Automation and Local Labour Markets: Impact of Immigrant Mobility

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Abstract

This paper illustrates the role of low-skilled immigrants' location choice as a channel through which local labour markets adjust to automation. Using a shift-share instrument, we show that low-skilled immigrants are significantly more mobile in response to automation than their native counterparts. Immigrant mobility acts as an important insurance mechanism for low-skilled native workers to 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

Automation has transformed the labour market in industrialised economies in the past 30 years (Abraham & Kearney 2020, Acemoglu & Restrepo 2020).[1] 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 little is currently known. First, are low-skilled immigrants more mobile than low-skilled natives in response to the introduction of robots? Second, if the answer to the preceding question is yes, does the impact of automation on the low-skilled native workforce diminish due to immigrant mobility?

We examine mobility responses to robot exposure in US commuting zones (CZs) and uncover several novel findings. First, robot exposure led to a significantly larger decline in the growth of the low-skilled immigrant population compared to similarly skilled natives. The population change of low-skilled immigrants was driven by both a decline in arrival from other areas in the US into robot-exposed CZs and an increase in departure from robot-exposed CZs. Second, the high sensitivity of low-skilled immigrants' location choices to automation reduced spatial inequality for low-skilled natives. More specifically, we find that the fall in wages as a result of robot penetration was significantly lower for low-skilled native workers in regions with a higher share of low-skilled immigrants.

The policy prescriptions for the increasing adoption of robots have mainly focused on regulating their use (Beraja & Zorzi 2021), implementing redistributive policies (Guerreiro et al. 2022), or training workers (Jaimovich et al. 2021). We provide evidence supporting a new mechanism, immigrant mobility, which offers insurance to low-skilled workers against automation. Furthermore, our paper is informative about the design of immigration policies, given the push for anti-immigration policies in response

[1]There is considerable debate on the effects of technological progress on workers (Acemoglu & Restrepo 2020, Adachi et al. 2024, Autor et al. 2024, Dauth et al. 2021, de Vries et al. 2020, Goldin & Katz 2009, Gathmann et al. 2025, Graetz & Michaels 2018, Hirvonen et al. 2022, Koch et al. 2021). In the US, robot adoption has caused job and wage losses (Acemoglu & Restrepo 2020), higher inequality (Acemoglu & Restrepo 2022), reduction in upward mobility (Guo 2022), worsening of mental health (Gihleb et al. 2022), and a decline in marriage rates and marital fertility (Anelli et al. 2024), which is the focus in this paper.

to job losses (Autor et al. 2020, Brey 2021), and the design of labour market policies, such as minimum wage (Cadena 2014, Lordan & Neumark 2018).

To guide our empirical strategy, we develop a stylised theoretical framework based on Acemoglu & Restrepo (2018) and Ottaviano & Peri (2012). The model shows that a drop in the low-skilled immigrant population attenuates the impact of automation on low-skilled native wages. In addition, the mitigating effect is stronger in regions with a higher share of immigrants. Therefore, in our empirical analysis, we first establish the impact of automation on mobility by nativity and then examine the consequences of immigrant mobility on the labour market outcomes of low-skilled native workers.

To causally analyse the impact of automation on local labour markets, we use a shift-share instrumental variable strategy. The instrument exploits variation in national growth in robot use by industry between 1990 and 2015 and historical employment shares at the industry-CZ level (1970 period). We instrument the growth of robot capital in the United States compared to that in five European countries to remove US-specific advances in robotics, following Acemoglu & Restrepo (2020).[2]

Focussing on the mobility response by nativity-skill status, we estimate the change in the log-working-age population to robot exposure using a stacked-differences regression (1990-2000 and 2000-2015).[3] We find a pronounced difference between the low-skilled population growth by nativity status to robots. 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 (pp), respectively. In contrast, there is no differential sensitivity among the high-skilled nativity groups. Hence, we only focus on the migration response of low-skilled workers throughout the paper.

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 a few industries in our identifying variation. Reassuringly, we find no significant pre-trends in the key outcomes of interest, and our results remain robust across specifications when excluding one industry at a time in constructing the robot exposure measure.

In investigating the channels of adjustment, low-skilled immigrants are less likely to

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

[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).

enter robot-exposed regions and also more likely to exit from robot-exposed areas. We find an insignificant effect of robot penetration on international migration indicating that most of the labour reallocation occurred among incumbent immigrants. For low-skilled natives, we find that ageing in or out of the sample explains most of the observed decline in population growth. This implies an increase in the population of older low-skilled natives and/or a decline in the population of young low-skilled natives, possibly due to becoming high-skilled.

We argue that the observed fall in population growth among low-skilled immigrants to robot exposure is likely driven by changes in labour market conditions. The asymmetric effect in migration by nativity is mirrored in the differential impact of automation on labour market outcomes (employment and wages) between the two nativity groups. Furthermore, consistent with the earlier finding on the significant decline in population growth of incumbent low-skilled immigrants, employment, and population losses to automation among low-skilled immigrants are concentrated among those who have lived in the US for more than a decade. Therefore, changes in labour market opportunities due to automation are likely an important factor behind the high mobility of low-skilled immigrants.

Having established that immigrant location choices are particularly sensitive to robot penetration, we analyse its impact on native workers to robot exposure. Using predictions from the theoretical framework, we exploit the proportion of low-skilled immigrant population across CZs to capture the change in immigrant population. Furthermore, we use the 1990 immigrant share instead of the current share to avoid the issue of reverse causality. To address the endogeneity issue of the non-random sorting of immigrants, we instrument the 1990 CZ immigrant share with the share in 1970, as new immigrants are more likely to reside in areas with higher past immigration levels (Borjas 1995). The correlation between the robot exposure measure and the share of 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. The decline in low-skilled native wages due to automation is 0.07 percentage points lower in the 50th percentile of the low-skilled immigrant share compared to the 25th percentile. On average, immigrant mobility does not alleviate employment opportunities for low-skilled natives to automation; the loss in employment is similar in both areas with many and few immigrants. However, the average effect hides considerable heterogeneity; immigrant mobility insures 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 to robot exposure is lower by 0.1 pp when comparing CZs in the 50th and 25th percentiles of the low-skilled established immigrant share.

We reinforce the interpretation of our findings with several robustness checks. First, we rule out pre-trends by demonstrating that, in 1970, there were no significant differences in labour market outcomes (employment and wages) of natives between areas with high and low concentrations of low-skilled immigrants in relation to future robot adoption. Second, a concern for our identification strategy is that previous immigration waves may generate long-term and persistent effects on local labour markets, potentially biasing our results. Jaeger et al. (2018) argues that the dynamic impact of past immigrant supply shocks can be mitigated by controlling for the immigrant share in subsequent years. Reassuringly, our results are robust to including the 1980 immigrant share as an additional control in our regressions.

The results thus far demonstrate a significantly low mobility response to automation by low-skilled natives. Part of this phenomenon, as we have highlighted, may be attributed to the attenuating effect of immigrant mobility on native wages. In the final section of the paper, we discuss other potential mechanisms, specifically human capital accumulation, that might explain the low sensitivity in natives' location choices. We find that young natives and older immigrants are more likely to enrol in college in more robot-exposed regions. This finding highlights why natives have a low propensity to use geographical mobility as an insurance channel (Cadena & Kovak 2016).

This paper contributes to multiple strands of literature. First, it contributes to the literature on the role of immigrant mobility in "greasing the wheels of the labour market" (Basso et al. 2019, Blanchard & Katz 1992, Borjas 2001, Cadena & Kovak 2016, Özgüzel 2021, Yu 2023). This paper complements the literature by examining the contribution of immigrant location choices in a new and topical context, automation. Regional labour mobility is declining in the US (Molloy et al. 2011, Olney & Thompson 2024), raising concerns that an important mechanism to reduce geographic inequality is weakening. We show that the ability of local labour markets to adjust to economic shocks increases due to the presence of highly responsive low-skilled immigrants. We also advance this literature by showing the effect of immigrant mobility in cushioning wage losses to adverse demand shocks, since most of this literature has documented mitigating effects only through the employment margin, except Özgüzel (2021). Since we focus on a persistent adverse shock, this may explain the stronger adjustment of local labour market through wages in our findings compared to other studies (Cadena & Kovak 2016).

Second, our study contributes to the literature on the role of heterogeneity in evaluating the effects of automation and other adverse demand shocks (Acemoglu & Restrepo 2020, Albinowski & Lewandowski 2024, Ge & Zhou 2020, Gathmann & Grimm 2022, Javed 2023, Lerch 2024). We argue that distinguishing by subgroups is crucial for understanding migration responses to changes in economic conditions. We find a decline in the population growth of both low-skilled immigrants and high-skilled natives, two of the most highly mobile groups. This distinction possibly explains why recent work that focusses on the total population (Acemoglu & Restrepo 2020) or total immigrants (Faber et al. 2022) finds a limited migration response to robot exposure. The strong response in location choice to automation suggests that the adverse effects of robot exposure might be higher in the US than originally documented. Furthermore, we highlight the heterogeneous response in post-secondary educational attainment across nativity groups to automation, an issue that has not been studied in much detail.

Third, 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, Black et al. 2005, Greenland et al. 2019, Notowidigdo 2020). The shocks in these studies are likely to be temporary in nature, where as we focus on a long-run shock that is likely to permanently change the composition of local labour markets. In general, we find, in line with the literature, that low-skilled immigrants are particularly responsive in their location choices to changes in labour market conditions. The decline in inflows into robot-exposed regions constitutes a significant proportion of the observed decrease in population growth, indicating that the inmigration of prospective migrants is a crucial adjustment mechanism to economic shocks in local labour markets (Dustmann et al. 2017, Monras 2020). Furthermore, we shed light on the reasons for the limited reliance of low-skilled natives on migration as an insurance mechanism, emphasising the roles of immigrant mobility and human capital accumulation.

Lastly, 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. 2023, 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 automation. We complement this literature by showing that young non-employed natives delay their entry into the labour market by enrolling into college in more robot-exposed regions. In addition, older employed immigrants also upgrade their skills by attending college in response to automation. Thus, we show that the accumulation of human capital is not limited to younger individuals (Corman 1983).

The rest of this article is organised as follows. We construct a model to guide our empirical strategy in Section 2. In Section 3, we discuss our data sources and describe the empirical methodology. Sections 4 and 5 present the migration responses by nativity and the implications of immigrant mobility on the native workforce. Section 6 discusses the role of education behind the lower migration sensitivity of low-skilled natives to robot exposure, and Section 7 concludes.

2 Theoretical Framework

We develop a stylised theoretical framework based on Acemoglu & Restrepo (2018) and Ottaviano & Peri (2012) to motivate our empirical specifications and help interpret our empirical results. The economy consists of low-skilled workers, differentiated by their place of birth (natives and immigrants). Following Acemoglu & Restrepo (2018), the final output is produced in a task-based framework where increased automation will imply a higher share of the output produced using capital rather than the aggregate of 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 through 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 the primary focus of the paper is examining the impact of robots on *between* nativity groups within a skill level, rather than *between* skill-levels.[4]

Consider a local labour market, i, 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.[5] α_K, α_L refers 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 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

[4]This assumption is unlikely to significantly alter our interpretations regarding the effect of automation on low-skilled workers by nativity groups. In the literature, it is common to assume a nested CES structure that separates labour aggregates by skill level, while maintaining the same degree of substitutability between natives and immigrants in all types of skills (Card 2009, Ottaviano & Peri 2012). Moreover, there is extensive evidence showing that robots and low-skilled labour are highly substitutable in the production process, while robots and high-skilled labour are less substitutable (Acemoglu & Restrepo 2020, Bonfiglioli et al. 2024, Humlum 2021, Koch et al. 2021). These assumptions would mitigate the feedback effect of automation on low-skilled workers through shifts in high-skilled labour demand.

