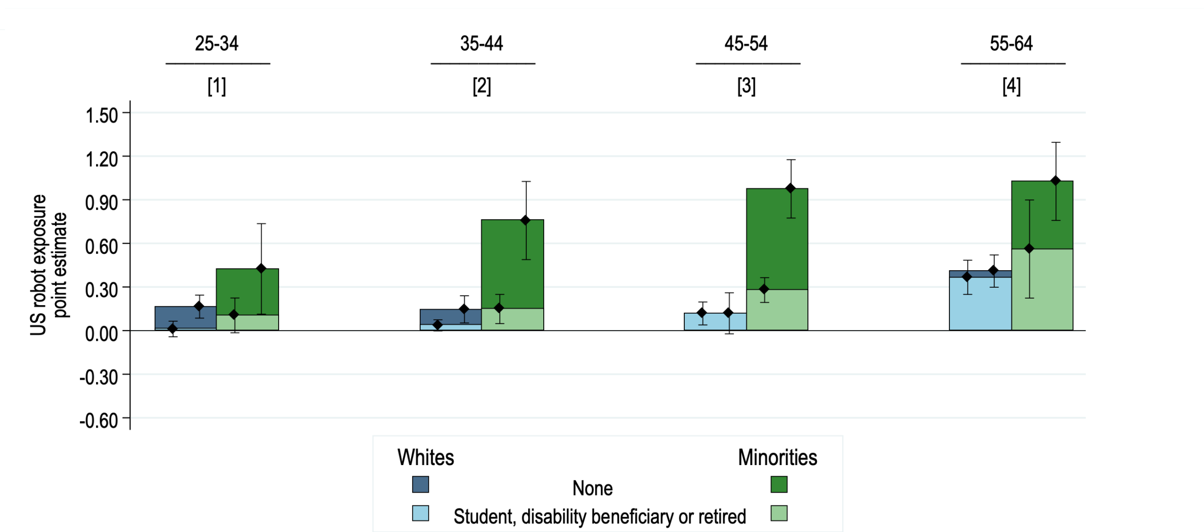
Notes: This figure illustrates the IV point estimates of the effect of US robot exposure on non-participation by age and education, decomposing them by the reliance on retirement income. Light-blue and light-green show non-participants who have at least 90 percent of their total income coming from Social Security or pension plan income. Regressions include the full battery of controls from my preferred specification and are weighted by CZ population in 1990. Confidence intervals of the effects on non-participants that do not rely on retirement income (left CI) and that fully rely on retirement income (right CI) are at the 95% level. Regressions are weighted by CZ population in 1990.

Figure B8: Schooling, disability take-up and early retirement

Panel A: College degree or more



Panel B: Less than a college degree



Notes: This figure illustrates the IV point estimates of the effect of US robot exposure on non-participation rate by age and education, decomposing them into non-participants who are students, disability beneficiaries or early retirees, and those who do not fall in either of these categories. Regressions include the full battery of controls from my preferred specification and are weighted by CZ population in 1990. Confidence intervals of the effects on non-participants that idle (left CI) and non-idle (right CI) are at the 95% level.

Table B1: Descriptive statistics: Industrial robots

	Robots in the US per thousand workers		Robots in EU7 countries per thousand workers		Employment in thousands
	1993	Δ_{14-93}	1993	Δ_{14-93}	1993
	[1]	[2]	[3]	[4]	[5]
Panel A: Manufacturing industries					
Automotive	24.25	82.69	18.2	57.12	1111
Basic Metals	1.39	5.37	0.84	7.34	712
Electronics	2.01	10.99	2.34	3.31	2868
Food and Beverages	1.02	4.62	0.38	8.93	1862
Industrial Machinery	0.39	1.52	3.01	6.18	1541
Metal Products	1.69	6.51	6.91	11.13	1689
Minerals	0.04	0.58	0.60	3.64	558
Miscellaneous	0.49	11.66	2.56	2.93	690
Paper and Printing	0.00	0.10	0.19	0.83	2467
Plastics and Chemicals	1.80	7.43	2.85	16.04	2205
Shipbuilding and Aerospace	0.02	0.44	0.73	2.18	1111
Textiles	0.00	0.05	0.24	0.88	1848
Wood and Furniture	0.00	0.12	1.14	2.75	1048
Panel B: Non-manufacturing industries					
Agriculture	0.00	0.03	0.00	0.18	2552
Construction	0.00	0.02	0.00	0.11	7108
Education and Research	0.00	0.04	0.03	0.33	12636
Mining	0.00	0.05	0.23	1.36	763
Services	0.00	0.00	0.00	0.00	84776
Utilities	0.00	0.02	0.00	0.25	745

Notes: This table reports the stock of industrial robots adopted in the US and in seven European countries (Denmark, Finland, France, Italy, Spain, Sweden and the United Kingdom) by year and industry. Panel A reports information on 13 manufacturing industries, while Panel B reports information on six sectors outside of manufacturing. Columns 1 and 3 report industry values of the stock robots in 1993, and Columns 2 and 4 report the respective changes between 1993 and 2014. Finally, Column 5 reports the baseline industry employment in the US.

Table B2: Labor market outcomes by gender

	All	Men	Women
	[1]	[2]	[3]
	Panel A: Employment		
US robot exposure	-0.391***	-0.564***	-0.226***
	(0.079)	(0.087)	(0.081)
	Panel B: Manufacturing employment		
US robot exposure	-0.115***	-0.308***	0.064***
	(0.039)	(0.068)	(0.024)
	Panel C: Unemployment		
US robot exposure	0.196***	0.217***	0.175***
	(0.024)	(0.028)	(0.025)
Observations	2166	2166	2166
Covariates:	✓	✓	✓

Notes: This table presents IV estimates of the effect of US robot exposure on the share of employment, manufacturing employment, and unemployment by gender. All regressions include the full battery of controls from my preferred specification. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Table B3: School enrollment and institution controls

	Whites		Racial/ethnic minorities	
	[1]	[2]	[3]	[4]
	Panel A: College degree or more			
US robot exposure	0.229***	0.191***	0.064	-0.002
	(0.064)	(0.036)	(0.083)	(0.092)
	Panel B: Less than a college degree			
US robot exposure	0.034	0.042*	0.067*	0.052
	(0.021)	(0.021)	(0.036)	(0.039)
Observations	2166	2166	2166	2166
Covariates:				
Divisions	✓	✓	✓	✓
Years	✓	✓	✓	✓
Chinese imports	✓	✓	✓	✓
Demographics	✓	✓	✓	✓
Industries	✓	✓	✓	✓
Occupations	✓	✓	✓	✓
Institutions in 1990	✓		✓	
Institutions in t_0		✓		✓

Notes: This table presents IV estimates of the effect of US robot exposure on the share of non-participants aged 25-34 who are enrolled in school. Every regression includes the covariates from my preferred specification. Additionally, I include covariates that account for the characteristics of educational institutions in the CZ (number of public institutions, for-profit institutions, non-profit institutions, community colleges and the number of top 20 schools in the university ranking) in 1990 and at the beginning of each subperiod. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Table B4: Health and access to healthcare services in the population

	Self-reported health			Smoking and drinking habits		Physical shape and activity		Access to healthcare services			
	No good health	Physical problems	Mental problems	Smoke	Drink	Obese	Regular exercise	Health coverage	Checkup last 12	Checkup too costly	Checkup more 24
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]
						Part I. Employed workers					
Panel A: Whites											
US robot exposure	-0.101	-0.201*	-0.041	-0.315	0.211***	0.024	-1.908***	0.313	2.272**	0.088	0.543**
	(0.078)	(0.101)	(0.121)	(0.250)	(0.069)	(0.259)	(0.696)	(0.294)	(0.879)	(0.067)	(0.221)
Panel B: Racial and ethnic minorities											
US robot exposure	-0.759*	-0.071	-0.379*	-0.667***	-0.042	0.022	-2.417***	1.576**	2.333**	0.210	0.587**
	(0.411)	(0.114)	(0.220)	(0.164)	(0.045)	(0.520)	(0.809)	(0.755)	(0.936)	(0.141)	(0.245)
						Part II. Population (employed + non-employed)					
Panel A: Whites											
US robot exposure	0.089	0.016	0.044	-0.107	0.221***	0.129	-1.864**	-0.001	2.214**	0.309**	0.573***
	(0.111)	(0.083)	(0.105)	(0.201)	(0.064)	(0.231)	(0.697)	(0.296)	(0.923)	(0.142)	(0.205)
Panel B: Racial and ethnic minorities											
US robot exposure	-0.782**	0.106	-0.192	-0.391*	-0.028	0.126	-2.514***	1.382	2.858**	-0.267	0.292
	(0.294)	(0.153)	(0.185)	(0.223)	(0.030)	(0.379)	(0.842)	(0.905)	(1.108)	(0.169)	(0.217)
Observations	1274	1274	1274	1274	1274	1274	1274	1274	1274	1274	1274
Covariates:	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes: This table presents IV estimates of the effect of US robot exposure on self-reported health, smoking and drinking habits, physical shape and exercises and access to healthcare services among employed individuals (Part I) and the overall population (Part II). Column 1 reports individuals that report fair or poor health. Columns 2 and 3 report individuals that suffered from physical or mental problems in more than 14 days of the previous 30 days. Columns 4 and 5 report smokers and individuals that consume alcohol in at least five days per week. Column 6 reports individuals that suffer from obesity, i.e. a BMI of over 30. Column 7 reports individuals that did physical activity outside of the work environment in at least one day in the previous 30 days. Column 8 reports individuals with healthcare coverage. Column 9 reports individuals that had a medical checkup in the previous year (12 months). Column 10 reports individuals that could not visit a doctor when needed for cost reasons. Column 11 reports individuals that had no medical checkup in the previous two years (24 months). All regressions include the full battery of controls from my preferred specification. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Table B5: Health conditions of non-employed individuals (in per capita terms)

	All	No good health	Physical problems	Mental problems
	[1]	[2]	[3]	[4]
		Panel A: Whites		
US robot exposure	0.318**	0.237***	0.247***	0.126**
	(0.153)	(0.073)	(0.047)	(0.056)
Observations	1276	1276	1276	1276
		Panel B: Racial and ethnic minorities		
US robot exposure	0.312	-0.165	0.155	0.112
	(0.302)	(0.149)	(0.126)	(0.089)
Observations	1206	1206	1206	1206
Covariates:	✓	✓	✓	✓

Notes: This table presents IV estimates of the effect of US robot exposure on the change in the share of non-employed individuals by self-reported health and race/ethnicity. Changes are expressed in percentage points of the *working-age population* of the respective race/ethnicity and are multiplied by 100. Column 1 includes all non-employed individuals. Column 2 reports individuals who report fair or poor health. Columns 3 and 4 report only non-employed individuals who suffered from physical or mental problems in more than 14 days of the previous 30 days. All regressions include the full battery of controls from my preferred specification. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Table B6: Self-reported physical and mental health of non-employed individuals

	Days of health problems in the last 30 days														
	7 day	8 days	9 days	10 days	11 days	12 days	13 days	14 days	15 days	16 days	17 days	18 days	19 days	20 days	21 days
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[14]	[15]
	Part I. Whites														
Panel A: Physical problems															
US robot exposure	0.708*	0.843**	0.979***	0.862***	0.900***	0.884***	0.989***	0.977***	0.691***	0.409**	0.407*	0.448**	0.433*	0.450**	0.509*
	(0.353)	(0.316)	(0.321)	(0.309)	(0.202)	(0.204)	(0.249)	(0.244)	(0.249)	(0.203)	(0.207)	(0.212)	(0.223)	(0.222)	(0.264)
Panel B: Mental problems															
US robot exposure	0.010	-0.017	0.199	0.233	0.383	0.394	0.379	0.357	0.184	0.518***	0.527***	0.533***	0.559***	0.560***	0.629***
	(0.243)	(0.274)	(0.320)	(0.306)	(0.239)	(0.243)	(0.251)	(0.253)	(0.236)	(0.162)	(0.158)	(0.152)	(0.153)	(0.153)	(0.155)
	Part II. Racial and ethnic minorities														
Panel A: Physical problems															
US robot exposure	1.072	0.546	0.694	0.617	0.225	0.298	0.409	0.336	0.656	0.829*	0.869*	0.894*	0.876*	0.916**	1.142***
	(0.641)	(0.626)	(0.649)	(0.620)	(0.541)	(0.529)	(0.502)	(0.503)	(0.535)	(0.450)	(0.447)	(0.449)	(0.441)	(0.433)	(0.419)
Panel B: Mental problems															
US robot exposure	-0.088	-0.130	-0.070	-0.147	0.219	0.220	0.066	0.003	0.106	-0.284	-0.343	-0.337	-0.434	-0.434	0.163
	(0.517)	(0.434)	(0.451)	(0.447)	(0.464)	(0.462)	(0.461)	(0.451)	(0.468)	(0.457)	(0.480)	(0.479)	(0.478)	(0.476)	(0.480)
Observations	1238	1238	1238	1238	1238	1238	1238	1238	1238	1238	1238	1238	1238	1238	1238
Covariates:	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes: This table presents IV estimates of the effect of US robot exposure self-reported health problems of non-employed individuals in the last 30 days. Panel A reports physical health problems and Panel B reports mental health problems. Changes are expressed in percentage points of non-employed working-age population multiplied by 100. All regressions include the full battery of controls from my preferred specification. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Table B7: Hospital admissions with disability-related diagnoses and mental disorders by length of stay

	Minimum length of stay														
	0 days	1 day	2 days	3 days	4 days	5 days	6 days	7 days	8 days	9 days	10 days	11 days	12 days	13 days	14 days
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[14]	[15]
	Panel A: Disability-related diagnosis														
US robot exposure	1.684***	0.944**	1.046**	1.125**	1.292**	1.403**	1.371**	1.151**	1.081**	1.051**	1.027**	1.014**	0.981**	0.985**	0.985**
	(0.571)	(0.450)	(0.423)	(0.439)	(0.497)	(0.579)	(0.606)	(0.486)	(0.459)	(0.462)	(0.465)	(0.463)	(0.452)	(0.454)	(0.457)
	Panel B: Mental disorders														
US robot exposure	0.601	0.552	0.813	1.105	1.521**	1.890***	1.972***	1.876***	1.862***	1.937***	2.047***	2.069**	2.011**	1.971**	2.012**
	(0.794)	(0.841)	(0.773)	(0.663)	(0.625)	(0.640)	(0.659)	(0.626)	(0.621)	(0.663)	(0.737)	(0.765)	(0.753)	(0.750)	(0.770)
Observations	469	469	469	469	469	469	469	469	469	469	469	469	469	469	469
Covariates:	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes: This table presents IV estimates of the effect of US robot exposure on the share of hospital admissions by minimum length of stay. Panel A reports hospital admissions with disability-related conditions (arthritis and rheumatism; back and spine problems; circulatory system diseases; respiratory system diseases; mental disorders; and diabetes). Panel B reports hospital admissions with mental disorders. Changes are expressed in percentage points of CZ hospital admissions multiplied by 100. All variables are standardized to have mean zero and standard deviation of one. Regressions are weighted by CZ hospital admissions. All regressions include the full battery of controls from my preferred specification. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Table B8: Hospital admissions with disability-related disorders (include also admissions with a stay of less than seven days)

	Arthritis & rheu-matology	Back or spine problems	Ciculato-ry system diseases	Respira-tory system diseases	Mental disorders	Diabetes
	[1]	[2]	[3]	[4]	[5]	[6]
US robot exposure	0.518**	0.064	0.570	0.559**	0.527	0.431**
	(0.253)	(0.230)	(0.475)	(0.210)	(0.790)	(0.203)
Observations	469	469	469	469	469	469
Covariates:	✓	✓	✓	✓	✓	✓

Notes: This table presents IV estimates of the effect of US robot exposure on the share of hospital admissions with a diagnosis related to a cause of disability. Changes are expressed in percentage points of CZ hospital admissions multiplied by 100. All variables are standardized to have mean zero and standard deviation of one. Columns 1 to 6 report admissions diagnosed with arthritis or rheumatology, back or spine problems, circulatory system diseases, respiratory system diseases, mental disorders and diabetes. Regressions are weighted by CZ hospital admissions. All regressions include the full battery of controls from my preferred specification. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Table B9: Hospital admissions with disorders not directly related to a disability

	Organic & physical diseases						
	Infectious & parasitic diseases	Cancer	Endocr. nutrition. metabolic diseases	Nervous system diseases	Digestive system diseases	Skin & subcut. tissue diseases	Unclassified pain
	[1]	[2]	[3]	[4]	[5]	[6]	[7]
	Panel A: Admissions by diagnosis						
US robot exposure	-0.079	-1.021	1.177***	0.534	0.366	0.494**	0.163
	(0.170)	(1.132)	(0.420)	(0.337)	(0.378)	(0.233)	(0.361)
	Panel B: Admissions by diagnosis a with length of stay of more than seven days						
US robot exposure	0.023	-0.359	0.596*	0.269	0.364	0.516*	0.021
	(0.194)	(1.189)	(0.321)	(0.192)	(0.310)	(0.256)	(0.286)
Observations	469	469	469	469	469	469	469
Covariates:	✓	✓	✓	✓	✓	✓	✓
	Substance abuse				External causes		
	Alcohol abuse	Tobacco products abuse	Drug abuse	Opioid abuse	Injuries	Suicide attempt	Accidents
	[1]	[2]	[3]	[4]	[5]	[6]	[7]
	Panel A: Admissions by diagnosis						
US robot exposure	0.297	-0.234	0.935	0.489	-1.449	-0.269	-2.035
	(0.324)	(0.840)	(0.576)	(0.468)	(1.123)	(0.509)	(1.279)
	Panel B: Admissions by diagnosis with a length of stay of more than seven days						
US robot exposure	0.644**	1.422**	3.767**	5.465*	-0.292	0.179	-1.303
	(0.247)	(0.541)	(1.446)	(2.758)	(0.470)	(0.749)	(0.937)
Observations	469	469	469	469	469	469	469
Covariates:	✓	✓	✓	✓	✓	✓	✓

Notes: This table presents IV estimates of the effect of US robot exposure on the share of hospital admissions with a diagnosis that is not directly related to a cause of disability. Panel A reports all hospital admissions by diagnosis type. Panel B reports hospital admissions with a length of stay of more than seven days by diagnosis type. Changes are expressed in percentage points of CZ hospital admissions multiplied by 100. All variables are standardized to have mean zero and standard deviation of one. Regressions are weighted by CZ hospital admissions. All regressions include the full battery of controls from my preferred specification. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

B2 Data sources and cleaning

This section provides details about the cleaning and the construction of labor market and health outcomes.

B2.1 Industrial robots

Robotics data from the IFR are praised for their reliability, but they include also some limitations. First, a fraction of the stock of industrial robots is not attributed to any industry and is referred to as "unclassified". Following Graetz and Michaels (2018), I attribute unclassified robots proportionally to each industry's share of total classified robots for each year. Second, up to 2011, the IFR provides data on the operational stock of robots only for North America as a whole, which includes the United States, Canada and Mexico. This aggregation introduces noise, but is not a major concern for the identification of US robot adoption, since the US account for more than 90 percent of the North American market and the instrumental variable (IV) strategy presented in Section 2.4 purges this type of measurement error (Acemoglu and Restrepo, 2020). Third, the stock of robots by industry going back to the 1990s is only available for a subset of countries: Denmark, Finland, France, Germany, Italy, Norway, Spain, Sweden, and the United Kingdom. The IFR provides data on the total stock of robots in North America from 1993, but it does not provide industry breakdowns until 2004. For these years, I attribute the aggregate number of robots to industries proportionally to their shares of the total stock in 2004.[90]

B2.2 Health outcomes

I measure health outcomes using data from the Behavioral Risk Factor Surveillance System (BRFSS) of the Centers for Disease Control and Prevention (CDC) and the National Inpatient Sample (NIS) of the Healthcare Cost and Utilization Project (HCUP) for 1993, 2000, 2007 and 2011. After 2011, the BRFSS and NIS datasets do not provide geographic indicators that allow me to identify observations at the CZ level.

The BRFSS is a health-related telephone survey that collects 400,000 adult interviews each

[90] I use the same procedure to impute the stock of robots for Denmark, a country included in the instrument, for which the industry breakdown starts in 1996.

year on health-related risk behaviors, chronic health conditions, and the use of preventive services. For each individual, I have information on basic demographics, employment status, self-reported health, smoking and drinking habits, body height and weight, physical activity, healthcare coverage and the use of healthcare services. Interviewees are also asked about their physical and mental health condition and report whether they suffered from physical illness or injuries, or from stress, depression or problems with emotions in the 30 days prior to the interview.

Similarly to the IPUMS data, I aggregate BRFSS data at the local labor market level, obtaining information on 634 CZs. I use the approach explained in footnote 49 to increase the sample size of each year including data of adjacent years. I construct representative individual weights by computing CZ gender-race-age shares from the BRFSS (NIS) and Census/ACS. Following Adda and Fawaz (2020), I divide the shares from the Census/ACS by the corresponding BRFSS (NIS) shares and multiply this ratio by the CZ share in the population for each sample year. The weights reflect the proportions of individuals according to the gender-race-age cell in the Census/ACS. Counties with a low population are anonymized and cannot be identified.

I build measures of health-related issues using these data by dividing the number of working-age individuals with given health characteristics and employment status in a CZ by all individuals with the same employment status in that CZ. For example, a CZ's share of non-employed individuals who suffer from a fair or bad health is computed as the number of individuals who report to suffer from fair or bad health and that are not employed, divided by all individuals that are not employed. These shares are clean from pure mechanical effects on health outcomes related to the increase in non-employment, but show whether the adoption of robots has changed the average health condition among non-employed individuals.

The NIS collects information on more than seven million hospital stays each year using a 20-percent stratified sample of discharges from US community hospitals. For each discharge, among others, I observe patients' basic demographics, the length of stay and information on up to 15 diagnoses using classification codes from the International Classification of Diseases, Ninth Revision (ICD-9). I group ICD-9 codes into six disability-related conditions (arthritis and rheumatism; back and spine problems; circulatory system diseases; respiratory system diseases; mental disorders; and diabetes) and 13 conditions that are not directly related to a disability (infectious and parasitic diseases; cancer, endocrine, nutritional and metabolic diseases; nervous system diseases; digestive system diseases; diseases of the skin and subcutaneous tissue; unclassified pain; alcohol abuse; tobacco abuse; drug abuse; opioid abuse; injuries; suicide attempts; and accidents). These data include hospital identifiers and county codes which allow me to match hospitals to CZs and to obtain information on 2,217 hospitals in 322 CZs.

I build measures of the hospitalization rate by diagnosis by dividing the number of admissions with a certain diagnosis with the total number of admissions over all hospitals in a CZ in a given year. For example, I compute a CZ's share of severe admissions with mental disorders as the number of admissions diagnosed with severe mental disorders divided by all hospital admissions in that CZ. I cannot compute the hospitalization rate in terms of the local population because the sample of US community hospitals is changing from year to year, which makes a comparison of CZs across years infeasible. For instance, in 1993 the NIS may collect information about hospital stays from two community hospitals in a CZ, and in 2000 may collect information from only one of the two hospitals, or even from other institutions. To account for this issue, shares are more appropriate, since they account for mechanical changes due to observation sampling that affect the numerator by adjusting the denominator.

B2.3 Import exposure

China – Following Autor et al. (2013), I use a shift-share approach to measure a labor market's exposure to imports from China. I interact CZs' industry employment shares in the manufacturing sector prior to the admission of China to the World Trade Organization in 2001 with the growth in product trade flows from China to the US:

$$\text{US import exposure}_{c,(t_0,t_1)} = \sum_{j \in J} \ell_{c,j}^{1990} \Delta IM_{j,(t_0,t_1)}^{US} \tag{79}$$

where $\Delta IM_{j,(t_0,t_1)}^{US}$ is the change in US imports from China in thousand dollars per worker. Analogously to Equation 75, I exploit plausibly exogenous variation in the trade shock by instrumenting the shift-component of the measure with trade flows from China to other industrialized countries with a similar trade development as the US:

$$\text{OT8 import exposure}_{c,(t_0,t_1)} = \sum_{j \in J} \frac{1}{8} \sum_{i \in OT8} \ell_{c,j}^{1990} \Delta IM_{j,(t_0,t_1)}^{i} \tag{80}$$

where $i \in OT8$ include Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland. I keep the baseline employment shares constant to avoid endogeneity and serial correlation concerns.

