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Automation and Local Labour Markets: Impact of Immigrant Mobility

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Abstract

This paper illustrates the role of low-skilled immigrants' location choice as a channel through which local labour markets adjust to automation. We employ a shift-share instrumental variable approach to demonstrate that low-skilled immigrants are more mobile than low-skilled native born in response to robot exposure. Low-skilled immigrants are less likely to enter and more likely to exit from highly robot-exposed regions. Immigrants' location decisions attenuate wage losses due to robot exposure for low-skilled natives. Low-skilled native workers experience a 0.07 percentage point smaller decline in wages comparing commuting zones at the 50^{th} and 25^{th} percentiles of low-skilled immigrant shares.

Keywords: Automation, Geographic labour mobility, Immigrants, Technology
JEL Classification: J15, J23, J31, J61, O33, R23

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1 Introduction

Automation has transformed the labour market in industrialized economies over the past 30 years (Abraham & Kearney 2020, Acemoglu & Restrepo 2020, Autor & Salomons 2018).[1] The geographical mobility of workers is an important channel to insure against adverse local economic shocks (Blanchard & Katz 1992). However, US-born workers, especially low-skilled workers, are less likely to move in response to changes in local labour demand than immigrants (Bound & Holzer 2000). In this context, we aim to answer two questions about which little is currently known. First, are low-skilled immigrants more mobile than low-skilled natives in response to the introduction of robots? Second, if the answer to the preceding question is yes, does the impact of automation on the low-skilled native workforce diminish due to immigrant mobility?

We examine mobility responses to robot exposure in US commuting zones (CZs). Our analysis reveals a novel finding: growth of low-skilled immigrant population fell much more than similarly skilled natives due to robot exposure. More importantly, the population change of low-skilled immigrants was driven by both a decline in arrival from other areas in the US into robot-exposed CZs and an increase in departure from robot-exposed CZs. The higher sensitivity of low-skilled immigrants to automation reduced spatial inequality. More specifically, we find that the fall in wages as a result of robot penetration was lower for low-skilled native workers in regions with a higher share of low-skilled immigrants.

Policy prescriptions for the increasing adoption of robots have mostly focused on regulating their use (Beraja & Zorzi 2021), implementing redistributive policies (Guerreiro et al. 2022, Lehr & Restrepo 2022, Prettner & Strulik 2020), or retraining workers (Jaimovich et al. 2021). We provide evidence supporting a new mechanism, immigrant mobility, which offers insurance to low-skilled workers against automation. Furthermore, our paper is informative about the design of immigration policies, given the rise in support for populist policies in response to automation-induced job losses (Anelli et al. 2021, Brey 2021).

[1]There is considerable debate on the effects of technological progress on workers (Acemoglu & Restrepo 2020, Adachi et al. 2024, Aghion et al. 2023, Autor et al. 2024, Boustan et al. 2022, Dauth et al. 2021, Goldin & Katz 2009, Graetz & Michaels 2018, Hirvonen et al. 2022, Humlum 2021, Koch et al. 2021). In the US, however, robot adoption has caused job and wage losses (Acemoglu & Restrepo 2020), higher inequality (Acemoglu & Restrepo 2022), worsening of mental health (Gihleb et al. 2022) and a decline in marriage rates and marital fertility (Anelli et al. 2021), which is the focus in this paper.

To causally analyse the impact of automation on local labour markets, we use a shift-share instrumental variable strategy. The instrument exploits variation in specific employment shares at the industry-CZ level in 1970 and national growth in robot use by industry.[2] We instrument the growth of robot capital in the US compared with that in five European countries to remove US-specific factors in automation, as per Acemoglu & Restrepo (2020).[3]

Focusing on the mobility response by nativity-skill status, we estimate the change in the log working-age population to robot exposure using a stacked-differences regression (1990-2000 and 2000-2015). We find a pronounced difference between the population growth of low-skilled by nativity status to robots. Specifically, an additional robot per thousand workers reduces the growth in the immigrant-to-native population by 4.45 percentage points (pp). Contrastingly, no differential sensitivity exists among the high-skilled nativity groups.[4]

Investigating the channels of adjustment, low-skilled immigrants are both less likely to enter robot-exposed regions and more likely to exit from robot-exposed areas. We find an insignificant effect of robot penetration on international migration indicating that most of the labour reallocation occurred among incumbent residents.[5] Robot penetration also leads to a decline in the arrival of low-skilled immigrant men, suggesting that the location choices we documented are driven by changes in economic conditions.

Having established that immigrant location choices are particularly sensitive to robot penetration, we now examine the implications on native-born workers. A lower inflow and higher outflow of low-skilled immigrants from adversely affected regions will reduce labor market competition for incumbent workers (Dustmann et al. 2017). To analyse the causal mitigating impact of immigrant mobility on natives' labour market outcomes, we exploit variation in the proportion of low-skilled immigrant population across CZs. Using the 1990 immigrant share instead of the current immigrant share

[2]The main identification assumption is the exogeneity of the national industry growth rates to local economic factors, as argued by Borusyak, Hull & Jaravel (2022).

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

[4]The sensitivity of population growth to robots is the largest for low-skilled immigrants relative to low- and high-skilled natives and high-skilled immigrants, as shown in Section 3.

[5]The reduction in the inflows of low-skilled immigrants is consistent with the broader observation that the in-migration of prospective migrants constitutes the bulk of reallocation to economic shocks in local labour markets occur (Dustmann et al. 2017, Monras 2020).

helps avoid the issue of reverse causality. We address the issue of the non-random sorting of immigrants by instrumenting the 1990 CZ immigrant share with the share in 1970, as new immigrants are more likely to reside in areas with higher past immigration levels (Borjas 1995).

The location choices of low-skilled immigrants attenuate the adverse effects of robot penetration. Wages of low-skilled natives experience a smaller wage decline, by 0.07 pp, between the CZs at 50$^{\text{th}}$ percentile relative to the 25$^{\text{th}}$ percentile of the low-skilled immigrant share. On average, immigrant mobility does not insure employment opportunities; the loss in employment of low-skilled natives is similar in both areas with many and few immigrants. However, the average effect hides considerable heterogeneity; immigrant mobility insures the employment opportunities of low-skilled manual workers in both the personal and professional service sectors. In contrast, most of the mitigating effects in wages occur in the routine occupations. Since automation adversely affects high-skilled workers as well (Acemoglu & Restrepo 2020, Faber et al. 2022), reduced demand from high-skilled workers can lead to slower growth of the low-skilled immigrant population in those areas, consequently mitigating wage losses for similarly skilled incumbent natives.

Finally, we investigate alternate mechanisms underlying the differential sensitivity of location choices to robots by nativity status. The stronger population effect among low-skilled immigrants might be in response to a more negative labour market impact (Javed 2023). Consistent with this hypothesis, we show that employment losses are larger among low-skilled immigrants than low-skilled natives. This might be due to the asymmetric intensity of robot exposure by nativity and/or spillover from highly skilled workers on the demand for low-skilled immigrant services. We provide suggestive evidence in line with the spillover hypothesis; immigrant population and employment decrease more significantly in response to robot exposure in CZs surrounded by highly skilled workers rather than low-skilled workers. However, we do not find convincing evidence to reject or support the differential exposure by nativity as a mechanism.

This paper contributes to multiple strands of literature. First, it contributes to the literature on the role of immigrant mobility in "greasing the wheels of the labour market" (Basso et al. 2019, Blanchard & Katz 1992, Borjas 2001, Cadena & Kovak 2016, Özgüzel 2021, Yu 2023). This paper complements the literature by examining the contribution of immigrant location choices in a new and topical context – automation. Regional labour mobility is declining in the US (Molloy et al. 2011, Olney & Thompson 2024), raising concerns that an important means of reducing geographic inequality is weakening. We show that the ability of local labour markets to adjust to economic shocks increases due to the presence of highly responsive low-skilled immigrants. Moreover, the lower inflow of low-skilled immigrant workers also matters in attenuating the labour market outcomes of incumbent natives. This represents an additional channel, as the literature to date has focused on outflow to other countries or within the same country as the primary channels through which immigrant mobility helps labour markets adjust to shocks. We also advance this literature by showing the contribution of immigrant mobility in cushioning of wage and employment losses to robot exposure. Most of this literature has documented mitigating effects only through the employment margin, except Özgüzel (2021).

Second, it contributes to the literature on internal migration as a response to labour demand shocks (Bartik 1991, Black et al. 2005, Bound & Holzer 2000, Faber et al. 2022, Greenland et al. 2019, Hershbein & Stuart 2022, Huttunen et al. 2018, Monras 2020, Notowidigdo 2020). We argue that distinguishing by subgroups is crucial for understanding migration responses to changes in economic conditions. Consistent with prior work, we confirm that high-skilled natives are much more responsive to demand shocks than low-skilled natives. Moreover, we demonstrate a pronounced migration response to robot exposure among the highly mobile subgroups. This distinction possibly explains why recent work focusing on total population (Acemoglu & Restrepo 2020) or total immigrants (Faber et al. 2022) finds a limited migration response to robot exposure.

Third, our findings complement the literature investigating the impact of robots on the demographic composition of the US economy (Acemoglu & Restrepo 2020, Faber et al. 2022, Javed 2023, Lerch 2022). We show that workers and labour markets adjusted in response to robot exposure. Hence, the adverse effects of automation might be higher than originally documented. Moreover, Lerch (2024) argues that robot exposure did not affect the race wage gap, whereas Ge & Zhou (2020) show that automation increased the male-female wage gap. We show that low-skill immigrant mobility can be a complementary channel to explain these patterns because it benefited blacks and women more relative to white men.

The rest of this article is organised as follows. In Section 2, we discuss our data sources and describe the empirical methodology. Sections 3 and 4 present the migration responses by nativity and the implications of immigrant mobility on the native workforce. Section 5 discusses the mechanisms behind the higher sensitivity of low-skilled immigrants to robot exposure, and Section 6 concludes.

2 Data and Empirical Strategy

In this section, we describe our primary data sources, summarise the construction of our key variables of interest and discuss our empirical strategy.

2.1 Data

2.1.1 Data on stock of industrial robots

Our data for the stock of robots for each industry-year-country level observation come from the International Federation of Robotics (IFR), which compiles data by surveying robot suppliers in more than 60 countries since 1993 (IFR 1993-2015). It is the most accessible and widely used cross-country data source for robot adoption currently available (Acemoglu & Restrepo 2020, Graetz & Michaels 2018). The IFR provides data for thirteen disaggregated categories in the manufacturing sector.[6] Data are also available for six broad sectors: agriculture, mining, utilities, construction, education, and services. Appendix Table A.1 highlights that the automotive, chemical and electronics sectors experienced the highest growth in robot use in the US over the sample period; while construction and services had the lowest growth. Data on employment and growth rate of output at the industry level come from (EU KLEMS) Growth and Productivity Accounts (Board 2023).

2.1.2 Outcomes and robot exposure at the commuting zone level

To measure long-term changes in local labour markets, we use the public-use Census samples from IPUMS for the years 1970, 1990 and 2000, as well as the 2013-2017 American

[6] In Appendix A.1, we discuss how we overcome some of the limitations of the IFR data.

Community Survey (ACS) (Ruggles et al. 2023).[7] Immigrants are defined as individuals born outside the US to non-US citizens. An individual with a high school degree or less is defined as low-skill, whereas an individual with some college education or more is categorized as high-skill. Our sample consists of non-institutionalised individuals between the ages of 16 and 64. Notably, we conduct our analysis at the CZ level, using data containing 722 CZs that cover the entire US except the states of Alaska and Hawaii.[8]

Following Acemoglu & Restrepo (2020), robot exposure in a given CZ i and year t $\left(\Delta R_{i,t}\right)$ is measured as the weighted sum of the change in robot use at the industry level, where the relevant weights are the industry's employment share. We use the employment share in 1970 to prevent any mechanical correlation between robot use and industry shares before the 1990s (Acemoglu & Restrepo 2020). Therefore, exposure to robots in the US is defined as follows:

$$\Delta R^{US}_{i,t} = \sum_{j} \left[\frac{L_{i,j,1970}}{L_{i,1970}} \cdot \Delta R_{j,t} \right] \tag{1}$$

where $\frac{L_{i,j,1970}}{L_{i,1970}}$ is the employment ratio of industry j in CZ i in 1970.[9]

2.1.3 Other data

Beaudry et al. (2010) argues that computer capital is complementary to high-skilled workers, but substitutable to low-skilled workers. The real stock of computer capital in the US almost doubled between 1990 and 2015. It is important to account for computer capital growth in order to capture technological changes unrelated to automation. Computer adoption is the growth in the value of computing equipment stock in US dollars per thousand workers, using data from EU KLEMS .[10] We use the trade exposure data from Autor et al. (2019*a*) to account for exposure to Chinese import competition,

[7] We measure outcomes in 2015 based on the 2013- 2017 ACS to increase the sample size, as per Autor et al. (2013). The sample size is 5% for the 1990 and 2000 Census and 1% for the 1970 Census.

[8] A CZ comprises counties with strong labour market and commuting ties (Tolbert & Sizer 1996) and that is amongst the most common geographical disaggregation type for the study of local labour markets (Autor & Dorn 2013).

[9] Appendix Figures A.2a and A.2b highlight sizeable geographical variation in robot exposure between 1990 and 2015 and the immigrant population share in 1990 across CZs, respectively. Appendix A.2 contains more details on the construction of the robot exposure measure.

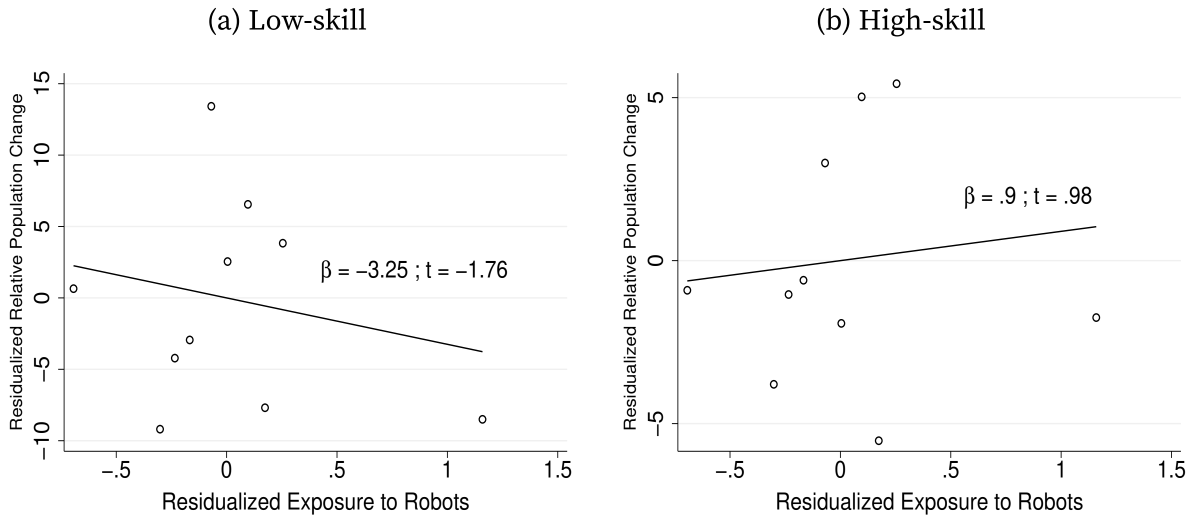
[10] EU KLEMS 2017 uses the ISIC Rev. 4 (NACE Rev. 2) industry classification to provide data for 34 distinct industries, including 11 categories for manufacturing. We harmonise industry classification across datasets and compute a regions' computer capital growth between 1990 and 2015, similar to the measure of robot growth in Appendix Equation (7).

which has considerably reduced employment in the US manufacturing industry (Bloom et al. 2019).[11]

2.2 Empirical specifications

Figures 1a and 1b show the binned scatter plots by skill groups for 10 deciles of robot exposure, including Census division fixed effects. The y-axis displays the difference in the log population of immigrants and natives, i.e., the change in the log of the relative number of immigrants to natives, which we refer to as *immigrant concentration*. The figure demonstrates our key finding: the location-choices of low-skilled immigrants are more sensitive to robot exposure than those of similarly skilled natives. On the other hand, highly-skilled immigrants and natives react similarly to robot penetration.

Figure 1: Binned scatterplot: change in immigrant concentration, 1990–2015



Note: Panels (a) and (b) plot the relationship between the deciles of robot exposure and changes in the log of the immigrant-to-native population of low-skilled and highly-skilled individuals, respectively. Clustered standard errors at the state level are shown in parentheses. Regression is weighted by the 1990 CZ population and controls for Census Division dummies.

To formally examine these patterns, we estimate the following regression:

$$\Delta y_{i,t} = \alpha_{d,t} + \beta \Delta R^{US}_{i,t} + \gamma X_{i,t} + \varepsilon_{i,t} \tag{2}$$

[11] 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. The endogeneity between industrial import demand and actual imports from China is accounted for by replacing the growth in Chinese imports to the US with those to eight other developed economies (Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland).

where $\Delta y_{i,t}$ is the dependent variable of CZ i at time t, $\alpha_{d,t}$ are the division-time dummies, $X_{i,t}$ denotes a rich vector of covariates and $\Delta R_{i,t}$ is the measure of robot exposure. The baseline specification is a stacked first-difference model with two periods (1990-2000 and 2000-2015), and the change in log population of each subgroup as the main dependent variable. All regressions are weighted by the CZ's working-age population in 1990 to reduce the influence of sparsely populated CZs. Standard errors are heteroskedasticity-robust and clustered at the state level to account for spatial correlations.

We include the interaction between time dummies and division dummies with a rich vector of demographic and industry characteristics in 1990.[12] Faber et al. (2022) argues that the interaction between period dummies and CZ covariates improves the precision of the population change estimates by accounting for potential underlying trends.[13] Division-time dummies are included to absorb region-specific trends in the dependent variable. The coefficient of interest, (β), is identified by comparing CZs within the same division during a given period.

We control for overall trends in the US labour market by including the employment share of routine and offshorable jobs in 1990 interacted with time dummies and exposure to Chinese imports.[14] We account for potentially confounding changes in computer-capital adoption by proxying the growth in the use of computer capital with the *level* of computer capital in 1990, following Michaels et al. (2014). Appendix Figures A.3a and A.3b highlight a strong relationship between the level in 1990 and growth between 1990 and 2015 of computer capital per worker at the industry and CZ level, respectively.

