Robots and Immigrants: Evidence from US

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Abstract

We investigate the effect of automation on employment, wages, and population size of native- and foreign-born individuals. Using an instrumental variable strategy that exploits variation in local industry employment shares and industry-level robot adoption, we estimate that automation reduced the employment and wages of both immigrant and native-born workers across US commuting zones. Moreover, the expansion of robots induced higher migration responses by immigrants than native-born workers but immigrants' migration had a limited contribution to overall labour market adjustment. Immigrants' migration choices can explain only 19% of the employment difference between high versus low robot-exposed regions.

Keywords: Employment, Immigrants, Migration, Automation

JEL Classification: J15, J23, J31, O33

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1 Introduction

Technological innovation through automation has reduced employment and wages and increased inequality across local labour markets (Acemoglu & Restrepo 2020, 2022*b*). Geographic mobility of workers is an important mechanism to mitigate against adverse local economic shocks (Blanchard & Katz 1992). US-born individuals, especially low-skilled, are less likely to move in response to changes in local labour demand (Bound & Holzer 2000, Notowidigdo 2020). On the other hand, immigrants are much more mobile and can play a crucial role in “greasing the wheels of the labour market" (Borjas 2001). But there is limited evidence that immigration can reduce regional inequality against structural shocks like automation.[1]

The share of immigrants in the US workforce has been rising rapidly since the last few decades and they are differentially distributed along the skill dimension than native-born workers (Borjas 2005, Peri & Sparber 2009). Moreover, immigrants have a stronger migration response than native-born individuals to labour demand shocks (Green et al. 2019). In this context, we ask two questions about which we know very little. First, what is the effect of automation on employment and wages of foreign- and native-born workers? Second, do immigrant migrate more than native-born in response to technology-driven local labour market shocks and what impact does immigrants' migration has on the native-born workers?

We investigate the effect of automation across US commuting zones (CZs) by exploiting variation in initial local employment shares combined with the national growth in industry-level robot use. Following Acemoglu & Restrepo (2020), we instrument for growth in robot capital for US with other European countries.[2] Our regression specification includes controls for the CZ's industry and demographic characteristics in 2000. We control for computer capital growth over our analysis period in our empirical specification to account for technological innovation other than automation.

Firstly, we highlight that automation negatively impacts both native- and foreign-born workers. The elasticity of employment to robot adoption is more negative but not statistically distinguishable from that of natives. The fall in employment occurs

[1]Faber et al. (2022) analyse migration response to automation but not separately by nativity. Moreover, we investigate the role of immigration in local labour market adjustment to automation.

[2]Autor et al. (2013*a*) use a similar approach to understand the role of Chinese import competition.

among both low- and high-skilled workers, irrespective of nativity status. Wages of both native-born and immigrants fall equally in response to robot adoption, leading to no change in the native-born immigrant wage gap. Thus, both native- and foreign-born workers experience adverse labour market outcomes due to technology-driven demand changes.

Second, immigrant population falls substantially in regions more exposed to automation. The effect among native-born is negative but insignificant from zero. The foreign-born population falls by 5.03 percentage points (pp) in response to a one robot increase per thousand workers compared to only 1.06pp for native-born, which is indistinguishable from zero. Our results are robust to including trade shocks and controlling for mis-specification arising from robot exposure of other locations (Borusyak, Dix-Carneiro & Kovak 2022). Moreover, we do not find any fall between 1980-2000 in immigrant or native-born employment, wage and population in response to automation growth from 2000 to 2015. This result provides a test to the hypothesis that our baseline results are not confounded by unobserved *past shocks* to CZs.

A distinguishing feature of this paper is that we quantify the role of immigrants' aggregate labour supply change induced by their migration on the overall employment changes due to automation. Comparing between CZs with 75$^{\text{th}}$ and 25$^{\text{th}}$ percentile of exposure to robots, immigrants' migration response can only explain 19% of the observed employment fall. Despite the much larger sensitivity to automation, immigration appears to have a limited role in labour market adjustment to robot adoption. This is simply because foreign-born accounted for only 9% of the population in 2000.

The loss in employment and wage due to automation can be potentially equalized across regions as immigrants migrate out of the more exposed areas, and immigrant and native-born workers are *perfect substitutes*. We include an interaction between robot exposure and immigrant population share in the regression to understand the effect of automation in labour markets in areas with varying immigrant population. One potential concern with the analysis is that immigrants are not randomly spread across regions; new immigrants are more likely to settle in areas with higher immigrant population share. We instrument for the recent distribution of immigrants across space using the historical distribution of immigrants in 1980 (Card 2001). The point estimate of the interaction between robot exposure and immigrant share on native-born employment and wage is only sometimes positive and always statistically insignificant from zero. Thus, it appears that immigration *does not* mitigate the negative impacts of automation on the labour market outcomes of native-born workers.

Our paper contributes to the literature on understanding the role of workers' geographic mobility to equilibrate local labour markets (Autor et al. 2023, Basso et al. 2019, 2020, Cadena & Kovak 2016, Faber et al. 2022, Yu 2023). Previous research has either focused on cyclical shocks (Basso et al. 2019, Cadena & Kovak 2016) or long-term shocks such as China shock or computerization. One exception is Faber et al. (2022) who investigate internal migration response to robot and trade exposure and find that robot growth led to a much larger fall in population than trade shocks. We also find that population fell more in regions with higher exposure to automation while controlling for trade exposure. More importantly, we show that this effect is driven by immigrants rather than native-born. A key contribution of this paper is that we use our estimated employment effect on total population and change in population to robot penetration to quantify the role that immigrants' migration decisions play in explaining the effect on employment. We document that immigration has a *limited* effect on labour market adjustment to technological changes stemming through industrial robot use.

Cadena & Kovak (2016) and Yu (2023) discuss the impact of immigrants' migration response on native-born workers in response to negative labour demand shocks due to cyclical factors and rising trade competition respectively. We fill a gap in the literature by investigating the role of immigration in ameliorating the adverse impact on native-born workers to a dominant structural shock experienced by the US economy (Abraham & Kearney 2020, Bergholt et al. 2022). We highlight that immigration does not help the native-born workers to adjust against automation. Following Cadena & Kovak (2016), we show that the labour market outcomes of native-born workers in areas with above median immigrant share are not better than below median share. We show similar results using a more general framework where we estimate the effect on native-born workers to robot exposure by varying the degree of immigrant population share in 2000. To address the issue of non-random sorting of immigrants across local labour markets, we instrument immigrant distribution in 2000 with distribution in 1980. The empirical specification can account for unobserved factors that correlate with foreign-born population share unlike the analysis like Cadena & Kovak (2016) of splitting the sample.

This paper contributes to understanding the distributional and long-term effects of automation by studying the effect on employment, wages and migration by nativity. Following the seminal paper by Acemoglu & Restrepo (2020) on the consequences of robot penetration across CZs, other papers have described the role of automation in reducing the labour share and increasing inequality over the past few decades (Bergholt et al. 2022, Graetz & Michaels 2018, Moll et al. 2022). We provide evidence about the differential impact of automation on foreign- and native-born and the restricted role of immigration to mitigate the inequalities across areas exacerbated by robot use.

The rest of the paper is organized as follows. Section 2 discusses in detail the data used and describes the methodology used to conduct the study. Section 3 presents the employment and wage results. Section 4 discusses the migration response of foreign- and native-born to automation and the limited effect of immigrants' migration on equalizing labour market outcomes spatially. We discuss heterogenity in immigrants' mobility response by age, education and years since arrival in the US in section 5 and finally, section 6 concludes.

2 Data and Empirical Specification

We describe our primary data sources in this section. We first outline trends in industrial robots since 2000 in the US and other countries. Second, we describe the construction and evolution of employment and wage dynamics over time by nativity at the local labour market level.

2.1 Robots

Our data on the stock of robots for each industry-year-country level comes from the International Federation of Robotics (IFR). IFR compiles data by surveying robot suppliers covering more than 60 countries since 1993. It is the most accessible and widely used cross-country data on robot adoption currently available (Acemoglu & Restrepo 2022*a*, Graetz & Michaels 2018). Employment data at the industry level comes from (EU KLEMS) Growth and Productivity Accounts (Board 2023).

