Automation and Local Labour Markets: Impact of Immigrant Mobility

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Abstract

This paper illustrates the role of low-skilled immigrant mobility as a channel through which local labour markets adjust to automation. Using a shift-share instrument, we show that low-skilled immigrants are significantly more mobile in response to robot exposure than their native counterparts. Low-skilled immigrant mobility acts as an important insurance mechanism for low-skilled natives against robot exposure, with wages falling 0.07 percentage points less in commuting zones at the median compared to those in the first quartile of immigrant share. Finally, we identify human capital accumulation as an additional factor that contributes to the low migration response of native workers.

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

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1 Introduction

The recent wave of industrial robot adoption has transformed labour markets across many advanced economies, including the US (Abraham & Kearney 2020, Acemoglu & Restrepo 2020).[1,2] The geographical mobility of workers is considered 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, our aim is to answer two questions about which currently little is known. First, are low-skilled immigrants more mobile than low-skilled natives in response to the introduction of robots? Second, does the mobility of low-skilled immigrants mitigate the effect of robot adoption on low-skilled native workers?

We examine the impact of robot adoption on U.S. local labour markets, specifically commuting zones (CZs), using a shift–share instrumental variable strategy to causally identify its effects. We exploit variation in national growth in robot use by industry from 1990 to 2015 and historical (1970) employment shares at the industry-CZ level. Following Acemoglu & Restrepo (2020), we instrument U.S. robot adoption using five European countries to remove US-specific advances in robotics. We estimate stacked-difference regressions for 1990–2000 and 2000–2015, controlling for CZ-specific differential trends based on baseline demographic and industry characteristics.[3]

We find a significant difference in low-skilled population growth by nativity status in response to robot exposure. Specifically, an additional robot per thousand workers reduces the growth in the low-skilled immigrant and native population by 5.49 and 1.04 percentage points, respectively. In contrast, the fall in population growth of high-skilled immigrants is smaller than that of high-skilled natives, but this gap is imprecisely estimated. Accordingly, the paper primarily focuses on the significant asymmetry in

[1] Our focus in this paper is on industrial robots that typically displace low-skilled manual or physical labour. We interpret automation as a broader form of technological progress that includes robotisation, computerisation and adoption of digital technology.

[2] There is considerable debate about the labour-market effects of robotisation (Acemoglu & Restrepo 2020, Adachi et al. 2024) and other forms of automation (Goldin & Katz 2009, Gathmann et al. 2025). This paper focuses on the United States, where the adoption of industrial robots has been linked to job and wage losses (Acemoglu & Restrepo 2020), rising inequality (Acemoglu & Restrepo 2022*b*), reduced upward mobility (Guo 2022), deteriorating mental health (Gihleb et al. 2022), and declines in marriage rates and marital fertility (Anelli et al. 2024).

[3] We control for low-skilled population growth between 1970 and 1990 to mitigate concerns of a negative association between robot exposure and lagged low-skilled population growth (Lewis 2011).

the migration responses of low-skilled workers by nativity and the implications of low-skilled immigrant mobility.

We address potential identification concerns associated with the shift-share instrument approach (Goldsmith-Pinkham et al. 2020), including pre-trends in the outcomes of interest and the disproportionate influence of an industry in our identifying variation, such as the automotive industry. Reassuringly, we find no significant pre-trends in the key outcomes of interest, and our results remain robust across specifications when excluding an industry in constructing the robot exposure measure.

Investigating the channels of population adjustment, we find that low-skilled immigrants are both less likely to enter and more likely to exit robot-exposed regions. We find no significant effect of robot penetration on international migration, indicating that most labour reallocation occurs among incumbent immigrants. By contrast, low-skilled natives are more likely to exit robot-exposed areas but do not exhibit a systematic reduction in entry. This pattern suggests that mechanisms other than mobility also contribute to shaping natives' responses to robot exposure. We discuss the role of human capital accumulation later in the paper.

The observed mobility response to robot exposure is likely driven by changes in labour market conditions.[4] Robot exposure leads to employment and wage losses among low-skilled workers, with substantially larger effects for immigrants than for natives. Part of this gap reflects occupational exposure, as robots disproportionately affect routine manual jobs in which low-skilled immigrants are overrepresented. However, occupational composition alone cannot explain the results: employment declines more sharply for low-skilled immigrants even in non-routine jobs, where immigrants are under-represented. Moreover, the disparity in mobility responses to robot exposure between low-skilled immigrants and natives is much larger than the corresponding difference in wage losses. Together, these patterns indicate that low-skilled immigrants are both more exposed to robots and more responsive to them than their native counterparts.

[4]Workers are aware of and concerned about automation risk. Golin & Rauh (2022) show that a substantial share of individuals expect to lose their jobs due to automation, while Cattaneo et al. (2025) finds that workers are willing to forgo a significant share of earnings to reduce automation risk. Additionally, we show that selection effects, due to lower inflow or higher outflow of higher-wage individuals from robot exposed regions, is not the main reason driving the observed negative labour market outcomes from robot exposure.

Having established that low-skilled immigrant location choices are particularly responsive, we analyse the impact of their mobility on native workers to robot adoption. We exploit the proportion of low-skilled immigrant population across CZs interacted with robot exposure to capture the mitigating effects of low-skilled immigrant mobility. Furthermore, we use the 1990 share instead of the current share of low-skilled immigrants to avoid the issue of reverse causality. To address the endogeneity issue of the non-random sorting of immigrants, we instrument the 1990 CZ low-skilled 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 correlation between the robot exposure measure and the share of low-skilled immigrants in 1970 at the CZ level is -0.03, indicating sufficient power to separately identify the effects of robot exposure and immigrant mobility.

The location choices of low-skilled immigrants attenuate the adverse effects of robot penetration for low-skilled native workers. The decline in low-skilled native wages due to robot adoption is 0.07 percentage points lower in the 50^{th} percentile of the low-skilled immigrant share compared to the 25^{th} percentile. On average, immigrant mobility does not alleviate employment opportunities for low-skilled natives from robot exposure; the loss in employment is similar in both areas with many and few immigrants. However, the average effect hides considerable heterogeneity; immigrant mobility protects the employment opportunities of natives' working in some of the service sectors or older native workers. The reduction in the employment of older low-skilled natives from robot exposure is lower by 0.1 percentage points when comparing CZs in the 50^{th} and 25^{th} percentiles of the low-skilled established immigrant share.

The policy prescriptions to limit the adverse impact of robot adoption have mainly focused on regulating their use (Beraja & Zorzi 2025), implementing redistributive policies (Guerreiro et al. 2022), or training workers (Jaimovich et al. 2021). We provide evidence supporting a new mechanism, low-skilled immigrant mobility, which offers insurance to low-skilled native workers against robot-adoption.

We reinforce the interpretation of our findings with several robustness checks. We rule out pre-trends by demonstrating that, in 1970, there were no significant differences in labour market outcomes of natives between areas with high and low concentrations of low-skilled immigrants in relation to future robot adoption. Another concern is

that persistent labour demand shocks cause the persistence in immigration patterns, potentially violating our exclusion restriction. To address this concern, we include the 1980 immigrant share as an additional control, following Jaeger et al. (2018), who argues that the dynamic effects of past immigration shocks can be mitigated by conditioning on immigrant shares in subsequent periods. Reassuringly, our results are robust to the inclusion of this control. Moreover, our results remain robust when using the 1950 or 1960 low-skilled immigrant share in place of the 1970 share as the instrument.

In the final section of the paper, we discuss other potential mechanisms, specifically human capital accumulation, that might explain the limited sensitivity in low-skilled natives' location choices. We find that young natives are more likely to enrol in college in more robot-exposed regions. Moreover, most of the increase in college enrolment occurs among individuals out of the labour force, which indicates that natives are delaying their entry into the job market due to robot exposure. We also find that robot exposure increases college enrolment for immigrants, especially among older immigrants. This effect is driven mainly by incumbent immigrants, who are overrepresented in routine-manual occupations and thus especially vulnerable to job displacement from robot adoption. In conclusion, beyond migration, individuals may mitigate the effects of robot exposure by accumulating human capital, a channel that seems particularly relevant for low-skilled natives.

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). We complements this literature by examining the contribution of immigrant location choices in a new and topical context: automation through robot adoption. While some recent studies suggest that immigration may reduce firms' incentives to automate by lowering labour costs (Danzer et al. 2024), our paper highlights low-skilled immigrant mobility as a complementary channel in mitigating the adverse labour market impacts of robot adoption. We show that immigrant mobility can cushion wage losses from adverse demand shocks, whereas most prior studies focus on mitigating effects on the employment margin, with the exception of Özgüzel (2021).[5] Such evidence informs the design of low-skill immigration policies, particularly in

[5]Focusing on a persistent adverse shock may explain the stronger adjustment of local labour markets through wages in our findings compared to other studies (Cadena & Kovak 2016).

light of the push for anti-immigration measures in response to job losses (Autor et al. 2020, Brey 2024) and declining regional mobility in the US (Molloy et al. 2011, Olney & Thompson 2024), as well as labour market policies such as the minimum wage (Cadena 2014, Lordan & Neumark 2018).

Second, our study contributes to the literature on the role of heterogeneity in evaluating the effects of robot adoption (Acemoglu & Restrepo 2020, Albinowski & Lewandowski 2024, Ge & Zhou 2020, Gathmann & Grimm 2022, Javed 2023, Lerch 2024). Faber et al. (2022) finds that individuals migrate in response to robot exposure. Relative to Faber et al. (2022), we examine migration responses to robot exposure by nativity-skill groups. Examining heterogeneous responses matters because they can help reveal additional channels to protect against adverse demand shocks, and shed light on aggregate results. For example, both we and Faber et al. (2022) find the puzzling result that, without disaggregating by skill, robot exposure reduces population growth of natives, but not of immigrants. However, disaggregating by skill type provides further insight into this finding. Low-skilled immigrants display a strong migration response to robot exposure, which is consistent with immigrants' migration response to adverse labour demand shocks (Cadena & Kovak 2016).

Third, we contribute to the large literature on skill-biased technological change and education (Goldin & Katz 2009, Acemoglu & Autor 2011). Several studies in the recent literature (Branco et al. 2025, Dauth et al. 2021, Di Giacomo & Lerch 2023) have shown that younger people are more likely to invest in additional human capital in response to robot exposure. We complement this literature by showing that young non-employed natives delay their entry into the labour market by enrolling in college in more robot-exposed regions. In addition, older employed immigrants also upgrade their skills by attending college in response to robot exposure. Thus, we show that human capital accumulation is not limited to younger individuals (Corman 1983) and represents an additional channel to mitigate against unfavourable labour demand shocks.

Lastly, this study contributes to the literature on internal migration as a response to labour demand shocks. In many studies, the variation in the shock to labour demand is captured through business cycle fluctuations (Hershbein & Stuart 2024, Monras 2020), as well as industry- or firm-specific demand shocks (Bound & Holzer 2000, Greenland et al. 2019, Notowidigdo 2020). The shocks in these studies are likely to be temporary

in nature, whereas we focus on a long-run shock that is likely to permanently change the composition of local labour markets. We find that individuals adjust locations in response to changes in labour market conditions, particularly low-skilled immigrants. This indicates that the internal reallocation of prospective migrants is a crucial adjustment mechanism to economic shocks in local labour markets (Dustmann et al. 2017, Monras 2020).

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 skill types and the implications of low-skilled immigrant mobility for the native workforce. Section 5 highlights the educational attainment channel as a response 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 Sources

2.1.1 Data on stock of industrial robots

Our data on the stock of industrial robots 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) defines an industrial robot as an "automatically controlled, reprogrammable multipurpose manipulator, programmable in three or more axes, which can be either fixed in place or fixed to a mobile platform for use in automation applications in an industrial environment". It is the most widely used cross-country data source for robot adoption (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 shows that the automotive, chemical, and electronics sectors experienced the highest growth in robot use in the US

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

over the sample period, while construction and services saw the lowest growth. Data on employment and the rate of growth of output at the country-industry level come from the EU KLEMS Growth and Productivity Accounts (The Conference 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 (Ruggles et al. 2023) for the years 1950, 1960, 1970, 1990 and 2000, as well as the 2013-2017 American Community Survey (ACS).[7] Immigrants are defined as individuals born outside the US to non-US citizens. An individual with a high school degree or less is classified as low-skilled, whereas someone with some college education or more is considered high-skilled. Our sample consists of non-institutionalised individuals 16 to 64 years of age. Notably, we conduct our analysis at the CZ level, using data containing 722 CZs that cover the entire US except for 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 1970 employment share to avoid a mechanical correlation between robot use and industry shares prior to 1990 (Acemoglu & Restrepo 2020). Therefore, exposure to robots in the US is defined as:

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

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

2.1.3 Other data

Beaudry et al. (2010) argue that computer capital is complementary to high-skilled workers but substitutable to low-skilled workers. The real stock of computer capital

[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 1960, 1990 and 2000 Census and 1% for the 1950 and 1970 Census.

[8] A CZ comprises counties with strong labour market ties. It is among the most common types of geographical disaggregation to study 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 1990 immigrant population share, respectively. Appendix A.2 contains more details on the construction of the robot exposure measure.

in the US almost doubled between 1990 and 2015, underscoring the importance of accounting for technological changes that are unrelated to robot adoption. Computer adoption is measured by the growth in the value of computing equipment stock in US dollars per thousand workers, using data from EU KLEMS.[10] We also incorporate trade exposure data from Autor et al. (2019) to account for the employment reduction caused by exposure to Chinese import competition.[11]

2.2 Empirical specification

To formally examine the impact of robot exposure on population growth, we estimate a stacked first-differences specification with two periods (1990-2000 and 2000-2015):

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

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 $\Delta R_{i,t}$ denotes robot exposure.

We include division-time dummies, along with a comprehensive set 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 estimates of population change by accounting for potential underlying trends. Division time dummies are included to absorb region-specific trends in the outcome variable. The coefficient of interest, β, is identified by comparing the CZs within the same division during a given period.

We control for overall trends in the US labour market by including the employment

[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 CZ's computer capital growth between 1990 and 2015, similar to the measure of robot exposure in equation (1).

[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. Autor et al. (2013) remove endogeneity between industrial import demand and actual imports from China by replacing the growth in Chinese imports to the US with those of eight other developed economies (Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland).

[12] The 1990 CZ demographic characteristics are: log population and population shares of: men; those older than 65 years old; those 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) argue that the decrease in employment in these industries is negatively related to robot penetration.

share of routine and offshorable jobs in 1990 interacted with time dummies and exposure to Chinese imports.[13] We control for potentially confounding technological advancements unrelated to robot adoption by accounting for computer capital adoption. The growth in the use of computer capital is proxied by its 1990 level, following Michaels et al. (2014). Appendix Figures A.3a and A.3b show that the level of computer capital per worker in 1990 effectively captures the variation in its growth from 1990 to 2015 at both the industry and the CZ levels, respectively.

An unobserved labour demand shock in a CZ may influence firms' technology choices in that labour market. To isolate the causal effect of robot adoption, we instrument robot exposure in the US using robot exposure in European countries, following Acemoglu & Restrepo (2020). This approach isolates technological advancements in robot technology in other developed countries, removing any bias from shocks specific to the US. In line with the literature, we consider five European countries (EURO5): Denmark, Finland, France, Italy, and Sweden. Appendix Figure A.1 shows that robot use has increased similarly since the 1990s in both the United States and the EURO5 countries. Germany exhibits a higher level and faster growth in robot adoption than the United States, while the United Kingdom (UK) has experienced substantially slower adoption than the other countries. These patterns motivate our choice of the EURO5 countries to instrument US robot adoption; nevertheless, we later show that our results are robust to including Germany and the UK in the instrument.

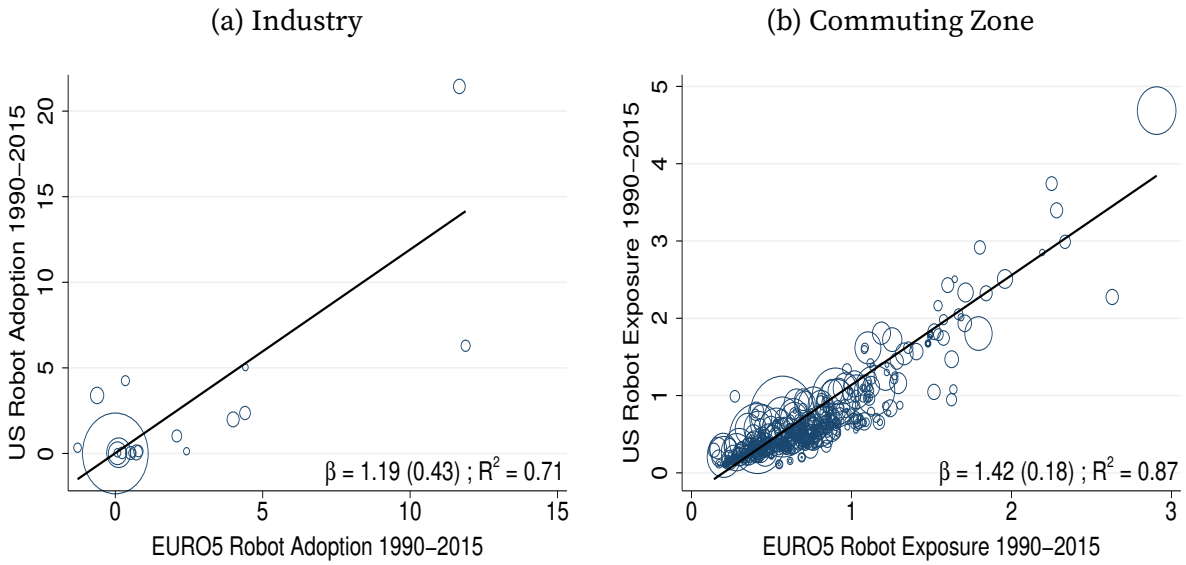
The EURO5 robot-exposure measure $\left(\Delta R_{i,t}^{EURO5}\right)$ is calculated by replacing the growth of the US industry-level robot growth in Equation (1) with the industry-level growth of EURO5 robots $\left(\Delta R_{j,t}^{EURO5}\right)$. The average growth in robot adoption for each industry in EURO5 is a simple average over all the countries:

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

Figure 1a shows a strong relationship between robot adoption at the industry level in the US and European countries. Therefore, exposure to robots in European countries can isolate the variation that stems from global progress in robotics. Figure 1b shows

[13] 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.

Figure 1: Relationship between US and EURO5 robot exposure



Note: In Panel (a), marker sizes reflect U.S. industry employment shares in 1990, and robust standard errors are reported in parentheses. In Panel (b), marker sizes correspond to 1990 population levels in each CZ, and standard errors clustered at the state level are shown in parentheses.

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 the exposure of US robots to local labour markets. Appendix Table A.2 shows that this relationship is quite stable even after accounting for various controls.

The key identifying assumption of the IV strategy in our setting is that the local employment shares are unrelated to factors affecting local population growth (Goldsmith-Pinkham et al. 2020). Following Acemoglu & Restrepo (2020), we use 1970 employment shares, a period that precedes the widespread adoption of robots, to mitigate this concern. We cannot formally test for the validity of the exclusion restriction, but we show in our robustness analysis below that our results are not driven by industry-specific trends. Appendix Table A.1 shows that robots were already an integral part of certain industries, such as automotive and chemical manufacturing, in the 1990s. Thus, we re-estimate our coefficients of interest leaving one industry out of the instrument and show that the main conclusions remain unchanged.

An additional concern might be that the rise in low-skilled immigration during the 1970s may have reduced the adoption of labour-substituting technology (Peri 2012),

potentially biasing our results if robots and low-skilled immigrants are highly substitutable in the production process (Danzer et al. 2024, Lewis 2011). Appendix Table A.3 shows a negative but insignificant association between the growth of the low-skill immigrant population from 1970 to 1990 and *future* robot-exposure, implying a lack of pre-trends in our outcomes of interest. Nonetheless, we include low-skilled population growth between 1970 and 1990 as a control to account for the possibility that more- and less- robot-exposed areas experienced differential population growth. We show the robustness of our results to controlling for pre-trends in various alternative ways.

2.3 Descriptive Statistics

Appendix Table A.4 reports the averages throughout the sample period in column 1, with the averages for the CZs in the fourth and first quartiles of robot exposure in columns 2 and 3, respectively. The fourth column shows the difference between these two quartiles, while the final column reports tests of equality for the summary statistics.

