Automation and Immigrants: Evidence from Local Labour Markets

Gopal Bhaskar [*] Anand Chopra [†] Ronit Mukherji [‡]

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Abstract

This paper examines the impact of automation on employment, wages, and migration of both native-born and foreign-born individuals. Employing an instrumental variable strategy that leverages variations in local industry employment shares and industry-level national robot adoption, we find that automation equally reduced the employment and wages of foreign- and native-born workers across US commuting zones. Robot adoption induced higher migration in immigrants than in native-born individuals, with immigrants' movements accounting for 19% of the employment difference between high and low robot-exposed commuting zones. We also find that immigrant mobility did not reduce the incidence of automation on native-born workers' employment or wages, such that the impact of automation on native-born workers is similar in high and low immigrant areas.

Keywords: Automation, Employment, Immigration, Migration

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[*] Northern Trust, Email: gbhaskar.gbh@gmail.com

[†] Management School, University of Liverpool, Email: achopra@liverpool.ac.uk

[‡] Department of Economics, Ashoka University, Email: ronit.mukherji@ashoka.edu.in

1 Introduction

Does immigrant mobility ease adjustment to technology shocks? Geographic mobility of workers is an important mechanism to mitigate against adverse local economic shocks (Blanchard & Katz 1992). US-born individuals, especially low-skilled ones, 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, Cadena & Kovak 2016). One of the most notable economic shocks experienced by US workers in recent decades has been automation (Bergholt et al. 2022). In this context, we aim to make progress on two questions about which little is known. First, what is the effect of automation on employment and wages of foreign- and native-born workers? Second, do foreign-born individuals move more than native-born individuals in response to automation, and what impact does immigrants' migration have on the native-born workers?

To understand the impact of automation, we exploit variation in initial industry-specific employment shares at US commuting zone (CZ) level combined with the national growth in industry-level robot use. We instrument for growth in robot capital for US with other European countries following Acemoglu & Restrepo (2020).[1] The validity of the IV depends on the exogeneity of the national industry growth rates while the local employment shares by industry can depend on local economic factors as shown by Borusyak, Hull & Jaravel (2022). Our regression specification includes industry and demographic controls in 2000 by CZ to control for region specific characteristics. We control for computer capital growth in our empirical specification as existing work has shown that computerization complements skilled labour but displaces unskilled labour; and immigrants in the US are largely unskilled.

Focusing on labour market outcomes, we find that automation negatively impacts the employment and wages of native and foreign-born workers equally. Wages of both native- and foreign-born workers fall similarly in response to robot adoption, leading to no change in the nativity wage gap. Overall, our first key result is that robot exposure hurts both native- and foreign-born workers, in line with the existing work on the negative consequences of higher robot use.

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

Next, we turn our attention to analyzing the mobility response of native- and foreign-born individuals to automation. We highlight that the immigrant population falls substantially in regions more exposed to automation, whereas the migration response of native-born individuals is almost one-fifth compared to that of immigrants. 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. About 19% of the difference in employment decline between CZs in the 25$^{\text{th}}$ and 75$^{\text{th}}$ percentiles of robot exposure can be attributed to the migration of foreign-born workers. Immigrants seem to have a limited role in labour market adjustment to robot adoption, despite their high migration sensitivity to automation. This is because immigrants account for only 9% of US population in 2000.

Job losses due to automation can be potentially diffused as immigrants move out of areas where they exist in larger proportions in response to higher robot exposure. To capture the mitigating effects of immigrants on labour market outcomes of native-born workers, we allow interaction of robot exposure with immigrant population share in the regression specification. The interaction term estimate captures the effect of automation on native-born workers in labour markets with varying immigrant population shares. 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 initial immigrant population share. We instrument for the recent distribution of immigrants across space using the historical distribution of immigrants in 1980 (Card 2001). We find that native-born workers in high immigration areas *do not* experience a weaker relationship between labour demand shock and local employment or wage compared to low immigration areas. Thus, our second important takeaway is that immigration might not substantially mitigate the negative impacts of automation on the labour market outcomes of native-born workers.

We show that the effect of automation on employment, wage and population by nativity status are robust to controlling for rising import competition – another notable shock experienced by US workers (Autor et al. 2013*a*). Moreover, we do not find any fall between 1980-2000 in foreign- or native-born individuals' employment, wage or 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.

Our paper contributes to the literature on understanding the role of workers' geographic mobility to equilibrate local labour markets. Previous research has either focused on cyclical shocks (Basso et al. 2019, Cadena & Kovak 2016) or localized shocks like rising Chinese manufacturing import competition (Autor et al. 2023, Yu 2023). Automation is one of the main drivers of falling labour share in developed countries and impacting workers across the skill distribution and industries (Abraham & Kearney 2020, Acemoglu & Restrepo 2020, Bergholt et al. 2022). More pertinent to the question at hand, Faber et al. (2022) show that introduction of robots led to sizable decline in local labour markets but not rising import competition. To the best of our knowledge, we are the first to investigate the role of immigrants in ameliorating the adverse impact on native-born workers in response to automation. We address this question in two ways. First, we use our estimated change in total employment and immigrant population to robot penetration to quantify the role that immigrants' migration plays in explaining the effect on employment. Second, we estimate the effect on native-born workers to robot exposure in regions with varying immigrant share. Overall, the results suggest that immigration has a *limited* effect on labour market adjustment to technological changes stemming from industrial robot use.

Following the seminal paper by Acemoglu & Restrepo (2020) on the consequences of robot penetration across CZs, other papers have highlighted the sustained and unequal impact of automation in many countries (Acemoglu & Restrepo 2022*b*, Aksoy et al. 2021, Grigoli et al. 2020). There is limited evidence on how to mitigate the negative impact of automation. Grigoli et al. (2020) and Schmidpeter & Winter-Ebmer (2021) show that government spending on labour market programs and training can dampen the unfavourable impact of automation. We provide novel evidence on the contribution of immigration in mitigating regional inequality exacerbated by robot use. Furthermore, this paper fills a gap in the literature to understand the distributional and long-term effects of automation by focussing on the impact on individuals differing by nativity status.