I collect product-level data at the six-digit Harmonized System (HS) on Chinese imports from the UN Comtrade Database which I match with industry employment shares from the 1991 County Business Pattern (CBP). The CBP classifies industry employment according to the Standard Classification System (SIC) until 1997 and according to the North American Industry Classification System (NAICS) afterwards. These systems are more detailed than the industrial classification system used in the IPUMS. I use crosswalks from Autor et al. (2013) to convert SIC and NAICS manufacturing industries and six-digit HS product-level trade data to 392 four-digit SIC industries. I construct the import penetration measure by matching local employment shares with converted product-level trade data on imports from China. For confidentiality reasons, county-industry observations with few cases are reported as ranges. In reconstructing these data, I follow Acemoglu et al. (2016).

Europe − I build a measure of international product market competition from Europe using a shift-share approach, as outlined previously. The share component is unchanged and corresponds to $\ell_{c,j}^{1990}$ in Equation 79, while the shift-component does not account anymore for imports from China, but includes the change in average trade flows from Denmark, Finland, France, Italy, Spain, Sweden and the United Kingdom to the US. Since US imports could be subject to domestic shocks that affect also the local demand for labor (demand shocks), I instrument imports to the US with trade flows from Europe to Canada, an industrialized country with a comparable trade engagement with European countries as the US (see Figure B11), but whose import intensity is less affected by US domestic shocks than the US itself.

B2.4 Industry employment and output

I obtain employment and aggregate output data at the industry level for the US and Europe from the Integrated Industry-Level Production Account (KLEMS) of the Bureau of Economic Affairs (BEA) and from the EU KLEMS database (Jägger, 2017). I use these data to build measures of robot density at the industry level in the shift components of Equations 74 and 75.

B2.5 CZ characteristics

I obtain individual-level data on a variety of demographic characteristics and labor market information of the US population from the IPUMS. I use these data to build measures of CZs' demographics and their industrial and occupational composition of employment. These variables include the share of white men, women, Blacks, Hispanics, college-educated individuals, individuals born in the same US state as their current residency, and the log population size and age structure of the population (25-34, 35-44 and 45-54 years). I also account for the share of employment in construction, education and research, manufacturing, mining, services, and utilities industries, as well as the share of routine task-intensive and offshorable jobs (Autor and Dorn, 2013). I keep CZ characteristics constant at their 1990 levels to avoid contamination by endogenous adjustments in the structure of labor markets in response to robot adoption. I provide summary statistics of these covariates in Table 2.2.

B2.6 Migration

I use Census/ACS data from Di Giacomo and Lerch (2021) on the migration status of individuals to construct changes in aggregate in- and out-flows of migrants at the CZ level in each subperiod of my sample (1993-2000, 2000-07, 2007-14), as a percentage of the working-age population. A major limitation in the data is that information about individuals' migration status changes over time. In particular, the Census asks whether a person changed its residence in the previous 5 years, while the ACS asks whether a person changed its residence in the previous year. An individual who moved twice in the previous 5 years is considered to be a one-time mover in the Census, but would be counted twice in the ACS (conditional on the fact that the moves occurred in different years). I follow Molloy et al. (2011) in building normalized measures of 5-year migration flows from the ACS by using four times the annual migration flow of a CZ.

B2.7 Institution controls

To control for the educational supply that could have influenced the demand for schooling of non-participants, I build measures of the local supply of post-secondary education institutions using data from the Integrated Postsecondary Education Data System (IPEDS) provided by Di Giacomo and Lerch (2021). They include the number of public institutions, for-profit institutions, non-profit institutions, community colleges and the number of top 20 US educational institutions in the 2020 university ranking in each CZ.

B2.8 Technology shocks

I control for technology shocks other than industrial robots using Bartik-style measures of the adoption of personal computers and IT capital intensity. I obtain data about the number of individuals that are using a computer in each industry from the 1993 Current Population Survey. Following Acemoglu and Restrepo (2020), I build a measure of exposure to computers by interacting the share of employees using a computer with CZ baseline employment shares in each industry. Analogously, I obtain data about the share of IT investments at the industry level from the 1992 American Survey of Manufacturing and build a measure of IT capital intensity by interacting the share of IT investments (available at the 4-digit SIC87) with the baseline CZ employment shares in each industry.

B3 Institutional background

US Social Security is the largest and one of the most successful anti-poverty programs in the United States. In 2019, the Social Security Administration (SSA) paid benefits for more than 1 trillion US dollars to more than 64 million American citizens, of which 75.3% received retirement benefits, 15.5% disability benefits and 9.2% survivor benefits (Social Security Beneficiary Statistics, 2019).

Individuals qualify for Social Security disability benefits if they have a physical or mental impairment that prevents them from engaging in any substantial gainful activity. The impairment is expected to last at least twelve months or result in death. Individuals have to be aged not more than

64 years and they must have paid enough contributions in form of labor taxes during their work life. Moreover, together with people who are blind or are older than 64 years, disabled individuals with limited income and few resources qualify for monthly payments from the Supplemental Security Income (SSI) program, also provided by the SSA.

Social Security survivors benefits are paid to widows, widowers, and dependents of eligible workers. Individuals qualify for survivor benefits from 50 years of age if they are disabled and from 60 years if they are not disabled.

Individuals qualify for Social Security retirement benefits after reaching the official retirement age. The full retirement age varies from 66 to 67 years depending on the year of birth of the claimant, conditional on having worked and paid Social Security taxes for at least 10 years. The US Social Security early retirement age starts at 62 years.

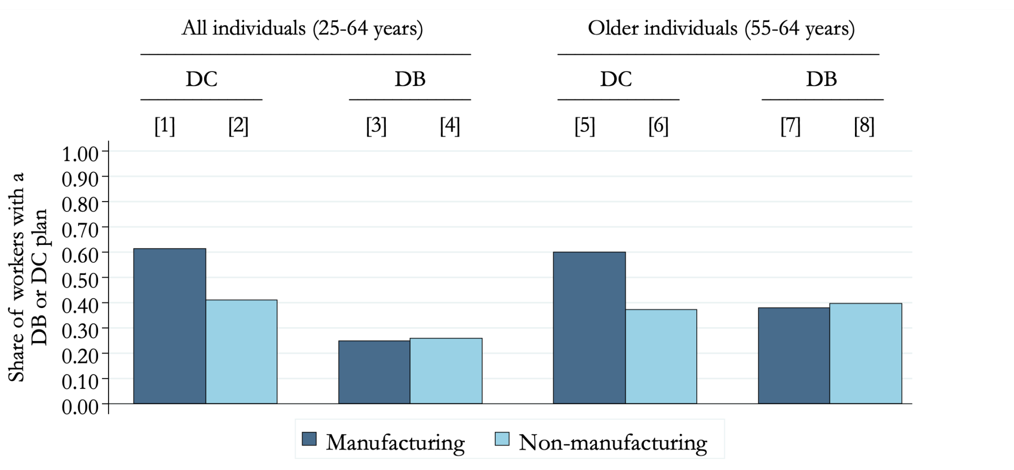
Retirees usually have access to other retirement income sources already before the age of 62 years, for example by withdrawing early their retirement income from pension plans. The most common pension plans are employed-sponsored plans, i.e. defined benefit (DB) and defined contribution (DC) plans. DB plans promise specified benefits at retirement that are predetermined according to an employee's earning history, tenure of service and age. Individuals with a DB plan become eligible to receive benefits when they reach 65 years or the retirement age specified in their plan. Early withdrawals are possible when they turn 62 years or earlier in case of employment termination for reasons such as disability or early retirement. DC plans, such as 401(k) plans, pay retirement benefits according to contributions corrected for investment gains or losses. Retirement income from DC plans can usually be withdrawn from the age of 59 and a half years. Withdrawals before the official age are subject to an early distribution penalty. However, early withdrawals are often exempted from the penalty in case of employment termination after the age of 55 years or in case of a disability. Other employer-provided plans are Individual Retirement Accounts (IRA), which are similar to 401(k) plans, but have lower contribution limits, and Keogh plans, which are pension plans for the self-employed.

In the last decades, the US have experienced an increasing popularity of DC plans, in particular 401(k) plans, leading to a shift from DB to DC plans (Poterba, 2014). This shift has a positive impact on the average retirement age, since workers with a DC plan retire on average 21 months later than comparable workers with a DB plan (Friedberg and Webb, 2005).

A shortcoming in the data from the IPUMS is that I cannot distinguish between pension plan types. In particular, I cannot identify whether workers withdraw retirement income from DB or DC plans. This shortcoming raises some concerns about a potential channel of correlation between the introduction of industrial robots and the local share of workers that have a DB or a DC plan. In this case, omitted variables that account for the type of plan of older workers may bias my estimates of the effect of robots on early retirement.

Using data from the 2010 Consumer Finance Survey, I find that workers of the manufacturing sector are more likely to have DC plans than workers from other sectors (see Figure B9). Since workers with a DC plan retire later (Friedberg and Webb, 2005) and robots are mostly adopted in manufacturing industries, the potential correlation between robot exposure and the pension plan type through a sector channel would bias my estimates downwards. This, in turn, would imply that the true effect of robots on early retirement would be even stronger than what I estimate.

Figure B9: DB and DC plans by sector



Notes: This figure illustrates the shares of workers with a DB or a DC pension plan by industry group. The bars represent the average share of workers in the manufacturing sector and in industries of other sectors with one particular type of plan. Columns 1 and 2 and Columns 5 and 6 are statistically different from each other.

B4 Robustness checks

This section performs a set of robustness checks in support of my identification strategy.

B4.1 Competition from Europe

As mentioned in Section 2.4, the adoption of robots in Europe could have affected US labor market conditions through increased international product market competition. This is an important threat to identification, since it could violate the exclusion restriction of my IV strategy. Although I cannot rule out this possibility, I show that it is rather unlikely that my results are driven by this causal link.

I control for international competition on the product market from European countries to the US by including a shift-share measure of US imports from Europe. Between the early 1990s and mid-2010s, trade flows from Europe to the US have increased substantially. This increase is mainly driven by a rise in US imports of manufacturing goods that is positively related to the introduction of robots in Europe (see Figure B10). International competition on the product market may therefore confound the effect of robots on US employment, and influence labor force participation accordingly. Similarly to robot adoption, US imports are also subject to domestic shocks that might influence the demand for labor. I account for this concern using a similar approach as Autor et al. (2013) for the China trade shock, using trade flows from Europe to Canada, a country with a comparable trade engagement with European countries as the US (see Figure B11). Table B10 illustrates the results. The estimates of the labor market effect of robots are economically and statistically unaffected by the inclusion of these measures, suggesting that they have not been driven by an increase in import competition from Europe.

In an alternative approach, I omit from the instrument European countries with a large trade engagement with the US, namely France, Italy, and the United Kingdom. The instrument now includes only the stock of robots in Denmark, Finland, Spain and Sweden (the countries that are least likely to impact US labor market conditions through their national adoption of robots). The results are quantitatively almost identical to the results of my preferred specification. These findings suggest again that my estimates are unlikely to be driven by an increase in international product market competition through the heavier utilization of robots in Europe.

B4.2 Industry trends

Another concern that I need to address is that my estimates could be driven by underlying industry trends. For instance, the high concentration of robots in the automotive industry might raise the concern that the results are affected by industry-specific shocks that influence the labor market conditions in CZs which are highly specialized in this industry.[91]

To address this concern, I decompose the stock of industrial robots into robots adopted in the automotive industry and robots adopted in other industries, and construct two separate measures of robot exposure. I extend this exercise by sequentially excluding each industry at a time from the shift-share measure to account for other industry-specific shocks that might confound the labor market effect of robots (Goldsmith-Pinkham et al., 2020). Figure B12 reports 19 point estimates of the effect of robot adoption on labor force participation including all IFR industries but one. The point estimates are not statistically different from my preferred specification's results. They are most sensitive to the exclusion of robots in the automotive industry, which is not surprising, considering that most robots are adopted in this industry. These results suggest that the labor market effect of robots on US labor force participation is not driven by unrelated industry-specific shocks.

B4.3 The Rust Belt

Figure 2.2 of Section 2.3 illustrates that the robot shock is mostly concentrated in labor markets of the Rust Belt due to their specialization in the steel and automotive industry. This finding raises the question of whether the effect of robots on labor force non-participation is specific to these CZs or whether this is a US wide phenomenon.

Table B12 reports the results when excluding from the sample the CZs with the highest robot exposure. I start by excluding the local labor market of Detroit, which is the CZs that is mostly exposed to the shock (between 1993 and 2014 the stock of robots increases by about 11 robots per

[91] Table B11 shows the average industry weights of the top eight industries of the shift-share measure (also known as Rotemberg weights, see Goldsmith-Pinkham et al., 2020) and the relative contribution of industries to the national change in the stock of robots between 1993 and 2014. The automotive industry has the highest Rotemberg weight and accounts for more than 50 percent of the change in robot adoption in these years. These results show that the exposure to the shock strongly depends on the development in robot adoption in this industry, which increases the sensibility of my estimates to other industry-specific shocks that affect labor markets which are specialized in the automotive industry.

thousand workers). I then exclude all CZs around the Great Lakes that are in the states of Michigan, Indiana and Ohio. The estimates remain economically and statistically significant at conventional levels, showing that the effect of robots is not limited to CZs in the Rust Belt. Interestingly, outside of the Great Lakes' CZs the effect of robots is larger, suggesting that, although they are adopted less frequently in those areas, the introduction of one additional robot has a stronger effect on labor force participation than in the Rust Belt.

B4.4 Pre-trends

The secular increase in the non-participation rate of men (see Table 2.2) raises the concern that labor force participation and the adoption of industrial robots could be driven by some common factors. For example, changes in non-participation and the adoption of robots could both stem from a local labor market's industrial composition. If so, our estimates could be confounding the impact of robot exposure with pre-existing trends that local labor markets were undergoing.

I account for this concern in my preferred specification by controlling for the change in the local labor force participation rate and the decline in manufacturing employment between 1970 and 1990. Table 2.3 shows that inclusion of these controls does not alter my estimates of the effect of robots (compare Columns 2 and 3). I test for the existence of pre-trends that could bias my results also from a different perspective. I perform a "placebo test" and estimate a two-period model in which I regress the change in the local non-participation rate for the 1970-80 and 1980-90 periods on the exposure to robots during the first two periods of my sample (1990-2000 and 2000-07). Table B13 summarizes the results. I do not find any significant relationship between the introduction of robots and trends in non-participation before the 1990s when using my preferred specification, neither in the overall population nor for men.

B4.5 The Great Recession

Another concern that I need to address is whether poor labor market conditions trigger workers' local labor supply responses against the automation shock differently than during ordinary times. In fact, labor force non-participation has increased particularly during the period of the Great Recession.

I account for this potential issue in two ways. First, I estimate Equation 73 by excluding the

2007-14 period to verify whether the effect of robot adoption on labor force participation is already visible before the Great Recession. Second, I interact robot exposure with a dummy for the 2007-14 period to test whether the effect of robots is statistically and economically different during the Great Recession. Results are reported in Table B14. I find that the effect of robots on labor force non-participation is already visible before the start of the Great Recession, and that in my preferred specification the impact of robots is not statistically different between the periods before and during the recession.

B4.6 Robots and imports

Columns 3 and 4 of Table 2.3 show that the inclusion of the China trade shock in the set of covariates is not affecting neither the size nor the significance of my estimates of the effect of robots on labor force non-participation. This result suggests that, in spite of both shocks being concentrated in the manufacturing sector, the labor market impacts of the two shocks are mostly orthogonal.

Table B15 reports the estimates of the effect of robots along with standardized estimates of US imports from China. Results show that the effect of imports on labor force non-participation is significantly smaller than the effect of robots. For men, I find that a one standard deviation increase in robot exposure increases non-participation by 75 percent more than a one standard deviation increase in import exposure.

In line with this result, Faber et al. (2022) argue that the adoption of robots exerts strong adverse spillover effects to local industries which are not directly exposed to the shock (e.g. to the service sector), while import competition does not (or it does to a smaller extent).

B4.7 Robots and other technologies

Table B16 compares the effect of robot exposure to other technologies. Results show that the impact of robots on non-participation is different from other technologies. In particular, the secular increase in the adoption of PCs has had the opposite effect, reducing the non-participation rate in exposed areas. This effect is entirely driven by an increase in the job prospects for women, whose employment experienced a significant stimulus in the last decades due to the rise of the service economy (Ngai and Petrongolo, 2017, Petrongolo and Ronchi, 2020). On the other side, non-participation has increased in areas with a high share of routine task-intensive occupations. Again, Column 2 shows that the effect disappears when focusing on men, suggesting that this result is driven by women, who are often over-represented in clerical middle-skill jobs (Lerch, 2021).

B4.8 Cross-sectional and temporal variation

The preferred specification of this paper analyzes the labor market effect of robots by exploiting both cross-sectional variation in robot exposure across CZs and temporal variation in robot exposure within CZs. I verify the relative importance of these sources of variation using a single long-difference specification over the 1990-2014 period, and using a stacked first-difference specification with CZ fixed effects respectively. The latter specification is more demanding and accounts also for unobserved time-invariant CZ trends which could influence the adoption of robots and labor market outcomes. The results are summarized in Table B17.

In the first part of the table, I observe that between-CZs variation in robot exposure accounts for most of the variation, suggesting that the adoption of robots is mainly driven by the secular industry specialization of local labor markets. The second part reports estimates of the labor market effect of robots by exploiting each source of variation individually. I find that robots have a significant impact on labor force participation in both specifications. These results support the use of the stacked first-difference model using dynamic division effects as in my preferred specification, since cross-sectional variation is an important source of the overall variation in robot exposure and unobserved heterogeneity across CZs does not bias my estimates of the labor market effect of robots.

B4.9 Construction of the shift-share measure

Table B18 shows that the exact construction of the shift-share measures in Equations 74 and 75 does not affect my results. Panels A and B report estimates of two more mixes of European countries that are used in the construction of the instrument. First, I exclude from my instrument Spain and the United Kingdom and replicate the measure of Acemoglu and Restrepo (2020). Second, I include Germany, a country that is ahead of the US in the adoption of robots. Panel C reports estimates using an instrument with 1990 industry employment shares, $\ell_{c,j}^{1990}$, rather than from 1970. Panel D reports estimates using a measure of US robot exposure and an instrument without adjusting for industry output growth, $g_{j,(t_0,t_1)} \frac{R_{j,t_0}}{L_{j,1990}}$. The estimates of the labor market effect of robots on non-participation do not differ economically or statistically from my preferred specification's results.

B4.10 Logarithmic outcomes

Table B19 illustrates the estimates of the effect of robots on labor market outcomes in logarithmic changes rather than in shares of the working-age population. I find robust estimates of the labor market effects of robots that are in line with my preferred specification's results. The estimates suggest that a one standard deviation increase in US robot exposure decreases labor force participation by 0.916 log-points.

B4.11 Robust standard errors

Borusyak et al. (2021) argue that standard errors need to consider also potential correlations across CZs resulting from common industry-level shocks. Table B20 reports the estimates of the effect of robots on US employment allowing for clustering at the IFR industry level. I find that employment decreased relatively more in industries that experienced high robot growth and that this result is robust to the inclusion of industry fixed effects. Table B21 further reports results on the effect of robots on non-participation at the CZ level allowing for arbitrary clustering at the division level. This specification considers also the potential correlation of the residuals between neighboring CZs that belong to different states. The standard errors are almost identical to my baseline specification and do not affect the significance of my results.

B4.12 Alternative covariates

Table B22 shows that also the choice of covariates included in the vector of regional characteristics and economic variables does not alter my results. Panel A reports estimates of the effect of robots when including a set of state fixed effects to control for state specific labor market conditions and policies that could affect my outcomes. Panel B includes shift-share measures of technology shocks (computer adoption and IT capital investments) that may confound the labor market effect of robots. The results show that the inclusion of these controls does not affect the economic and statistical significance of my results. Panel C includes time-varying covariates of CZs' demographics and their industrial and occupational composition of employment (1990, 2000 and 2007) rather than fixed at 1990 levels. Panel D reports estimates using a two-step LASSO procedure for the selection of covariates (Belloni et al., 2014). Again, the estimates of the labor market effect of robots are quantitatively and qualitatively similar as in my preferred specification. Table B23 includes also estimates of the effect of robots using a more demanding specification that includes the beginning-of-period share of white and non-white men interacted with time dummies. Results are unaffected by the inclusion of these additional covariates.

B4.13 Stock of robots using the perpetual inventory method

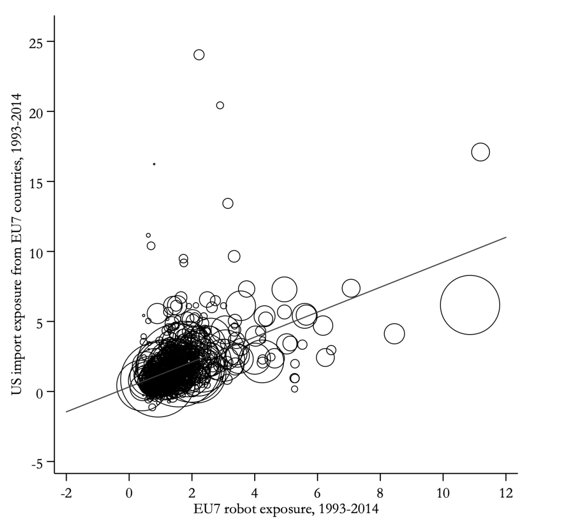
The IFR estimates the operational stock of robots assuming no depreciation of robot capital in the first 12 years of service and full depreciation in the 13th year. I stress this assumption and, following Graetz and Michaels (2018), I build measures of the stock of robots based on yearly shipments using the perpetual inventory method at different depreciation rates. Table B24 illustrates the results of the effect of robots on non-participation assuming a depreciation rate of robot capital of 5%, 10% and 15%. The alternative measures provide estimates of the labor market effect of robots that are quantitatively and qualitatively similar to my preferred specification.

B4.14 Unweighted results

Table B25 reports a set of estimates of the effect of robots on non-participation at the CZ level without population weights in the regressions. This specification provides less precise estimates, in particular when considering the total population. The effect is statistically significant at conventional levels for men.

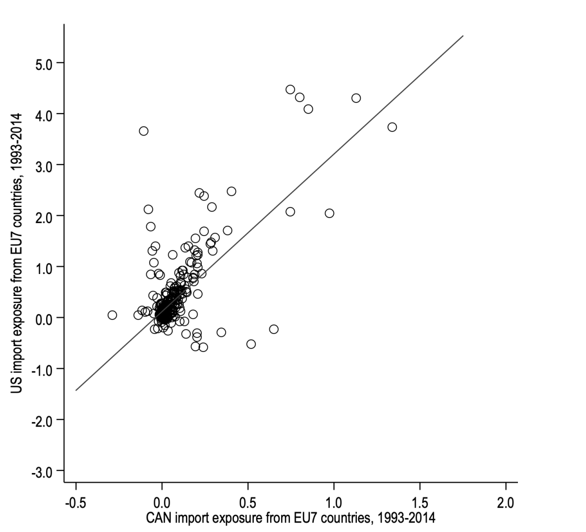
As pointed out in the main text, when analyzing outcomes across labor markets of different sizes, efficient weights must consider individuals' sampling weights to account for inherent heteroskedasticity. Cadena and Kovak (2016) show that optimal weights are strongly correlated with initial population sizes and are well approximated by the initial population of a local labor market. Therefore, I am confident that the results of my preferred specification are providing better estimates of the underlying effect of robots on non-participation than the results of Table B25.

Figure B10: European robot exposure and imports to the US



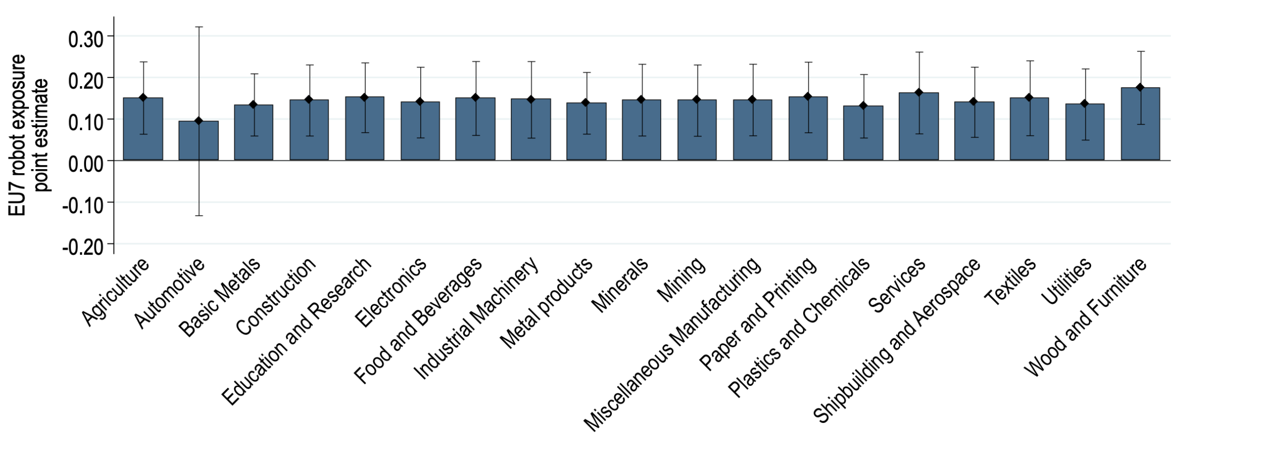
Notes: This figure illustrates the unweighted correlation between robot exposure in European countries, as presented in Equation 75, and a shift-share measure of imports from these countries to the US. The size of the circles represent a labor market's size in terms of population in 1990. The solid line represents a prediction for US import exposure from European countries from a linear regression on robot exposure in Europe.