[5]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).

stock of immigrant and native labour and capital. The first order conditions are:

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

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

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

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:

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

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. 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).[6]

The labour market is in equilibrium when the labour demand (equation 1 and 2) equals the labour supply (equation 4) for each nativity group. Let $\hat{x}$ denote the logarithmic deviation of a variable x from its steady-state value. We log-linearise the model wherein $\hat{x}$ denotes the log deviation of a variable x from its steady-state value and omit the time subscript for brevity. The first-order condition for labour demand of natives becomes (see Appendix A for the full set of equations):

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

$$\hat{Y} = s_K \hat{K} + (1-s_K)\hat{L} \tag{6}$$

$$\hat{L} = (1-s_I)\hat{L}_U + s_I \hat{L}_I \tag{7}$$

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

[6]Alternatively, in the Card et al. (2018) framework, equation 4 represents the labour supply facing a firm. Lower values of ϵ_g indicate that firms exert greater monopsony power, as individual labour supply is less sensitive to changes in wages.

exogenous increase in the share of tasks performed by capital (s_K). We will conduct comparative static exercises to examine the effect of change in s_K on native wages. [7]

Result 1: Keeping capital and labour fixed, an increase in automation results in a fall in native wages (downward shift in labour demand) if $\hat{L} > \hat{K}$.

Differentiating equation (5) w.r.t. s_K after substituting the log-linearized production function, we get:

$$\frac{\partial \hat{w}_U}{\partial s_K} = (1-\mu)\left(\hat{K}-\hat{L}\right)$$

Thus, the labour demand curve will shift to the left given labour and capital fixed if labour occupies a bigger share in the production process. [8] Given an upward-sloping labour supply curve, a downward shift in native labour demand will lead to a reduction of native employment in equilibrium.

Result 2: Keeping capital and native labour supply fixed, but allowing immigrant labour supply to adjust, an increase in automation will lead to a lower fall in wages than when all factors were fixed, if $s_K\sigma_\beta > \sigma_\mu$ and $\hat{L} > \hat{K}$ (see Appendix A for details).

$$\frac{\partial \hat{w}_U}{\partial s_K} = \frac{(1-\mu)\left(\hat{K}-\hat{L}\right)}{1+\left[(1-\mu)\,s_K-(1-\beta)\right]s_I\epsilon_I\frac{\epsilon_U(1-\beta)+1}{\epsilon_I(1-\beta)+1}} \tag{8}$$

Immigrant mobility will dampen the fall in native wages to allow firms to attract native labour into the production process if 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 (8) reflects the feedback effect of a decrease in the supply of immigrant labour on native wages. The term s_I denotes the share of immigrant labour in the production process. ϵ_I is the elasticity of the labour supply of

[7]We model automation as a change in s_K rather than α_K and ignore general equilibrium effects, as we want to examine shifts in the labour demand curve for the firm rather than changes in steady-state values.

[8]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 effect native wages, we need the *displacement effect* to outweigh the *productivity effect* for automation to reduce native wages.

immigrants and $\frac{\epsilon_U(1-\beta)+1}{\epsilon_I(1-\beta)+1}$ measures the change in the equilibrium of the immigrant wage as the native wage changes. The first 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 (8). Second, the attenuating effect will be stronger the higher the labour supply elasticity of immigrants ϵ_I. Thus, this stylized model highlights 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.

In Section 4, we first establish that the introduction of robots reduces the immigrant population. We then examine the attenuating effect of immigrant mobility on native wages in Section 5.

3 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.

3.1 Data Sources

3.1.1 Data on stock of industrial robots

Our data for the robot stock for each industry-year-country-level observation come from the International Federation of Robotics (IFR), which compiles data by surveying robot suppliers in more than 60 countries since 1993. It is the most widely used cross-country data source for robot adoption currently available (Acemoglu & Restrepo 2020, Graetz & Michaels 2018). The IFR provides data for thirteen disaggregated categories in the manufacturing sector.[9] Data are also available for six broad sectors: agriculture, mining, utilities, construction, education, and services. Appendix Table B.1 highlights that the automotive, chemical, and electronics sectors experienced the highest growth in robot use in the US over the sample period, while construction and services saw the lowest growth. Data on employment and the rate of growth of output at the industry level come from the EU KLEMS Growth and Productivity Accounts (Board 2023).

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

3.1.2 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 1970, 1990 and 2000, as well as the 2013-2017 American Community Survey (ACS).[10] 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 the states of Alaska and Hawaii.[11]

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 the 1990's (Acemoglu & Restrepo 2020). Therefore, exposure to robots in the US is defined as:

$$\Delta R_{i,t}^{US} = \sum_{j} \left[\frac{L_{i,j,1970}}{L_{i,1970}} \times \Delta R_{j,t} \right] \tag{9}$$

where $\frac{L_{i,j,1970}}{L_{i,1970}}$ represents the employment ratio of industry j in CZ i in 1970.[12]

3.1.3 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 in the US almost doubled between 1990 and 2015, underscoring the importance of accounting for technological changes that are unrelated to automation. 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.[13] We also incorporate

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

[11]A CZ comprises counties with strong labour market and commuting ties (Tolbert & Sizer 1996). It is amongst the most common type of geographical disaggregation used in the examination of local labour markets (Autor & Dorn 2013).

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

[13]EU KLEMS 2017 uses the ISIC Rev. 4 (NACE Rev. 2) industry classification to provide data for 34

trade exposure data from Autor et al. (2019*a*) to account for the employment reduction caused by exposure to Chinese import competition.[14]

3.2 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):

$$\Delta y_{i,t} = \alpha_{d,t} + \beta \Delta R^{US}_{i,t} + \gamma X_{i,t} + \varepsilon_{i,t} \tag{10}$$

where $\Delta y_{i,t}$ is the dependent variable of CZ i at time t, $\alpha_{d,t}$ are the division-time dummies, $X_{i,t}$ denotes a rich vector of covariates and $\Delta R_{i,t}$ is the measure of robot exposure. The main dependent variable is the change in logarithmic population of a nativity group.

We include division-time dummies, along with a comprehensive set of demographic and industry characteristics from 1990.[15] Faber et al. (2022) argue 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 share of routine and offshorable jobs in 1990 interacted with time dummies and exposure to Chinese imports.[16] We control for potentially confounding technological

distinct industries, including 11 categories for manufacturing. We harmonise industry classification across datasets and compute a region's computer capital growth between 1990 and 2015, similar to the measure of robot growth in equation (9).

[14]CZ trade exposure is computed as the sum of growth in Chinese import penetration in an industry weighted by the share of employment in that industry. The endogeneity between industrial import demand and actual imports from China is removed 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).

[15]The 1990 CZ demographic characteristics are: log population and population shares of: men; those older than 65 years old; 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.

[16]Following Autor et al. (2013), we compute the share of workers performing routine, manual, and

advancements unrelated to automation 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 B.3a and B.3b highlight 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 automation, 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 non-US developed countries, removing any bias from shocks specific to the US. We consider five European countries (EURO5): Denmark, Finland, France, Italy, and Sweden. 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 (9) with the industry-level growth of EURO5 robot $\left(\Delta R_{j,t}^{EURO5}\right)$[17]:

$$\Delta R_{i,t}^{EURO5} = \sum_{j} \left[\frac{L_{i,j,1970}}{L_{i,1970}} \times \Delta R_{j,t}^{EURO5} \right] \tag{11}$$

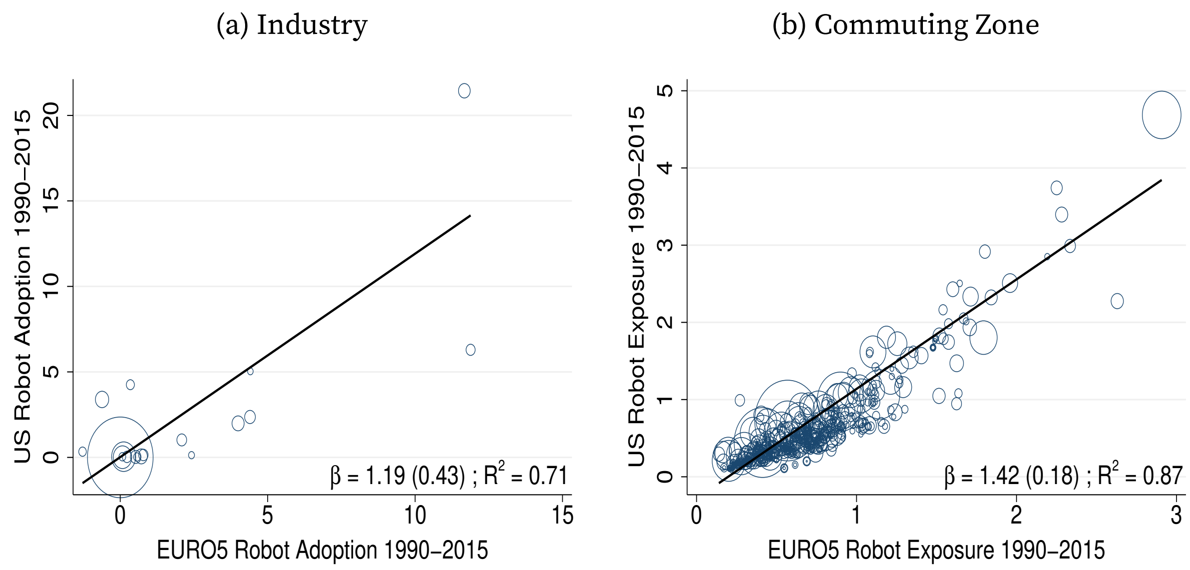
Figure 1a shows a strong relationship between robot adoption at the industry level in US and European countries. Therefore, exposure to robots in European countries can isolate the variation that stems from global progress in robotics. Figure 1b highlights that the EURO5 measure of robot exposure strongly predicts robot penetration in the US at the CZ level. The regression coefficient is statistically significant and the instrument captures 87% of the variation in the exposure of US robots to local labour markets.

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). 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. We re-estimate our coefficients leaving-one industry out of the instrument and show that the main conclusions remain unchanged. An additional

abstract tasks and construct the standardised measure of 'task offshorability' per industry.

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

Figure 1: Relationship between US and EURO5 robot exposure



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

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 B.2 shows there is a positive but insignificant association between the growth of low-skill immigrant population between 1970 and 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 ways.

3.3 Descriptive Statistics

Appendix Table B.3 reports the averages throughout the sample period in column 1, with the averages for the CZ in the fourth and first quartiles of robot exposure in columns 2 and 3, respectively. The fourth column highlights 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.

4 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 differences in migration response by nativity arise due to differences in the impact of automation on employment.

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 are weighted by the CZ's working-age population in 1990 to reduce the influence of sparsely populated CZs. Standard errors are heteroskedasticity-robust and clustered at the state level to account for spatial correlations.

4.1 Results for population adjustments

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

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

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

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

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.[18] The implied

[18]The population-to-employment elasticity for low-skilled immigrants is slightly higher than what has been estimated in the existing literature. We estimate a 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). Yu (2023) finds an elasticity of 0.76 due to increased import competition, while Cadena & Kovak (2016)

decrease in the relative population of low-skilled immigrants by 4.45 pp is statistically significant at the 5% level (column 6). Moreover, a unit increase in robot exposure is close to the average decadal increase in robot 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 highlight that highly-skilled natives are more sensitive to adverse labour demand shocks than low-skilled natives, a well-established empirical fact (Bound & Holzer 2000). However, the coefficient for highly-skilled immigrants is imprecisely estimated (column 4) and the corresponding difference in the growth rates between the responses of immigrants and natives to robot exposure is statistically insignificant (columns 5 and 6). The finding that the location choices of low-skilled immigrants are more sensitive to automation than those of natives is a novel result, which will be the focus of the remainder of this paper.[19]

Our regression specification incorporates a broader set of controls than those typically used in the literature. Appendix Table C.2 highlights the roles 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.[20]

We document in Appendix Table C.4 that directly controlling for pre-trends through various ways in the regressions does not materially alter our conclusions. Additionally, C.5 illustrates the robustness of our findings to potential identification threats (dispro-

finds an elasticity of 0.569 for low-skilled Mexican-born men during the Great Recession. The higher elasticity is likely because automation is an ongoing adverse shock, rather than the Great Recession.