An unobserved labour demand shock in a CZ may affect the technology choices of firms in that labour market. Hence, we isolate the causal effect of automation, by instrumenting for robot exposure in the US with robot exposure in other European

[12]The 1990 CZ demographic characteristics are: log population and shares in the population of men; those older than 65 years old; populations with no college education, some college education, and a college education or higher; the populations of White, Black and Hispanic individuals. The 1990 CZ industry characteristics include: employment shares of manufacturing, light manufacturing, agriculture, construction and mining. We control for the employment share of light manufacturing industries (textiles and printing) as Acemoglu & Restrepo (2020) argues that the decrease in employment in these industries is negatively related to robot penetration.

[13]The exclusion of period dummies and CZ covariates can help explain the stronger effect of robot exposure on mobility found by Faber et al. (2022) relative to Acemoglu & Restrepo (2020).

[14]Following Autor et al. (2013), we compute the share of workers performing routine, manual and abstract tasks and construct the standardised measure of 'task offshorability' per industry.

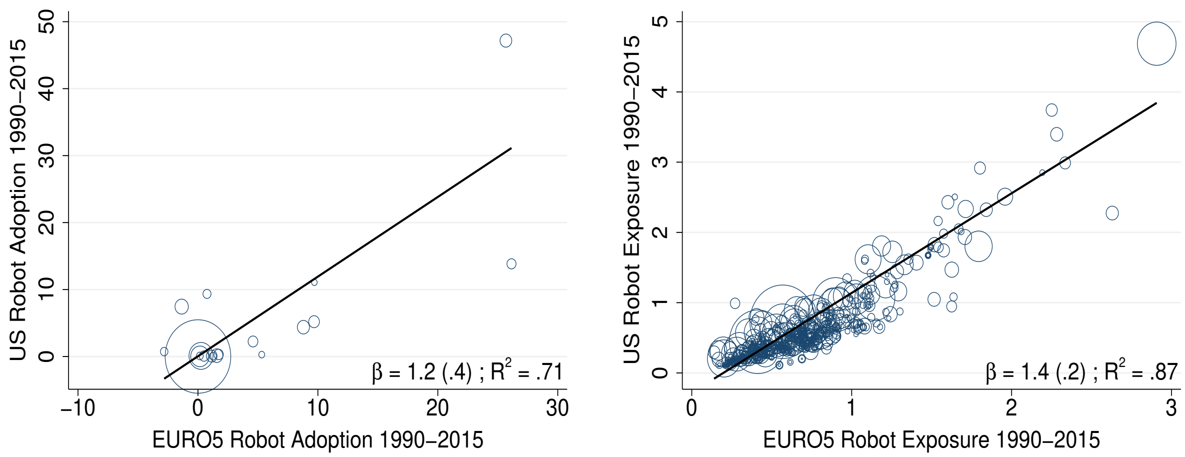
countries. This allows us to isolate technological advancements in robot technology in non-US developed countries and remove any bias from shocks that are specific to the US. Following Acemoglu & Restrepo (2020), we consider five European countries (EURO5): Denmark, Finland, France, Italy and Sweden. EURO5 robot-exposure measure $\left(\Delta R_{i,t}^{EURO5}\right)$ is computed by replacing US industry-level robot growth in Equation (1) with the EURO5 industry-level robot growth $\left(\Delta R_{j,t}^{EURO5}\right)$, as follows[15]:

$$\Delta R_{i,t}^{EURO5} = \sum_{j} \left[\frac{L_{i,j,1970}}{L_{i,1970}} \cdot \Delta R_{j,t}^{EURO5} \right] \tag{3}$$

Figure 2a shows a strong relationship between robot adoption at the industry level in US and European countries, helping isolate variation stemming from global technological progress. Figure 2b highlights that the EURO5 measure of robot exposure strongly predicts robot penetration in the US at the CZ level. The regression coefficient is statistically significant, and the instrument captures 87% of the variation in US robot exposure across local labour markets.

Figure 2: Relationship between US and EURO5 robot exposure

(a) Industry (b) Commuting Zone



Note: Panel (a) plots the growth in robots per thousand workers at the industry level in US and EURO5 countries. The marker size indicates the US industry employment shares in 1990. Robust standard errors are displayed parentheses. Panel (b) shows the relationship between US and EURO5 robot exposure at the CZ level. The marker size indicates the 1990 population in the CZ. Clustered standard errors at the state level are displayed in parentheses.

[15] The average growth in robot adoption for each industry in EURO5 is a simple average over all the countries. Appendix Figure A.1 shows that robot use has increased consistently from the 1990's in North America, Germany and EURO5 countries.

The key identification assumption of the IV in our setting is the exogeneity between the national trends in robot use and local economic conditions (Borusyak, Hull & Jaravel 2022). If the robot capital shocks are "as-good-as randomly" assigned to CZs, we expect them to be uncorrelated with our controls. We corroborate this interpretation by reporting CZ-level balance tests in Appendix Table A.2; the table highlights that there is no statistically significant correlation for 16 out of 17 potential confounders.[16] Only the fraction of employment in routine occupations is significantly related with the shocks, but we show below that its inclusion/exclusion does not change the quantitative results.

3 The effect of robots on mobility by nativity

In this section, we examine the changes in populations in response to the introduction of robots, following which we analyse the margins along which the migration responses occur. We scale the outcome variables to 10-year equivalent changes and multiply them by 100. The estimated coefficient β should be interpreted as a percentage point (pp) change in the outcome variable due to an increase in robot exposure of one robot per thousand workers.

3.1 Results for population adjustments

Table 1 reports the results of our two-stage least-squares (2SLS) estimation by skill and nativity, with each coefficient originating from a separate regression. Columns 1, 3 and 5 present results using a parsimonious specification that includes only Census dummies; columns 2, 4 and 6 report our findings using the full set of controls. The first four columns present results for changes in the log population headcount by nativity, whereas the last two columns display results for the difference in the population growth between immigrants and natives.

Focusing on the low-skilled individuals in Panel A, immigrants are much more responsive to robot exposure than natives. This result remains robust even when a stringent set of controls is included. Using the full controls, a unit increase in robot

[16] The coefficients are obtained by regressing each potential confounder on the robot exposure instrument (standardised to unit variance) and Census division dummies.

Table 1: Effects on population growth, stacked-differences 1990–2015 (2SLS)

Dependent variable: Change in log population or change in log relative population						
	Native		Immigrant		Immigrant/Native	
	(1)	(2)	(3)	(4)	(5)	(6)
	A: Low-Skill					
Exposure to robots	-1.40**	-1.04**	-6.40**	-5.49**	-5.00*	-4.45**
	(0.65)	(0.45)	(2.86)	(2.19)	(2.60)	(2.18)
Observations	1444	1444	1444	1444	1444	1444
R^2	0.46	0.82	0.21	0.70	0.18	0.69
	B: High-skill					
Exposure to robots	-2.20***	-1.41***	-2.92*	0.28	-0.72	1.69
	(0.74)	(0.38)	(1.64)	(1.22)	(1.34)	(1.15)
Observations	1444	1444	1444	1444	1444	1444
R^2	0.31	0.73	0.17	0.55	0.06	0.46
Kleibergen-Paap F	101.53	109.63	101.53	109.63	101.53	109.63
Division dummies	Yes		Yes		Yes	
Division x time dummies		Yes		Yes		Yes
Covariates		Yes		Yes		Yes

Note: All regression estimates are weighted by the CZ population in 1990. Standard errors clustered at the state level are reported in parentheses. ***, ** and * represent the statistical significance at 1%, 5% and 10% levels respectively. Covariates include stock of computer capital per worker in 1990; exposure to Chinese imports; year interaction with demographic and industry characteristics in 1990 (log population, low-skill population change between 1970-1990, share of male population, population shares of Whites, Blacks and Hispanics, share of the population over 65 years old, shares of the population with no college, some college and more than college, female employment share, share of employment in agriculture, mining, construction, light manufacturing and manufacturing, routine employment share and average offshorability index).

exposure leads to a 5.49 pp and 1.04 pp decrease in the population growth of low-skilled immigrants and natives (Columns 2 and 4 in Panel A), respectively.[17] The implied decrease in the low-skilled immigrant concentration by 4.45 pp is statistically significant

[17] The population-to-employment elasticity for low-skilled immigrants is slightly higher compared to what is estimated in the literature. We estimate a -6.53 pp effect on log employment due to a unit change in robot exposure, which implies a population-to-employment elasticity of 0.84 (=5.49/6.53). Yu (2023) finds an elasticity of 0.76 due to increasing import competition, whereas Cadena & Kovak (2016) finds an elasticity of 0.569 for low-skilled Mexican-born men during the Great Recession. The higher elasticity is likely a result of a fall in inflow of low-skilled immigrants, a channel missing in the above papers, which we discuss below in more details.

at the 5% level. Moreover, a unit increase in robot exposure is close to the average decadal increase in robot per thousand workers over the sample period. Therefore, one additional robot per thousand workers reduces the growth in the low-skilled immigrant concentration by 9.56% (= 4.45*100/46.55) compared to the average decadal growth in immigrant concentration (46.55%) across CZs.

Appendix Table B.1 highlights the roles of the various controls in affecting the estimated coefficients. The inclusion of the employment share of routine jobs leads to a marginal change in coefficients, implying that the correlation between the instrument and the control variable is unlikely to generate bias in the estimates. The inclusion of the interaction between the period dummies and Census division dummies reduces the point estimate and standard error substantially, while the magnitude of the coefficient decreases somewhat when including the interaction between the CZ characteristics in 1990 with the period dummies. Notably, our analysis does not suffer from a weak instrument problem, as all the first-stage F-statistics in Table 1 are greater than 100. Therefore, the remainder of the analysis uses the 2SLS specification.[18]

The estimates in Panel B of Table 1 highlight that the highly-skilled natives are more sensitive to adverse labour demand shocks than low-skilled natives, a well-established empirical fact (Bound & Holzer 2000). The coefficient for highly-skilled immigrants is imprecisely estimated though, and the corresponding difference in the growth rates between the responses of immigrants and natives to robot exposure is statistically insignificant (column 6). The finding that low-skilled immigrants are much more sensitive to automation than natives is a novel result. We show in Appendix Table B.3 that the combined results in Panels A and B of Table 1 imply that the change in immigrant population growth due to robot exposure is statistically insignificant, consistent with Faber et al. (2022).

Appendix Figure B.1 shows that low-skilled immigrant mobility in response to automation is strongest among those who have lived in the US for a long time. Moreover, an additional robot per thousand workers reduces the population growth of low-skilled immigrants who have lived in the US for more than 21 years by 10.61 pp. On the other hand, the introduction of robots had an insignificant effect on population growth of

[18] Appendix Table B.2 displays the results from the ordinary least-squares (OLS) and reduced-form specifications. The magnitude of the OLS coefficient for the change in low-skilled immigrant concentration is smaller than the 2SLS estimate, which suggests that the correlation between the unobserved shocks and robot exposure generates downward bias for the OLS estimate.

recent immigrants. Thus, internal migration liked played an important role in labor reallocation, which we will examine next.

Appendix Figure B.2 exhibits heterogeneous effects by age, gender, marital status, fertility and home-ownership using the change in low-skilled immigrant concentration for each subgroup as the dependent variable. Older low-skilled immigrants are much more responsive than their native counterpart as established immigrants are more likely to be older. We also find low-skilled immigrant home-owners to be more responsive than renters, as most of the immigrant home-owners have been residing in the US for many years. Immigrant men are slightly more responsive than immigrant women because immigrant men have a stronger attachment to the labour market, and robot exposure affects men more than women (Acemoglu & Restrepo 2020, Lerch 2024).

3.2 Results for migration flows

A CZ's working-age population is affected by: (1) in-migration from another CZ, (2) out-migration to another CZ, (3) ageing in or out of the sample, (4) arrival into the US from another country, and (5) departure from the US. The latter two channels are more relevant for immigrants than natives.[19] We measure the importance of the various channels as follows (ignoring channel 5, as it is unobservable in the data):

$$\frac{N_{i,t+1}^{16-64} - N_{i,t}^{16-64}}{N_{i,t}^{16-64}} = \frac{N_i^{\text{in}}}{N_{i,t}^{16-64}} - \frac{N_i^{\text{out}}}{N_{i,t}^{16-64}} + \frac{N_i^{\text{net-ageing}}}{N_{i,t}^{16-64}} + \frac{N_i^{\text{new arrival}}}{N_{i,t}^{16-64}} \tag{4}$$

where $N_{i,t+1}^{16-64}$ is CZ i working-age population at time $t+1$, $N_i^{\text{new arrival}}$ consists of immigrants who entered the country between t and $t+1$, N_i^{in}, N_i^{out} denotes the number of individuals within the US that entered or exited the CZ i after time t and $N_i^{\text{net-ageing}}$ measures the difference in the number of people who aged in and aged out of the sample.

The 2000 Census sample provides information about an individual's location five years prior. We use this data to measure the number of individuals entering or leaving a CZ. The number of new international immigrants is the sum of individuals who arrived in the country within the five years prior to 2000. We use the number of non-movers

[19] Natives who returned to the US in the past five years constituted less than 1% of the native population in 2000.

aged 16 to 20 years in 2000 to identify those who have aged in, while those aged 65 to 69 years are assumed to have aged out (see Appendix B.6 for a detailed description).

We use a modified version of the specification in Equation (2), with each of the four components serving as the dependent variable. The labour force participation of working-age immigrant men and women in 2000 is 84.37% and 62.93%, respectively. Therefore, we also report findings separately for men because immigrant men are more likely to decide on a location motivated by labour market conditions. All regressions include the full set of control, but exclude time dummies due to the availability of only one year of data.

Table 2: Effects on the five-year migration flows of low-skilled (2SLS)

	Immigrant				Native		
	In	Out	Net-aging	New Arrival	In	Out	Net-aging
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	A: Overall						
Exposure to robots	-2.68**	2.35**	-2.40***	-2.60	-0.50	0.62	-1.52***
	(1.34)	(1.06)	(0.83)	(2.34)	(0.64)	(0.55)	(0.48)
Observations	722	722	722	722	722	722	722
R^2	0.70	0.44	0.39	0.60	0.82	0.72	0.87
	B: Men						
Exposure to robots	-3.14**	1.52	-2.35**	-4.74	-0.19	0.26	-1.40***
	(1.50)	(1.19)	(1.11)	(2.89)	(0.69)	(0.49)	(0.46)
Observations	722	722	722	722	722	722	722
R^2	0.66	0.38	0.18	0.60	0.81	0.73	0.87

Note: The dependent variable in columns (2) and (6) is the growth in the local population due to internal outflows, i.e., the negative of the proportional change in population due to outflows. All regression estimates are weighted by the CZ population in 1990. Standard errors clustered at the state level are reported in parentheses. ***, ** and * represent the statistical significance at 1%, 5% and 10% levels respectively. Regressions include division dummies and covariates: stock of computer capital per worker in 1990; exposure to Chinese imports; demographic and industry characteristics in 1990 (log population, low-skill population change between 1970-1990, share of male population, population shares of Whites, Blacks and Hispanics, share of the population over 65 years old, shares of the population with no college, some college and more than college, female employment share, share of employment in agriculture, mining, construction, light manufacturing and manufacturing, routine employment share and average offshorability index).

Table 2 presents the importance of each channel in explaining the population responses to robot exposure among low-skilled immigrants and natives. Consistent with Figure B.1, the effect of robot penetration on new immigrant arrivals (column 4) into the US is insignificant. This suggests, that most of the labour reallocation due to robot penetration occurrs among existing residents. Focusing on internal migration, columns 1 and 2 in Panel A present that an additional robot per thousand workers reduces the inflow and increases the outflow of low-skilled immigrants by 2.68 pp and 2.35 pp, respectively. However, given the lack of data for immigrants exiting the US and the wide confidence intervals for each of the components, we cannot precisely determine the role of return migration.

The net-aging coefficient of -2.43 implies that the population of older low-skilled immigrants increases more than similarly skilled younger individuals in CZs with higher robot exposure. The rise in the number of older low-skilled individuals is consistent with the presence of significant mobility costs or non-monetary frictions (like, home-bias) that prevent all individuals from exiting adversely affected regions. Another interpretation of this result is that some of the younger individuals received a college education, becoming highly-skilled (Dauth et al. 2021, Di Giacomo & Lerch 2023). The coefficient for net-ageing is much weaker for highly-skilled immigrants and natives (Appendix Table B.6), which suggests that both these channels are plausible. Consistent with prior work, Appendix Table B.6 shows that native-born high-skilled are much more responsive to economic shocks than their low-skilled counterparts.

We showed previously that the response of low-skilled natives to population growth is muted. Columns 5 and 6 in Panel A of Table 2 confirm this finding by highlighting the insignificance of the coefficients for inflows and outflows, respectively. Furthermore, most of the change in population growth of low-skilled natives is explained by the fall in net-ageing (column 7 in Panel A).

Panel B presents the decomposition of the population response for low-skilled men. The coefficients for inflows and net-ageing for low-skilled immigrants remain significant and similar in magnitude to the overall results displayed in Panel A. The coefficient for outflows is positive, but smaller and less precisely estimated. Overall, the results indicate that changes in inflows are quantitatively important for understanding migration behaviour, as much of the literature has focused on out-migration.[20] In

[20]Low-skilled established immigrants exhibit a similar pattern (Appendix Table B.7): immigrant entry decreases and exiting increases in markets with higher robot adoption.

Section 5, we discuss several pieces of evidence to shed light on the factors responsible for the location choice of immigrants.

Table 3: Effects on five-year migration flows of low-skilled, (2SLS): Robustness

	Immigrant				Native		
	In	Out	Net-aging	New Arrival	In	Out	Net-aging
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	A: Baseline						
Exposure to robots	-2.68**	2.35**	-2.40***	-2.60	-0.50	0.62	-1.52***
	(1.34)	(1.06)	(0.83)	(2.34)	(0.64)	(0.55)	(0.48)
Observations	722	722	722	722	722	722	722
R^2	0.70	0.44	0.39	0.60	0.82	0.72	0.87
	B: Controlling for neighbouring robot exposure						
Exposure to robots	-2.68**	2.27**	-2.54***	-4.13*	-0.40	0.28	-1.25***
	(1.36)	(1.02)	(0.84)	(2.25)	(0.65)	(0.52)	(0.48)
Observations	722	722	722	722	722	722	722
R^2	0.70	0.44	0.40	0.61	0.82	0.73	0.88
	C: Excluding CZs with < 100 immigrants						
Exposure to robots	-2.67**	2.33**	-2.40***	-2.61	-0.48	0.60	-1.53***
	(1.33)	(1.06)	(0.83)	(2.33)	(0.64)	(0.55)	(0.48)
Observations	652	652	652	652	652	652	652
R^2	0.70	0.44	0.40	0.60	0.82	0.72	0.87
	D: Excluding states bordering Mexico						
Exposure to robots	-2.94**	2.41**	-1.79**	-2.12	-0.05	0.37	-1.70***
	(1.41)	(1.10)	(0.76)	(2.49)	(0.67)	(0.57)	(0.58)
Observations	621	621	621	621	621	621	621
R^2	0.65	0.45	0.37	0.55	0.84	0.72	0.77

Note: The dependent variable in columns (2) and (6) is the growth in the local population due to internal outflows, i.e., the negative of the proportional change in population due to outflows. All regression estimates are weighted by the CZ population in 1990. Standard errors clustered at the state level are reported in parentheses. ***, ** and * represent the statistical significance at 1%, 5% and 10% levels respectively. Regressions include division dummies and covariates: stock of computer capital per worker in 1990; exposure to Chinese imports; demographic and industry characteristics in 1990 (log population, low-skill population change between 1970-1990, share of male population, population shares of Whites, Blacks and Hispanics, share of the population over 65 years old, shares of the population with no college, some college and more than college, female employment share, share of employment in agriculture, mining, construction, light manufacturing and manufacturing, routine employment share and average offshorability index).