Figure B11: Trade flows from Europe to the US and Canada by industry



Notes: This figure illustrates the unweighted correlation between imports from seven European countries (Denmark, Finland, France, Italy, Spain, Sweden and the United Kingdom) to the US and Canada. Imports are represented by SIC industry of the manufacturing sector (392) in billions of US dollars in 2017 prices. For visibility reasons, for either country I omitt outlying industries with imports that exceed six billion US dollars in the US, Canada or both. These industries are yarn spinning mills (2281), fiber cans, drums and similar products (2655), pharmaceutical preparations (2834), petroleum refining (2911), gypsum products (3275), minerals, ground or treated (3295), primary nonferrous metals, nec (3339), valves and pip fittings, nec (3494), machine tool accessories (3545), welding apparatus (3548) food products machinety (3556), noncurrent-carrying wiring devices (3644), motor vehicles and car bodies (3711), motor vehicle parts and accessories (3714), aircraft (3721). The solid line represents a prediction for US import exposure from European countries from a linear regression on Canadian import exposure from European countries based on all 392 SIC industries of the manufacturing sector.

Figure B12: Sequential exclusion of IFR industries



Notes: This figure illustrates the reduced form point estimates of the effect of robot exposure on non-participation by excluding each industry from the shift-share measure one at a time. For example, *Automotive* excludes robots adopted in the automotive industry. Regressions include the full battery of controls from my preferred specification and are weighted by CZ population in 1990. Confidence intervals are at the 95% level.

Table B10: Product market competition from Europe

	Population				Men
	[1]	[2]	[3]	[4]	[5]
	Panel A: Import competition in the US				
US robot exposure	0.219**	0.239**	0.236***	0.203***	0.356***
	(0.093)	(0.095)	(0.086)	(0.065)	(0.072)
US imports from EU7	0.031	0.022	0.010	-0.054	-0.075
	(0.045)	(0.044)	(0.043)	(0.050)	(0.072)
	Panel B: Import competition in Canada				
US robot exposure	0.220**	0.238**	0.233***	0.193***	0.343***
	(0.090)	(0.092)	(0.083)	(0.062)	(0.070)
CAN imports from EU7	0.205*	0.193	0.185	0.119	0.154
	(0.113)	(0.115)	(0.117)	(0.105)	(0.114)
	Panel C: EU4 countries (Denmark, Finland, Spain, Sweden)				
US robot exposure	0.226*	0.248*	0.236**	0.170**	0.258***
	(0.123)	(0.125)	(0.113)	(0.083)	(0.091)
Observations	2166	2166	2166	2166	2166
Covariates:					
Divisions	✓	✓	✓	✓	✓
Years	✓	✓	✓	✓	✓
Pre-trends		✓	✓	✓	✓
Chinese imports			✓	✓	✓
Demographics				✓	✓
Industries				✓	✓
Occupations				✓	✓

Notes: This table presents estimates of the effect of US robot exposure on non-participation. Panel A reports IV estimates using the standard instrument with seven European countries and estimates of the effect of US imports from these countries. Panel B reports IV estimates using the standard instrument with seven European countries and estimates of the effect of Canadian imports from these countries. Panel C reports IV estimates using an instrument that includes only the three European countries with the lowest trade engagement with the US (Denmark, Finland, Spain and Sweden). Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Table B11: Rotemberg weights

	Rotemberg weights				Share of robot change
	[1]	[2]	[3]	[4]	[5]
Automotive	.557	.578	.583	.619	.563
Plastics and Chemicals	.157	.145	.144	.148	.103
Electronics	.080	.078	.057	.057	.007
Basic Metals	.079	.077	.079	.068	.057
Food and Beverages	.076	.077	.084	.082	.068
Industrial Machinery	.015	.015	.020	.017	.035
Shipbuilding and Aerospace	.015	.011	.013	.008	.022
Mining	.003	.004	.007	.006	.004
Covariates:					
Divisions	✓	✓	✓	✓	
Pre-trends		✓	✓	✓	
Chinese imports			✓	✓	
Demographics				✓	
Industries				✓	
Occupations				✓	

Notes: This table presents Rotemberg weights for the eight industries with the highest robot adoption between 1993 and 2014 – as explained in Goldsmith-Pinkham et al. (2020) – and the share of the overall change in robot stock between 1993 and 2014 that comes from these industries. Columns 1 to 5 report the average industry Rotemberg weights over the sample period for different model specifications. Column 6 reports the fraction of robot introduction over the sample period that comes from the eight industries with the highest average Rotemberg weights.

Table B12: Exclusion of the CZs with the highest robot exposure

	Population				Men
	[1]	[2]	[3]	[4]	[5]
	Panel A: Exclusion of Detroit				
US robot exposure	0.437**	0.470**	0.449**	0.313	0.441**
	(0.197)	(0.193)	(0.190)	(0.204)	(0.212)
Observations	2163	2163	2163	2163	2163
	Panel B: Exclusion of CZs around Great Lakes				
US robot exposure	0.748***	0.783***	0.810***	0.781*	0.875*
	(0.245)	(0.225)	(0.238)	(0.425)	(0.467)
Observations	2010	2010	2010	2010	2010
Covariates:					
Divisions	✓	✓	✓	✓	✓
Years	✓	✓	✓	✓	✓
Pre-trends		✓	✓	✓	✓
Chinese imports			✓	✓	✓
Demographics				✓	✓
Industries				✓	✓
Occupations				✓	✓

Notes: This table presents IV estimates of the effect of US robot exposure on the non-participation rate, excluding a set of outlying CZs. Panel A reports estimates excluding Detroit from the sample. Panel B reports estimates excluding CZs in the most exposed states around the Great Lakes (Indiana, Michigan and Ohio). Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Table B13: Robots and non-participation between 1970-90: Placebo test

	Population			Men
	[1]	[2]	[3]	[4]
US robot exposure	0.061**	0.061**	-0.005	0.025
	(0.027)	(0.026)	(0.028)	(0.023)
Observations	1444	1444	1444	1444
Covariates:				
Divisions	✓	✓	✓	✓
Years	✓	✓	✓	✓
Chinese imports		✓	✓	✓
Demographics			✓	✓
Industries			✓	✓
Occupations			✓	✓

Notes: This table presents IV estimates of the effect of US robot exposure on the non-participation rate between 1970 and 1990. There are two time periods (1970-80 and 1980-90 for non-participation and 1990-2000 and 2000-07 for robot exposure) and 722 CZs. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Table B14: The Great Recession

	Population				Men
	[1]	[2]	[3]	[4]	[5]
	Panel A: Exclude 2007-14 period (IV)				
US robot exposure	0.206**	0.221***	0.207***	0.151**	0.307***
	(0.084)	(0.081)	(0.065)	(0.063)	(0.067)
Observations	1444	1444	1444	1444	1444
	Panel B: Effect prior and during 2007-14 period (reduced form)				
EU7 robot exposure	0.162**	0.181***	0.170***	0.139***	0.262***
	(0.063)	(0.066)	(0.053)	(0.044)	(0.049)
EU7 robot exposure × 2007-14	0.564*	0.496*	0.699**	0.354	-0.367
	(0.294)	(0.279)	(0.277)	(0.243)	(0.231)
Observations	2166	2166	2166	2166	2166
Covariates:					
Divisions	✓	✓	✓	✓	✓
Years	✓	✓	✓	✓	✓
Pre-trends		✓	✓	✓	✓
Chinese imports			✓	✓	✓
Demographics				✓	✓
Industries				✓	✓
Occupations				✓	✓

Notes: This table presents estimates of the effect of US robot exposure on the non-participation rate, and examines the role of the Great Recession. Panel A reports IV estimates and excludes the period of the Great Recession (2007-14) using only the first two periods in my sample. Panel B reports reduced form estimates and interacts robot exposure with a time dummy for the period of the Great Recession. This specification includes all three periods. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Table B15: Robots, imports and non-participation

	Population				Men
	[1]	[2]	[3]	[4]	[5]
			Panel A: IV estimates		
US robot exposure	0.224**	0.242**	0.237***	0.195***	0.345***
	(0.093)	(0.095)	(0.085)	(0.063)	(0.072)
US import exposure			0.258**	0.127	0.197*
			(0.122)	(0.094)	(0.099)
			Panel B: First-stage of US robot exposure		
EU7 robot exposure	0.773***	0.792***	0.787***	0.743***	0.742***
	(0.055)	(0.044)	(0.055)	(0.048)	(0.049)
OT8 import exposure			0.249***	0.134***	0.135***
			(0.033)	(0.043)	(0.042)
			Panel C: First-stage of US import exposure		
EU7 robot exposure			-0.006	-0.004	-0.004
			(0.011)	(0.011)	(0.012)
OT8 import exposure			1.006***	1.007***	1.007***
			(0.023)	(0.023)	(0.022)
Observations	2166	2166	2166	2166	2166
Covariates:					
Divisions	✓	✓	✓	✓	✓
Years	✓	✓	✓	✓	✓
Pre-trends		✓	✓	✓	✓
Chinese imports			✓	✓	✓
Demographics				✓	✓
Industries				✓	✓
Occupations				✓	✓

Notes: This table presents IV estimates of the effect of robot exposure and import exposure on the non-participation rate. Panels B and C report first stage estimates of robot exposure and import exposure. Independent variables are standardized to have mean zero and standard deviation of one. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Table B16: Robots, non-participation and other shocks

	Population	Men
	[1]	[2]
US robot exposure	0.202***	0.351***
	(0.065)	(0.073)
PC adoption	-0.125***	-0.057
	(0.044)	(0.050)
IT intensity	0.028	0.044
	(0.068)	(0.095)
Routine occupations	0.122*	-0.091
	(0.069)	(0.077)
Offshorable occupations	-0.060	-0.081
	(0.062)	(0.066)
Observations	2166	2166
Covariates:	✓	✓

Notes: This table presents IV estimates of the effect of US robot exposure, personal computer adoption, IT capital intensity, the share of routine task-intensive occupations and the share of offshorable occupations on the non-participation rate. Independent variables are standardized to have mean zero and standard deviation of one. All regressions include the full battery of controls from my preferred specification. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Table B17: Robot exposure across and within local labor markets

	US robot exposure	
	Mean	Std. Dev.
Panel A: Robots per thousand workers		
Overall	0.526	0.491
Between		0.452
Within		0.192
Panel B: Standardized		
Overall	0.000	1.000
Between		0.921
Within		0.391

	Estimates of US robot exposure			
	Between CZs		Within CZs	
	All	Men	All	Men
	[1]	[2]	[3]	[4]
US robot exposure	0.067	0.170**	0.619**	1.077***
	(0.078)	(0.084)	(0.270)	(0.306)
Observations	722	722	2166	2166
Covariates:				
Divisions	✓	✓	✓	✓
Years			✓	✓
Pre-trends	✓	✓		
Chinese imports	✓	✓	✓	✓
Demographics	✓	✓		
Industries	✓	✓		
Occupations	✓	✓		
CZ fixed effects			✓	✓

Notes: The first part of this table presents unweighted averages and the between and within CZ standard deviation of US robot exposure. Panel A reports the mean and standard deviations in robots per thousand workers. Panel B reports standardized measures with mean zero and overall standard deviation of one. The second part of the table presents IV estimates of the effect of US robot exposure on the non-participation rate and exploits between and within CZ variation in robot adoption separately. Changes are expressed in percentage points of the working-age population and are multiplied by 100. Independent variables are standardized to have mean zero and standard deviation of one. Columns 1 and 2 use a long-difference specification between 1993 and 2014 and includes the full battery of controls. There is one period and there are 722 CZs. Columns 3 and 4 use a stacked first-difference specification and includes year dummies, nine census divisions, their interactions and CZ fixed effects. There are three time periods and 722 CZs. Standard errors are robust against heteroskedasticity and allow for clustering at the state level. Regressions are weighted by CZ population in 1990. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Table B18: Alternative construction of measures of robot exposure

	Population				Men
	[1]	[2]	[3]	[4]	[5]
	Panel A: EU5 countries (Acemoglu and Restrepo, 2020)				
US robot exposure	0.263**	0.283**	0.277**	0.230**	0.379***
	(0.124)	(0.126)	(0.116)	(0.092)	(0.102)
	Panel B: EU7 countries and Germany				
US robot exposure	0.185**	0.201***	0.197***	0.157***	0.287***
	(0.073)	(0.073)	(0.065)	(0.046)	(0.054)
	Panel C: EU7 countries with $\ell_{c,j}^{1990}$				
US robot exposure	0.325**	0.323**	0.311***	0.238***	0.385***
	(0.128)	(0.126)	(0.115)	(0.078)	(0.086)
	Panel D: EU7 countries without $g_{j,(t_0,t_1)} \frac{R_{j,t_0}}{L_{j,1990}}$				
US robot exposure	0.180**	0.197***	0.189***	0.146***	0.261***
	(0.068)	(0.072)	(0.059)	(0.038)	(0.037)
Observations	2166	2166	2166	2166	2166
Covariates:					
Divisions	✓	✓	✓	✓	✓
Years	✓	✓	✓	✓	✓
Pre-trends		✓	✓	✓	✓
Chinese imports			✓	✓	✓
Demographics				✓	✓
Industries				✓	✓
Occupations				✓	✓

Notes: This table presents IV estimates of the effect of US robot exposure on the non-participation rate using different instrument measures. Panel A reports estimates using an instrument that includes only five European countries. I exclude Spain and the United Kingdom as in the measure in Acemoglu and Restrepo (2020). Panel B reports estimates using an instrument which includes seven European countries and Germany. Panel C reports estimates using an instrument with seven European countries, but US employment shares of 1990 instead of 1970. Panel D reports estimates using an endogenous variable and an instrument of robot density without the adjustment term of industry growth. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Table B19: Logarithmic changes

	Population				Men
	[1]	[2]	[3]	[4]	[5]
US robot exposure	1.027**	1.099***	1.080***	0.916***	2.056***
	(0.385)	(0.385)	(0.347)	(0.260)	(0.471)
Observations	2166	2166	2166	2166	2166
Covariates:					
Divisions	✓	✓	✓	✓	✓
Log-population	✓	✓	✓	✓	✓
Years	✓	✓	✓	✓	✓
Pre-trends		✓	✓	✓	✓
Chinese imports			✓	✓	✓
Demographics				✓	✓
Industries				✓	✓
Occupations				✓	✓

Notes: This table presents IV estimates of the effect of US robot exposure on the non-participation rate. Changes are expressed in logarithms and are multiplied by 100. All columns control for changes in the logarithmic working-age population. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Table B20: The effect of robots on employment with standard errors clustered at the IFR industry level

	[1]	[2]	[3]	[4]
US robot density	-3.459	-2.887	-4.768**	-8.400***
	(1.996)	(2.364)	(2.074)	(2.606)
Observations	57	57	57	57
Covariates:				
Years	✓	✓	✓	✓
Pre-trends		✓		
Demographics		✓		
Occupations		✓		
Industry FE			✓	✓

Notes: This table presents IV estimates of the effect of US robot density on the change in employment at the industry level. Changes are expressed in logarithmic changes and are multiplied by 100. Robot density is equal to the shift component of Equations 74 and 75 and is standardized to have mean zero and standard deviation of one. There are three time periods and 19 IFR industries. Column 1 includes year dummies. Column 2 includes also changes in IFR log-employment between 1970 and 1990, as well as demographic (share of individuals aged between 25 and 34 years, 35 and 44 years, 45 and 54 years, the share of white men, Blacks, Hispanics, women and individuals with less than a college degree) and occupational (share of offshorable and routine task-intensive occupations) controls at the industry level in 1990. Columns 3 and 4 include IFR industry FE. Standard errors are robust against heteroskedasticity and allow for clustering at the industry level. Regressions are weighted by industry employment in 1990. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Table B21: Clustering at the division level

	Population				Men
	[1]	[2]	[3]	[4]	[5]
US robot exposure	0.224*	0.242*	0.237*	0.195**	0.345***
	(0.115)	(0.120)	(0.108)	(0.080)	(0.079)
Observations	2166	2166	2166	2166	2166
Covariates:					
Divisions	✓	✓	✓	✓	✓
Years	✓	✓	✓	✓	✓
Pre-trends		✓	✓	✓	✓
Chinese imports			✓	✓	✓
Demographics				✓	✓
Industries				✓	✓
Occupations				✓	✓

Notes: This table presents IV estimates of the effect of US robot exposure on the non-participation rate. Standard errors are robust against heteroskedasticity and allow for clustering at the division level. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Table B22: Alternative covariates

	Population				Men	
	[1]	[2]	[3]	[4]	[5]	[6]
	Panel A: Inclusion of state fixed effects					
US robot exposure	0.289*	0.319*	0.306*	0.283**	0.536***	
	(0.162)	(0.160)	(0.152)	(0.135)	(0.168)	
	Panel B: Inclusion of non-robot automation technologies					
US robot exposure	0.216**	0.224**	0.223**	0.202***	0.351***	
	(0.087)	(0.085)	(0.084)	(0.065)	(0.073)	
	Panel C: Period covariates					
US robot exposure	0.224**	0.242**	0.237***	0.152***	0.310***	
	(0.093)	(0.095)	(0.085)	(0.051)	(0.060)	
	Panel D: Selection of covariates using a two-step lasso					
US robot exposure						0.806***
						(0.140)
Observations	2166	2166	2166	2166	2166	2166
Covariates:						
Divisions	✓	✓	✓	✓	✓	
Years	✓	✓	✓	✓	✓	
State	✓	✓	✓	✓	✓	
Pre-trends		✓	✓	✓	✓	
Chinese imports			✓	✓	✓	
Demographics				✓	✓	
Industries				✓	✓	
Occupations				✓	✓	
LASSO covariates						✓

Notes: This table presents IV estimates of the effect of US robot exposure on the non-participation rate, including state fixed effects and a selection of covariates using a two-step LASSO. Panel A reports estimates including state FE, Panel B includes beginning of subperiod (1990, 2000 and 2007) covariates and Panel C reports estimates selecting a set of covariates using a LASSO approach. Column 1 includes year dummies, nine census divisions and their interactions. Column 2 includes also changes in the non-participation rate and in the manufacturing employment rate between 1970 and 1990. Column 3 includes also exposure to Chinese imports. Columns 4 and 5 control also for demographic (share of individuals aged between 25 and 34 years, 35 and 44 years, 45 and 54 years, the share of white men, Blacks, Hispanics, women and individuals with less than a college degree and logarithmic population), industry (shares of employment in the construction, manufacturing, mining, research, service and utilities sector) and occupation (share of offshorable and routine task-intensive occupations) characteristics of CZ in 1990 in Panel A and in 1990, 2000 and 2007 in Panel B. Column 6 includes the nine census divisions, the share of individuals with less than a college degree, the logarithmic population, the share of employment in the above mentioned sectors, and the share of routine task-intensive occupations in 1990, all interacted with time dummies. In addition, it includes the employment share in the automotive industry, male manufacturing and heavy manufacturing in 1990 and exposure to US imports from China. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Table B23: Control for the share of whites and racial and ethnic minority men interacted with time dummies

	Population	Men
	[1]	[2]
US robot exposure	0.175***	0.326***
	(0.042)	(0.040)
Observations	2166	2166
Covariates:	✓	✓

Notes: This table presents IV estimates of the effect of US robot exposure on the non-participation rate. Both columns include the full battery of controls from my preferred specification and the share of white and non-white men in the population interacted with year dummies. All regressions include the full battery of controls from my preferred specification. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Table B24: Perpetual inventory method

	Population				Men
	[1]	[2]	[3]	[4]	[5]
	Panel A: 5% depreciation rate				
US robot exposure	0.210*	0.228**	0.217**	0.177**	0.276***
	(0.111)	(0.111)	(0.099)	(0.079)	(0.082)
Observations	2166	2166	2166	2166	2166
	Panel B: 10% depreciation rate				
US robot exposure	0.268*	0.283*	0.279**	0.242*	0.378***
	(0.144)	(0.144)	(0.137)	(0.123)	(0.130)
Observations	2166	2166	2166	2166	2166
	Panel C: 15% depreciation rate				
US robot exposure	0.322	0.328	0.337*	0.299	0.459**
	(0.202)	(0.202)	(0.200)	(0.192)	(0.201)
Observations	2166	2166	2166	2166	2166
Covariates:					
Divisions	✓	✓	✓	✓	✓
Years	✓	✓	✓	✓	✓
Pre-trends		✓	✓	✓	✓
Chinese imports			✓	✓	✓
Demographics				✓	✓
Industries				✓	✓
Occupations				✓	✓

Notes: This table presents IV estimates of the effect of US robot exposure on the non-participation rate. The operational stock of robots is constructed based on yearly shipments using the perpetual inventory method, assuming a depreciation rate of 5%, 10% and 15%. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Table B25: Unweighted regressions

	Population				Men	Women
	[1]	[2]	[3]	[4]	[5]	[6]
US robot exposure	0.236**	0.276**	0.238**	0.123	0.352**	-0.091
	(0.102)	(0.106)	(0.089)	(0.087)	(0.138)	(0.135)
Observations	2166	2166	2166	2166	2166	2166
Covariates:						
Divisions	✓	✓	✓	✓	✓	✓
Years	✓	✓	✓	✓	✓	✓
Pre-trends		✓	✓	✓	✓	✓
Chinese imports			✓	✓	✓	✓
Demographics				✓	✓	✓
Industries				✓	✓	✓
Occupations				✓	✓	✓

Notes: This table presents IV estimates of the effect of US robot exposure on the non-participation rate. Regressions are unweighted. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

B5 General equilibrium and adjustment effects

General equilibrium effects – According to the results illustrated in Table 2.3, each additional robot decreases the local labor force by about four workers. This result includes only local effects of robot adoption and does not account for aggregate effects resulting from cross-CZ spillovers that could influence labor market conditions in other areas.

Acemoglu and Restrepo (2020) argue that, when considering general equilibrium effects, the labor market impact of robots on employment halves in size, likely because of productivity gains and reduced prices of tradable goods that are shared with the rest of the US economy (Bloom et al., 2019). The authors present a parametric model to quantify the aggregate employment effects of robots in the US and estimate that the local labor market impact of robots decreases from an employment reduction of 6 workers to about 3.3 workers. A full blown model that accounts for the general equilibrium effects of robots on labor force non-participation and displaced individuals' margins of adjustment is outside of the scope of this paper. The focus is primarily on the margins of adjustment of workers who *drop out* of the labor force because of a displacement through the introduction of robots in their local labor market.

Adjustment mechanism – A second point that is worth mentioning is that local shocks may trigger general equilibrium adjustments that gradually offset their local impact, with a period of positive labor market conditions following the negative initial effect. This is an identification issue that has been recently addressed by Jaeger et al. (2019) with focus on the immigration literature. Analogously to this paper, this literature commonly uses a shift-share approach to identify the supply channel of migration flows. This measure usually combines past settlement patterns of migrants in local labor market areas (baseline industry shares of employment in this paper) with current aggregate inflows of migrants from a variety of countries of origin (robot adoption at the country-industry level in this paper) (e.g. Card, 2001).

In this setting, Jaeger et al. (2019) raise the concern that the country of origin composition and settlement patterns of immigrants are often persistent, with the same cities repeatedly receiving large inflows (which is the underlying relevance assumption for this instrument). They argue, however, that such a spatial correlation approach may conflate the (presumably negative) partial equilibrium wage impact of recent immigrant inflows with the (presumably positive) local labor market adjustment to *previous* immigrant supply shocks.