The table reveals our first key finding: the low-skilled immigrant population declined far more than the low-skilled native population in CZs with greater robot exposure. We separate our results by nativity not only because immigrants tend to be more mobile, but also because labour market conditions likely play a more significant role in shaping their location choices. Additionally, the table shows that this pattern holds across both nativity and skill groups for employment, suggesting that the observed population decline is likely a response to shifts in labour market opportunities.

3 The effect of robots on mobility by nativity

In this section, we examine the changes in population by nativity in response to the introduction of robots, following which we analyse the margins along which the migration responses occur. We then argue that the migration response arises due to the impact of robot exposure on employment and wages.

In all regressions, the outcome variables are scaled to equivalent 10-year changes and multiplied by 100. An estimated coefficient 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. All regressions use the same set of controls described

above, unless stated otherwise. All regressions are weighted by a 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 within-state spatial correlations.

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 division 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. This difference is equal to the change in the logarithm of the relative number of immigrants to natives, or, in other words, the change in the logarithm of immigrant concentration.

Focussing on 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 set of controls, a unit increase in robot 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.[14] The implied decrease in the relative population of low-skilled immigrants by 4.45 pp is statistically significant at the 5% level (column 6). A unit increase in robot exposure is close to the average decadal increase in robots per thousand workers over the sample period. Therefore, an additional robot per thousand workers reduces the growth in the relative low-skilled immigrant population by 9.56% (= 4.45*100/46.55) compared to the average decadal growth (46.55%) in the CZ.

The estimates in Panel B of Table 1 show that highly-skilled natives are more sensitive to adverse labour demand shocks than low-skilled natives. However, the coefficient

[14]The population-to-employment elasticity for low-skilled immigrants is slightly higher than what has been estimated in the existing literature. We estimate an effect of -6.53 pp 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). Cadena & Kovak (2016) finds an elasticity of 0.569 for low-skilled Mexican-born men during the Great Recession, which is somewhat smaller, potentially reflecting that automation represents a more persistent adverse shock than the Great Recession.

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
Mean (%)	-4.68	-4.68	41.87	41.87	46.55	46.55
	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
Mean (%)	17.14	17.14	47.08	47.08	29.93	29.93
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).

for highly-skilled immigrants is imprecisely estimated (column 4) and the corresponding difference in the growth rates between the responses of high-skilled immigrants and natives to robot exposure is statistically insignificant (columns 5 and 6). This may appear puzzling, as immigrants are typically considered more mobile. We revisit this result in our discussion of labour market outcomes (Section 3.3), showing that the seemingly lower mobility of high-skilled immigrants likely reflects compositional effects,

specifically, the recent arrival of immigrants in robot-complementary occupations, rather than inherently lower mobility.

Combining the results from Panels A and B of Table 1, we present the aggregate implications in Appendix Table B.1, disaggregated by nativity group and skill group. Consistent with Faber et al. (2022), we find that the change in the immigrant population (including both low- and high-skilled groups) in response to robot exposure is statistically insignificant, while native population growth declines in areas more exposed to robots. Moreover, robot adoption reduces the population growth of both low- and high-skilled individuals by a similar magnitude. While low-skilled natives are less responsive than high-skilled natives, this difference is much smaller than the large difference between low-skilled and high-skilled immigrants.

The heterogeneous responses of individuals across nativity-skill groups to robot adoption, particularly the high sensitivity of low-skilled immigrants, constitute a novel finding. In Section 4, we discuss the implications of low-skilled immigrant mobility for the labour market outcomes of native workers in areas more exposed to robot adoption.

Our regression specification incorporates a broader set of controls than those typically used in the literature. Appendix Table B.2 shows the role of the various controls in affecting the estimated coefficients in Table 1. Including the interaction between period dummies and Census division dummies substantially reduces the point estimates and standard errors, while including the interaction between the 1990 CZ characteristics and period dummies decreases the low-skilled coefficient magnitude. Thus, the additional controls strengthen the robustness of our results. Additionally, our analysis does not suffer from a weak instrument problem, as all the first-stage F-statistics are greater than 100. Therefore, the remainder of the analysis uses the 2SLS specification.[15]

We document in Appendix Table B.4 that directly controlling for pre-trends through various ways in the regressions does not materially alter our conclusions. Additionally, Appendix Section B.5 illustrates the robustness of our findings to potential identification threats (disproportionate robot adoption across industries and alternative set of countries to instrument US robot adoption), or potential confounders such as the Great Recession and spillover from neighbouring CZs (Borusyak, Dix-Carneiro & Kovak

[15]Appendix Table B.3 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, suggesting that the correlation between unobserved shocks and robot exposure generates a downward bias for the OLS estimate.

2022) and results sensitive to states with high international migration. Finally, we also show the robustness of our findings with respect to alternative weights (Appendix Table B.10) and standard errors (Appendix Table B.11). Thus, the considerable decline of low-skilled immigrants due to robot exposure is a robust result.

The population decline could occur due to a lower inflow of individuals into areas more exposed to robots and/or a higher outflow from these areas. In the following subsection, we decompose the migration channels in response to robot exposure.

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 likely more relevant for immigrants than natives.[16] We measure the importance of these various channels as follows (ignoring channel 5, as it is not observable 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 the working-age population in CZ i 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} denote the number of individuals within the US who entered or exited CZ i between t and $t+1$, and $N_i^{\text{net-ageing}}$ measures the difference in the number of people who aged in and aged out of the sample. We use the 2000 Census sample and 2013-2017 ACS sample from IPUMS (Ruggles et al. 2023) to measure migration flows.[17] Table 2 presents the importance of each channel in the migration response to robot exposure by nativity-skill groups.

We find that internal migration within the US is the main channel through which the population decline of low-skilled immigrants occurred due to robot adoption. Column 1 in Panel A demonstrates that an additional robot per thousand workers reduced inflows

[16] In our calculations, we exclude natives who returned to the U.S. within the past five years, as they accounted for less than 1% of the native population in 2000.

[17] The 2000 Census sample provides migration information about the past five years, whereas the 2013-2017 ACS sample provides information about migration activity in the last year. Following Molloy et al. (2011) and to make the coefficients comparable with the population response point estimates, we convert the data for both years into 10-year migration rates. See Appendix A.2.1 for a detailed description of the construction of the migration flows.

of low-skilled immigrants by 1.65 pp. Moreover, the introduction of robots induced immigrant outflow of 1.68 pp for every one additional robot per thousand workers. Combining the coefficients from column 4 in panel A of Table 1 and columns 1 and 2 in Table 2, internal migration explains 61% (= (1.65+1.68)/5.49) of the total decrease in low-skilled immigrants due to robot exposure. Column 4 reveals a negative but statistically insignificant reduction in the arrival of international immigrant in more robot-exposed regions.[18] Overall, our results align with Cadena & Kovak (2016), who also established that labour reallocation within the country is an important mechanism through which low-skilled immigrants insure against adverse labour demand shocks.

Columns 5 and 6 in Panel A decompose the population response for low-skilled natives to robot exposure into inflows and outflows, respectively. The introduction of robots induces an outflow of low-skilled natives, while having little impact on their in-migration. Furthermore, these coefficients are nearly one-third the size of those for low-skilled immigrants, affirming our finding that immigrants are much more responsive to robot adoption in their location choices than natives.

Focusing on high-skilled individuals in Panel B, columns 5 and 6 show that high-skilled natives respond to robot exposure by reducing entry and increasing exit.[19] High-skilled immigrants, by contrast, are more likely to leave robot-exposed areas but do not significantly reduce entry into such regions. Overall, the migration responses of high-skilled immigrants are somewhat weaker than those of high-skilled natives.

Finally, the results in Table 2 also include a net-ageing term, defined as the number of 16 to 19 year old in $t+1$ (ageing in) minus the number of 65 to 69 year old in $t+1$ (ageing out). The negative coefficients on net-ageing could reflect either a mechanical correlation between robot exposure and ageing or a behavioural response; Acemoglu & Restrepo (2022*a*) document that robot adoption is higher in CZs with a higher share of older individuals.[20] We conduct additional exercises to assess whether behavioural responses contribute to the net-ageing patterns. Appendix Table B.12 shows that the change in population of 65-69 year old low-skilled natives and high-skilled immigrants

[18]The wide confidence intervals limit our ability to precisely estimate the role of return migration. However, based on the point estimates for inflow and outflow responses, it appears unlikely that return migration is the primary channel through which low-skilled immigrants respond to robot exposure.

[19]The sharp decline in in-migration rates aligns with findings from Faber et al. (2022) and Monras (2020), who emphasise that in-migration is a key mechanism through which local labour markets adjust to economic shocks.

[20]We control for the share of population above 65 to prevent this from biasing our estimates.

Table 2: Effects on migration flows by nativity-skill groups, stacked-differences (2SLS)

	Immigrant				Native		
	In	Out	Net-aging	New Arrival	In	Out	Net-aging
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	A: Low-skill						
Exposure to robots	-1.65**	1.68*	-1.49	-1.42	-0.45	0.62*	-1.17***
	(0.77)	(0.92)	(0.95)	(1.15)	(0.55)	(0.37)	(0.35)
Observations	1444	1444	1444	1444	1444	1444	1444
R^2	0.61	0.40	0.43	0.76	0.78	0.68	0.91
Mean (%)	22.28	-17.74	-5.03	29.59	16.02	-16.84	15.26
	B: High-skill						
Exposure to robots	-0.44	1.95**	-1.08***	-1.13	-1.43*	1.05**	-0.73***
	(0.98)	(0.94)	(0.40)	(0.87)	(0.80)	(0.46)	(0.19)
Observations	1444	1444	1444	1444	1444	1444	1444
R^2	0.64	0.57	0.51	0.78	0.81	0.78	0.95
Mean (%)	32.63	-32.59	-9.54	29.67	30.51	-31.21	-10.75

Note: The dependent variable in columns (2) and (6) is 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; 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).

is not significantly affected by robot exposure, confirming that ageing out does not capture their behavioural migration response. Educational responses to robot exposure, which we examine in detail in Section 5, can affect ageing in only through the behaviour of 19 year old entering the sample, limiting the likelihood of ageing in contributing significantly as a behavioural channel. Overall, our results suggest that net-ageing should not be interpreted as capturing a primary behavioural response of mobility.

Lastly, to ensure that our results are not driven by large changes in migration in a few CZs, we re-estimate our coefficients after excluding the top 1 percentile of observations of the dependent variable. Appendix Table B.13 shows that although the magnitudes of

our point estimates decrease, our overall conclusions remain unchanged.

3.3 Effect on labour market outcomes by nativity

The results in Sections 3.1 and 3.2 show that low-skilled immigrants are more mobile in response to robot exposure than low-skilled natives. Borjas (2001) documents that immigrants exhibit higher geographic mobility in response to labour market shocks. However, differential exposure to robot adoption might also explain the asymmetric migration patterns we observe. To investigate these explanations, we estimate the effects of robot exposure on the change in log employment and the change in log average wages, running separate regressions for each nativity-skill group.[21]

Panel A of Table 3 shows that both low-skilled immigrant and native workers experience employment and wage losses from robot exposure. The employment effects (columns 1 and 2) exceed the population changes shown in Table 1, indicating that job losses due to robot penetration were not fully offset by migration. Importantly, the impact is substantially larger for low-skilled immigrants than for low-skilled natives, consistent with Javed (2023). An additional robot per thousand workers reduces employment by 6.53 pp for low-skilled immigrants compared to 1.3 pp for low-skilled natives. Similarly, wage losses are larger for low-skilled immigrants (2.67 pp) than for low-skilled natives (1.11 pp).

In contrast, this asymmetric impact by nativity does not hold among high-skilled workers. Panel B shows that robot exposure reduces employment more for high-skilled natives than for high-skilled immigrants, while wage effects are similar in magnitude across the two groups (though imprecisely estimated for high-skilled immigrants). While the negative employment effects of robot exposure on high-skilled workers may appear surprising, they are consistent with the literature on US local labour markets (Acemoglu & Restrepo 2020, Faber et al. 2022). Acemoglu & Restrepo (2020) argue that

[21] Acemoglu & Restrepo (2019) consider a simplified framework where output is produced using labour and capital in a CES production structure and automation affects the share of tasks performed by labour (Acemoglu & Restrepo 2018). Our stylised model in Appendix Section C.1 also follows this structure, which allows automation to affect both employment and wages. Other simple extensions to Acemoglu & Restrepo (2018) that allow automation to affect both wages and labour include: (1) models featuring search frictions in the labour market (Leduc & Liu 2024) where workers choose between working or not working, allowing for automation to affect unemployment rate and wages; or (2) models allowing for labour mobility across regions (Faber et al. 2022) such that automation in the economy affects local employment and wages.

Table 3: Effects on employment and wage, stacked-differences 1990–2015 (2SLS)

Dependent variable: Change in log employment or log wage				
	Employment		Wage	
	(1) Immigrant (1)	(2) Native (2)	(3) Immigrant (3)	(4) Native (4)
	A: Low-Skill			
Exposure to robots	-6.53***	-1.30**	-2.67***	-1.11***
	(2.29)	(0.51)	(0.55)	(0.20)
Observations	1443	1444	1443	1444
R^2	0.69	0.82	0.34	0.88
Mean (%)	43.72	-9.71	-3.03	-2.26
	B: High-skill			
Exposure to robots	0.04	-1.58***	-0.82	-1.02***
	(1.14)	(0.38)	(0.53)	(0.19)
Observations	1444	1444	1444	1444
R^2	0.54	0.74	0.33	0.88
Mean (%)	46.38	14.63	3.20	1.35

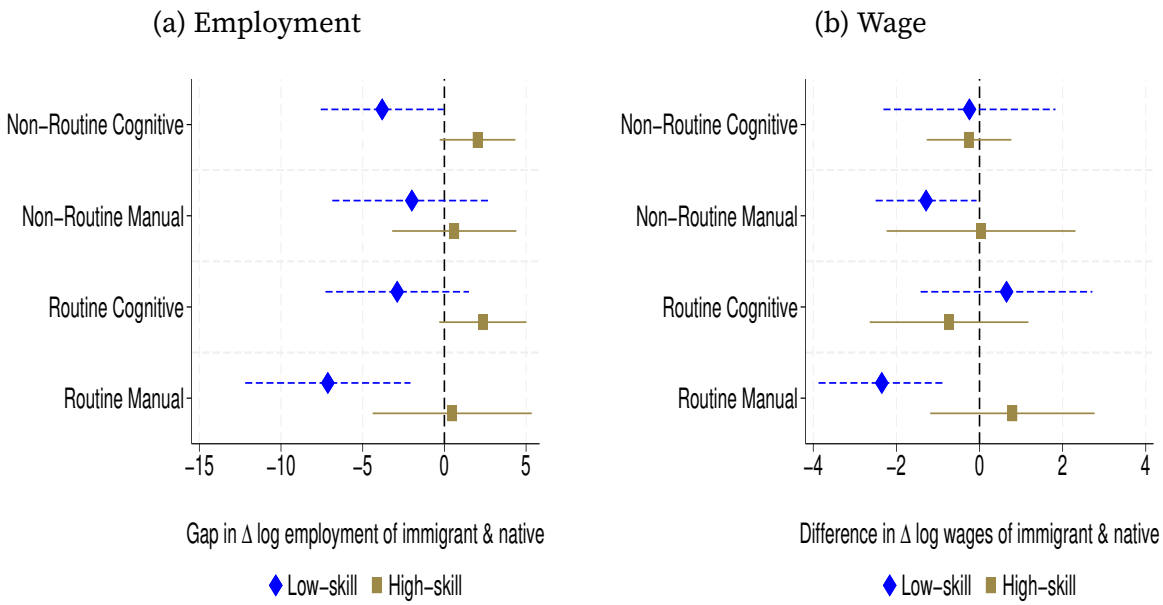
Note: All regression estimates are weighted by the CZ population in 1990. Standard errors clustered at the state level are reported in parentheses. ***, ** and * represent the statistical significance at 1%, 5% and 10% levels respectively. Regressions include time-division dummies and covariates: stock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

job losses among low-skilled workers following robot adoption reduce local demand, which in turn lowers employment of high-skilled workers in regions more exposed to robots. This local demand channel explains why negative regional effects for high-skilled workers can arise despite their complementarity with robots at the firm level.[22]

What explains the asymmetric labour market impacts of robot exposure between immigrants and natives? We present evidence that differences in task specialization,

[22]This pattern is not universal across countries, as studies in other settings typically find non-negative effects of robots on high-skilled workers (Dauth et al. 2021, Graetz & Michaels 2018).

Figure 2: Effects on difference in employment and wage growth between immigrants and natives by tasks and skill groups, stacked-differences 1990–2015 (2SLS)



Note: Bars indicate 95% confidence interval. The dependent variables in panel (a) and panel(b) are the difference in growth between immigrant and native workers' employment and wages, respectively. All regression estimates are weighted by the CZ population in 1990. Standard errors are clustered at the state level.

combined with the uneven impact of robots across tasks, provide a plausible explanation. Acemoglu & Restrepo (2020) show that robots disproportionately displace workers in routine manual occupations, such as machine operators and assemblers, while having smaller effects on workers in non-routine cognitive occupations, such as administrative and managerial roles.

Among low-skilled workers, immigrants are substantially more concentrated in routine manual occupations than natives. In 1990, 49% of low-skilled immigrants worked in routine manual occupations compared with 43% of low-skilled natives. Although the share of workers in these occupations declined for both groups over time, the gap widened from 6 to 8 percentage points by 2015, as shown in Appendix Figure B.2.

Consistent with this pattern, Figures 2a and 2b show that employment and wage losses for low-skilled immigrants relative to low-skilled natives are largest in routine manual occupations. However, low-skilled immigrants also experience larger employment and wage declines in non-routine manual occupations, indicating that differences in task exposure alone do not fully account for the asymmetric effects.

Compositional differences across immigrant cohorts offer one plausible explanation

for the reversal in employment loss patterns by nativity among high-skilled workers. Appendix Figure B.3 shows that recent high-skilled immigrants increasingly specialize in non-routine cognitive occupations, with their share rising from 46.5% in 1990 to 57.1% in 2015. In contrast, this share remains broadly stable for high-skilled natives and established high-skilled immigrants. Correspondingly, Appendix Figures B.4d and B.4e show that robot exposure has a substantially weaker effect on employment and population growth for recent high-skilled immigrants than for established immigrants. Moreover, Figure 2a shows that in non-routine cognitive occupations, high-skilled natives experience the largest employment losses relative to high-skilled immigrants. Together, these patterns suggest that the shift of recent high-skilled immigrants toward less robot-exposed tasks helps explain why high-skilled immigrants experience smaller employment losses than high-skilled natives.

Jointly these results indicate that the higher exposure of low-skilled immigrants to routine manual tasks partly explains their larger employment and wage losses relative to low-skilled natives. Table 2 shows that the migration responses of low-skilled natives, both inflows into and outflows from robot-exposed regions, are at least one-third smaller than those of low-skilled immigrants, while their wage losses are only half as large. Together with the larger employment declines for low-skilled immigrants even in non-routine occupations, these patterns suggest that low-skilled immigrants are both more exposed to robots and more mobile in response to a similar shock than their native counterparts.[23]

We interpret population adjustment as a response to the adverse labour market effects of robot exposure. However, average wages could also fall more in areas exposed to more robots if higher-paid workers disproportionately exit or avoid entering these regions. We provide two complementary pieces of evidence suggesting that selection effects are not the key driver of the negative labour market impacts of robot exposure.

First, we restrict the analysis of labour market outcomes to incumbents, defined as individuals who report not having previously migrated, to rule out selection effects driven by in-migration. Appendix Table B.14 reports the effects of robot exposure

[23]There may be other factors that contribute to the strong migration response by low-skilled immigrants. For example, immigrants might have better social networks than natives, allowing them to evaluate the attractiveness of different locations more effectively (Munshi 2003). Future research using firm-worker longitudinal data could investigate the role of social networks in shaping the migratory response to automation.

on employment and wages for incumbents across skill and nativity groups. Robot exposure reduces both employment and wages across all groups, with point estimates comparable to or larger than those in Table 3. Importantly, the larger adverse effects for low-skilled immigrants relative to low-skilled natives persist when the sample is restricted to incumbents.[24]

Second, while the incumbent analysis rules out selection through in-migration, it cannot address selection through out-migration. If higher-wage immigrants disproportionately leave robot-exposed areas, the remaining workforce would be negatively selected, potentially explaining the larger observed wage losses associated with robot exposure. To address this concern, we residualise wages with respect to observable individual characteristics to assess whether compositional changes drive the estimated wage effects of robot adoption. We predict individual wages using two sets of covariates; the first includes demographic controls only, while the second additionally incorporates occupation and industry dummies.[25] Appendix Table B.15 shows that robot exposure reduces residualised wages across all nativity and skill groups. Comparing baseline and residualised estimates indicates that while compositional changes play some role, particularly for low-skilled immigrants, they cannot fully account for the negative wage effects of robot exposure.