The rest of the paper is organized as follows. Section 2 discusses the data and describes the methodology. Section 3 presents the employment and wage results. Section 4 discusses the migration response of foreign- and native-born individuals 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. Additionally, we outline trends in industrial robots since 2000 in the US and other countries. Then we describe the construction of labour market and population 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: Robots per thousand worker in US and selected countries

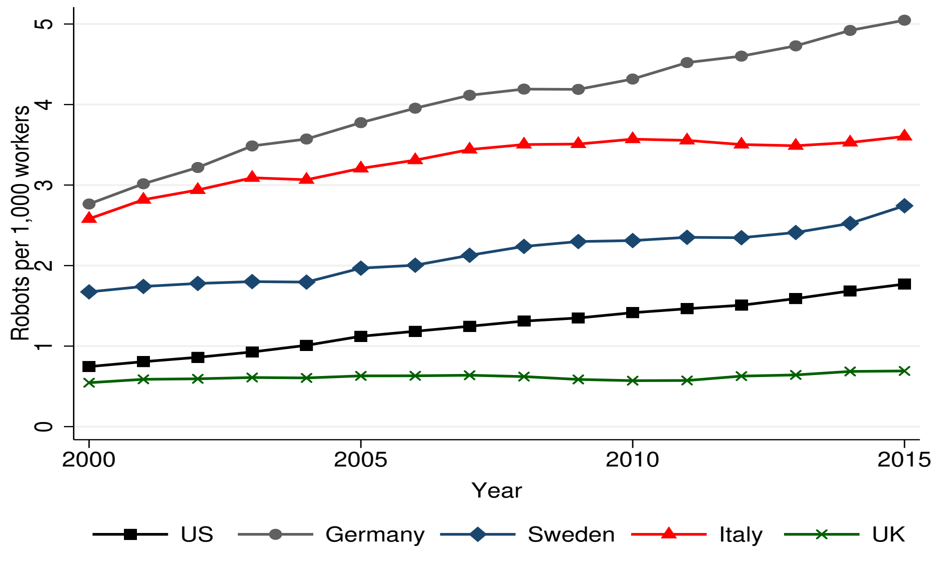


Figure 1 shows the trend of robots per thousand workers in the United States, Germany, Italy, Sweden and the UK. The stock of industrial robots per thousand worker has risen steadily in all countries except the United Kingdom since 2000. It increased in the US from 0.75 per thousand workers in 2000 to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

IFR provides data for 13 disaggregated categories in the manufacturing sector.[2] Data is also available on six broad sectors: agriculture, mining, utilities, construction, education, and services.[3] Appendix table A.1 shows that automotive and electronics experienced the highest growth in robots in the US, whereas services displayed the least.

2.2 Commuting Zone and Robot Exposure Data

A commuting zone (CZ) is the level of disaggregation most commonly used to understand local labour markets (Acemoglu et al. 2016). A CZ comprises of 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 areas. Our data contains 722 Commuting Zones (CZs) that cover the entire US except the states of Alaska and Hawaii.[4]

We use the public use 5% sample for year 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 outcomes in 2015 from the ACS using 2013 to 2017 to increase the sample size following Autor et al. (2013*b*). Our sample of workers consists of non-institutionalized individuals between ages 16-64. 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

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

[3] Not all data can be categorized by sectors; for example, around 11% of total robots remained unclassified in 2015. We allocated them in the same proportion as the classified data.

[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.

individual wage as the pre-tax annual labour income of privately employed individuals divided by annual working hours. We compute annual working hours by multiplying the number of weeks worked in the year and the usual number of hours worked per week. Top-coded income is set equal to 1.5 times the value of the top-code following Acemoglu & Autor (2011). Real wage below $2 is winsorized and real wage above the 99^{th} percentile is excluded from the analysis. The Consumer Price Index of 1999 is used to deflate nominal wages.

Foreign-born population or immigrants comprise of individuals born outside the US and not currently US citizen. Appendix figure A.1 highlights substantial variation in the share of foreign-born workers in the US. The change in population of a demographic group in CZ j 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 individuals and I denotes immigrants, and $\Delta Pop^d_{j,(t_0,t_1)}$ computes the change in population size of group d between periods t_0 and t_1. The change in employment of a demographic group is computed relative to the group's population in the initial year as it helps to isolate the impact by nativity status (Card & Peri 2016).

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

where $\Delta L^d_{j,(t_0,t_1)}$ measures the change in employment relative to the group's CZ population in year t_0. The growth in wage of a demographic group in CZ j between the years 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 j and period t. The nativity 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 $\Delta w^I_{j(t_0,t_1)}$ are the wage growth of US- and foreign-born workers respectively.

Following Acemoglu & Restrepo (2020), the growth in robots in a CZ j between periods t_0 and t_1 is defined as the weighted sum of the change in robot use at the industry level, where weights are an industry's employment share in the year t_0 and in CZ j. The growth in the stock of industrial robots in industry i between periods 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 year t, L_{i,t_0} is the employment count (in thousands) in industry i in year t_0 and $g_{i,(t_0,t_1)}$ is the growth rate of output over the years from t_0 to t_1 in industry i. Employment and output data by industry is from 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 t_0. The expansion of robots 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 employment ratio of industry i in CZ j and year t_0. Appendix figure A.2 displays the geographical variation in robot expansion in the US with lighter shades reflecting lower growth of robot use.