[19] Combining the results in Panels A and B of Table 1, we show in the Appendix Table C.1 that the change in the growth of the total immigrant population due to robot exposure is statistically insignificant, consistent with Faber et al. (2022).

[20] Appendix Table C.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.

portionate robot adoption across industries and alternate robot exposure measures), or potential confounders such as the Great Recession, spillover from neighbouring CZs (Borusyak, Dix-Carneiro & Kovak 2022) and states with high international migration. Finally, we also show the robustness of our findings with respect to alternate weights (Appendix Table C.9) and standard errors (Appendix Table C.10). Thus, the considerable decline of low-skilled immigrants in areas experiencing adverse labour market conditions 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 automation and/or a higher outflow from these areas. In the following subsection, we decompose the migration channels in response to robot exposure.

4.2 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.[21] We measure the importance of these various channels as follows (ignoring channel 5, as it is not observable in the data):

$$\frac{N_{i,t+1}^{16-64} - N_{i,t}^{16-64}}{N_{i,t}^{16-64}} = \frac{N_i^{\text{in}}}{N_{i,t}^{16-64}} - \frac{N_i^{\text{out}}}{N_{i,t}^{16-64}} + \frac{N_i^{\text{net-ageing}}}{N_{i,t}^{16-64}} + \frac{N_i^{\text{new arrival}}}{N_{i,t}^{16-64}} \tag{12}$$

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 that entered or exited the 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.[22]

Table 2 presents the importance of each channel in the migration response to

[21] 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.

[22] 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 B.2.1 for a detailed description of the construction of the migration flows.

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

	Immigrant				Native		
	In	Out	Net-aging	New Arrival	In	Out	Net-aging
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
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

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).

robot exposure among low-skilled immigrants and natives. It shows that internal migration within the US is the main channel through which the population decline of low-skilled immigrants occurred due to automation. Column 1 demonstrates that an additional robot per thousand workers reduced inflows 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. Column 4 reveals that there is some reduction in international immigrant arrivals in more robot-exposed regions, but this is statistically insignificant.

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. The wide confidence intervals prevent a precise estimate of the role of return migration, but it is unlikely that it will be the primary migration response of low-skilled immigrants to robot exposure. 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 in the US insure against adverse labour demand shocks.

Columns 5 and 6 decompose the population response for low-skilled natives to automation into inflows and outflows, respectively. The introduction of robots leads to an outflow of low-skilled native workers, with a minimal effect on in-migration of low-skilled natives. Furthermore, these coefficients are at least half the size of those for low-skilled immigrants, affirming our finding that immigrants are much more responsive to automation in their location choices than natives. Finally, column 7 shows that most of the change in population of low-skilled natives can be attributed to the decrease in the proportion of younger (16-19) low-skilled individuals relative to older ones. Older people tend to be much less mobile than young people, which might partly explain this result (Schwartz 1976). Moreover, the decline in the share of young low-skilled natives may also indicate a shift toward attaining post-secondary education in regions more exposed to robots (Dauth et al. 2021). We discuss this further in Section 6.

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 C.11 shows that although the point estimates decrease, our overall conclusions remain unchanged. Furthermore, this section also highlights that, consistent with Faber et al. (2022) and Monras (2020), in-migration is a crucial mechanism through which local labour markets adjust to economic shocks.

4.3 Effect on labour market outcomes by nativity

The results so far highlight that immigrants are particularly sensitive in their location choices. We argue that changes in labour market conditions due to robot exposure are likely the primary driver of these migration responses. We analyse both changes in log employment and log average wages. We run a separate regression for each low-skilled nativity group, with the results shown in Table 3.

Table 3 reveals that both low-skilled immigrant and native workers face employment and wage losses due to robot exposure. However, immigrants are significantly more affected than natives, which aligns with the findings of Javed (2023). Columns 1 and 2 of Table 3 show that an additional robot per thousand workers reduces the employment of low-skilled immigrants and natives by 6.53 pp and 1.3 pp, respectively. Furthermore, these coefficients are larger than the estimates for population changes

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

Dependent variable: Change in log employment or log wage				
	Employment		Wage	
	Immigrant	Native	Immigrant	Native
	(1)	(2)	(3)	(4)
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

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 1), suggesting that job losses due to automation were not fully offset by migration. Columns 3 and 4 indicate that wages for low-skilled immigrants and natives fell by 2.67 pp and 1.11 pp, respectively. The reduction in wages for low-skilled immigrants is more than double that for natives. From the perspective of our theoretical framework, these results highlight that low-skilled labour and robots are imperfect substitutes in the production process. The decline in labour market conditions for low-skilled individuals is consistent with evidence in Acemoglu & Restrepo (2020), which shows that low-skilled jobs are particularly vulnerable to automation.

What explains the higher sensitivity of immigrants to robot exposure? We provide evidence to support two common explanations found in the literature on why immigrants may be more vulnerable to labour demand shocks.

The first explanation is based on the concentration of tasks of immigrants and natives, as well as the varying effects of robots on different types of tasks. Robots are more likely to displace workers in routine and manual tasks (Acemoglu & Restrepo 2020), and immigrants are more concentrated in these types of jobs compared to natives

(Basso et al. 2020, Javed 2023). We analyse changes in the relative employment of low-skilled immigrants to natives across seven broad industries and three task categories (routine, manual, and abstract) as the dependent variable. A negative coefficient implies that immigrant workers are more adversely affected by robot exposure than natives. Appendix Figure C.2a illustrates that immigrant workers are more affected than native workers in most industry-task groups. The impact is strongest in routine and manual manufacturing jobs, which are more likely to be displaced by robots. Thus, differences in composition might be one of the reasons for the asymmetric effect of automation on labour market outcomes by nativity status.[23]

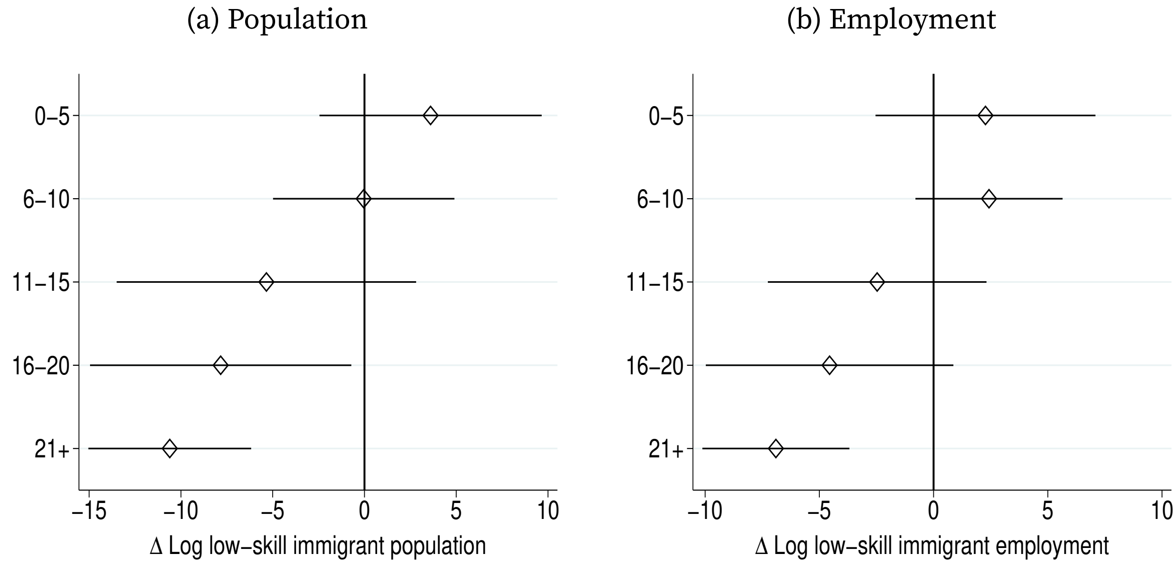
The second explanation relates to increased competition from newly arriving immigrants. Before the Great Recession, the US experienced a significant increase in low-skilled immigration (Hanson et al. 2017). Albert et al. (2022) show that when immigrants and natives are imperfect substitutes, the arrival of new immigrants increases competition for incumbent immigrants, reducing their wages. Galeone & Görlach (2021) argue that as immigrants stay longer in the country, they become more substitutable with natives and more recent immigrants. In both cases, higher competition from new immigrants would amplify the adverse technological changes for immigrants who have been residing in the US for many years.

We test this hypothesis by estimating the consequences of automation on population and employment growth among low-skilled immigrants based on the number of years they have spent in the US. Figures 2a and 2b show a clear pattern: immigrants who have lived in the US for a longer period are much more affected than recent arrivals. The population growth of immigrants who have been in the US for more than 21 years declined by 10.5 pp, while their employment growth fell by 6.9 pp in regions with higher robot exposure. On the other hand, the change in population and employment of recent immigrants is insignificantly associated with robot exposure.[24] This finding is consistent with the insignificant effect of robot exposure on new international arrivals,

[23] We do not find strong evidence to suggest that low-skilled immigrants and natives differ in their intensity of robot exposure. Appendix Figure C.4 highlights that the industrial composition of low-skilled natives and immigrants is quite similar, implying that nativity-specific robot exposure would also be similar. Appendix C.7.2 discusses in detail the conclusions of investigating the effect on employment to nativity-specific robot exposure in Appendix Table C.12.

[24] Appendix Figure C.5 illustrates that immigrants who have lived in the United States for many years suffer greater wage losses compared to new arrivals, though to a lesser extent potentially due to their choice of migrating away from high robot exposed locations.

Figure 2: Effects on low-skill immigrants by years living in US, stacked-differences 1990–2015 (2SLS)



Note: Note: Bars indicate 95% confidence interval. Panel (a) and (b) shows the β coefficient in Equation (10) for change in log population and log employment, respectively for each low-skill immigrant subgroup by years in the US. All regression estimates are weighted by the CZ population in 1990. Standard errors are clustered at the state level.

as seen in column 4 of Table 2.

The minimal impact on recent arrivals may also reflect their improved skills in response to automation, such as higher English proficiency. Appendix Table C.13 provides evidence to support this hypothesis, showing that recent immigrants tend to have higher English proficiency in areas more exposed to robots. Thus, increased competition from recent arrivals may be an additional factor behind the strong mobility response from established immigrants.

There maybe other factors that contribute to the strong migration response by low-skilled immigrants. For example, immigrants might have better social networks than natives, enabling them to evaluate the attractiveness of different locations more effectively (Caballero et al. 2023, Munshi 2003). Future research using firm-worker longitudinal data could investigate the role of social networks in shaping the migratory response to automation.

In conclusion, this section presents distinct differences between nativity groups in their migration response to robot exposure. The introduction of robots has induced a substantial reallocation of the low-skilled immigrant workforce within the US, particularly those who have lived in the US for many years.

5 Immigrant mobility and native-born workers

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

Equation (8) in the theoretical framework shows that the wages of low-skilled native workers decrease less in areas with a greater decline in immigrants. To estimate the mitigating impact of immigrant mobility, the ideal regression specification would be:

$$\Delta y_{i,t} = \alpha_{d,t} + \beta_1 \Delta R^{US}_{i,t} * \frac{\Delta N^I_{i,t}}{N_{i,t}} + \beta_2 \Delta R^{US}_{i,t} + \beta_3 \frac{\Delta N^I_{i,t}}{N_{i,t}} + \gamma X_{i,t} + \varepsilon_{i,t} \tag{13}$$

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.