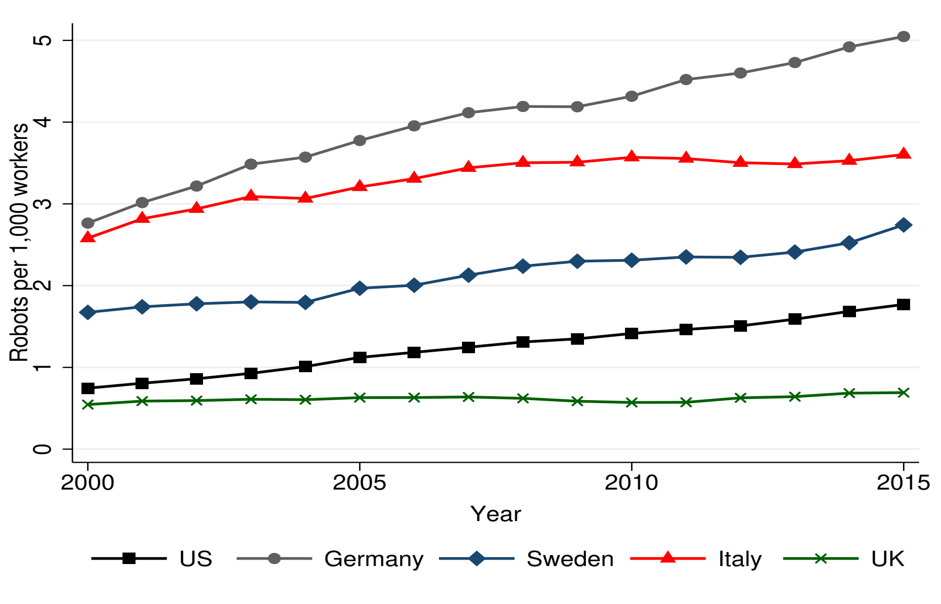


Figure 1: Robot per thousand worker in US and selected countries

Figure 1 shows the trend of robots per thousand workers in the United States, Germany, Italy, Sweden and the UK. The stock of robots per worker has risen steadily in all countries except the United Kingdom since 2000. It increased in the US from 0.75 per thousand workers in 2000 to 1.77 in 2015. Robot per worker is higher in Germany, Sweden and Italy and displayed a similar trajectory over time in the US

IFR provides data for 13 disaggregated categories in the manufacturing sector. Additionally, it provides data on six broad sectors: agriculture, mining, utilities, construction, education, and services. In 2015, about 11% total robots remained unclassified. We allocated them in the same proportion as the classified data.[3] Online Appendix table 7 shows that automotive and electronics experienced the highest growth in robots, whereas services displayed the least.

2.2 Commuting Zone and Robot Exposure Data

A commuting zone (CZ) is the commonly used level of disaggregation to understand local labour markets like Acemoglu et al. (2016). CZ contain counties with strong labour market and commuting ties (Tolbert & Sizer 1996). The advantage of using CZs over Metropolitan Statistical Areas (MSAs) is that MSAs are limited to urban areas with a sizeable population (greater than 50,000) unlike CZs that include both urban and rural

[3]Industry-specific data is available post 2003. Data from the year 2000 is classified into industries using the distribution in the year 2015.

areas. We focus on 722 Commuting Zones (CZs) that cover the entire US except the states of Alaska and Hawaii.[4]

We use the public use 5% 2000 and 2013-2017 American Community Survey (ACS) samples to measure wage and employment at the CZ level (Ruggles et al. 2023).[5] We measure the 2015 outcomes from the ACS using 2013 to 2017 following Autor et al. (2013*b*) to increase the sample size. Our sample of workers consists of non-institutionalized individuals between 16-64 age. We drop unpaid family workers, employed individuals with missing information about occupation and individuals working in the armed forces or public administration from the sample. We define individual wage as the pre-tax annual labour income of privately employed individuals divided by working hours in a year. We compute annual working hours by multiplying the number of weeks worked and the usual number of hours worked per week. Following Acemoglu & Autor (2011), top-coded income is set equal to its 1.5 times value. Real wage below \$2 is winsorized and real wage above the 99$^{\text{th}}$ percentile is excluded from the analysis. The Consumer Price Index of 1999 is used to deflate nominal wages.

Foreign-born or immigrants are individuals born outside the US and not currently US citizen. Figure 2 highlights substantial variation in the share of foreign-born workers in the US.

The change in population of a demographic between 2015 and 2000 is defined as:

$$\Delta Pop^{d}_{j,(t_0,t_1)} = \frac{Pop^{d}_{j,t_1} - Pop^{d}_{j,t_0}}{Pop^{d}_{j,t_0}} * 100 \tag{1}$$

where $d = \{U, I\}$. U refers to US-born and I denotes immigrants and $\Delta Pop^{d}_{j,(t_0,t_1)}$ computes the change in population size. The change in employment of a demographic group relative to CZ population is defined as the change in the number of employed workers in that group (in thousands) from 2000 to 2015 divided by the CZ population in 2000.

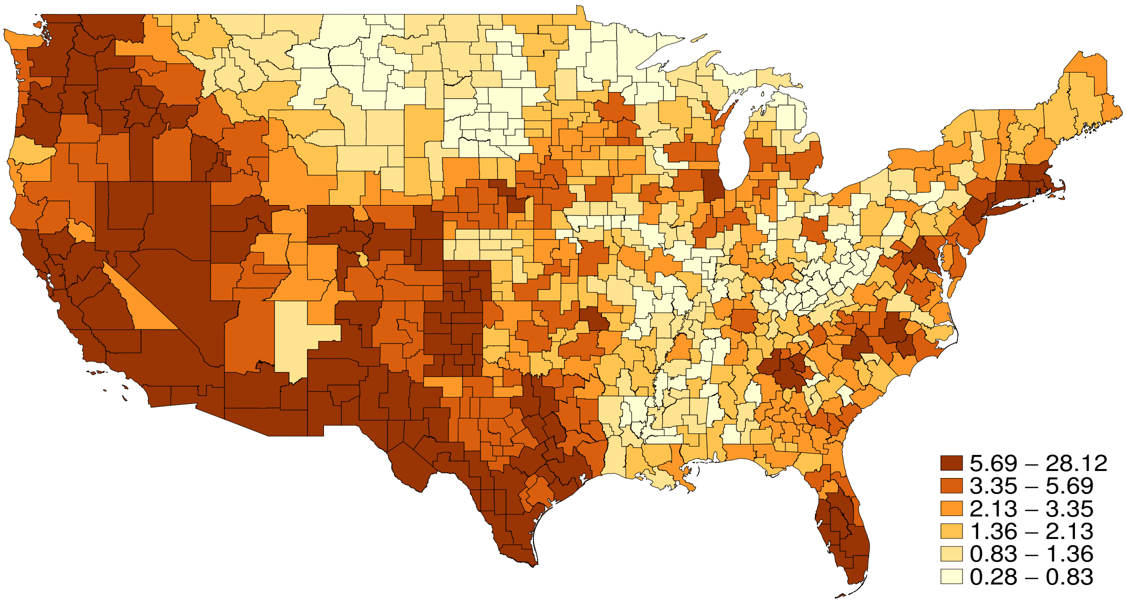
$$\Delta L^{d}_{j,(t_0,t_1)} = \frac{L^{d}_{j,t_1} - L^{d}_{j,t_0}}{Pop^{d}_{j,t_0}} * 100 \tag{2}$$

[4] We convert Public Use Micro Areas (PUMA) areas into CZs using the procedure outlined in Autor & Dorn (2013).

[5] We focus on the post-2000 period as the number of robots in the US increased by 144,365 units between 2000-2015 but by only 46,426 units between 1990-2000.

where $\Delta L^d_{j,(t_0,t_1)}$ measures the change in employment relative to CZ population of that native group d in CZ j and year t.

Figure 2: Immigrant population share across CZs in 2000



The growth in wage of a demographic group in CZ i between year t_0 and t_1 is:

$$\Delta w^d_{j(t_0,t_1)} = w^d_{j,t_1} - w^d_{j,t_0} \tag{3}$$

where $w^d_{j,t}$ is log of average wage of the demographic group $d = \{I, U\}$ in CZ i at time t. The US-born and immigrant wage gap is defined as:

$$\Delta w^U_{j(t_0,t_1)} - \Delta w^I_{j(t_0,t_1)} \tag{4}$$

where $w^U_{j(t_0,t_1)}$ and $\Delta w^I_{j(t_0,t_1)}$ is the wage growth of US-born and immigrants respectively.

The change in robot use in a CZ j between time t_0 and t_1 is defined as the weighted sum of the change in robot use at the industry level where weights are the industry's employment share in the year 2000 and in CZ j. The growth in the stock of industrial robots in industry i between time t_0 and t_1 is:

$$\Delta R_{i,(t_0,t_1)} = \frac{R_{i,t_1} - (1 + g_{i,(t_0,t_1)}) \cdot R_{i,t_0}}{L_{i,t_0}} \tag{5}$$

where $R_{i,t}$ is the number of robots in industry i at time t, $L_{i,2000}$ is the employment count (in thousands) in industry i in year 2000 and $g_{i,(t_0,t_1)}$ is the growth rate of output between time t_0 and t_1 in industry i. The employment and output data by industry is available in the EU KLEMS database. Equation 5 captures the additional acquisition of robot capital taking into account the growth of the industry while keeping employment fixed at year 2000. Thus, the expansion of robotic technology in a CZ is measured in the following manner:

$$\Delta R_{j,(t_0,t_1)} = \sum_i \left[\frac{L_{i,j,t_0}}{L_{j,t_0}} \cdot \Delta R_{i,(t_0,t_1)} \right] \tag{6}$$

where $\frac{L_{i,j,t_0}}{L_{j,t_0}}$ is the baseline employment ratio of industry i in CZ j and year t_0.

Online Appendix figure 3 highlights the geographical variation in robot expansion in the US. Lighter shades reflect lower growth of robot usage. Robot use has expanded rapidly in the automotive industry, leading to areas with large automobile manufacturers and suppliers like Michigan and Ohio witnessing significant increases in robot use and reduction in labour demand.