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 but can displace unskilled labour (Autor et al. 1998, Beaudry et al. 2010, Krueger 1993). The growth in computer adoption is measured as the value of computing equipment stock in US dollars per thousand workers, using data from EU KLEMS. 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 various datasets and create a measure of computer capital growth in a region between 2000 and 2015, similar to the robot growth measure in equation (5). The correlation between the growth in robot and computer use across CZs is -0.22, which implies that the adoption of industrial robots and computer use did not occur together in local labour markets.

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:

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

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] Census dummies absorb region-specific trends in the dependent variable. Moreover, their inclusion implies that the coefficient of interest (β_1) is identified by comparing CZs within the same Census region.

The proxy of computer capital use is included in all regressions to account for technological change unrelated to automation. X_{j,t_0} includes demographic and industry shares in CZ j and year 2000 to control for the baseline characteristics of the CZ. 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 incorporate the population share of above age 65 as a control as Acemoglu & Restrepo (2022*a*) argue that firms use more robots in regions with a larger share of older individuals. We include the share of employment in manufacturing and light manufacturing (paper and textile industries), and the employment share of women in manufacturing as Acemoglu & Restrepo (2020) point out that these variables are strong predictors of robot exposure. ε_j is the zero-mean random error that we cluster at the state level.

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 automation, we instrument for robot adoption in US with robot adoption in other European countries

[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.

(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 robot usage in Germany, Italy and Sweden as the stock of robots per worker in EURO3 countries (Germany, Italy and Sweden) is higher than in the US (figure 1).[7] We combine employment data from EU KLEMS and construct the average growth in robot adoption for each industry in EURO3 as:

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

where $R^c_{i,t}$ is the number of robots in industry i in country c and year 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,t_0} is industry i's employment in country c in period t_0. The corresponding CZ measure of robot exposure is calculated by replacing the EURO3 industry level robot adoption from equation (8) in equation (6).

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

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

Appendix figure A.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 the instrument captures 80% of the variation in robot growth across CZs. We proxy for the growth in computer capital usage using the *level* of computer capital in 2000 following Michaels et al. (2014). Appendix figure A.4 highlights a strong relationship between computer capital in 2000 and the growth in computer capital adoption with a R^2 of 0.54.

3 Employment and Wage Results

Table 1 presents the IV estimates of higher robot use on employment losses for all workers, and separately by nativity. We report in parentheses standard errors robust against

[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.

[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.

heteroskedasticity and clustered at the state level to account for spatial correlations. The IV estimate of all workers in US is -1.87 (standard error=0.55), implying that a unit increase in robots per thousand workers reduces employment by 1.87 pp, consistent with Acemoglu & Restrepo (2020). Robot exposure is 0.53 and 1.5 at the 25th and 75th percentile CZs respectively with the resulting loss in employment between the CZs being 1.81pp. Focusing on immigrants in the second column, the 2SLS estimate is -3.745 with a standard error of 2.09. Among natives, a 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 workers are adversely impacted by automation.

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	0.705	0.435	0.703
Computer Capital	Yes	Yes	Yes
Covariates	Yes	Yes	Yes
1st stage F-stat	96.866	96.866	96.866
A-R F-test	8.944	2.895	6.417

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 census dummies; 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.

The first-stage F-statistic value of 96.87 denotes that the instrument has high predictive power. However, Keane & Neal (2023) argue that the two-stage least squares (2SLS) estimation can suffer from low power even when instruments have large F-statistics. The bias in OLS can lead to artificially small 2SLS standard errors, and the coefficient of interest becoming statistically significant. The reduced-form specification 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 the coefficient of interest. The last line in Table 1 shows that the smallest A-R F-test value is 2.9, meaning that the reduced-form coefficient of robot exposure is always significant at the 10% level.

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

Appendix table A.2 shows that high-skilled immigrants are affected as much as low-skilled immigrants. In contrast, low-skilled native-born workers experience higher employment losses than high-skilled native-born workers.[9] We further show in Appendix table A.3 that abstract foreign-born individuals are hit particularly hard whereas manual, routine and cognitive native-born workers are adversely impacted similarly. One potential explanation for the large coefficient of high-skilled immigrant workers is their mobility response. Cognitive occupations employ more high-skilled workers than low-skilled ones. Given that high-skilled immigrant workers are more mobile than their low-skilled counterparts (Notowidigdo 2020), this leads to a larger drop in labour supply and employment. We will return to this point while discussing the migration responses by nativity and skill in Section 5. Overall, we stress that the negative effect of automation is not restricted to low-skilled manufacturing jobs unlike import competition as also emphasized by Bloom et al. (2019) and Faber et al. (2022).

Next, we turn our attention to the impact of robot exposure on the wage income of foreign- and US-born workers in table 2. Columns (2) and (3) show that an increase of one robot per thousand workers leads to a fall in wages by 1.8% (standard error=0.01) and 1% (standard error=0.006) for foreign- and native-born workers respectively. The nativity wage gap is defined as the difference in the wage growth of native- and foreign-born workers. Column (1) highlights that the implied nativity wage gap changes by only

[9] A reason for the lower impact on high-skilled native-born workers relative to low-skilled could be that the entry of low-skilled immigrants encourages native-born workers to become high-skilled workers through training (Mandelman & Zlate 2022, Schmidpeter & Winter-Ebmer 2021).

0.8pp and is statistically indistinguishable from zero. Acemoglu & Restrepo (2022*b*), Krenz et al. (2021) and Moll et al. (2022) argue that the effect of automation is unequal along the wage distribution. We show in Appendix table A.4 that wages for both low- and high-skilled workers fall, irrespective of nativity status. This leads to no change in the nativity wage gap of low- and high-skilled workers. In Appendix figure A.5 we show this pattern holds along the entire wage distribution (10^{th}, 25^{th}, 50^{th}, 75^{th} and 90^{th} percentiles). Thus, higher robot exposure leads to a similar fall in wages for both nativity groups.