$\frac{\Delta N^I_{i,t}}{N_{i,t}}$ comprises 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 issue of reverse causality, as we have demonstrated that automation affects the growth of the immigrant population $\left(\frac{\Delta N^I_{i}}{N^I_{i,t}}\right)$. Motivated by equation (8), we use the fraction of immigrant population to capture the mitigating effect of the reduction in immigrant population to circumvent this issue. If locations with a higher share of immigrants experience a larger decline in their population growth, then the variation through immigrant population shares are sufficient to capture the attenuating effect of immigrant mobility.

To show 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 column shows that there is no difference in the mobility response of natives between CZs with above- and below-median immigrant share. This implies that the larger reduction in total population in the above median immigrant share CZs is being driven by low-skilled immigrants. We also analyse population growth among high-skilled people (total and native) as a *placebo* to rule out factors other than low-skilled immigrant mobility that might explain

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

Dependent variable: Change in log population				
	Low-skill		High-skill	
	Overall	Native	Overall	Native
	(1)	(2)	(3)	(4)
Exposure to robots x Above-median	-2.28***	-1.17***	-1.43**	-1.49***
	(0.46)	(0.44)	(0.57)	(0.49)
Exposure to robots x Below-median	-0.86	-0.91	-1.37**	-1.55**
	(0.74)	(0.69)	(0.69)	(0.67)
Observations	1444	1444	1444	1444
R-squared	0.81	0.82	0.70	0.73
Test of equality	0.04	0.63	0.94	0.94

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).

this result. Columns 3 and 4 illustrate that the population growth of high-skilled, either as a whole or natives, does not differ in response to robot exposure between below- and above-median immigrant share areas. Thus, immigrant share proxies the reduction in labour supply and competition for native workers due to immigrant mobility.

We modify our regression specification as follows:

$$\Delta y_{i,t} = \alpha_{d,t} + \beta_1 \Delta R_{i,t}^{US} * \frac{N_{i,1990}^I}{N_{i,1990}} + \beta_2 \Delta R_{i,t}^{US} + \beta_3 \frac{N_{i,1990}^I}{N_{i,1990}} + \gamma X_{i,t} + \varepsilon_{i,t} \tag{14}$$

where, $\frac{N_{i,1990}^I}{N_{i,1990}}$ is the immigrant share in CZ i in 1990. The coefficient of interest is β_1; a positive coefficient implies that immigrants' location choices reduce the impact of robot exposure on natives. In contrast, a null coefficient indicates that immigrants' location choices do not equalise spatial differences in the effect of robot exposure on native workers.

A possible concern with this approach is that the distribution of immigrants across local labour markets is not random, 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 locations where previous immigrants were concentrated (Borjas 1995, Card & DiNardo 2000). Appendix Figure D.1 shows that the 1970 low-skilled immigrant share explains 73% of the variation in the 1990 immigrant share. Furthermore, the correlation between robot exposure and the 1970 immigrant share is low (-0.03), implying that areas with a high robot concentration and those with a high proportion of immigrants do not overlap. A low correlation indicates sufficient power to independently isolate the effects of robot exposure and immigrant mobility.

The first row of Table 5 reports the attenuation effect on native employment and wages against robot exposure due to immigrant mobility. 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. 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.[25]

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 against automation. The lack of an average effect does not preclude the possibility that some native workers, especially in some age groups, benefit from immigrant mobility, an issue that we discuss in more detail below.

[25] Table 5 also highlights an adverse effect of automation on wages and employment of both high- and low-skilled native workers (Acemoglu & Restrepo 2020). 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

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).

5.1 Robustness

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 to adverse shocks. If such a mechanism was 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 automation on high-skilled workers is equally adverse in areas with high- and low-immigrant share, 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 our findings are driven by regions with more wage flexibility. We estimate the mitigating effects in states with and without Right-to-work laws (Appendix Table D.1), and find similar attenuation of low-skill native wages in both types of local labour markets.

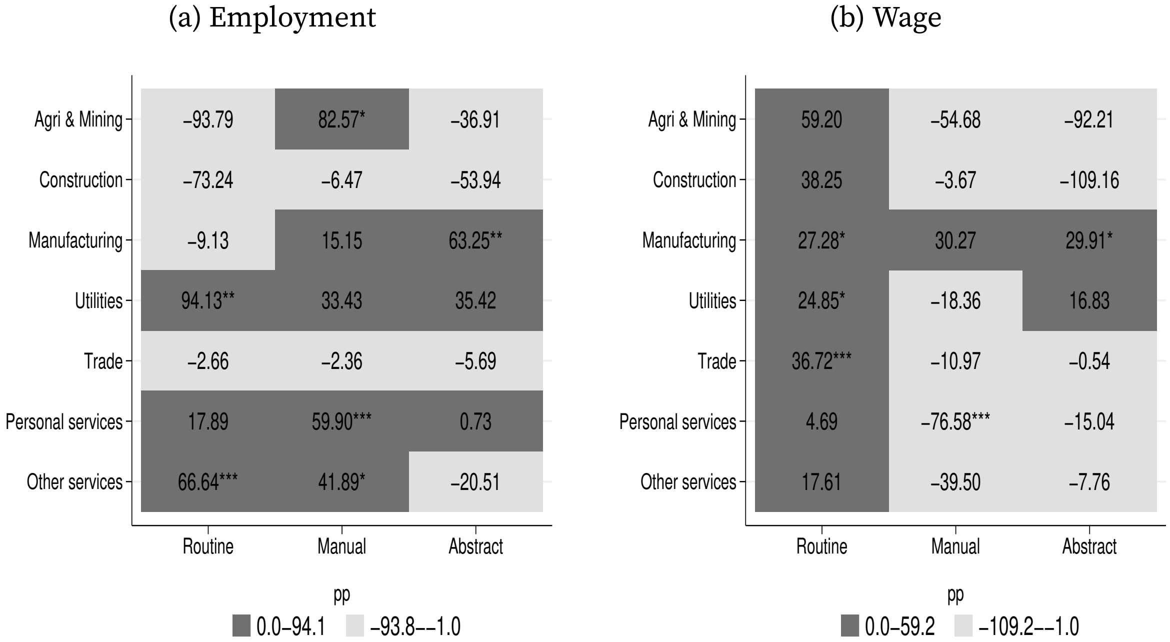
One potential concern with the lagged immigrant share as an IV is the possibility of past immigration shocks generating persistent effects, leading to violation of the exclusion restriction. Jaeger et al. (2018) argues that including the immigrant share of the intervening years in the regression can alleviate the impact of past immigration shocks. Appendix Table D.2 shows that the point estimates are slightly smaller and more precisely estimated when we control for the 1980 immigrant share. Finally, we also check for pre-trends to examine the confounding effects of unobserved past shocks on local labour markets. If the effects of past immigrant shocks are highly persistent, this should also generate positive effects on native-born before introduction of robots. Appendix Table D.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. Overall, there is little evidence to support the hypothesis that our findings are driven by dynamic effects of past immigration shocks.

The mitigating effects of immigrant mobility on the labour market outcomes of native workers to automation is the second novel 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, automation, 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 D.4 demonstrates that our findings are robust when using stacked-differences specifications that excludes the Great Recession period (1990-2000 and 2000-2007), or specifically accounts 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).

5.2 Heterogeneity by industry-task

While this paper illustrates the attenuating effect of immigrant mobility, it might adversely effect native workers by reducing the demand for local goods and services (Hong & McLaren 2015). This concern is less pronounced for immigrants, as they remit a significant portion of their earnings (Nekoei 2013). However, 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 (14) for change in log employment and change in log wages, respectively. All regression estimates are weighted by the CZ population in 1990. Standard errors are clustered at the state level. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels respectively.

Figures 3a and 3b show that the employment and wages of native workers are also attentuated 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 average effect on employment, as native employment in these industry-task groups is small (Appendix Figure D.2). Finally, these figures highlight 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.

5.3 Heterogeneity by age

Previous results have shown that the decline in low-skilled population growth in response to robot exposure is driven by the response of established immigrants (those who have lived in the US for more than 10 years). Established immigrants are older than new immigrants entering the US.[26] 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 change in the labour market outcomes of young (16-39) and older (40-64) native workers to robot exposure and mobility of established low-skilled immigrants.[27]

Table 6 reveals much stronger mitigating effects on mobility of established immigrants 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 50^{th} and 25^{th} 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 CZ in the 50^{th} and 25^{th} of the established low-skilled immigrant share.

Appendix Table D.6 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

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

[27] Appendix Table D.5 shows the mitigating effects of low-skilled immigrants are quite similar using established low-skill immigrant share than 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]) comparing CZs in the 50^{th} and 25^{th} 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 (1)	Employment (2)	Wage (3)	Employment (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

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).

age groups remains. In conclusion, the mobility of low-skilled immigrants can mitigate losses from automation, especially for older native-born workers.

6 Why natives have a low sensitivity to automation?

The limited mobility of low-skilled natives as a means of insuring against adverse labour demand shocks is well documented in the literature, as we also show in Section 4. 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?

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
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).

Branco et al. (2023), Dauth et al. (2021) and Di Giacomo & Lerch (2023) document that individuals, particularly younger ones, increase investment in human capital in response to automation.[28] Acemoglu & Restrepo (2020) show that automation 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 reduce due to automation. 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.[29]

Table 7 shows that the acquisition of human capital is an additional channel among young natives and older immigrants to insure against robot exposure. Column 1 demon-

[28] There are other margins of adjustment, such as, family members entering the workforce (Lundberg 1985), or relying on savings, which we do not consider (Lerch 2022).

[29] 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 ACS. Census reports the enrolment status of an individual since February 1 of that year, where as ACS reports their status three months prior.

strates that an additional robot per thousand workers induced a 0.14 pp increase in college enrolment among young natives. In 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 insuring against automation, rather than moving out of robot-exposed areas. This is consistent with the earlier result of the negative effect on net ageing on automation (Table 2). Older natives, who benefit from immigrant mobility, seem less likely to move or invest in human capital to mitigate the effects of automation.

Furthermore, Table 7 shows a positive but insignificant increase in college enrolment among young immigrants due to automation. However, the college enrolment of older immigrants increased by 0.15 pp in more robot-exposed regions. Thus, to insure against the risk of displacement by robots, low-skilled older immigrants also accumulate human capital.

Lastly, we decompose the results by employment status for young natives and older immigrants in the Appendix Table E.1. Most young natives who enrol in college due to automation are out of the labour force, indicating that they are delaying their entry into the labour market in response to adverse labour demand shocks (Charles et al. 2018). In contrast, most older immigrants enroled in college are employed, suggesting that they are likely attending local community colleges. Overall, this section underscores human capital accumulation as an additional mechanism for mitigating adverse labor demand shocks, particularly among young natives.

7 Conclusion

In this paper, we demonstrate that low-skilled immigrants' are more responsive in their location choices to robot exposure than those of 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 automation are not significantly influenced by immigrant mobility, older native workers experience significantly lower job losses due to 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.

Finally, we explore the reasons behind the asymmetric mobility response to automation between low-skilled immigrants and natives. We provide suggestive evidence that the higher impact of automation on low-skilled immigrants could be explained by increased competition from recent immigrants. However, the limited mobility of low-skilled natives may be explained by both the mitigating effects of immigrant mobility and the accumulation of human capital. We show that young natives acquire human capital in response to automation, which may explain their limited mobility. In conclusion, this study highlights the importance of labour heterogeneity in evaluating the effects of local shocks.

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Appendix (Not for Publication)

Sections A, B, C, D and E correspond to appendix for sections 2, 3, 4, 5 and 6, respectively.

A Section 2 Appendix: Theoretical Framework

In this Appendix, first, we derive the relationship between relative wages and labour supply between immigrants and natives, which will be useful in deriving the two results mentioned in Section 2.