Taken together, these analyses suggest that selection effects are not the primary driver of the observed labour market impacts, supporting our interpretation that population adjustments reflect responses to robot-induced adverse labour market conditions.

In conclusion, this section shows that low-skilled immigrants respond more strongly than natives to robot exposure in their location choices, driving substantial reallocation of the low-skilled immigrant workforce within the US.

[24]The larger employment effects for incumbent low-skilled immigrants reflect heterogeneity in the impact of robot exposure between recent and established immigrants. Appendix Figures B.4b and B.4c show that employment and wage losses from robot adoption are larger for immigrants who have been in the US for more than 15 years than for recent arrivals. Because the incumbent sample excludes recent arrivals, who experience smaller employment effects, the estimated employment losses in Appendix Table B.14 exceed those in the baseline estimates reported in Table 3.

[25]The first set includes indicators for nativity status, age, gender, education, marital status, presence of children, and race or ethnicity. The second set additionally includes three-digit occupation and industry dummies. Appendix Section B.7.1 provides further details on this exercise.

4 Immigrant mobility and native-born workers

In this section, we study the consequences of low-skilled immigrants' location choices for the labour market outcomes of native workers in response to robot exposure.

4.1 Empirical Specification

To estimate the mitigating impact of immigrant mobility, the ideal regression specification would be:

$$\Delta y_{i,t} = \alpha_{d,t} + \beta_1 \Delta R^{US}_{i,t} * \frac{\Delta N^I_{i,t}}{N_{i,t}} + \beta_2 \Delta R^{US}_{i,t} + \beta_3 \frac{\Delta N^I_{i,t}}{N_{i,t}} + \gamma X_{i,t} + \varepsilon_{i,t} \tag{5}$$

where $\frac{\Delta N^I_{i,t}}{N_{i,t}}$ denotes the change in the low-skilled immigrant population relative to the total population in a local labour market.

$\frac{\Delta N^I_{i,t}}{N_{i,t}}$ consists of two terms: the change in the immigrant population $\left(\frac{\Delta N^I_{i,t}}{N^I_{i,t}}\right)$ and the share of immigrants in the population $\left(\frac{N^I_{i,t}}{N_{i,t}}\right)$. Using $\frac{\Delta N^I_{i,t}}{N_{i,t}}$ directly as a regressor would create an issue of reverse causality, as we have demonstrated that robot exposure affects the growth of the immigrant population $\left(\frac{\Delta N^I_{i}}{N^I_{i,t}}\right)$. Using a stylised framework based on Acemoglu & Restrepo (2020) and Ottaviano & Peri (2012), we show in Appendix C.1 that the wages of low-skilled natives decrease less in areas with a greater proportion of low-skilled immigrants. Hence, we use the fraction of the immigrant population to capture the mitigating effect of the reduction in immigrant population. The intuition is the following: if locations with a higher share of immigrants experience a larger decline in their population growth, then the variation through immigrant population shares is sufficient to capture the attenuating effect of immigrant mobility.

To show that this variation holds in our context, we first examine the effect of robot exposure on total low-skilled population (immigrants and natives) in regions with above- and below-median immigrant shares. Column 1 in Table 4 shows that the low-skilled population declined by 2.28 pp in CZs with above-median immigrant share, compared to a decrease of 0.86 pp in CZs with a below-median immigrant share. This 1.42 pp difference is statistically significant. The second and third columns show that this differential growth in overall low-skilled population between CZs with above- and

Table 4: Effects on population by above- and below-median low-skill immigrant share, stacked-differences 1990–2015 (2SLS)

Dependent variable: Change in log population						
	Low-skill			High-skill		
	Overall (1)	Native (2)	Immigrant (3)	Overall (4)	Native (5)	Immigrant (6)
Exposure to robots x Above-median	-2.28***	-1.17***	-5.05**	-1.43**	-1.49***	0.22
	(0.46)	(0.44)	(2.20)	(0.57)	(0.49)	(1.31)
Exposure to robots x Below-median	-0.86	-0.91	-5.99	-1.37**	-1.55**	-2.05
	(0.74)	(0.69)	(4.88)	(0.69)	(0.67)	(2.04)
Observations	1444	1444	1444	1444	1444	1444
R-squared	0.81	0.82	0.70	0.70	0.73	0.55
Test of equality	0.04	0.63	0.83	0.94	0.94	0.30
Mean (%)	0.52	-4.68	41.87	20.07	17.14	47.08

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).

below-median immigrant share is driven by low-skilled immigrants. We also analyse population growth among high-skilled people (total, natives and immigrants) as a *placebo* to rule out factors other than low-skilled immigrant mobility that might explain this result. Columns 4, 5 and 6 illustrate that the population growth of the high-skilled, either as a whole or by nativity groups, does not differ in response to robot exposure between below- and above-median immigrant share areas. Thus, the share of low-skilled immigrants can serve as a proxy for the reduction in aggregate labour supply due to low-skilled immigrant mobility.

We modify our regression specification as follows:

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

where $\frac{N^I_{i,1990}}{N_{i,1990}}$ is the immigrant share in CZ i in 1990. The coefficient of interest is β_1; a

positive coefficient implies that low-skilled immigrants' location choices reduce the impact of robot exposure on natives. In contrast, a null coefficient indicates that immigrant mobility does not equalise spatial differences in the effect of robot exposure on native workers.[26]

A possible concern with this approach is that the distribution of immigrants across local labour markets is not random, as current economic prospects strongly influence location choices of immigrants (Lewis & Peri 2015). We address this by instrumenting the 1990 immigrant share with the 1970 share, as recent immigrants are more likely to settle in areas where previous immigrants are concentrated (Borjas 1995). Appendix Figure C.1 shows that the low-skilled immigrant share in 1970 is strongly predictive of the 1990 share. Appendix Table C.2 shows that this relationship remains robust even after controlling for demographic and industry characteristics. The key exclusion restriction for this IV strategy is that persistent labour demand shocks do not drive the persistence in migration patterns. We assess the validity of our empirical strategy through a battery of robustness checks, including instrumenting using longer lags and controlling for the low-skilled immigrant share in intermediate years.

An additional concern may be that our coefficient of interest, the interaction between robot exposure and immigrant mobility, is confounded by underlying factors jointly influencing both robot adoption and immigration. To address this concern, we first note that the correlation between robot exposure and the 1970 immigrant share is low (-0.03), implying that areas with a high robot concentration and those which had a high proportion of immigrants do not systematically overlap. Second, we examine potential pre-trends to assess whether unobserved historical shocks to local labour markets could bias our estimates. Appendix Table C.3 demonstrates that the growth of native employment and wages between 1970 and 1990 is largely uncorrelated with *future* robot exposure, regardless of the local concentration of low-skilled immigrants. Finally, we demonstrate below that our main results are robust to controlling for pre-trends in various ways or accounting for state-specific time trends.

[26] Appendix Table C.1 demonstrates that robot exposure depresses wages of low-skilled natives less in regions with above-median low-skilled immigrant shares compared to those with below-median shares. However, the differences are imprecisely estimated due to limited variation in immigrant shares, which further supports the credibility of our empirical strategy.

4.2 Main result for the mitigating effects and sensitivity checks

The first row of Table 5 reports the attenuation effect on native employment and wages against robot exposure due to immigrant mobility, controlling for division-time dummies and the same covariates as in Table 1. Immigrant mobility attenuates wage losses from robot exposure for low-skilled natives. The coefficient of 19.82 in column 1 implies that the decrease in native workers' wages due to robot exposure is lower by 0.07 pp when comparing between CZs at the 50th and 25th percentiles of low-skilled immigrant share.[27]

In contrast, the coefficient for low-skilled employment in the second column is positive (7.70), but imprecisely estimated. Therefore, on average, low-skilled immigrants' location choices do not alleviate employment opportunities for low-skilled natives from robot exposure. The lack of an average effect does not preclude the possibility that some native workers could benefit from immigrant mobility, an issue that we examine in further detail below.[28]

Appendix Table C.4 presents OLS and reduced-form results, which are broadly in line with our above findings. Furthermore, Appendix Table C.5 shows that our conclusions are robust to including demographic and industry covariates sequentially. Finally, we demonstrate that our conclusions are robust to alternative methods of computing standard errors. Consistent with the literature (Acemoglu & Restrepo 2020, Autor et al. 2013), we cluster standard errors at the state level. Appendix Table C.6 shows that clustering at the CZ level yields similar results. We also compute standard errors allowing for arbitrary correlation between CZs that lie within a distance of 100 km, or 250 km, or 500 km (Conley 1999). These standard errors are similar to those obtained using state-level or CZ-level clustering, reinforcing the robustness of our findings.

The findings presented so far do not rule out the possibility that unobserved differences in areas with high immigrant shares enable natives to adjust more favourably

[27]The mean exposure to robots is 0.9, and the 50th and 25th 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, native wages in the 75th percentile of the share of low-skilled immigrant share (2.1%) would decrease by 0.285 pp (0.285 = 0.9*0.1982*[2.1-0.5]) less compared to the 25th percentile.

[28]Table 5 also shows an adverse effect of robot exposure on wages and employment of both high- and low-skilled native workers. The impact of immigration is strongly negative for low-skilled natives compared to the weakly negative estimate for high-skilled workers. In general, there is a lack of consensus in the literature on the impact of immigration on local labour markets (Borjas 2003, Caiumi & Peri 2024, Card 1990, Dustmann et al. 2017).

Table 5: 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				
	Low-skill		High-skill	
	Wage	Employment	Wage	Employment
	(1)	(2)	(3)	(4)
Exposure x Share 1990	19.82***	7.70	8.63	1.18
	(7.64)	(12.80)	(9.29)	(19.97)
Exposure to robots	-1.57***	-1.66***	-1.21***	-1.70***
	(0.23)	(0.60)	(0.26)	(0.58)
LS Immigrant Share 1990	-17.67***	-50.42***	-5.75	-24.19
	(4.10)	(10.99)	(6.73)	(19.19)
Observations	1444	1444	1444	1444
R-squared	0.88	0.83	0.88	0.74
Mean (%)	-2.26	-9.71	1.35	14.63

Note: LS denotes Low-skill. US robot exposure and 1990 low-skilled immigrant share are instrumented using EURO5 robot exposure and 1970 low-skilled immigrant share, 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).

to adverse shocks. If such a mechanism were driving our results, the impact of robot exposure on labour market outcomes of high-skilled natives would also be mitigated in areas with a higher low-skilled immigrant share. Columns 3 and 4 of Table 5 show that the effect of robot exposure on high-skilled workers is equally adverse in areas with high- and low-immigrant shares, indicating that CZs with a substantial immigrant share do not appear to be better equipped to absorb labour demand shocks. We also rule out alternative interpretations, including that our finding is driven by regions with more wage flexibility. We estimate the mitigating effects in states with and without Right-to-work laws (Appendix Table C.7), and find similar attenuation of low-skill native wages in both types of local labour markets.

One potential concern with the lagged immigrant share as an instrument for current

immigrant share is the possibility of persistent labour demand shocks generating persistence in immigration patterns, leading to a violation of the exclusion restriction. While we cannot formally test the validity of the exclusion restriction, we conduct various analyses to assess the validity of our empirical strategy. First, Jaeger et al. (2018) argues that including the immigrant share of the intervening years as a control can absorb the impact of past immigration-inducing shocks. Appendix Table C.8 shows that the point estimates are slightly smaller and more precisely estimated when we control for the 1980 immigrant share. Second, we show in Appendix Table C.9 that our results are robust to using the 1950 or 1960 low-skilled immigrant shares as instruments, instead of the 1970 share. The first-stage using older lags is smaller in magnitude compared to using the 1970 share, as shown in Appendix Table C.10. Nonetheless, our 2SLS estimates remain remarkably consistent across specifications, suggesting that the labour demand shocks attracting immigrants were not very persistent in nature.

Another potential concern is that our estimates may be disproportionately driven by robot adoption in specific industries, such as the automotive industry, or by immigration flows from particular countries, such as Mexico. To mitigate these concerns, we re-estimate the coefficients of interest using leave-one-out strategies. Appendix Figure C.2 presents the attenuating effect of low-skilled immigrant mobility on low-skilled native wages and employment from robot exposure where we sequentially exclude immigrants from one country/region at a time from the instrument. The 16 point estimates are indistinguishable from our baseline estimate, indicating that the mitigating effects are not driven by immigrants from a particular country. Similarly, Appendix Figure C.3 presents the 19 point estimates for the mitigating effect of immigrant mobility on low-skilled native wages and employment, including all industries in the robot exposure measure except one. The 19 point estimates are not meaningfully different from our baseline estimate, and they display the highest deviation when excluding the automotive industry. This finding is commonly observed in the literature given the high robot adoption in this industry (Acemoglu & Restrepo 2020). Appendix Table C.11 shows that our results are robust to considering different set of European countries to instrument US robot adoption. Finally, Appendix Table C.12 shows that our results are robust to excluding CZs with the highest robot exposure, as well as states around the Great Lakes (Indiana, Michigan, and Ohio) that experienced disproportionately high

levels of robot adoption.

Common factors that jointly influence robot adoption and immigration pose a potential threat to identifying the effects of immigrant mobility. For instance, if low-skilled immigration reduces robot adoption (Danzer et al. 2024, Lewis 2011), failing to account for pre-existing immigration trends could lead us to incorrectly attribute the mitigating effects to current immigrant mobility. To address this concern, Appendix Table C.13 shows that our findings are robust to controlling for pre-trends using the 1950 and/or 1960 low-skilled immigrant shares, as well as the growth in low-skilled immigrants between 1970 and earlier decades. Additionally, to mitigate the risk of unobserved factors that may influence both immigration and robot adoption trends over the period of analysis, we control for state-specific time trends. Appendix Table C.14 demonstrates that our estimated mitigating wage effects are quite similar when accounting for either state-time fixed effects or state-specific linear time trends.

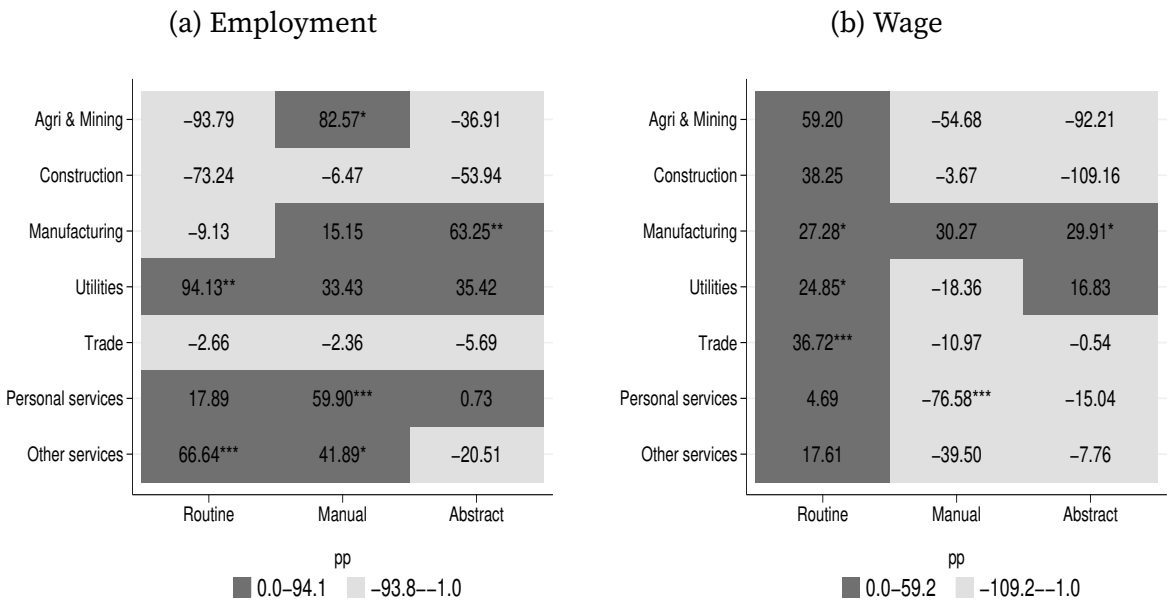
The mitigating effect of immigrant mobility on the labour market outcomes of native workers from the introduction of robots is the second novel and robust finding of our paper. These findings are similar in spirit to the seminal work of Cadena & Kovak (2016). Cadena & Kovak (2016) demonstrated that the mobility of Mexican workers reduced the impact of adverse employment shocks at the city level on low-skilled natives during the Great Recession. This paper highlights that the benefit of immigrant mobility can also manifest through wage attenuation. Although we focus on a different demand shock, robot exposure, we generalise our findings by considering a much longer time horizon (more than a decade) and a broader definition of local labour markets (CZs) compared to Cadena & Kovak (2016). Additionally, we show that our results are not driven by the Great Recession. Appendix Table C.15 demonstrates that our findings are robust when using stacked-differences specifications that exclude the Great Recession period (1990-2000 and 2000-2007), or specifically account for the Great Recession period (1990-2000, 2000-2007, and 2007-2015), as well as when estimating long-run effects using a long-difference specification (1990-2015).

4.3 Heterogeneity by industry-task

While this paper illustrates the attenuating effect, immigrant mobility might adversely affect native workers by reducing the local demand for local goods and services (Hong

& McLaren 2015). To investigate this issue further, we assess the mitigating effects on employment and wages of low-skilled natives by industry-task categories.

Figure 3: Effects on low-skilled natives' labour market outcomes by industry-task 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. US robot exposure and 1990 low-skilled immigrant share are instrumented using EURO5 robot exposure and 1970 low-skilled immigrant share, 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.

Figures 3a and 3b show that the employment and wages of native workers are also attenuated in personal services and other service sectors. This suggests that the decline in immigrant consumption has a limited impact on reducing their role as an insurance mechanism for native workers. The mitigating effects of immigrant mobility on native employment in the utilities and other service sectors mask the limited aggregate effect on employment, as native employment in these industry-task groups is small (Appendix Figure C.4). Finally, these figures show that mitigating effects are stronger in routine occupations and manufacturing industries. This is reassuring, as labour and robots are more substitutable in these roles, and therefore, the mitigating effects would be expected to be more pronounced in such jobs.

4.4 Heterogeneity by age

Appendix Figure B.4a shows that the decline in low-skilled immigrant population growth to robot exposure is particularly pronounced among established immigrants (those who have lived in the US for more than 10 years). Established immigrants are much older than new immigrants entering the US.[29] Since young and older workers are imperfect substitutes (Card & Lemieux 2001), the migration decisions of established immigrants may have different effects on young and older low-skilled natives. We analyse the attenuating effect of established low-skilled immigrant mobility on the labour market outcomes of young (16-39) and older (40-64) native workers from robot exposure.[30]

Table 6 reveals much stronger mitigating effects of established immigrant mobility for older workers than for younger ones. Focussing on employment, the point estimate for younger natives (5.62) is significantly smaller than that of their older counterparts (48.03). The coefficient for older workers is statistically significant, unlike that for younger workers. The attenuation effects are substantial: the decline in the employment of low-skilled older workers would be lower by 0.1 pp (=0.4803*0.9*[0.56-0.33]) at the mean level of robot exposure when comparing CZs in the 50th and 25th percentiles of the share of low-skilled established immigrants. In contrast, the wage attenuation effects are strong for both old and young native workers and less distinct from each other. The wages are mitigated by 0.067 pp and 0.05 pp for older and younger natives, respectively, when comparing the CZs in the 50th and 25th percentiles of the established low-skilled immigrant share.

Appendix Table C.17 presents coefficients using the total share of low-skilled immigrants instead of the share of established low-skilled immigrants. The coefficients are smaller, as expected, but the distinction in the mitigating employment effects between age groups remains. In conclusion, the mobility of low-skilled immigrants mitigates losses from robot adoption, especially for older native-born workers.

[29] The average age of established and recent immigrants in 1990 was 41.4 and 31.7 years, respectively.

[30] Appendix Table C.16 shows the mitigating effects of low-skilled immigrants are quite similar using the established low-skill immigrant share compared to the total low-skill immigrant share. Although the point estimates are slightly higher, the implied mitigating effects remain unchanged. For example, at the mean robot exposure, the wage losses of low-skilled native workers are lower by 0.07 pp (= 0.3398 * 0.9 * [0.56-0.33]) when comparing CZs in the 50th and 25th percentiles of the share of low-skilled established immigrants, which is identical to the number we derived using the coefficients in column 1 of Table 5.