2.2.1 Computer Capital

The real stock of computer capital almost doubled in the US between 2000-2015. Computer capital deepening enhances the productivity of high-skilled labour (Autor et al. 1998, Beaudry et al. 2010, Krueger 1993). Computer capital is a factor-augmenting technology which is different from labour-displacing robot technology. But, Basso et al. (2020) argues that immigrant location choices are responsive to computerization, which could affect employment and robot technological adoption in other firms. We account for the growth in computer adoption using computer capital data from EU KLEMS measured as the value of computing equipment stock in US dollars per thousand workers. EU KLEMS 2017 uses the ISIC Rev. 4 (NACE Rev. 2) industry classification to provide data on 34 distinct industries, including 11 categories for manufacturing. We harmonize the industry classification across the various datasets and create a measure of change in computer capital intensity in CZ i between 2000 and 2015 similar to the change in robot intensity using equation 5. The correlation between change in robot and computer intensity across CZs is -0.22, similar to Acemoglu & Restrepo (2020). Thus, the growth of industrial robots is presumably unrelated to the expansion of computers in the US.

2.3 Regression Specification and IV Strategy

To estimate the effect of the expansion of robot use on employment and wages of foreign- and US-born individuals, we use the following empirical formulation:

$$y^{d}_{j,(t_0,t_1)} = \alpha_{j,i} + \beta_1 \Delta R_{j,(t_0,t_1)} + \beta_2 \Delta C_{j,(t_0,t_1)} + \gamma X_{j,2000} + \varepsilon_j \tag{7}$$

where $y^{d}_{j,(t_0,t_1)}$ is the dependent variable of nativity group d, $\alpha_{j,i}$ are Census division dummies, and $\Delta R_{j,(t_0,t_1)}$ and $\Delta C_{j,(t_0,t_1)}$ denote change in robot and computer capital adoption respectively.[6] β_1 is the coefficient of interest and ε_j is the zero-mean random error that we cluster at the state level. $X_{j,2000}$ includes demographic and industry shares in CZ j and year 2000 to control for the baseline characteristics of the CZ. We incorporate the share of the population above 65 as a control in our empirical specification as Acemoglu & Restrepo (2022*a*) argue that firms adopt robots more in regions with a higher share of older individuals.

An unobserved labour demand shock in a CZ may affect the technology choice of the firms in that local labour market. To isolate the causal effect of increased robot adoption, we instrument the US robot adoption with the robot adoption in other European countries (Acemoglu & Restrepo 2020). The goal is to isolate the global technological advancement in robot technology and purge out any US-specific factors. We follow Ge & Zhou (2020) by using the robot usage in Germany, Italy and Sweden to construct the change in robot adoption between 2000-2015 at the industry level.[7] The stock of robots per worker in EURO3 countries (Germany, Italy and Sweden) is higher than in the US (figure 1). We combine employment data from EU KLEMS and construct the average growth in robot adoption for each industry in EURO3 as:

$$\Delta \overline{R}_{i,(t_0,t_1)} = \frac{1}{3} \sum_{c \in EURO3} \frac{R^{c}_{i,t_1} - (1 + g^{c}_{i,(t_0,t_1)}) \cdot R^{c}_{i,t_0}}{L^{c}_{i,2000}} \tag{8}$$

where $R^{c}_{i,t}$ is the number of robots in industry i in country c at time t, $g^{c}_{i,(t_0,t_1)}$ is the output growth of industry i in country c between t_0 and t_1, and $L^{c}_{i,2000}$ is the industry i's

[6] Borusyak, Hull & Jaravel (2022) argue that employing a first-difference specification can help to both maximize the first stage and isolate the shock variation when exposure shares in levels for many periods are unavailable.

[7] We show later that our results are robust to including France and UK, two countries with lower robot adoption per worker than the US.

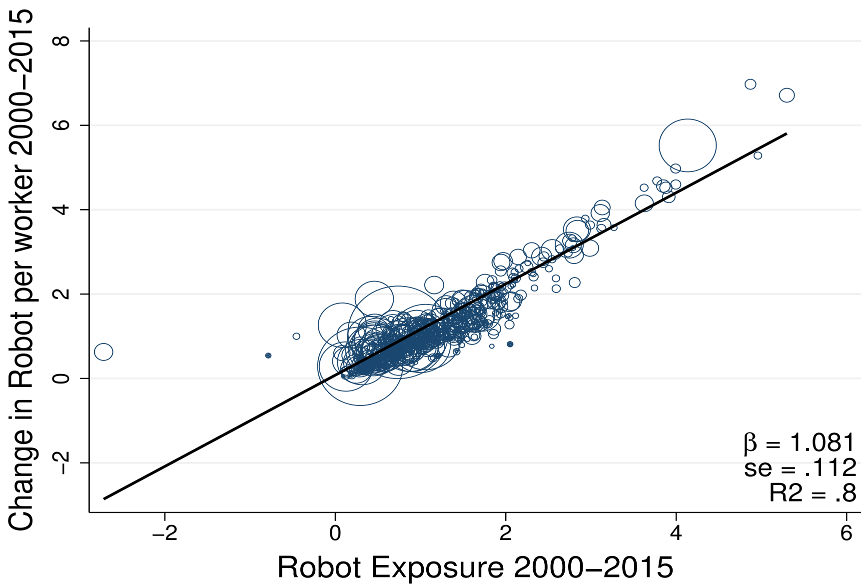
baseline employment in country c in 2000. The corresponding CZ measure of robot exposure or robot intensity is calculated by replacing the EURO3 industry level robot adoption from equation (8) in equation (6).

$$\Delta\overline{R}_{j,(t_0,t_1)} = \sum_i \left[\frac{L_{i,j,2000}}{L_{j,2000}} \cdot \Delta\overline{R}_{i,(t_0,t_1)} \right] \tag{9}$$

where $\Delta\overline{R}_{j,(t_0,t_1)}$ captures the exposure of robots to CZ j.[8]

Figure 3 shows that the EURO3 measure of robot exposure can predict the expansion of robot utilization in the US. The regression coefficient is significantly different from zero at the 1% level of significance and captures 80% of the variation in robot growth across CZs. We proxy for growth in computer capital usage using the level of computer capital in 2000 following Michaels et al. (2014). Online Appendix figure 7 highlights a strong relationship between computer capital in 2000 and the growth in computer capital adoption with a R^2 of 0.54.

Figure 3: Relation between growth in robot per worker and robot exposure



[8] Borusyak, Hull & Jaravel (2022) point out the validity of the IV depends on the exogeneity of the national industry growth in robot adoption while the allocation of labour in industries can be correlated with local economic factors.

3 Employment and Wage Results

Table 1 presents the IV estimates of robot use on employment in the entire US, and separately by nativity. Proxy of computer capital usage is included in all regressions to account for technological changes unrelated to automation. Further, we include demographic and industry shares in 1990 to allow for differential trends across CZs. Demographic shares include log population, women share in the population, the population share over 65 years old, shares of population with no college, some college, and college and above, and population shares of white and black individuals. We account for a share of employment in manufacturing and light manufacturing (paper and textile industries) and the employment share of women in manufacturing. We report in parentheses standard errors robust against heteroskedasticity and clustered at the state level to account for spatial correlations.

The IV estimate of all US employment is -1.87 (standard error=0.55), implying that a unit increase in robot per thousand workers reduces employment by 1.87 pp, consistent with Acemoglu & Restrepo (2020). Robot exposure was 0.53 and 1.5 at the 25$^{\text{th}}$ and 75$^{\text{th}}$ percentile CZ respectively. The loss in employment between the 75$^{\text{th}}$ and 25$^{\text{th}}$ percentile CZ is 1.81pp. Focusing on immigrants, the second column displays the 2SLS estimate of -3.745 with a standard error of 2.09. Among natives, one unit increase in robots per thousand workers is associated with a decline in employment of -2pp (standard error = 0.685) as shown in the third column. Thus, both foreign- and US-born are adversely impacted by automation.

Keane & Neal (2023) argue that two-stage least squares (2SLS) can suffer from low power even with instruments having large F-statistics. OLS bias can lead to artificially small 2SLS standard errors which can lead to the coefficient of interest being statistically significant. The reduced-form estimation does not suffer from this problem and so, the Anderson-Rubin test (referred to as “A-R F-test" henceforth) provides a better measure to gauge the true significance of robot adoption. The last line shows that all A-R F-test values are at least 2.9, meaning that the reduced-form coefficient of robot exposure is significant at the 10% level. Moreover, the first-stage F-statistic value of 96.87 denotes that the instrument has high predictive power.

Borjas (2005) and Peri (2016) stress that the skill mix of immigrants and US-born are distinct. In 2000, 66% of immigrants were low-skilled compared to 47% of native-

Table 1: IV estimate of robot exposure on employment

	Overall	Immigrant	US-born
	(1)	(2)	(3)
Robot adoption	-1.871***	-3.745*	-1.999***
	(0.551)	(2.093)	(0.685)
Observations	722	722	722
R-squared	0.71	0.44	0.70
Census Dummy	Yes	Yes	Yes
Computer Capital	Yes	Yes	Yes
Covariates	Yes	Yes	Yes
1st stage F-stat	96.866	96.866	96.866
A-R F-test	8.94	2.9	6.42

Note: All regression estimates are weighted by the CZ population in 2000. Robust standard errors clustered at the state level are reported in the parentheses. ***, **, * and + represent the statistical significance at 1%, 5%, 10% and 15% levels respectively. Covariates include log population; share of female population; share of the population over 65 years old; shares of the population with no college, some college and college and above; population shares of whites and blacks; manufacturing share of employment; light manufacturing share of employment; and share of female employed in manufacturing.

born. We define the low-skill type as those with a high school degree or less and the high-skill type as those with some college education or more. We investigate the effects of automation by nativity and skill groups using the change in log employment of a subgroup as the dependent variable. Online Appendix table 8 shows that high-skilled immigrants are affected as much as low-skilled immigrants. In contrast, low-skilled native-borns experience higher employment losses than high-skilled native-borns. We further show in Online Appendix table 9 that abstract foreign-born individuals are hit particularly hard whereas manual, routine and cognitive native-born are adversely impacted similarly.