To address this issue, they show that the labor market adjustment process can be considered to be a function of lagged immigration inflows, leading to an omitted variable bias in the conventional IV estimator. The inclusion of a lagged variable of the shock in the estimating equation would allow to isolate the variation in inflows that is uncorrelated with current local demand shocks as well as the adjustment to past supply shocks. Their results suggest that a "dynamic shift-share" procedure provides estimates of the initial impact of immigration on natives' wages that are more negative than estimates based on the conventional shift-share instrument alone.[92]

Although I find that the automation shock has a negative effect on labor force participation, it may still be that local labor markets are undergoing an adjustment dynamic in response to previous shocks that are confounding the partial equilibrium effect, which is stronger than the effect that the estimates in Table 2.3 are suggesting.

I address this issue by including a lagged measure of US robot exposure in my main specification. The results are provided in Table B26. Since the IFR provides no data on robot adoption before the early 1990s, I need to exclude my first sample period from this part of the analysis (1993-2000) in order to work with lagged variables. Panels A and B illustrate reduced form and IV estimates of the effect of robots on labor force participation using my preferred specification for the 2000-07 and 2007-14 periods. The results are not significantly different from those in Table 2.3. As argued in Jaeger et al. (2019), when there is little change in the flow variables across periods, the instruments are likely to be highly correlated with one another.

To gauge the degree of independent information in the two variables, Panel C presents results from reduced form regressions of changes in labor force participation on the instruments of robot exposure in the same period and robot exposure in the previous period. Panel D reports the IV results together with the Kleibergen-Paap rk LM statistic for underidentification, whose null-hypothesis can be rejected only at the 10 percent level in my main specification (5 percent for men), suggesting that there may be some degree of linear dependence between the estimated coefficients, which may lead to problems of identification in the second stage. Panel C shows that the inclusion of

[92] The dynamic shift-share procedure addresses the adjustment bias by controlling for its source, lagged shocks, rather than directly controlling for the individual adjustment channels that contribute to this bias, such as internal migration, inter-city trade, or internal capital flows, for which little data is usually available.

the lagged shock does not economically nor significantly affect the impact of current robot exposure on labor force participation. The coefficient of the lagged variable is slightly negative, but not significantly different from zero (at the 10 percent level for men). When considering the IV results in Panel D, instead, the estimated effect of current robot exposure increases to 0.317 (compared to 0.227 in Panel B), while the estimated effect of the lagged shock becomes significantly negative (-0.192), suggesting that my estimates from Table 2.3 could be biased towards zero, since the negative partial equilibrium effect is conflated by the (positive) adjustment process that local labor markets are undergoing in response to the past shock.

As has been also acknowledged in Jaeger et al. (2019), the dynamic shift-share procedure is quite demanding on the data. Because the instruments are potentially highly collinear, the mechanical relationship between the current instrument and past shocks is interfering a clean identification of the separate shocks, resulting in a (joint) weak instrument problem in finite samples.[93] In these cases, the focus should be directed towards reduced form results, which suggest no significant difference with respect to my main specification's results, when including a measure of the lagged shock.

[93] I find that there may indeed be underidentification, since the (unreported) first-stage results show a significant correlation of lagged US robot exposure with the lagged instrument and with the current instrument.

Table B26: Dynamic shift-share estimation

	Population				Men
	[1]	[2]	[3]	[4]	[5]
	Panel A: Conventional shift-share (reduced form)				
EU7 robot exposure	0.225**	0.250**	0.244**	0.159***	0.275***
	(0.105)	(0.107)	(0.097)	(0.041)	(0.053)
	Panel B: Conventional shift-share (IV)				
US robot exposure	0.302**	0.330**	0.326**	0.227***	0.392***
	(0.147)	(0.147)	(0.140)	(0.058)	(0.072)
	Panel C: Dynamic shift-share (reduced form)				
EU7 robot exposure	0.219**	0.232**	0.231***	0.162***	0.289***
	(0.090)	(0.092)	(0.084)	(0.046)	(0.058)
EU7 robot exposure lagged	0.020	0.059	0.046	-0.011	-0.062*
	(0.063)	(0.067)	(0.062)	(0.036)	(0.037)
	Panel D: Dynamic shift-share (IV)				
US robot exposure	0.411**	0.417**	0.425**	0.317***	0.584***
	(0.166)	(0.167)	(0.166)	(0.101)	(0.119)
US robot exposure lagged	-0.200**	-0.163*	-0.184*	-0.192*	-0.407***
	(0.089)	(0.082)	(0.094)	(0.103)	(0.114)
Kleibergen-Paap rk LM stat	2.256	2.251	2.269	2.954	3.969
P-value	0.133	0.133	0.132	0.086	0.046
Observations	1444	1444	1444	1444	1444
Covariates:					
Divisions	✓	✓	✓	✓	✓
Years	✓	✓	✓	✓	✓
Pre-trends		✓	✓	✓	✓
Chinese imports			✓	✓	✓
Demographics				✓	✓
Industries				✓	✓
Occupations				✓	✓

Notes: This table presents reduced form and IV estimates of the effect of robot exposure on the non-participation rate using a conventional and dynamic shift-share estimates, as proposed by Jaeger et al. (2019). There are two time periods (2000-07 and 2007-14) and 722 CZs. Panel A reports reduced form estimates using robot exposure in the current period. Panel B reports IV estimates using robot exposure in the current period. Panel C reports reduced form estimates using robot exposure in the current and in the previous period. Panel D reports IV estimates using robot exposure in the current and in the previous period. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

B6 Contribution of margins of adjustment

This section helps the reader follow the estimation of the relative contribution of each margin of adjustment from Table 2.1, based on the results from Figures 2.4 to 2.9 in Section 2.6. Table B27 reports estimates of the margins of adjustment of non-participants expressed in percentage of the population of the respective subgroup (Panel A), like the above mentioned figures ($\mathrm{NP}_{c,t}^{m,\dot{g}}$), and in terms of the overall population of men (Panel B), in the style of Table 2.5 ($\mathrm{NP}_{c,t}^{m,g}$). Note that the latter is also affected by the relative population size of subgroups ($N_{c,t}^{g}/N_{c,t}$). The relative contribution measures of each margin are computed by summing the estimated effect of robots on all subgroups within a particular margin of adjustment ($\mathrm{NP}_{c,t}^{m} = \sum_g \mathrm{NP}_{c,t}^{m,g}$), and by dividing it by the estimated effect on aggregate non-participation ($\mathrm{NP}_{c,t}$).

Let's take, for example, school enrollment. From Figure 2.4, we know that robot exposure increases the non-participation rate among white individuals between 25 and 34 years with at least a college degree by 0.3 percentage points. This increase comes along with an increase in schooling of these individuals of about 0.2 percentage points. This result can be found also in Column 1 of Panel A of Part I (0.199). Panel B further shows that this increase accounts for 0.008 percentage points of the increase of the overall male non-participation. By summing all estimates (Columns 1 to 16) of Panel B in Part I, we obtain 0.025 percentage points, which corresponds to the increase in schooling of non-participants for the entire working-age population of males. If we now divide this value by the estimated effect of robots on non-participation from Column 5 of Panel B of Table 2.3, we obtain the relative contribution of schooling as a margin of adjustment of non-participants, i.e. 7.2 percent. Note that small differences may occur due to rounding errors. Without rounding at three decimal digits, this value corresponds to 7.7 percent, as reported in Table 2.1.

Table B27 can be used further to compute other combinations of non-participation increases that are not reported in Table 2.1. For instance, Figure 2.6 shows that a one standard deviation increase in robot exposure increases the non-participation rate among white individuals between 55 and 64 years without a college degree who receive Social Security income (disability benefits or early retirement benefits) and/or withdraw pension plan income by 0.355 percentage points. This result can be computed by summing over Panel A and Column 12 of Part II and III: 0.075 (disability take-up) + 0.277 (early retirement). Panels B tell us that these individuals make up 0.079 percentage points (0.014 + 0.066) of the overall increase in labor force non-participation, and therefore account for almost 23 percent of its increase (0.079/0.346 from Table 2.3).

Table B27: Robots and margins of adjustment of non-participants

	College degree or more								Less than a college degree							
	Whites				Racial and ethnic minorities				Whites				Racial and ethnic minorities			
	25-34	35-44	45-54	55-64	25-34	35-44	45-54	55-64	25-34	35-44	45-54	55-64	25-34	35-44	45-54	55-64
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[14]	[15]	[16]
Part I. School enrollment																
Panel A: NP$^{m,\dot{g}}_{c,t}$																
US robot exposure	0.199***	0.016	0.021*	-0.016	0.241	-0.107	-0.038	0.111	0.033*	0.015	0.024***	0.008	0.077**	0.041	-0.052	0.100***
	(0.033)	(0.014)	(0.011)	(0.015)	(0.168)	(0.070)	(0.108)	(0.083)	(0.017)	(0.011)	(0.009)	(0.007)	(0.033)	(0.029)	(0.035)	(0.028)
Panel B: NP$^{m,g}_{c,t}$																
US robot exposure	0.008***	0.001	0.001**	-0.001	0.001	-0.002***	-0.000	0.001	0.003	0.001	0.003**	0.001	0.002	0.003	0.000	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.003)	(0.002)	(0.002)	(0.001)
Part II. Disability take-up																
Panel A: NP$^{m,\dot{g}}_{c,t}$																
US robot exposure	0.009	0.044***	0.007	-0.042*	0.005	-0.155	-0.165*	0.237**	-0.032**	0.052**	0.046	0.075***	0.024	0.039	0.232***	-0.073
	(0.008)	(0.012)	(0.024)	(0.022)	(0.025)	(0.113)	(0.089)	(0.103)	(0.016)	(0.021)	(0.033)	(0.027)	(0.050)	(0.066)	(0.070)	(0.127)
Panel B: NP$^{m,g}_{c,t}$																
US robot exposure	0.000	0.003***	0.000	-0.003*	0.000	-0.001	-0.002**	0.002***	-0.003	0.006**	0.011**	0.014***	-0.000	0.002	0.006*	0.000
	(0.000)	(0.001)	(0.001)	(0.002)	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)	(0.005)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
Part III. Early retirement																
Panel A: NP$^{m,\dot{g}}_{c,t}$																
US robot exposure	0.006	0.008	0.022	0.246**	-0.009	0.043	-0.007	0.555**	0.008	0.001	0.043	0.277***	0.050***	0.049*	0.222***	0.584***
	(0.008)	(0.010)	(0.013)	(0.113)	(0.012)	(0.026)	(0.040)	(0.248)	(0.011)	(0.015)	(0.026)	(0.060)	(0.012)	(0.025)	(0.060)	(0.186)
Panel B: NP$^{m,g}_{c,t}$																
US robot exposure	0.000	0.000	0.002**	0.017**	-0.000	0.001**	-0.000	0.004***	0.001	0.000	0.013***	0.065***	0.003***	0.003***	0.008***	0.020***
	(0.000)	(0.001)	(0.001)	(0.008)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.002)	(0.003)	(0.006)	(0.001)	(0.001)	(0.002)	(0.006)
Part IV. Reliance on household																
Panel A: NP$^{m,\dot{g}}_{c,t}$																
US robot exposure	0.220***	0.024	-0.012	0.082	0.143	-0.038	-0.338	-0.270	0.089*	0.115***	0.111**	0.244***	0.256***	0.563***	0.439***	0.414**
	(0.039)	(0.037)	(0.024)	(0.069)	(0.106)	(0.116)	(0.228)	(0.198)	(0.050)	(0.036)	(0.046)	(0.034)	(0.093)	(0.153)	(0.095)	(0.196)
Panel B: NP$^{m,g}_{c,t}$																
US robot exposure	0.007***	0.002	-0.000	0.002	0.000	-0.001	-0.002	-0.000	0.005	0.015**	0.023***	0.044***	0.012	0.032***	0.017***	0.018***
	(0.002)	(0.002)	(0.002)	(0.004)	(0.002)	(0.002)	(0.002)	(0.001)	(0.007)	(0.007)	(0.008)	(0.005)	(0.014)	(0.010)	(0.006)	(0.006)
Part V. Personal income																
Panel A: NP$^{m,\dot{g}}_{c,t}$																
US robot exposure	0.155**	0.069	-0.081*	0.089	0.097	-0.129	-0.175	0.618**	0.160**	0.052	0.014	0.121	0.376**	0.432***	0.533***	-0.583
	(0.058)	(0.055)	(0.044)	(0.122)	(0.190)	(0.153)	(0.307)	(0.246)	(0.073)	(0.053)	(0.061)	(0.086)	(0.149)	(0.134)	(0.184)	(0.438)
Panel B: NP$^{m,g}_{c,t}$																
US robot exposure	0.004	0.005	-0.004	0.009	-0.001	0.000	-0.003	0.008***	0.008*	0.002	0.008	0.066***	0.031	0.033	0.023*	0.004
	(0.004)	(0.003)	(0.002)	(0.008)	(0.003)	(0.003)	(0.003)	(0.002)	(0.005)	(0.006)	(0.007)	(0.009)	(0.026)	(0.021)	(0.012)	(0.006)
Observations	2166	2166	2166	2166	2166	2166	2166	2166	2166	2166	2166	2166	2166	2166	2166	2166
Covariates:	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes: This table presents IV estimates of the effect of robot exposure on the male non-participation rate by education, age, and race/ethnicity and margin of adjustment. Panels A report estimates of the effect of robot exposure on non-participation as a share of the population subgroups, while Panel B reports estimates as a share of the total population of men in a CZ. Regressions include the full battery of controls from my preferred specification and are weighted by CZ population in 1990. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Chapter 3

Automation and Human Capital Adjustment: The Effect of Robots on College Enrollment

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3.1 Introduction

Technological progress has spurred stunning growth in educational attainment across the twentieth century, leading to what is often defined to as a race between education and technology (Goldin and Katz, 2010, Tinbergen, 1974). For years, skill-biased technological change (SBTC) fueled the demand for high-skilled labor, generating educational wage gains that raised the supply of more educated workers (Katz and Murphy, 1992, Krusell et al., 2000). Although this link appears to have weakened in the last decades (Acemoglu and Autor, 2012, Goldin et al., 2020), rapid progress in automation, including robotics and artificial intelligence, has revitalized the debate about the role of technological advances for human capital accumulation (Aoun, 2017).

This paper investigates the effect of the introduction of industrial robots – one of the leading automation technologies of the last decades – on human capital adjustments in the US labor market. Industrial robots are machines that can be programmed to perform autonomously a variety of manual tasks in the manufacturing sector. Between 1993 and 2007, more than 120,000 robots have been installed in the US, displacing thousands of workers from the labor market (Acemoglu and Restrepo, 2020). These technologies differ fundamentally from SBTC, as they mainly displace workers from low-skill jobs, but they do not directly complement workers employed in high-skill jobs (Acemoglu and Restrepo, 2021). As a response, exposed workers may invest in additional human capital as a form of self-insurance against the employment risks associated with these adverse shocks, rather than increases in the college wage premium (Atkin, 2016, Beaudry et al., 2016, Betts and McFarland, 1995, Cameron and Taber, 2004).

We analyze the impact of robot adoption on human capital adjustments using a local labor market analysis, and proxy local labor markets using US Commuting Zones (CZs). To exploit plausibly exogenous variation in robot exposure across CZs, we match industry-level data from the International Federation of Robotics (IFR) with individual-level data from the Census. We follow Acemoglu and Restrepo (2020) in using a shift-share design that interacts baseline industry employment shares within local labor markets with the adoption of robots in the US. Identification builds on the assumption that advances in robotics vary by industry and expose local labor markets differently depending on their industrial composition of employment.

To identify individuals' human capital adjustments, we obtain information on the schooling status and detailed socio-demographic characteristics from the Census and the American Community Survey (ACS). We use these data to build measures of college enrollment at the CZ level. We complement these information using administrative data from the Integrated Postsecondary Education Data System (IPEDS) that provide data on human capital adjustments from the intensive margin, including the characteristics of the institutions in which students enroll, graduation rates, and their field of study.

Our results show that each additional robot increases local college enrollment by about four students, suggesting that the introduction of industrial robots between 1993 and 2007 has increased college enrollment rates by roughly three percent. This result is driven by young individuals who delay their full-time labor market entry to acquire college education, highlighting that the educational response to robot exposure is different from that of other (non-technology) shocks, such as trade and immigration, which have been shown to mainly increase college enrollment among displaced middle-aged workers (Hickman and Olney, 2011).

We further show that these results are driven by students who enroll in local public community colleges. These institutions are often less expensive, and they are praised for their quick response to labor market demand shifts (Betts and McFarland, 1995), making them a valuable option for low-skilled prime-age workers and for non-traditional students to rapidly re-train and increase their competitiveness on the labor market. We do not find evidence of students migrating away from exposed areas to enroll in college, but we observe a decrease in incoming students. This result follows from the fact that also workers with a post-secondary education are exposed to the adverse effects of robots to some extent (Acemoglu and Restrepo, 2020), inducing prospective migrants to avoid these local labor markets (Faber et al., 2022).

Turning to the intensive margin of the human capital adjustment, we observe a shift in the distribution of graduations towards more applied fields. In particular, we find that students are graduating more often in fields related to Computer Science and Engineering, which are likely to offer better job prospects in the years to come due to their complementary role to new technologies. Robots also increase the share of students who graduate in subjects requiring interpersonal skills that are more difficult to automate, such as Business and Economics, and other Social Sciences.[94]

To pin down the mechanism through which the adoption of robots increases the share of the population that attends college, we build a task-based model with heterogeneous workers and endogenous college enrollment. The model predicts that the adoption of robots may affect college enrollment through two distinct channels. First, they reduce the opportunity cost of college enrollment, as robots take over low-skill tasks. Second, they increase the college wage premium, as they potentially complement high-skill tasks.[95] We test these predictions in the data, and find that our results are likely to be driven by the opportunity cost channel. We find that workers without any college education experience the largest risk of displacement through robots along with a reduction in wages, which induces marginal individuals to enroll in college to increase their competitiveness on the labor market. However, also workers with an Associate degree experience a wage loss that is not significantly different from less educated workers. Therefore, we can rule out the college wage premium channel.[96,97]

This paper relates to several streams of literature. In particular, our work builds on but fundamentally departs from the traditional literature on SBTC and education (Acemoglu and Autor, 2012, Goldin and Katz, 2010, Goldin et al., 2020, Tinbergen, 1974). While SBTC corresponds to technology becoming more favorable to high-skilled workers (Card and DiNardo, 2002, Juhn et al., 1993, Katz and Murphy, 1992), we focus on automation technologies that displace low-skilled

[94] These results are in line with the literature, which argues that individuals respond to labor market shocks by selecting fields of study with larger earnings returns (Blom et al., 2021, Foote and Grosz, 2020).

[95] This assumption is drawn from Prettner and Strulik (2020), who use an R&D-driven growth model to show how automation technologies increase income and wealth inequality in the labor market, and decrease the labor share, encouraging a larger share of the population to graduate from college.

[96] Although also wages of workers with a Bachelor's degree decrease in exposed CZs, they decrease to a smaller extent, suggesting that robots increase the four-year university wage premium, both compared to community colleges and to no college education. These relative changes, however, do not trigger a visible increase in enrollment rates in these institutions at the local labor market level.

[97] Note that due to the weaker displacement effect of robots on workers with an Associate degree, relative to workers without any college education, they increase the expected wage income of these workers in the long run.

workers, but do not necessarily complement high-skill labor (Acemoglu and Restrepo, 2021). We provide novel evidence about the effects of the introduction of industrial robots on post-secondary education enrollment in the US.

Our work also relates to the literature that analyzes the margins of adjustment of workers exposed to automation. Acemoglu and Restrepo (2020) show that the adoption of industrial robots contributed to significant employment and wage losses in the US between the early 1990s and 2007. Faber et al. (2022) show that the adverse effects of robots on the labor market are visible also among the internal migration flows of workers. In particular, they show that the introduction of robots has decreased the share of incoming migrants in exposed areas, but that it has not affected outflows; a result that, according to our findings, can be applied also to college students. Lerch (2020) further shows that robots have also an adverse effect on labor force participation, increasing disability take-up, early retirement and college enrollment of non-participants. Our work adds to this literature by analyzing the impact of robots on human capital adjustments both from the extensive and the intensive margin, and focuses on the working-age population, providing evidence that the rise in college enrollment goes significantly beyond its impact on non-participation. Also, Dauth et al. (2021) show that robots have increased within-firm upgrading, raising the share of college-educated workers employed in Germany at the expense of the share of employees who completed an apprenticeship. This result might be driven by workers adjusting their human capital, but also by employers altering their hiring decisions. We complement these findings by focusing on the impact of robots on the educational decision of individuals, again from the extensive and the intensive margin. Moreover, we provide evidence on the US, a country that has experienced significant employment losses due to the introduction of robots compared to Germany, and where education is much more expensive.

Most closely related to our work, a contemporaneous and independent manuscript by Branco et al. (2022) investigates the impact of robots on college attainment in the US. They show that people who were born in states which are more exposed to robot adoption are more likely to earn a Bachelor's degree. We complement this finding in two ways. First, we focus on the impact of robots on actual college enrollment at the time of exposure rather than focusing on college attainment of exposed cohorts later in life. A higher share of the college-educated population might be the effect of higher college enrollment rates or higher graduation rates. Using our approach we can distinguish between these two channels. We show that human capital accumulation as an adjustment margin against robot exposure is primarily driven by higher enrollment rates.

Second, using CZ-level variation in robot exposure we show that individuals enroll in local community colleges to attain an Associate degree, while Branco et al. (2022) exploit state-level variation and find an increase in Bachelor's degree attainments from four-year institutions. We replicate their finding and perform a state-level analysis using our empirical approach. We show that extending the shock beyond the local labor market of residence of individuals also increases enrollment in four-year institutions.[98] This result holds to the exclusion of the shock in students' CZ of residence, suggesting that individuals who base their college enrollment decision on the exposure to robots outside of their local labor market are more likely to pursue a Bachelor's degree than individuals who focus on the exposure in their local labor market of residence.

These results are in line with other studies which show that individuals who adjust their human capital as a response against adverse shocks in their local labor market enroll in community colleges rather than in four-year universities (Foote and Grosz, 2020, Weinstein, 2020). These individuals might lack the necessary skills to complete a Bachelor's degree and might have different socio-economic characteristics than individuals who account also for shocks outside of their local labor market in their decision on whether to enroll in college (Manski and Wise, 2013).

We also contribute to the growing literature that studies the impact of local labor market shocks on human capital adjustments, including business cycles (Betts and McFarland, 1995, Blom et al., 2021, Liu et al., 2019), industry and firm-specific shocks (Cascio and Narayan, 2022, Foote and Grosz, 2020, Weinstein, 2020). While these studies focus on temporary shocks whose effects are likely to vanish in the long run, we investigate the impact of automation technologies that are disrupting labor markets at an unprecedented speed, and that are likely to heavily affect the skill requirements of future jobs, as well as the composition of labor markets.

Our results are in line with the literature that analyzes the educational response of structural shocks on the manufacturing sector. Greenland and Lopresti (2016) show that rising US imports from China increase the share of high school graduations in the country. Hickman and Olney (2011) show that offshoring and immigration have increased enrollment rates of community colleges in the

[98] Note that on average each state includes 15 CZs, i.e. states consist of multiple local labor markets. The number of CZs on the US mainland is 722, ranging from one CZ in the states of Rhode Island and Connecticut to 64 in Texas.

US, but not of other types of institutions, in particularly for older, non-traditional students. Atkin (2016) shows that rising exports in the manufacturing industry in Mexico have increased high school dropouts, while Tuhkuri (2021) shows that the decline in manufacturing production in the US had a negative effect on local high school dropout rates. We complement this stream of the literature by focusing on post-secondary education outcomes. This is an important topic, since it is not a priori clear whether rising high school graduation rates have a positive impact on college enrollment rates. For instance, liquidity and credit constraints (Lovenheim, 2011, Manoli and Turner, 2018), imperfect information on the returns to education (Jensen, 2010), or the lack of the necessary skills to attend college (Athreya and Eberly, 2021) may prevent individuals from acquiring additional human capital as a response to adverse labor market shocks.

The remainder of the paper is organized as follows. Section 3.2 describes the data. Section 3.3 presents the empirical strategy. Section 3.4 reports the results of the empirical analysis. Section 3.5 introduces a theoretical framework to illustrate the mechanism through which robot adoption affects college enrollment, and Section 3.6 concludes.

3.2 Data and summary statistics

This section describes the main data used in the empirical analysis along with a set of summary statistics.

3.2.1 Industrial robots

We obtain data on the adoption of industrial robots from the International Federation of Robotics (IFR). Industrial robots are machines that can be programmed to autonomously perform several manual tasks without further intervention of a human worker. The IFR defines an industrial robot as an "automatically controlled, re-programmable, multipurpose manipulator, programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications" (IFR, 2018). Assembly lines, elevators or industrial looms are excluded from this category, since they do not meet these requirements.