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	0.133	0.215	0.566
Computer Capital	Yes	Yes	Yes
Covariates	Yes	Yes	Yes
1st stage F-stat	96.866	96.866	96.866
A-R F-test	.436	2.087	1.751

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 census dummies; 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.

3.1 Robustness checks

One concern with the current analysis might be that some pre-existing CZ trend explains the labour market outcomes to higher robot adoption. For example, Basso et al. (2020) argues that immigrant location choices are responsive to technological innovation, which subsequently could affect labour demand and robot technological adoption by firms. To assess the strength of this issue, we conduct a falsification exercise by regressing the change in employment, wage and population size over 1980-2000 on *future* CZ robot exposure between 2000-2015. The evidence in Appendix table A.5 shows that in CZs more exposed to automation, foreign- and native-born individuals did not experience worse wages or employment prospects and differential migration relative to less exposed CZs.

Additionally, we conduct several robustness checks, whose results are highlighted in Appendix table A.6. In the second column, we include more regressors: exposure to trade shocks, the share of routine jobs in the year 2000 and the foreign-born population share in 2000. We control for rising import competition from China as Bloom et al. (2016) show that changes in import competition affects firms' technological decisions.[10] 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. We had excluded the foreign-born population share as a control in the baseline regression since the share of immigrants in a region can affect the labour market outcomes of native-born workers (Borjas 2006). Moreover, it can bias the effect on labour market outcomes as the immigrant population share might be strongly correlated with local economic conditions. But, the nativity wage gap estimate remains unchanged and the estimate for native-born workers falls slightly from -2 to -1.89 as shown in the second column after including all the additional 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 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 individuals that includes naturalized citizens. Our baseline definition excludes naturalized citizens as attaining citizenship is an endogenous choice due to past outcomes. The alternate immigrant definition 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

[10] A CZ trade exposure is computed as the sum of growth in Chinese import penetration in an industry 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 eight other 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).

estimate of immigrants from -3.745 in the baseline specification to -5.22. The alternate definition includes more high-skilled immigrant workers who are particularly prone to automation. The nativity wage gap remains close to zero as before and statistically 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 the contribution of immigrants' mobility in explaining the impact of robots on employment. Finally, we investigate whether immigrants' presence mitigates the negative impact of automation on native-born workers.

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. The fall in population at 75$^{\text{th}}$ percentile CZ of robot exposure is 1.42pp larger than the 25$^{\text{th}}$ percentile. Faber et al. (2022) also document that the higher adoption of robots induces migration.

The migration response is quite different between the two nativity groups. The 2SLS point estimate is -5.03 and -1.06 for foreign- and native-born individuals respectively. The inter-quartile increase in robot exposure generates only a 1.02pp larger response among native-born population compared to 4.88pp among the foreign-born population. Both the IV and reduced-form estimates for the foreign-born population are statistically significant at standard levels of significance unlike for the native-born population. Thus, we find a weak response of US-born individuals 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 immigrants' mobility to the fall in employment in response to automation, we compare the 25$^{\text{th}}$ and 75$^{\text{th}}$ percentile of robot exposed CZs. We assume that the foreign-born population share and their labour force participation rate are equal in the 25$^{\text{th}}$ and 75$^{\text{th}}$ percentile CZ. In year 2000, 9% of the working-age population were immigrants and their labour force participation

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	0.606	0.454	0.625
Computer Capital	Yes	Yes	Yes
Covariates	Yes	Yes	Yes
A-R F-test	2.892	3.514	1.466

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 census dummies; 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.

rate was 79%. The estimated IV coefficients in column (2) of table 3 can be utilized 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 percentiles respectively in response to automation. Thus, immigrant mobility can lead to an extra 34.6pp decline in labour supply 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]).[11] Migrants' location choices can account for 19% (0.346/1.814) of the net employment decline due to automation. The effect is not large simply because immigrants account for a small share of US population (9%).

Our estimate of immigrants' mobility on employment losses from automation is likely to be an upper bound estimate due to the following reasons. First, Lewis (2011) and Mann & Pozzoli (2023) argue that low-skilled labour supply and robot adoption are negatively correlated. Also, Acemoglu & Restrepo (2020) show that labour force participation falls in areas more exposed to robots. Both of these factors will lead to a

[11]The 1.87 coefficient of employment comes from the first column in table 1.

smaller difference in the immigrants' aggregate labour supply between high versus low robot exposed regions. Second, we make the extreme assumption that the observed overall employment decline 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 decline in jobs from automation is due to migrants' location choices. Autor et al. (2023) finds that the contribution of foreign-born population change to employment effect from trade exposure is one-fifth, quite similar to our estimate. 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 immigrants' mobility in helping native-born workers adjust to automation. If foreign-born individuals are elastic in their migration response to labour demand shocks then their movement out of high immigration areas might insulate the native-born workers' employment losses from adverse shocks (Cadena & Kovak 2016). An assumption made is that foreign- and native-born workers are highly substitutable in the production process. We compare labour market outcomes of native-born workers with above and below median immigrant share following.

The first and second column of table 4 shows the impact on employment of native-born workers in CZs with above and below median immigrant share to robot pentration. We find that the employment of native-born workers 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 nativity wage gap does not change to automation in areas with high or low immigrant population share. We show in Appendix table A.7 that our results are unchanged if we instead use an alternate definition of immigrants, which includes naturalized citizens. These results suggest that native-born workers are not better off in areas with more immigrants. This could be if native- and foreign-born workers are imperfect substitutes in the production process rather than perfect substitutes (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 workers by above and below median immigrant population share in 2000

	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	0.708	0.608	0.222	0.126
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 census dummies; 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 the native-born workers across areas with varying immigrant shares.