Table 6: Effects on low-skill natives' labour market outcomes by age, stacked-differences 1990–2015 (2SLS): Interacting robot exposure and low-skill established immigrant share

Dependent variable: Change in log employment or change in log wages				
	Young (16-39)		Old (40-64)	
	Wage	Employment	Wage	Employment
	(1)	(2)	(3)	(4)
Exposure x Share Established 1990	24.55**	5.62	32.23**	48.03**
	(11.76)	(29.58)	(14.33)	(22.38)
Exposure to robots	-1.15***	-1.95**	-2.32***	-1.60**
	(0.27)	(0.77)	(0.31)	(0.68)
LS Immigrant Share Established 1990	-31.03***	-52.65	-18.17	-136.22***
	(6.27)	(32.24)	(12.88)	(20.58)
Observations	1444	1444	1444	1444
R-squared	0.89	0.78	0.78	0.84
Mean (%)	-4.98	-15.51	-1.61	-2.22

Note: LS denotes Low-skill. US robot exposure and 1990 low-skilled established immigrant share are instrumented using EURO5 robot exposure and 1970 low-skilled immigrant share, 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 Human capital adjustment to robot exposure

The limited mobility of low-skilled natives as a means of protecting against adverse labour demand shocks is well documented in the literature, as we also show in Section 3. This study suggests that part of this phenomenon may be attributed to immigrant mobility, which partially mitigates the wage and employment losses for native workers in response to robot exposure. However, are there other factors that can explain why low-skilled natives do not rely on migration as an insurance mechanism?

Branco et al. (2025), Dauth et al. (2021) and Di Giacomo & Lerch (2023) document that individuals, particularly younger ones, increase investment in human capital in

Table 7: Effects on share attending college, stacked-differences 2000–2015 (2SLS)

Dependent variable: Change in share attending college				
	Native		Immigrants	
	Young	Old	Young	Old
	(1)	(2)	(3)	(4)
Exposure to robots	0.14**	0.01	0.18	0.15*
	(0.07)	(0.02)	(0.21)	(0.08)
Observations	1444	1444	1444	1444
R^2	0.54	0.55	0.15	0.11
Mean(%)	1.20	-0.13	-0.22	-0.11
Kleibergen-Paap F	234.57	234.57	234.57	234.57

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).

response to robot adoption.[31] Acemoglu & Restrepo (2020) show that robot adoption affects high-skilled jobs much less than low-skilled ones. In addition, the opportunity cost of being out of the labour market decreases as the wages of low-skilled workers fall due to robot adoption. We examine the impact of robot exposure on human capital adjustment by nativity, and further break down the impact by young (19-39) and older (40-64) individuals.[32]

Table 7 shows that the acquisition of human capital is an additional channel to insure against robot exposure. Column 1 demonstrates that an additional robot per thousand workers increase college enrolment among young natives by 0.14 pp. In

[31]We do not consider other adjustment margins, such as family members joining the workforce or drawing on savings (Lerch 2022).

[32]We use the years 2000, 2007 and 2013-17 as the question about currently attending college was not asked in 1990. Also note that the question on college enrolment changed between 2000 Census and 2013-17 ACS. Census reports the enrolment status of an individual since February 1 of that year, whereas ACS reports their status three months prior.

contrast, there is almost no change in the share of older natives attending college in more robot-exposed areas. These results suggest that younger natives are more likely to invest in human capital as a way of protecting against robot adoption, rather than moving out of robot-exposed areas. Older natives, who benefit from immigrant mobility, seem less likely to move or invest in human capital to mitigate the effects of robot exposure.

Furthermore, Table 7 shows a positive but insignificant increase in college enrolment among young immigrants due to robot exposure. However, the college enrolment of older immigrants increased by 0.15 pp in more robot-exposed regions. Since established immigrants, 75% of older low-skilled immigrants are established, are particularly negatively impacted by robot adoption, human capital accumulation might be another channel to protect against the risk of displacement by robots. Additionally, we show that newly arriving foreign workers are not driving our results. To support this argument, Appendix Table D.1 demonstrates that college enrolment increased among incumbent older immigrants, individuals who did not recently migrate, in robot-exposed areas, indicating that recent arrivals into the US or prospective students did not selectively enter highly exposed CZs.

Lastly, we decompose the results by employment status for young natives and older immigrants in Appendix Table D.2. Most young natives who enrol in college due to robot exposure are out of the labour force, indicating that they delay their entry into the labour market in response to adverse labour demand shocks (Charles et al. 2018). In contrast, both employed and non-employed older immigrants enrol in college, suggesting that they are likely attending local community colleges in response to robot exposure. Overall, this section underscores human capital accumulation as an additional mechanism for mitigating adverse labour demand shocks, particularly among young natives.

6 Conclusion

In this paper, we demonstrate that low-skilled immigrants are more responsive in their location choices to robot exposure than similarly skilled natives. Low-skilled immigrants respond by avoiding or leaving local labour markets with higher levels of

robot exposure. In addition, immigrants' location choices reduce spatial inequality for native workers. The decrease in income of low-skilled natives due to robot exposure is smaller in areas with a larger low-skilled immigrant population. Although, on average, job losses from robot exposure are not significantly influenced by immigrant mobility, older native workers experience significantly lower job losses due to low-skilled immigrant mobility.

These novel findings have significant economic implications. Policymakers are seeking solutions to mitigate the long-term economic impact of technological advancements that displace labour. Low-skilled immigrants can play a crucial role in insulating native workers from local shocks. This is particularly relevant given the increasing support for restricting the entry of low-skilled immigrants into the US, especially when native workers experience job losses. Furthermore, our findings suggest that future research should take into account the role of migration, particularly immigrant mobility, when analysing the effects of localised shocks. Our findings suggest that immigrant location choices play a stabilising role in the aftermath of robot adoption. This interpretation complements recent work that highlights the ex-ante role of immigration in influencing robot adoption. A promising direction for future work would be to integrate both margins i.e., the role of immigration in shaping both the pace of robot adoption and its consequences for native workers.

Finally, we explore channels other than mobility that individuals use to protect against displacement risk from robots. We find that the accumulation of human capital may also explain the limited mobility of low-skilled natives, as young natives acquire human capital in response to robot exposure. This channel is not limited to young natives, as older immigrants also accumulate human capital in response to robot adoption. In conclusion, this study highlights the role of geographic mobility and human capital accumulation in protecting against the adverse effects of local shocks.

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Appendix (Not for Publication)

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

A Section 2 Appendix: Data

A.1 IFR Robot data

The IFR has collected data on the stock of industrial robots at the country-industry level since 1993, however the data have a few limitations. Industry-specific data are available for North America from 2004 onwards. For the years before 2004, we classify the data into industries using the distribution from 2010. Not all data can be categorised by sectors; for example, around 11% of total robots remained unclassified in 2015. We allocated these unclassified robots proportionally to the classified data. Additionally, the stock of robots for the US includes data from Canada and Mexico before 2011. To ensure consistency, we use the data for North America. This is not problematic as our instrumental variable strategy will account for any measurement errors.

A.1.1 Robots per thousand workers in industrialised economies

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

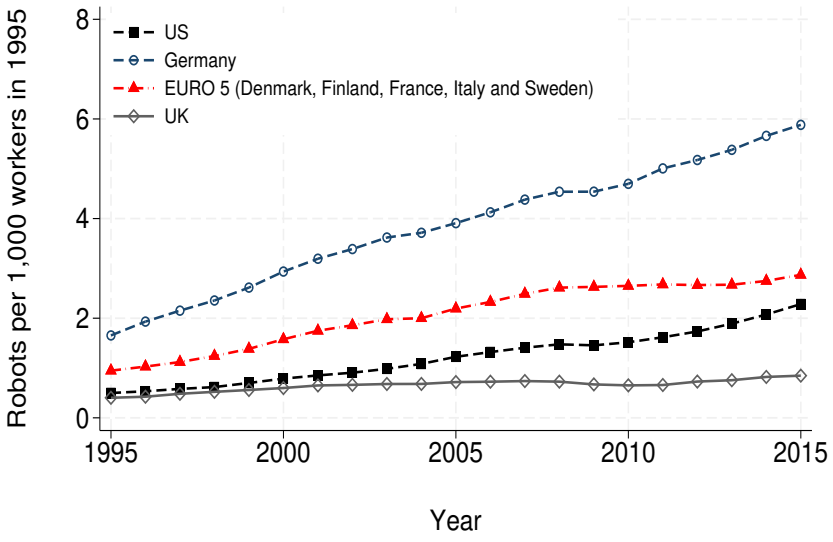


Figure A.1 displays the steady increase of robots per thousand workers in North America, Germany, and EURO5 (Denmark, Finland, France, Italy and Sweden) countries. Robots per thousand workers for the EURO5 countries are a simple average of values over all the countries. In North America, the stock of robots increased from 0.5 per thousand workers in 1995 to 2.28 per thousand workers in 2015.

A.1.2 Robot per thousand workers by industry in US

Table A.1 shows that the automotive industry experienced the strongest growth in North America between 1993 and 2015, while the service industry saw the smallest increase in robot usage.

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-institutionalised individuals from age 16 to 64. We drop from the sample: unpaid family workers, employed individuals with missing information about their occupation, and individuals working in the armed forces and public administration.

Individuals are classified as employed if they have worked in the past year. This definition of employment ensures that the number of employed individuals is equal to the number of individuals with a positive wage. This would not be true if employment status were defined using the current working status of an individual. The hourly wage of each worker is computed as the pre-tax annual labour income divided by annual working hours. Annual working hours are computed 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 the usual number of hours worked per week. Top-coded income is set equal to 1.5 times the value of the top-code. Real wages below the bottom 1% percentile are censored and real wages above the 99$^{\text{th}}$ percentile are winsorised. 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:

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

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 (A.1) captures the additional acquisition of robot capital while considering the overall growth of the industry and keeping employment fixed at year t. Similarly, the EURO5 industry-level robot growth is calculated as:

$$\Delta R^{EURO5}_{j,t} = \frac{1}{5} \sum_{c} \frac{R^{c}_{j,t_1} - (1 + g^{c}_{j,(t,t_1)}) \cdot R^{c}_{j,t}}{L^{c}_{j,t}} \tag{A.2}$$

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 Construction of Migration flows

IPUMS provides migration data at the Public Use Microdata Area (MIGPUMA) level. MIGPUMA only reveals the first three digits of the five-digit PUMA code. We combine this with state codes to create the corresponding PUMA categories. We compute inflows and outflows at the CZ level using a PUMA-CZ crosswalk. A CZ can span multiple PUMAs and multiple CZs can contain a single PUMA. Following Molloy et al. (2011), we assume that an individual has not migrated if at least one CZ belongs to both their current and 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:

$$\frac{N^{16-64}_{i,t+1} - N^{16-64}_{i,t}}{N^{16-64}_{i,t}} = \frac{N^{\text{in}}_i}{N^{16-64}_{i,t}} - \frac{N^{\text{out}}_i}{N^{16-64}_{i,t}} + \frac{N^{\text{net-ageing}}_i}{N^{16-64}_{i,t}} + \frac{N^{\text{new arrival}}_i}{N^{16-64}_{i,t}} \tag{A.3}$$

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

Using the 2000 Census, inflows are calculated using individuals who moved into their current CZ residence five years ago, while outflows are defined using people who exited their CZ five years ago. The baseline population in 1995 is computed as the population in 2000 divided by the 5-year equivalent change in population between 1990 and 2000. We multiply the rates by 2 to convert them into ten-year rates.

The 2013-17 ACS reports migration activity over a one-year reference period. Data from 2013 and 2014 are used to establish the initial population at time t, and data from 2017 are used to determine the population at time $t+1$. Immigrants present in the US in 2017 who arrived from outside the US after 2013 are defined as international immigrants. Individuals who did not move in the past year and were aged between 16 and 19 in 2017 are classified as aged in, while non-movers aged between 61 and 64 in 2013-14 are classified as aged out. Inflows and outflows are based on individuals

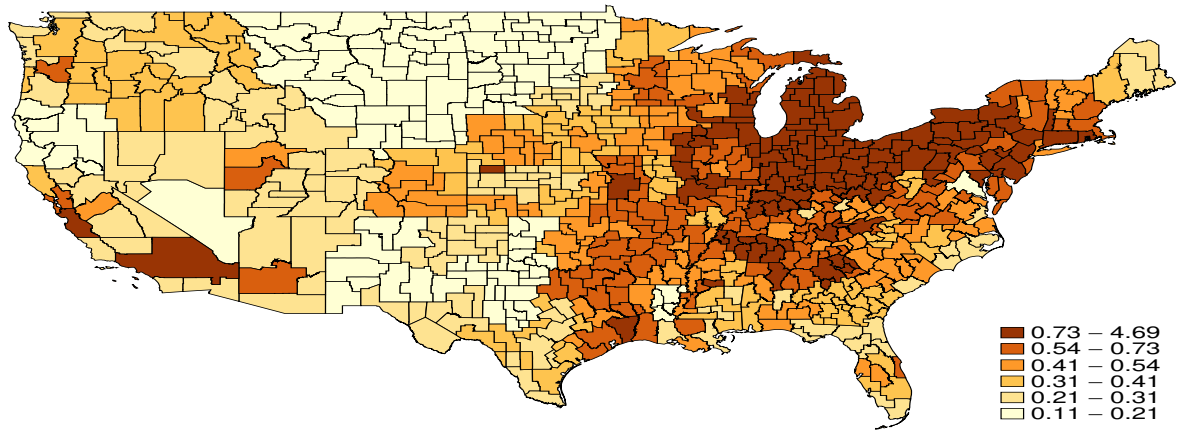
who arrived in the US before 2013 and moved out after 2015. We used these data to create three-year migration flows and then multiplied them by 10/3 to convert them into ten-year migration rates.

A.2.2 Geographic distribution of robot exposure and immigrant share

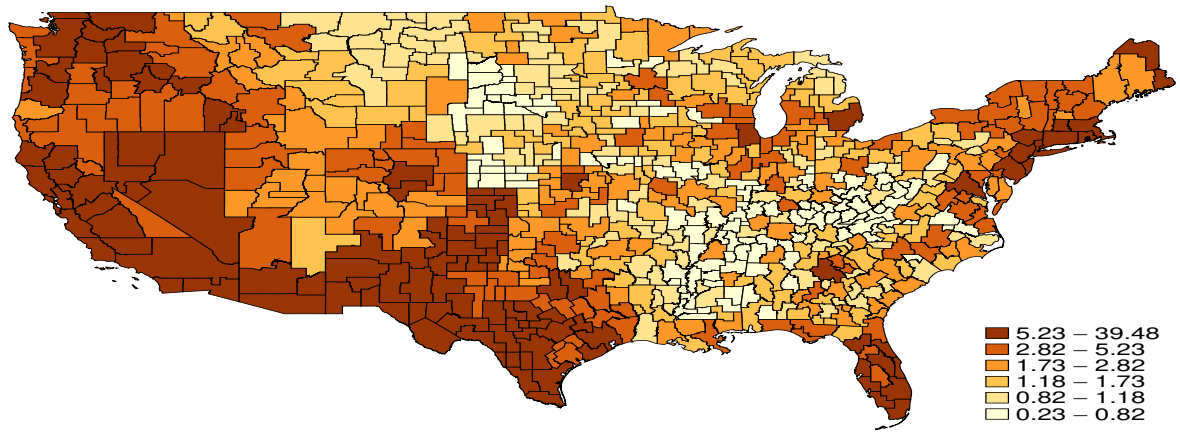
Figure A.2a shows substantial variation in robot exposure across US CZs. The growth in robot use was most pronounced in states like Michigan and Ohio due to the significant increase in robot adoption in the automotive industry. In contrast, robot growth was lower in parts of the West North Central and South Central divisions. Figure A.2b shows that the share of the immigrant population in 1990 varied considerably across the US, with a higher proportion in 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 First Stage: Robot Exposure

Table A.2 shows a strong and robust relationship between the US and EURO5 robot exposure measures at the CZ level. The inclusion of demographic and industry controls has a negligible impact on the first-stage coefficient.

Table A.2: First-Stage of robot-exposure

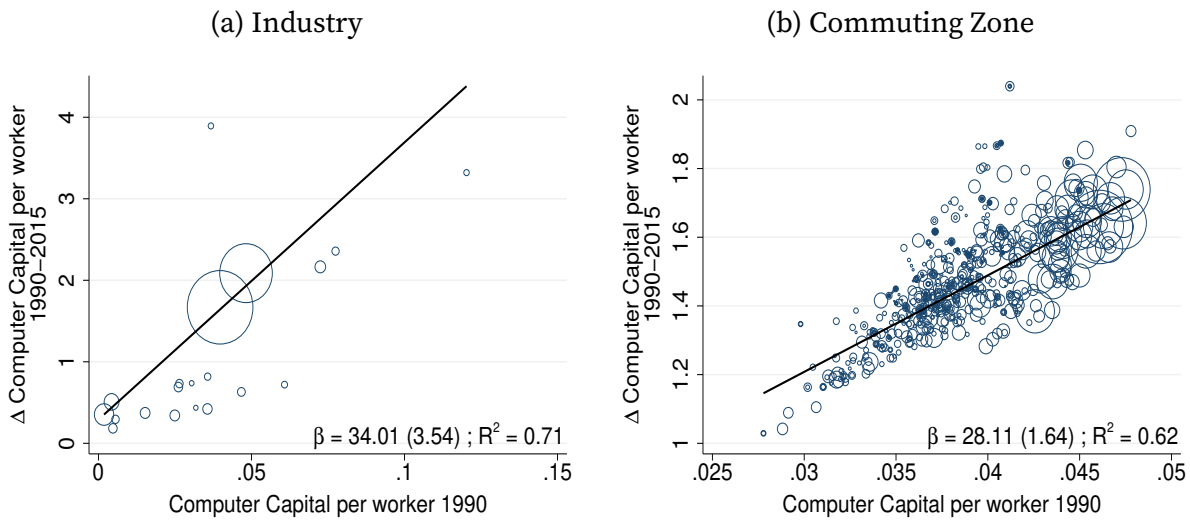
Dependent variable: US Robot-exposure						
	(1)	(2)	(3)	(4)	(5)	(6)
EURO5 Robot-exposure	1.38***	1.41***	1.35***	1.35***	1.36***	1.37***
	(0.14)	(0.09)	(0.11)	(0.11)	(0.13)	(0.13)
Observations	1444	1444	1444	1444	1444	1444
R^2	0.91	0.93	0.94	0.94	0.94	0.94
Division dummies	Yes	Yes	Yes	Yes		
Division x time dummies					Yes	Yes
Demographics		Yes	Yes	Yes	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, 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 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, share of employment in routine occupations and average offshorability index). Column (4) also includes stock of computer capital per worker in 1990 and exposure to Chinese imports. Column (5) includes division-time dummies instead of division dummies. Column (6) further includes year interaction with demographic and industry characteristics in 1990.

A.4 Computer capital exposure

Following Michaels et al. (2014), we instrument the *growth* in the use of computer capital between 1990 and 2015 using the 1990 *level* of computer capital per worker. The rationale is that industries or regions with a higher initial *level* of computer capital would also experience greater growth in their use of computer capital over time. Figures A.3a and A.3b validate this idea at both the industry and the CZ level. Furthermore, the high R^2 values in both cases suggest that the relationship is quite strong.

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



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

A.5 Pre-trends

One concern for causality is that prior immigration trends could drive variation in robot penetration across CZs. For example, Danzer et al. (2024) and Lewis (2011) suggest that firms are less likely to adopt robots in areas with an abundance of low-skilled labour. To assess the relevance of this issue, we conduct a falsification exercise by regressing the change in log population from 1970 to 1990 on *future* CZ robot exposure between 1990 and 2015. Table A.3 shows a negative but insignificant association between robot exposure and the growth of the low-skilled immigrant population (column 1) and native population (column 3) between 1970 and 1990.

Table A.3: 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	-6.17	-2.78	-1.86	0.02
	(4.41)	(2.70)	(1.27)	(1.65)
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).