The IFR collects data about the shipment and operational stock of industrial robots using yearly surveys of robot suppliers that capture around 90 percent of the world market. It estimates that the stock of industrial robots in the US has increased by about one robot per thousand workers between 1993 and 2007, or roughly 120,000 units. The IFR provides an industry breakdown of robot adoption following the International Standard Industrial Classification (ISIC, 4th review) for about 50 countries since the 1990s. Industry classifications consist of seven broad sectors (Agriculture, Construction, Manufacturing, Mining, Education and Research, Services, and Utilities) and more granular industries within the manufacturing sector (including Automotive, Basic Metals, Electronics, Food and Beverages, Industrial Machinery, Metal Products, Minerals, Paper and Printing, Plastics and Chemicals, Shipbuilding and Aerospace, Textiles, Wood and Furniture, and miscellaneous manufacturing). For details, see Table C2.

IFR data are praised for their reliability, but they include also some limitations that we address in Appendix C1.

3.2.2 Post-secondary education

We match robotics data with information on college enrollment and educational attainment at the local labor market level using data from two sources, the US Census/ACS and IPEDS.

Census and ACS – We obtain demographic data of the US population from the Integrated Public Use Microdata Series (IPUMS) of the decennial Census samples for 1970, 1980, 1990 and 2000, and the American Community Survey (ACS) for 2007 (Ruggles et al., 2019).[99] These datasets are repeated cross-sectional surveys that include between 1 and 5 percent of the US population and provide a comprehensive set of information at the individual level. We restrict our sample to the non-institutionalized civilian population and focus on individuals aged between 19 and 64 years, since they are above the usual high school age and below the retirement age. We consider as students those individuals who report to be enrolled in school with the pursuit of a degree.[100] Schooling does not include enrollment in a trade or business school, company training, or tutoring unless the course would be accepted for credit at a regular college. We also use information about students' current

[99] Following the literature, we increase the sample size of the ACS using data from the 3-year sample of 2006-2008.

[100] Note that questions regarding school enrollment changed somewhat between the Census and the ACS. In the Census, individuals are asked if they attended school since February 1st of the respective year, while in the ACS they are asked if they attended school in the three months prior to the interview. Although we cannot directly test for it, we show that our results are not affected by this change in the questionnaire text. To do this, in Section 3.4 we compare our findings from the Census/ACS samples and the IPEDS (see following section for a description of the latter), and find very similar results.

and previous place of residence to track their internal migration flows across local labor markets.[101]

We follow the literature and proxy US local labor markets using 722 Commuting Zones (CZs, Tolbert and Sizer, 1996). These areas cover the entire US mainland and are formed by clusters of counties with strong commuting ties within CZs and weak commuting ties across CZs, representing economically relevant regions for labor markets (Autor and Dorn, 2013).[102] This aggregation allows us to build measures of college enrollment at the local labor market level:

$$s_{cz,t} = \frac{S_{cz,t}}{N_{cz,t}} \tag{81}$$

where $S_{cz,t}$ and $N_{cz,t}$ represent the number of students and the working-age population in CZ cz in year t. This measure includes students who have migrated across CZs to enroll in college and students who were already living in the area in which the college is located. We come back to this point when discussing student migration flows in Section 3.4.

IPEDS – We complement Census/ACS data with institutional data from the Integrated Postsecondary Education Data System (IPEDS), a publicly available database provided by the National Center for Education Statistics (NCES). These data report annual information about the universe of title IV higher education institutions, including college enrollment, admission rules, tuition fees, student grants, graduation rates, and fields of graduation. Title IV institutions are entities that process US federal student aid and include public and private (for profit and non-profit) institutions. Additionally, the IPEDS includes sporadic data on non-Title IV colleges that submit information on a voluntary basis. We exclude these institutions from our analysis due to inconsistencies in the data and due to selection issues. Following previous studies, we exclude also for-profit institutions, institutions that enroll on average less than 50 first-year students, and those that provide data for less than three years of our sample period (Ebrahimian, 2022, Foote and Grosz, 2020).[103] Using

[101] A limitation in the Census and ACS data is that the questions about the migration status of individuals change over time. In particular, the Census asks whether a person changed residence in the previous 5 years, while the ACS asks whether a person changed its residence in the previous year. Appendix C1 provides detailed information about how we deal with this issue.

[102] The IPUMS provide county groups or Public Use Microdata Areas as smallest geographic units. Following Autor and Dorn (2013), we aggregate data at the CZ level using a crosswalk that provides a probabilistic matching of sub-state geographic units in US Census Public Use Files to CZs.

[103] The IPEDS often undercounts the number of for-profit institutions and is not accurate in identifying their location (Foote and Grosz, 2020), which, in our analysis, is particularly important for the determination of the local labor market in which institutions are located. For additional information on shortcomings in the data about for-profit institutions, see Cellini (2005, 2010) and Cellini and Goldin (2014).

ZIP codes from institutions' campuses, we aggregate these data at the local labor market level and obtain information on 603 CZs.[104]

3.2.3 Summary statistics

College education is likely to be a good investment when facing the risks of automation on the labor market. Table 3.1 shows that only 1 percent of the workers with a Bachelor's degree are employed in jobs that are replaceable by robots. This share increases to 3.69 for workers with an Associate degree from community colleges, and to more than 10 percent for workers without a college degree.[105] This result follows from the fact that robots are mainly adopted to perform low-skill and middle-skill job tasks (as illustrated in Figure C1). These jobs often have a high physical workload which requires manual dexterity and are performed by blue-collar workers of the manufacturing sector (Ge and Zhou, 2020, Lerch, 2021). College-educated workers are less likely to work in these jobs and are usually employed in occupations which require the use of communication and interpersonal skills that are more difficult to automate (Acemoglu and Autor, 2011). Hence, individuals may invest in additional human capital as a form of self-insurance against the employment risks of automation. In line with this hypothesis, Table 3.1 shows that between 1990 and 2007, the share of the population aged between 19 and 34 years that is enrolled in college increased by one fourth, from 20.5 to almost 25 percent.

The table further illustrates descriptive statistics on post-secondary education institutions' characteristics and students' fields of study. The average CZ hosts 3.13 public institutions and 2.44 private institutions. About 60 percent of the institutions are universities that offer four-year programs, while the remaining 40 percent are community colleges which usually offer programs that do not exceed two years of length. Public institutions are three times as large as private institutions, with an average enrollment of 6,200 students, while both, universities and community colleges, count about 4,500 students. In the 1990s, most students graduated in fields related to Arts and Humanities (27.3 percent), Health sciences (23.7 percent), and Business and Economics (18.8 percent). Only 7.02 percent of the students graduated in Computer Science or Engineering, a share that, however,

[104] We do not observe the full universe of CZs since not all of them have a college based in the area, and, as described above, we exclude some colleges due to inconsistencies in the data.

[105] We follow Graetz and Michaels (2018) and classify 1980 US Census occupations according to their replaceability by robots. Occupations are considered to be replaceable if, by 2012, their work could have been performed, completely or in part, by robots.

Table 3.1: Descriptive statistics

	1990				Δ_{07-90}
	Mean	Std	Min	Max	Mean
	[1]	[2]	[3]	[4]	[5]
Panel A: Population					
Employment in jobs that are replaceable by robots					
All individuals	7.73	3.04	2.27	20.6	-1.00
Bachelor's degree	1.08	0.38	0.00	3.34	-0.03
Associate's degree	3.69	1.48	0.38	11.7	-0.18
No college degree	10.1	3.48	3.63	24.3	-0.61
Share of college-educated population					
Bachelor's degree	20.7	5.93	6.32	36.9	6.37
Associate's degree	6.89	1.58	2.15	13.8	1.13
Share of students					
Total	11.8	2.88	4.67	37.0	-0.84
19-34 years	20.5	4.74	8.21	56.5	4.41
35-64 years	4.96	1.31	1.76	8.30	-1.40
Panel B: Institutions					
Number of institutions in CZ					
Public institutions	3.13	4.36	0.00	60.0	0.14
Private institutions	2.44	6.71	0.00	78.0	0.05
Community colleges	2.13	3.31	0.00	47.0	0.06
Universities	3.10	7.11	0.00	88.0	0.03
Number of students enrolled (in thousands)					
Public institutions	6.24	7.35	0.04	52.6	1.20
Private institutions	1.98	3.16	0.02	34.1	0.54
Community colleges	4.41	5.42	0.06	49.0	1.08
Universities	4.70	6.94	0.02	52.6	0.93
Panel C: Fields of study					
Business and Economics	18.8	8.59	0.00	49.0	-7.40
Computer Science and Engineering	7.02	6.01	0.00	40.8	0.66
Health Science	23.7	12.5	0.00	91.0	3.54
Arts and Humanities	27.3	19.5	0.00	100	5.45
Manufacturing	12.6	13.2	0.00	80.9	-3.00
Natural Science	2.71	5.61	0.00	63.0	-0.58
Public and Military	3.12	3.38	0.00	17.6	0.78
Social Science	4.60	6.20	0.00	61.8	0.60

Notes: This table illustrates descriptive statistics of the main variables used in the empirical analysis at the CZ level. Columns 1 to 4 include average values, standard deviations, minimum and maximum values in 1990. Column 5 includes average changes between 1990 and 2007. Shares are multiplied by 100. Panel A presents populations shares of the respective population group. For instance, the share of students between 19 and 34 years is computed as a CZ's number of students in this age range divided by the population of 19 to 34 year old individuals in that CZ. All means are weighted by the respective CZ population group in 1990. Panel B presents statistics about the number of institutions in a CZ and the average number of individuals within institutions expressed in thousands of students. Note that the latter is not expressed at the CZ level, but at the institution level. Panel C presents the distribution in the fields of study among eight broad categories. By construction, the sum of the shares is equal to 100.

has increased by about 10 percent until 2007 and, as we will show later, goes hand-in-hand with the introduction of industrial robots.

3.3 Empirical strategy

The aim of this paper is to estimate the effect of robot adoption on human capital adjustments at the CZ level. There are two challenges that we need to overcome to perform this type of analysis. First, the IFR provides data only at the country-industry level. Second, robot exposure and human capital adjustments may be jointly determined by unobserved labor market factors.

To address the limitation in the data, we follow Acemoglu and Restrepo (2020) in using a shift-share design which allows us to apportion robot adoption at the industry level across regions according to their shares of the industry's total employment:[106]

$$\text{US robot exposure}_{cz,t} = \sum_{j \in J} \ell^{90}_{cz,j} \left[\frac{R^{US}_{j,t} - R^{US}_{j,t-1}}{L^{US}_{j,90}} - g^{US}_{j,t} \frac{R^{US}_{j,t-1}}{L^{US}_{j,90}} \right] \tag{82}$$

This approach is common practice in studies where an industry-level shock has differential effects on regions due to differences in the local industry structure (Dauth et al., 2021).[107]

The share component, $\ell^{90}_{cz,j} = \frac{L^{90}_{cz,j}}{L^{90}_{cz}}$, is defined as industry j's employment share in CZ cz in 1990. We keep the baseline employment shares constant to avoid endogeneity and serial correlation concerns across our sample periods. The shift component measures the national adoption of robots in industry j, $\Delta R^{US}_{j,t}$, relative to its workforce in 1990, $L^{US}_{j,90}$, adjusted for the adoption of robots that is driven by overall industry output growth, $g^{US}_{j,t} = \Delta \ln(Y^{US}_{j,t})$.

Identification builds on the assumption that advances in robotics vary by industry and expose local labor markets differently depending on the industrial composition of employment. However, robot adoption may also be the fueled by domestic industry-specific demand shocks (Bonfiglioli et al., 2020). For instance, a positive shock may induce US firms to raise both capital and employment, increasing the opportunity cost of attending college (Atkin, 2016). This condition would bias our estimates of the effect of robots on human capital adjustment towards downwards.

We address endogeneity concerns by instrumenting the shift-component of Equation 82 with contemporaneous changes in the stock of robots in seven European countries that have a comparable

[106] Note that the shift-share approach is also addressing part of the endogeneity concerns that would emerge if we could observe the actual adoption of robots at the regional level.

[107] We are implicitly assuming that changes in the industry's stock of robots are homogeneous across regions, conditional on the industry structure of employment.

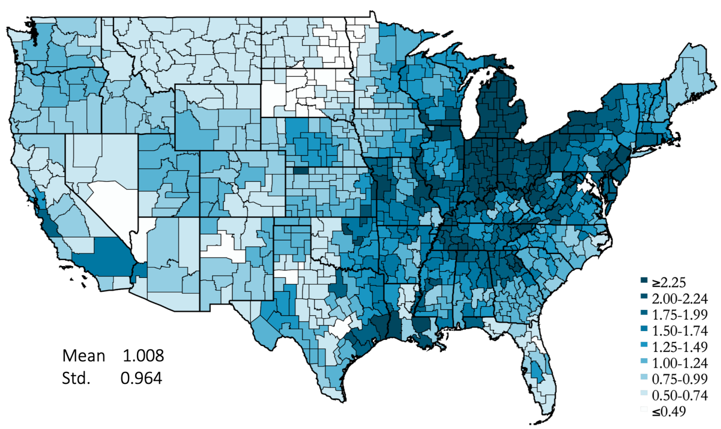
adoption of robots as the US:

$$\text{EU7 robot exposure}_{cz,t} = \sum_{j \in J} \ell^{70}_{cz,j} \frac{1}{7} \sum_{i \in EU7} \left[\frac{R^i_{j,t} - R^i_{j,t-1}}{L^i_{j,90}} - g^i_{j,t} \frac{R^i_{j,t-1}}{L^i_{j,90}} \right] \tag{83}$$

where $R^i_{j,t}$ is the stock of robots in country $i \in EU7$ at time t in industry j. $EU7$ countries include Denmark, Finland, France, Italy, Spain, Sweden and the United Kingdom. On average, these countries had a similar development in the adoption of robots as the US.[108]

The IV strategy aims at identifying the labor market effects of exogenous improvements in robotics available to US firms. It relies on the assumptions that the adoption of robots in European countries is positively related to the adoption of robots in the US (relevance assumption), but that it is unrelated to domestic labor market conditions (exclusion restriction). Table 3.2 shows that the instrument clearly satisfies the relevance assumption. Although we cannot test formally for the validity of the exclusion restriction, we discuss potential threats to identification in Appendix C4, including international product market competition, pre-trends in college enrollment, and industry trends (using a leave-one-out strategy), showing that our estimates are robust and unlikely to be driven by these channels.

Figure 3.1: Robot adoption at the CZ level, 1993-2007



Notes: This figure illustrates the distribution of robot exposure, in robots per thousand workers, across US labor markets between 1993 and 2007, as well as the US mean and its standard deviation.

Figure 3.1 illustrates the distribution of the shock across US CZs. Robot exposure is clearly

[108] Note that the instrument uses also industry employment shares from 1970 to focus on the industrial composition of employment that precedes the introduction of industrial robots, as suggested by Acemoglu and Restrepo (2020) and Goldsmith-Pinkham et al. (2020).

concentrated in the Northeast and Midwest of the US, including the states of Indiana, Michigan and Ohio. These regions – often referred to as the Rust Belt – host a significant fraction of firms that are specialized in the steeling and automotive industry, and hence are likely to adopt industrial robots in their production processes.

We exploit variation in the exposure to industrial robots across local labor markets over time using a stacked first-difference specification with two time periods (1993-2000 and 2000-07).[109] Our sample period ends in 2007 to avoid the potentially confounding effects of the Great Recession and the increase in online learning in the 2010s.[110] The estimating equation is given by:

$$\Delta s_{cz,t} = \beta \cdot \text{US robot exposure}_{cz,t} + \mathbf{X}'_{cz,90}\mathbf{\Gamma} + \varepsilon_{cz,t} \tag{84}$$

where $\Delta s_{cz,t}$ is the change in our educational outcome of interest in cz between t and $t-1$ (e.g. the share of students). US robot exposure measures a CZ's exposure to industrial robots, as defined in Equations 82. We also include a set of covariates that account for factors that could confound our estimates of the effect of robots on human capital adjustments, including the China trade shock (Autor et al., 2013), non-robot technology shocks, pre-trends, the supply of education institutions, demographic characteristics, and the employment composition of CZs. We provide detailed information about these controls in Table 3.2 and in Appendix C1. We keep CZ characteristics constant at their 1990 levels to avoid contamination by endogenous labor market adjustments to robot adoption during our sample period.

3.4 Robots and human capital adjustments

This section presents the results of the empirical analysis.

[109] Note that in the 1990s the IPUMS includes only data from the 1990 Census. For comparability across periods, we rescale the 1990-2000 period to a 7-year equivalent change.

[110] According to NCES, in 2003 less than 5 percent of the students were enrolled in complete distance learning programs (NCES, Students Enrolled in Distance Education, accessed in June 2021). This number has more than doubled until 2015 (11 percent). The change is even higher when looking at students who had at least some distance education, increasing from 16 to 43 percent. We exclude from our sample the 2010s, since the rapid rise in online learning increases the share of students of whom we cannot observe the local labor market of reference in the IPEDS data. For completeness, we illustrate a set of results including a third period from 2007 to 2014 in Table C3 in Appendix. Census estimates are more noisy, but they are not significantly different from our main specification's results.

3.4.1 College enrollment

We start by analyzing the impact of automation on human capital adjustments from the extensive margin, focusing on college enrollment rates. Table 3.2 reports the results from Equation 84. Regressions are weighted by the CZ population in 1990 and standard errors are clustered at the state level.

Table 3.2: Robots and college enrollment

	Census/ACS		IPEDS		
	All students		All students	Undergrad.	Graduate
	[1]	[2]	[3]	[4]	[5]
			Panel A: OLS results		
US robot exposure	0.232*	0.215***	0.257**	0.249***	0.008
	(0.130)	(0.066)	(0.104)	(0.088)	(0.033)
			Panel B: IV results		
US robot exposure	0.277*	0.349***	0.309**	0.314**	-0.005
	(0.163)	(0.100)	(0.141)	(0.131)	(0.031)
			Panel C: First-stage		
EU7 robot exposure	0.558***	0.526***	0.521***	0.521***	0.521***
	(0.032)	(0.017)	(0.016)	(0.016)	(0.016)
Kleibergen-Paap F stat	301.2	30.7	28.2	28.2	28.2
Observations	1444	1444	1161	1161	1161
Covariates:					
State FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Pre-trends		✓	✓	✓	✓
Chinese imports		✓	✓	✓	✓
Demographics		✓	✓	✓	✓
Industries		✓	✓	✓	✓
Occupations		✓	✓	✓	✓
Institutions		✓	✓	✓	✓

Notes: This table illustrates OLS and IV estimates of the effect of robot exposure on changes in the share of students at the CZ level. Changes are expressed in percentage points of the working-age population and are multiplied by 100. Panel C also reports first-stage results. Column 1 controls only for state fixed effects, division fixed effects, year dummies and the interactions of the latter two. All remaining columns include also changes in the college enrollment rate between 1970 and 1990, a measure of the China trade shock, CZ demographic (share of females, Blacks, Hispanics, 25-34 year, 35-44 year, and 45-54 year old individuals, individuals without a college degree, and the logarithmic population), industries (share of employment in the construction, manufacturing, mining, research, service and utilities industry), occupations (share of routine task-intensive and offshorable occupations), and institution (public, private, count of universities ranked among the top 30 US university ranking of 2020, institutions with an average number of students above 20 thousand, and the share of students that receive financial aid) characteristics of CZs in 1990. Columns 1 and 2 use data on outcomes from the Census/ACS and Columns 3 to 5 use data from the IPEDS. Standard errors are robust against heteroskedasticity and allow for clustering at the state level. Regressions are weighted by CZ population in 1990. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Column 1 presents baseline estimates of the effect of robots on the share of students controlling only for state fixed effects and division-specific business cycles. The estimates show that the introduction of robots has a positive effect on the share of individuals who enroll in college. Columns 2 to

5 further include additional covariates to minimize the exposure of the estimates to confounding effects of omitted variables. The inclusion of these controls improves the precision of our estimates.[111] In line with the endogeneity concerns, OLS estimates are smaller than IV estimates, since they are likely to be biased towards zero. In the remainder of the analysis, we focus on the IV results.

In our preferred specification (Column 2 using the Census/ACS and Column 3 using the IPEDS), estimates show that one additional robot per thousand workers increases the share of students between 0.30 and 0.35 percentage points. In other words, each additional robot has increased college enrollment by about four students, a result which suggests that the introduction of industrial robots has contributed to an increase in the share of students that is equivalent to almost three percent of its 1990 level.[112] Columns 4 and 5 use IPEDS data to split the estimates between students who are pursuing an undergraduate or a graduate degree. We show that our results are driven by students who enroll in undergraduate programs.

Table 3.3: Robots and college enrollment: Institution characteristics

	Ownership		Program length		
	Public	Private	Four-year	Two-year	< Two-year
	[1]	[2]	[3]	[4]	[5]
US robot exposure	0.279**	0.036	0.070	0.284***	-0.039
	(0.109)	(0.044)	(0.072)	(0.083)	(0.028)
Observations	1161	1161	1161	1161	1161
Covariates:	✓	✓	✓	✓	✓

Notes: This table illustrates IV estimates of the effect of robot exposure on the share of undergraduate students and decomposes the effect by institution characteristics using data from the IPEDS. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Table 3.3 decomposes the estimate of the effect of robots on undergraduate students (Column 4 of Table 3.2) by institution characteristics. We find that students respond to robot exposure by

[111] In Table C4 of the Appendix, we provide estimates also for the impact of import competition from China. The inclusion of this variable does not affect the estimates of the effect of robots, i.e. the impacts of the two shocks are mostly unrelated to each other. When standardized, the size of the estimates is almost the same (0.185 and 0.170), suggesting that both the robot shock and the trade shock have a similar impact on college enrollment in the US.

[112] These estimates are computed as follows. (i) We compute the effect of the introduction of one additional industrial robot on the increase of students using the estimated effect of one robot per thousand workers on the share of students ($0.30 - 0.35$) and multiply it with the US sample population in 1990 (147,437,773) and the increase in the number of robots per thousand workers between 1993 and 2007 (1). We then divide this product by the increase in the number of robots between 1993 and 2007 (120,000) to obtain the change in the number of students for each additional robot. (ii) We compute the percent change in the share of students by dividing the estimated effect of one robot per thousand workers on the share of students ($0.30 - 0.35$) with the share of students in 1990 from Table 3.1 (11.8).

enrolling in public institutions, in particular in two-year institutions, such as community colleges. This result is consistent with the literature which shows that enrollment rates in community colleges are more sensitive to local labor market conditions than enrollment rates in four-year universities (Betts and McFarland, 1995, Hickman and Olney, 2011, Manski and Wise, 2013).[113] The short time frame required to attain a degree, the focus on technical skills, and the relatively low cost of tuition make community colleges a valuable option for low-skilled prime-age workers and for non-traditional students to rapidly re-train and increase their competitiveness on the labor market (Foote and Grosz, 2020, Hickman and Olney, 2011).[114]

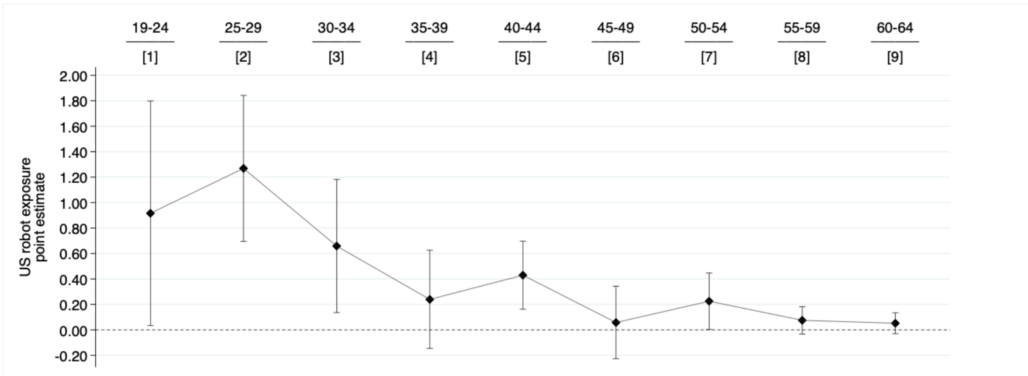
Figure 3.2 further provides details about the age composition of students, breaking down the effect of robots on college enrollment into 5-year age groups. Results show that the effect is strongest among students between 19 and 34 years of age. These individuals account for 70 percent of the total effect, with most of them being unlikely to have much experience on the labor market. They may therefore be delaying their full labor force entry to acquire additional skills, since the opportunity cost of enrolling in school are lower during poor labor market conditions (Altonji et al., 2016), and they have the most to gain from additional human capital given their longer working-life horizon. Although the effect decreases in size after the age of 35, it remains statistically significant at conventional levels for most age groups. These individuals are instead likely to enroll in college after a job loss.[115]

[113] In Appendix C5, we perform a state-level analysis which shows that the extension of the exposure to robots outside of the local labor market of residence of individuals increases enrollment also in four-year institutions. This result holds to the exclusion of the shock in students' CZ of residence, suggesting that individuals who base their college enrollment decision on the exposure to robots outside of their local labor market are more likely to pursue a Bachelor's degree than individuals who focus on the exposure in their local labor market of residence.