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

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 the periods t_0 and t_1 and Immigrant Share$_{j,t_0}$ is the foreign-born population share in CZ j and year t_0. The coefficient of interest is β_2; a negative value signifies that the effect of robot adoption on labour market outcomes is lower in a CZ with a 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). Appendix figure A.6 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 Appendix table A.5.

Table 5 presents the estimates of native-born workers' employment and wage, and the nativity wage gap. 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 the share in 2000. The first and second column show that both the OLS and IV interaction coefficient on native employment is negative. This implies that in counties with higher robot exposure and immigrant share, native-born workers experienced a bigger reduction in employment. The IV interaction coefficient on native-born workers' wage and the nativity wage gap are slightly positive but imprecisely estimated. Taken together, these results suggest that the presence of immigrants *does not* mitigate the labour market outcomes of native-born workers. Our conclusions remain the same if we consider the alternate immigrant definition with naturalized citizens, as highlighted in Appendix table A.8.

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

	Employment		Wage gap		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	0.712	0.705	0.137	0.133	0.588	0.580
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 census dummies; 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 exposure from rising import competition, 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 statistically distinguishable from zero. 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 individuals.[12]

Borusyak, Dix-Carneiro & Kovak (2022) show that migration choices of people living in a region depend not only on shocks hitting that region but also on the shocks experienced by the surrounding regions. Misspecification arising from not accounting for exposure of robots to other regions will lead to biased estimates. We include a migration-weighted robot exposure of other CZs in our regression specification which according to Autor et al. (2023) is defined 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. The weights are similar to gravity models of trade which measure the importance of trade flows between locations using distance.[13] When adding the control in column (5), our estimates are almost identical for the native-born population and fall a bit for the immigrant-born population. The various exercises highlight that the magnitude of the immigrant mobility response and the resulting contribution to overall employment remain robust.

[12] Performing similar calculations as before, 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 mobility.

[13] 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	0.454	0.489	0.454	0.466	0.459
Computer Capital	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes
1st stage F-stat	76.781	179.966	76.781	76.781	73.929
	B: US-born Population				
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	0.625	0.686	0.625	0.611	0.625
Computer Capital	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes
1st stage F-stat	76.781	179.966	76.781	76.781	73.929

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 census dummies; 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.

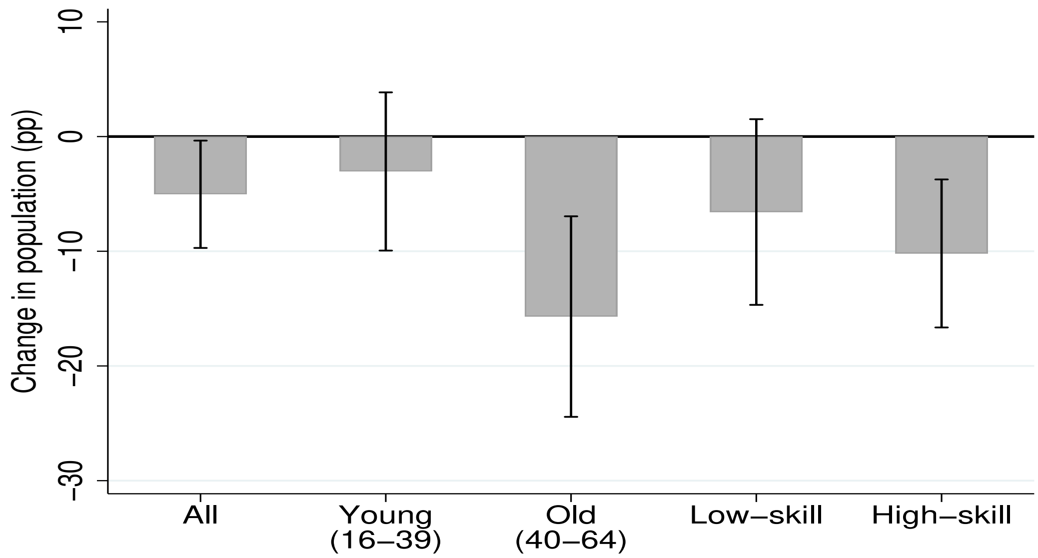
5 Discussion

Table 3 in section 4 shows that immigrants are more mobile than native-born individuals 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 2 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 of high-skilled individuals help explain the larger employment losses of high-skilled immigrant workers than low-skilled immigration workers. 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. Appendix figure A.7 shows that the change of native-born population to automation is indistinguishable from zero across age and education groups.

Figure 2: Immigrant migration response by age and skill-groups

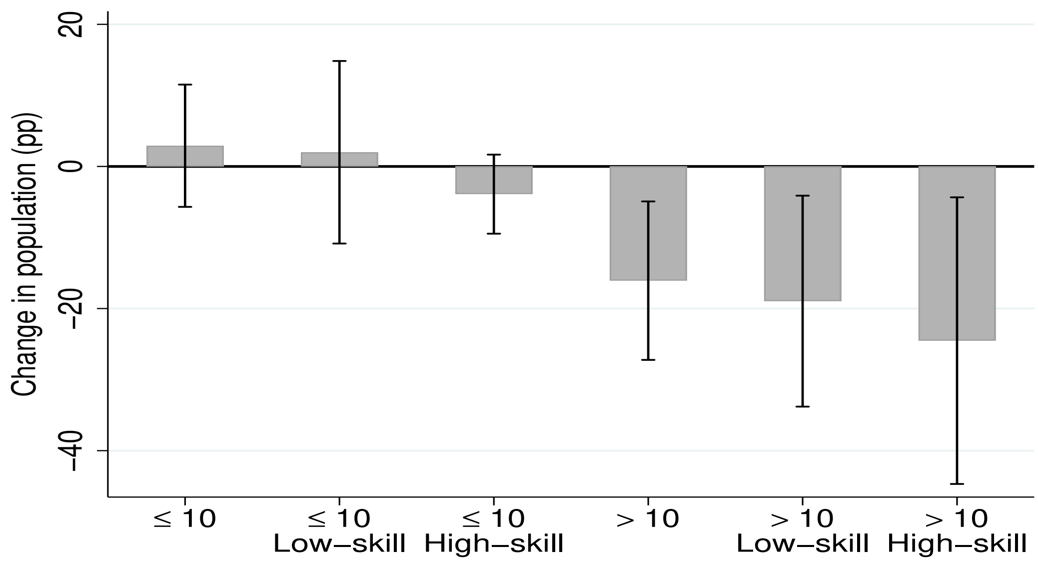


Note: Bars denote 95% CI. All regression estimates are weighted by the CZ population in 2000. Regressions include census dummies, computer capital use and covariates. Dependent variable is change in population of that subgroup between 2000 and 2015.