One potential explanation is that cognitive occupations employ more high-skilled workers and high-skilled immigrant workers are more mobile than their low-skilled counterparts (Notowidigdo 2020). The bigger fall in the labour supply of high-skilled immigrants leads to a larger drop in employment. We will return to this point while discussing the migration responses by nativity and skill in Section 5. A reason for the lesser impact on high-skilled native-born could be that the entry of low-skilled immigrants encourages native-born to become high-skilled workers through training (Mandelman & Zlate 2022). Overall, we stress that the negative effect of automation is not restricted to low-skilled manufacturing jobs unlike import competition as also emphasized by Faber et al. (2022) and Bloom et al. (2019).

Next, we turn our attention to the impact of robot exposure on the wage income of immigrants and US-born workers in table 2. Columns (2) and (3) show that an increase in one robot per worker leads to a fall in wages by 1.8% (standard error=0.01) and 1% (standard error=0.006) for immigrants and native-born respectively. The US-born and immigrant wage gap is defined as the difference in the wage growth of native-born minus the wage growth of immigrants as shown in equation (4). Column (1) highlights that the implied native-born and immigrant wage gap is only 0.8pp and is insignificant from zero. Moll et al. (2022) argue that the effect of robot adoption is unequal along the wage distribution. Acemoglu & Restrepo (2022*b*) point out that automation is an important contributor to the rising wage inequality in the US. We show in Online Appendix table 10 that wages of both foreign- and US-born fall for both low- and high-skilled workers. This leads to no change in the native-born immigrant wage gap for both low- and high-skilled workers. In Online Appendix figure 8 we show this is also true along the wage distribution (10^{th}, 25^{th}, 50^{th}, 75^{th} and 90^{th} percentiles). Thus, higher robot exposure leads to a similar but significant fall in wages for both groups.

3.1 Robustness checks

One concern with the current analysis might be that some pre-existing CZ trend explains the labour market outcomes of both immigrants and natives to robot adoption. To address this issue, we conduct a falsification exercise in Online Appendix table 11 by regressing the change in employment, wage and population size over 1980-2000 on *future* CZ robot exposure between 2000-2015. The evidence shows that CZs more exposed to automation did not experience worse wages, employment prospects or differential migration for both immigrants and native-born relative to less exposed CZs.

We conduct several robustness checks whose results are highlighted in table 12. In the second column, we include more regressors: China shock, the share of routine jobs in the year 2000 and the foreign-born population share in 2000. We control for the rising import competition mainly from China as Bloom et al. (2016) show that higher import

Table 2: IV estimate of robot exposure on wage

	Wage gap	Immigrant	US-born
	(1)	(2)	(3)
Robot adoption	0.008	-0.018^{+}	-0.010*
	(0.012)	(0.012)	(0.006)
Observations	722	722	722
R-squared	0.13	0.21	0.57
Census Dummy	Yes	Yes	Yes
Computer Capital	Yes	Yes	Yes
Covariates	Yes	Yes	Yes
1st stage F-stat	96.866	96.866	96.866
A-R F-test	.44	2.09	1.75

Note: All regression estimates are weighted by the CZ population in 2000. Robust standard errors clustered at the state level are reported in the parentheses. ***, **, * and $^{+}$ represent the statistical significance at 1%, 5%, 10% and 15% levels respectively. Covariates include log population; share of female population; share of the population over 65 years old; shares of the population with no college, some college and college and above; population shares of whites and blacks; manufacturing share of employment; light manufacturing share of employment; and share of female employed in manufacturing.

competition can affect firms' technological decisions.[9] We also include the share of routine jobs in the year 2000 as an additional regressor since routine jobs are more likely to be automated. The share of immigrants in a region can affect the jobs and earnings of natives (Borjas 2006). It can also bias the effect on native-born employment as the immigrant population share might be strongly correlated with economic conditions or concentration in manufacturing which is why we excluded it from the baseline specification. Nonetheless, the wage gap estimate remains unchanged and the 2SLS estimate for native-born falls slightly from -2 to -1.89 as shown in the second column after including all the extra covariates.

The baseline measure of robot exposure included countries (Germany, Sweden and Italy) whose robot adoption per worker is higher than the US. We create an EURO5

[9] A CZ trade exposure is computed as the growth in Chinese import penetration in the CZ's industries weighted by the share of employment in that industry. To account for the endogeneity that industry import demand shocks are correlated with actual imports from China, the growth in imports from China in the US is adjusted by the growth in other 8 developed economies (Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland.). We use the trade exposure data from the replication material of Autor et al. (2020).

measure of robot exposure including France and the UK where robot usage is similar or lower than the US. Our results are almost identical using the baseline and EURO5 measures. Lastly, we consider an alternate definition of foreign-born that includes naturalized citizens which leads to an increase in the share of foreign-born residents in the US from 9% using the baseline definition to 14.3% in 2000. The main change is to the estimate of immigrants from -3.745 in the baseline specification to -5.22. The native-born immigrant wage gap remains close to zero as before and insignificant from zero.

4 Migration Results

In this section, we first provide evidence about the effect of automation on population headcounts by nativity and discuss how much of the immigrants' migration choices can explain the impact of robots on employment. Finally, we investigate whether immigrants' presence mitigates the negative impact of automation on the native-born.

Table 3 displays the 2SLS estimates of change in overall population, US-born population and foreign-born population to robot exposure. The regressions control for computer capital exposure, and CZ demographic and industry shares in 2000. One robot per thousand workers increase leads to a 1.46pp (standard error=0.825) fall in population, consistent with Faber et al. (2022). The fall in population at 75$^{\text{th}}$ percentile CZ of robot exposure is 1.42pp larger than the 25$^{\text{th}}$ percentile.

The migration response of the overall population is driven by immigrants and not by native-born. The 2SLS point estimate is -5.03 (standard error = 2.39) for immigrants. In contrast, the coefficient is smaller for US-born (-1.06) and is imprecisely estimated (t-stat = 1.3). The inter-quartile increase in robot exposure generates only a 1.02pp larger response among native-born compared to 4.88pp among foreign-born. Both the IV and reduced-form estimates for native-born are insignificant at standard levels of significance unlike for foreign-born. Thus, we find a weak response of US-born to labour demand shock which is similar in spirit to the finding of Cadena & Kovak (2016) for the Great Recession and Autor et al. (2023) and Yu (2023) for the China trade shock.

To understand the contribution of the foreign-born migration to aggregate labour supply response to automation, we compare the 25$^{\text{th}}$ and 75$^{\text{th}}$ percentile of robot

Table 3: IV estimate of robot exposure on migration

	Overall	Immigrant	US-born
	(1)	(2)	(3)
Robot adoption	-1.457*	-5.033**	-1.056
	(0.825)	(2.387)	(0.811)
Observations	722	722	722
R-squared	0.61	0.45	0.62
Census Dummy	Yes	Yes	Yes
Computer Capital	Yes	Yes	Yes
Covariates	Yes	Yes	Yes
1st stage F-stat	96.866	96.866	96.866
AR F-test	2.89	3.51	1.47

Note: All regression estimates are weighted by the CZ population in 2000. Robust standard errors clustered at the state level are reported in the parentheses. ***, **, * and + represent the statistical significance at 1%, 5%, 10% and 15% levels respectively. Covariates include share of female population; share of the population over 65 years old; shares of the population with no college, some college and college and above; population shares of whites and blacks; manufacturing share of employment; light manufacturing share of employment; and share of female employed in manufacturing.

exposed CZs. Assuming that the foreign-born are 9% of the working-age population with a labour force participation rate of 79% in both the 25th and 75th percentile CZ, we can utilize the estimated IV coefficients in column (2) of table 3 to compute the automation induced decrease in immigrant labour supply. Migration would lead to a fall in labour supply of 0.536pp (0.536 = 5.03*1.5*0.09*0.79) and 0.19pp (0.19 = 5.03*0.53*0.09*0.79) at the 75th and 25th percentile respectively. Thus, immigrant location choices can lead to an extra 34.6pp decline in employment in more robot exposed region compared to less robot exposed region. The estimated fall in employment between more versus less automated region is 1.814pp (1.814 = 1.87*[1.5-0.53]).[10] Migrants' location choices can account for 19% (0.346/1.814) of the net employment decline due to automation. The small effect is simply because immigrants account for a small population share (9%).

Our estimate of immigrants labour supply response between the 25th and 75th percentile CZ is likely to be an upper bound estimate. Lewis (2011) and Mann & Pozzoli (2023) argue that areas with higher low-skilled labour supply are associated with lower

[10]The 1.87 coefficient of employment comes from the first colum in table 1.

robot adoption. Acemoglu & Restrepo (2020) show that labour force participation reduced in areas more exposed to robots. Both of these factors will lead to a smaller difference in the aggregate labour supply between high versus low robot exposed regions. Moreover, we have made the extreme assumption that the overall employment decline we observe is composed of both labour demand and labour supply change. If instead we assume that we have precisely identified both labour demand and labour supply changes separately, then only 16% (0.346/[1.814+0.346]) of employment change due to automation is due to migrants' location choices. Autor et al. (2023) find that the contribution of net foreign-born population change to employment effect of trade shock is one-fifth, a number very similar to ours. Thus, immigration might be less beneficial in response to structural regional changes rather than cyclical shocks.