[114] According to the NCES, in 2007-08 the average tuition fees at four-year (two-year) public institution were around 7,000 (2,500) dollars, while they were almost 25,500 (15,500) dollars at private institutions. Tuition fees are expressed in 2018-19 dollars and do not include room and board cost. For public institutions, in-state tuition fees are used (NCES, Tuition Fees, 2020, accessed in June 2021). Tuition fees for out-state students are usually higher. As a comparison, Ehrenberg (2020) estimates that in 2007-08 the average tuition fees at four-year public institution were around 6,000 dollars for in-state students and 16,500 dollars for out-state students.

[115] Table C6 explores the employment status of students. We find that 62 percent of the younger students and 85 percent of the older students are not employed while being enrolled in college, with the remaining ones being employed part-time. This result confirms our hypothesis that students are either delaying their full labor market entry in their young ages, or that they enroll in college after a job loss. Only a minority of students is employed while enrolled in college.

Figure 3.2: Robots and schooling by age



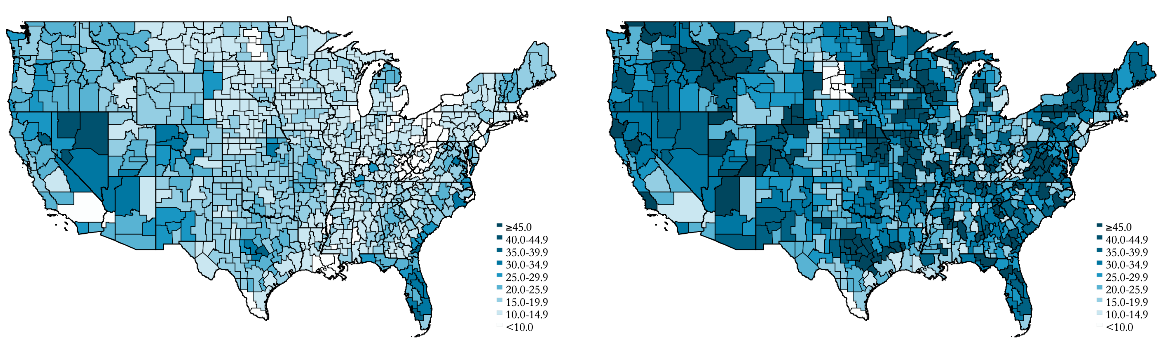
Notes: This figure illustrates IV point estimates of the effect of robot exposure on the share of students by age groups using Census/ACS data. Confidence intervals are at the 95% level.

3.4.2 Student migration

Figure 3.3 shows that college students are substantially more mobile than the rest of the population: 26 percent of them have migrated across CZs in the previous five years, while this number is about 10 percentage points lower for non-students. For migrating students, the decision to accumulate additional human capital is unlikely to be driven by the shock in the CZ in which the college is located, as assumed using Equation 84, but by the shock in the CZ they are coming from. If these individuals account for a large share of students who enroll in college because of robots, our estimates may be biased (since we are not identifying whether these students were exposed in the CZ in which they grew up).

Figure 3.3: Share of migrating population, 1990

Panel A: Non-students Panel B: Students



Notes: This figure illustrates the share of the population that migrated across CZs in the previous five years in 1990 using Census data. Shares are multiplied by 100. For instance, a value of 20 percent implies that one fifth of the CZ's current population was living in another CZ in the previous 5 years. Panel A shows the share of migrants among individuals that are not enrolled in school. Panel B shows the share of migrants among students.

To address this concern, we use Census and ACS data to compute all possible cross-CZ migration flow combinations of students (movers, 722×721), as well as counts of the residual group of non-migrating students (stayers, 722×1). We use these data to study the migration decisions of prospective students from two perspectives, (i) the perspective of the college's CZ (in-migrants and stayers) and (ii) the perspective of their CZ of origin (out-migrants and stayers). Table 3.4 illustrates the results.[116]

Table 3.4: Robots and student migration

	All students	Stayers	Movers
	[1]	[2]	[3]
	Panel A: Perspective from college CZ		
US robot exposure	0.325***	0.379***	-0.053***
	(0.081)	(0.074)	(0.016)
	Panel B: Perspective from origin CZ		
US robot exposure	0.262*	0.267*	-0.004
	(0.151)	(0.138)	(0.018)
Observations	1444	1444	1444
Covariates:	✓	✓	✓

Notes: This table illustrates IV estimates of the effect of robot exposure on the share of students and decomposes the effect by stayers and movers using Census/ACS data. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Panel A analyzes enrollment and migration flows of students from the perspective of the CZ in which the college is located. For this purpose, we decompose the share of students who are enrolled in college in cz from Equation 81 between students who were already living in this CZ in the previous five years (stayers), S_d, and those who have moved there from one of the other 721 CZs (incoming movers), S_o:

$$s_{cz} = \frac{S_{cz}}{N_{cz}} = \frac{S_d}{N_{cz}} + \frac{1}{N_{cz}} \sum_{\substack{o=1 \\ o \neq d}}^{722} S_o \tag{85}$$

We find that robots significantly increase the share of students among the stayers, i.e. these individuals enroll in colleges located in their CZ of origin. When considering movers, we find that robot exposure in the college's CZ has a deterrent effect on incoming students. In other words,

[116] Note that these estimates are subject to some measurement error, since the Census/ACS provide less granular information on the CZ of origin of students (3-digit PUMA rather than 5-digit PUMA). This affects only a relatively small fraction of PUMAs which cannot be assigned unambiguously to a CZ using the crosswalk provided by Autor and Dorn (2013). We overcome this issue by adding two zero digits at the end of the 3-digit code. The measurement error is modest in size since "00" accounts for almost two thirds of the 5-digit PUMA final digits, and these PUMAs are very likely to be in the same CZ as PUMAs which end by "01", "02", "03", and so on.

movers avoid colleges located in highly exposed CZs. This result holds for students who are both migrating from within and outside the college's state (see Table C5), and may follow from the fact that, as we will show in Section 3.5, robot exposure has an adverse impact also on the labor market outcomes of college-educated workers.

Panel B analyzes whether students migrate away from their CZ of origin to enroll in college when exposed to robots. To do so, we build aggregate counts of students at the level of their CZ of origin. For movers, this CZ is different from their college's CZ, while for stayers they are the same. With reference to the decomposition exercise in Equation 85, cz is now defined as their CZ of origin, not the CZ of the college (S_o are now students from cz who migrated to some other CZ to enroll in college).

Results show that robot exposure does not affect the share of students who move away from their CZ of origin to enroll in college. Together with the finding from Panel A, these results suggest that the effect of robots on college enrollment is driven by students who enroll in a local college (stayers).[117] This finding also matches with the result that increasing enrollment rates are driven by community colleges. It is rather unlikely that individuals migrate across CZs to enroll in a two-year program, as the (perceived) quality of these institution is less heterogeneous than for four-year universities.[118]

Finally, note that the sum of the estimates from Columns 2 and 3 of Panel A (as illustrated in the decomposition exercise of Equation 85) provides the total share of students in the CZ of the college (see Column 2 of Table 3.2). On the other hand, the sum over Columns 2 and 3 of Panel B provides the share of students from the perspective of their CZ of origin (rather than from the college's CZ).[119]

[117] This result is in line with the findings of the literature at the population level showing tha robot exposure does not increase out-migration but reduces in-migration (Faber et al., 2019, Lerch, 2020).

[118] In Table C11 of Appendix C4, we show disaggregated results in which we analyze the impact of robot exposure both in the CZ of origin and the CZ of the college on individual migration flows of students. The findings are analogous to the results from our simple aggregation exercise.

[119] Note that the estimate of Column 1 of Panel A of Table 3.4 is slightly different from the estimate in Table 3.2 because some individual observations are dropping out from the sample due to missing information about their migration status. Moreover, Column 1 of Panels A and B is different because the estimates have been computed using different populations of reference (denominator of Equation 85), correcting for the respective inflow (A) and outflow (B) of students. When comparing these findings with the results from Census/ACS and IPEDS data (Table 3.2), one should use Panel A, since it uses student counts from the perspective of the college's location (and it has the same denominator).

3.4.3 Educational attainment

We now turn to human capital adjustments from the intensive margin, as an increase in college enrollment does not necessary imply that more students actually graduate and acquire the necessary skills to be more competitive on the labor market (Burga and Turner, 2022). We therefore investigate the impact of robots on students' commitment to complete their studies, based on average graduation rates, and their field of study choice.

Graduation rates – We compute average graduation rates using data from the IPEDS Graduation Rate Survey (GRS) focusing on community colleges, since they are driving our results on enrollment. These data include the share of individuals who graduate within one-and-a-half times of the program length.[120]

Table 3.5: Robots and graduation rates

		College-educated individuals	
	Graduation rates	Bachelor's degree	Associate degree
	[1]	[2]	[3]
US robot exposure	0.974	-0.066	0.173***
	(0.921)	(0.079)	(0.064)
Observations	870	1444	1444
Covariates:	✓	✓	✓

Notes: This table illustrates IV estimates of the effect of robot exposure on graduation rates in two-year institutions. Column 1 includes graduation rates computed as the share of students belonging to a specific cohort that completes college within three years after enrollment. Columns 2 and 3 include the share of individuals with a Bachelor's and an Associate degree using Census/ACS data. The latter two estimates are computed from a regression of the outcomes in period $t+1$ on robot exposure in t. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Column 1 of Table 3.5 shows the estimated impact of robots on graduation rates. We find that one additional robot per thousand workers increases graduation rates in community colleges by about one percentage point (from a base of about 23 percent), suggesting that on average enrolled students might be more committed to complete their studies. Although this is an economically sizeable effect, the small sample size on graduation rates from the IPEDS and the large standard errors that come with it do not allow us to claim that it is statistically different from zero. Therefore,

[120] Specifically, the GRS computes graduation rates as the share of graduates in the adjusted number of students of the corresponding cohort. For example, the share of 1993 graduates from a two-year institution is computed as the number of students who started college in 1993 and graduated between 1993 and 1996 divided by the cohort of students who started college in 1993. The adjustment accounts for student transfers.

we cannot exclude that college graduations are moving proportionally with enrollment.

Based on this result, we should expect that robot exposure is raising the share of the college-educated population. To test this, we regress the share of individuals with a college degree from the Census/ACS samples in period $t+1$ (2000-07, 2007-14) on robot exposure in period t (1990-2000, 2000-07).[121] We use the lagged shock since college takes some time to complete (while in the previous analysis enrollment rates may react immediately).

In line with the previous results, we find that the introduction of robots increases the share of the population with an Associate degree from two-year institutions, but that it does not affect the share of the population with a Bachelor's degree (which is awarded by four-year institutions).[122]

Field of study – Another interesting question is whether robot exposure has affected students' field of study choice (in the perspective of future job prospects). We use IPEDS data on college completions and decompose students according to eight broad field of study groups, expressed as a share of total students in the CZ. These groups are Business and Economics, Computer Science and Engineering, Health Sciences, Arts and Humanities, Manufacturing, Natural Sciences, Public and Military, and Social Sciences.[123] We then regress the share of students in each field of study on robot exposure. Figure 3.4 illustrates the estimates.

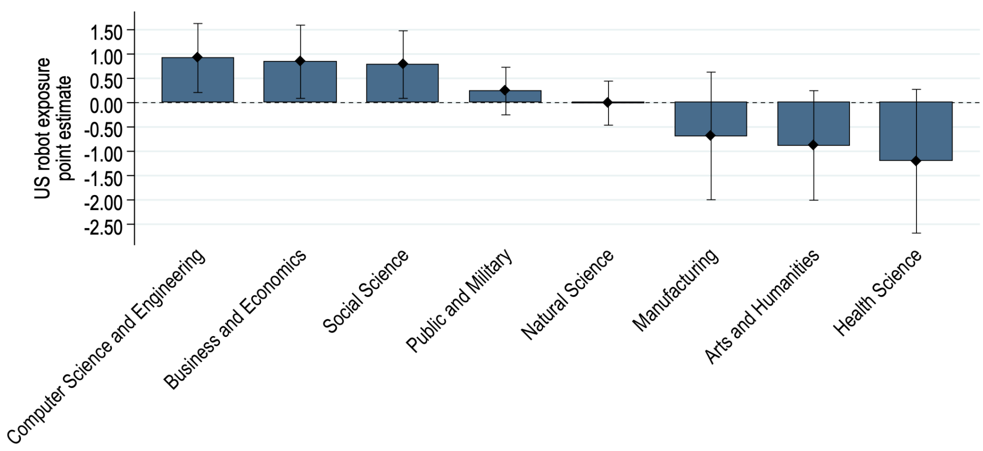
Our findings show that the adoption of robots has increased significantly the share of students who graduate in applied fields, such as Computer Science and Engineering. These fields are likely to be the main source of job creation in the years to come due to their complementary to automation technologies. We also find that robots increase the share of students who graduate in fields related to Business and Economics, and other Social Sciences (e.g. communication and journalism, education and psychology, see Table C1). Jobs in these fields are likely to be impacted only marginally by the adoption of robots, which makes them also particularly attractive. We do not find evidence, however, of an increase in the share of completions in Natural Science related fields, such as mathematics and physics. This result might follow in part from the fact that the increase in enrollment is concentrated

[121] To keep two sample subperiods and to account for the graduation of students who enrolled in college between 1993 and 2007, we shift our sample period to 2000-2014. This specification is dictated by data availability, as we do not observe robot adoption before 1993.

[122] In this setting, one may again worry that robots are influencing the share of college-educated individuals in the area through migratory adjustments. However, as we point out in Section 3.4.2, the impact of robot exposure on internal migration flows is modest.

[123] Appendix C1 provides further details on the aggregation of the fields of study together with a list of the Classification of Instructional Programs (CIP) 2-digit codes included in each category.

Figure 3.4: Robots and field of study



Notes: This figure illustrates IV point estimates of the effect of robot exposure on the share of students by field of study using IPEDS data. Changes are expressed in percentage points of the total number of students and are multiplied by 100. For example, the share of students that graduate in *Computer Science and Engineering* is computer as a CZ's number of students that graduate in this field of study divided by the total number of students that graduate in the CZ. By construction, the sum of shares equals 100 and the sum of changes equals zero. Confidence intervals are at the 95% level.

among community colleges, which are more likely to offer applied programs.

3.5 Mechanism

This section introduces a model to illustrate the mechanism through which the adoption of robots affects the demand of human skills and the subsequent human capital adjustment.

3.5.1 Conceptual framework

We use a simple Roy model with heterogeneous workers and endogenous college enrollment (Roy, 1951). The model builds on a task-based framework in which robots compete with human labor in the execution of various tasks (Autor et al., 2003). We group tasks that can be performed only by college-educated workers (e.g. tasks that involve cognitive and problem solving skills) and those which can be performed by everybody (e.g. routine manual tasks). The latter tasks are exposed to the risks of automation (Acemoglu and Autor, 2011).[124]

[124] It is worth mentioning that the recent literature on task-based technological change observes an increasing polarization of the labor market as new technologies (such as personal computers) are taking over routine task-intensive jobs in the middle of the wage distribution (Autor and Dorn, 2013, Goos et al., 2009).

We consider a production model with two task inputs, automatable and non-automatable tasks, that are used to produce an output good Y in a competitive labor supply-demand environment in a closed economy. Automatable tasks (ℓ) can be carried out by workers, regardless of their education level, L_ℓ, or they can be automated through the adoption of robot capital, R. Non-automatable tasks (h) can be performed only by workers with a college degree, L_h, and cannot be automated. The production of Y combines both types of labor and robots, measured in efficiency units, using the following technology:

$$Y_t = L_{h,t}^{1-\beta}\big(L_{\ell,t}^{\rho} + R_t^{\rho}\big)^{\frac{\beta}{\rho}} \tag{86}$$

with $\beta, \rho \in (0, 1)$. The elasticity of substitution between L_ℓ and L_h is 1, while the elasticity of substitution between robot capital and L_ℓ is $1/(1-\rho)$ and, by assumption, it is greater than 1. Hence, robot capital is a relative substitute of L_ℓ.

Perfect competition implies that in equilibrium labor is paid its marginal productivity. The first order conditions of the production function with respect to labor inputs provide the following endogenous labor demand functions:

$$\omega_{h,t} = (1-\beta)L_{h,t}^{-\beta}\big(L_{\ell,t}^{\rho} + R_t^{\rho}\big)^{\frac{\beta}{\rho}} \tag{87}$$

$$\omega_{\ell,t} = \beta L_{h,t}^{1-\beta}\big(L_{\ell,t}^{\rho} + R_t^{\rho}\big)^{\frac{\beta}{\rho}-1} L_{\ell,t}^{\rho-1} \tag{88}$$

where ω_h and ω_ℓ are the respective labor wages per efficiency unit. Given these equations, we can compute an expression of the wage premium:

$$\omega_t \equiv \frac{\omega_{h,t}}{\omega_{\ell,t}} = \frac{1-\beta}{\beta}\left[1 + \left(\frac{R_t}{L_{\ell,t}}\right)^{\rho}\right]\frac{L_{\ell,t}}{L_{h,t}} \tag{89}$$

Robots are produced and competitively supplied each period using the following technology $R_t = Y_{R,t}\frac{e^{\delta t}}{\theta}$, where $Y_{R,t}$ is the amount of the final good allocated to produce robots and $\theta = e^{\delta}$ is an efficiency parameter, with productivity rising at rate $\delta > 0$ due to technological progress (Autor and Dorn, 2013).[125] In the first period ($t = 1$), one unit of $Y_{R,t}$ can be used to produce one efficiency unit of R ($1 = \frac{e^{\delta}}{\theta}$). Competition guarantees that the real price of robot capital (per efficiency unit)

[125] This assumption implies that robot capital fully depreciates in each period or, in other words, that the flow of services provided by robots is continuously paid its rental price as these services are consumed (Autor and Dorn, 2013).

is equal to marginal (and average) cost: $p_t = \theta e^{-\delta t}$. The price is falling exogenously over time due to technical advances and is the causal force of the model. From here on, we omit time subscripts.

A continuum of individuals $i \in [0, 1]$ who live one period are endowed with one unit of labor that they supply on the labor market. At the beginning of each period, individuals graduate from high school and are equipped with the necessary knowledge to carry out ℓ-tasks. These individuals can join the labor force right away, earning wage ω_ℓ. Alternatively, they can delay their labor market entry to enroll in college, pursuing a Bachelor's or an Associate degree to acquire additional human capital. College education provides the necessary know-how to perform h-tasks and earn a fraction of ω_h that is proportional to their time spent on the labor market. For simplicity, we assume that individuals do not discount future earnings and, in case they enroll in college, they do not drop out of school.[126]

Individuals are heterogeneous with respect to the cost of attending college, measured as a function of time they spend in college, η_i. In particular, individual i may spend η_i of his or her time to graduate from a four-year university with a Bachelor's degree. This assumption follows from the fact that some individuals have a better predisposition to learn and therefore spend less time in school (low η_i), paying less tuition fees and experiencing lower foregone earnings compared to individuals who are less suited for college (high η_i).[127] Costs are distributed independently and identically across all individuals according to a density function $f(\eta_i)$ with support over $\eta_i \in (0, 1)$.[128]

Individuals may spend only $\frac{\eta_i}{x}$ of their time in college if they choose a community college over a university to attain an Associate degree, where $x \geq 2$. An Associate degree, however, does not guarantee that individuals will find employment in L_h. The probability of ending up working in L_ℓ (earning ω_ℓ like less educated workers) is $\lambda \in (0, 1)$. This probability is equal to zero for individuals with a Bachelor's degree.

[126] This assumption implies that individuals are perfectly patient over their lifetime and have perfect information about their college ability and future earnings outcomes.

[127] This parameter can be interpreted as the fraction of endowment that individuals allocate to invest in their education to improve their labor market skills, which varies with their ability in college. In this context, η_i may be influenced by a set of elements, including tuition fees, credit constrains, family background, and the time spent on the labor market.

[128] In our simple framework, this parameter captures the idiosyncratic characteristics that affect individuals' earnings, but it does not influence their productivity, which is homogeneous within task groups. For instance, the productivity of workers in automatable jobs is equal to the right-hand side of Equation 88, such that they all earn exactly ω_ℓ, independently from their η_i or their education.

Individuals choose the college allocation that maximizes their expected income:

$$U_i(\omega,\eta) = \max\Bigg\{ \underbrace{\Big(1-\eta_i\Big)\omega}_{\text{Bachelor}}, \underbrace{\Big(1-\frac{\eta_i}{x}\Big)\Big[\Big(1-\lambda\Big)\omega+\lambda\Big]}_{\text{Associate}}, \underbrace{1}_{\text{No college}} \Bigg\} \tag{90}$$

Without a college degree, workers can only supply L_ℓ, while after graduating, they may supply L_h, L_ℓ or any convex combination of the two. Note that in equilibrium all workers with a Bachelor's degree will choose L_h. The same holds among workers with an Associate degree, although only a fraction $1-\lambda$ of them will be able to find employment in L_h, with the remaining fraction λ supplying L_ℓ.

Next, we compute two thresholds that determine which college allocation individuals choose in accordance with their endowment of η_i:

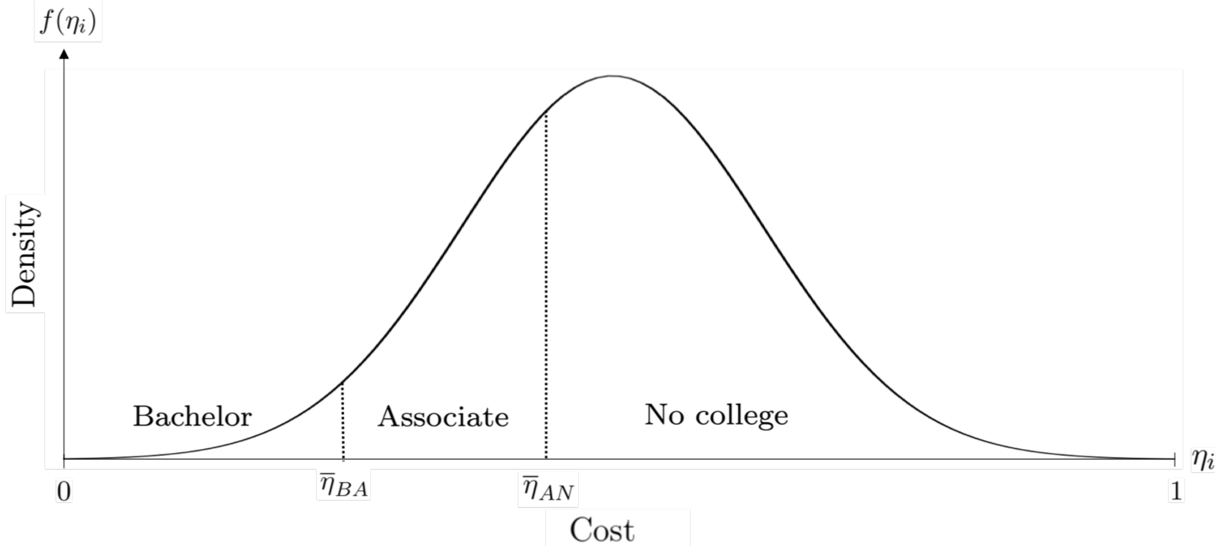
$$\overline{\eta}_{BA} = \frac{\omega-\theta(\omega)}{\omega-\frac{\theta(\omega)}{x}} \quad \text{and} \quad \overline{\eta}_{AN} = \frac{\omega-1}{\frac{\theta(\omega)}{x}} \tag{91}$$

with $\theta(\omega) = (1-\lambda)\omega+\lambda$. $\overline{\eta}_{BA}$ is the threshold at which individuals are indifferent between enrolling in a university or a community college, while at $\overline{\eta}_{AN}$ they are indifferent between a community college and no college. If λ is smaller than some value $\underline{\lambda}$, individuals are either enrolling in a community college or they do not go to college at all. No individual will enroll in a four-year university, since the expected income is always lower than from a community college due to the long time they would spend in school. If λ is larger than some value $\overline{\lambda}$, individuals are either enrolling in a four-year university or they do not go to college at all. No individual will enroll in a community college, since the expected income is always lower than that of a four-year university. In other words, the lower time in college cannot compensate for the high probability of ending up in L_ℓ. If $\lambda \in (\underline{\lambda}, \overline{\lambda})$, there is a fraction of individuals in all three possible states (Bachelor, Associate, no college), i.e. $0 < \overline{\eta}_{BA} < \overline{\eta}_{AN} < 1$.[129] As illustrated in Figure 3.5, individuals with a very low η_i enroll in university, those with a middle-level η_i enroll in a community college, and those with a high η_i do not enroll in college and join the labor force right away.