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 3 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.[14] We also show that both low- and high-skilled established immigrants display more elastic migration behaviour than new immigrants in response to robot exposure. 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 3: 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.

[14]The publicly available Census data does not contain detailed past migration responses of individuals to correctly compute inflows or outflows by nativity or decompose the mobility responses into internal versus international migration. Future research using more detailed migration data can investigate migration flows in response to automation.

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? This study shows that while immigrant mobility in response to automation is higher than native-born individuals, immigrants' migration response has a limited contribution in accounting for the employment change between high and low robot-exposed regions. Moreover, we find that immigration *does not* alleviate the unfavourable impact of automation on the native-born workers' employment or wages. Native-born workers in high immigration areas did not experience a lower incidence of automation than low immigration areas. Thus, the less mobile native-born workers might have to bear a larger burden to ease labour market adjustments across regions.

A future area of research could be to disentangle the effects of automation and migration. Both displace low-skilled workers but depending on the nature of the production process might interact differently with high-skilled workers. This might also help to understand the “productivity" and “displacement" effect of automation.

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Appendix

Additional Tables

Table A.1: 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 A.2: 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	0.467	0.368	0.746	0.554
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 census dummies; 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 A.3: 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	0.321	0.444	0.257	0.685	0.737	0.562
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 census dummies; 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 A.4: 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	0.061	0.128	0.119	0.205	0.643	0.574
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 census dummies; 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 A.5: 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	0.373	0.174	0.366	0.456	0.788	0.500
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 A.6: Robustness checks

	Baseline estimate (1)	Additional controls (2)	EURO5 (3)	Alternate immigrant definition (4)
	A: Employment Growth of Immigrant Workers			
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	0.435	0.461	0.435	0.454
Computer Capital	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes
1st stage F-stat	96.866	145.245	96.866	96.866
	B: Employment Growth of US-born Workers			
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	0.703	0.716	0.703	0.652
Computer Capital	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes
1st stage F-stat	96.866	145.245	96.866	96.866
	C: Nativity 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	0.133	0.141	0.133	0.287
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 census dummies; 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 A.7: IV estimate on US-born workers by above and below median population share in 2000 of immigrant by alternate definition

	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	0.712	0.573	0.223	0.119
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 census dummies; 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 A.8: IV estimate on US-born workers by interaction with immigrant population share by alternate definition

	Employment		Wage gap		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	0.710	0.704	0.136	0.136	0.579	0.575
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 census dummies; 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 A.1: Immigrant population share across CZs in 2000