In standard spatial economics models, an individual's location choice depends not only on the labour market opportunities in their region but also on those in the other regions. While our specification controls for changes in labour market opportunities in the current CZ, failing to account for robot exposure in neighbouring CZs may lead to biased estimates. Motivated by Borusyak, Dix-Carneiro & Kovak (2022), we include the distance-weighted exposure to robots in surrounding CZs in our regression specification.[21] Panel B of Table 3 shows that our results do not materially change by adding this control.

We contend that our results are not driven by areas with too many or too few immigrants. Panel C indicates that our results are unchanged if we exclude regions with less than 100 immigrants. On the other hand, immigrants, especially undocumented immigrants, comprise a much larger proportion of the population in states that share a border with Mexico (Arizona, California, New Mexico and Texas). Removing these states from the analysis results in no significant changes, as shown in Panel D.[22]

Another potential concern might be that the results are based on only one period (2000). The 2013-2017 ACS contains information about respondents' movement for the past year, as opposed to for the past five years, as in the 2000 Census. We thus construct annual migration rates by aggregating inflows and outflows over the last two years of the sample. Appendix Table B.8 displays the response to robot exposure through the various channels for low-skilled men. Annual migration rates are much smaller than migration rates over five years (Molloy et al. 2011), which implies that the response to robot exposure using annual migration rates would also be smaller. Only the coefficient for inflows (-1.79) is statistically significant at the 5% level. Estimates based on annual migration rates are likely to be a lower bound of true migration responses, as mobility costs reduce labour market adjustments in the short term (Caliendo et al.

[21]This measure is computed as:

$$\Delta R^{EURO5}_{-i,t} = \sum_{k \neq i} \phi_{ki} \Delta R^{EURO5}_{k,t} \tag{5}$$

where $\Delta R_{k,t}$ is the robot exposure to CZ k and ϕ_{kj} captures the strength of migration flows between CZ k and j using the inverse of the geographical distance between the CZs. Greenland et al. (2019) applies a similar concept while analyzing the effect of import competition from China on internal migration. The weights reflect the importance of migration costs across origin-destination pairs as in gravity models of trade. We assume that the attractiveness of other locations is identical for immigrants and natives.

[22]We provide several sensitivity checks to also alleviate such concerns about our findings in Table 1. First, coefficients are unchanged when excluding CZs with a few immigrants (< 100) and are insensitive to the exclusion of states that share a boundary with Mexico (Appendix Table B.4). Second, the striking difference in the growth of low-skilled population by nativity becomes more prominent when using nativity-specific weights to account for heteroskedasticity in CZ population sizes by nativity (Appendix Table B.5), as recommended by Cadena & Kovak (2016).

2019). Nonetheless, we demonstrate that internal migration of low-skilled immigrants in response to robot exposure occurred during both the early and later periods in the sample.

3.3 Robustness

We now briefly report the various ways through which we probe the sensitivity of our findings regarding the population change in low-skilled immigrants to automation, as detailed in Appendix B.9. First, our results are not driven by pre-existing CZ trends (Appendix Table B.9), i.e., the supply of low-skilled labour before 1990 is associated with labour-displacing robot adoption (Lewis 2011, Mann & Pozzoli 2023). We also show that our results are robust to controlling for pre-trends through immigrant share in 1990, or change in population between 1970 and 1990 (Appendix Table B.10). Second, Appendix Table B.11 highlights that our results are robust when using long-difference, three periods (1990-2000, 2000-2007 and 2007-2015) and two periods (1990-2000 and 2000-2007) stacked-differences specifications. The similarity of the results between the three and two periods stacked-differences models implies that the financial crisis of 2007 cannot account for our findings.

Third, our results are robust to alternate robot-exposure measures or empirical specifications (Appendix Table B.12), such as when 1) including more countries (Germany and UK) in the robot exposure measure; 2) removing CZs with the highest exposure; 3) including robot exposure of neighbouring CZs; and, 4) including state-period dummies instead of division-year dummies. Finally, the precision of the estimates is robust to clustering standard errors at the CZ instead of the state level, or accounting for between-state correlations due to industry shocks, following Borusyak, Hull & Jaravel (2022) (Appendix Table B.13).

In conclusion, this section presents distinct differences in the sensitivity of low-skilled immigrants and natives to robot exposure. The introduction of robots led to a substantial labor reallocation of the low-skilled immigrant workforce.

4 Immigrant mobility and native-born workers

The decreased entry and increased exit of low-skilled immigrants from highly robot-exposed regions would reduce the immigrant labour supply in those areas.[23] If less skilled immigrants and natives work in similar industries, then the location choice of immigrants can impact natives' labour market outcomes across CZs. Figure 3 highlights the employment share of low-skilled immigrants and natives, and robot adoption for each industry. Low-skilled immigrants and natives compete for similar jobs, as only a few industries, such as agriculture and education, employ a disproportionate share of immigrant and native workers.[24]

The higher out-migration and lower in-migration of low-skilled immigrants to robot-exposed locations would lower the competition experienced by the low-skilled native workforce (Dustmann et al. 2017). The cushioning effect can manifest through increased employment opportunities and/or higher wages for the same jobs. The lower entry of immigrants can also mitigate the impact on native workers by reducing congestion in the housing market (Monras 2020).[25] By contrast, the lower population growth of low-skilled immigrants can amplify the negative impact of industrial robots by further reducing the demand for local goods and services (Hong & McLaren 2015).

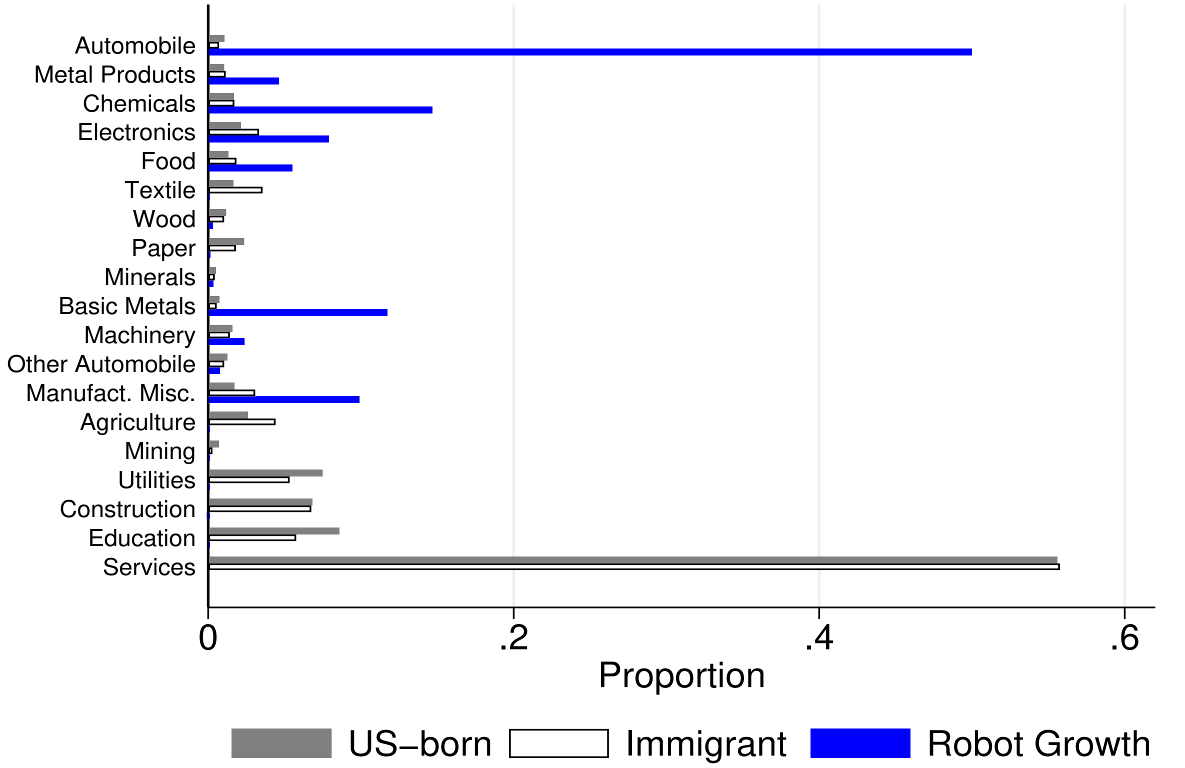
We exploit variation in the share of immigrants across US CZs to examine the effect of immigrant mobility on the native workforce due to robot exposure. The baseline empirical specification (Equation 2) is modified by including an interaction term between the immigrant share in CZ i in 1990 $\left(\frac{N^I_{i,1990}}{N_{i,1990}}\right)$ and robot exposure at the CZ level. We use the immigrant share in 1990 instead of the current immigrant share in our stacked-difference specification to overcome potential reverse causality, as outlined

[23] Consistent with our hypothesis, we show in Appendix Table C.1 that CZs with an above-median low-skilled immigrant share in 1990 experienced: (1) a larger decrease in the low-skilled CZ population; and, 2) a smaller decrease in the highly skilled CZ population, relative to below-median low-skilled immigrant share areas.

[24] The maximum absolute difference in employment share is 3.7 pp. Moreover, one can compute the measure of labour market competition suggested by Altonji & Card (1991). As per this measure, a value of one implies a homogeneous labour market. We show that the labour market competition index between low-skilled immigrants and natives is 0.99 using the 1990 Census sample. See Appendix C.7 for more details.

[25] A fall in the arrival of immigrants would place less upward pressure on local housing prices, thus diminishing, the decrease in a location's real value (nominal wages relative to housing price).

Figure 3: The employment shares of low-skilled workers within a nativity group and growth in robot per thousand workers by industry



Note: Employment shares are computed for low-skilled workers within each nativity group. Growth in robots per thousand workers is normalised such that the maximum and minimum growth rates are 0.5 and 0, respectively.

below:

$$\Delta y_{i,t} = \alpha_{d,t} + \beta_1 \Delta R^{US}_{i,t} * \frac{N^I_{i,1990}}{N_{i,1990}} + \beta_2 \Delta R^{US}_{i,t} + \beta_3 \frac{N^I_{i,1990}}{N_{i,1990}} + \gamma X_{i,t} + \varepsilon_{i,t} \tag{6}$$

The dependent variables are the changes in log employment and log average hourly wages of native workers. We multiply the dependent variables by 100 and scale them to 10-year equivalent changes. The coefficient of interest is β_1; a positive coefficient implies that the migration response of immigrants reduces the incidence of robot exposure on natives. In contrast, a null coefficient indicates that immigrants' location choices do not equalise spatial differences in the impact of robot exposure on native workers.

A possible concern with this approach is that the distribution of immigrants across local labour markets is not random but is usually influenced by economic prospects (Abramitzky & Boustan 2017). We address this concern by instrumenting the immigrant share in 1990 with the share in 1970, as recent immigrants are more likely to settle in locations where past immigrants are concentrated, following Borjas (1995) and Card & DiNardo (2000). Appendix Figure C.1 shows that the low-skilled immigrant share in 1970 explains 73% of the variation in the immigrant share in 1990. Furthermore, the correlation between robot exposure and the 1990 immigrant share is low (-0.11), implying that areas with a high robot concentration and those with a high proportion of immigrants do not overlap. A low correlation suggests that there is sufficient power to independently isolate the effects of robot exposure and immigrant mobility.[26]

Table 4: Effects on natives' labour market outcomes, stacked-differences 1990–2015 (2SLS): Interacting robot exposure and low-skilled immigrant share

Dependent variable: Change in log employment or change in log wages						
	Employment			Wage		
	Overall	Low-skill	High-skill	Overall	Low-skill	High-skill
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure x Share 1990	0.79	7.70	1.18	11.62	19.82***	8.63
	(16.37)	(12.80)	(19.97)	(10.01)	(7.64)	(9.29)
Exposure to robots	-1.68***	-1.66***	-1.70***	-1.27***	-1.57***	-1.21***
	(0.52)	(0.60)	(0.58)	(0.26)	(0.23)	(0.26)
Immigrant Share 1990	-24.98	-50.42***	-24.19	-8.46	-17.67***	-5.75
	(16.09)	(10.99)	(19.19)	(7.05)	(4.10)	(6.73)
Observations	1444	1444	1444	1444	1444	1444
R-squared	0.79	0.83	0.74	0.89	0.88	0.88

Note: All regression estimates are weighted by the CZ population in 1990. Standard errors clustered at the state level are reported in parentheses. ***, ** and * represent the statistical significance at 1%, 5% and 10% levels respectively. Regressions include time-division dummies and covariates: stock of computer capital per worker in 1990; exposure to Chinese imports; year interaction with demographic and industry characteristics in 1990 (log population, share of male population, population shares of Whites, Blacks and Hispanics, share of the population over 65 years old, shares of the population with no college, some college and more than college, female employment share, share of employment in agriculture, mining, construction, light manufacturing and manufacturing, routine employment share and average offshorability index).

The first row of Table 4 reports the 2SLS estimates on the employment and wages of native-workers related to robot exposure and immigrants' location choices.[27] The coefficient for total native employment is small (0.79) and insignificant, which suggests

[26] We rule out any significant pre-trends between the employment and wages of natives and robot exposure in areas with many and few low-skilled immigrants (Appendix Table C.2).

[27] In line with Acemoglu & Restrepo (2020) and Javed (2023), we also find that robot penetration adversely affects the labour market outcomes of natives. There is, however, a lack of consensus in the literature on the impact of an immigration shock on local labour markets (Borjas 2003, Boustan et al. 2010, Caiumi & Peri 2024, Card 1990, Dustmann et al. 2017, Gyetvay & Keita 2023).

that the impact of automation on employment is similar in areas with many and few immigrants. The coefficient for low-skilled employment is stronger (7.90), but imprecisely estimated. Therefore, on average, low-skilled immigrants' location choices do not alleviate employment opportunities for low-skilled natives to automation. The null average effect also does not preclude the possibility of natives workers in some industries benefiting from immigrant mobility, an issue that we discuss in more detail below.

Contrastingly, immigrant mobility attenuates wage losses from robot exposure for low-skilled natives. The coefficient of 19.82 in column 5 predicts that the decrease in the wages of native workers is lower by 0.07 pp when comparing between CZs at the 50^{th} and 25^{th} percentiles of the low-skilled immigrant share. The mean robot exposure is 0.9, and the 50^{th} and 25^{th} percentiles of the shares of low-skilled immigrants are 0.9% and 0.5%, respectively (0.07 = 0.9*0.1982*[0.9-0.5]). Alternatively, the wages of natives at the 75^{th} percentile of the share of low-skilled immigrants share (2.1%) would decrease by 0.285 pp (0.285 = 0.9*0.1982*[2.1-0.5]) less relative to the 25^{th} percentile.

One possible explanation for our findings is that there is an unobserved factor that causes some CZs to adjust favourably to adverse shocks and is also correlated with the share of low-skilled immigrants (e.g., Cortes & Tessada (2011) finds that a higher proportion of low-skilled workers leads to an increase in the labour supply of high-skilled women.). One way to test this hypothesis is to compare the labour market outcomes of high-skilled native workers in areas with different shares of low-skilled immigrants. The insignificant effects in columns 3 and 6 show that such a hypothesis is unlikely to be the main explanation for our findings. Furthermore, this is not because automation does not affect high-skilled workers. Consistent with Acemoglu & Restrepo (2020), the significantly negative estimates in the second row prove that robot exposure also adversely impacts high-skilled workers.

The mobility of low-skilled natives cannot rationalize our finding because the decline in low-skilled native population in response to robot penetration does not differ between CZs with many and few immigrants (Appendix Table C.3). One potential concern with the lagged immigrant share as an IV is the possibility of long-term effects of past immigration. Jaeger et al. (2018) argues that including the immigrant share of intervening years in the regression can absorb the impact of past immigration shocks.

Appendix Table C.4 shows that our results change little after including the intermediate immigrant share in 1980 as a control. Appendix Table C.4 also shows that the mitigating wage effects are insensitive to using established low-skill immigrant share rather than the average low-skilled immigrant share. Furthermore, results are robust to using alternate stacked- and long-difference specifications (Appendix Table C.5).

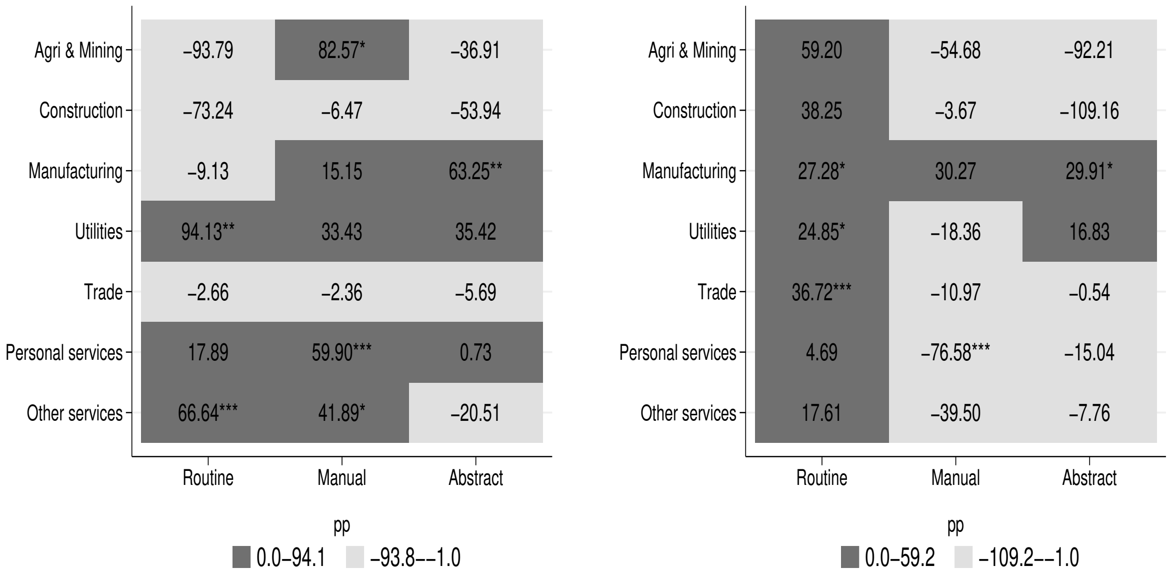
4.1 Heterogeneity by task and industry

We investigate the impact of immigrant mobility on low-skilled natives' labour market outcomes along the task-industry dimension. The outcome variables are changes in the log employment and log average hourly wages in each task-industry cell for low-skilled natives. In Figures 4a and 4b, we report the coefficient of the interaction term (β_1) in Equation (6) by 24 task-industry combinations in relation to native employment and wages, respectively.