Combining the labour demand equations (equation 1 and 2):

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

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

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

The labour market is in equilibrium when labour demand (equation 1 and 2) equals labour supply (equation 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 system, where $\hat{x}$ denotes the log deviation of a variable x from its steady-state value. The log-linearised system is:

$$\begin{aligned}
\hat{w}_U &= (1-\mu)\left(\hat{Y}-\hat{L}\right)+(1-\beta)\left(\hat{L}-\hat{L}_U\right) && \text{(A.1)}\\
\hat{w}_I &= \frac{\epsilon_U(1-\beta)+1}{\epsilon_I(1-\beta)+1}\hat{w}_U && \text{(A.2)}\\
\hat{r} &= (1-\mu)\left(\hat{Y}-\hat{K}\right) && \text{(A.3)}\\
\hat{Y} &= s_K\hat{K}+(1-s_K)\hat{L} && \text{(A.4)}\\
\hat{L} &= (1-s_I)\hat{L}_U+s_I\hat{L}_I && \text{(A.5)}\\
\hat{L}_U &= \epsilon_U\hat{w}_U && \text{(A.6)}\\
\hat{L}_I &= \epsilon_I\hat{w}_I && \text{(A.7)}\\
& && \text{(A.8)}
\end{aligned}$$

A.1 Derivation of Result 1

Keeping capital and labour fixed, an increase in automation results in a fall in native wages if $\hat{L} > \hat{K}$. Differentiating native wages (equation A.1) after substituting the log-linearized production function

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

A.2 Derivation of Result 2

Keeping capital and native labour supply fixed, but allowing immigrant labour supply to adjust, an increase in automation will lead to a lower fall in wages than when all factors were fixed, if $(1-\mu)s_K > (1-\beta)$ and $\hat{L} > \hat{K}$.

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

To derive $\frac{\partial \hat{L}_I}{\partial \hat{w}_U}$, we will use the linearized labour aggregate equation (A.5) and linearized relative wage equation (A.2).

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

Thus, substituting this expression back, we get:

$$
\frac{\partial \hat{w}_U}{\partial s_K} = \frac{(1-\mu)\left(\hat{K}-\hat{L}\right)}{1+\left[(1-\mu)\, s_K-(1-\beta)\right] s_I \epsilon_I \frac{\epsilon_U(1-\beta)+1}{\epsilon_I(1-\beta)+1}}
$$

The fall in native wages due to automation will be smaller with allowing for immigrant labour supply change 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: $s_K \sigma_\beta > \sigma_\mu$.

B Section 3 Appendix: Data

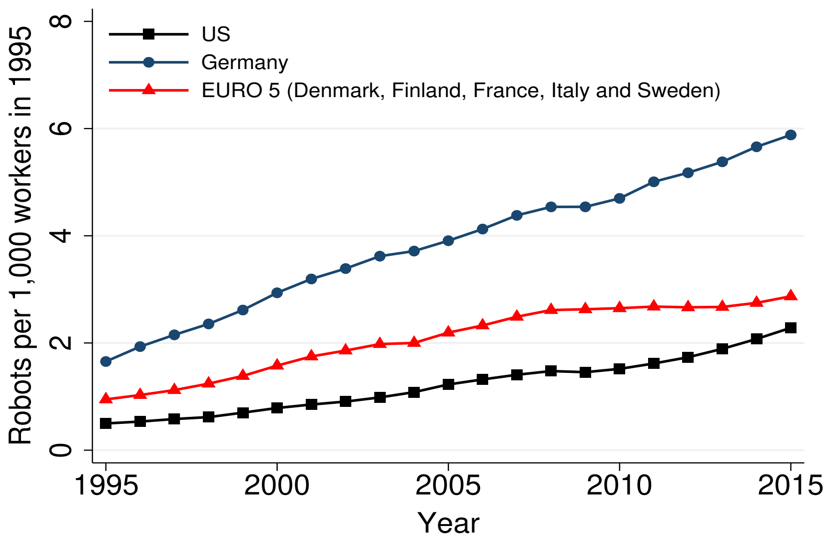
B.1 IFR Robot data

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

The IFR data has a few limitations. Industry-specific data is 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.

B.1.1 Robots per thousand workers in industrialised economies

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



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

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

B.1.2 Robot per thousand workers by industry in US

Table B.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 B.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

B.2 Outcomes and exposure at local labour market level

Our sample consists of non-institutionalised individuals between ages 16-64. 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. 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. This definition of employment ensures that the number of employed individuals is equal to the number individuals with a positive wage. This would not be true if employment was defined using the current working status of an individual. Top-coded income is set equal to 1.5 times the value of the top-code. Real wage below the bottom 1% percentile is censored and real wage above the 99th percentile is winsorized. The Consumer Price Index of 1999 is used to deflate nominal wages.

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

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

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 (B.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:

$$\Delta R_{j,t}^{EURO5} = \frac{1}{5} \sum_c \frac{R_{j,t_1}^c - (1 + g_{j,(t,t_1)}^c) \cdot R_{j,t}^c}{L_{j,t}^c} \tag{B.2}$$

where $R_{j,t}^c$ is the stock of robots in country c and industry j at year t, $g_{j,(t,t_1)}^c$ 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.

B.2.1 Construction of Migration flows

The Census 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 PUMAs can contain a single CZ. 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:

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

where $N^{16-64}_{i,t+1}$ is CZ i working-age population 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 denotes the number of individuals within the US that entered or exit CZ i after time t 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 as the number of individuals who moved into their current CZ residence five years ago, while outflow is defined as the sum of people who exited their CZ five years ago. The baseline population in 1995 is computed as the population in 2000 divided by the 5-year equivalent change in population between 1990 and 2000.

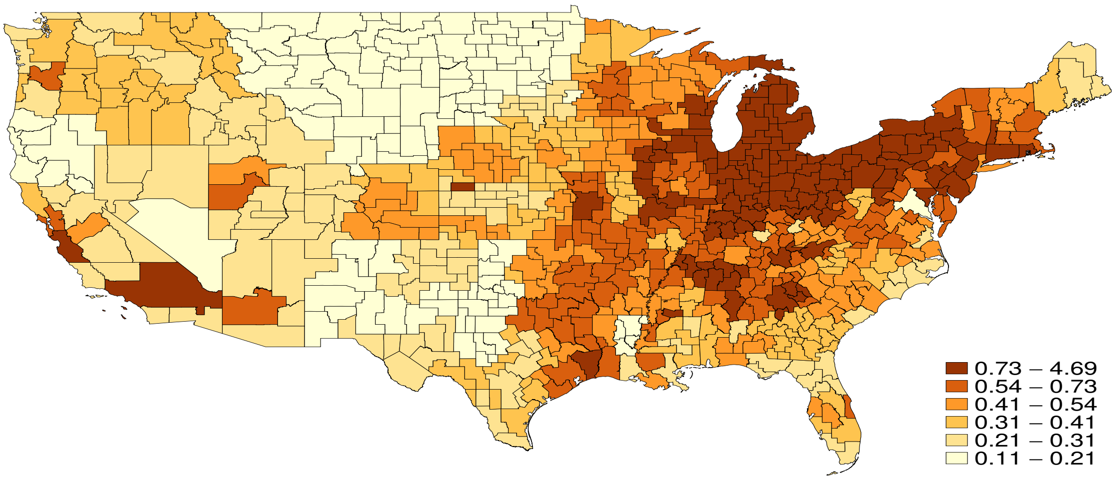
The 2013-17 ACS reports migration activity over a one-year reference period. Data from 2013 and 2014 are used to establish the initial population at time t, and data from 2017 are used to determine the population at time $t+1$. Immigrants present in the US in 2017 who arrived from outside the US after 2013 as defined as international immigrants. Individuals who did not move in the past year and were aged 16-19 in 2017 are classified as aged in, while non-movers aged 61-64 in 2013-14 are classified as aged out. Inflows and outflows are based on individuals who arrived to the US before 2013 and moved after 2015. We used these data to create three-year migration flows and then multiply them by 10/3 to convert them into ten-year migration rates.

B.2.2 Geographic distribution of robot exposure and immigrant share

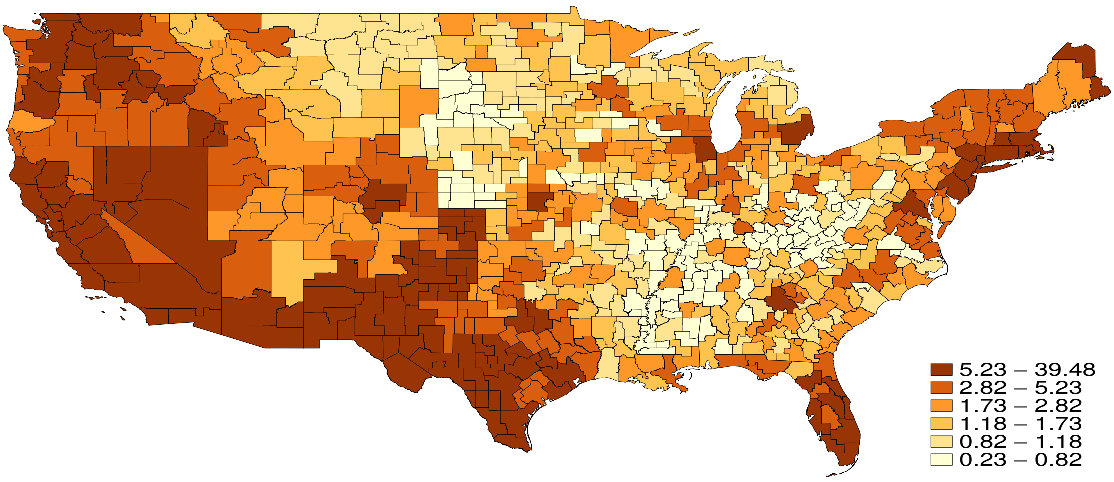
Figure B.2a shows substantial variation in robot exposure across US CZs. The growth in robot use was most pronounced in states like Michigan and Ohio due to the significant increase in automation in the automotive industry. In contrast, robot growth was lower in parts of the West North Central and South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

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

(a) Robot exposure 1990-2015



(b) Immigrant population share in 1990

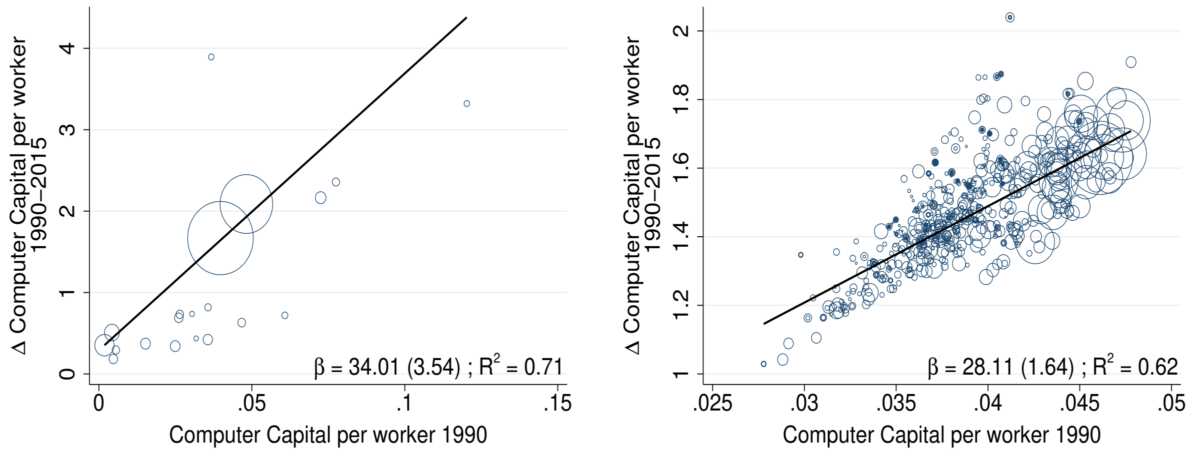


B.3 Computer capital exposure

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 higher initial *levels* of computer capital would also experience a greater growth in the use of computer capital over time. Figures B.3a and B.3b validate this idea at both the industry and the CZ level. Furthermore, the high R^2 values in both cases suggest a robust first stage.