To obtain a well-defined solution, we continue with the case in which $\lambda \in (\underline{\lambda}, \overline{\lambda})$. Aggregate

[129] Note that $(1-\eta_i)\omega = (1-\frac{\eta_i}{x})[(1-\underline{\lambda})\omega+\underline{\lambda}]$ and $(1-\frac{\eta_i}{x})[(1-\overline{\lambda})\omega+\overline{\lambda}] = 1$. Solving for these equations provides the values of $\underline{\lambda}$ and $\overline{\lambda}$.

Figure 3.5: College education choice



Notes: This figure uses a normal distribution of η to illustrate the share of the population that enrolls in a four-year university, in a community college, or in no college.

labor supplies are computed as the sum over the labor units that individuals supply on the market:

$$L_h = \int_0^{\overline{\eta}_{BA}} (1-\eta_i) f(\eta_i) d\eta_i + \int_{\overline{\eta}_{BA}}^{\overline{\eta}_{AN}} (1-\lambda)\left(1-\frac{\eta_i}{x}\right) f(\eta_i) d\eta_i \tag{92}$$

$$L_\ell = \int_{\overline{\eta}_{BA}}^{\overline{\eta}_{AN}} \lambda\left(1-\frac{\eta_i}{x}\right) f(\eta_i) d\eta_i + \int_{\overline{\eta}_{AN}}^{1} f(\eta_i) d\eta_i \tag{93}$$

In equilibrium, wages adjust such that labor supply equals labor demand. Average wages of Bachelor graduates, Associate graduates, and less educated workers are ω_h, $(1-\lambda)\omega_h + \lambda\omega_\ell$ and ω_ℓ, respectively. The model abstracts from unemployment such that labor markets clear.

Now that the equilibrium conditions are set, we analyze how firms' adoption of robots affects the college enrollment rate, and how it is doing so.

As the price of robots decreases over time, firms are going to increase their demand for capital, raising the intensity of task input ℓ in firms' production, and boosting the productivity of h-type workers. As a consequence, firms demand relatively more L_h, which is reflected in an increase of the wage premium from Equation 89. This increase is driven by an increase of ω_h. The size of the effect, however, depends also on the impact of robots on the demand for ℓ-type labor and, therefore on ω_ℓ. Changes in the demand of less educated workers depend on the degree of substitutability between L_ℓ and robots. If they are strong substitutes (ρ is high), firms demand less labor and ω_ℓ decreases. In this case, the opportunity costs of enrolling in college decrease. On the contrary, if L_ℓ and R are weak substitutes (ρ is low), firms may increase their demand of labor and ω_ℓ increases.

As workers with a Bachelor's degree and those with only a high school diploma unambiguously work in L_h and L_ℓ respectively, the college wage premium between these groups is equal to $\overline{\omega}_{BN} = \omega$. The college wage premium of Associate graduates equals $\overline{\omega}_{AN} = \theta(\omega)$, while the wage premium between graduates with a Bachelor's and an Associate degree is equal to $\overline{\omega}_{BA} = [(1-\lambda) + \lambda\omega^{-1}]^{-1}$. These results imply that all wage premia should increase monotonically as the price of robot capital decreases, due to the complementarity of high-skill labor and robot capital (proofs are illustrated in Appendix C3). Therefore, the adoption of robots induces marginal workers who would otherwise have worked in L_ℓ to enroll in community colleges due to lower opportunity costs and/or rising wage premia. Moreover, it may induce also some workers who have a low enough η_i to choose a four-year university over a community college, if the increase in the wage premium compensates for the additional time they have to spend in school. In other words, an exogenous reduction in the price of robot capital shifts the thresholds $\overline{\eta}_{BA}$ and $\overline{\eta}_{AN}$ from Figure 3.5 to the right, such that also individuals with a higher cost of attending college, η_i, enroll in a community college or switch to a four-year university.

From the empirical analysis, we know that the effect of robots on college enrollment is driven by individuals who enroll in community colleges. This finding suggests that our results are driven by the shift of threshold $\overline{\eta}_{AN}$, inducing marginal individuals to enroll in college, when they are exposed to robots.

3.5.2 Opportunity cost or college wage premium?

We now discuss the potential channels that drive the impact of robots on college enrollment using an empirical approach. To do so, we refer to the influential work of Acemoglu and Restrepo (2020), which shows that the introduction of robots has decreased aggregate employment and wages, in particular among workers without a college degree (although also somewhat among workers with a college degree), suggesting that the degree of substitutability between labor and robot capital is high (in our model, $\rho > \beta$).[130] In Table 3.6, we replicate their results and differentiate further between college-educated workers with a Bachelor's degree and workers with an Associate degree.

Table 3.6: Robots and income

	Wage income	Premium (·/ Less)	Premium (·/ Ass.)
	[1]	[2]	[3]
	Panel A: Bachelor's degree		
US robot exposure	-1.598***	2.524***	1.700**
	(0.384)	(0.775)	(0.838)
	Panel B: Associate degree		
US robot exposure	-2.960***	0.267	
	(0.356)	(0.387)	
	Panel C: Less than college		
US robot exposure	-2.778***		
	(0.423)		
Observations	1444	1444	1444
Covariates:	✓	✓	✓

Notes: This table illustrates IV estimates of the effect of robot exposure on yearly wage income and the college premium using data from the Census/ACS. Income is expressed in log differences. The college premium is computed as the ratio between average income across different education groups and is multiplied by 100. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Table C7 shows that robots decrease employment among workers from all education levels. The effect is strongest for less educated workers, followed by workers with an Associate degree. The impacts on income are relatively similar across workers with an Associate degree and those without a college degree. Workers with a Bachelor's degree experience a smaller loss. This result leads to an increase in the wage premium of these workers, while we find only a small and insignificant effect of robots on the college premium of workers with an Associate degree. This finding suggests that the enrollment in community colleges is unlikely to be driven by the college wage premium channel, but rather by the decrease in opportunity costs.[131]

To conclude, we compare the results on the impact of robots on employment and college enroll-

[130] Even though robots are often assumed to be relative substitutes of low-skill labor and relative complements of high-skill labor, Acemoglu and Restrepo (2020) argue that the reduction of blue-collar work in exposed CZs may contract aggregate demand in the local economy, decreasing also the demand for labor in occupations that are not directly affected by the shock (such as high-skilled workers). This, in turn, may explain why college-educated workers avoid to migrate in highly exposed areas.

[131] Even if they do not benefit from higher wages, workers with an Associate degree are likely to experience more stable income in the future relative to less educated individuals, due to the lower displacement risk through robots.

ment. According to our estimates, for every four workers who have been displaced by automation, one individual enrolls in college (0.35/-1.21).[132] This finding does not imply that one fourth of the displaced workers are enrolling in college after losing their job (this would be an implausibly high result), but that individuals are adjusting their human capital based on the shock's intensity in the CZ. This supposition is in line with Figure 3.2 which shows that the increase in college enrollment is driven by young individuals who delay their labor market entry to adjust their human capital to become more competitive on the labor market.

3.6 Conclusions

Technological progress is poised to shape the future of labor markets, changing the skill requirements of jobs and exposing millions of workers to the risk of becoming obsolete, unless they are endowed with easily redeployable human capital.

This paper analyzes the effect of the introduction of industrial robots at the local labor market level on individuals' decision to enroll in college. Results show that individuals who are exposed to robots enroll more often in local community colleges to attain an Associate degree, and that they choose fields of study which are complementary to the new technologies. According to our estimates, every additional robot increases college enrollment by about four students. These individuals are usually aged between 19 and 34 years, they are not employed while being enrolled in school, and they opt for colleges located in their local labor market of origin.

We further investigate the underlying mechanism that drives more individuals in college when exposed to robots, and show that this result may be fueled by an increase in the college wage premium and a drop in the opportunity costs of schooling. We test these predictions empirically and find that robots decrease aggregate wages, but they do not increase the college wage premium for workers with an Associate degree, suggesting that our results are driven by the opportunity cost channel.

These findings suggest that the race between education and technology is still ongoing, as the advent of automation technologies, such as industrial robots, induces individuals to acquire human capital as a mechanism of self-insurance against the adverse risks of technological progress.

[132] We compute this estimation based on the IV results in Column 2 of Table 3.2 and the estimate of the effect of robots on employment in Column 1 of Table C7.

Appendix C

C1 Data and cleaning

This section provides further details about the data cleaning process.

IFR data – IFR data on the adoption of industrial robots are praised for their reliability, but they include also some limitations that we briefly address in the following. First, a fraction of the stock of industrial robots is not assigned to any industry. Following Graetz and Michaels (2018), we attribute these robots to each industry proportionally to its share of total classified robots for each year. Second, the stock of robots by industry going back to the 1990s is available only for a subset of European countries: Denmark, Finland, France, Germany, Italy, Norway, Spain, Sweden, and the United Kingdom. Industry-level data for countries in North America are only available from 2004. We address this limitation by apportioning the total stock of robots across industries proportionally to their shares in 2004.[133] Third, before 2012 the IFR aggregates robotics data for North America as a whole, including robots in the United States, Canada and Mexico. Although this aggregation introduces noise in the data, it is not a major concern for the identification of US robot adoption, since the Unites States account for more than 90 percent of the North American market, and the instrumental variable (IV) strategy presented in Section 3.3 purges this type of measurement error (Acemoglu and Restrepo, 2020).

IPEDS data – The Integrated Postsecondary Education Data System (IPEDS) is a publicly available database provided by the National Center for Education Statistics (NCES). These data are available on the IPEDS Data System site and provide annual information about the universe of title IV institutions, which include all entities that process US federal student aid in the private and public sector (for profit and non-profit institutions).[134] We merge four distinct surveys that include the variables used in the empirical analysis for all years between 1992 and 2008, namely institutional characteristics, fall enrollment, graduation rates and completions by field of study. Following

[133] We follow the same procedure to impute the stock of robots for Denmark, for which the industry breakdown started in 1996.

[134] Additionally, the IPEDS includes sporadic data on non-Title IV colleges that submit information on a voluntary basis.

the literature, we increase the sample size (and decrease measurement error) by computing average values of our sample years (1993, 2000 and 2007) with adjacent years.

We merge these datasets using institutional information and match them to local labor markets using zip codes. The latter, however, are often inconsistent or imprecise since institutions use postal boxes that do not represent their true location, or because of typos in survey. We deal with these issues by searching for the correct address of universities and colleges on the internet, correcting about 250 codes manually.

We then use a zip-to-county crosswalk from The Office of Policy Development and Research combined with a county-to-CZ crosswalk from Autor and Dorn (2013) in order to assign each institution to a specific CZ. The match is not always perfect, since zip codes may be located in more than one county. To address this hurdle, we attribute institutional counts to counties proportionally to the relative size of the land overlap within zip codes. We use a similar approach in the county-to-CZ crosswalk from Autor and Dorn (2013) and obtain information on post-secondary education institutions in 603 CZs.

In a next step, we exclude from our dataset the set of institutions that provide highly noisy and inconsistent data. These include non-Title-IV and for-profit institutions, institutions that provide data for less than three years of our sample period, and institutions that enroll an average of less than 50 first-year students during our sample years.

The analysis of enrollment performed on the IPEDS data draws from the fall enrollment survey. These data provide information on the number of students enrolled part-time and full-time, as well as the type of program in which they are enrolled (1-year program, two-year program, and four-year program to obtain a Bachelor's degree.)

From the completions survey, we draw information on the number of students who complete their studies in a given year, as well as the program type and field of study. To perform our analysis on the field of study choice, we group the list of 2-digit CIP codes provided by the IPEDS into eight broad groups, according to common subject characteristics that we collected from various websites of higher education institutions in the US.[135] Table C1 reports the fields of study that are included in each of our broad groups at the 2-digit CIP code level.

[135] The Classification of Instructional Programs (CIP) provides a taxonomic scheme that supports the accurate tracking and reporting of fields of study and program completions activity.

Table C1: Aggregation of CIP codes.

Category	**Course (2 digits CIP code)**
Natural Science	Agriculture and Relates Sciences
	Natural Resources and Conservation
	Biological Sciences
	Mathematics and Statistics
	Physical Sciences
Social Science	Ethnic, Cultural and Group studies
	Communication and Journalism
	Education
	Consumer and Human Sciences
	Psychology
	Social Sciences
Engineering and Computer Science	Architecture
	Communication Technologies
	Technicians and Support Services
	Computer and Information Sciences
	Engineering
	Engineering Technologies
	Science Technologies
Business and Economics	Business
	Management
	Marketing
	Economics
Arts and Humanities	Personal and Culinary Services
	English and Foreign Languages and Literature
	Legal Profession and studies
	Library Science
	Multy-disciplinary studies
	Recreation and Leisure studies
	Citizenship activities
	Interpersonal and Social skills
	Personal Awareness and Self-Improvement
	Philosophy and Religious Studies
	Theology and Religious vocation
Manufacturing	Industrial Arts Constructions Trades
	Mechanic and Repair technologies
	Precision Production
	Transportation and Materials Moving
Health Science	Health related knowledge and skills
	Health professional and related programs
Public and Military	Military Science
	Military Technologies
	Homeland Security and Law Enforcement
	Public Administration and Social Service professions

Notes: This table reports the aggregation of college fields of study at the 2-digit CIP code level into eight broad groups. These groups were constructed using the Completions survey from IPEDS data.

Internal migration flows – We build measures of the aggregate in- and outflows of migrants across CZs using individual-level data from the Census and ACS. A major limitation in these data is that information about individuals' migration status changes over time. In particular, the Census asks whether a person changed its residence in the previous 5 years, while the ACS asks whether a person changed its residence in the previous year. When building aggregate migration measures, we follow Molloy et al. (2011) and construct measures of 5-year migration flows from the ACS by using four times the annual migration flow of a CZ.

Individuals are asked whether they have been living in the same house, moved within or between states, and whether they lived abroad in the period of reference. College students who moved out from their parents' house have to indicate the place where they live and sleep most of the time, which usually means their college town. If an individual has not been living in the same house, the Census and ACS provide geographic information about its previous residence at the 3-digit PUMA level. Information about the previous residence is less precise than information about the current residence, which is expressed at the 5-digit PUMA level. This is not a major concern, since in the aggregation of geographic units from PUMAs to CZs, the last two digits are usually not influencing the CZs to which the location is assigned to.

We aggregate the data using the procedure described in footnote 102 and build a novel database with 521,284 observations (722 × 722) that include all cross-CZ migration flows. Note that stayers have the same CZ of origin and destination (where the college is located). These data are used to build aggregate measures of the share of movers and stayers within the population of the CZ in which the college is located.

Table C12 in the robustness checks provides a set of results in which we deviate from the construction of migration variables suggested by Molloy et al. (2011), but measure 5-year migration flows from the ACS using five times the annual migration flow of a CZ. The estimates are almost identical to our main specification's results.

Imports from China – Following Autor et al. (2013), we use a shift-share approach to measure a labor market's exposure to imports from China. We interact CZs' industry employment shares in the manufacturing sector prior to the admission of China to the World Trade Organization in 2001 with the growth in product trade flows from China to the US:

$$\text{Import exposure}_{c,t}^{US} = \sum_{j \in J} \ell_{c,j}^{90} \Delta IM_{j,t}^{US} \tag{94}$$

where $\Delta IM_{j,t}^{US}$ is the change in US imports from China in thousand dollars per worker. Similarly to Equation 83, we exploit plausibly exogenous variation in the trade shock by instrumenting the shift-component of the measure with trade flows from China to other industrialized countries with a similar trade development as the US:

$$\text{Import exposure}_{c,t}^{OT8} = \sum_{j \in J} \frac{1}{8} \sum_{i \in OT8} \ell_{c,j}^{90} \Delta IM_{j,t}^{i} \tag{95}$$

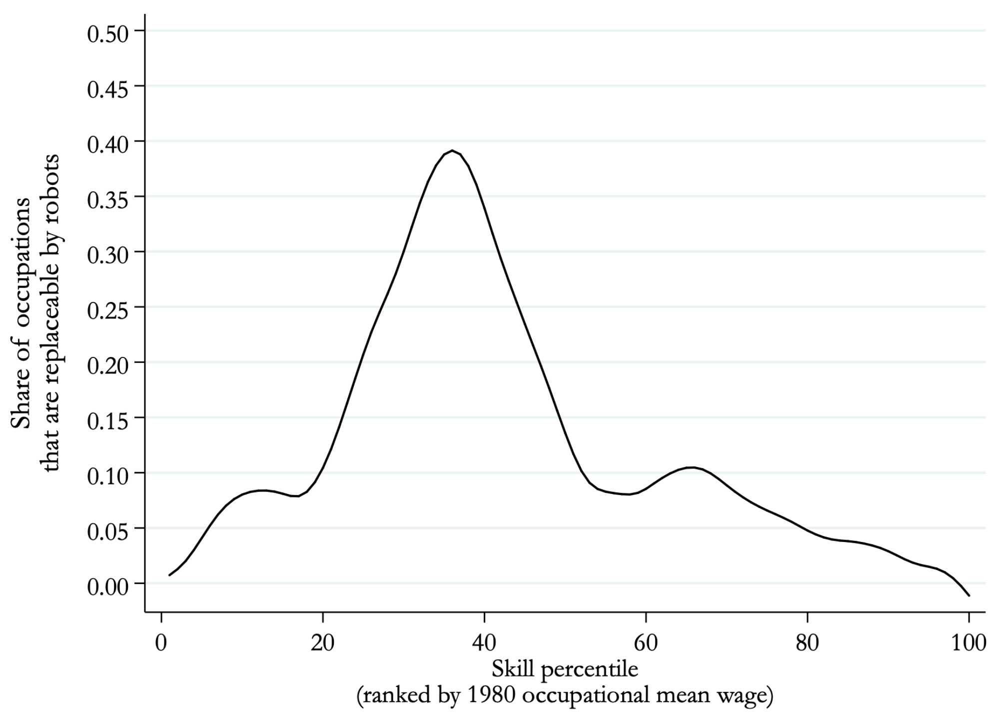
where $i \in OT8$ include Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland. We keep the baseline employment shares constant to avoid endogeneity and serial correlation concerns.

We collect product-level data at the six-digit Harmonized System (HS) on Chinese imports from the UN Comtrade Database which we match with industry employment shares from the 1991 County Business Pattern (CBP). The CBP classifies industry employment according to the Standard Classification System (SIC) until 1997 and according to the North American Industry Classification System (NAICS) afterwards. These systems are more detailed than the industrial classification system used in the IPUMS. We use a crosswalk from Autor et al. (2013) to convert SIC and NAICS manufacturing industries, as well as six-digit HS product-level trade data, to 392 four-digit SIC industries. We construct the import penetration measure by matching local employment shares with converted product-level trade data on imports from China. For confidentiality reasons, county-industry observations with few cases are reported as ranges. In reconstructing these data, we follow Acemoglu et al. (2016). Table C4 reports the results.

Labor market characteristics – We obtain individual-level data on a variety of demographic and economic characteristics of the US population from the IPUMS. We use these data to build measures of CZs' demographics and their industrial and occupational composition of employment. These variables include the share of female, Black, and Hispanic individuals, the share of college-educated individuals, the log population size, and age structure of the population (25-34, 35-44 and 45-54 years). Moreover, we account for the share of employment in construction, education and research, manufacturing, mining, services, and utilities industries, as well as the share of routine task-intensive and offshorable jobs (Autor and Dorn, 2013).

C2 Figures and tables

Figure C1: Robots along the skill distribution



Notes: This figure illustrates the share of occupations that are replaceable by robots, as defined in Graetz and Michaels (2018), by occupational skill percentile. This is a modified version of Figure 4 in Autor and Dorn (2013).

Table C2: Descriptive statistics: Industrial robots

	Robots in the US per thousand workers		Robots in EU7 countries per thousand workers		Employment in thousands
	1993	Δ_{07-93}	1993	Δ_{07-93}	1993
	[1]	[2]	[3]	[4]	[5]
Panel A: Manufacturing sector					
Automotive	24.25	61.47	18.2	53.72	1111
Basic Metals	1.39	3.63	0.84	4.61	712
Electronics	2.01	6.65	2.34	5.21	2868
Food and Beverages	1.02	2.90	0.38	4.45	1862
Industrial Machinery	0.39	1.03	3.01	3.20	1541
Metal Products	1.69	4.40	6.91	10.47	1689
Minerals	0.04	0.19	0.60	2.71	558
Miscellaneous	0.49	1.47	2.56	0.93	690
Paper and Printing	0.00	0.00	0.19	0.53	2467
Plastics and Chemicals	1.80	5.15	2.85	18.31	2205
Shipbuilding and Aerospace	0.02	0.10	0.73	2.80	1111
Textiles	0.00	0.01	0.24	0.72	1848
Wood and Furniture	0.00	0.01	1.14	2.62	1048
Panel B: Other sectors					
Agriculture	0.00	0.00	0.00	0.12	2552
Construction	0.00	0.01	0.00	0.07	7108
Education and Research	0.00	0.01	0.03	0.32	12636
Mining	0.00	0.01	0.23	2.07	763
Services	0.00	0.00	0.00	0.00	84776
Utilities	0.00	0.00	0.00	0.11	745

Notes: This table illustrates the number of robots adopted in the United States and seven European countries (Denmark, Finland, France, Italy, Spain, Sweden and the United Kingdom) by year and industry. Panel A reports the number of robots for 13 manufacturing industries. Panel B reports the number of robots for six sectors outside of manufacturing. Columns 1 and 3 report the stock robots per thousand workers in 1993. Columns 2 and 4 report the change in the stock of robots between 1993 and 2014 per thousand workers in 1993. Column 5 reports the number of workers by industry in 1993.

Table C3: Robots and college enrollment until 2014

	Census/ACS		IPEDS		
	All students		All students	Undergrad.	Graduate
	[1]	[2]	[3]	[4]	[5]
US robot exposure	0.213	0.256*	0.311***	0.302***	0.009
	(0.154)	(0.149)	(0.099)	(0.099)	(0.027)
Observations	2166	2166	1738	1738	1738
Covariates:					
State FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Pre-trends		✓	✓	✓	✓
Chinese imports		✓	✓	✓	✓
Demographics		✓	✓	✓	✓
Industries		✓	✓	✓	✓
Occupations		✓	✓	✓	✓
Institutions		✓	✓	✓	✓

Notes: This table illustrates IV estimates of the effect of robot exposure on the share of students. Every regression includes three periods (1993-2000, 2000-07, 2007-14) with 722 observations (CZs). Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Table C4: Robots, imports and college enrollment

	Not standardized				Standard.
	[1]	[2]	[3]	[4]	[5]
US robot exposure	0.279*	0.277*	0.306**	0.349***	0.185***
	(0.154)	(0.144)	(0.124)	(0.100)	(0.053)
US import exposure		0.074	0.098**	0.097**	0.170**
		(0.050)	(0.040)	(0.038)	(0.067)
Observations	1444	1444	1444	1444	1444
Covariates:					
State FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Pre-trends	✓	✓	✓	✓	✓
Chinese imports		✓	✓	✓	✓
Demographics			✓	✓	✓
Industries			✓	✓	✓
Occupations			✓	✓	✓
Institutions				✓	✓

Notes: This table illustrates IV estimates of the effect of robot and import exposure on the share of students using Census/ACS data. Column 5 standardizes the variables to have mean 0 and standard deviation of 1. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Table C5: Robots and incoming students:
In-state and out-state students

	In-state	Out-state
	[1]	[2]
US robot exposure	-0.034**	-0.019*
	(0.013)	(0.011)
Observations	1444	1444
Covariates:	✓	✓

Notes: This table illustrates IV estimates of the effect of robot exposure on the share of students by migration status using Census/ACS data. Column 1 reports students migrating within the same state and Column 2 includes students migrating from another state. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Table C6: Robots and college enrollment by employment status

	Employment			Non-employment	
	Full-time: >30 hours	Part-time: 20-30 hours	Part-time: <20 hours	Unemploy-ment	Non-participation
	[1]	[2]	[3]	[4]	[5]
	Panel A: Individuals between 19 and 34 years				
US robot exposure	-0.074	0.136***	0.324***	0.265***	0.386***
	(0.054)	(0.027)	(0.092)	(0.075)	(0.087)
	Panel B: Individuals between 35 and 64 years				
US robot exposure	-0.056*	0.028***	0.047***	0.031***	0.080**
	(0.028)	(0.008)	(0.010)	(0.006)	(0.039)
Observations	1444	1444	1444	1444	1444
Covariates:	✓	✓	✓	✓	✓

Notes: This table illustrates IV estimates of the effect of robot exposure on the share of students by employment status using Census/ACS data. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Table C7: Robots and employment by education level

	All	Bachelor's	Associate	No college
	[1]	[2]	[3]	[4]
US robot exposure	-1.215***	-0.522***	-0.928**	-1.522**
	(0.450)	(0.191)	(0.356)	(0.580)
Observations	1444	1444	1444	1444
Covariates:	✓	✓	✓	✓

Notes: This table illustrates IV estimates of the effect of robot exposure on the employment rate using Census/ACS data. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

C3 Conceptual framework: Proofs

This section provides proofs of the claims made in the model and discusses further details about the equilibrium impact of robots on college enrollment. As stated in the main text, the model assumes a basic production function which combines L_ℓ, L_h and R, to produce an output good Y (Equation 86). The perfectly competitive environment implies that input factors are paid their marginal productivity (Equations 87 and 88). Robot capital is produced and competitively supplied each period through the following technology $R_t = Y_{R,t}\frac{e^{\delta t}}{\theta}$ (Autor and Dorn, 2013), where $Y_{R,t}$ is the amount of the final good allocated to produce robots and $e^{\delta(t-1)}$ is the total factor productivity. Firms can sell their output good at a normalized price of 1 or they can invest a share $Y_{R,t}$, in the production of robot capital at price p_t:

$$\pi_t = Y_{R,t} - p_t R_t \tag{96}$$

Taking the first order condition of Equation 96 with respect to $Y_{R,t}$ gives:

$$\frac{\partial \pi_t}{\partial Y_{R,t}} = 1 - p_t\frac{e^{\delta t}}{\theta} = 0 \tag{97}$$

which solves to $p_t = \theta e^{-\delta t}$.