Figure 4: Effects on natives' labour market outcomes by task-industry cells, stacked-differences 1990–2015 (2SLS)

(a) Employment

(b) Wage



Note: Panels (a) and (b) show the β_1 coefficient in Equation (6) for change in log employment and change in log wages, respectively. All regression estimates are weighted by the CZ population in 1990. Standard errors are clustered at the state level. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels respectively.

A few distinct patterns emerge when analysing the Figures 4a and 4b. First, most of the mitigating effects are concentrated among routine and manual occupations.

Since these occupations heavily rely on low-skilled labour, the reduction in competition through low-skilled immigrant mobility, benefits native workers in these occupations. Second, the null average effect for employment masks considerable heterogeneity along the task-industry dimension. That is, mitigating effects of immigrant mobility on native employment exist in the utilities and other service sectors. The insignificant average cushioning effect on employment in Table 4 is because these industries do not constitute a large proportion of the workforce (Appendix Figure C.2). The mitigating wage effects are concentrated among routine occupations, which is sensible since robots can easily replace routine tasks. Third, attenuating effects are present in the non-manufacturing sectors, which indicates that robot exposure can also indirectly affect low-skilled workers. The decline in the population growth of high-skilled workers from robot-exposed regions, as we documented in Table 1, can reduce employment of low-skilled workers through fall in aggregate demand. The mobility of low-skilled immigrant workers can reduce some of the losses of incumbent low-skilled native workers.[28]

Differences in the degree of competition between immigrants and groups of natives that vary by race (White, Black and Hispanic) and gender can also lead to heterogeneous effects. Figures 5a and 5b report the mitigating effect of immigrant mobility on low-skilled natives' employment and wages, respectively. The decrease in wages due to robot exposure is significantly lower for Hispanic men and women, as well as White and Black women, in areas with a higher share of immigrants. Immigrant mobility has the strongest smoothening effect on the employment of Hispanic men, but the point estimate is insignificant.

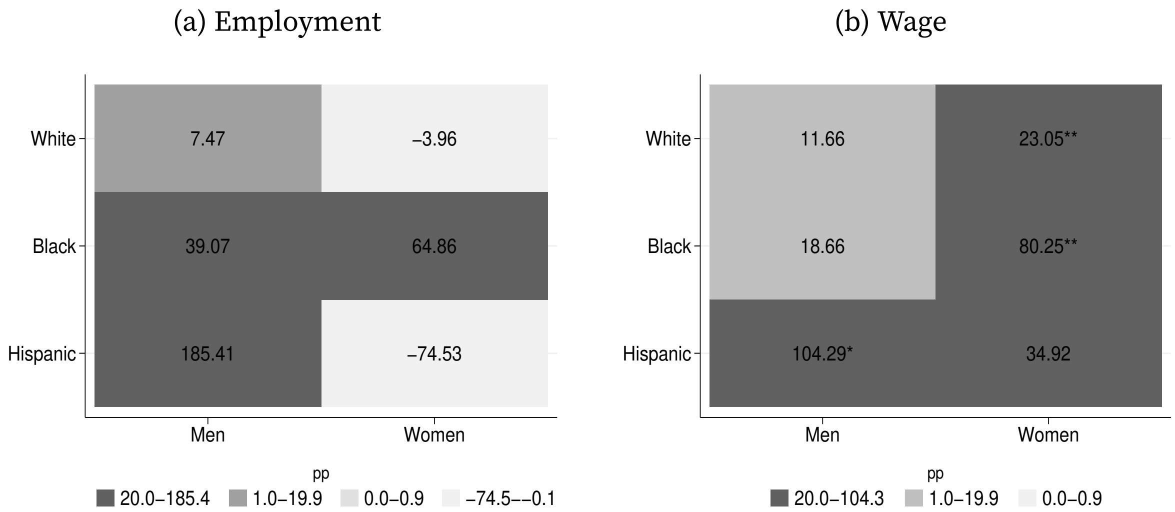
Appendix Table C.6 shows that competition experienced by these groups (low-skilled women and low-skilled Hispanic men) reacts the most to changes in low-skilled immigrant population.[29] Lerch (2024) documents that robot exposure increased the race/ethnicity employment gap, but not the wage gap. Moreover, robot penetration reduced the gender wage gap (Ge & Zhou 2020, Lerch 2024). Ge & Zhou (2020) and Lerch (2024) argue that differences in physical and cognitive skills across groups explains

[28] Other possible explanations for the observed heterogeneous effects include differences in contractual practises (e.g., wage rigidity and firing restrictions) or the nature of production processes (e.g., the degree of substitutability between robots, low-skilled immigrants and low-skilled natives) across sectors.

[29] See Appendix C.7 for more details on the construction of the labour market competition index following Altonji & Card (1991).

these patterns. Our results show that the mobility of low-skilled immigrants can be an additional channel that contributed to the change in wage gap to robot exposure across groups.

Figure 5: Effects on natives' labour market outcomes by gender-race cells, stacked-differences 1990–2015 (2SLS)



Note: Panels (a) and (b) show the β_1 coefficient in Equation (6) for change in log employment and change in log wages, respectively. All regression estimates are weighted by the CZ population in 1990. Standard errors are clustered at the state level. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels respectively.

Overall, the findings in this section highlight that immigrants' location choices reduce spatial inequality for native-workers. We show that the mitigating effects of immigrant mobility exist in both the manufacturing and the non-manufacturing sectors, suggesting that the effects experienced by immigrant workers in the service sector might be a potential mechanism underlying their strong migratory response to robot penetration.

5 Why immigrants are more mobile

We now examine the reasons for the greater decrease in population growth among low-skilled immigrants compared with native-born individuals.

5.1 Employment: Direct and indirect effects

The overt differences in the migratory responses of low-skilled immigrants and natives may be due to differences in the effects of robot exposure on employment opportunities. Table 5 provides evidence supporting this hypothesis. Specifically, the reduction in the employment of low-skilled immigrants due to robot exposure is five times more than the corresponding reduction for equally skilled natives. The differential incidence of robot exposure between high-skilled immigrants and natives is also in line with their population response. Hence, economic factors influence location decisions.

Table 5: Effects on employment by skill, stacked-differences (2SLS)

Dependent variable: Change in log employment				
	Low-skill		High-skill	
	Immigrant	Native	Immigrant	Native
	(1)	(2)	(3)	(4)
Exposure to robots	-6.53***	-1.30**	0.04	-1.58***
	(2.29)	(0.51)	(1.14)	(0.38)
Observations	1443	1444	1444	1444
R^2	0.69	0.82	0.54	0.74

Note: All regression estimates are weighted by the CZ population in 1990. Standard errors clustered at the state level are reported in parentheses. ***, ** and * represent the statistical significance at 1%, 5% and 10% levels respectively. Regressions include time-division dummies and covariates: stock of computer capital per worker in 1990; exposure to Chinese imports; year interaction with demographic and industry characteristics in 1990 (log population, low-skill population change between 1970-1990, share of male population, population shares of Whites, Blacks and Hispanics, share of the population over 65 years old, shares of the population with no college, some college and more than college, female employment share, share of employment in agriculture, mining, construction, light manufacturing and manufacturing, routine employment share and average offshorability index).

Both direct and indirect effects might be responsible for the differential incidence of robot exposure between low-skilled immigrants and natives. Javed (2023) shows that a higher proportion of immigrants are employed in routine manual jobs than natives. This can directly lead to an asymmetric impact of robot exposure by nativity groups. Another potential channel is the spillover from highly skilled workers. Appendix Table B.6 that high-skilled workers depart robot-exposed regions because of decline in jobs (Table 5). The resulting fall in demand can also adversely affect low-skilled immigrants.

We provide suggestive evidence to corroborate this view.

We show that the effect of robot penetration on low-skilled immigrants' population and employment is stronger in CZs that are surrounded by highly skilled workers. We thus compute the share of highly skilled workers in the vicinity of a CZ. We classify a CZ as having a 'high-skilled neighbour' (HSN) if the share of high-skilled workers in neighbouring areas is greater than the national average, while it is classified as a 'low-skilled neighbour' (LSN) otherwise. Table 6 shows that the introduction of robots leads to a greater decrease in the low-skilled immigrant population and employment in CZs surrounded by highly skilled workers compared with low-skilled workers. Therefore, both direct and indirect effects might be responsible for the pronounced migration response of low-skilled immigrants.

Table 6: Effects on relative low-skilled immigrant population or employment growth by neighbouring CZs' initial skill intensity, stacked-differences (2SLS)

Dependent variable: Change in log of immigrant to native population or employment of low-skill individuals				
	Population		Employment	
	HSN	LSN	HSN	LSN
	(1)	(2)	(3)	(4)
Exposure to robots	-8.93*	-4.59*	-8.93**	-5.44**
	(4.61)	(2.56)	(3.83)	(2.69)
Observations	416	1028	416	1027
R^2	0.79	0.68	0.75	0.66

Note: HSN and LSN refer to High-skill and Low-skill neighbouring CZ, respectively. All regression estimates are weighted by the CZ population in 1990. Standard errors clustered at the state level are reported in parentheses. ***, ** and * represent the statistical significance at 1%, 5% and 10% levels respectively. Regressions include time-division dummies and covariates: stock of computer capital per worker in 1990; exposure to Chinese imports; year interaction with demographic and industry characteristics in 1990 (log population, low-skill population change between 1970-1990, share of male population, population shares of Whites, Blacks and Hispanics, share of the population over 65 years old, shares of the population with no college, some college and more than college, female employment share, share of employment in agriculture, mining, construction, light manufacturing and manufacturing, routine employment share and average offshorability index).

5.2 Differential exposure and other explanations

Our baseline measure of robot exposure does not distinguish between labour demand shocks that differentially affect immigrants and natives. Differences in employment shares within industries by nativity can imply asymmetric response to robot exposure by nativity status. We compute nativity-specific robot exposure using the group-specific industry employment share and standardise the two measures to ease comparison of estimates. Appendix D.1 contains further details about the construction of these two measures.

Table 7 shows the 2SLS and first-stage estimates using regression specifications for which we introduce the two measures separately and then jointly. Consistent with our previous findings, the population growth of low-skilled immigrants decreases more significantly than the population of low-skilled natives using either of the two measures. The low-skilled immigrant (native) population growth estimate is -2.32 (-0.35) and -3.94 (-0.79) using the immigrant-specific and native-specific robot exposure measures, respectively. However, the coefficient for low-skilled immigrants is smaller in magnitude using the immigrant-specific robot exposure (-1.18) measure compared to when using the native-specific measure (-3.18), as shown in the top panel of column 3. This is likely due to the lack of statistical predictive power in the first-stage when both measures are used; the Kleibergen-Paap F-statistic is only 17.85 for the EURO5 native-specific robot measure in column 3, while it is less than 2 for immigrant-specific robot exposure when we use both measures in column 6.

The correlation between the two nativity-specific measures is high (0.64), and their distributions overlap considerably (Appendix Figure D.1). This low predictive power stems from the similarity in the employment shares of natives and immigrants across industries, as we showed in Figure 3. Therefore, we lack sufficient power to test whether the asymmetric mobility responses among nativity groups are due to the differential intensity of robot exposure by nativity.

There may be other relevant factors; for example, immigrants might have a better social network than natives, allowing them to better evaluate the attractiveness of other locations (Caballero et al. 2023, Munshi 2003). Future research using firm-worker longitudinal data can test the role of social networks in explaining migratory responses to automation.

Table 7: Effects on low-skilled population change to nativity-specific robot exposure, stacked-differences 1990–2015 (2SLS)

Dependent variable: Change in log population						
	Immigrant			Native		
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure to robots (Immigrant-specific)	-2.32		-1.18	-0.35		-0.08
	(1.61)		(1.80)	(0.32)		(0.36)
Exposure to robots (Native-specific)		-3.94**	-3.18*		-0.79**	-0.74
		(1.61)	(1.89)		(0.38)	(0.50)
Observations	1426	1444	1426	1426	1444	1426
R^2	0.70	0.70	0.70	0.81	0.82	0.82
2SLS First Stage: Native-specific robot exposure						
Instrumented by:	Immigrant-specific			Native-specific		
	(1)	(2)	(3)	(4)	(5)	(6)
Predicted Exposure to robots (Immigrant-specific)	0.67***		0.59***	0.24**		-0.02
	(0.08)		(0.09)	(0.10)		(0.01)
Predicted Exposure to robots (Native-specific)		0.61***	0.30***		0.97***	0.98***
		(0.07)	(0.07)		(0.07)	(0.07)
Observations	1426	1426	1426	1426	1444	1426
R-squared	0.77	0.61	0.79	0.71	0.96	0.96
Kleibergen-Paap F (Immigrant)	69.66		45.71	5.43		1.76
Kleibergen-Paap F (Native)		76.17	17.85		179.14	179.07

Note: All regression estimates are weighted by the CZ population in 1990. Standard errors clustered at the state level are reported in parentheses. ***, ** and * represent the statistical significance at 1%, 5% and 10% levels respectively. Covariates include stock of computer capital per worker in 1990; exposure to Chinese imports; year interaction with demographic and industry characteristics in 1990 (log population, low-skill population change between 1970-1990, share of male population, population shares of Whites, Blacks and Hispanics, share of the population over 65 years old, shares of the population with no college, some college and more than college, female employment share, share of employment in agriculture, mining, construction, light manufacturing and manufacturing, routine employment share and average offshorability index).

6 Conclusion

In this paper, we demonstrate that low-skilled immigrants' location choices are more sensitive to robot exposure than similarly skilled natives. The introduction of robots reduced entry and increased departure of low-skilled immigrants into CZs with robot penetration. Moreover, immigrants' location choices reduce spatial inequality for native workers. The decrease in income due to robot exposure is smaller in areas with substantial low-skilled immigrant populations. Although, on average, job losses from automation are not influenced by immigrant mobility, there is sizeable heterogeneity along the task-industry dimension.

These novel findings have significant economic implications. Policymakers are struggling to find long-term solutions to alleviate the economic impact of labour-displacing technological changes. Low-skilled immigrants can play an important role in insulating native-workers from local shocks. This is particularly relevant given the stronger support for restricting the entry of low-skilled immigrants into the US when natives experience job losses.

Finally, our results highlight that individuals' respond to changes in economic opportunities through location choices. Therefore, future research should consider the role of migration when examining the effects of localized shocks.

References

Abraham, K. G. & Kearney, M. S. (2020), 'Explaining the decline in the us employment-to-population ratio: A review of the evidence', *Journal of Economic Literature* **58**(3), 585–643.

Abramitzky, R. & Boustan, L. (2017), 'Immigration in american economic history', *Journal of economic literature* **55**(4), 1311–1345.

Acemoglu, D. & Restrepo, P. (2020), 'Robots and jobs: Evidence from us labor markets', *Journal of Political Economy* **128**(6), 2188–2244.

Acemoglu, D. & Restrepo, P. (2022), 'Tasks, Automation, and the Rise in U.S. Wage Inequality', *Econometrica* **90**(5), 1973–2016.

Adachi, D., Kawaguchi, D. & Saito, Y. U. (2024), 'Robots and employment: Evidence from japan, 1978–2017', *Journal of Labor Economics* **42**(2), 591–634.

Aghion, P., Antonin, C., Bunel, S. & Jaravel, X. (2023), 'The local labor market effects of modern manufacturing capital: Evidence from france', *AEA Papers and Proceedings* **113**, 219–23.

Altonji, J. G. & Card, D. (1991), The effects of immigration on the labor market outcomes of less-skilled natives, *in* 'Immigration, Trade, and the Labor Market', University of Chicago Press, chapter 7, pp. 201–234.

Anelli, M., Colantone, I. & Stanig, P. (2021), 'Individual vulnerability to industrial robot adoption increases support for the radical right', *Proceedings of the National Academy of Sciences of the United States of America* **118**(47), e2111611118.

Autor, D., Chin, C., Salomons, A. & Seegmiller, B. (2024), 'New frontiers: The origins and content of new work, 1940–2018', *The Quarterly Journal of Economics* .
URL: *https://doi.org/10.1093/qje/qjae008*

Autor, D., Dorn, D. & Hanson, G. (2019*a*), 'Replication data for: When Work Disappears: Manufacturing Decline and the Falling Marriage Market Value of Young Men'.

Autor, D., Dorn, D. & Hanson, G. (2019*b*), 'When Work Disappears: Manufacturing Decline and the Falling Marriage Market Value of Young Men', *American Economic Review: Insights* **1**(2), 161–178.

Autor, D. H. & Dorn, D. (2013), 'The growth of low-skill service jobs and the polarization of the us labor market', *American Economic Review* **103**(5), 1553–1597.

Autor, D. H., Dorn, D. & Hanson, G. H. (2013), 'The china syndrome: Local labor market effects of import competition in the united states', *American economic review* **103**(6), 2121–2168.

Autor, D. & Salomons, A. (2018), 'Is Automation Labor Share-Displacing? Productivity Growth, Employment, and the Labor Share', *Brookings Papers on Economic Activity* pp. 1–63.

Bartik, T. J. (1991), 'Who benefits from state and local economic development policies?', *WE Upjohn Institute for Employment Research* .

Basso, G., D'Amuri, F. & Peri, G. (2019), 'Immigrants, labor market dynamics and adjustment to shocks in the euro area', *IMF Economic Review* **67**, 528–572.

Basso, G., Peri, G. & Rahman, A. S. (2020), 'Computerization and immigration: Theory and evidence from the united states', *Canadian Journal of Economics* **53**(4), 1457–1494.

Beaudry, P., Doms, M. & Lewis, E. (2010), 'Should the Personal Computer Be Considered a Technological Revolution? Evidence from U.S. Metropolitan Areas', *Journal of Political Economy* **118**(5), 988–1036.

Beraja, M. & Zorzi, N. (2021), 'Inefficient Automation', *NBER Working Paper 30154* .

Black, D., McKinnish, T. & Sanders, S. (2005), 'The economic impact of the coal boom and bust', *The Economic Journal* **115**(503), 449–476.