4.1 Native Employment Effect by Initial Immigrant Population

We provide further evidence of the limited contribution of foreign-born migration decisions in helping native-born adapt to automation. If foreign-born are more elastic in their moving response to negative labour demand shocks then the larger reduction in aggregate labour supply in high immigration areas might insulate the native-born's employment prospects from negative shocks. Cadena & Kovak (2016) compare labour market outcomes in areas with above and below median Mexican-born population. We provide a broader perspective by extend their discussion to all immigrants in a CZ.

The first and second column of table 4 shows the impact on employment of native-born in CZs with above and below median immigrant share to robot pentration. We find that the employment of native-born falls by -1.78% (standard error=0.77) in CZs with higher immigrant share compared to -0.97% (standard error=0.54) in regions with lower immigrant share. Moreover, the native-born immigrant wage gap does not change to automation in areas with high or low immigrant population share. We show in Online Appendix table 13 that our results to using the alternate definition of immigrants including naturalized citizens. Thus, native-born in areas with more immigrants are not worse off which suggests that native-born and immigrants might be imperfect substitutes to each other (Ottaviano & Peri 2012).

High and low immigration areas could be different in terms of their economic conditions or demographic characteristics which we did not control for in the previous

Table 4: IV estimate on US-born by above and below median immigrant population share in 2000

	Native Employment		Wage gap	
	Above median	Below median	Above median	Below median
	(1)	(2)	(3)	(4)
Robot adoption	-1.776**	-0.970*	0.004	-0.003
	(0.768)	(0.536)	(0.013)	(0.026)
Observations	361	361	361	361
R-squared	0.71	0.61	0.22	0.13
Census Dummy	Yes	Yes	Yes	Yes
Computer Capital	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes

Note: All regression estimates are weighted by the CZ population in 2000. Robust standard errors clustered at the state level are reported in the parentheses. ***, **, * and + represent the statistical significance at 1%, 5%, 10% and 15% levels respectively. Covariates include log population; share of female population; share of the population over 65 years old; shares of the population with no college, some college and college and above; population shares of whites and blacks; manufacturing share of employment; light manufacturing share of employment; and share of female employed in manufacturing.

analysis. We consider a specification (equation 10) where we include the foreign-born population share in 2000 to address this concern. Moreover, we interact the foreign-born population share in 2000 and robot use to allow us to capture the effect of automation on native-born across areas with varying immigrant shares.

$$\begin{aligned} y^d_{j,(t_0,t_1)} &= \alpha_{j,i} + \beta_1 \Delta R_{j,(t_0,t_1)} + \beta_2 \Delta R_{j,(t_0,t_1)} * \text{Immigrant Share}_{j,t_0} \\ &+ \beta_3 \text{Immigrant Share}_{j,t_0} + \beta_4 \Delta C_{j,(t_0,t_1)} + \gamma X_{j,2000} + \varepsilon_j \end{aligned} \tag{10}$$

where $y^d_{j,(t_0,t_1)}$ is the dependent variable of nativity group d in CZ j, $\Delta R_{j,(t_0,t_1)}$ denotes robot growth over time t_0 and t_1 and Immigrant Share_{j,t_0} is the foreign-born population share in CZ j at time t_0. The coefficient of interest is β_2 with a negative value signifying that the effect of robot adoption is lower in CZs with higher immigrant share.

A potential concern is that the distribution of immigrants across CZ is not random as new immigrants are more likely to settle where past immigrants are concentrated (Borjas 1995). We instrument current immigration share with past immigration share following Card (2001) and Jaeger et al. (2018). Online Appendix figure 9 shows that immigrant share in 1980 predicts immigrant share in 2000 with a R^2 of 0.9. More importantly, immigrant population growth between 1980-2000 is not significantly related to *future* robot exposure in 2000-2015 as shown in Online Appendix table 11.

Table 5 presents the effect on native-born employment and wage and the native-born immigrant wage gap with the interaction between robot exposure and lagged immigrant share. The first, third and fifth columns show the estimates with immigrant share in 2000 whereas second, fourth and sixth columns show the results using the immigrant share in 1980 as instrument for foreign-born population in 2000. The first column displays that the interaction coefficient on native employment is negative and statistically significant from zero. The 2SLS estimate is also negative which is reassuring. This implies that counties with higher robot exposure and immigrant share lead to a bigger reduction in native employment. The IV interaction coefficient on native-born wage and the native-born immigrant wage gap are slightly positive but imprecisely estimated. Overall we conclude that the presence of immigrants *does not* mitigate the labour market outcomes of native-born.

Table 5: IV estimate on US-born by interaction with immigrant population share

	US-born Employment		Wage gap		US-born Wage	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Robot adoption	-0.724	-0.436	0.017	0.008	-0.012^{*}	-0.011^{+}
	(0.867)	(0.919)	(0.012)	(0.012)	(0.006)	(0.007)
Robot adoption x Share	-39.425^{**}	-50.394^{***}	-0.332	0.006	0.022	0.013
	(17.289)	(16.088)	(0.254)	(0.284)	(0.109)	(0.086)
Immigrant Share 2000	53.553^{***}	44.988^{**}	-0.050	0.019	-0.252^{***}	-0.106
	(19.083)	(18.491)	(0.178)	(0.259)	(0.073)	(0.125)
Observations	722	722	722	722	722	722
R-squared	0.71	0.70	0.14	0.13	0.59	0.58
Census Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Computer Capital	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes

Note: All regression estimates are weighted by the CZ population in 2000. Robust standard errors clustered at the state level are reported in the parentheses. ***, **, * and $^{+}$ represent the statistical significance at 1%, 5%, 10% and 15% levels respectively. Covariates include log population; share of female population; share of the population over 65 years old; shares of the population with no college, some college and college and above; population shares of whites and blacks; manufacturing share of employment; light manufacturing share of employment; and share of female employed in manufacturing.

4.2 Robustness checks

We report a range of robustness exercises on the impact of automation on population headcounts by nativity in table 6. First, we include the China shock, routine share of employment and foreign-born population share in 2000 as additional controls to the baseline empirical specification. The point estimate of immigrants changes from -5.03 (standard error=2.39) to -4.71 (standard error=2.53) though the standard errors are large on each to rule out the difference being significant. The migration estimates are identical when including more countries while constructing the robot adoption instrument. The immigrant migration estimate slightly falls to -4.82 while counting naturalized citizens as foreign-born. From our earlier calculations, this estimate would imply that 28.5% (0.517/1.814) of the employment fall due to an interquartile increase in robot exposure can be accounted for by immigrant location decisions.

Borusyak, Dix-Carneiro & Kovak (2022) show that migration choices depend on not just shocks to a region but also to other regions. Misspecification arising from not accounting for exposure of robot to other regions will lead to biased estimates. We include a migration-weighted robot exposure of other CZs relative in our regression specification (Autor et al. 2023, Faber et al. 2022). We define the migration-weighted robot exposure to other CZs as:

$$\Delta R_{-j,(t_0,t_1)} = \sum_{k \neq j} \phi_{kj} \Delta R_{k,(t_0,t_1)} \tag{11}$$

where $\Delta R_{-j,(t_0,t_1)}$ is the robot exposure to CZ k and ϕ_{kj} captures the strength of migration flow between CZ k and j using geographic distance. This is similar to gravity models of trade which measure the importance of flows between locations using distance.[11] When adding the control in column (5), our estimates are almost identical for native-born and fall a bit for immigrant-born. Thus, our conclusions remain unchanged that mobility of immigrants have limited effect on the labour market adjustment to structural shocks.

[11] Our formulation assumes that attractiveness of CZs as source and destinations are identical for both native- and foreign-born residents.

Table 6: Robustness checks

	Baseline estimate	Additional controls	EURO5	Alternate immigrant definition	Exposure to other location
	(1)	(2)	(3)	(4)	(5)
	A: Immigrant				
Robot adoption	-5.033**	-4.709*	-5.033**	-4.818**	-4.659*
	(2.387)	(2.530)	(2.387)	(1.955)	(2.463)
Observations	722	722	722	722	722
R-squared	0.45	0.49	0.45	0.47	0.46
Census Dummy	Yes	Yes	Yes	Yes	Yes
Computer Capital	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes
1st stage F-stat	76.78	179.97	76.78	76.78	73.93
	B: US-born				
Robot adoption	-1.056	-1.629*	-1.056	-0.816	-1.085
	(0.811)	(0.886)	(0.811)	(0.905)	(0.818)
Observations	722	722	722	722	722
R-squared	0.62	0.69	0.62	0.61	0.62
Census Dummy	Yes	Yes	Yes	Yes	Yes
Computer Capital	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes
1st stage F-stat	76.78	179.97	76.78	76.78	73.93

Note: All regression estimates are weighted by the CZ population in 2000. Robust standard errors clustered at the state level are reported in the parentheses. ***, **, * and $^{+}$ represent the statistical significance at 1%, 5%, 10% and 15% levels respectively. Covariates include share of female population; share of the population over 65 years old; shares of the population with no college, some college and college and above; population shares of whites and blacks; manufacturing share of employment; light manufacturing share of employment; and share of female employed in manufacturing. Additional controls include exposure to imports from China, foreign-born population share and employment share of routine jobs.