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

(a) Industry (b) Commuting Zone



Note: Panel (a) plots the 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.

B.4 Pre-trends

One potential concern with the current analysis is that pre-existing trends in immigration patterns across CZs might influence the intensity of robot penetration or introduce omitted variable bias. For example, Danzer et al. (2024), Lewis (2011), and Mann & Pozzoli (2023) 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 first conduct a falsification exercise by regressing the change in log population between 1970-1990 in *future* CZ robot exposure between 1990-2015. Table B.2 shows a negative but insignificant association between low-skilled immigrant population (column 1) and native population (column 3) between 1970-1990 and the entry of robots after 1990.

Table B.2: 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).

B.5 Descriptive Statistics

Table B.3: 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

C Section 4 Appendix: Effect on population and mobility by nativity

C.1 Effects on growth of overall immigrants and natives

To replicate the findings of Faber et al. (2022), we include the change in logarithmic population between 1970 and 1990 as a control. Consistent with Faber et al. (2022), Table C.1 shows no significant change in immigrant population growth in response to robot exposure, while native population growth declined significantly after robot introduction. As demonstrated in our main results, the insignificant change in high-skilled immigrant population growth is responsible for the muted overall change in immigrant population growth.

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

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

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

C.2 Effects on relative population change gradually adding controls

Table C.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)	(7)	(8)
	A: Low-Skill							
Exposure to robots	-5.00*	-7.16**	-8.67***	-10.35***	-10.29***	-9.54***	-5.09**	-4.45**
	(2.60)	(2.88)	(3.25)	(3.53)	(3.93)	(2.76)	(2.36)	(2.18)
Observations	1444	1444	1444	1444	1444	1444	1444	1444
R^2	0.18	0.28	0.28	0.30	0.31	0.43	0.63	0.69
Kleibergen-Paap F	101.53	196.45	221.66	130.07	151.39	146.51	114.54	109.63
	B: High-skill							
Exposure to robots	-0.72	-0.42	-0.48	-0.98	-0.97	0.03	1.68	1.69
	(1.34)	(1.63)	(1.63)	(1.42)	(1.49)	(1.28)	(1.17)	(1.15)
Observations	1444	1444	1444	1444	1444	1444	1444	1444
R^2	0.06	0.11	0.11	0.16	0.16	0.28	0.39	0.46
Kleibergen-Paap F	101.53	196.45	221.66	130.07	151.39	146.51	114.54	109.63
Division dummies	Yes	Yes	Yes	Yes	Yes	Yes		
Division x time dummies							Yes	Yes
Demographics w/o pre-trends		Yes						
Demographics			Yes	Yes	Yes	Yes	Yes	
Industry w/o routine				Yes				
Industry					Yes	Yes	Yes	
Demo+Ind x time								Yes
Computers, trade						Yes	Yes	Yes

Note: All regression estimates are weighted by the CZ population in 1990. Standard errors clustered at the state level are reported in parentheses. ***, ** and * represent the statistical significance at 1%, 5% and 10% levels respectively. Column (1) includes census division dummies. Column (2) further includes demographic characteristics (log population, share of male population, population shares of Whites, Blacks and Hispanics, share of the population over 65 years old and shares of the population with no college, some college and more than college and female employment share). Column (3) additionally includes the low-skill population change between 1970-1990. Column (4) further includes industry shares (share of employment in mining, construction, light manufacturing and manufacturing, and average offshorability index). Column (5) includes share of employment in routine occupations. Column (6) also includes stock of computer capital per worker in 1990 and exposure to Chinese imports. Column (7) includes division-time dummies. Column (8) further includes year interaction with demographic and industry characteristics in 1990.

C.3 OLS and Reduced form effects on population growth

The OLS and reduced form results in panels A and B, respectively, in Table C.3 are consistent with the 2SLS findings. The OLS coefficient of the change in the logarithmic immigrant to native population (-3.13) is smaller than the 2SLS estimate (-4.45), suggesting that the unobservables generate a downward bias for the OLS estimates.

Table C.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).

C.4 Including alternate pre-trends

Table C.4 displays that our findings remain robust when controlling for pre-trends in several ways. We include: (1) skill-specific immigrant concentration in 1970-1990 in columns 1 and 5; (2) skill-specific immigrant concentration in 1970-1990 interacted with period dummies in columns 2 and 6; (3) overall change in CZ population between 1970 and 1990 interacted with time dummies, instead of controlling for the change in the subgroup population, in columns 3 and 7; and (4) the proportion of foreign-born population share in 1990 in columns 4 and 8. The striking fall in the growth of low-skilled immigrant-to-native population to robot exposure continues to hold across the various specifications.

Table C.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).

C.5 Robustness checks of population growth by nativity

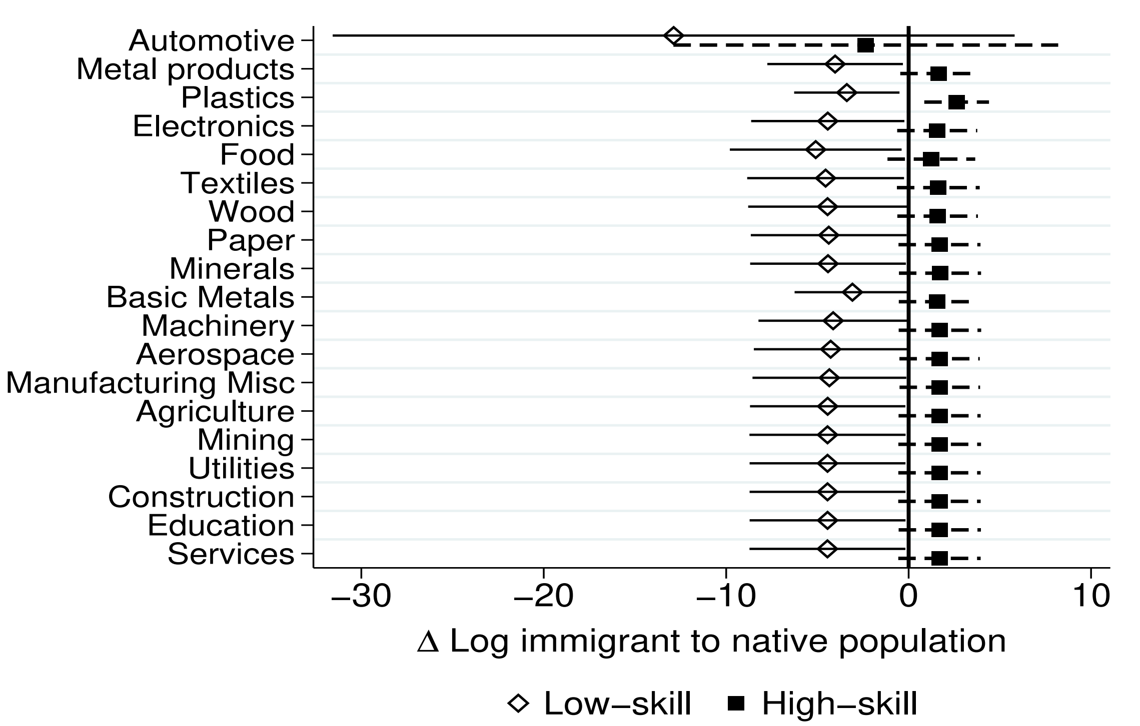
In this subsection, we probe the robustness on the effect of robot exposure on population growth of low-skilled immigrants and natives. We begin by listing the various exercises, followed by a more detailed discussion of each exercise.

- Industry-specific robot adoption: exclude one industry at a time from the robot-exposure measure
- Alternate measures of robot exposure: use 7 European countries instead of 5 to create the instrument, drop CZ with highest robot exposure and exclude CZs at the top 1 percentile of robot exposure.
- Alternate three and two periods stacked-differences and long-difference specifications
- Additional controls: include robot exposure to neighbouring CZs, or use state-time dummies instead of division-time dummies
- Removing regions with extreme immigrant shares
- Nativity group-specific weights
- Alternate methods for computing standard errors

C.5.1 Industry-specific robot adoption

Appendix Table B.1 showed that robot adoption was not uniform across industries. To assess the impact of robot accumulation by a particular industry in driving the results, we sequentially exclude one industry when constructing the robot exposure measure. Figure C.1 illustrates that the point estimates remain fairly consistent. The biggest change occurs when excluding the automotive industry. The effect on immigrants is still larger than native-born, but the coefficients are much less precisely estimated. This finding is not surprising, as the automotive industry has accumulated the largest number of robots over this period (Acemoglu & Restrepo 2020). Overall, Figure C.1 demonstrates that our main findings are not driven by automation in a few industries.

Figure C.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.

C.5.2 Alternate measures of robot exposure

Table C.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 alternate measure (EURO7) of robot exposure by adding robot adoption in Germany and the UK to the baseline measure. Column 2 shows that the results remain identical using the EURO5 and EURO7 robot exposure measures.

Furthermore, we demonstrate 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 strengthens our conclusions (Column 3) while excluding commuting zones at the top 1 percentile of robot exposure leaves our estimates unchanged.

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

Dependent variable: Change in log of immigrant to native population				
	Baseline	EURO7	Highest exposure	Drop top 1% exposure
	(1)	(2)	(3)	(4)
	A: Low-skill			
Exposure to robots	-4.45**	-4.46**	-5.03*	-4.45**
	(2.18)	(2.17)	(2.75)	(2.18)
Observations	1444	1444	1443	1444
R^2	0.69	0.69	0.69	0.69
Kleibergen-Paap F	109.63	120.76	62.41	109.63
	B: High-skill			
Exposure to robots	1.69	1.76	1.53	1.69
	(1.15)	(1.14)	(1.56)	(1.15)
Observations	1444	1444	1443	1444
R^2	0.46	0.46	0.46	0.46
Kleibergen-Paap F	109.63	120.76	62.41	109.63

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) regression uses EURO7 exposure as instrument instead of EURO5 exposure. Column (3) excludes CZs' with top 1% US robot exposure. Column (4) regression uses 1990 instead of 1970 employment share to create robot exposure measure.

C.5.3 Alternate 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 C.6 shows that the baseline results are robust to alternate long- and stacked-differences specifications. Coefficients in columns 1-2, 3-4 and 5-6 are based on three periods stacked-differences (1990-2000, 2000-2007 and 2007-2015), two periods stacked-differences (1990-2000 and 2000-2007) and long-difference specifications, respectively. The dependent variable in the long-difference specification 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 periods and two periods stacked-differences models are quite close, implying that our results are not explained by the Great recession. The coefficient in the long-difference specification of 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.

Table C.6: 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 (1)	High-skill (2)	Low-skill (3)	High-skill (4)	Low-skill (5)	High-skill (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).

C.5.4 Alternate 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 the other

Table C.7: 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.

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:

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

where $\Delta R_{k,t}$ is the robot exposure to CZ k and ϕ_{kj} captures the strength of migration flows between CZ k and j, using the sum of 5-year inflow and outflow rates in the 1990 Census between the 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. Column 2 of Table C.7 shows that our point estimates do not change significantly by adding this control. The main change is an increase in standard errors.

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 alternate specification with state-year dummies ($48 \times 2 = 96$) instead of division-year dummies ($9 \times 2 = 18$) to account for any state-specific trends, such as changes in immigration 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 similar patterns to those in our baseline regression.

C.5.5 Robustness to CZs with extreme immigrant shares

Table C.8: 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).

In this subsection, we show that CZs with very low or high immigrant shares do not drive our results. The dependent variable is the change in immigrant concentration by skill level. First, in columns 2 and 5 of Table C.8 we show that the results remain essentially unchanged when excluding CZs with fewer than 100 immigrants. Columns 3 and 6 show that our findings are robust to excluding states that border Mexico (Arizona, California, New Mexico, and Texas), where a high share of low-skilled documented and undocumented immigrants reside. Therefore, our findings cannot be explained by a reduction in the population of low-skilled immigrants in CZs at the extremes of the immigrant share distribution.