Blanchard, O. & Katz, L. F. (1992), 'Regional evolutions', *Brookings Papers on Economic Activity* **1992**(1), 1–75.

Bloom, N., Handley, K., Kurman, A. & Luck, P. (2019), 'The Impact of Chinese Trade on U.S. Employment : The Good, The Bad, and The Debatable', *Working Paper* .

Board, T. C. (2023), EU KLEMS July 2018 Release, DataverseNL.
URL: *https://doi.org/10.34894/6GDD7Q*

Borjas, G. J. (1995), 'Ethnicity, Neighborhoods, and Human-Capital Externalities', *American Economic Review* **85**, 365–390.

Borjas, G. J. (2001), 'Does Immigration Grease the Wheels of the Labor Market?', *Brookings Papers on Economic Activity* **2001**(1), 69–119.

Borjas, G. J. (2003), 'The Labor Demand Curve Is Downward Sloping: Reexamining the Impact of Immigration on the Labor Market', *The Quarterly Journal of Economics* **118**(4), 1335–1374.

Borusyak, K., Dix-Carneiro, R. & Kovak, B. (2022), 'Understanding migration responses to local shocks', *SSRN Working Paper 4086847* .

Borusyak, K., Hull, P. & Jaravel, X. (2022), 'Quasi-Experimental shift-share research designs', *The Review of Economic Studies* **89**(1), 181–213.

Bound, J. & Holzer, H. J. (2000), 'Demand Shifts, Population Adjustments, and Labor Market Outcomes during the 1980s', *Journal of Labor Economics* **18**(1), 20–54.

Boustan, L. P., Choi, J. & Clingingsmith, D. (2022), 'Automation After the Assembly Line: Computerized Machine Tools, Employment and Productivity in the United States', *NBER Working Paper No. 30400* .

Boustan, L. P., Fishback, P. V. & Kantor, S. (2010), 'The Effect of Internal Migration on Local Labor Markets: American Cities during the Great Depression', *Journal of Labor Economics* **28**(4), 719–746.

Brey, B. (2021), 'The Effect of Recent Technological Change on US Immigration Policy', *CESifo Working Paper No. 9302* .

Caballero, M. E., Cadena, B. C. & Kovak, B. K. (2023), 'The international transmission of local economic shocks through migrant networks', *Journal of International Economics* **145**, 103832.

Cadena, B. C. & Kovak, B. K. (2016), 'Immigrants Equilibrate Local Labor Markets: Evidence from the Great Recession', *American Economic Journal: Applied Economics* **8**(1), 257–290.

Caiumi, A. & Peri, G. (2024), 'Immigration's effect on us wages and employment redux', *NBER Working Paper No. 32389* .

Caliendo, L., Dvorkin, M. & Parro, F. (2019), 'Trade and labor market dynamics: General equilibrium analysis of the china trade shock', *Econometrica* **87**(3), 741–835.

Card, D. (1990), 'The impact of the mariel boatlift on the miami labor market', *Ilr Review* **43**(2), 245–257.

Card, D. & DiNardo, J. (2000), 'Do immigrant inflows lead to native outflows?', *American Economic Review* **90**(2), 360–367.

Cortes, P. & Tessada, J. (2011), 'Low-skilled immigration and the labor supply of highly skilled women', *American Economic Journal: Applied Economics* **3**(3), 88–123.

Dauth, W., Findeisen, S., Suedekum, J. & Woessner, N. (2021), ' The Adjustment of Labor Markets to Robots', *Journal of the European Economic Association* **19**(6), 3104–3153.

Di Giacomo, G. & Lerch, B. (2023), 'Automation and Human Capital Adjustment', *Journal of Human Resources (Forthcoming)* .

Dustmann, C., Schönberg, U. & Stuhler, J. (2017), 'Labor Supply Shocks, Native Wages, and the Adjustment of Local Employment', *The Quarterly Journal of Economics* **132**(1), 435–483.

Faber, M., Sarto, A. & Tabellini, M. (2022), 'Local Shocks and Internal Migration : The Disparate Effects of Robots and Chinese Imports in the US', *NBER Working Paper No. 30048* .

Ge, S. & Zhou, Y. (2020), 'Robots, computers, and the gender wage gap', *Journal of Economic Behavior and Organization* **178**, 194–222.

Gihleb, R., Giuntella, O., Stella, L. & Wang, T. (2022), 'Industrial robots, workers' safety, and health', *Labour economics* **78**, 102205.

Goldin, C. & Katz, L. F. (2009), *The race between education and technology*, harvard university press.

Graetz, G. & Michaels, G. (2018), 'Robots at Work', *The Review of Economics and Statistics* **100**(5), 753–768.

Greenland, A., Lopresti, J. & Mchenry, P. (2019), 'Import competition and internal migration', *The Review of Economics and Statistics* **101**(March), 44–59.

Guerreiro, J., Rebelo, S. & Teles, P. (2022), 'Should robots be taxed?', *The Review of Economic Studies* **89**(1), 279–311.

Gyetvay, S. & Keita, S. (2023), 'Competition, mobility and immigration', *Working Paper* .

Hershbein, B. & Stuart, B. (2022), 'The evolution of local labor markets after recessions', *FRB of Philadelphia Working Paper No. 22-16* .

Hirvonen, J., Stenhammar, A. & Tuhkuri, J. (2022), 'New Evidence on the Effect of Technology on Employment and Skill Demand', *SSRN Working Paper 4081625* .

Hong, G. & McLaren, J. (2015), 'Are immigrants a shot in the arm for the local economy?', *NBER Working Paper No. 21123* .

Humlum, A. (2021), 'Robot adoption and labor market dynamics', *Working Paper* .

Huttunen, K., Møen, J. & Salvanes, K. G. (2018), 'Job Loss and Regional Mobility', *Journal of Labor Economics* **36**(2), 479–509.

IFR (1993-2015), International Federation of Robotics.
URL: *https://ifr.org/*

Jaeger, D. A., Stuhler, J. & Joakim, R. (2018), 'Shift-Share Instruments and the Impact of Immigration', *NBER Working Paper No. 24285* .

Jaimovich, N., Saporta-Eksten, I., Siu, H. & Yedid-Levi, Y. (2021), 'The macroeconomics of automation: Data, theory, and policy analysis', *Journal of Monetary Economics* **122**, 1–16.

Javed, M. (2023), 'Robots, natives and immigrants in us local labor markets', *Labour Economics* **85**, 102456.

Koch, M., Manuylov, I. & Smolka, M. (2021), 'Robots and Firms', *The Economic Journal* **131**(638), 2553–2584.

Lehr, N. H. & Restrepo, P. (2022), 'Optimal Gradualism', *NBER Working Paper No. 30755* .

Lerch, B. (2022), 'Robots and Non-Participation in the Us: Where Have All the Workers Gone?', *SSRN Electronic Journal* .

Lerch, B. (2024), 'From blue to steel-collar jobs: The decline in employment gaps?', *American Economic Journal: Macroeconomics (Forthcoming)* .

Lewis, E. (2011), 'Immigration, Skill Mix and Capital Skill Complementarity', *The Quarterly Journal of Economics* **126**(2), 1029–1069.

Mann, K. & Pozzoli, D. (2023), 'Robots and Low-skill Labor', *Working Paper* .

Michaels, G., Natraj, A. & Reenen, J. V. (2014), 'Has ICT polarized skill demand? Evidence from eleven countries over 25 years', *The Review of Economics and Statistics* **96**(1), 60–77.

Molloy, R., Smith, C. L. & Wozniak, A. (2011), 'Internal Migration in the United States', *Journal of Economic Perspectives* **25**(3), 173–96.

Monras, J. (2020), 'Economic shocks and internal migration', *Working Paper* .

Munshi, K. (2003), 'Networks in the modern economy: Mexican migrants in the us labor market', *The Quarterly Journal of Economics* **118**(2), 549–599.

Notowidigdo, M. J. (2020), 'The incidence of local labor demand shocks', *Journal of Labor Economics* **38**(3), 687—-725.

Olney, W. W. & Thompson, O. (2024), 'The Determinants of Declining Internal Migration', *NBER Working Paper No. 32123* .

Özgüzel, C. (2021), 'The cushioning effect of immigrant mobility', *CESifo Working Paper, No. 9268, Center for Economic Studies and ifo Institute (CESifo), Munich* .

Prettner, K. & Strulik, H. (2020), 'Innovation, automation, and inequality: Policy challenges in the race against the machine', *Journal of Monetary Economics* **116**, 249–265.

Ruggles, S., Flood, S., Sobek, M., Brockman, D., Cooper, G., Richards, S. & Schouweiler, M. (2023), 'Ipums usa: Version 13.0 [dataset]', *Minneapolis, MN: IPUMS* .

Tolbert, C. M. & Sizer, M. (1996), Us commuting zones and labor market areas: A 1990 update, Technical report, ERS Staff Paper 9614, Rural Economic Division, US Department of Agriculture.

Yu, C. (2023), 'The role of immigrants in the united states labor market and chinese import competition', *Journal of International Economics* **144**, 103792.

Appendix

Sections A, B, C and D correspond to appendix for sections 2, 3, 4 and 5, respectively.

Table of Contents

A Section 2 Appendix: Data

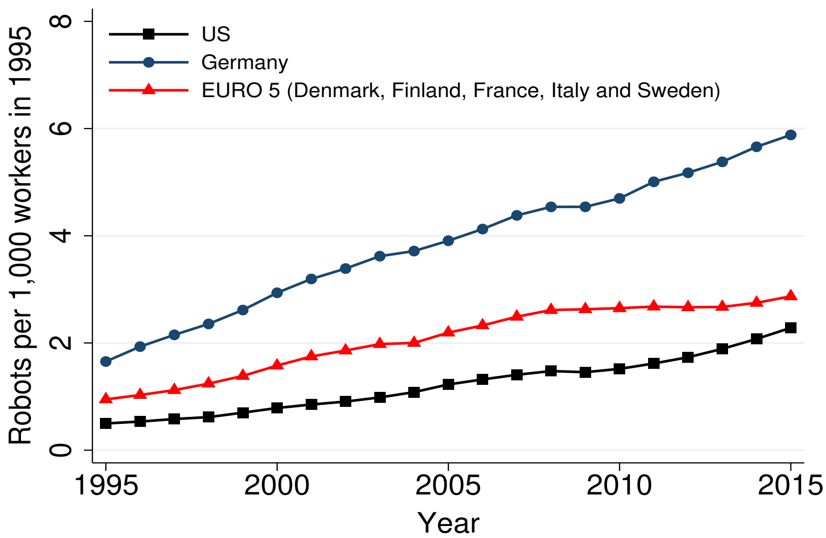
A.1 IFR Robot data

IFR collects data on the stock of industrial robots at the country-industry level since 1993. Industrial robots are defined as an "automatically controlled, reprogrammable multipurpose manipulator, programmable in three or more axes, which can be either fixed in place or fixed to a mobile platform for use in automation applications in an industrial environment (ISO 8373:2021)."[30]

The IFR data have a few shortcomings. Industry-specific data is available for North America from 2004. For years before 2004, we classify the into industries using the distribution in the year 2010. 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. Finally, the stock of robots for US includes Canada and Mexico before 2011. Hence, to maintain consistency, we use the data for North America. This is not an issue because our IV strategy would purge out such measurement error.

A.1.1 Robots per thousand workers in industrialized economies

Figure A.1: Robots per thousand workers in US and selected countries



[30]The definition can be viewed at the IFR website https://ifr.org/industrial-robots.

Figure A.1 shows the trend of robots per thousand workers in North America, Germany, and EURO5 (Denmark, Finland, France, Italy and Sweden) countries. The average growth in robot adoption for EURO5 countries is a simple average over all the countries. The number of industrial robots per thousand workers has steadily increased in all the aforementioned countries. In North America, the stock of robots increased from 0.5 per thousand workers in 1995 to 2.28 in 2015.

A.1.2 Robot per thousand workers by industry in US

Table A.1 shows that automotive industry showed the strongest growth between 1993 and 2015 in North America, whereas the least increase in robot use has occurred in the service industry.

Table A.1: Robot per thousand workers by industry

	Robot per 1,000 workers in 1990		
Industry	1993	2015	Difference
All Industries	0.404	2.424	2.02
Automotive	11.033	65.117	54.083
Metal products	1.777	6.411	4.633
Plastics and chemicals	3.298	17.757	14.459
Electronics	2.611	14.869	12.259
Food and beverages	1.227	6.678	5.451
Textiles	0.003	0.062	0.06
Wood and furniture	0.009	0.294	0.285
Paper and printing	0.002	0.131	0.129
Minerals	0.028	0.342	0.314
Basic metals	0.046	11.123	11.078
Industrial machinery	0.052	2.317	2.265
Shipbuilding and aerospace	0.047	0.815	0.768
Manufacturing Miscellaneous	0.387	9.825	9.437
Agriculture	0.004	0.074	0.07
Mining	0.001	0.056	0.054
Utilities	0	0.085	0.085
Construction	0.004	0.027	0.023
Education and Research	0.008	0.105	0.098
Services	0	0.005	0.004

A.2 Outcomes and exposure at local labour market level

Our sample consists of non-institutionalized individuals between ages 16-64. Individuals are classified as employed if they have worked in the past year. 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. Hourly wage of each worker is computed as the pre-tax annual labour income 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. Midpoints for the values in each category of the typical hours worked per week are used to compute usual number of hours worked per week. Our definition of employed ensures that the number of employed individuals are equal to the number individuals with a positive wage. This would not be true if employment was defined using the current working status of an individual. Top-coded income is set equal to 1.5 times the value of the top-code. Real wage below the bottom 1% percentile is censored and real wage above the 99$^{\text{th}}$ percentile is winsorized. The Consumer Price Index of 1999 is used to deflate nominal wages.

Following Acemoglu & Restrepo (2020), the growth in the stock of industrial robots in industry j over time is expressed as follows:

$$\Delta R_{j,t} = \frac{R_{j,t_1} - (1 + g_{j,(t,t_1)}) \cdot R_{j,t}}{L_{j,t}} \tag{7}$$

where $R_{j,t}$ is the number of robots in industry j at year t, $L_{j,t}$ is the employment count (in thousands) in industry j in year t and $g_{j,(t,t_1)}$ is the rate of growth of output over the period from t to t_1 in industry j. t_1 is 2000 and 2015 when t equals 1990 and 2000, respectively. Equation (7) captures the additional acquisition of robot capital while considering the growth of the industry and keeping employment fixed at year t. Similarly, EURO5 industry-level robot growth is calculated as:

$$\Delta R^{EURO5}_{j,t} = \frac{1}{5} \sum_{c} \frac{R^{c}_{j,t_1} - (1 + g^{c}_{j,(t,t_1)}) \cdot R^{c}_{j,t}}{L^{c}_{j,t}} \tag{8}$$

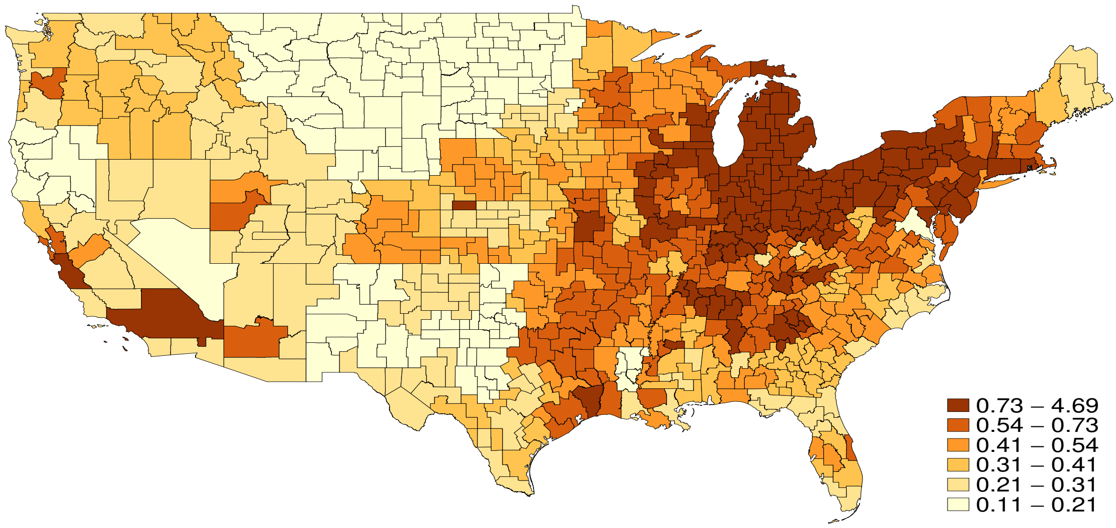
where $R^{c}_{j,t}$ is the stock of robots in country c and industry j at year t, $g^{c}_{j,(t,t_1)}$ is the growth rate of output in country c and industry j between time t and t_1, and $L^{c}_{j,t}$ denotes the number of employed workers in country c and industry j at time t.

A.2.1 Geographic distribution of robot exposure and immigrant share

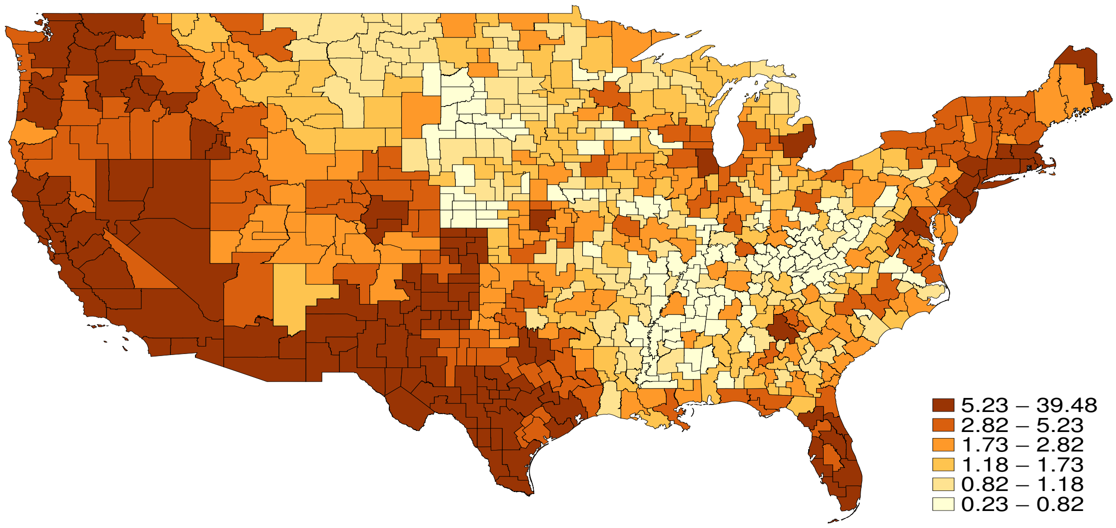
Figure A.2a shows substantial variation in robot exposure across US CZs. Robot growth increased the most in states like Michigan and Ohio due to the substantial rise in automation within the automobile industry. On the other hand, robot growth was lower in various parts of the West North Central and South Central divisions. Figure A.2b highlights that the immigrant population share in 1990 varied considerably across the US with a higher proportion in the states bordering Mexico.