Labor is supplied by a continuum of individuals $i \in [0, 1]$ who live one period and are endowed with one unit of labor that they supply on the labor market. At the beginning of the period, workers can either work in ℓ-type jobs and earn ω_ℓ, or they may enroll in college to acquire the necessary skills to perform tasks h. Individuals who enroll in a four-year university incur cost $\eta_i\omega_h$ to pursue a Bachelor's degree and will earn income $(1 - \eta_i)\omega_h$ on the labor market. Individuals who enroll in a two-year community college incur cost $\frac{\eta_i}{x}\omega_h$ to pursue an Associate degree (where $x \geq 2$) and will earn $(1 - \frac{\eta_i}{x})\omega_h$ with probability $1 - \lambda$ and $(1 - \frac{\eta_i}{x})\omega_\ell$ with probability λ on the labor market.

Individuals choose the college allocation that maximizes their income. They choose to pursue a Bachelor's degree if $\eta_i \leq \overline{\eta}_{BA}$, an Associate degree if $\overline{\eta}_{BA} < \eta_i \leq \overline{\eta}_{AN}$, and no college if $\overline{\eta}_{AN} < \eta_i$, where the thresholds are defined in Equation 91 in the main text. Labor supplies are computed accordingly, as illustrated in Equations 92 and 93.

From Equation 97, we know that the price of robots decreases exogenously over time, $\frac{\partial p_t}{\partial t} < 0$, such that $\frac{\partial R_t}{\partial t} > 0$. Taking the total differential from Equation 89 and solving for $\frac{\partial \omega_t}{\partial p_t}$ it follows that:

$$\frac{\partial \omega}{\partial p} = \frac{p\left(\frac{R}{L_\ell}\right)^{\rho-1}\frac{\partial R}{\partial p}}{\left[1+\left(\frac{R}{L_\ell}\right)^{\rho}\right]\left(\frac{L_\ell}{L_h}\frac{\partial L_h}{\partial \omega}+\frac{L_\ell}{\omega}\right)-\left[1+(1-\rho)\left(\frac{R}{L_\ell}\right)^{\rho}\right]\frac{\partial L_\ell}{\partial \omega}} < 0 \tag{98}$$

since $\frac{\partial R_t}{\partial p_t} < 0$ and:

$$\begin{aligned}\frac{\partial L_h}{\partial \omega} &= (1-\overline{\eta}_{BA})f(\overline{\eta}_{BA})\frac{\partial \overline{\eta}_{BA}}{\partial \omega} + \\ &+ (1-\lambda)\left(1-\frac{\overline{\eta}_{AN}}{x}\right)f(\overline{\eta}_{AN})\frac{\partial \overline{\eta}_{AN}}{\partial \omega} - \\ &- (1-\lambda)\left(1-\frac{\overline{\eta}_{BA}}{x}\right)f(\overline{\eta}_{BA})\frac{\partial \overline{\eta}_{BA}}{\partial \omega} > 0\end{aligned} \tag{99}$$

$$\begin{aligned}\frac{\partial L_\ell}{\partial \omega} &= \lambda\left(1-\frac{\overline{\eta}_{AN}}{x}\right)f(\overline{\eta}_{AN})\frac{\partial \overline{\eta}_{AN}}{\partial \omega} - \\ &- \lambda\left(1-\frac{\overline{\eta}_{BA}}{x}\right)f(\overline{\eta}_{BA})\frac{\partial \overline{\eta}_{BA}}{\partial \omega} - \\ &- f(\overline{\eta}_{AN})\frac{\partial \overline{\eta}_{AN}}{\partial \omega} \;\; > 0\end{aligned} \tag{100}$$

with:

$$\frac{\partial \overline{\eta}_{AN}}{\partial \omega} = x\left[\frac{1-\lambda}{[(1-\lambda)\omega+\lambda]^2}\right] > 0 \tag{101}$$

$$\frac{\partial \overline{\eta}_{BA}}{\partial \omega} = x\left[\frac{\lambda(x-1)}{[x\omega-(1-\lambda)\omega-\lambda]^2}\right] > 0 \tag{102}$$

where Equation 99 holds for well defined parameters, λ and x. In words, an exogenous decrease in the price of robot capital increases the wage premium between non-automatable and automatable labor, $\omega = \frac{\omega_h}{\omega_\ell}$. As a consequence, college enrollment rates of workers who want to perform tasks h increase due to an increase in the relative wage of non-automatable jobs, $\overline{\eta}_{AN}$ increases. At the same time, individuals who would have enrolled in a community college have an incentive to enroll in four-year colleges, since the increase in the wage premium compensates for the additional time spend in school, $\overline{\eta}_{BA}$ increases. ■

Note that robot capital unambiguously increases ω_h, $\frac{\partial \omega_h}{\partial p} < 0$, but may increase or decrease ω_ℓ depending on the substitutability between R and L_ℓ, ρ. If L_ℓ and R are strong substitutes (ρ is high), firms demand less labor and ω_ℓ decreases, $\frac{\partial \omega_\ell}{\partial p} > 0$. If L_ℓ and R are weak substitutes (ρ

is low), firms demand more labor and ω_ℓ increases, $\frac{\partial \omega_\ell}{\partial p} < 0$. As shown in Equation 98, the wage premium ω increases in either case.

C4 Robustness checks

This section presents a set of robustness checks and additional results in support of our preferred specification.

Identification – A concern that we need to address is that the adoption of robots in Europe is influencing US labor market conditions through increased product market competition, or that transnational industry trends have affected the adoption of robots both in Europe and in the US, violating the exclusion restriction of our IV strategy. Although we cannot fully rule out this possibility, we address these potential threats to identification through the construction of the instrument and a set of robustness checks.

Table C8: Robots and college enrollment: Product market competition from Europe

	[1]	[2]	[3]	[4]	[5]
US robot exposure	0.320	0.320	0.299	0.327**	0.364***
	(0.206)	(0.195)	(0.180)	(0.156)	(0.125)
Observations	1444	1444	1444	1444	1444
Covariates:					
State FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Pre-trends		✓	✓	✓	✓
Chinese imports			✓	✓	✓
Demographics				✓	✓
Industries				✓	✓
Occupations				✓	✓
Institutions					✓

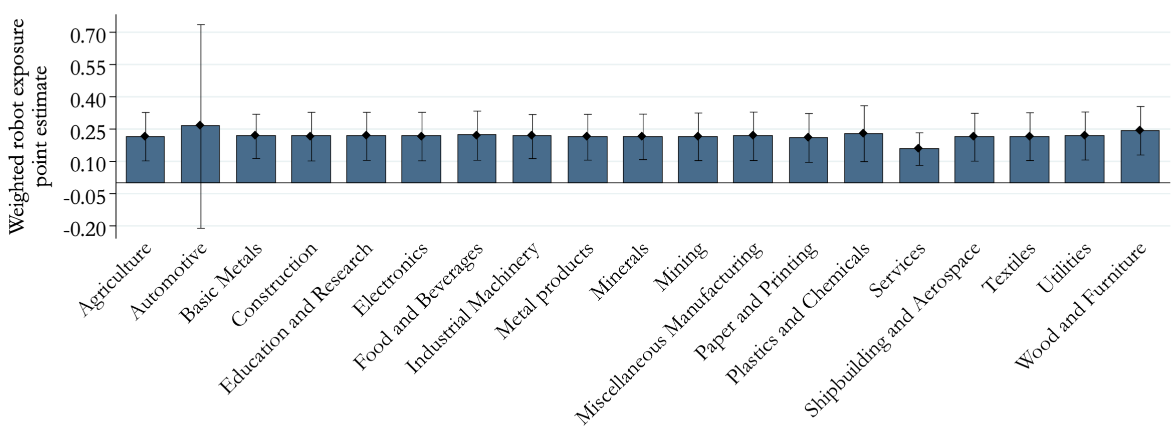
Notes: This table illustrates IV estimates of the effect of robot exposure on the share of students using Census/ACS data. The instrument uses only the adoption of robots in Denmark, Finland, Spain and Sweden. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

The instrument purposely does not include the countries with the world's heaviest adoption of industrial robots, namely South Korea, Germany, and Japan. These countries are also among the main trading partners of the US and could directly affect US labor market conditions through their national adoption of robots. Furthermore, we build an alternative measure of the instrument that includes only countries which are least engaged in trade with the US (Denmark, Finland and

Sweden), whose adoption of robots is unlikely to affect US labor market conditions. Table C8 shows that the estimated effect of robots on college enrollment remains positive and is not economically nor statistically different from the estimates of our main specification. This finding suggests that our estimates are unlikely to be driven by an increase in product market competition through the heavier utilization of robots in Europe.

To control for industry-specific shocks that might confound the labor market effect of robots, we sequentially exclude each industry at a time from the shift-share measure, as suggested in Goldsmith-Pinkham et al. (2020). Figure C2 reports 19 point estimates of the effect of robot adoption on college enrollment including all IFR industries but one. The point estimates are not significantly different from our preferred specification's estimates and are most sensitive to the exclusion of robots in the automotive industry. This finding is not surprising, considering that most robots are adopted in this industry (see Table C2). Overall, these results suggest that the labor market effect of robots is not driven by unrelated industry-specific shocks.

Figure C2: Robot exposure by industry exclusion



Notes: This figure illustrates the reduced form point estimates of the effect of robot exposure on the share of students, when excluding each industry from the shift-share measure one at a time, using Census/ACS data. For example, *Automotive* excludes robots adopted in the automotive industry. Confidence intervals are at the 95% level.

Pre-trends – The secular increase in the share of the population with a college degree raises the concern that college enrollment rates and the adoption of industrial robots could be driven by some common factors. For example, changes in schooling and the adoption of robots could both stem from a local labor market's industrial composition. If so, our estimates could be confounding the impact of robot exposure with pre-existing trends that local labor markets were undergoing. We account for this concern in our preferred specification by controlling for past changes in college enrollment between 1970 and 1990.

We further perform a ‘placebo test’ in which we analyze the relationship between past schooling and the subsequent adoption of robots to verify that our results are capturing the period-specific effects of robots on college enrollment. The results are reported in Tables C9 and C10. We find that changes in college enrollment in the 1970s and 1980s are related negatively to college enrollment between the 1990s and 2007, but, reassuringly, we do not find evidence that this trend is influencing the impact of robots on college enrollment, and no economically or statistically significant association between past schooling trends and the subsequent adoption of robots.

Table C9: Robots and college enrollment pre-trends

	[1]	[2]	[3]	[4]	[5]
US robot exposure	0.277*	0.279*	0.277*	0.306**	0.349***
	(0.163)	(0.154)	(0.144)	(0.124)	(0.100)
College enrollment$_{1970-1990}$		-0.058***	-0.057***	-0.029*	-0.037***
		(0.013)	(0.013)	(0.014)	(0.011)
Observations	1444	1444	1444	1444	1444
Covariates:					
State FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Pre-trends		✓	✓	✓	✓
Chinese imports			✓	✓	✓
Demographics				✓	✓
Industries				✓	✓
Occupations				✓	✓
Institutions					✓

Notes: This table illustrates IV estimates of the effect of robot exposure on the share of students, and includes the estimates of pre-trends, using Census/ACS data. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

CZ-specific migration flows – In Table 3.4, we show that robot exposure decreases the share of incoming students, but does not affect the share of outgoing students. We explore this result further by breaking down the share of movers in 520,562 individual CZ migration flows (722 × 721).

This procedure allows us to estimate the effect of robots in the CZ of origin and the CZ of the college on each individual CZ-to-CZ flow of students. For instance, we estimate how the shock in Detroit and in San Diego affect the share of students who moved from Detroit to San Diego (before we were only analyzing the total flow of incoming students to San Diego and the total flow of outgoing students from Detroit). Table C11 illustrates the results.

Table C10: Robots and college enrollment: Placebo test

	[1]	[2]	[3]
US robot exposure	-0.013	-0.013	-0.117
	(0.095)	(0.096)	(0.117)
Observations	1444	1444	1444
Covariates:			
State FE	✓	✓	✓
Year FE	✓	✓	✓
Chinese imports		✓	✓
Demographics			✓
Industries			✓
Occupations			✓

Notes: This table illustrates IV estimates of the effect of robot exposure during our sample period on the share of students between the 1970s and 1990s using Census/ACS data. Regressions are weighted by CZ population in 1970. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

In line with our main results, we find that the adoption of robots in cz_o has no statistically significant effect on the flow of students who move from cz_o to cz (outflow), while the inflow of students decreases if robot exposure in cz is large. Although the result on outflows is not statistically significant, its (absolute) economic size is similar to the result on inflows.

Table C11: Robots and students' CZ-specific migration flows

	[1]	[2]	[3]
US robot exposure$_{cz}$	-0.068***		-0.067***
	(0.015)		(0.015)
US robot exposure$_{cz_o}$		0.073	0.072
		(0.145)	(0.145)
Observations	1041124	1041124	1041124
Covariates:	✓	✓	✓

Notes: This table illustrates IV estimates of the effect of robot exposure in the CZ in which the college is located and in students' CZ of origin on the share of students by migration status, using Census/ACS data. Changes are expressed in percentage points of the working-age population and are multiplied by 1000. Every regression includes two time periods with 722×721 observations (CZs). For comparability, independent variables have been standardized to have mean zero and standard deviation of one. Robot exposure in the CZ of origin includes only the CZ-specific shock from which a group of students is migrating from. Covariates are included for the CZ in which the college is located and the CZ of origin. The 5-year migration flows for the ACS data are built using four times the annual migration flow of a CZ. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Adjusted migration flows – As we show in Appendix C1, a major limitation of migration data from the Census and the ACS is that the period of relevance for the question about past migration changes from five years to one year. When building aggregate migration measures, we follow Molloy et al. (2011) and construct measures of 5-year migration flows from the ACS by using four times the annual migration flow of a CZ. The results are reported in Table 3.4. To show that these results are not driven by the choice of the normalization parameter across periods, Table C12 provides the same results, but using a normalization parameter equal to five, rather than four. The results are almost identical to our preferred specification. Stayers are affected only by the shock in the CZ in which the college is located, which is also their CZ of origin, while the share of movers is not affected by robot exposure in their place of origin, cz_o (Panel B), but decreases with the shock's intensity in the CZ in which the college is located, cz (Panel A).

Table C12: Robots and student migration using a 5-year normalization

	All students	Stayers	Movers
	[1]	[2]	[3]
Panel A: Perspective from CZ of college (incoming movers)			
US robot exposure	0.325***	0.393***	-0.068***
	(0.081)	(0.076)	(0.018)
Panel B: Perspective from CZ of origin (outgoing movers)			
US robot exposure	0.256*	0.267*	-0.011
	(0.149)	(0.138)	(0.017)
Observations	1444	1444	1444
Covariates:	✓	✓	✓

Notes: This table illustrates IV estimates of the effect of robot exposure on the share of students and decomposes the effect by stayers and movers using Census/ACS data. Here, we multiply the annual ACS flows by five (rather than four) to obtain 5-year migration flows. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Alternative construction of shift-share measure – Table C13 shows that the exact construction of the shift-share measures does not affect our results. Columns 1 and 2 report estimates of two more mixes of European countries that are used in the construction of the instrument. First, we include Germany as an additional European country in the instrument, a country that is ahead of the US in the adoption of robots. Second, we exclude Spain and the United Kingdom, replicating the measure of Acemoglu and Restrepo (2020). Column 3 reports estimates using a measure of robot exposure in the US and an instrument without adjusting for industry output growth, $g_{j,(t_0,t_1)}\frac{R_{j,t_0}}{L_{j,90}}$. Column 4 reports estimates using an instrument with 1990 industry employment shares, $\ell^{90}_{c,j}$, rather than from 1970. Using these alternative measures, the estimates of the labor market effect of robots on college enrollment do not differ economically or statistically from our preferred specification's results.

Table C13: Robots and college enrollment: Alternative construction of robot exposure measures

	EU8 countries (incl. Germany)	EU5 countries (Acemoglu and Restrepo, 2020)	No adjustment $g_{j,(t_0,t_1)} \frac{R_{j,t_0}}{L_{j,1990}}$	EU7 countries with shares of 1990, $\ell_{c,j}^{1990}$
	[1]	[2]	[3]	[4]
US robot exposure	0.309***	0.429***	0.195**	0.354***
	(0.089)	(0.112)	(0.080)	(0.088)
Observations	1444	1444	1444	1444
Covariates:	✓	✓	✓	✓

Notes: This table illustrates IV estimates of the effect of robot exposure on the share of students using different shift-share measures and Census/ACS data. Column 1 reports estimates using an instrument which includes seven European countries and Germany. Column 2 reports estimates using an instrument that includes only five European countries. We exclude Spain and the United Kingdom as in the measure of Acemoglu and Restrepo (2020). Column 3 reports estimates using an endogenous variable and an instrument of robot density without the adjustment term of industry growth. Column 4 reports estimates using an instrument with seven European countries, but US employment shares of 1990 instead of 1970. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Exclusion of most exposed CZs – Figure 3.1 of Section 3.2 illustrates that the shock is mainly concentrated in labor markets of the Rust Belt due to their specialization in the steel and automotive industry. This finding raises the question of whether the effect of robots on college enrollment is specific to these CZs or whether this is a US wide phenomenon. Table C14 reports the results when excluding from the sample the CZs with the highest robot exposure. First, we exclude the CZ of Detroit, which is the labor market that is mostly exposed to the shock. Second, we exclude the CZs in the top 1 percentile of the distribution of robot exposure. Besides Detroit, these CZs include the labor markets of Jackson, Lansing, Saginaw (Michigan), Richmond, Kokomo, Muncie (Indiana) and Defiance (Ohio). Third, we exclude all CZs around the Great Lakes that are in the states of Michigan, Indiana and Ohio. The estimates remain economically and statistically significant at conventional levels in all specifications, showing that the effect of robots is not limited to CZs in the Rust Belt. Interestingly, outside of the Great Lakes' CZs the effect of robots is larger, suggesting that, although they are adopted less frequently in those areas, the introduction of one additional robot has a stronger effect on college enrollment than in the Rust Belt.

Unweighted results – Table C15 presents a set of estimates of the effect of robots on college enrollment without regression weights. This specification provides smaller, but less precisely estimated, effects. When analyzing outcomes across labor markets of different sizes, efficient weights must consider individuals' sampling weights to account for inherent heteroskedasticity. Cadena and Kovak (2016) show that optimal weights are strongly correlated with initial population sizes and

Table C14: Robots and college enrollment: Exclusion of CZs with highest robot exposure

	Detroit	Top 1%	Great Lakes
	[1]	[2]	[3]
US robot exposure	0.466***	0.662***	0.771*
	(0.159)	(0.239)	(0.405)
Observations	1442	1429	1340
Covariates:	✓	✓	✓

Notes: This table illustrates IV estimates of the effect of robot exposure on the share of students, excluding from the sample the CZs with the highest robot exposure, using Census/ACS data. Column 1 excludes the CZ of Detroit. Column 2 excludes the CZs in the top 1 percentile. Column 3 excludes the CZs in the most exposed states around the Great Lakes (Indiana, Michigan and Ohio). Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

are well approximated by the initial population of a local labor market. Therefore, we are confident that the results of our preferred specification are providing better estimates of the underlying effect of robots on college enrollment than the results of Table C15.

Table C15: Robots and college enrollment: Unweighted results

	[1]	[2]	[3]	[4]	[5]
US robot exposure	0.127	0.133	0.133	0.154	0.174*
	(0.089)	(0.079)	(0.081)	(0.093)	(0.091)
Observations	1444	1444	1444	1444	1444
Covariates:					
State FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Pre-trends		✓	✓	✓	✓
Chinese imports			✓	✓	✓
Demographics				✓	✓
Industries				✓	✓
Occupations				✓	✓
Institutions					✓

Notes: This table illustrates IV estimates of the effect of robot exposure on the share of students using Census/ACS data. Regressions are unweighted. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

C5 Robots and college enrollment at state level

From Table 3.3, we know that robot exposure at the local labor market level increases enrollment rates in community colleges, but not in four-year universities. However, as anticipated in Section 3.1, Branco et al. (2022) show that individuals who were born in states that are more exposed to the adoption of robots are more likely to attain a Bachelor's degree from a four-year institution. This divergence in the results might follow from changes in the geographical unit of reference, which identify a different subset of individuals who adjust their human capital in response to the shock. We document these differences in Table C16. To compare robot exposure across different geographical units, we standardize the estimates to have mean zero and standard deviation of one.

Column 1 reports estimates of the effect of robot exposure at the local labor market level on college enrollment in two-year and four-year institutions at the local labor market level, as in our preferred specification of Table 3.3 (but now standardized). Column 2 reports estimates of the effect of robot exposure at the state level on enrollment rates at the local labor market level. Using this approach, we identify individuals who react to robot exposure within their state of residence on college enrollment at the CZ level. Column 3 reports estimates of the effect of robot exposure at the state level, but excluding the CZ of reference, on enrollment rates at the local labor market level (in the CZ of reference). This approach is similar to a leave-one-out strategy and helps understand how individuals respond to the exposure to robots within their state of residence, but outside of their local labor market. Finally, Column 4 reports estimates of the effect of robot exposure at the state level on college enrollment in the state.

Table C16: Robots and college enrollment at state level

	Enrollment: Local labor market			Enrollment: State
	Exposure CZ	Exposure state	Exposure state (excl. CZ)	Exposure state
	[1]	[2]	[3]	[4]
	Panel A: Four-year university			
US robot exposure	0.037	0.114***	0.099**	0.178***
	(0.038)	(0.040)	(0.049)	(0.038)
	Panel B: Two-year community college			
US robot exposure	0.150***	0.389***	0.177*	0.335**
	(0.044)	(0.097)	(0.103)	(0.139)
Observations	1161	1161	1161	96
Covariates:	✓	✓	✓	✓

Notes: This table illustrates standardized IV estimates of the effect of robot exposure on the share of undergraduate students and decomposes the effect by institution characteristics using data from the IPEDS. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Results in Columns 2, 3 and 4 show that when we include measures of robot exposure outside of the local labor market of residence of individuals, but within state boundaries, also enrollment in four-year universities increases significantly. On the other hand, Column 1 shows that (myopic) individuals who account only for robot exposure in their CZ of residence enroll more often in community colleges. These individuals might lack the necessary skill to complete a Bachelor's degree and might have different socio-economic characteristics than individuals who account also for shocks outside of their local labor market in their decision on whether to enroll in college (Manski and Wise, 2013).

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