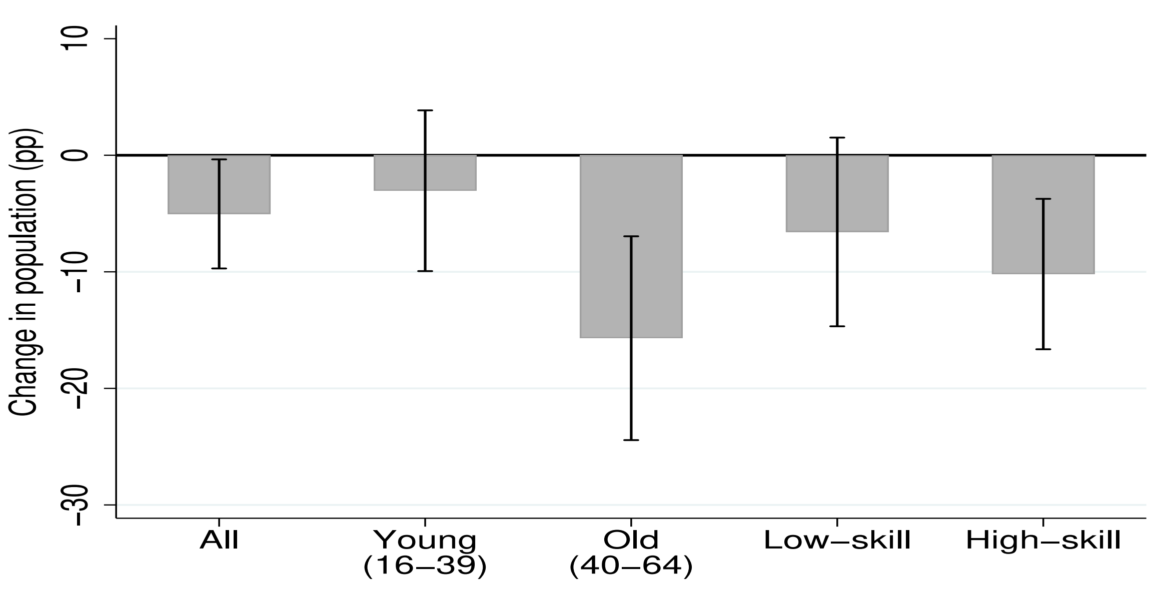
5 Discussion

Section 4 shows that immigrants are more mobile than native-born to negative labour demand shocks. In this section, we explore the heterogeneity by age, skill and years living in the US to understand the factors behind the higher mobility of immigrants.

5.1 Migration response by age and skill-groups

Figure 4 shows the change in the population of immigrant subgroup to robot penetration. The migration response of high-skilled immigrants is stronger than low-skilled immigrants, though not statistically different from each other. The higher migration response can also explain why employment losses of high-skilled immigrants are larger as we discussed previously. Furthermore, middle-aged and old foreign-born individuals are more likely to migrate to negative shocks than young ones. Faber et al. (2022) also find that middle-aged individuals have a higher migration response than young workers to automation. Online Appendix figure 10 shows that the population change for native-born is indistinguishable across age and education groups.

Figure 4: Immigrant migration response by age and skill-groups

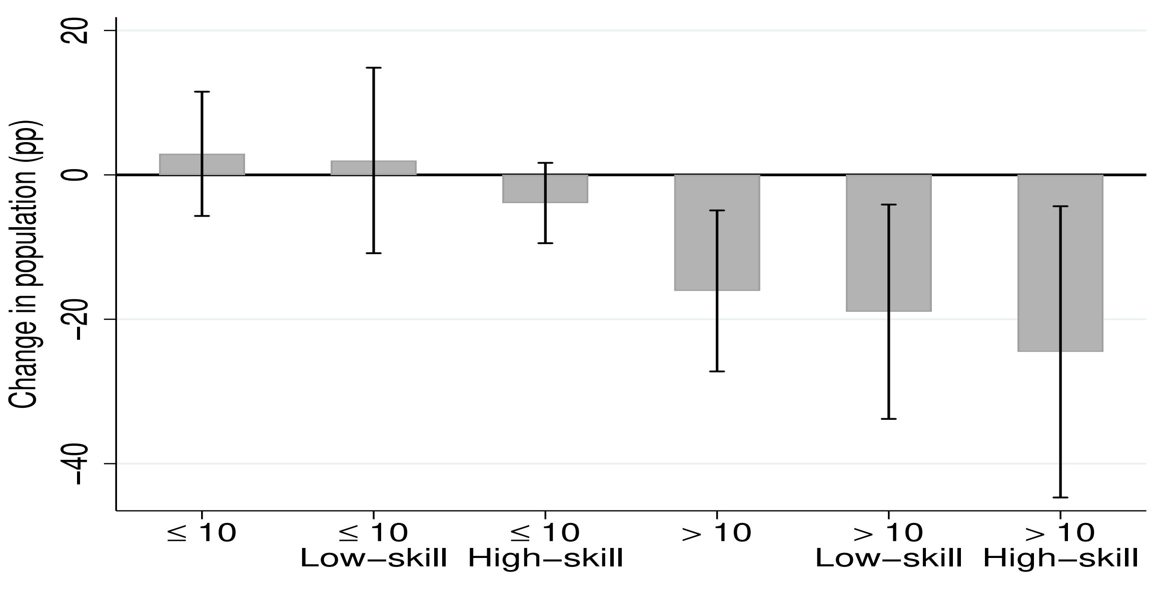


Note: Bars denote 95% CI. All regression estimates are weighted by the CZ population in 2000. Regressions include census dummies, computer capital use and covariates. Dependent variable is change in population of that subgroup between 2000 and 2015.

5.2 Migration response by years in US

Next, we look at the migration decisions of new and established immigrants. We define new immigrants as those who have been in the US for less than or equal to ten years and established as those who have been in for more than ten years. Figure 5 shows the difference in population size of immigrants by years in the US and skill groups. Older immigrants display a much stronger response to automation than younger immigrants. This true holds across low and high-skill types. A possible justification is that young and old immigrants are close substitutes for each other (Ottaviano & Peri 2012). Hence, successive waves of immigration increases the competition among immigrants leading to stronger response among existing and older immigrants (Albert et al. 2022). Another reason for the insignificant change in the migration of young workers could be that some young workers enter occupations and industries that have benefited from automation (Boustan et al. 2022, Hirvonen et al. 2022, Humlum 2021).

Figure 5: Immigrant migration response by years in US



Note: Bars denote 95% CI. All regression estimates are weighted by the CZ population in 2000. Regressions include census dummies, computer capital use and covariates. Dependent variable is change in population of that subgroup between 2000 and 2015.

6 Conclusion

Research has shown that automation has substantial negative consequences on employment and income. A key question when thinking about the future of work is: how to mitigate the adverse impact of labour displacing technological change? Previous research has argued that immigrants might have an important role to play in facilitating adjustment to negative economic shocks. This study shows that first, robot use adversely affects both native- and foreign-born workers. Second, immigrants display a more prominent migration response to automation than native-born. But, given the low share of the foreign-born population, their migration response has only a limited role in the overall employment loss in a region with higher robot exposure. Moreover, we find that immigration *does not* alleviate the unfavourable impact of robot growth on the native-born. Thus, the less mobile native-born workers might have to bear the larger burden to ease labour market adjustments across regions.

A future area of research could be the impact of automation in countries with a large share of emigrants or internal migration among countries that are producers and exporters of robots. Facchini et al. (2019) show that rising import competition from China also led to large internal migration within China. Robot production might generate employment and internal migration towards regions with robot producers but drive residents away from areas with high robot adoption. It could help understand the "productivity" versus the "displacement" effect of automation on migration.

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Online Appendix

Additional Tables

Table 7: Robot per worker by Industry 2000–2015

	Robot per worker		
Industry	2000	2015	Change 2000-2015
All industries	.75	1.77	1.02
Automotive	31.97	94.48	62.51
Metal products	2.92	10.17	7.26
Plastics and chemicals	5.78	13.59	7.81
Electronics	5.75	26.94	21.18
Food and beverages	2.21	5.55	3.34
Apparel and textiles	.04	.21	.17
Wood and furniture	.1	.39	.29
Paper and publishing	.09	.36	.27
Glass and minerals	.12	.51	.39
Basic metals	4.74	16.52	11.79
Industry machinery	.79	2.48	1.69
Aerospace	.2	.59	.39
Miscellaneous manufacturing	1.99	5.33	3.34
Agriculture	.03	.07	.04
Mining	.03	.05	.01
Utilities	.01	.03	.02
Construction	.01	.02	.01
Education and research	.03	.06	.03
Services	0	0	0

Table 8: IV estimate of robot adoption on employment by skill-groups

	Immigrant		US-born	
	Low-skill	High-skill	Low-skill	High-skill
	(1)	(2)	(3)	(4)
Robot adoption	-5.303^{+}	-6.213***	-2.655**	-2.028***
	(3.329)	(2.107)	(1.138)	(0.724)
Observations	722	722	722	722
R-squared	0.47	0.37	0.75	0.55
Census Dummy	Yes	Yes	Yes	Yes
Computer Capital	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes

Note: All regression estimates are weighted by the CZ population in 2000. Robust standard errors clustered at the state level are reported in the parentheses. ***, **, * and $^{+}$ represent the statistical significance at 1%, 5%, 10% and 15% levels respectively. Covariates include share of female population; share of the population over 65 years old; shares of the population with no college, some college and college and above; population shares of whites and blacks; manufacturing share of employment; light manufacturing share of employment; and share of female employed in manufacturing. Low-skill are high school degree or less and high-skill are some college education or more.