Figure A.2: Geographic distribution of exposure to robots and immigrant share

(a) Robot exposure 1990-2015



(b) Immigrant population share in 1990

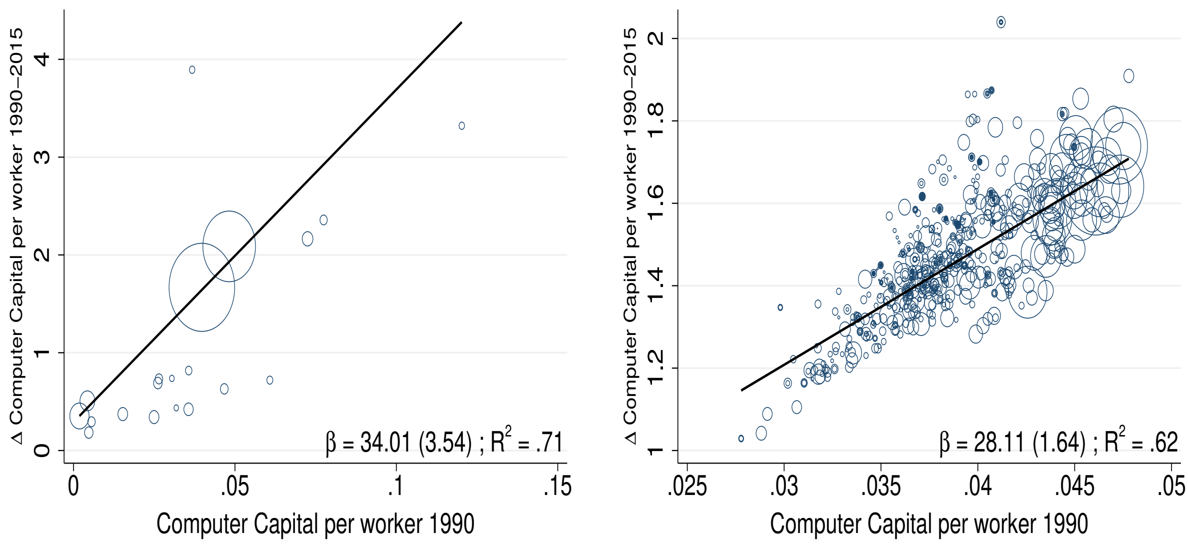


A.3 Computer capital exposure

Following Michaels et al. (2014), we instrument the growth in computer capital use between 1990-2015 with the level of computer capital use in 1990. The intuition is that industries or regions with the higher *level* of computer capital would also adopt more computer capital over time. Figure A.3a demonstrates that industries with the higher level of computer capital per worker in 1990 also witnessed larger increase in computer capital per worker between 1990-2015. A similar idea holds across CZs as shown in Figure A.3b. The R^2 is quite high in both cases suggesting that the first-stage is robust.

Figure A.3: Relation between level in 1990 and growth between 1990 and 2015 of computer capital per thousand workers

(a) Industry (b) Commuting Zone



Note: Panel (a) plots the level in 1990 and growth between 1990 and 2015 of computer capital per thousand workers. Marker size indicates the US industry employment shares in 1990. Robust standard errors in parentheses. Panel (b) shows the relationship between level and growth of computer capital at CZ level. Marker size indicates the 1990 population in the CZ. Clustered standard errors at state level in parentheses.

A.4 Shock balance test at CZ level

Following Borusyak, Hull & Jaravel (2022), each coefficient in Table A.2 is computed by regressing the CZ level covariate on robot exposure instrument and Census division dummies. Only the coefficient of the proportion of employment in routine occupations is significant at standard levels of significance. Overall, it highlights that the potential confounders do not have a significant association with the robot capital shocks.

Table A.2: Shock balance test at CZ level

Dependent variable (1990)	Coefficient	T-statistic
% of male population	0.0887	(0.69)
% of white population	1.128	(0.55)
% of black population	0.311	(0.28)
% of Asian population	-0.518	(-1.27)
% of high-school or less population	1.190	(0.89)
% of less than college population	-0.0726	(-0.12)
% of college and above population	-1.140	(-1.06)
% of above 65 years old population	-0.113	(-0.42)
Log population	0.0758	(0.29)
% of employment among women	-0.291	(-1.21)
% of manufacturing employment	3.051	(1.62)
% of agriculture employment	-0.432	(-1.05)
% of mining employment	-0.00158	(-0.01)
% of construction employment	-0.0903	(-1.29)
% of light-manufacturing employment	-0.00594	(-0.01)
% of employment in routine occupations	1.223*	(1.72)
Offshorability index	-0.103	(-0.49)
Number of Commuting Zones	722	

Note: All regression estimates are weighted by the employment share in the industry in 1990. T-statistics computed using exposure-robust standard errors, following Borusyak, Hull & Jaravel (2022). ***, ** and * represent the statistical significance at 1%, 5% and 10% levels respectively.

B Section 3 Appendix: mobility by nativity

B.1 Effects on relative population change gradually adding controls

Table B.1: Effects on relative population change, stacked-differences 1990–2015 (2SLS): Inclusion of controls

	Dependent variable: Change in log relative population						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	A: Low-Skill						
Exposure to robots	-5.00*	-8.67***	-10.35***	-10.29***	-9.54***	-5.09**	-4.45**
	(2.60)	(3.25)	(3.53)	(3.93)	(2.76)	(2.36)	(2.18)
Observations	1444	1444	1444	1444	1444	1444	1444
R^2	0.18	0.28	0.30	0.31	0.43	0.63	0.69
Kleibergen-Paap F	101.53	221.66	130.07	151.39	146.51	114.54	109.63
	B: High-skill						
Exposure to robots	-0.72	-0.48	-0.98	-0.97	0.03	1.68	1.69
	(1.34)	(1.63)	(1.42)	(1.49)	(1.28)	(1.17)	(1.15)
Observations	1444	1444	1444	1444	1444	1444	1444
R^2	0.06	0.11	0.16	0.16	0.28	0.39	0.46
Kleibergen-Paap F	101.53	221.66	130.07	151.39	146.51	114.54	109.63
Division dummies	Yes	Yes	Yes	Yes	Yes		
Division x time dummies						Yes	Yes
Demographics		Yes	Yes	Yes	Yes	Yes	
Industry w/o routine			Yes				
Industry				Yes	Yes	Yes	
Demo+Ind x time							Yes
Computers, trade					Yes	Yes	Yes

Note: All regression estimates are weighted by the CZ population in 1990. Standard errors clustered at the state level are reported in parentheses. ***, ** and * represent the statistical significance at 1%, 5% and 10% levels respectively. Column (1) includes census division dummies. Column (2) further includes demographic characteristics (log population, share of male population, population shares of Whites, Blacks and Hispanics, share of the population over 65 years old and shares of the population with no college, some college and more than college and female employment share). Column (3) further includes industry shares (share of employment in mining, construction, light manufacturing and manufacturing, and average offshorability index). Column (4) includes share of employment in routine occupations. Column (5) also includes stock of computer capital per worker in 1990 and exposure to Chinese imports. Column (7) further includes year interaction with demographic and industry characteristics in 1990.

B.2 OLS and Reduced form effects on population growth

The OLS and reduced form results in panels A and B, respectively in Table B.2 are consistent with the 2SLS findings. The OLS coefficient of low-skilled immigrant concentration (-3.13) is smaller than the 2SLS estimate (-4.45) suggesting that the unobservables generate a downward bias for the OLS estimates.

Table B.2: Effects on population growth, stacked-differences 1990–2015: OLS and Reduced Form

Dependent variable: Change in log relative population				
	Low-Skill		High-Skill	
	(1)	(2)	(3)	(4)
	A: OLS			
Exposure to robots	-8.31***	-3.13*	-1.47	2.01**
	(3.09)	(1.58)	(1.81)	(0.99)
Observations	1444	1444	1444	1444
R^2	0.18	0.69	0.06	0.46
	B: Reduced Form			
EURO5 Exposure to robots	-6.93*	-6.51**	-1.00	2.00
	(3.74)	(2.98)	(1.83)	(1.95)
Observations	1444	1444	1444	1444
R^2	0.17	0.70	0.06	0.47
Division dummies	Yes		Yes	
Division x time dummies		Yes		Yes
Covariates		Yes		Yes

Note: All regression estimates are weighted by the CZ population in 1990. Standard errors clustered at the state level are reported in parentheses. ***, ** and * represent the statistical significance at 1%, 5% and 10% levels respectively. Covariates: stock of computer capital per worker in 1990; exposure to Chinese imports; year interaction with demographic and industry characteristics in 1990 (log population, low-skill population change between 1970-1990, share of male population, population shares of Whites, Blacks and Hispanics, share of the population over 65 years old, shares of the population with no college, some college and more than college, female employment share, share of employment in agriculture, mining, construction, light manufacturing and manufacturing, routine employment share and average offshorability index).

B.3 Effects on growth of overall immigrants and natives

To replicate findings of Faber et al. (2022), we include the change in log population between 1970 and 1990 as a control. Consistent with Faber et al. (2022), we find in Table B.3 that there is no significant change in immigrant population growth to robot exposure, but native population growth declined considerably in response to introduction of robots. As we show in the main results, the insignificant change of the high-skilled immigrant population growth is responsible for the muted change in the overall immigrant population growth.

Table B.3: Effects on growth of immigrants and natives population growth, stacked-differences 1990–2015 (2SLS)

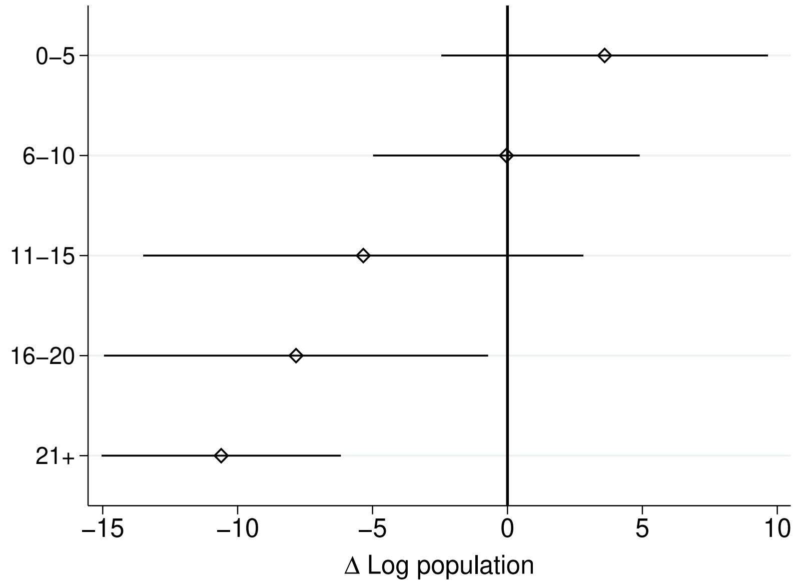
Dependent variable: Change in log population		
	Immigrants (1)	Natives (2)
Exposure to robots	-2.13	-1.65***
	(1.58)	(0.24)
Observations	1442	1444
R^2	0.70	0.81
Kleibergen-Paap F	109.63	109.63
Division x time dummies	Yes	Yes
Covariates	Yes	Yes

Note: All regression estimates are weighted by the CZ population in 1990. Standard errors clustered at the state level are reported in parentheses. ***, ** and * represent the statistical significance at 1%, 5% and 10% levels respectively. Covariates include pre-trends and stock of computer capital per worker in 1990; exposure to Chinese imports; year interaction with demographic and industry characteristics in 1990 (log population, low-skill population change between 1970-1990, share of male population, population shares of Whites, Blacks and Hispanics, share of the population over 65 years old, shares of the population with no college, some college and more than college, female employment share, share of employment in agriculture, mining, construction, light manufacturing and manufacturing, routine employment share and average offshorability index).

B.4 Effects on low-skilled immigrant population by years living in US

Figure B.1 shows that the population growth of low-skilled immigrants who have been living in the US for more than 15 years reduced drastically due to robot exposure. On the other hand, there are no changes in the population growth of low-skilled immigrants in CZs more exposed to robots who arrived less than 10 years ago.

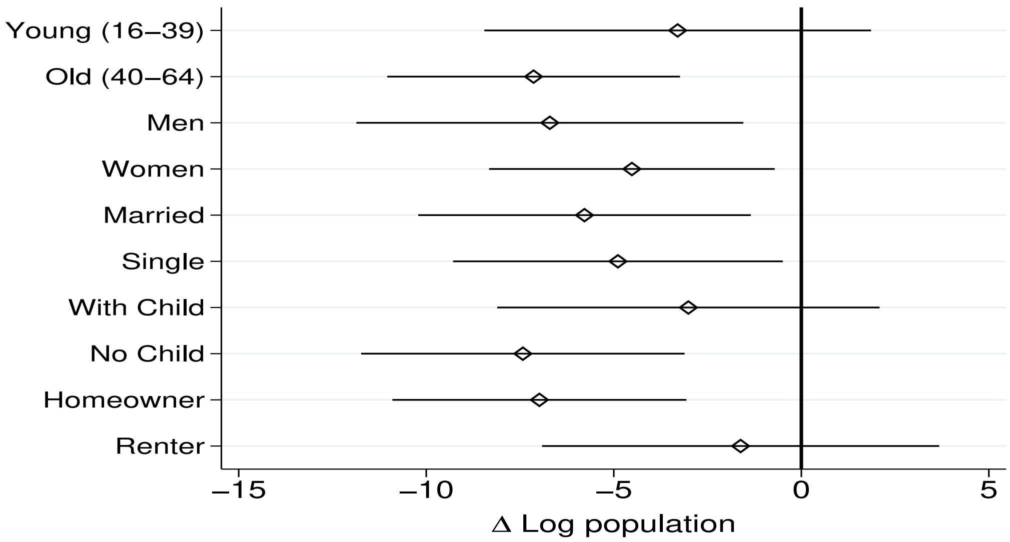
Figure B.1: Effects on low-skilled immigrant population growth by years living in US



Note: Bars indicate 95% confidence interval. Figure shows coefficient to robot exposure of subgroup-specific immigrant working-age population as the outcome variable.

B.5 Heterogeneous effects on low-skilled immigrant population

Figure B.2: Effects on the growth of immigrant concentration by demographic subgroups, with stacked-differences (2SLS)



Note: The bars indicate a 95% confidence interval. The figure shows the coefficient to robot exposure of the subgroup-specific working-age population as the outcome variable.

B.6 Construction of Migration flows

The Census provides migration sample at the Public Use Microdata Area (MIGPUMA) level. MIGPUMA only shows the first three digits of the five-digit PUMA code. We combine it with state codes to create corresponding PUMA categories. The MIGPUMA codes allow us to focus on migration when individuals move to a different PUMA code, either within or across states. We compute inflows and outflows at the CZ level using PUMA-CZ crosswalk. It is possible for multiple PUMA's to contain a CZ or a CZ to span multiple PUMAs. Following Molloy et al. (2011), we assume that an individual did not migrate across if there is at least one CZ that belongs to the set of possible CZs of current or previous residence. This leads to a lower bound on migration rates at the CZ level.

We use the following definition to decompose population change in a CZ:

$$\frac{N_{i,t+1}^{16-64} - N_{i,t}^{16-64}}{N_{i,t}^{16-64}} = \frac{N_i^{\text{in}}}{N_{i,t}^{16-64}} - \frac{N_i^{\text{out}}}{N_{i,t}^{16-64}} + \frac{N_i^{\text{net-ageing}}}{N_{i,t}^{16-64}} + \frac{N_i^{\text{new arrival}}}{N_{i,t}^{16-64}} \tag{9}$$

where $N_{i,t+1}^{16-64}$ is CZ i working-age population at time $t+1$, $N_i^{\text{new arrival}}$ consists of immigrants who entered the country between t and $t+1$, N_i^{in} and N_i^{out} denotes the number of individuals within the US that entered or exit CZ i after time t and $N_i^{\text{net-ageing}}$ measures the difference in the number of people who aged in and aged out of the sample.

Using the 2000 Census, inflows are calculated as the number of individuals who move into their current CZ residence five years ago, while outflow is defined as the sum of people who exited their CZ five years ago. The baseline population in 1995 is computed as the population in 2000 divided by the five-year equivalent change to population between 1990 and 2000.

The 2013-17 ACS reports migration activity based on a one-year reference period. 2013 and 2014 are used to create the initial population at time t. 2017 is used to create the population at period $t+1$. Immigrants present in the US in 2017, but who arrived from outside the US post 2013 as defined as international immigrants. Individuals who did not move during the past years and aged 16-19 in 2017 are classified as aged in, where as non-movers aged 61-64 in 2013-14 are defined as aged out. Inflows and outflows are based on individuals who arrived to the US before 2013 and moved post 2015.

B.7 Robustness to CZs with extreme immigrant shares

In this subsection, we show through various ways that CZs with very low or high immigrant shares do not drive our results. The dependent variable is the change in immigrant concentration by skill level. First, we show in columns 2 and 5 of Table B.4 that results remain unchanged when we exclude CZs with fewer than 100 immigrants. We show in columns 3 and 6 that our results are robust to excluding states that border Mexico (Arizona, California, New Mexico and Texas) where a high share of low-skilled documented and undocumented immigrants live. Therefore, our findings cannot be explained by a reduction in the population of low-skilled immigrants in a few CZs.