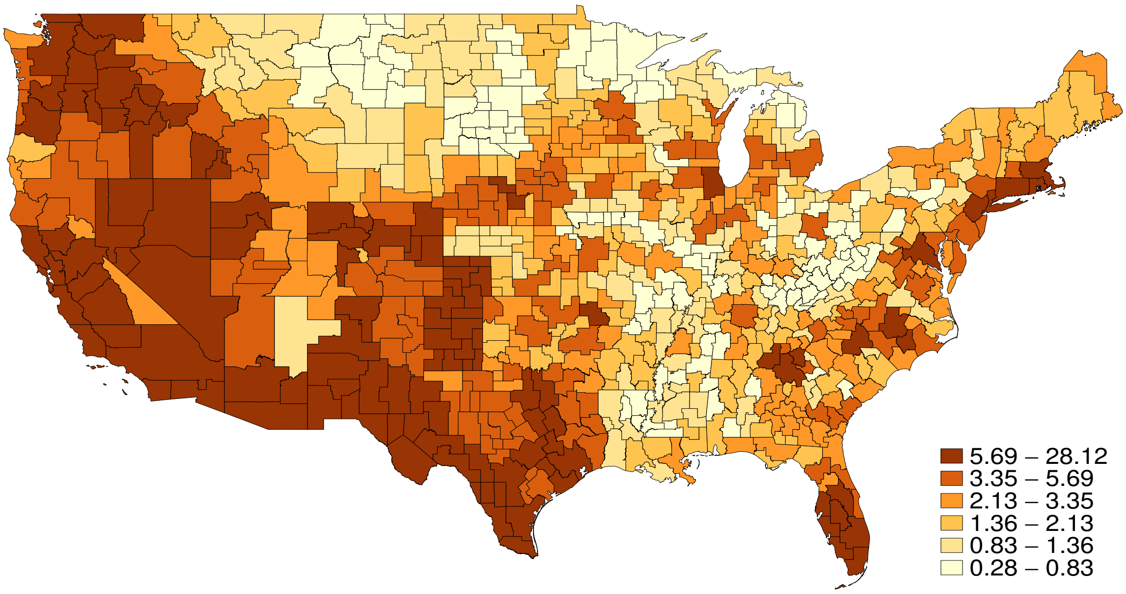


Figure A.2: Change in robot per worker 2000-2015

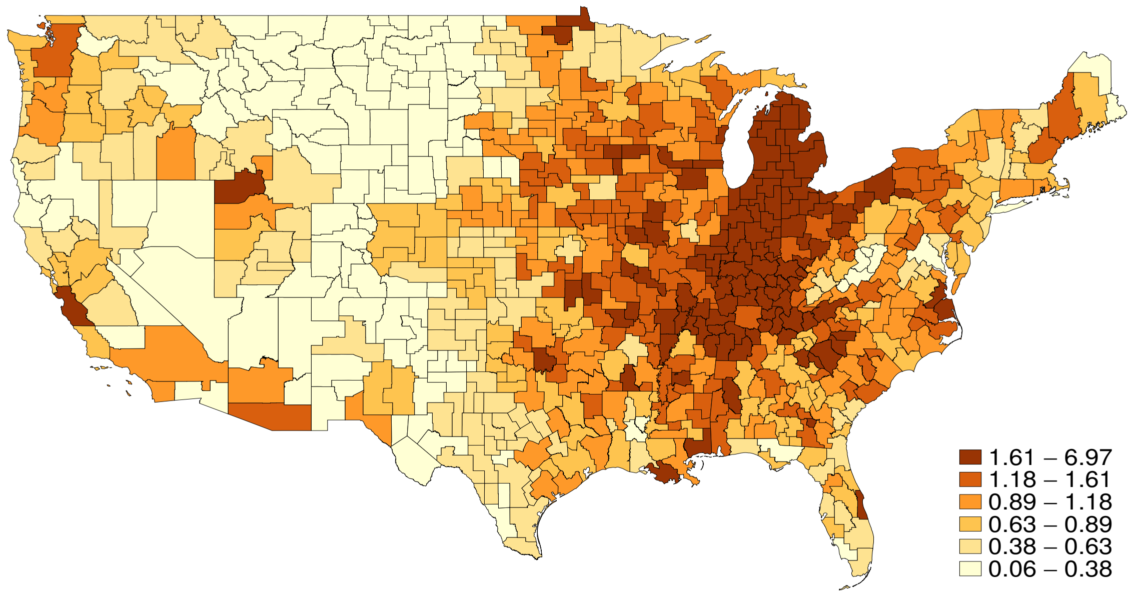


Figure A.3: Relation between growth in robot per worker and robot exposure

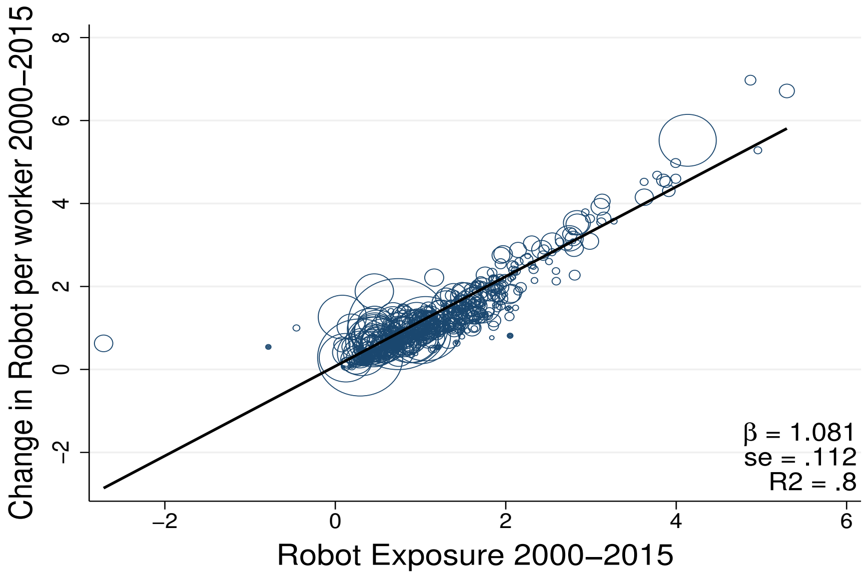


Figure A.4: Relation between change in computer capital and adjusted computer capital