A.6 Descriptive Statistics

Table A.4: Change in outcomes by skill level and employment status by robot exposure quartile, 1990-2015

Variable	All	Q4	Q1	Q4-Q1	P-value
Log Immigrant Population Low-skill	41.9	28.1	49.8	-21.7	0.01
Log Immigrant Population High-skill	47.1	38.1	53.3	-15.2	0
Log Native Population Low-skill	-4.7	-10	-1	-9.1	0
Log Native Population High-skill	17.1	12.8	20.3	-7.5	0
Log Immigrant Employment Low-skill	43.7	29.5	51.8	-22.3	0.01
Log Immigrant Employment High-skill	46.4	36.9	53.4	-16.6	0
Log Native Employment Low-skill	-9.7	-14.9	-6.2	-8.7	0
Log Native Employment High-skill	14.6	10.5	17.6	-7.1	0

B Section 3 Appendix: Effect on population and mobility by nativity

B.1 Effects on population growth separately by nativity and skill

To replicate the findings of Faber et al. (2022), we control for the change in the dependent variable between 1970 and 1990. Consistent with their results, Table B.1 shows that robot exposure did not significantly affect immigrant population growth, while native population growth declined markedly following the introduction of robots. This differential response is primarily driven by the muted change in high-skilled immigrants. Furthermore, the decline in population growth from robot exposure was similar in magnitude for low- and high-skilled groups. Although high-skilled natives exhibited a somewhat stronger response than low-skilled natives, this difference was not sufficient to offset the stronger difference between low- and high-skilled immigrants.

Table B.1: Effects on growth of immigrants and natives population growth, stacked-differences 1990–2015 (2SLS)

	Dependent variable: Change in log population			
	Nativity		Skill	
	Immigrants	Natives	Low-skill	High-skill
	(1)	(2)	(3)	(4)
Exposure to robots	-2.13	-1.65***	-1.54***	-1.26***
	(1.58)	(0.24)	(0.46)	(0.39)
Observations	1442	1444	1444	1444
R^2	0.70	0.81	0.80	0.71

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 pre-trends, time-division dummies and covariates: change in dependent variable between 1990 and 1970 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.2 Effects on relative population change gradually adding controls

Table B.2: 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)
	A: Low-Skill					
Exposure to robots	-5.00*	-8.67***	-10.29***	-9.54***	-5.09**	-4.45**
	(2.60)	(3.25)	(3.93)	(2.76)	(2.36)	(2.18)
Observations	1444	1444	1444	1444	1444	1444
R^2	0.18	0.28	0.31	0.43	0.63	0.69
Kleibergen-Paap F	101.53	221.66	151.39	146.51	114.54	109.63
	B: High-skill					
Exposure to robots	-0.72	-0.48	-0.97	0.03	1.68	1.69
	(1.34)	(1.63)	(1.49)	(1.28)	(1.17)	(1.15)
Observations	1444	1444	1444	1444	1444	1444
R^2	0.06	0.11	0.16	0.28	0.39	0.46
Kleibergen-Paap F	101.53	221.66	151.39	146.51	114.54	109.63
Division dummies	Yes	Yes	Yes	Yes		
Division x time dummies					Yes	Yes
Demographics		Yes	Yes	Yes	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, 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 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, share of employment in routine occupations and average offshorability index). Column (4) also includes stock of computer capital per worker in 1990 and exposure to Chinese imports. Column (5) includes division-time dummies instead of division dummies. Column (6) further includes year interaction with demographic and industry characteristics in 1990.

B.3 OLS and Reduced form effects on population growth

The OLS and reduced form results in panels A and B, respectively, in Table B.3 are consistent with the 2SLS findings.

Table B.3: 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. 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.4 Including alternative pre-trends

Table B.4 displays that our findings remain robust when controlling for pre-trends in several ways. We include: (1) skill-specific immigrant concentration between 1970 and 1990 in columns 1 and 5; (2) skill-specific immigrant concentration between 1970 and 1990 interacted with period dummies in columns 2 and 6; (3) 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 the foreign-born population share in 1990 in columns 4 and 8. The striking fall in the growth of low-skilled immigrant-to-native population from robot exposure continues to hold across the various specifications.

Table B.4: 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).

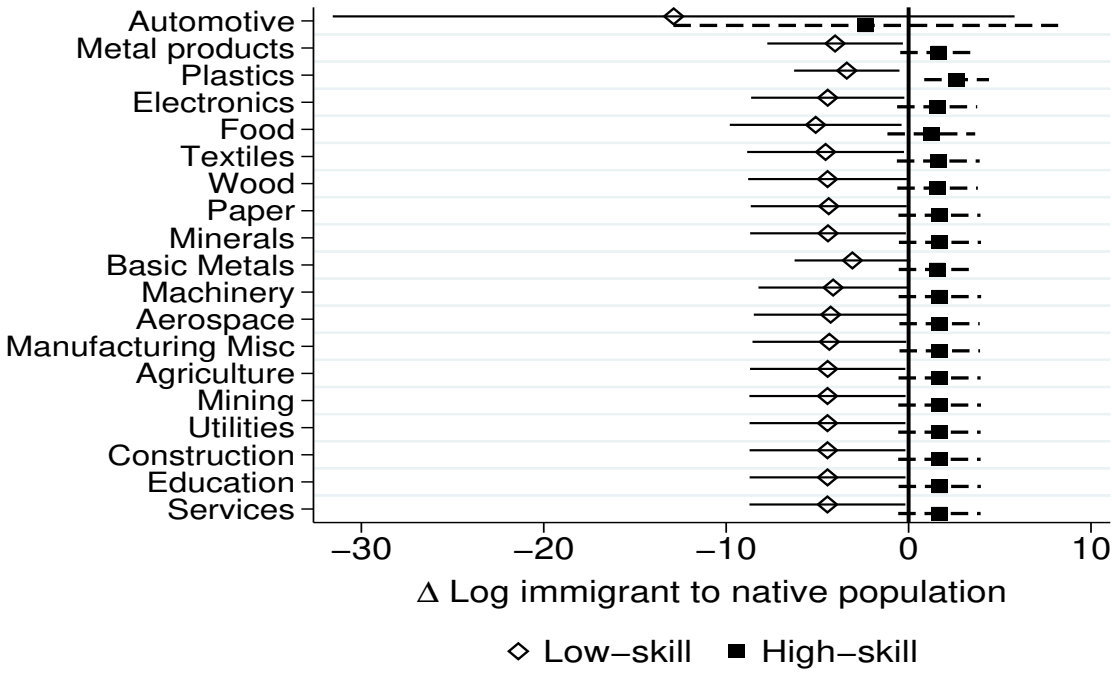
B.5 Robustness checks of population growth by nativity

In this subsection, we probe the robustness of the effect on low-skilled immigrant and native population growth from robot exposure in various ways.

B.5.1 Trends in industry-specific robot adoption

Appendix Table A.1 shows that the growth in robot adoption is not uniform across industries. To assess the impact of robot accumulation by a particular industry in driving the results, we sequentially exclude one industry at a time when constructing the robot exposure measure. Figure B.1 illustrates that the point estimates remain fairly consistent across the 19 specifications. The biggest change occurs when excluding the automotive industry. The effect on immigrants continues to be larger than that on the native-born, but the coefficients are much less precisely estimated. This finding is not surprising, as the automotive industry accumulated the largest number of robots over this period. Overall, Figure B.1 demonstrates that our main findings are not driven by robot adoption in a few industries.

Figure B.1: Effects on change in relative population, excluding one industry at a time



Note: Figure shows the effect of robot exposure on the change in immigrant to native population by skill-type. Each estimate represents the effect when a particular industry is not considered in creating the robot exposure measure. All regression estimates are weighted by the CZ population in 1990. Standard errors are clustered at the state level.

B.5.2 Alternative measures of robot exposure

Table B.5 shows that our results are robust to alternative measures of robot exposure. The baseline measure of robot exposure includes five European countries (Denmark, Finland, France, Italy, and Sweden) following Acemoglu & Restrepo (2020). We create an alternative measure (EURO7) of robot exposure by adding robot adoption in Germany and the UK to the baseline measure. Column 7 shows that the results remain identical using the EURO5 and EURO7 robot exposure measures.

Table B.5: Effects on relative population growth, stacked-differences 1990–2015 (2SLS): Alternate instruments

Dependent variable: Change in log of immigrant to native population							
		Leave-one-out					
	Baseline	Denmark	Finland	France	Italy	Sweden	EURO7
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	A: Low-skill						
Exposure to robots	-4.45**	-4.12**	-4.78*	-4.79**	-4.18**	-4.39**	-4.46**
	(2.18)	(1.89)	(2.46)	(2.38)	(2.11)	(2.14)	(2.17)
Observations	1444	1444	1444	1444	1444	1444	1444
R^2	0.69	0.69	0.69	0.69	0.69	0.69	0.69
	B: High-skill						
Exposure to robots	1.69	1.68	1.63	1.57	1.71	1.85	1.76
	(1.15)	(1.07)	(1.30)	(1.22)	(1.10)	(1.13)	(1.14)
Observations	1444	1444	1444	1444	1444	1444	1444
R^2	0.46	0.46	0.46	0.46	0.46	0.46	0.46
Kleibergen-Paap F	109.63	219.5	43.79	73.13	183.73	120.94	120.76

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 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) to Column (6) use four countries out of 5 from the EURO5 set of countries as instrument with each column indicating which country is excluded from the baseline measure. Column (7) regression uses EURO7 exposure as instrument instead of EURO5 exposure.

Furthermore, we demonstrate in Table B.6 that our findings are not driven by robot exposure in a few locations. The CZ with the highest robot exposure includes Clay and Cleburne counties in Alabama. Excluding this CZ does not change our conclusions

Table B.6: Effects on relative population growth, stacked-differences 1990–2015 (2SLS): Removing regions with high robot exposure

Dependent variable: Change in log of immigrant to native population				
	Baseline	Drop top exposure	Drop top 1% exposure	Drop states
	(1)	(2)	(3)	(4)
	A: Low-skill			
Exposure to robots	-4.45**	-5.03*	-7.90	-4.76
	(2.18)	(2.75)	(5.91)	(5.43)
Observations	1444	1443	1430	1340
R^2	0.69	0.69	0.69	0.73
Kleibergen-Paap F	109.63	62.41	184.28	130.61
	B: High-skill			
Exposure to robots	1.69	1.53	-0.62	2.55
	(1.15)	(1.56)	(3.21)	(3.37)
Observations	1444	1443	1430	1340
R^2	0.46	0.46	0.46	0.47
Kleibergen-Paap F	109.63	62.41	184.28	130.61

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 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) excludes CZ with the highest US robot exposure. Column (3) excludes CZs' with top 1% US robot exposure. Column (4) excludes states with highest exposure: Indiana, Michigan and Ohio.

(Column 2). Excluding commuting zones at the top 1 percentile of robot exposure increases the magnitude for the low-skilled immigrant concentration, but also increases the standard errors considerably. Finally, we drop the three states around the Great Lakes (Indiana, Michigan and Ohio) with the highest robot exposure. Dropping these states from the analysis does not change the point estimate much, as shown in column 4 of Panel A relative to the baseline estimates, but the standard errors increase sharply. Overall, dropping regions with high robot exposure does not meaningfully change our

conclusions.

B.5.3 Alternative stacked and long period specifications

In the baseline stacked-differences specification, we exploit variation in robot exposure over two periods: 1990-2000 and 2000-2015. Table B.7 shows that the baseline results are robust to alternative long- and stacked-differences specifications. Coefficients in columns 1-2, 3-4 and 5-6 are based on three-period stacked-differences (1990-2000, 2000-2007 and 2007-2015), two-period stacked-differences (1990-2000 and 2000-2007) and long-difference specifications, respectively. The dependent variable in the long-difference specification is the 10-year equivalent average of 1990-2000, 2000-2007 and 2007-2015.

Overall, we reach the same conclusion as the baseline findings across all specifications, as the coefficient for the relative low-skilled population growth is negative and significant and the coefficient for the relative high-skilled population growth is insignificant. Moreover, the coefficients using the three-period and two-period stacked-differences models are quite close, implying that our results are not explained by the Great Recession. The coefficient using the long-difference specification for the low-skilled immigrant concentration is larger in magnitude than the other regressions, suggesting that including controls with time dummies is important to account for trends in population growth by nativity.

B.5.4 Alternative controls

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 other regions. Although 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 exposure to robots in surrounding CZs weighted by migration flow in our regression specification. This measure is computed as:

$$\Delta R^{EURO5}_{-i,t} = \sum_{k \neq i} \phi_{ki} \Delta R^{EURO5}_{k,t} \tag{B.1}$$

Table B.7: 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).

where $\Delta R_{k,t}$ is the robot exposure of CZ k and ϕ_{kj} captures the strength of migration flows between CZ k and j, using the sum of 5-year inflow and outflow rates in the 1990 Census between two CZs. 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. Including this control raises the first-stage F-statistic from 109.6 to 129.8, indicating stronger instrument relevance. At the same time, Column 2 of Table B.8 shows that the estimated coefficients remain very similar after adding this control. This stability suggests that potential spillovers from neighbouring areas are unlikely to materially bias our estimates.

The coefficient of interest in our baseline specification estimates the change in population size due to robot exposure within a division region during a given period. We consider an alternative 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 laws. The coefficient in column 3 (-4.56) is very close to the baseline coefficient (-4.45), but is much less precisely estimated. In general, we observe patterns similar to those in our baseline regression.

Table B.8: Effects on relative population growth, stacked-differences 1990–2015 (2SLS)

Dependent variable: Change in log of immigrant to native population			
	Baseline	Exposure Neighbours	State-time dummies
	(1)	(2)	(3)
	A: Low-skill		
Exposure to robots	-4.45**	-4.60*	-4.56
	(2.18)	(2.61)	(3.85)
Observations	1444	1444	1444
R^2	0.69	0.69	0.78
Kleibergen-Paap F	109.63	129.83	44.43
	B: High-skill		
Exposure to robots	1.69	1.86	1.13
	(1.15)	(1.29)	(2.00)
Observations	1444	1444	1444
R^2	0.46	0.46	0.55
Kleibergen-Paap F	109.63	129.83	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 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) additionally includes robot exposure to neighbouring location as a control. Column (3) uses state-time instead of division-time dummies.

B.5.5 Robustness to CZs with extreme immigrant shares

Table B.9: 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).

B.5.6 Nativity group-specific weights

Table B.10: 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.5.7 Alternative methods for computing standard errors

Column 2 in panels A and B of Table B.11 shows that standard errors become slightly smaller if we cluster at a more granular level (CZ) rather than the state level. Column 3 in panels A and B shows the standard errors using the Borusyak, Hull & Jaravel (2022) method to account for any potential between-region correlations due to industry shocks; they are quite similar to the baseline standard errors. Finally, we allow for arbitrary spatial correlation, following Conley (1999), between CZs that lie within 100 km, or 250 km or 500 km distance. Reassuringly, our conclusions remain unchanged.[33]

Table B.11: Effects on relative population growth with alternative standard errors, stacked-differences 1990–2015 (2SLS)

Dependent variable: Change in log of immigrant to native population						
	Baseline	Cluster	Borusyak	Conley		
		CZ	et al. (2022)	100 km	250 km	500 km
	(1)	(2)	(3)	(4)	(5)	(6)
	A: Low-skill					
Exposure to robots	-4.45**	-4.45***	-4.45**	-4.45**	-4.45**	-4.45***
	(2.18)	(1.72)	(2.25)	(2.09)	(1.83)	(1.70)
Observations	1444	1444	38	1444	1444	1444
R^2	0.69	0.69	0.07	0.69	0.69	0.69
	B: High-skill					
Exposure to robots	1.69	1.69	1.69	1.69	1.69	1.69
	(1.15)	(1.07)	(1.10)	(1.11)	(1.12)	(1.08)
Observations	1444	1444	38	1444	1444	1444
R^2	0.46	0.46	0.26	0.46	0.46	0.46

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 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 (1) clusters standard errors at state level. Column (2) clusters standard errors at CZ level. Column (3) allows for correlations across CZs due to industry shocks between regions. Columns (4), (5) and (6) allow for temporal correlation and arbitary spatial correlation among CZs within 100 kilometres, 250 kilometres and 500 kilometres, respectively.

[33] We use the *acreg* command in Stata by Colella et al. (2019) to compute Conley standard errors.

B.6 Migration flows: additional results

Table B.12 examines whether robot adoption affects the population growth of individuals aged 65–69, by nativity and skill group. Robot exposure leads to a large decline in the population of low-skilled immigrants aged 65–69. , hence ageing out is not an important driver of migration response of low-skilled immigrants. On the other hand, robot exposure has an insignificant effect on low-skilled natives or high-skilled immigrants. Individuals aged 65-69 usually account for a small percent of total population (around 5%). Overall, this indicates that ageing out does not represent an important behavioural driver of migration response. Instead, the mechanical correlation between robot exposure and ageing is likely the key explanation.

Table B.12: Effect on population growth of 65-69 year old by nativity-skill, stacked-differences 1990–2015 (2SLS)

	Low-skill		High-skill	
	Immigrant	Native	Immigrant	Native
	(1)	(2)	(3)	(4)
Exposure to robots	-6.96***	0.38	-0.96	1.58*
	(2.13)	(0.64)	(2.04)	(0.84)
Observations	1361	1444	1216	1444
R^2	0.75	0.99	0.73	0.99

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 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).

Table B.13 presents the effect of robot exposure on migration flows by nativity-skill groups, where we exclude observations in the top 1 percentile of the dependent variables. Overall, our findings are similar to the baseline results. Low-skilled immigrants are particularly sensitive to robot exposure, with the reduction in inflows accounting for a significant portion of labour adjustment. The inflow and outflow coefficients for

low-skilled natives are smaller than those for low-skilled immigrants, indicating that low-skilled natives are much less mobile than similarly skilled immigrants. Additionally, both a reduction in in-migration and higher out-migration explain the population decline of high-skilled natives in response to robot exposure.

Table B.13: Effects on migration flows of low- and high-skilled (2SLS), excluding outliers

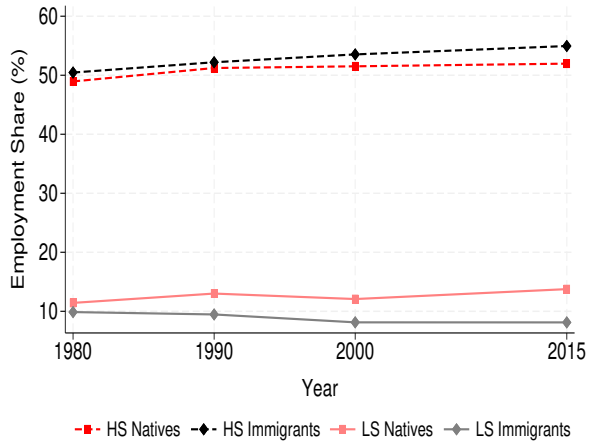
	Immigrant				Native		
	In	Out	Net-aging	New Arrival	In	Out	Net-aging
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	A: Low-skill						
Exposure to robots	-1.54**	0.89	-1.29*	-0.93	-0.57	0.67*	-1.02***
	(0.61)	(0.74)	(0.77)	(1.15)	(0.49)	(0.36)	(0.33)
Observations	1362	1374	1392	1415	1419	1413	1433
R^2	0.72	0.50	0.50	0.82	0.78	0.69	0.92
	B: High-skill						
Exposure to robots	-0.15	1.60	-1.11***	-0.46	-1.50**	1.12**	-0.76***
	(1.09)	(1.10)	(0.43)	(0.76)	(0.70)	(0.44)	(0.19)
Observations	1363	1371	1381	1395	1423	1395	1416
R^2	0.69	0.62	0.54	0.84	0.80	0.80	0.95

Note: The dependent variable in columns (2) and (6) is the negative of the proportional change in population due to outflows. Sample size is lower than 1444 (722 $\times$ 2) as the top 1 percentile observations of the dependent variable are excluded. 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; 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).