Cadena & Kovak (2016) argue that it is more efficient to use nativity-specific weights in the regression given the significant variation in population sizes by nativity across regions in the US. The alternate weighting scheme does not meaningfully change our results. The standard errors are slightly lower in columns 5, 6 and 7 relative to 1, 2 and 3, as shown in Table B.5. More importantly, the reduction in population of low-skilled immigrants to robot exposure rises from -5.49 (column 3) to -6.35 (column 7),

Table B.4: Effects on relative population growth with excluding certain regions, stacked-differences 1990–2015 (2SLS)

	Dependent variable: Change in log of immigrant to native population					
	Low-skill			High-skill		
	Baseline	Drop Czs < 100 immigrants	Exclude states border Mexico	Baseline	Drop Czs < 100 immigrants	Exclude border Mexico
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure to robots	-4.45**	-4.46**	-4.39**	1.69	1.65	1.37
	(2.18)	(2.18)	(2.13)	(1.15)	(1.15)	(1.09)
Observations	1444	1304	1242	1444	1304	1242
R^2	0.69	0.69	0.66	0.46	0.47	0.42
Kleibergen-Paap F	109.63	109.54	159.21	109.63	109.54	159.21

Note: All regression estimates are weighted by the CZ population in 1990. Border states include Arizona, California, New Mexico and Texas. ***, ** and * represent the statistical significance at 1%, 5% and 10% levels respectively. Regressions include time-division dummies and covariates: stock of computer capital per worker in 1990; exposure to Chinese imports; year interaction with demographic and industry characteristics in 1990 (log population, low-skill population change between 1970-1990, share of male population, population shares of Whites, Blacks and Hispanics, share of the population over 65 years old, shares of the population with no college, some college and more than college, female employment share, share of employment in agriculture, mining, construction, light manufacturing and manufacturing, routine employment share and average offshorability index).

whereas the coefficient of low-skilled natives falls slightly from -1.04 in column 1 to -0.98 in column 5. Thus, our baseline finding of the gap in the response of low-skilled by nativity becomes more pronounced using nativity-specific weights in the regression.

Table B.5: Effects on population growth, group-specific weights stacked-differences 1990–2015 (2SLS)

	Dependent variable: Change in log population							
	Baseline				Group-specific weights			
	Native		Immigrant		Native		Immigrant	
	LS	HS	LS	HS	LS	HS	LS	HS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Exposure to robots	-1.04**	-1.41***	-5.49**	0.28	-0.98**	-1.57***	-6.35***	0.05
	(0.45)	(0.38)	(2.19)	(1.22)	(0.44)	(0.37)	(2.17)	(1.42)
Observations	1444	1444	1444	1444	1444	1444	1444	1444
R-squared	0.82	0.73	0.70	0.55	0.79	0.73	0.81	0.75

Note: LS and HS refer to low-skill and high-skill, respectively. Regressions are weighted by the CZ population in 1990 for columns (1)-(4) and by group-specific CZ population in 1990 from columns (5)-(8). Standard errors clustered at the state level are reported in parentheses. ***, ** and * represent the statistical significance at 1%, 5% and 10% levels respectively. Regressions include time-division dummies and covariates: stock of computer capital per worker in 1990; exposure to Chinese imports; year interaction with demographic and industry characteristics in 1990 (log population, low-skill population change between 1970-1990, share of male population, population shares of Whites, Blacks and Hispanics, share of the population over 65 years old, shares of the population with no college, some college and more than college, female employment share, share of employment in agriculture, mining, construction, light manufacturing and manufacturing, routine employment share and average offshorability index).

B.8 Migration flows: other results

B.8.1 Effects on migration rates of high-skilled individuals

Table B.6 shows the migration response of high-skilled immigrants and natives to robot penetration. The reduction in the population of high-skilled natives is driven strongly by their outflow from robot-exposed regions (column 6). There is also a reduction in the entry of high-skilled natives into more robot-exposed CZs (column 5), but this channel is imprecisely estimated. On the other hand, introduction of robots increases the likelihood of some high-skilled immigrants (column 2) to leave those areas, but some continue to stay leading to a fall in net-ageing, as shown in column 3. Consistent with previous results, robot exposure does not change the entry of international arrivals into the US (column 4).

Table B.6: Effects on migration rates of high-skilled individuals, (2SLS)

	Immigrant				Native		
	In	Out	Net-aging	New Arrival	In	Out	Net-aging
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Exposure to robots	-0.28	3.56**	-0.56*	-0.07	-1.40	1.48**	-0.16
	(1.28)	(1.49)	(0.31)	(1.73)	(1.09)	(0.64)	(0.21)
Observations	722	722	722	722	722	722	722
R^2	0.65	0.57	0.27	0.51	0.76	0.62	0.61

Note: The dependent variable in columns (2) and (6) is the growth in the local population due to internal outflows, i.e., the negative of the proportional change in population due to outflows. All regression estimates are weighted by the CZ population in 1990. Standard errors clustered at the state level are reported in parentheses. ***, ** and * represent the statistical significance at 1%, 5% and 10% levels respectively. Regressions include division dummies, robot exposure to neighbouring locations and covariates: stock of computer capital per worker in 1990; exposure to Chinese imports; demographic and industry characteristics in 1990 (log population, low-skill population change between 1970-1990, share of male population, population shares of Whites, Blacks and Hispanics, share of the population over 65 years old, shares of the population with no college, some college and more than college, female employment share, share of employment in agriculture, mining, construction, light manufacturing and manufacturing, routine employment share and average offshorability index).

B.8.2 Effects on migration rates of low-skilled established immigrants

Table B.7 shows the inflow, outflow and net-ageing channels of population adjustment for low-skilled established immigrants to robot exposure. Columns 1 to 3 focus on the overall sample, while we restrict the analysis to men in columns 4 to 6. Consistent with the findings throughout the paper, there is a noticeable decrease in the entry of low-skilled established immigrants to more robot-exposed areas and simultaneously a strong out-migration due to the introduction of robots. Furthermore, the net-age of the CZs decrease too in areas more exposed to robots either due to older individuals not being able to move out of those areas, or some younger individuals becoming high-skilled.

Table B.7: Effects on migration rates of low-skilled established immigrants, (2SLS)

	Overall			Men		
	In	Out	Net-aging	In	Out	Net-aging
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure to robots	-4.72**	4.07***	-3.27***	-5.86**	4.02*	-2.99**
	(2.01)	(1.39)	(1.02)	(2.31)	(2.09)	(1.37)
Observations	722	722	722	722	722	722
R^2	0.67	0.43	0.39	0.65	0.27	0.23

Note: The dependent variable in column (2) is the growth in the local population due to internal outflows, i.e., the negative of the proportional change in population due to outflows. All regression estimates are weighted by the CZ population in 1990. Standard errors clustered at the state level are reported in parentheses. ***, ** and * represent the statistical significance at 1%, 5% and 10% levels respectively. Regressions include division dummies and covariates: stock of computer capital per worker in 1990; exposure to Chinese imports; demographic and industry characteristics in 1990 (log population, low-skill population change between 1970-1990, share of male population, population shares of Whites, Blacks and Hispanics, share of the population over 65 years old, shares of the population with no college, some college and more than college, female employment share, share of employment in agriculture, mining, construction, light manufacturing and manufacturing, routine employment share and average offshorability index).

B.8.3 Effects on annual migration rates of low-skilled men

Table B.8 shows the distinct channels of adjustment of low-skilled immigrants and natives to robot exposure using the one-year migration questions in the 2013-17 ACS sample. A similar pattern emerges as the baseline findings, but with much lower statistical significance. Though, the coefficient on in-migration of low-skilled immigrants is negative and significant from zero (column 1). Also, net-ageing remains the strongest channel that explains the fall in population of low-skilled natives (column 7). The in- and out-migration coefficients for low-skilled natives continue to be imprecisely estimated (columns 5 and 6).

Table B.8: Effects on annual migration rates of low-skilled men between 2013-2017, (2SLS)

	Immigrant				Native		
	In	Out	Net-aging	New Arrival	In	Out	Net-aging
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Exposure to robots	-1.79**	1.20	-1.11	-0.38	-0.57	0.60	-0.98**
	(0.89)	(0.93)	(1.36)	(0.43)	(0.76)	(0.41)	(0.39)
Observations	677	692	696	693	696	693	692
R^2	0.31	0.21	0.26	0.12	0.67	0.47	0.86

Note: The dependent variable in columns (2) and (6) is the growth in the local population due to internal outflows, i.e., the negative of the proportional change in population due to outflows. All regression estimates are weighted by the CZ population in 1990. Standard errors clustered at the state level are reported in parentheses. ***, ** and * represent the statistical significance at 1%, 5% and 10% levels respectively. Regressions include division dummies, robot exposure to neighbouring locations and covariates: stock of computer capital per worker in 1990; exposure to Chinese imports; demographic and industry characteristics in 1990 (log population, low-skill population change between 1970-1990, share of male population, population shares of Whites, Blacks and Hispanics, share of the population over 65 years old, shares of the population with no college, some college and more than college, female employment share, share of employment in agriculture, mining, construction, light manufacturing and manufacturing, routine employment share and average offshorability index).

B.9 Robustness checks of population growth by nativity

In this subsection, we elaborate more on the various exercises to probe the robustness on the effect of robot exposure on population growth of low-skilled immigrants and natives.

B.9.1 Pre-trends

Table B.9: Effects on change in population, long-difference 1970–1990 (2SLS)

Dependent variable: Change in log population				
	Immigrant		Native	
	Low-skill	High-skill	Low-skill	High-skill
	(1)	(2)	(3)	(4)
Exposure to robots	-15.42	-6.94	-4.66	0.06
	(11.02)	(6.74)	(3.17)	(4.13)
Observations	721	721	722	722
R-squared	0.63	0.43	0.52	0.53

Note: All regression estimates are weighted by the CZ population in 1970. Standard errors clustered at the state level are reported in parentheses. ***, ** and * represent the statistical significance at 1%, 5% and 10% levels respectively. Regressions include division dummies and covariates: demographic and industry characteristics in 1970 (population shares of Whites, Blacks and Hispanics, share of the population over 65 years old, share of female employment in manufacturing and share of employment in agriculture, mining, construction and manufacturing).

One concern with the current analysis might be that pre-existing CZ trends explain the differential population change among native groups to robot adoption. For example, Basso et al. (2020) argues that immigrant location choices are responsive to computerization, which subsequently could affect labour demand and technological adoption by firms. To assess the strength of this issue, we conduct a falsification exercise by regressing the change in log population between 1970-1990 on *future* CZ robot exposure between 1990-2015. Table B.9 shows that there are no significant association between population growth among nativity-skill groups between 1970-1990 and the entry of robots post 1990.

Table B.10 shows that our findings are robust to controlling for pre-trends in several ways. We include: 1) skill-specific immigrant concentration in 1970-1990 in columns

1 and 5; 2) skill-specific immigrant concentration in 1970-1990 interacted with period dummies in columns 2 and 6; 3) overall change in CZ population between 1970 and 1990 interacted with time dummies instead of controlling for the change in the subgroup population in columns 3 and 7; and, 4) the proportion of foreign-born population share in 1990 in columns 4 and 8. The striking fall in the growth of low-skilled immigrant-to-native population to robot exposure continues to hold across the various specifications.

Table B.10: Effects on change in relative population while flexibly controlling for pre-trends, stacked-differences 1990–2015 (2SLS)

Dependent variable: Change in log of immigrant to native population								
	Low-skill				High-skill			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Exposure to robots	-3.99*	-4.03*	-4.69**	-5.05**	0.72	0.79	1.47	1.36
	(2.12)	(2.11)	(2.33)	(2.33)	(1.14)	(1.17)	(1.30)	(1.25)
Change in dep. variable 1970-90	0.04	0.12*			-0.18***	-0.32***		
	(0.03)	(0.06)			(0.04)	(0.06)		
Change in dep. variable 1970-90 x 2000-2015		-0.17**				0.29***		
		(0.08)				(0.07)		
Change in population 1970-90			1.77***				0.87***	
			(0.66)				(0.29)	
Change in population 1970-90 x 2000-2015			-1.92***				-0.43*	
			(0.67)				(0.22)	
Share Immigrant 1990				-106.80***				-58.32***
				(19.72)				(14.95)
Observations	1442	1442	1444	1444	1442	1442	1444	1444
R-squared	0.69	0.70	0.70	0.70	0.48	0.49	0.47	0.47

Note: All regression estimates are weighted by the CZ population in 1990. Standard errors clustered at the state level are reported in parentheses. ***, ** and * represent the statistical significance at 1%, 5% and 10% levels respectively. Regressions include time-division dummies, pre-trends and covariates: stock of computer capital per worker in 1990; exposure to Chinese imports; year interaction with demographic and industry characteristics in 1990 (log population, low-skill population change between 1970-1990, share of male population, population shares of Whites, Blacks and Hispanics, share of the population over 65 years old, shares of the population with no college, some college and more than college, female employment share, share of employment in agriculture, mining, construction, light manufacturing and manufacturing, routine employment share and average offshorability index).

B.9.2 Alternate specifications

In the baseline stacked-differences specification, we exploit variation in robot exposure over two periods: 1990-2000 and 2000-2015. Table B.11 shows that the baseline results are robust to alternate long- and stacked-differences specifications. Coefficients in columns 1-2, 3-4 and 5-6 are based on a three periods stacked-differences (1990-2000, 2000-2007 and 2007-2015), two periods stacked-differences (1990-2000 and 2000-2007) and long-difference specifications, respectively. The dependent variable in the long-difference specification are 10-year equivalent averages of 1990-2000, 2000-2007 and 2007-2015.

Overall, we reach the same conclusion as the baseline findings across all specifications. Moreover, the coefficients using the three periods and two periods stacked-differences models are quite close implying that our results are not explained by the 2007 recession. The coefficient in the long-difference specification of low-skilled immigrant concentration is bigger in magnitude than the regression using stacked-differences coefficients suggesting that including controls with time dummies is important in explaining some of the observed patterns.

Table B.11: Effects on change in relative population, multiple time periods (2SLS)

Dependent variable: Change in log of immigrant to native population						
	3 stacked		2 stacked		Long	
	Low-skill	High-skill	Low-skill	High-skill	Low-skill	High-skill
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure to robots	-2.51*	0.40	-2.65*	0.02	-5.28***	-0.22
	(1.46)	(1.14)	(1.59)	(1.27)	(1.65)	(1.28)
Observations	2166	2166	1444	1444	722	722
R^2	0.61	0.37	0.60	0.31	0.62	0.34
Kleibergen-Paap F	197.23	197.23	179.8	179.8	54.37	54.37

Note: 3 stacked-difference model includes 1990-2000, 2000-2007 and 2007-2015. 2 stacked-difference model includes 1990-2000 and 2000-2007. Long difference model is over 1990-2015. All regression estimates are weighted by the CZ population in 1990. Standard errors clustered at the state level are reported in parentheses. ***, ** and * represent the statistical significance at 1%, 5% and 10% levels respectively. Regressions include time-division dummies in panels A and B and division dummies in panel C. Covariates include: stock of computer capital per worker in 1990; exposure to Chinese imports; year interaction with demographic and industry characteristics in 1990 in panels A and B and without year interaction in panel C (log population, low-skill population change between 1970-1990, share of male population, population shares of Whites, Blacks and Hispanics, share of the population over 65 years old, shares of the population with no college, some college and more than college, female employment share, share of employment in agriculture, mining, construction, light manufacturing and manufacturing, routine employment share and average offshorability index).

B.9.3 Alternate definition of robot exposure and additional controls

Table B.12 shows that our results are robust to alternate measures of robot exposure. The baseline measure of robot exposure include five European countries (Denmark, Finland, France, Italy and Sweden) following Acemoglu & Restrepo (2020). We create another measure (EURO7) of robot exposure including Germany and UK to the baseline measure. Column 2 shows that our results are identical using the EURO5 and EURO7 robot exposure measures.

Excluding commuting zones with the top 1% robot exposure leads to a more stronger point estimate for low-skilled immigrant concentration, but also increases the standard errors (column 3). The baseline results become stronger when we control for the robot exposure to neighbouring locations in column 4. Thus, the misspecification resulting from not accounting for exposure of robots to other regions cannot explain our findings.

The coefficient of interest in our baseline specification estimates the change in population size due to a robot exposure within a division region in a given period. We consider an alternate specification with state-year dummies ($48 \times 2 = 96$) instead of division-year dummies ($9 \times 2 = 18$) to account for any state-specific trends, such as changes in immigration policies. The relative growth in low-skilled immigrants to natives coefficient in column 5 (-4.56) is very close to the baseline coefficient (-4.45), but is much less precisely estimated.

Table B.12: Effects on relative population growth, stacked-differences 1990–2015 (2SLS)

Dependent variable: Change in log of immigrant to native population					
	Baseline	EURO7	Drop top 1% exposure	Exposure neighbours	State-time dummies
	(1)	(2)	(3)	(4)	(5)
	A: Low-skill				
Exposure to robots	-4.45**	-4.46**	-7.90	-5.40**	-4.56
	(2.18)	(2.17)	(5.91)	(2.21)	(3.85)
Observations	1444	1444	1430	1444	1444
R^2	0.69	0.69	0.69	0.69	0.78
Kleibergen-Paap F	109.63	120.76	184.28	108.53	44.43
	B: High-skill				
Exposure to robots	1.69	1.76	-0.62	2.06*	1.13
	(1.15)	(1.14)	(3.21)	(1.21)	(2.00)
Observations	1444	1444	1430	1444	1444
R^2	0.46	0.46	0.46	0.46	0.55
Kleibergen-Paap F	109.63	120.76	184.28	108.53	44.43

Note: All regression estimates are weighted by the CZ population in 1990. Standard errors clustered at the state level are reported in parentheses. ***, ** and * represent the statistical significance at 1%, 5% and 10% levels respectively. All regressions except column (5) include time-division dummies and covariates: stock of computer capital per worker in 1990; exposure to Chinese imports; year interaction with demographic and industry characteristics in 1990 (log population, low-skill population change between 1970-1990, share of male population, population shares of Whites, Blacks and Hispanics, share of the population over 65 years old, shares of the population with no college, some college and more than college, female employment share, share of employment in agriculture, mining, construction, light manufacturing and manufacturing, routine employment share and average offshorability index). Column (2) regression uses EURO7 exposure as instrument instead of EURO5 exposure. Column (3) excludes CZs' with top 1% US robot exposure. Column (4) includes robot exposure to neighbouring location in addition to those in column (1).

B.9.4 Alternate standard errors

Standard errors in the baseline regression are computed by clustering at the state level. Columns 2 and 5 in Table B.13 shows that standard errors do become a bit smaller if we cluster at a more granular level (CZ). Moreover, the standard errors in the baseline model account for within-region spatial correlation. However, they do not account for potential between-region correlations arising from other industry shocks. We compute standard errors following Borusyak, Hull & Jaravel (2022) to account for such correlations. Standard errors are very similar in columns 3 and 6 using the method by Borusyak, Hull & Jaravel (2022) compared to the baseline standard errors in columns 1 and 4.

Table B.13: Effects on relative population growth with alternate standard errors, stacked-differences 1990–2015 (2SLS)

Dependent variable: Change in log of immigrant to native population						
	Low-skill			High-skill		
	Baseline	Cluster CZ	Borusyak et al. (2022)	Baseline	Cluster CZ	Borusyak et al. (2022)
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure to robots	-4.45**	-4.45***	-4.45**	1.69	1.69	1.69
	(2.18)	(1.72)	(2.25)	(1.15)	(1.07)	(1.10)

Note: All regression estimates are weighted by the CZ population in 1990. 19 industries used for inference using Borusyak et al. (2022). ***, ** and * represent the statistical significance at 1%, 5% and 10% levels respectively. Regressions include time-division dummies and covariates: stock of computer capital per worker in 1990; exposure to Chinese imports; year interaction with demographic and industry characteristics in 1990 (log population, low-skill population change between 1970-1990, share of male population, population shares of Whites, Blacks and Hispanics, share of the population over 65 years old, shares of the population with no college, some college and more than college, female employment share, share of employment in agriculture, mining, construction, light manufacturing and manufacturing, routine employment share and average offshorability index).