C.5.6 Nativity group-specific weights

Table C.9: 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).

Cadena & Kovak (2016) argue that it is more efficient to use nativity-specific weights in the regression, given the significant variation in population sizes by nativity across the US. Table C.9 shows that this alternative weighting scheme does not substantially alter the estimated coefficients. The standard errors are slightly lower in columns 5, 6 and 7 compared to columns 1, 2, and 3, respectively. More importantly, the reduction in the population of low-skilled immigrants to robot exposure becomes more pronounced using nativity-specific weights in the regressions (-5.49 in column 3 to -6.35 in column

7), while the coefficient of low-skilled natives does not change substantially (-1.04 in column 1 to -0.98 in column 5).

C.5.7 Alternate methods for computing standard errors

Standard errors in the baseline regression are clustered at the state level, which is common in the literature. Columns 2 and 5 in Table C.10 show that standard errors become slightly smaller if we cluster at a more granular level (CZ). Moreover, the standard errors in the baseline model account for within-region spatial correlation but do not account for potential between-region correlations (which can arise due to industry shocks between regions). We compute the standard errors following Borusyak, Hull & Jaravel (2022) to account for such correlations. The standard errors are very similar in columns 3 and 6 using the Borusyak, Hull & Jaravel (2022) method compared to the baseline method in columns 1 and 4.

Table C.10: Effects on relative population growth with alternate standard errors, stacked-differences 1990–2015 (2SLS)

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

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

C.6 Migration flows: additional results

Table C.11 presents the effect of automation 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-skill immigrants are particularly sensitive to automation, with the reduction of 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 C.11: 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 × 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).

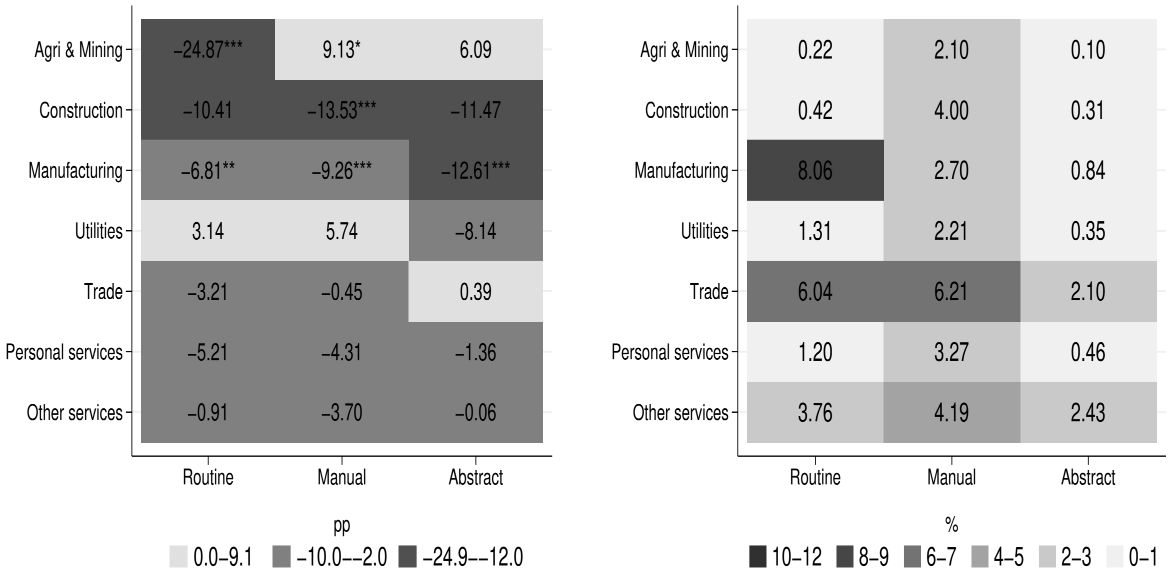
C.7 Labour market effects by nativity: additional results

C.7.1 Effect by industry-task cells

The dependent variable in Figure C.2a is the difference between the change in the log of employment for low-skilled immigrants and the change in the log of employment for low-skilled natives. This represents the change in the relative employment of immigrants compared to natives. Figure C.2b shows the share of employment in each industry-task combinations involving both immigrants and natives.

Figure C.2: Effects on low-skill immigrant to native employment by industry-task cells, stacked-differences 1990–2015 (2SLS)

(a) Effect on employment   (b) Overall employment share

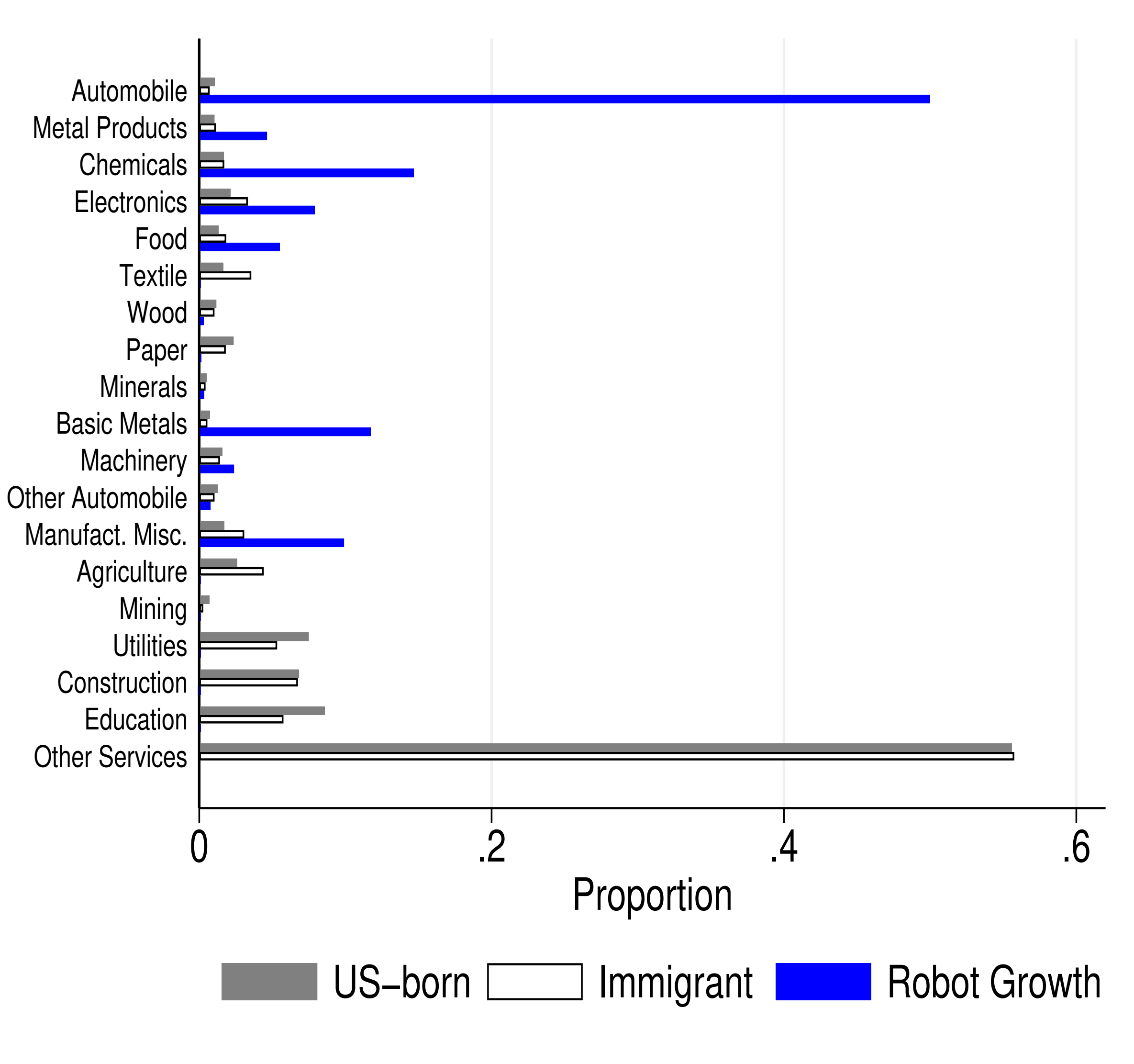


Note: Panel (a) shows the β coefficient in Equation (10) for change in relative employment of low-skill immigrants to natives. All regression estimates are weighted by the CZ population in 1990. Standard errors are clustered at the state level. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels respectively. Panel (b) shows the combined (natives and immigrants) employment share in each industry-task cell. Other services include Finance, Insurance and Real Estate, Entertainment and Recreation services and Professional services.

C.7.2 Nativity-specific robot exposure

Figure C.3 illustrates that the industrial composition of low-skilled immigrants and natives is largely similar. Only a few industries, such as agriculture and education, employ a disproportionate share of immigrant and native workers. Therefore, it is unlikely that differences in industrial composition explain the varying impact of automation on low-skilled immigrants and natives.

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



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

But, to formally analyse the role of differential industry composition, we construct nativity-specific measures of robot exposure. We used group-specific employment share in an industry of low-skilled workers in a CZ to compute robot exposure at the CZ level by nativity status.

$$\Delta R_{i,t}^{g,US} = \sum_{j} \left[\frac{L_{i,j,1970}^{g}}{L_{i,1970}^{g}} \cdot \Delta R_{j,t} \right] \tag{C.2}$$

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

Figure C.4 presents the histogram of the two robot exposure measures. The exposure of immigrant robots has a larger mass at highly negative values. However, the weighted correlation between the two measures is 0.78 (the unweighted correlation is 0.55) and the distributions appear fairly similar.

Figure C.4: Distribution of Immigrant- and Native-specific Robot Exposure

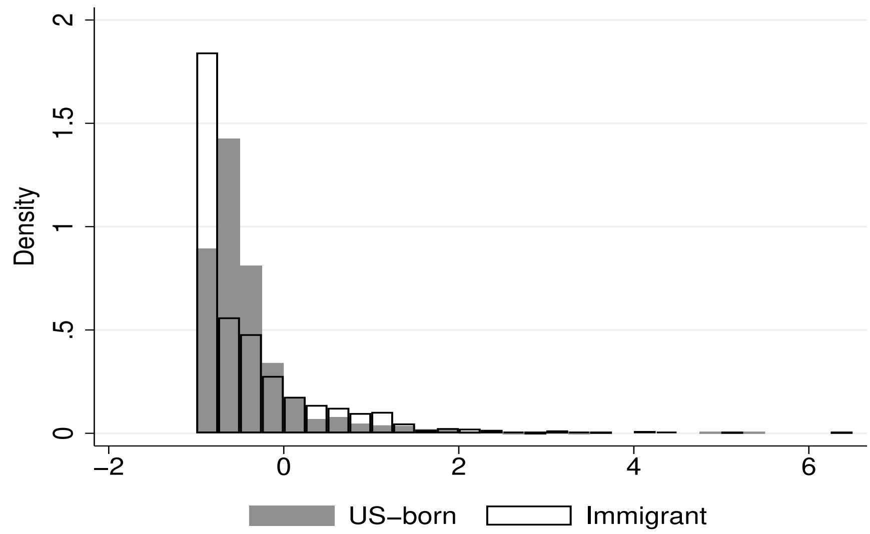


Table C.12 shows the 2SLS and first-stage estimates using regression specifications for which we introduce the two measures separately and then jointly. The dependent variable is log employment of each subgroup. Consistent with our previous findings, the employment growth of low-skilled immigrants decreases more significantly than that of similarly skilled natives when using either of the two measures. The estimate of low-skilled immigrant (native) employment growth is -2.3 (-0.31) and -4.67 (-1) using the immigrant-specific and native-specific robot exposure measures, respectively.