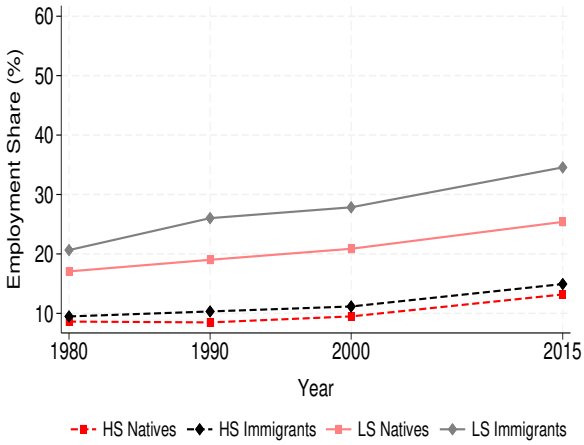
B.7 Labour market effects by nativity: additional results

Figure B.2: Employment shares across tasks by skill-nativity groups

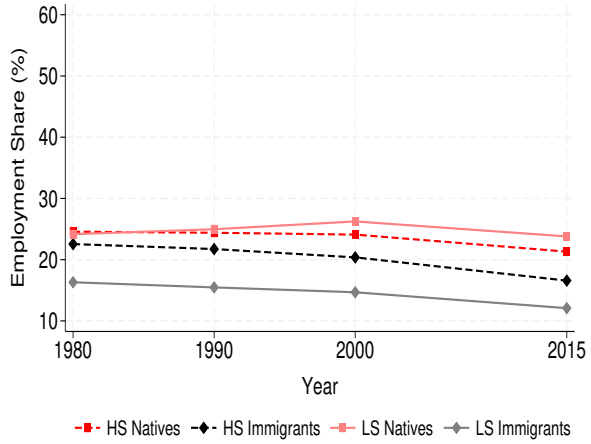
(a) Non-Routine Cognitive



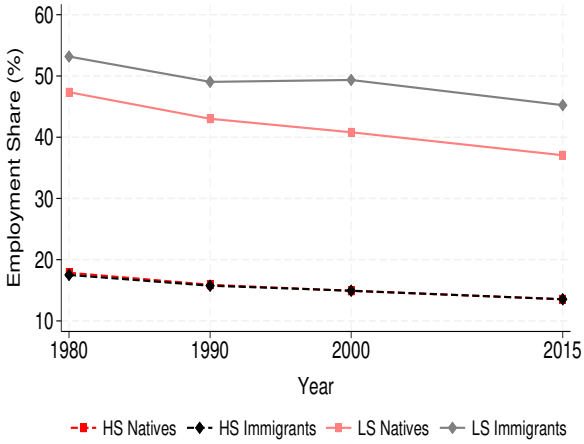
(b) Non-Routine Manual



(c) Routine Cognitive



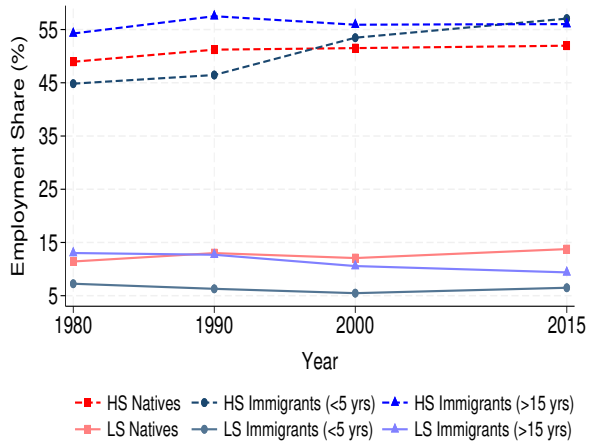
(d) Routine Manual



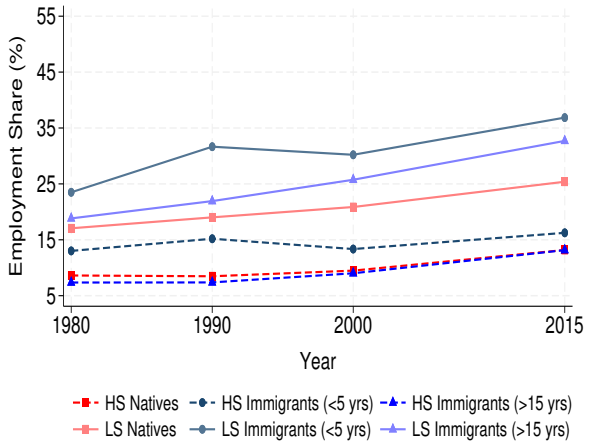
Note: HS and LS denote high-skill and low-skill, respectively.

Figure B.3: Employment shares across tasks of recent and established immigrants and natives by skill

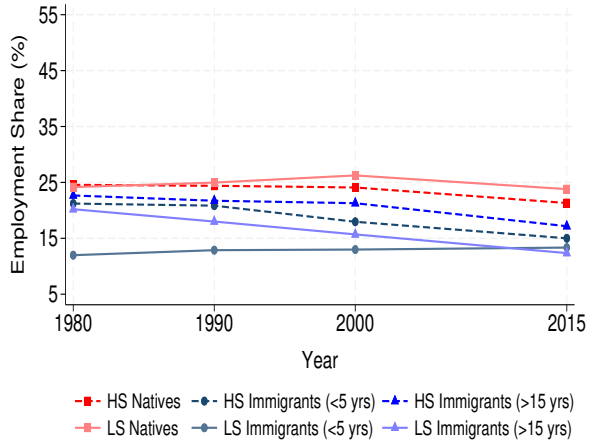
(a) Non-Routine Cognitive



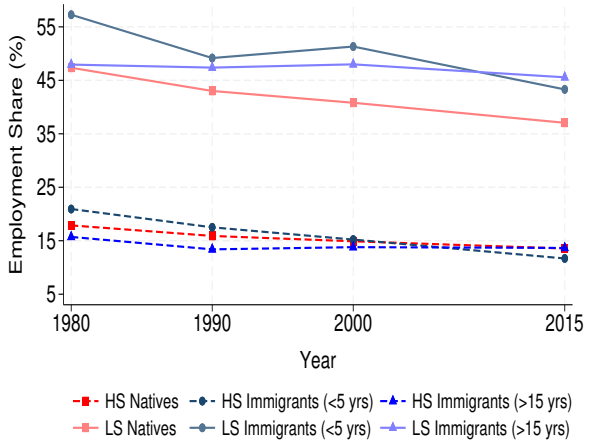
(b) Non-Routine Manual



(c) Routine Cognitive

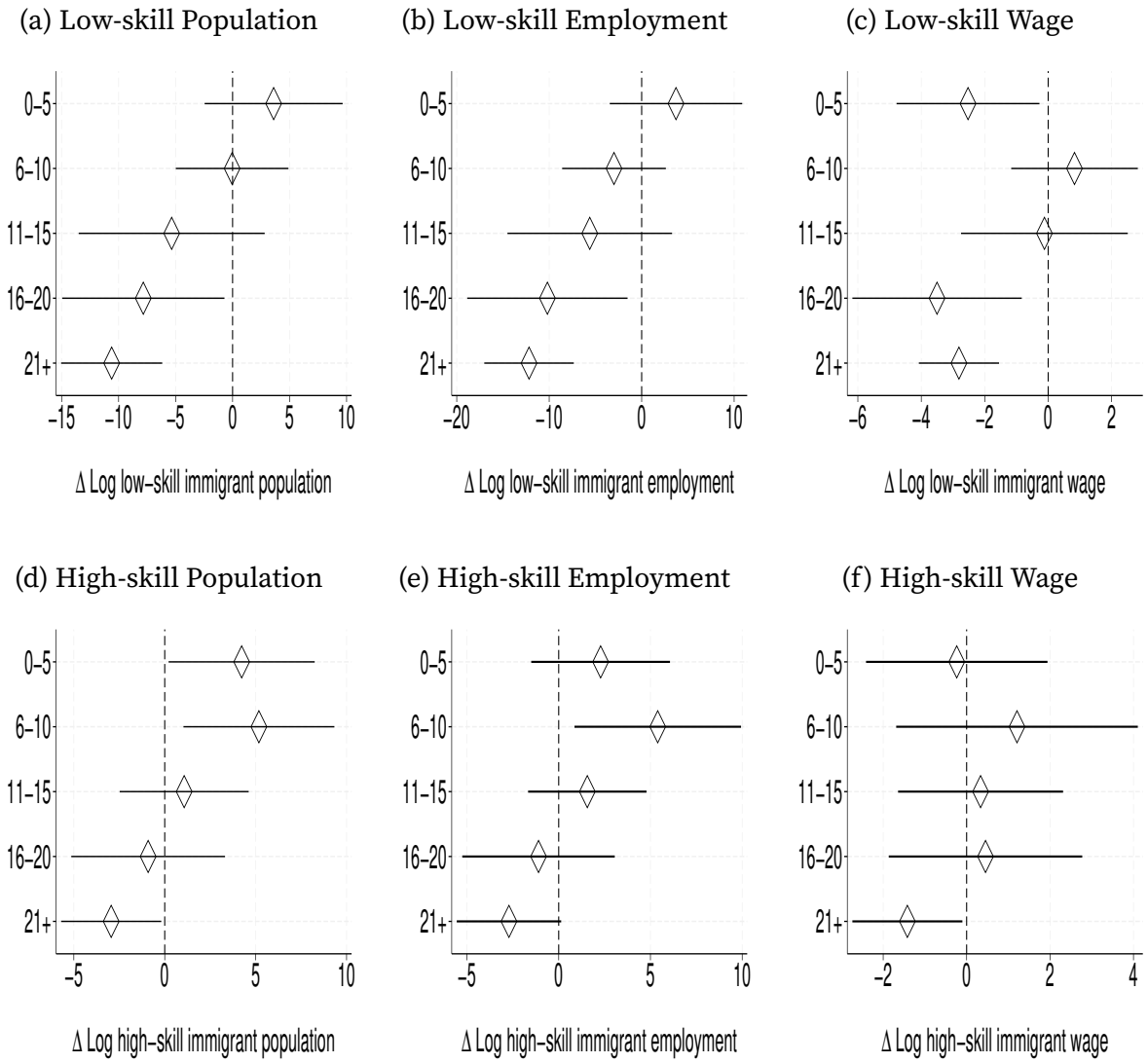


(d) Routine Manual



Note: HS and LS denote high-skill and low-skill, respectively. Years refer to number of living in US.

Figure B.4: Effect on immigrants by years lived in US, stacked-differences 1990–2015



Note: Note: Bars indicate 95% confidence interval. Each panel shows the β coefficient in Equation (2) of the change in the dependent variable for an immigrant-skill subgroup by years living in the US. All regression estimates are weighted by the CZ population in 1990. Standard errors are clustered at the state level.

B.7.1 Role of selection effects

Appendix Table B.14 shows the change in log employment and change in log average wage of incumbent individuals by nativity-skill status. The negative coefficient across most groups, suggests that our results are not driven by the lower inflow of positively selected individuals to robot exposure.

Results in Appendix Table B.14 confirm that selection through in-migration does not drive our findings, but cannot rule selection through out-migration explaining our results. To rule out selection effects driving our findings, we show that robot exposure

Table B.14: Effects on employment and wage for stayers, stacked-differences 1990–2015 (2SLS)

Dependent variable: Change in log employment or log wage				
	Employment		Wage	
	(1) Immigrant (1)	(2) Native (2)	(3) Immigrant (3)	(4) Native (4)
	A: Low-Skill			
Exposure to robots	-10.03***	-2.10***	-2.53***	-1.09***
	(2.35)	(0.47)	(0.63)	(0.19)
Observations	1443	1444	1442	1444
R^2	0.69	0.95	0.32	0.80
	B: High-skill			
Exposure to robots	-3.20**	-2.58***	-0.88	-0.73***
	(1.45)	(0.51)	(0.68)	(0.23)
Observations	1442	1444	1442	1444
R^2	0.65	0.94	0.17	0.81

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).

negatively affects wages after residualising wages on individual characteristics.

We predict individual wages in each year of the Census using two sets of covariates. The first is a simple set using dummies of nativity status, age, gender, education, marital status, presence of child, White, Black and Hispanic. In the second set, we additionally use three-digit occupation dummies and three-digit industry dummies to predict wages. We separate these because robot exposure varies by industry and affects occupations differentially, which might absorb some of the treatment effect itself. We intentionally exclude geographic controls, as robot-exposure varies by regions and conditioning on

Table B.15: Effects on residualised wage growth, stacked-differences 1990–2015 (2SLS)

	Low-skill		High-skill	
	Immigrant	Native	Immigrant	Native
	(1)	(2)	(3)	(4)
	A: Baseline			
Exposure to robots	-2.67***	-1.11***	-0.82	-1.02***
	(0.55)	(0.20)	(0.53)	(0.19)
R^2	0.34	0.88	0.33	0.88
	B: Simple set of covariates			
Exposure to robots	-2.14***	-1.29***	-0.92**	-0.94***
	(0.42)	(0.16)	(0.41)	(0.17)
R^2	0.24	0.71	0.16	0.61
	C: Including industry and occupation dummies			
Exposure to robots	-1.73***	-1.09***	-1.00***	-0.78***
	(0.42)	(0.15)	(0.37)	(0.15)
Observations	1443	1444	1444	1444
R^2	0.20	0.65	0.13	0.57

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. In panel B, wages predicted in first stage using dummies of nativity status, age, gender, education, marital status, presence of child, White, Black and Hispanic. In Panel C, three-digit occupation dummies and three-digit industry dummies are also used to predict wages. CZ level regressions include 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).

geography would absorb the treatment itself. We compute residualised wage growth at the CZ level as the difference in average wage growth and average predicted wage growth.

Appendix Table B.15 shows the effect of robot exposure on non-residualised wage growth in panel A and residualised wage growth in panels B and C. The coefficients are significantly negative for all nativity-skill groups indicating that worker composition

cannot fully explain the fall of wages to robot adoption. The coefficients for low- and high-skilled natives and high-skilled immigrants in panel B and C are quite similar to those in panel A suggesting that worker composition has limited effect in explaining the impact of robot exposure on wages for these groups. In contrast, worker characteristics are more important to understand the impact of robot exposure on low-skilled immigrant wages. Including the most rich set of controls to predict wages in panel C, worker composition explains one-third of the total wage effect to robot exposure. The adverse impact of robot exposure even after accounting for worker composition is stronger for low-skilled immigrants than natives. Thus, composition explains part of the differential effect between low-skilled immigrants and natives to robot exposure.

C Section 4 Appendix: Mitigating effects on natives

C.1 Theoretical Framework

We develop a stylised theoretical framework based on Acemoglu & Restrepo (2018) and Ottaviano & Peri (2012) to motivate our empirical specification about the mitigating effect of low-skilled immigrants on low-skilled natives against robot exposure.

The economy consists of low-skilled workers, differentiated by their place of birth (natives and immigrants). Following Acemoglu & Restrepo (2019), final output is produced in a task-based framework where higher automation implies a larger share of the output being produced using physical capital rather than low-skilled labour. This structure allows us to investigate the effect of immigrant mobility on native workers' wages, driven by an exogenous fall in the share of output being produced by labour due to automation. Each local labour market is assumed to be small relative to the aggregate economy. We do not consider an economy with high-skilled workers, as our empirical results show that the mobility of low-skilled immigrants has no effect on high-skilled natives.

Consider a local labour market that produces a consumption good using the following technology:

$$
\begin{aligned}
Y_t &= \left[\alpha_K K_t^{\mu} + \alpha_L L_t^{\mu}\right]^{\frac{1}{\mu}} \\
L_t &= \left[\gamma L_{U,t}^{\beta} + (1-\gamma)\, L_{I,t}^{\beta}\right]^{\frac{1}{\beta}}
\end{aligned}
$$

where L_t is a nested CES function of immigrant $(L_{I,t})$ and native $(L_{U,t})$ workers.[34] α_K and α_L refer to the share of tasks performed by capital and labour, respectively. The elasticity of substitution between capital and labour is given by $\sigma_\mu = \frac{1}{1-\mu}$, with $\mu \leq 1$. $\gamma \in [0, 1]$ measures the share of native to immigrant workers, and $\sigma_\beta = \frac{1}{1-\beta}$ is the elasticity of substitution between native and immigrant workers, with $\beta \leq 1$. Higher values of μ and β indicate greater substitution between the factors of production. We restrict our attention to $\mu, \beta \in [0, 1]$ due to substantial evidence that low-skilled

[34] We do not include further classification by age groups, as that is more relevant when examining the impact of assimilation on incumbent immigrants (Borjas 1985) and less pertinent when examining the effects on native workers (Ottaviano & Peri 2012).

immigrants and natives are substitutes (Card 2009) and low-skilled labour and capital are highly substitutable (Acemoglu & Restrepo 2020) in the production process.

The representative firm that produces the final good operates under perfect competition in both the input and output markets. The wages paid to immigrant and native workers are indicated by $w_{I,t}$ and $w_{U,t}$, respectively. The final good is the numéraire good, with its price normalised to 1. The firm maximises profits by choosing the optimal stock of immigrant and native labour and capital. The first order conditions are:

$$\alpha_L \gamma \left(\frac{Y_t}{L_t}\right)^{1-\mu} \left(\frac{L_t}{L_{U,t}}\right)^{1-\beta} = w_{U,t} \tag{C.1}$$

$$\alpha_L (1-\gamma) \left(\frac{Y_t}{L_t}\right)^{1-\mu} \left(\frac{L_t}{L_{I,t}}\right)^{1-\beta} = w_{I,t} \tag{C.2}$$

$$\alpha_K \left(\frac{Y_t}{K_t}\right)^{1-\mu} = r_t \tag{C.3}$$

These first order conditions imply that the marginal cost of an input must equal its marginal product.

The labour supply of a nativity group $g = \{I, U\}$ in a local labour market is given by:

$$L_g = w_g^{\epsilon_g} \tag{C.4}$$

where $\epsilon_g \geq 0$ measures the labour supply elasticity. Individuals choosing their preferred work location across regions provides the most straightforward approach to micro-found this labour supply equation.[35] ϵ_I and ϵ_U can capture additional adjustment mechanisms, such as transitioning between employment and non-employment and labour supply at the intensive margin (Dustmann et al. 2017).

Combining the labour demand equations (equations C.1 and C.2) gives us:

$$\frac{\gamma}{1-\gamma} \left(\frac{L_I}{L_U}\right)^{1-\beta} = \frac{w_U}{w_I}$$

Plugging in the labour supply equation (equation C.4) into the equation above, the relative wage of immigrants can be expressed as a function of native wages in the

[35] Our reduced-form aggregate labour supply curve captures the insights of Faber et al. (2022), who use a spatial model to show that population growth among workers declines in areas more exposed to robots.

following way:

$$w_I^{\epsilon_I(1-\beta)+1} = \left(\frac{1-\gamma}{\gamma}\right) w_U^{\epsilon_U(1-\beta)+1}$$

The labour market is in equilibrium when labour demand (equations C.1 and C.2) equals labour supply (equation C.4) for each nativity group. This is summarised by the following set of equations:

$$\begin{aligned}
w_{U,t} &= \alpha_L \gamma \left(\frac{Y_t}{L_t}\right)^{1-\mu} \left(\frac{L_t}{L_{U,t}}\right)^{1-\beta} \\
w_I^{\epsilon_I(1-\beta)+1} &= \left(\frac{1-\gamma}{\gamma}\right) w_U^{\epsilon_U(1-\beta)+1} \\
r_t &= \alpha_K \left(\frac{Y_t}{K_t}\right)^{1-\mu} \\
L_I &= w_I^{\epsilon_I} \\
L_U &= w_U^{\epsilon_U} \\
Y &= \left[\alpha_K K^{\mu} + \alpha_L L^{\mu}\right]^{\frac{1}{\mu}} \\
L &= \left[\gamma L_U^{\beta} + (1-\gamma) L_I^{\beta}\right]^{\frac{1}{\beta}}
\end{aligned}$$

To understand the effect of automation, we log-linearise the model wherein $\hat{x}$ denotes the log deviation of a variable x from its steady-state value. We omit the time subscript for brevity. The log-linearised system is given by:

$$\hat{w}_U = (1-\mu)\left(\hat{Y} - \hat{L}\right) + (1-\beta)\left(\hat{L} - \hat{L}_U\right) \tag{C.5}$$

$$\hat{w}_I = \frac{\epsilon_U(1-\beta)+1}{\epsilon_I(1-\beta)+1}\hat{w}_U \tag{C.6}$$

$$\hat{r} = (1-\mu)\left(\hat{Y} - \hat{K}\right) \tag{C.7}$$

$$\hat{Y} = s_K \hat{K} + (1-s_K)\hat{L} \tag{C.8}$$

$$\hat{L} = (1-s_I)\hat{L}_U + s_I \hat{L}_I \tag{C.9}$$

$$\hat{L}_U = \epsilon_U \hat{w}_U \tag{C.10}$$

$$\hat{L}_I = \epsilon_I \hat{w}_I \tag{C.11}$$

$$\tag{C.12}$$

where $s_K = \frac{\alpha_K \bar{K}^{\mu}}{\alpha_K \bar{K}^{\mu} + \alpha_L \bar{L}^{\mu}}$ and $s_I = \frac{(1-\gamma)\bar{L}_I^{\beta}}{\gamma \bar{L}_U^{\beta} + (1-\gamma)\bar{L}_I^{\beta}}$. Automation in the model involves an exogenous increase in the share of tasks performed by capital (s_K). We will conduct comparative static exercises by shifting the labour demand curve to examine the effect of changes in s_K on native wages, wherein we ignore general equilibrium effects.