Table 9: IV estimate of robot adoption on employment across tasks

	Immigrant			US-born		
	Routine	Manual	Abstract	Routine	Manual	Abstract
	(1)	(2)	(3)	(4)	(5)	(6)
Robot adoption	-3.619	-3.544	-9.283***	-2.345**	-2.900***	-2.058**
	(2.543)	(3.006)	(3.281)	(1.035)	(0.834)	(0.828)
Observations	720	722	722	722	722	722
R-squared	0.32	0.44	0.26	0.69	0.74	0.56
Census Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Computer Capital	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes

Note: All regression estimates are weighted by the CZ population in 2000. Robust standard errors clustered at the state level are reported in the parentheses. ***, **, * and $^{+}$ represent the statistical significance at 1%, 5%, 10% and 15% levels respectively. Covariates include log population; share of female population; share of the population over 65 years old; shares of the population with no college, some college and college and above; population shares of whites and blacks; manufacturing share of employment; light manufacturing share of employment; and share of female employed in manufacturing.

Table 10: IV estimate of robot adoption on wage by skill-groups

	Wage gap		Immigrant		US-born	
	LS	HS	LS	HS	LS	HS
	(1)	(2)	(3)	(4)	(5)	(6)
Robot adoption	0.005	0.017	-0.016*	-0.028**	-0.012**	-0.011+
	(0.011)	(0.012)	(0.010)	(0.014)	(0.006)	(0.007)
Observations	722	722	722	722	722	722
R-squared	0.06	0.13	0.12	0.21	0.64	0.57
Census Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Computer Capital	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes

Note: All regression estimates are weighted by the CZ population in 2000. Robust standard errors clustered at the state level are reported in the parentheses. ***, **, * and + represent the statistical significance at 1%, 5%, 10% and 15% levels respectively. Covariates include log population; share of female population; share of the population over 65 years old; shares of the population with no college, some college and college and above; population shares of whites and blacks; manufacturing share of employment; light manufacturing share of employment; and share of female employed in manufacturing. LS and HS denote low-skill and high-skill respectively. Low-skill are high school degree or less and high-skill are some college education or more.

Table 11: IV estimate of employment, wage and migration change between 1980-2000

	Immigrant			US-born		
	Emp.	Wage	Migration	Emp.	Wage	Migration
	(1)	(2)	(3)	(4)	(5)	(6)
Robot adoption	-8.439	0.029***	-13.041	-0.256	0.000	-0.749
	(8.709)	(0.008)	(12.179)	(0.730)	(0.004)	(0.853)
Observations	722	719	722	722	722	722
R-squared	0.37	0.17	0.37	0.46	0.79	0.50
Census Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Computer Capital	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
1st stage F-stat	308.532	289.398	308.532	308.532	308.532	308.532

Note: Emp. denotes employment. All regression estimates are weighted by the CZ population in 1980. Robust standard errors clustered at the state level are reported in the parentheses. ***, **, * and + represent the statistical significance at 1%, 5%, 10% and 15% levels respectively. Covariates in year 1980 include log population; share of female population; share of the population over 65 years old; shares of the population with no college, some college and college and above; population shares of whites and blacks; manufacturing share of employment; light manufacturing share of employment; and share of female employed in manufacturing. Computer capital is proxied using US computer capital level in 1990 and dependent variables are rescaled to 15-year equivalent change.

Table 12: Robustness checks

	Baseline estimate	Additional controls	EURO5	Alternate immigrant definition
	(1)	(2)	(3)	(4)
	A: Immigrant Employment Growth			
Robot adoption	-3.745*	-4.213*	-3.745*	-5.222***
	(2.093)	(2.187)	(2.093)	(1.987)
Observations	722	722	722	722
R-squared	0.44	0.46	0.44	0.45
Census Dummy	Yes	Yes	Yes	Yes
Computer Capital	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes
1st stage F-stat	96.866	145.245	96.866	96.866
	B: US-born Employment Growth			
Robot adoption	-1.999***	-1.885***	-1.999***	-1.659**
	(0.685)	(0.637)	(0.685)	(0.725)
Observations	722	722	722	722
R-squared	0.70	0.72	0.70	0.65
Census Dummy	Yes	Yes	Yes	Yes
Computer Capital	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes
1st stage F-stat	96.866	145.245	96.866	96.866
	C: US-born and Immigrant Wage gap			
Robot adoption	0.008	0.007	0.008	0.004
	(0.012)	(0.013)	(0.012)	(0.008)
Observations	722	722	722	722
R-squared	0.13	0.14	0.13	0.29
Census Dummy	Yes	Yes	Yes	Yes
Computer Capital	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes
1st stage F-stat	96.866	145.245	96.866	96.866

Note: All regression estimates are weighted by the CZ population in 2000. Robust standard errors clustered at the state level are reported in the parentheses. ***, **, * and + represent the statistical significance at 1%, 5%, 10% and 15% levels respectively. Covariates include log population; share of female population; share of the population over 65 years old; shares of the population with no college, some college and college and above; population shares of whites and blacks; manufacturing share of employment; light manufacturing share of employment; and share of female employed in manufacturing. Additional controls include exposure to imports from China, foreign-born population share and employment share of routine jobs.

Table 13: IV estimate on US-born by above and below median population share in 2000 of immigrant by alternate definition

	Native Employment		Wage gap	
	Above median	Below median	Above median	Below median
	(1)	(2)	(3)	(4)
Robot adoption	-1.802**	-0.841	0.003	-0.010
	(0.736)	(0.639)	(0.013)	(0.025)
Observations	361	361	361	361
R-squared	0.71	0.57	0.22	0.12
Census Dummy	Yes	Yes	Yes	Yes
Computer Capital	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes

Note: All regression estimates are weighted by the CZ population in 2000. Robust standard errors clustered at the state level are reported in the parentheses. ***, **, * and + represent the statistical significance at 1%, 5%, 10% and 15% levels respectively. Covariates include log population; share of female population; share of the population over 65 years old; shares of the population with no college, some college and college and above; population shares of whites and blacks; manufacturing share of employment; light manufacturing share of employment; and share of female employed in manufacturing.

Table 14: IV estimate on US-born by interaction with immigrant population share by alternate definition

	Native Employment		Wage gap		Native Wage	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Robot adoption	-0.529	-0.222	0.016	0.011	-0.011^{+}	-0.009
	(0.898)	(0.901)	(0.013)	(0.013)	(0.007)	(0.007)
Robot adoption x Share	-27.802***	-33.507***	-0.155	-0.061	0.011	-0.016
	(9.219)	(8.411)	(0.151)	(0.161)	(0.063)	(0.048)
Immigrant Share 2000	27.847***	23.681***	-0.025	-0.008	-0.115**	-0.060
	(9.741)	(8.335)	(0.104)	(0.125)	(0.050)	(0.067)
Observations	722	722	722	722	722	722
R-squared	0.71	0.70	0.14	0.14	0.58	0.57
Census Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Computer Capital	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes

Note: All regression estimates are weighted by the CZ population in 2000. Robust standard errors clustered at the state level are reported in the parentheses. ***, **, * and $^{+}$ represent the statistical significance at 1%, 5%, 10% and 15% levels respectively. Covariates include log population; share of female population; share of the population over 65 years old; shares of the population with no college, some college and college and above; population shares of whites and blacks; manufacturing share of employment; light manufacturing share of employment; and share of female employed in manufacturing.