C Section 4 Appendix: mitigating effects on natives

C.1 Effects on population growth by CZs' initial low-skilled immigrant share

Table C.1: Effects on population growth by CZs' initial low-skilled immigrant share, stacked-differences 1990–2015 (2SLS)

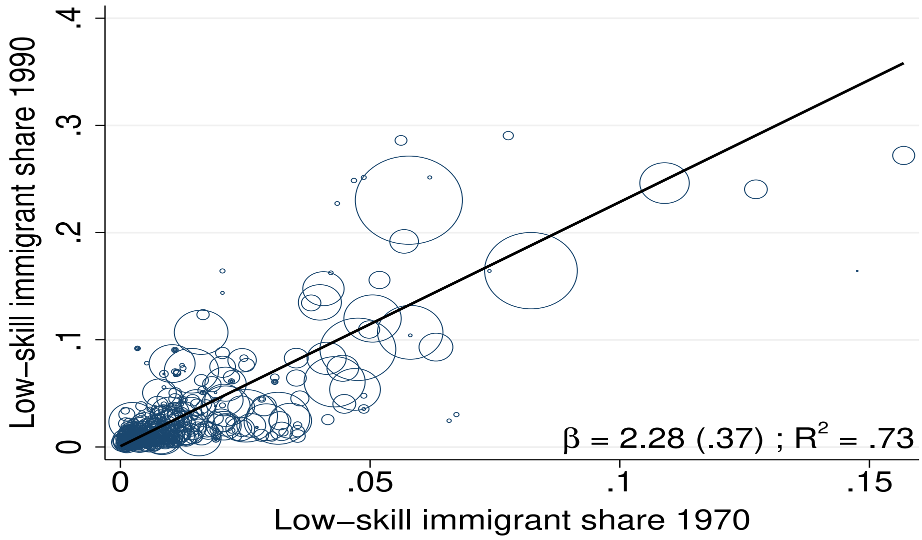
Dependent variable: Change in log population						
	Low-skill			High-skill		
	Overall	Above-median	Below-median	Overall	Above-median	Below-median
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure to robots	-1.54***	-1.45***	-0.79	-1.16**	-0.78	-1.55
	(0.46)	(0.50)	(1.20)	(0.46)	(0.56)	(1.44)
Observations	1444	716	728	1444	716	728
R^2	0.80	0.85	0.78	0.69	0.75	0.65

Note: All regression estimates are weighted by the CZ population in 1990. Standard errors clustered at the state level are reported in parentheses. ***, ** and * represent the statistical significance at 1%, 5% and 10% levels respectively. Regression includes above-median immigrant share dummy, interaction of time-division dummies and covariates: stock of computer capital per worker in 1990; exposure to Chinese imports; year interaction with demographic and industry characteristics in 1990 (log population, low-skill population change between 1970-1990, share of male population, population shares of Whites, Blacks and Hispanics, share of the population over 65 years old, shares of the population with no college, some college and more than college, female employment share, share of employment in agriculture, mining, construction, light manufacturing and manufacturing, routine employment share and average offshorability index).

C.2 Low-skilled immigrant share in 1990 and 1970

citeBorjas1995 argues that recent immigrants are more likely to arrive into areas where immigrants from those countries are located. This implies that the lagged and current immigrant shares should be positively associated. Figure C.1 reports a significantly positive relationship between the low-skilled immigrant share in 1970 and 1990. Moreover, the geographic distribution of immigrants in 1970 strongly predicts the distribution in 1990 ($R^2 = 73\%$).

Figure C.1: Relation between low-skilled immigrant share in 1990 and 1970



Note: Figure shows the relationship between share of immigrant at 1970 and 1990 at CZ level. Marker size indicates the 1990 population in the CZ. Clustered standard errors at state level in parentheses.

C.3 Pre-trends

Table C.2 shows the changes in log native employment and log average native wages between 1970 and 1990 to robot exposure between 1990-2015 and 1990 immigrant share. The table clearly shows a lack of significant pre-trends in labour market outcomes of native workers to robot exposure. The second row shows that in areas with no immigrant share, robot exposure between 1990-2015 has no significant association with lagged growth in native employment or wages. Moreover, the first row shows that the effect of robot exposure did not vary by where immigrants settled in 1990.

Table C.2: Effects on labour market outcomes of natives, long-difference 1970-1990 (2SLS): Interacting robot exposure with share of low-skilled immigrant

Dependent variable: Change in log employment or log wages				
	Employment		Wage	
	Overall	Low-skill	Overall	Low-skill
	(1)	(2)	(3)	(4)
Exposure x Share 1990	46.94	-26.74	10.48	-0.61
	(47.79)	(51.02)	(16.57)	(19.31)
Exposure to robots	-1.80	-1.37	0.27	0.11
	(1.77)	(1.81)	(0.47)	(0.52)
Immigrant Share 1990	-55.11	-53.31	3.36	1.91
	(34.85)	(32.92)	(8.63)	(9.47)
Observations	722	722	722	722
R-squared	0.54	0.60	0.77	0.73

Note: All regression estimates are weighted by the CZ population in 1970. Standard errors clustered at the state level are reported in parentheses. ***, ** and * represent the statistical significance at 1%, 5% and 10% levels respectively. Regressions include division dummies and covariates: demographic and industry characteristics in 1970 (population shares of Whites, Blacks and Hispanics, share of the population over 65 years old, share of female employment in manufacturing and share of employment in agriculture, mining, construction and manufacturing).

C.4 Effects on native population

Table C.3 shows that the sensitivity of robot exposure on the growth of native population does not vary with the share of immigrant population. The second row shows that native population growth of both low- and high-skilled individuals declined due to robot penetration in areas with no immigrant share. Furthermore, the first row shows that the change in native population growth is insignificant, implying that the fall in native population growth to robot exposure is similar in CZs with few and many low-skilled immigrants.

Table C.3: Effects on native population, stacked-differences 1990–2015 (2SLS):

Dependent variable: Change in log population			
	Overall (1)	Low-skill (2)	High-skill (3)
Exposure x Share 1990	9.08	14.16	5.85
	(13.78)	(10.67)	(18.94)
Exposure to robots	-1.62***	-1.49***	-1.63***
	(0.49)	(0.53)	(0.58)
Immigrant Share 1990	-24.96*	-40.21***	-26.20
	(13.80)	(9.17)	(19.24)
Observations	1444	1444	1444
R-squared	0.79	0.82	0.74

Note: All regression estimates are weighted by the CZ population in 1990. Standard errors clustered at the state level are reported in parentheses. ***, ** and * represent the statistical significance at 1%, 5% and 10% levels respectively. Regressions include time-division dummies and covariates: .

C.5 Robustness checks

Table C.4: Effects on labour market outcomes of low-skilled natives, stacked-differences 1990–2015 (2SLS)

Dependent variable: Change in log employment or change in log wages						
	Baseline		1980 Immigrant Share		Established Share	
	Employment	Wage	Employment	Wage	Employment	Wage
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure x Share 1990	7.70	19.82***	5.95	14.77**	25.53	33.98***
	(12.80)	(7.64)	(15.43)	(6.84)	(21.04)	(10.71)
Observations	1444	1444	1444	1444	1444	1444
R-squared	0.83	0.88	0.82	0.88	0.83	0.88

Note: All regression estimates are weighted by the CZ population in 1990. Standard errors clustered at the state level are reported in parentheses. ***, ** and * represent the statistical significance at 1%, 5% and 10% levels respectively. Regressions include time-division dummies and covariates: stock of computer capital per worker in 1990; exposure to Chinese imports; year interaction with demographic and industry characteristics in 1990 (log population, share of male population, population shares of Whites, Blacks and Hispanics, share of the population over 65 years old, shares of the population with no college, some college and more than college, female employment share, share of employment in agriculture, mining, construction, light manufacturing and manufacturing, routine employment share and average offshorability index).

Columns 1 and 2 in Table C.4 show the interaction term between robot exposure and immigrant share for the changes in log employment and log average wage of low-skilled native workers, respectively. We include 1980 immigrant share in columns 3 and 4 to absorb the dynamic effects of past immigration shocks. The coefficients and standard errors reduce a bit, but the main conclusions remain unchanged.

Our previous results showed that the change in low-skilled population growth is driven by the mobility of established immigrants (living for more than 10 years in US). Therefore, our baseline findings might not be representative, as we should analyse the impact of low-skilled established immigrants rather than the representative low-skilled immigrant. Column 6 shows that wages of low-skilled natives are attenuated to robot exposure in areas with a higher fraction of low-skilled established immigrants. The low-skilled established immigrant share at the 50^{th} and 25^{th} percentiles are 0.56% and 0.33%, respectively. This implies that at the mean robot exposure, wage losses of low-skilled native workers are lower by 0.07 pp comparing CZs at the 50^{th} and 25^{th} percentiles of low-skilled established immigrant share, which is identical to the number we derived using the coefficients in column 2 (0.07 = 0.3398*0.9*[0.56-0.23]).

Table C.5 shows that low-skilled immigrant mobility mitigates wage losses due to automation of low-skilled native workers using three periods and two periods stacked-differences specifications and long-difference specification. The interaction term between robot exposure and 1990 immigrant share is economically and statistically significant for low-skilled native workers' wages across all the alternate specifications.

Table C.5: Effects on labour market outcomes of natives, multiple time periods (2SLS): Interacting robot exposure with share of low-skilled immigrant

Dependent variable: Change in log employment or change in log wages						
	Employment			Wage		
	Overall	Low-skill	High-skill	Overall	Low-skill	High-skill
	(1)	(2)	(3)	(4)	(5)	(6)
	A: Three period stacked-differences (1990-2000, 2000-2007, 20007-15)					
Exposure x Share 1990	-11.60	2.17	-17.62	19.84*	33.81***	17.04*
	(20.66)	(20.12)	(22.87)	(11.09)	(9.89)	(10.30)
Exposure to robots	-1.69**	-2.12**	-1.41**	-1.55***	-1.89***	-1.63***
	(0.69)	(0.83)	(0.70)	(0.33)	(0.35)	(0.30)
Immigrant Share 1990	-17.32	-42.18***	-16.32	-13.33*	-21.26***	-11.89*
	(18.43)	(14.08)	(21.22)	(7.26)	(5.18)	(6.69)
Observations	2166	2166	2166	2166	2166	2166
R-squared	0.73	0.80	0.66	0.87	0.83	0.84
	B: Two period stacked-differences (1990-2000, 2000-2007)					
Exposure x Share 1990	-14.03	-0.19	-24.28	22.07	37.84**	18.64
	(31.94)	(34.34)	(32.94)	(15.60)	(17.02)	(13.70)
Exposure to robots	-1.64	-2.12*	-1.23	-1.60***	-2.01***	-1.66***
	(1.03)	(1.19)	(1.02)	(0.42)	(0.48)	(0.34)
Immigrant Share 1990	-32.79	-56.26***	-28.94	-6.84	-19.44***	-2.38
	(24.32)	(19.27)	(27.68)	(7.76)	(7.34)	(6.96)
Observations	1444	1444	1444	1444	1444	1444
R-squared	0.71	0.76	0.68	0.91	0.87	0.88
	C: Long-difference (1990-2015)					
Exposure x Share 1990	-14.25	8.05	-24.45	11.40	32.09***	7.07
	(23.08)	(24.08)	(25.77)	(10.20)	(9.55)	(9.81)
Exposure to robots	-1.55**	-2.24**	-1.22	-1.62***	-2.35***	-1.50***
	(0.75)	(0.89)	(0.81)	(0.27)	(0.31)	(0.27)
Immigrant Share 1990	-34.65**	-57.32***	-37.85**	-14.11***	-21.57***	-11.34**
	(15.00)	(16.44)	(15.77)	(5.47)	(4.27)	(5.43)
Observations	722	722	722	722	722	722
R-squared	0.72	0.80	0.67	0.67	0.71	0.67

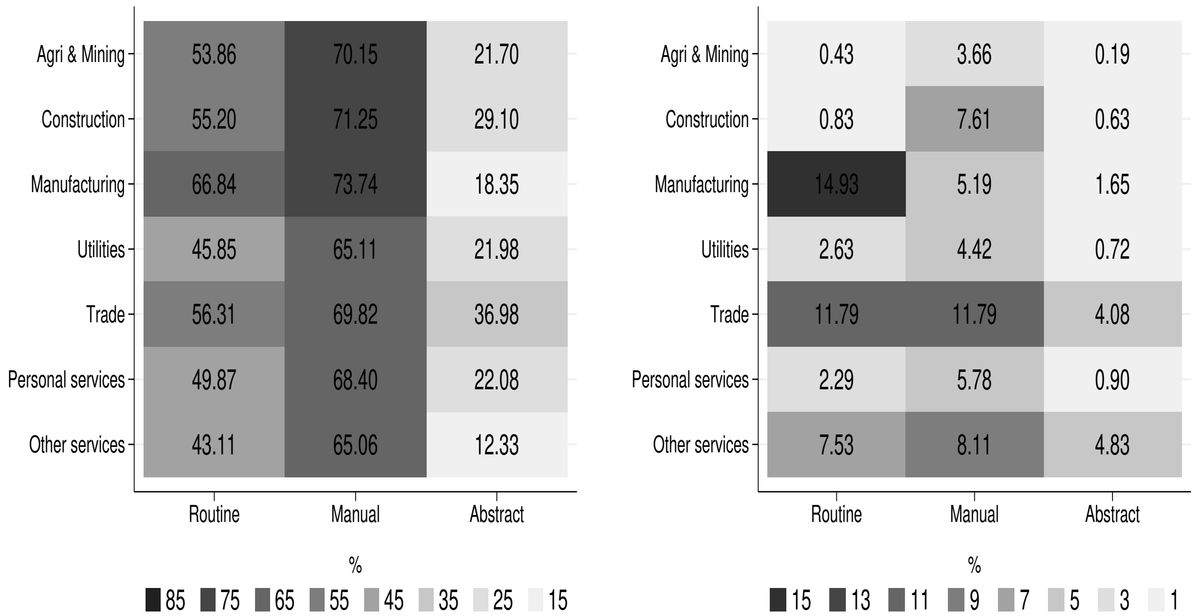
Note: All regression estimates are weighted by the CZ population in 1990. Standard errors clustered at the state level are reported in parentheses. ***, ** and * represent the statistical significance at 1%, 5% and 10% levels respectively. Regressions include time-division dummies and covariates: stock of computer capital per worker in 1990; exposure to Chinese imports; year interaction with demographic and industry characteristics in 1990 in panels A and B and without year interaction in panel C (log population, share of male population, population shares of Whites, Blacks and Hispanics, share of the population over 65 years old, shares of the population with no college, some college and more than college, female employment share, share of employment in agriculture, mining, construction, light manufacturing and manufacturing, routine employment share and average offshorability index).

C.6 Low-skilled native population and employment share

Panel a of Figure C.2 shows the proportion of low-skilled natives across different industry and routine jobs. As expected, the majority of the low-skilled native workers are employed in manual and routine occupations than abstract occupations. Panel b of Figure C.2 presents the employment share of low-skilled native workers in industry-occupation cells; manufacturing, trade and other service sectors employ a substantial share of low-skilled native workers.

Figure C.2: Share of low-skilled natives and employment among low-skilled natives in 1990

(a) Low-skilled share (b) Employment share



C.7 Labour market competition

Our analysis of the mitigating effects of immigrant mobility assumes that low-skilled immigrants and natives compete for similar jobs. Altonji & Card (1991) argue that one way to compute labour market competition is to measure the similarity of the industrial composition between the two groups of workers.

$$\text{Competition} = \frac{S_j^I S_j^U}{S_j} \tag{10}$$

where S_j is the share of workers employed in industry j out of total employment, S_j^g is the number of workers employed in industry j of group $g = \{I, N\}$ divided by total employed in group g. I, N stand for immigrants and natives, respectively. A value of 1 implies a homogeneous labour market, whereas values much higher than 1 indicate strong competition between the two groups. We compute this value between the average low-skilled immigrant worker and low-skilled native worker by race/ethnicity and gender. Moreover, we calculate it separately for CZs which are above or below the median value of immigrant share in 1990.

Table C.6 shows the labour market competition index for the subgroups for above and below the median immigrant share in columns 1 and 2, respectively. The third column calculates the difference in the index. A higher difference implies larger potential impact of immigrant mobility. The gap in the labour market index is largest for Hispanic and Black women and smallest for White men.

Table C.6: Index of labour market competition between immigrants and native groups

	Below median immigrant share (1)	Above median immigrant share (2)	Difference (3)
White men	0.967	0.994	-0.027
White women	1.024	0.957	0.066
Black men	1.004	0.972	0.032
Black women	1.051	0.973	0.077
Hispanic men	1.08	1.025	0.055
Hispanic women	1.099	1.002	0.098

D Section 5 Appendix: Mechanisms

D.1 Construction of low-skilled nativity-specific robot exposure

We construct nativity-specific robot exposure by exploiting the difference in low-skilled foreign- and native-born workers' employment shares by industries. We use group-specific employment share in an industry of low-skilled workers in a CZ to compute robot exposure at the CZ level by nativity status.

$$\Delta R^{N,US}_{i,t} = \sum_j \left[\frac{L^U_{i,j,1970}}{L^N_{i,1970}} \cdot \Delta R_{j,t} \right] \quad (11)$$

$$\Delta R^{I,US}_{i,t} = \sum_j \left[\frac{L^I_{i,j,1970}}{L^I_{i,1970}} \cdot \Delta R_{j,t} \right] \quad (12)$$

where $\frac{L^g_{i,j,1970}}{L^g_{i,1970}}$ is the employment share of a citizenship group $g = \{I, N\}$ in industry j, CZ i and year 1970. We standardize the two measures such that their mean is 0 and standard error is 1. Autor et al. (2019*b*) and Yu (2023) apply a similar definition in examining gender-specific and nativity-specific exposure to Chinese competition, respectively.

Figure D.1 reports the histogram of the two robot exposure measures. Immigrant robot exposure has a larger mass at the high negative values whereas, natives' robot exposure is more concentrated around 0. However, the weighted correlation between them is 0.76 (unweighted correlation is 0.55) and the distributions look fairly similar.

Figure D.1: Distribution of Immigrant- and Native-specific Robot Exposure