Result 1: Given the price of capital, an increase in automation reduces natives' wages.

Combining the equations, native wages can be expressed as:

$$\hat{w}_U = -\frac{s_K}{1 - s_K}\hat{r} \times \frac{\varepsilon_I (1 - \beta) + 1}{(1 - \beta)(\varepsilon_I (1 - s_I) + s_I \varepsilon_U)}$$

Partially differentiating w.r.t. s_k implies that

$$\frac{\partial \hat{w}_U}{\partial s_K} = -\frac{1}{(1 - s_K)^2}\hat{r} \times \frac{\varepsilon_I (1 - \beta) + 1}{(1 - \beta)(\varepsilon_I (1 - s_I) + s_I \varepsilon_U)} < 0$$

Thus, a downward shift in the labour demand curve, given a price of capital, will reduce wages of native workers, and also their employment.[36]

Result 2: Keeping the price of capital and native labour supply fixed, an increase in automation will reduce wages less when s_I is higher, if $s_K \sigma_{\beta} > \sigma_{\mu}$.

$$\frac{\partial \hat{w}_U}{\partial s_K} = -\frac{\hat{r}}{1 - s_K} \times \frac{1}{1 + \left[(1 - \mu) s_K - (1 - \beta)\right] s_I \epsilon_I \frac{\epsilon_U (1-\beta)+1}{\epsilon_I (1-\beta)+1}} \tag{C.13}$$

Immigrant mobility will dampen the fall in native wages to allow firms to attract native labour into the production process if either the substitutability between immigrant and native labour (σ_{β}) is high enough, or the aggregate substitutability of capital and labour (σ_{μ}) is sufficiently low.

The denominator in equation (C.13) reflects the feedback effect of a fall in the supply of immigrant labour on native wages. The growth in immigrant wages relative to native wages is given by the expression: $\frac{\epsilon_U (1-\beta)+1}{\epsilon_I (1-\beta)+1}$. The key point to note is that the attenuation effect of immigrant mobility will be stronger in areas with a higher immigrant share (s_I), as it only affects the denominator in equation (C.13). Thus, this stylised model

[36] This is similar to the *displacement effect* discussed in Acemoglu & Restrepo (2018). Relative to the model setup in Acemoglu & Restrepo (2018), we have shut down the *productivity effect* of automation for the tractability of the model. If we allow the *productivity effect* of automation to positively affect native wages, we need the *displacement effect* to outweigh the *productivity effect* for automation to reduce native wages.

shows that immigrant mobility can dampen the pass-through of automation into native wages, and the attenuation will be stronger in areas with a higher immigrant share.

To derive the above result, we proceed with partially differentiating $\hat{w}_U$ w.r.t. s_K:

$$\begin{aligned}
\hat{w}_U &= (1-\mu)\, s_K \left(\hat{K} - \hat{L}\right) + (1-\beta)\left(\hat{L} - \hat{L}_U\right) \\
\hat{w}_U &= (1-\mu)\, s_K \hat{K} + \Big[(1-\beta) - (1-\mu)\, s_K\Big]\hat{L} - (1-\beta)\,\hat{L}_U \\
\frac{\partial \hat{w}_U}{\partial s_K} &= (1-\mu)\left(\hat{K} - \hat{L}\right) + \Big[(1-\beta) - (1-\mu)\, s_K\Big]\frac{\partial \hat{L}}{\partial \hat{w}_U}\frac{\partial \hat{w}_U}{\partial s_K}
\end{aligned}$$

To derive $\frac{\partial \hat{L}_I}{\partial \hat{w}_U}$, we will use the linearized labour aggregate equation (C.9) and linearized relative wage equation (C.6).

$$\begin{aligned}
\frac{\partial \hat{L}}{\partial \hat{w}_U} &= s_I \frac{\partial \hat{L}_I}{\partial \hat{w}_U} = s_I \frac{\partial \hat{L}_I}{\partial \hat{w}_I}\frac{\partial \hat{w}_I}{\partial \hat{w}_U} \\
&= s_I \epsilon_I \frac{\epsilon_U\,(1-\beta)+1}{\epsilon_I\,(1-\beta)+1}
\end{aligned}$$

Thus, substituting this expression, we get:

$$\frac{\partial \hat{w}_U}{\partial s_K} = -\frac{\hat{r}}{1-s_K} \times \frac{1}{1 + \Big[(1-\mu)\, s_K - (1-\beta)\Big] s_I \epsilon_I \frac{\epsilon_U(1-\beta)+1}{\epsilon_I(1-\beta)+1}}$$

where $\hat{r} = -(1-s_K)(1-\mu)\left(\hat{K} - \hat{L}\right)$. The fall in native wages due to automation will be smaller in Result 2 than in Result 1 if the denominator is greater than 1, which implies $(1-\mu)\, s_K > (1-\beta)$. This condition can be re-written in terms of the elasticity of substitution as: $s_K \sigma_\beta > \sigma_\mu$.

Table C.1: Effects on natives' labour market outcomes by low-skill immigrant share, stacked-differences 1990–2015 (2SLS)

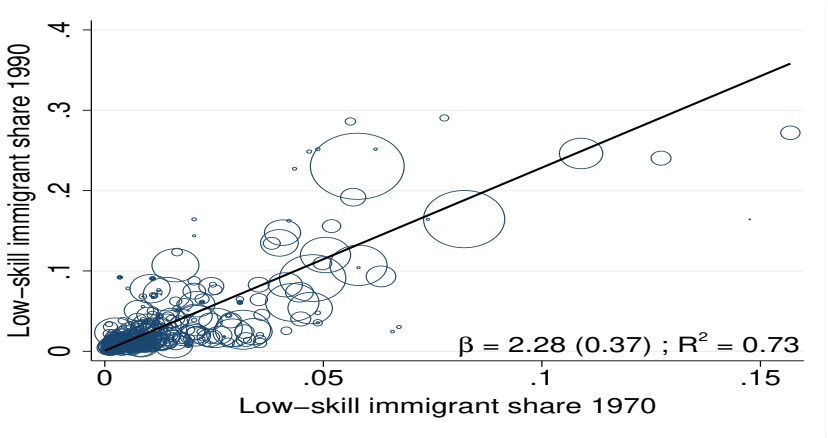
Dependent variable: Change in log wages or change in log employment				
	Low-skill		High-skill	
	Wage	Employment	Wage	Employment
	(1)	(2)	(3)	(4)
Exposure to robots x Above-median	-1.12***	-1.24***	-1.08***	-1.63***
	(0.23)	(0.47)	(0.19)	(0.50)
Exposure to robots x Below-median	-1.36***	-1.04	-1.20***	-1.61**
	(0.28)	(0.78)	(0.22)	(0.68)
Observations	1444	1444	1444	1444
R-squared	0.88	0.82	0.88	0.74
Test of equality	0.37	0.78	0.64	0.98

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).

C.2 First Stage: Immigrant Share IV

Figure C.1 displays a strong positive relationship between the share of low-skilled immigrants in 1970 and 1990.

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



Note: Marker size indicates the 1990 population in the CZ. Clustered standard errors at state level in parentheses.

Table C.2 shows that the low-skilled immigrant shares in 1970 and 1990 are strongly correlated, even after controlling for various demographic and industry characteristics.

Table C.2: First-Stage of 1970 low-skilled immigrant share IV

Dependent variable: Low-skilled Immigrant Share 1990					
	(1)	(2)	(3)	(4)	(5)
Low-skilled Immigrant Share 1970	2.28***	2.24***	1.54***	1.51***	1.48***
	(0.37)	(0.20)	(0.23)	(0.24)	(0.22)
Observations	722	722	722	722	722
R^2	0.73	0.87	0.95	0.95	0.95
Division dummies		Yes	Yes	Yes	Yes
Demographics			Yes	Yes	Yes
Industry				Yes	Yes
Computers, trade					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 no controls. Column (2) includes census division dummies. Column (3) 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) and change in low-skill population between 1970 and 1990. Column (4) further includes industry shares (share of employment in mining, construction, light manufacturing and manufacturing, and average offshorability index). Column (6) also includes stock of computer capital per worker in 1990 and exposure to Chinese imports.

C.2.1 Pre-trends

Table C.3 shows the changes in log native employment and log average native wages between 1970 and 1990, in relation to robot exposure between 1990 and 2015 and the 1990 immigrant share. The table clearly shows a lack of significant pre-trends in labour market outcomes of native workers from robot exposure. The second row demonstrates that in areas with no immigrant share, *future* robot exposure had no significant impact on lagged growth in native employment or wages. Moreover, the first row shows that the effect of robot exposure did not vary based on where immigrants settled in 1990.

Table C.3: 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)
LS 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: LS denotes Low-skill. US robot exposure and 1990 low-skilled immigrant share are instrumented using EURO5 robot exposure and 1970 low-skilled immigrant share, respectively. 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.3 Robustness checks for mitigating effects

C.3.1 OLS and Reduced-Form results

Table C.4: Effects on natives' labour market outcomes, stacked-differences 1990–2015: OLS and Reduced-Form

Dependent variable: Change in log wages or change in log employment				
	Low-skill		High-skill	
	Wage (1)	Employment (2)	Wage (3)	Employment (4)
	A: OLS			
Exposure x Share 1990	10.13**	30.30**	1.79	-3.10
	(4.23)	(12.20)	(5.29)	(12.63)
Exposure to robots	-1.29***	-2.06***	-0.98***	-1.62***
	(0.13)	(0.58)	(0.21)	(0.41)
LS Immigrant Share 1990	-22.81***	-57.08***	-13.28***	-39.42***
	(2.50)	(7.80)	(3.49)	(12.23)
Observations	1444	1444	1444	1444
R-squared	0.89	0.83	0.88	0.74
	B: Reduced-Form			
Exposure x Share 1970	30.83**	18.60	10.32	0.19
	(11.60)	(24.34)	(15.63)	(38.41)
EURO5 Robot-exposure	-2.32***	-2.08*	-1.67***	-2.06
	(0.50)	(1.08)	(0.50)	(1.23)
LS Immigrant Share 1970	-30.81***	-79.91***	-8.63	-34.71
	(10.62)	(26.38)	(14.21)	(41.61)
Observations	1444	1444	1444	1444
R-squared	0.88	0.82	0.88	0.74

Note: LS denotes Low-skill. 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).

C.3.2 Gradually adding controls

Table C.5: Effects on low-skilled natives' labour market outcomes, stacked-differences 1990–2015 (2SLS): Gradual Inclusion of controls

Dependent variable: Change in log wages or change in log employment						
	(1)	(2)	(3)	(4)	(5)	(6)
	A: Wage					
Exposure x Share 1990	25.67	56.97**	52.12**	50.92***	22.56***	19.82***
	(19.98)	(23.06)	(22.60)	(19.26)	(8.14)	(7.64)
Exposure to robots	-3.47***	-4.10***	-4.31***	-3.85***	-1.74***	-1.57***
	(0.63)	(0.62)	(0.65)	(0.39)	(0.24)	(0.23)
LS Immigrant Share 1990	-35.83***	-30.13***	-28.44***	-19.54*	-17.93***	-17.67***
	(12.20)	(7.89)	(9.18)	(9.97)	(4.00)	(4.10)
Observations	1444	1444	1444	1444	1444	1444
R^2	0.17	0.15	0.17	0.44	0.84	0.88
	B: Employment					
Exposure x Share 1990	-1.41	57.95**	68.44***	63.49***	33.26**	7.70
	(36.17)	(28.28)	(22.69)	(19.65)	(15.05)	(12.80)
Exposure to robots	-2.56*	-3.70***	-4.01***	-4.05***	-2.35***	-1.66***
	(1.39)	(0.94)	(0.91)	(0.79)	(0.55)	(0.60)
LS Immigrant Share 1990	-25.11	-60.65***	-76.18***	-65.41***	-59.31***	-50.42***
	(26.26)	(10.20)	(9.73)	(10.85)	(9.52)	(10.99)
Observations	1444	1444	1444	1444	1444	1444
R^2	0.36	0.53	0.55	0.58	0.73	0.83
Division dummies	Yes	Yes	Yes	Yes		
Division x time dummies					Yes	Yes
Demographics		Yes	Yes	Yes	Yes	
Industry			Yes	Yes	Yes	
Demo+Ind x time						Yes
Computers, trade				Yes	Yes	Yes

Note: US robot exposure and 1990 low-skilled immigrant share are instrumented using EURO5 robot exposure and 1970 low-skilled immigrant share, 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. Column (1) includes census division dummies. Column (2) further includes demographic characteristics (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 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, share of employment in routine occupations and average offshorability index). Column (4) also includes stock of computer capital per worker in 1990 and exposure to Chinese imports. Column (5) includes division-time dummies instead of division dummies. Column (6) further includes year interaction with demographic and industry characteristics in 1990.

C.3.3 Alternative methods for computing standard errors

Table C.6 shows that our conclusions are robust to clustering standard errors at the CZ level in column 2 instead of the state level. Moreover, our results remain robust to allowing for arbitrary spatial correlation between CZs that lie at varying distances, following Conley (1999).

Table C.6: Effects on low-skilled natives' labour market outcomes, stacked-differences 1990–2015 (2SLS): Alternative standard errors

Dependent variable: Change in log wages or change in log employment					
	Baseline	Cluster	Conley		
		CZ	100 km	250 km	500 km
	(1)	(2)	(3)	(4)	(5)
	A: Wage				
Exposure x Share 1990	19.82***	19.82***	19.82***	19.82***	19.82***
	(7.64)	(6.48)	(7.61)	(7.65)	(7.39)
Exposure to robots	-1.57***	-1.57***	-1.57***	-1.57***	-1.57***
	(0.23)	(0.26)	(0.24)	(0.26)	(0.25)
LS Immigrant Share 1990	-17.67***	-17.67***	-17.67***	-17.67***	-17.67***
	(4.10)	(3.67)	(4.58)	(4.56)	(4.31)
Observations	1444	1444	1444	1444	1444
R^2	0.88	0.88	0.88	0.88	0.88
	B: Employment				
Exposure x Share 1990	7.70	7.70	7.70	7.70	7.70
	(12.80)	(14.56)	(13.31)	(12.47)	(12.50)
Exposure to robots	-1.66***	-1.66***	-1.66***	-1.66***	-1.66***
	(0.60)	(0.49)	(0.61)	(0.59)	(0.54)
LS Immigrant Share 1990	-50.42***	-50.42***	-50.42***	-50.42***	-50.42***
	(10.99)	(8.54)	(12.29)	(12.21)	(12.41)
Observations	1444	1444	1444	1444	1444
R^2	0.83	0.83	0.83	0.83	0.83

Note: US robot exposure and 1990 low-skilled immigrant share are instrumented using EURO5 robot exposure and 1970 low-skilled immigrant share, 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. All regressions include time-division dummies and covariates: . Column (1) clusters standard errors at state level. Column (2) clusters standard errors at CZ level. Columns (3), (4) and (5) allow for temporal correlation and arbitary spatial correlation among CZs within 100 kilometres, 250 kilometres and 500 kilometres, respectively.

C.3.4 Differences between Right-to-work regions

We split our sample by states that had Right-to-work (RTW) laws before 1990 and those that did not, and normalise the robot exposure measure between states with and without RTW to make the coefficients comparable. Table C.7 shows that the mitigating wage effects are very similar between states with and without Right-to-work policies.

Table C.7: Effects on labour market outcomes of low-skilled natives by Right-to-work states, stacked-differences 1990–2015 (2SLS)

Dependent variable: Change in log employment or change in log wages		
	Wage	Employment
	(1)	(2)
Exposure x Share 1990 x RTW Present	18.89**	26.20
	(8.42)	(22.02)
Exposure x Share 1990 x RTW Absent	17.13***	-5.24
	(6.33)	(17.34)
Exposure x RTW Present	-0.74***	-2.17***
	(0.27)	(0.67)
Exposure x RTW Absent	-1.64***	-1.04
	(0.27)	(0.68)
LS Immigrant Share 1990 x RTW Present	-116.18**	-56.83
	(50.83)	(153.57)
LS Immigrant Share 1990 x RTW Absent	-129.23***	-86.92
	(49.49)	(152.25)
Observations	1444	1444
R-squared	0.88	0.82

Note: LS denotes Low-skill. US robot exposure and 1990 low-skilled immigrant share are instrumented using EURO5 robot exposure and 1970 low-skilled immigrant share, 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, interaction of robot exposure and dummy for right-to-work (RTW) states, interaction of RTW and immigrant share 1990, 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.3.5 Controlling for 1980 immigrant share

Jaeger et al. (2018) argues that controlling for immigrant shares in intermediate periods can account for the dynamic impact of past immigration shocks. Columns 1 and 3 in Table C.8 show the coefficients in the baseline model for the changes in log employment and log average wages of low-skilled native workers, respectively. We include the 1980 immigrant share in columns 2 and 4 to account for the dynamic effects of past immigration shocks. The coefficients and standard errors decrease slightly relative to the baseline estimates, but the main conclusions remain unchanged.

Table C.8: Effects on low-skilled natives' labour market outcomes, stacked-differences 1990–2015 (2SLS): adding 1980 immigrant share as control

Dependent variable: Change in log employment or change in log wages				
	Wage		Employment	
	(1)	(2)	(3)	(4)
Exposure x Share 1990	19.82***	14.77**	7.70	5.95
	(7.64)	(6.84)	(12.80)	(15.43)
Exposure to robots	-1.57***	-1.70***	-1.66***	-1.70***
	(0.23)	(0.33)	(0.60)	(0.65)
LS Immigrant Share 1990	-17.67***	-136.94**	-50.42***	-91.80
	(4.10)	(63.85)	(10.99)	(148.68)
Immigrant Share 1980		93.37*		32.40
		(49.21)		(121.35)
Observations	1444	1444	1444	1444
R-squared	0.88	0.88	0.83	0.82

Note: LS denotes Low-skill. US robot exposure and 1990 low-skilled immigrant share are instrumented using EURO5 robot exposure and 1970 low-skilled immigrant share, 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).

C.3.6 Using longer lags as instruments

Table C.9: Effects on low-skilled natives' labour market outcomes, stacked-differences 1990–2015 (2SLS): 1950 or 1960 low-skilled immigrant share as instrument

Dependent variable: Change in log employment or change in log wages				
	Low-skill		High-skill	
	Wage	Employment	Wage	Employment
	(1)	(2)	(3)	(4)
	A: 1960			
Exposure x Share 1990	19.31**	-3.39	10.52	-10.61
	(9.79)	(19.59)	(12.61)	(30.37)
Exposure to robots	-1.53***	-1.43**	-1.17***	-1.24
	(0.28)	(0.72)	(0.31)	(0.85)
LS Immigrant Share 1990	-8.19	-47.30***	13.40	31.74
	(7.16)	(14.98)	(11.73)	(29.32)
Observations	1444	1444	1444	1444
R-squared	0.88	0.83	0.87	0.72
	B: 1950			
Exposure x Share 1990	24.20**	-10.32	15.76	-14.08
	(11.84)	(22.60)	(14.64)	(36.23)
Exposure to robots	-1.60***	-1.35*	-1.22***	-1.19
	(0.34)	(0.77)	(0.40)	(0.95)
LS Immigrant Share 1990	-1.26	-62.69***	26.48	27.05
	(9.46)	(19.61)	(16.95)	(31.95)
Observations	1444	1444	1444	1444
R-squared	0.87	0.82	0.86	0.72

Note: LS denotes Low-skill. US robot exposure and 1990 low-skilled immigrant share are instrumented using EURO5 robot exposure and 1950/1960 low-skilled immigrant share, 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).