Additional Figures

Figure 6: Change in robot per worker 2000-2015

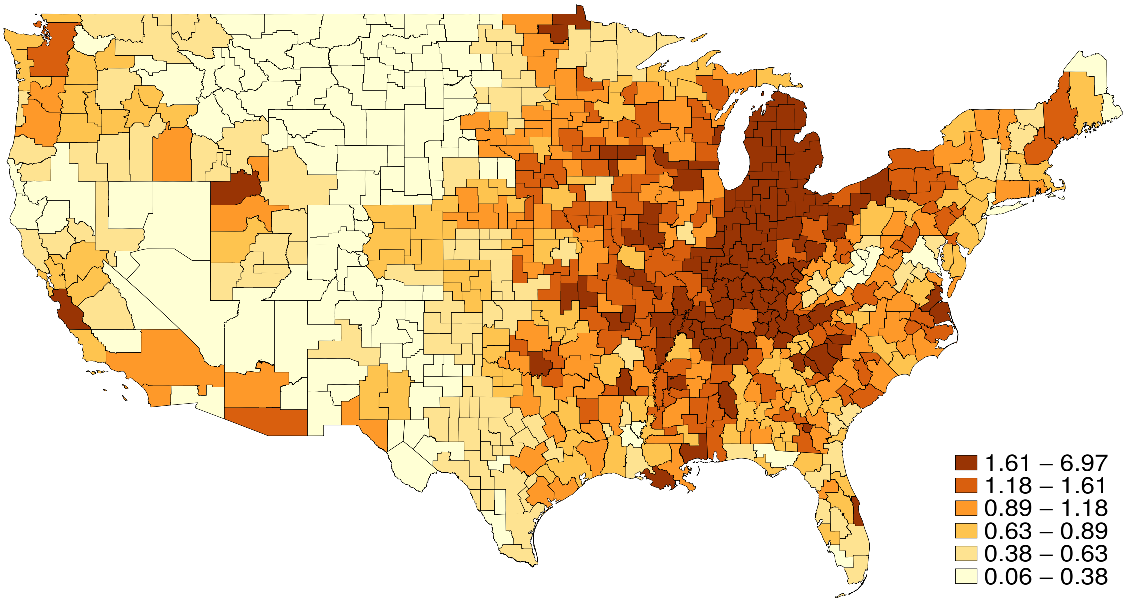


Figure 7: Relation between change in computer capital and adjusted computer capital

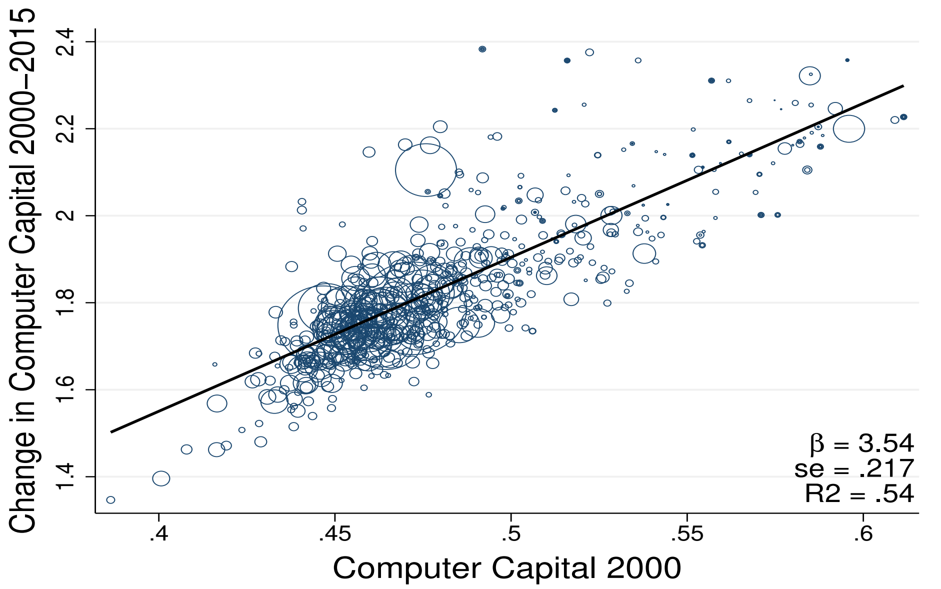


Figure 8: Effect of change in robot adoption on wage distribution

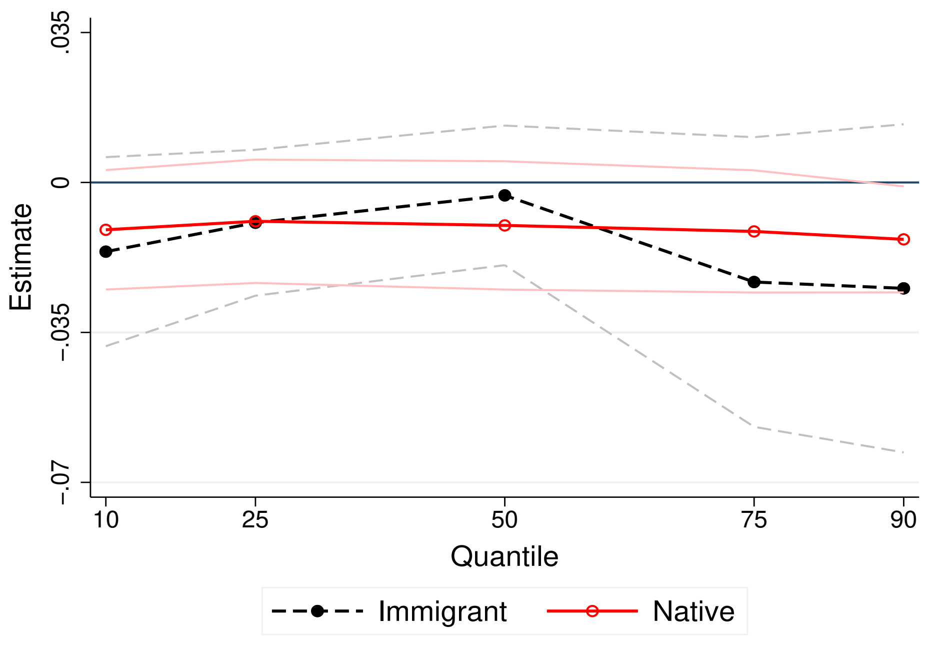


Figure 9: Relation between immigrant share in 2000 and 1980

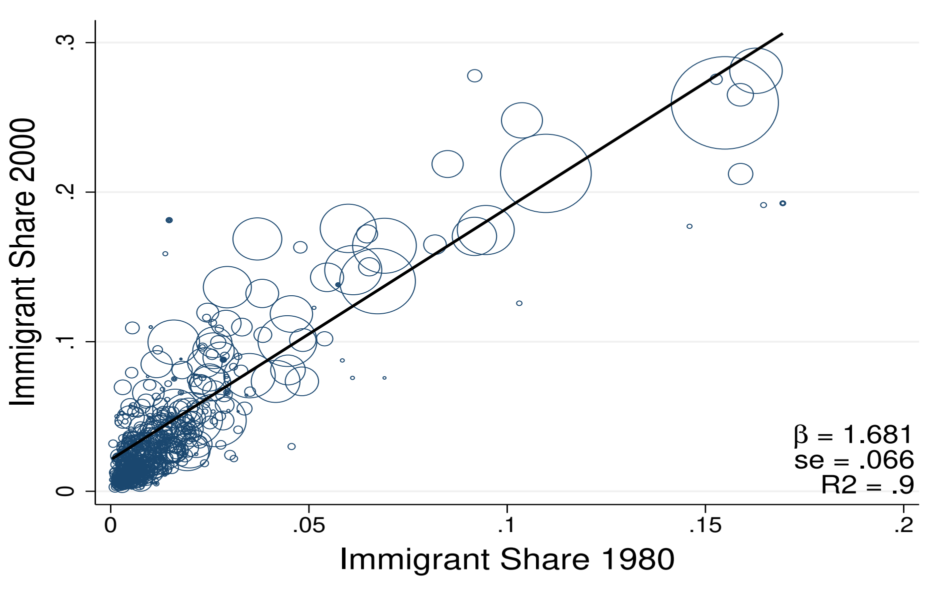
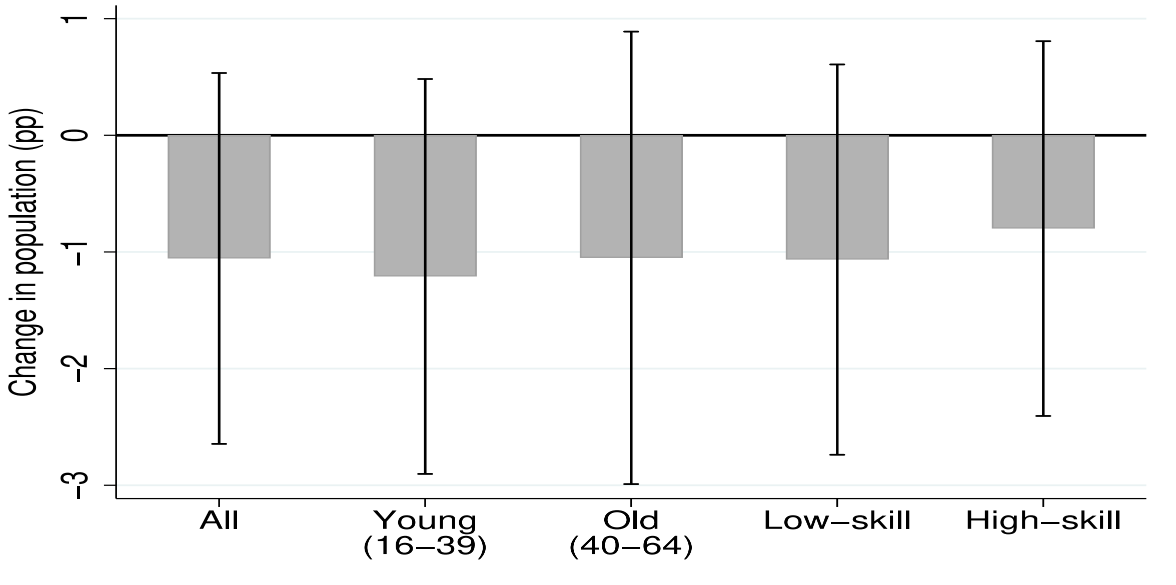


Figure 10: US-born migration response by age and skill-groups



Note: Bars denote 95% CI. All regression estimates are weighted by the CZ population in 2000. Regressions include census dummies, computer capital use and covariates. Dependent variable is change in population of that subgroup between 2000 and 2015.