However, the coefficient for low-skilled immigrants is smaller in magnitude using the immigrant-specific robot exposure measure (-0.82) compared to the native-specific measure (-4.12), as shown in the top panel of column 3. A similar pattern emerges for low-skilled natives in column 6. This is likely due to the lack of statistical predic-

Table C.12: Effects on low-skilled employment growth to nativity-specific robot exposure, stacked-differences 1990–2015 (2SLS)

Dependent variable: Change in log employment						
	Immigrant			Native		
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure to robots (Immigrant-specific)	-2.30		-0.82	-0.31		0.06
	(1.74)		(1.93)	(0.36)		(0.38)
Exposure to robots (Native-specific)		-4.67***	-4.12**		-1.00**	-1.03*
		(1.65)	(2.03)		(0.44)	(0.56)
Observations	1425	1443	1425	1426	1444	1426
R^2	0.69	0.69	0.69	0.81	0.82	0.82

2SLS First Stage: Native-specific robot exposure						
Instrumented by:	Immigrant-specific			Native-specific		
	(1)	(2)	(3)	(4)	(5)	(6)
Predicted Exposure to robots (Immigrant-specific)	0.67***		0.59***	0.24**		-0.02
	(0.08)		(0.09)	(0.10)		(0.01)
Predicted Exposure to robots (Native-specific)		0.61***	0.30***		0.97***	0.98***
		(0.07)	(0.07)		(0.07)	(0.07)
Observations	1426	1426	1426	1426	1444	1426
R-squared	0.77	0.61	0.79	0.71	0.96	0.96
Kleibergen-Paap F (Immigrant)	69.66		45.71	5.43		1.76
Kleibergen-Paap F (Native)		76.17	17.85		179.14	179.07

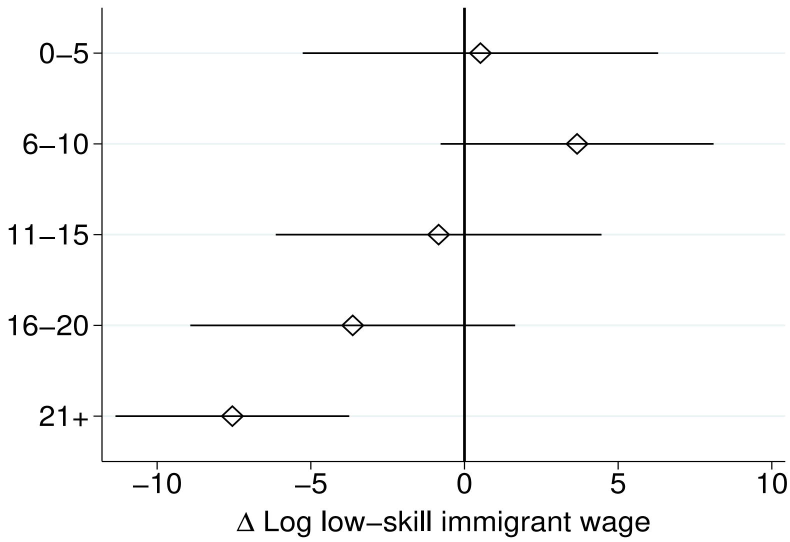
Note: All regression estimates are weighted by the CZ population in 1990. Standard errors clustered at the state level are reported in parentheses. ***, ** and * represent the statistical significance at 1%, 5% and 10% levels respectively. Covariates include stock of computer capital per worker in 1990;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

tive power in the first-stage when both measures are included in the regression; the Kleibergen-Paap F-statistic is only 17.85 for the EURO5 native-specific robot measure in column 3, while it is less than 2 for immigrant-specific robot exposure in column 6. The low predictive power arises from the similarity in the employment shares of natives and immigrants across industries. In conclusion, the lack of sufficient power prevents a definite conclusion about the role of differential intensity in robot exposure by nativity in explaining the results. However, it is clear that differential intensity is unlikely to be the primary reason behind our findings.

C.7.3 Effect on immigrant wage by years living in US

Figure C.5 shows that the wage growth of low-skilled immigrants living in the US for more than 15 years reduced due to robot exposure. However, the wage growth of low-skilled immigrants living in the US for less than ten years to automation did not change.

Figure C.5: Effects on low-skilled immigrant wage growth by years living in US



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

C.7.4 Effect on English proficiency of immigrants

We measure English proficiency as either “Speak only English" or “Speak English very well". The dependent variable is the change in the proportion of English proficient speakers among immigrants, or the change in the proportion of new immigrants among total immigrants that are proficient in English. Column 1 in Table C.13 illustrates that the share of immigrants that are proficient in English does not differ between regions with high and low exposure to robots. However, focusing on recent immigrants, a higher fraction of individuals proficient in English are found in areas with greater robot-exposure. Therefore, regions more exposed to robots have seen the arrival of immigrants with higher English speaking skills.

Table C.13: Effects on share of English proficient immigrants (2SLS), excluding outliers

Dependent variable: Change in fraction proficient in english		
	Overall	Recent Immigrants
	(1)	(2)
Exposure to robots	0.00	0.65^{***}
	(0.34)	(0.17)
Observations	1444	1444
R^2	0.62	0.24

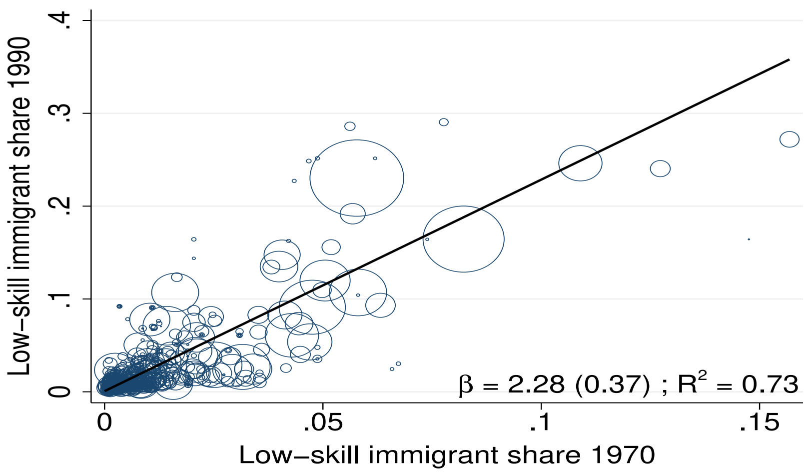
Note: All regression estimates are weighted by the CZ population in 1990. Standard errors clustered at the state level are reported in parentheses. ***, ** and * represent the statistical significance at 1%, 5% and 10% levels respectively. Regressions include time-division dummies and covariates: stock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

D Section 5 Appendix: Mitigating effects on natives

D.1 Low-skilled immigrant share in 1990 and 1970

Borjas (1995) argues that recent immigrants are more likely to settle in areas where immigrants from their home countries are already located. This implies that the past and current immigrant shares should be positively associated. Figure D.1 displays a significantly positive relationship between the share of low-skilled immigrants in 1970 and 1990. Moreover, the geographic distribution of immigrants in 1970 strongly predicts their distribution in 1990 (R^2 = 73%).

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



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

D.2 Robustness checks

We test the hypothesis that the mitigating effects for native workers are driven among regions with greater wage flexibility. To do so, we split our sample by states that had Right-to-work (RTW) laws before 1990 and those that did not. Additionally, we normalise the robot exposure measure states with and without RTW to make the coefficients comparable. Table D.1 shows that the mitigating wage effects are very similar between states with and without RTW policies. However, mitigating employment effect is much higher for states with RTW than without RTW, but they are both insignificant. In conclusion, our results are not explained by some states having more wage flexibility.

Table D.1: 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 (1)	Employment (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. 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).

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 D.2 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, but the main conclusions remain unchanged.

Table D.3 shows the changes in log native employment and log average native wages

Table D.2: Effects on labour market outcomes of low-skilled natives, 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. 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).

between 1970 and 1990, in relation to robot exposure between 1990-2015 and the 1990 immigrant share. The table clearly shows a lack of significant pre-trends in labour market outcomes of native workers to robot exposure. The second row demonstrates that in areas with no immigrant share, robot exposure between 1990-2015 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 D.4 shows that low-skilled immigrant mobility mitigates wage losses due to automation of low-skilled native workers using three periods and two periods stacked-differences specifications and long-difference specification. Coefficients in columns 1-2, 3-4 and 5-6 are based on a three periods stacked-differences (1990-2000, 2000-2007

Table D.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. 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).

and 2007-2015), two periods stacked-differences (1990-2000 and 2000-2007) and long-difference specifications, 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 periods are quite similar, indicating that our results are not driven by the Great Recession.

Table D.4: Effects on labour market outcomes of natives, multiple time periods (2SLS): Interacting robot exposure with share of low-skilled immigrant

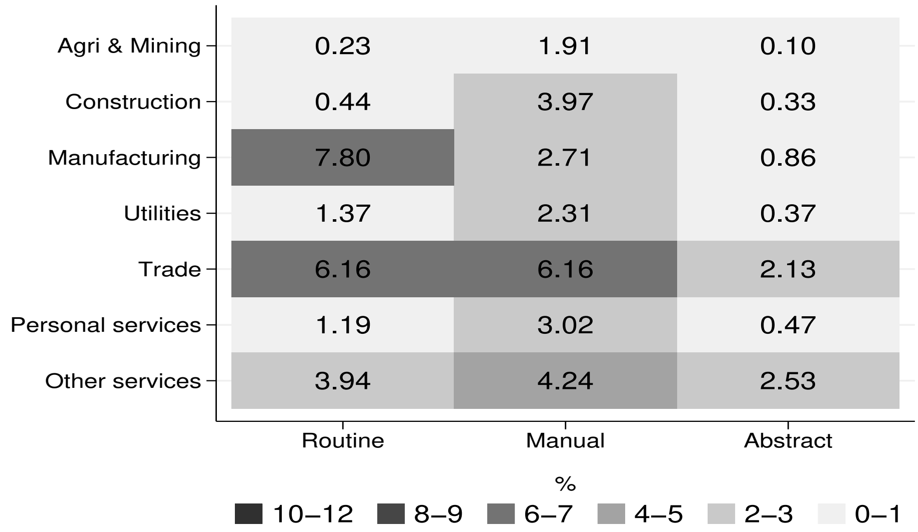
Dependent variable: Change in log employment or change in log wages						
	3 stacked		2 stacked		Long	
	Wage	Employment	Wage	Employment	Wage	Employment
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure x Share 1990	33.96***	2.17	38.40**	-0.19	32.16***	8.05
	(9.91)	(20.12)	(17.11)	(34.34)	(9.54)	(24.08)
Exposure to robots	-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. 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).

D.3 Additional result: Heterogeneity by industry-task

Figure D.2 shows the employment share of low-skilled natives across the industry-task cells in 1990. Low-skilled natives are mostly employed in manufacturing or trade jobs.

Figure D.2: Share of native employment among low-skilled in 1990



D.4 Additional results: Heterogeneity by age

Table D.5 highlights 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 between CZs at the 50th and 25th percentiles of the low-skilled established immigrant share. The mean robot exposure is 0.9, and the 50th and 25th 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]). Moreover, we reach the same conclusions as our baseline results.

Table D.6 illustrates the mitigating effect to automation due to mobility of 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 D.5: 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. 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.6: 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. 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).

E Section 6 Appendix: Human capital adjustment

Table E.1 presents the effect of automation on the college enrollment rates of young natives and older immigrants, broken down by employment status. We focus on these groups as they demonstrated an increase in college enrolment in response to automation. Employment status is categorised by whether they worked any positive number of hours in the previous year or were out of the labour force. The findings reveal that most of the increase in college enrollment among young natives occurred while they were out of the labour force, suggesting that young natives delay their entry into the labour market in areas with higher level of robot exposure. In contrast, the rise in college enrollment among older immigrants largely took place while they were employed, indicating that they often attend local community colleges while working full- or part-time. Some older immigrants also enrolled in college while out of the labour force, likely to upgrade their skills following a job loss.

Table E.1: Effects on share attending college by working status, stacked-differences 2000–2015 (2SLS)

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).