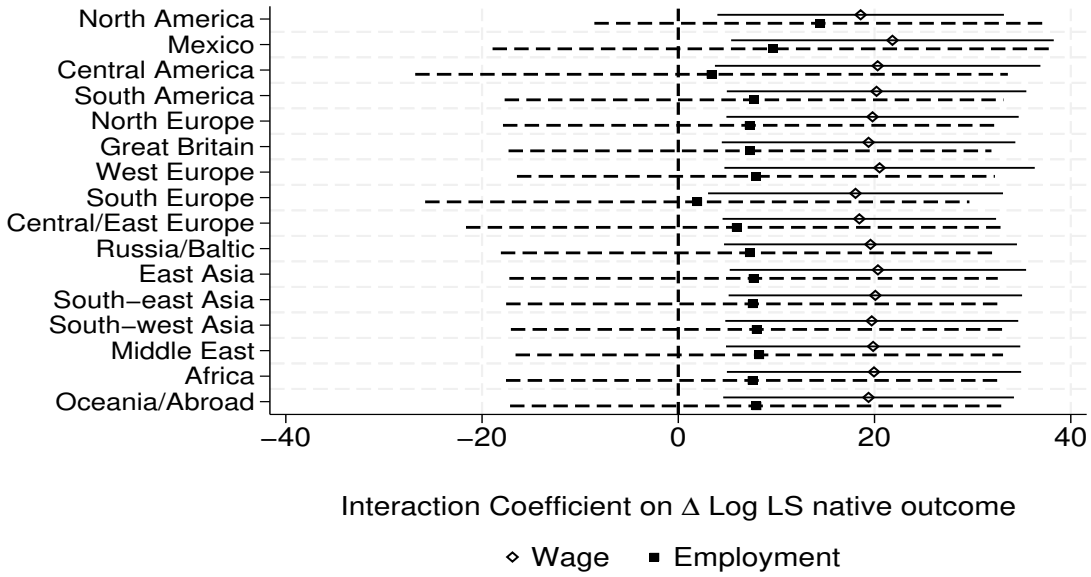
Table C.10: First-Stage of 1950 or 1960 low-skilled immigrant share IV

Dependent variable: Low-skilled Immigrant Share 1990					
	A: 1960				
	(1)	(2)	(3)	(4)	(5)
Low-skilled Immigrant Share 1960	0.93***	1.05***	0.55***	0.53***	0.52***
	(0.20)	(0.12)	(0.14)	(0.13)	(0.12)
Observations	722	722	722	722	722
R^2	0.49	0.75	0.90	0.91	0.91
	B: 1950				
	(1)	(2)	(3)	(4)	(5)
Low-skilled Immigrant Share 1950	0.65***	0.80***	0.35***	0.32***	0.32***
	(0.10)	(0.10)	(0.12)	(0.10)	(0.09)
Observations	722	722	722	722	722
R^2	0.36	0.66	0.89	0.90	0.90
Division dummies		Yes	Yes	Yes	Yes
Demographics			Yes	Yes	Yes
Industry				Yes	Yes
Computers, trade					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 no controls. Column (2) includes census division dummies. Column (3) 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) and change in low-skill population between 1970 and 1990. Column (4) further includes industry shares (share of employment in mining, construction, light manufacturing and manufacturing, and average offshorability index). Column (6) also includes stock of computer capital per worker in 1990 and exposure to Chinese imports.

C.3.7 Exclude immigrant group from a specific region

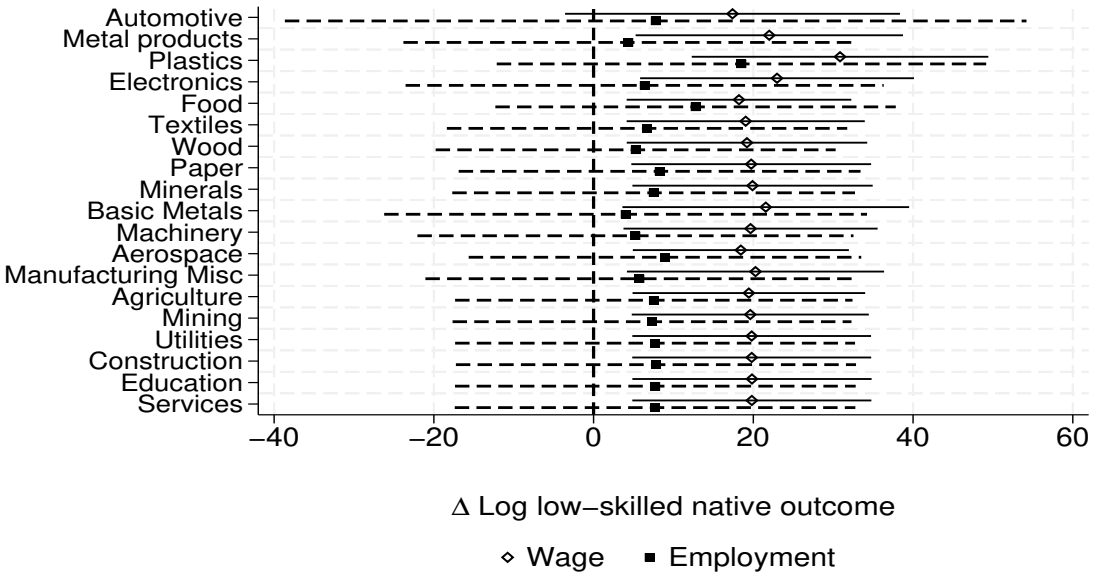
Figure C.2: Effect of interaction between robot exposure and low-skilled immigrant share on low-skilled natives' labour market outcomes, excluding one region at a time



Note: US robot exposure and 1990 low-skilled immigrant share are instrumented using EURO5 robot exposure and 1970 low-skilled immigrant share, respectively. Each estimate represents the effect when a particular country/region is excluded from the 1970 immigrant share. All regression estimates are weighted by the CZ population in 1990. Standard errors are clustered at the state level.

C.3.8 Trends in industry-specific robot adoption

Figure C.3: Effect of interaction between robot exposure and low-skilled immigrant share on low-skilled natives' labour market outcomes, excluding one industry at a time



Note: US robot exposure and 1990 low-skilled immigrant share are instrumented using EURO5 robot exposure and 1970 low-skilled immigrant share, respectively. Each estimate represents the effect when a particular industry is excluded from the robot exposure measure. All regression estimates are weighted by the CZ population in 1990. Standard errors are clustered at the state level.

C.3.9 Alternative measures of robot exposure

Table C.11: Effects on natives' labour market outcomes, stacked-differences 1990–2015: Alternate instruments of robot-exposure

Dependent variable: Change in log wages or change in log employment							
		Leave-one-out					
	Baseline	Denmark	Finland	France	Italy	Sweden	EURO7
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	A: Wage						
Exposure x Share 1990	19.82***	22.33**	18.97***	20.16***	18.70***	19.62**	19.80**
	(7.64)	(9.51)	(7.33)	(7.69)	(6.56)	(7.89)	(7.83)
Exposure to robots	-1.57***	-1.62***	-1.56***	-1.62***	-1.52***	-1.57***	-1.53***
	(0.23)	(0.25)	(0.26)	(0.25)	(0.19)	(0.23)	(0.23)
LS Immigrant Share 1990	-17.67***	-18.52***	-17.38***	-17.73***	-17.34***	-17.60***	-17.72***
	(4.10)	(4.38)	(4.08)	(4.09)	(4.02)	(4.14)	(4.14)
Observations	1444	1444	1444	1444	1444	1444	1444
R^2	0.88	0.88	0.88	0.88	0.88	0.88	0.88
	B: Employment						
Exposure x Share 1990	7.70	1.91	8.46	7.98	12.20	6.18	8.23
	(12.80)	(15.47)	(12.90)	(12.82)	(12.41)	(12.73)	(12.88)
Exposure to robots	-1.66***	-1.61***	-1.61***	-1.72***	-1.63***	-1.67***	-1.59***
	(0.60)	(0.62)	(0.62)	(0.60)	(0.62)	(0.57)	(0.58)
LS Immigrant Share 1990	-50.42***	-48.39***	-50.76***	-50.45***	-52.08***	-49.85***	-50.70***
	(10.99)	(11.48)	(10.93)	(10.88)	(11.06)	(10.87)	(10.91)
Observations	1444	1444	1444	1444	1444	1444	1444
R^2	0.83	0.83	0.83	0.83	0.83	0.83	0.83

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 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). US robot exposure and 1990 low-skilled immigrant share are instrumented using different robot exposure measures and 1970 low-skilled immigrant share, respectively. Column (2) to Column (6) use four countries out of 5 from the EURO5 set of countries as instrument with each column indicating which country is excluded from the baseline measure. Column (7) regression uses EURO7 exposure as instrument instead of EURO5 exposure.

Table C.12: Effects on natives' labour market outcomes, stacked-differences 1990–2015: Removing regions with high robot exposure

Dependent variable: Change in log wages or change in log employment				
	Baseline	Drop top exposure	Drop top 1% exposure	Drop top 3 states
	(1)	(2)	(3)	(4)
	A: Wage			
Exposure x Share 1990	19.82***	22.57**	16.29**	11.77**
	(7.64)	(9.33)	(6.69)	(5.78)
Exposure to robots	-1.57***	-1.44***	-1.72***	-1.54**
	(0.23)	(0.28)	(0.55)	(0.76)
LS Immigrant Share 1990	-17.67***	-18.12***	-17.38***	-17.43***
	(4.10)	(4.32)	(3.79)	(3.56)
Observations	1444	1443	1430	1340
R^2	0.88	0.88	0.88	0.87
	B: Employment			
Exposure x Share 1990	7.70	21.40	10.54	16.45
	(12.80)	(15.36)	(12.81)	(15.37)
Exposure to robots	-1.66***	-1.01	0.10	-0.33
	(0.60)	(0.66)	(0.84)	(1.16)
LS Immigrant Share 1990	-50.42***	-52.66***	-48.37***	-47.61***
	(10.99)	(10.00)	(10.69)	(11.00)
Observations	1444	1443	1430	1340
R^2	0.83	0.83	0.83	0.83

Note: US robot exposure and 1990 low-skilled immigrant share are instrumented using EURO5 robot exposure and 1970 low-skilled immigrant share, 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. All 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). Column (2) excludes CZ with the highest US robot exposure. Column (3) excludes CZs' with top 1% US robot exposure. Column (4) excludes states with highest exposure: Indiana, Michigan and Ohio.

C.3.10 Controlling for pre-trends

Table C.13: Effects on low-skilled natives' labour market outcomes, stacked-differences 1990–2015 (2SLS): Controlling for pre-trends

Dependent variable: Change in log employment or change in log wages							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	A: Wage						
Exposure x Share 1990	19.82***	17.18***	19.37***	17.20***	19.93**	19.93***	20.01**
	(7.64)	(5.71)	(6.26)	(5.91)	(7.89)	(7.65)	(7.93)
Exposure to robots	-1.57***	-1.68***	-1.66***	-1.68***	-1.58***	-1.58***	-1.58***
	(0.23)	(0.22)	(0.23)	(0.22)	(0.23)	(0.23)	(0.23)
LS Immigrant Share 1990	-17.67***	-26.29***	-25.71***	-26.33***	-17.76***	-17.61***	-17.74***
	(4.10)	(4.45)	(5.73)	(5.82)	(4.03)	(4.06)	(3.97)
LS Immigrant Share 1950		8.99***		8.90			
		(2.88)		(6.73)			
LS Immigrant Share 1960			9.37*	0.14			
			(4.81)	(10.08)			
Change in LS Immigrant Population 1950-1960					0.04		0.04
					(0.15)		(0.16)
Change in LS Immigrant Population 1960-1970						-0.01	0.00
						(0.21)	(0.22)
Observations	1444	1444	1444	1444	1430	1442	1428
R-squared	0.88	0.89	0.89	0.89	0.88	0.88	0.88
	B: Employment						
Exposure x Share 1990	7.70	10.14	7.64	14.09	5.90	6.40	4.32
	(12.80)	(13.11)	(12.68)	(13.14)	(13.19)	(13.29)	(13.78)
Exposure to robots	-1.66***	-1.56**	-1.67***	-1.62***	-1.64***	-1.63***	-1.61***
	(0.60)	(0.62)	(0.61)	(0.62)	(0.60)	(0.61)	(0.61)
LS Immigrant Share 1990	-50.42***	-42.46***	-51.51***	-49.66***	-50.93***	-51.81***	-52.54***
	(10.99)	(12.57)	(12.76)	(12.16)	(10.94)	(11.21)	(11.10)
LS Immigrant Share 1950		-8.30		-26.53**			
		(6.32)		(12.79)			
LS Immigrant Share 1960			1.27	28.77*			
			(8.66)	(17.15)			
Change in LS Immigrant Population 1950-1960					0.29		0.36
					(0.43)		(0.42)
Change in LS Immigrant Population 1960-1970						0.49	0.52
						(0.57)	(0.56)
Observations	1444	1444	1444	1444	1430	1442	1428
R-squared	0.83	0.83	0.83	0.83	0.83	0.83	0.83

Note: LS denotes Low-skill. US robot exposure and 1990 low-skilled immigrant share are instrumented using EURO5 robot exposure and 1970 low-skilled immigrant share, 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).

C.3.11 Controlling for state-time trends

Table C.14: Effects on natives' labour market outcomes, stacked-differences 1990–2015: State-time trends

Dependent variable: Change in log wages or change in log employment				
	State-time Dummies		State time trend	
	Wage	Employment	Wage	Employment
	(1)	(2)	(3)	(4)
Exposure x Share 1990	19.50*	44.43**	23.67*	42.93*
	(11.35)	(21.58)	(13.57)	(22.93)
Exposure to robots	-1.06***	-2.01***	-1.30***	-2.21***
	(0.25)	(0.73)	(0.31)	(0.78)
LS Immigrant Share 1990	-17.92***	-55.15***	-19.00***	-55.76***
	(4.69)	(9.98)	(5.29)	(10.65)
Observations	1440	1440	1444	1444
R-squared	0.48	0.59	0.85	0.73

Note: LS denotes Low-skill. US robot exposure and 1990 low-skilled immigrant share are instrumented using EURO5 robot exposure and 1970 low-skilled immigrant share, 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 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.3.12 Alternative stacked and long period specifications

Table C.15 shows that low-skilled immigrant mobility mitigates wage losses due to robot exposure for low-skilled native workers using three-period and two-period stacked-differences specifications and a long-difference specification. Coefficients in columns 1-2, 3-4 and 5-6 correspond to estimates using a three-period stacked-differences specification (1990-2000, 2000-2007 and 2007-2015), a two-period stacked-differences specification (1990-2000 and 2000-2007) and a long-difference specification, respectively. The interaction term between robot exposure and the 1990 immigrant share is both economically and statistically significant for the wages of low-skilled native workers across all specifications. Furthermore, the coefficients for the three- and two-period

specifications are quite similar, indicating that our results are not driven by the Great Recession.

Table C.15: Effects on labour market outcomes of natives, multiple time periods (2SLS): Interacting robot exposure with share of low-skilled immigrant

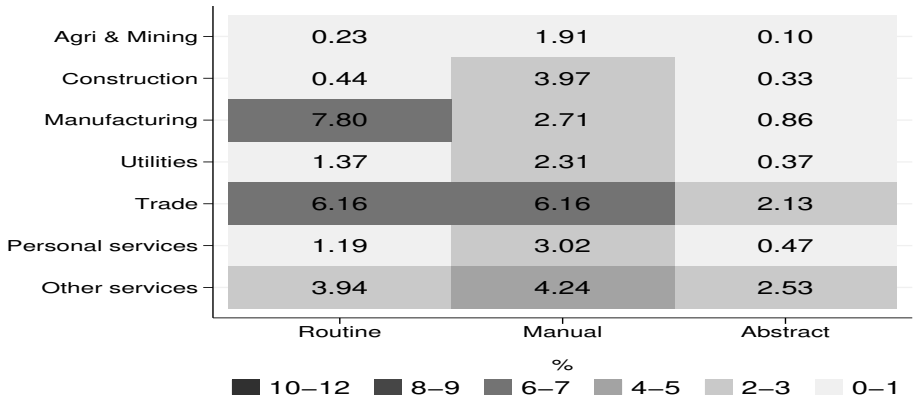
Dependent variable: Change in log employment or change in log wages						
	3 stacked		2 stacked		Long	
	Wage	Employment	Wage	Employment	Wage	Employment
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure x Share 1990	33.96***	2.17	38.40**	-0.19	32.16***	8.05
	(9.91)	(20.12)	(17.11)	(34.34)	(9.54)	(24.08)
Exposure to robots	-1.88***	-2.12**	-2.01***	-2.12*	-2.35***	-2.24**
	(0.34)	(0.83)	(0.47)	(1.19)	(0.31)	(0.89)
LS Immigrant Share 1990	-21.38***	-42.18***	-20.26***	-56.26***	-21.63***	-57.32***
	(5.20)	(14.08)	(7.41)	(19.27)	(4.27)	(16.44)
Observations	2166	2166	1444	1444	722	722
R-squared	0.82	0.80	0.87	0.76	0.71	0.80

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. LS denotes Low-skill. US robot exposure and 1990 low-skilled immigrant share are instrumented using EURO5 robot exposure and 1970 low-skilled immigrant share, 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 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.4 Additional result: Heterogeneity by industry-task

Figure C.4 shows the employment share of low-skilled natives across industry-task cells in 1990. Low-skilled natives are mostly employed in manufacturing or trade jobs.

Figure C.4: Share of native employment among low-skilled in 1990



C.5 Additional results: Heterogeneity by age

Table C.16 presents the mitigating effects using the share of low-skilled established immigrants instead of the overall share of low-skilled immigrants. The point estimates are slightly higher than the baseline coefficients, but the implied mitigating impacts are quite similar. The coefficient of 33.98 in column 1 predicts that the decrease in the wages of native workers is lower by 0.07 pp when comparing CZs at the 50^{th} and 25^{th} percentiles of the low-skilled established immigrant share. The mean robot exposure is 0.9, and the 50^{th} and 25^{th} percentiles of the shares of low-skilled established immigrants are 0.56% and 0.33%, respectively (0.07 = 0.9*0.3398*[0.56-0.33]). Thus, we reach the same conclusions as our baseline results.

Table C.16: Effects on natives' labour market outcomes, stacked-differences 1990–2015 (2SLS): Interacting robot exposure and low-skilled established immigrant share

Dependent variable: Change in log employment or change in log wages				
	Low-skill		High-skill	
	Wage	Employment	Wage	Employment
	(1)	(2)	(3)	(4)
Exposure x Share Established 1990	33.98***	25.53	14.24	8.57
	(10.71)	(21.04)	(14.49)	(33.22)
Exposure to robots	-1.68***	-1.76***	-1.26***	-1.74**
	(0.26)	(0.66)	(0.29)	(0.70)
LS Immigrant Share Established 1990	-33.27***	-95.57***	-10.80	-45.89
	(8.04)	(22.72)	(12.65)	(38.13)
Observations	1444	1444	1444	1444
R-squared	0.88	0.83	0.88	0.74

Note: LS denotes Low-skill. US robot exposure and 1990 low-skilled established immigrant share are instrumented using EURO5 robot exposure and 1970 low-skilled immigrant share, 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).

Table C.17 illustrates the mitigating effect from robot exposure due to mobility of

the overall low-skilled immigrant share on both young and old low-skilled natives. The interaction term is distinctly different for older natives compared to younger natives, although it is less precisely estimated than when using the low-skilled established immigrant share.

Table C.17: Effects on low-skill natives' labour market outcomes by age, stacked-differences 1990–2015 (2SLS): Interacting robot exposure and low-skill immigrant share

Dependent variable: Change in log employment or change in log wages				
	Young (16-39)		Old (40-64)	
	Wage	Employment	Wage	Employment
	(1)	(2)	(3)	(4)
Exposure x Share 1990	13.61*	-1.53	20.17**	18.93
	(8.06)	(17.83)	(9.84)	(13.57)
Exposure to robots	-1.07***	-1.92***	-2.21***	-1.42**
	(0.24)	(0.70)	(0.28)	(0.61)
LS Immigrant Share 1990	-16.44***	-27.74*	-9.71	-71.92***
	(3.58)	(16.75)	(6.86)	(8.88)
Observations	1444	1444	1444	1444
R-squared	0.89	0.78	0.77	0.84

Note: LS denotes Low-skill. US robot exposure and 1990 low-skilled immigrant share are instrumented using EURO5 robot exposure and 1970 low-skilled immigrant share, 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).

D Section 5 Appendix: Human capital adjustment

Table D.1: Effects on share of immigrants attending college by migration status

Dependent variable: Change in share attending college				
	Young		Old	
	Stayer	Mover	Stayer	Mover
	(1)	(2)	(3)	(4)
Exposure to robots	0.14	0.04	0.15**	0.01
	(0.24)	(0.22)	(0.07)	(0.04)
Observations	1444	1444	1444	1444
R^2	0.43	0.56	0.08	0.29

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).

Table D.2: Effects on share attending college by working status

Dependent variable: Change in share attending college				
	Native Young		Immigrants Old	
	Worked	Non-participation	Worked	Non-participation
	(1)	(2)	(3)	(4)
Exposure to robots	0.04	0.10***	0.11	0.05*
	(0.06)	(0.03)	(0.07)	(0.03)
Observations	1444	1444	1444	1444
R^2	0.57	0.54	0.09	0.07

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. 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).