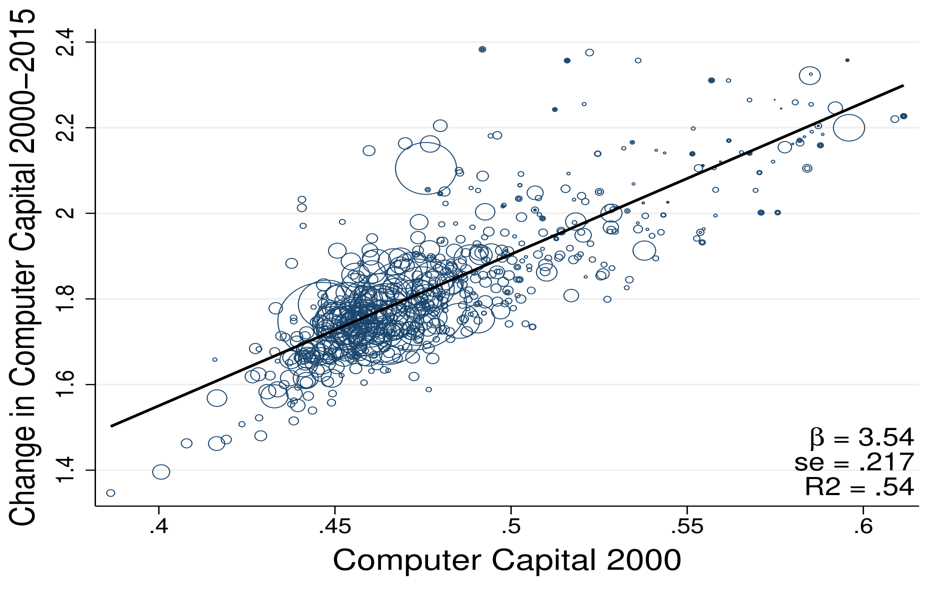


Figure A.5: Effect of change in robot adoption on wage distribution

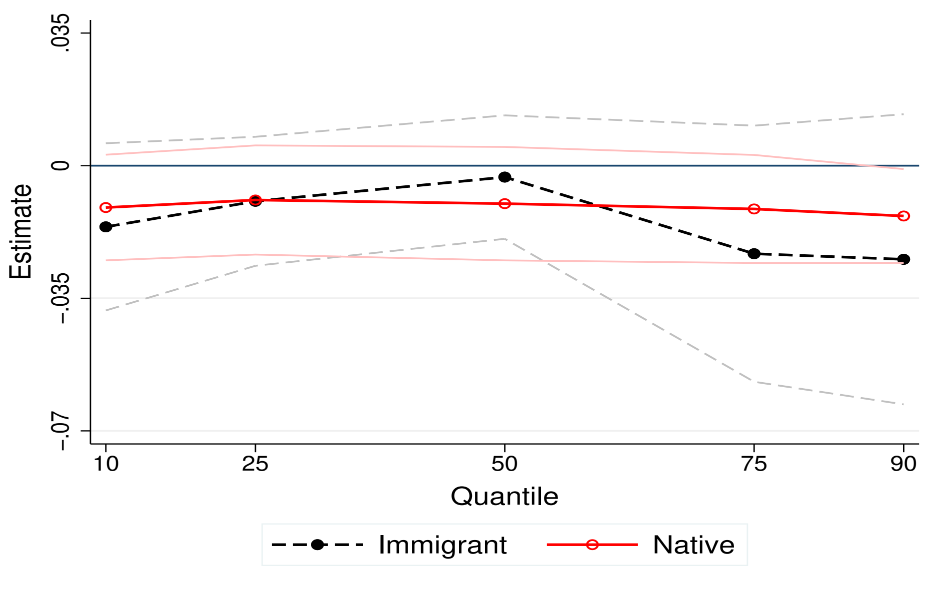


Figure A.6: Relation between immigrant share in 2000 and 1980

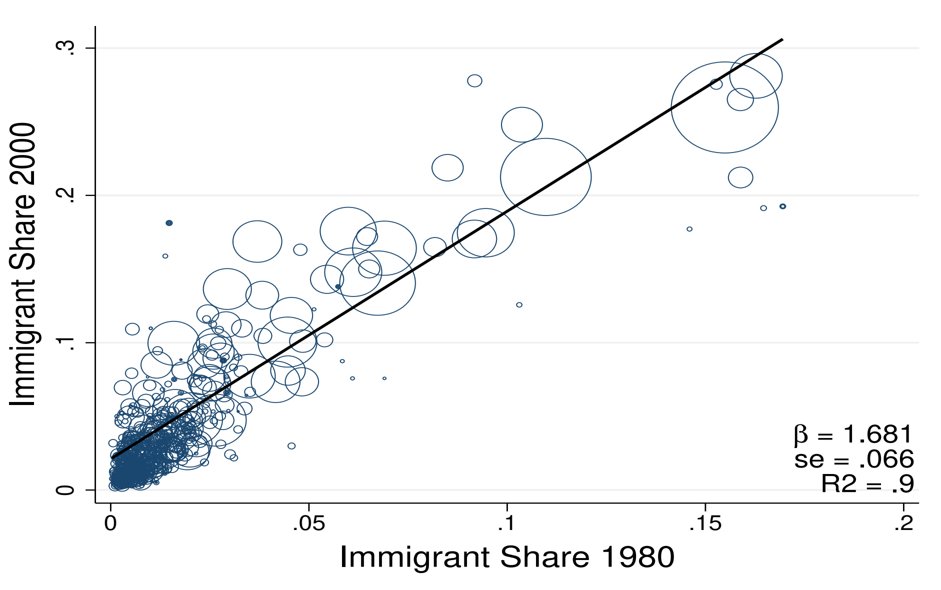
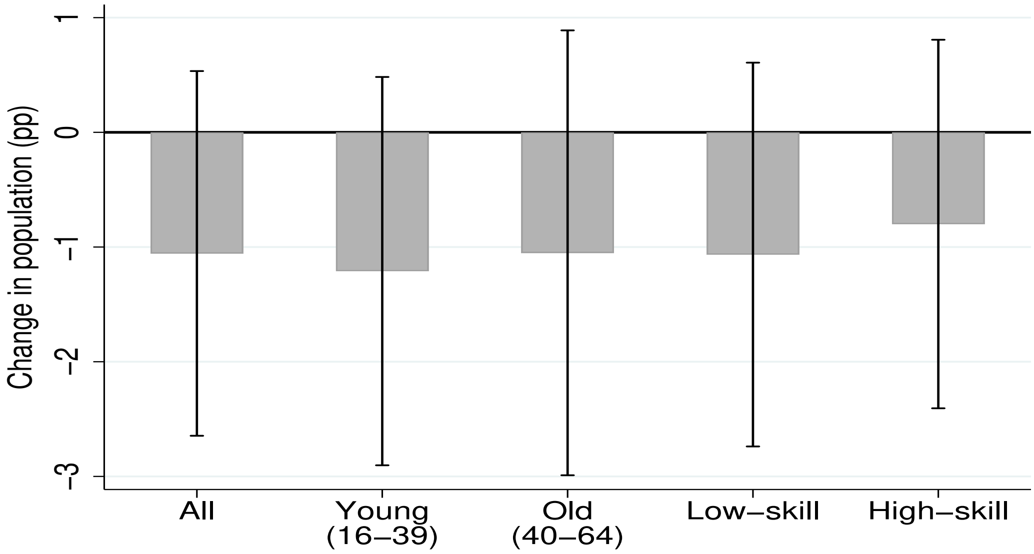


Figure A.7: US-born individuals' migration response by age and skill-groups



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.