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Local Shocks and Internal Migration: The Disparate Effects of Robots and Chinese Imports in the US*

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Abstract

Do local labor markets adjust to economic shocks through migration? In this paper, we study this question by focusing on two of the most important shocks that hit US manufacturing since the 1990s: Chinese import competition and the introduction of industrial robots. We find that, even though both shocks drastically reduced manufacturing employment, only robots led to a sizable decline in population. We provide evidence that negative employment spillovers outside manufacturing, caused by robots but not by Chinese imports, can explain the different migration responses.

Keywords: Migration, employment, technology, trade.
JEL Classification: J21, J23, J61.

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1 Introduction

Workers' geographic mobility is an important mechanism for the adjustment of labor markets to local economic shocks (Blanchard and Katz, 1992). It is also viewed as a distinctive feature of American workers, who are perceived to be more mobile and more responsive to differential economic opportunities across labor markets, compared to their European counterparts (Moretti, 2012). Yet, evidence suggests that the high propensity to migrate among American workers has declined in the past 30 years (Molloy et al., 2011), possibly explaining why the negative effects of strong, localized shocks that hit the US economy since the early 2000s – most notably, Chinese import competition and the adoption of industrial robots – lasted for so long (Cadena and Kovak, 2016; Abraham and Kearney, 2018; Charles et al., 2019).

Do American workers still migrate in response to local labor market shocks? Does the decision to migrate depend on the characteristics of the shocks hitting local labor markets? If so, which characteristics matter the most? In this paper, we aim to make progress on these questions by studying the effects of Chinese import competition and the adoption of industrial robots on migration across US commuting zones (CZs) between 1990 and 2015. Following the literature (Autor et al., 2013; Acemoglu and Restrepo, 2020), we construct plausibly exogenous measures of local exposure to both shocks by combining the pre-period CZ industrial composition with the growth in, respectively, import competition and robot adoption in other developed countries.

Using these variables, and splitting the sample in three periods (1990-2000; 2000-2007; and 2007-2015), we estimate stacked first difference regressions to identify the causal impact of both shocks on the changes in CZ population. Our preferred specification controls for any CZ specific, time invariant characteristics, and allows CZs to be on differential trends depending on several baseline characteristics.[1]

We document a puzzling asymmetry: while industrial robots caused a substantial reduction in population size, Chinese imports did not. Such asymmetric effects are particularly surprising, given the existing evidence that both shocks reduced manufacturing employment (Autor et al., 2013; Acemoglu and Restrepo, 2020). Examining the margins along which the migration response takes place, we show that lower in-migration, rather than increased out-migration, is responsible for the reduction in CZ population induced by robots.[2] The

[1] We allow for time period specific differential trends in nine Census regions, a rich set of demographic characteristics, four broad industries, pre-period population growth, and the degree of routine-intensity and offshorability.

[2] These findings are consistent with recent works by Monras (2018) for the US and Dustmann et al. (2017) for Germany, which suggest that local labor markets adjustments often occur through changes in the behavior of prospective migrants rather than that of incumbent workers.

magnitude of our estimates is large, and implies that each new robot reduced in-migration by about four working-age individuals.

We probe the robustness of results in several ways. First, we verify that our findings are not driven by differential pre-trends in population growth. Second, we show that results cannot be explained by either the differential timing of the shocks or CZ baseline characteristics. Third, we document that results are unlikely to be driven by noise due to correlated shocks across CZs (Adao et al., 2019), and that they are robust to: *i*) constructing the import shock following Pierce and Schott (2016); *ii*) adjusting standard errors for spatial correlation; and, *iii*) controlling for migration-weighted shocks to other locations (Borusyak et al., 2022).

In the second part of the paper, we investigate the mechanisms. In line with previous work (Acemoglu and Restrepo, 2020), we document that the employment effects of robots spilled over to industries that were not directly affected, such as retail and business and professional services. Instead, the negative effects of import competition remained concentrated within the manufacturing sector. If anything, Chinese imports led to employment growth outside manufacturing (Bloom et al., 2019; Ding et al., 2019).

Next, we provide evidence that spillovers into high-skilled industries contributed to the differential migration response triggered by the two shocks. First, although robots reduced employment of both low-skilled and high-skilled individuals, the migration response to robots was driven by the latter. Second, while the employment effects of robots (and Chinese imports) were similar across CZs surrounded by migrants with a different skill level, robots reduced population growth only in areas that had a larger share of high-skilled individuals in neighboring CZs (also driven by lower in-migration rather than higher out-migration). This suggests that at least some of the employment losses due to the introduction of robots can be accounted for by high-skill jobs that, in the absence of robots, would have been created and taken by prospective in-migrants.

We document similar patterns, in the opposite direction, for Chinese imports, once heterogeneous employment effects are accounted for. In particular, Chinese imports generated positive and statistically significant employment effects outside manufacturing in CZs with a high degree of specialization in services (high service intensity regions, HSI), and slightly negative, though not statistically significant, effects in CZs with a low degree of specialization in services (low service intensity regions, LSI).[3] Linking the employment effects to migration, import competition led to higher in-migration and population growth in HSI CZs, and to a mild, but not statistically significant, reduction in population in LSI CZs.

[3] This result is in line with Bloom et al. (2019), who show that reallocation of employment into non-manufacturing in response to Chinese imports was particularly strong in areas with high levels of human capital.

Our results suggest that the migration response to local labor market shocks depends on the employment effects in both directly (e.g., manufacturing) and indirectly (e.g., non-manufacturing) exposed sectors. This may be because the transmission of a shock into indirectly affected sectors amplifies its initial effect, making the CZ as a whole less attractive to in-migrants. Alternatively, indirectly hit industries may host more mobile individuals, whose migration elasticity to economic shocks is higher. Our evidence is more consistent with the second possibility. In a longer version of this paper (Faber et al., 2022), we develop a quantitative spatial economic model with geographically mobile labor, where workers compete with either robots or foreign labor in the completion of tasks. The model sheds light on the factors driving the different spillovers into non-manufacturing between robot adoption and Chinese imports. These asymmetric effects, in turn, influence individuals' migration decisions.[4]

Our paper contributes to the literature on the effects of local economic shocks on workers' geographic mobility (Cadena and Kovak, 2016; Dustmann et al., 2017; Bartik, 2018; Kearney and Wilson, 2018; Monras, 2018; Greenland et al., 2019). We complement these studies by comparing the response of the same local labor markets to two simultaneous, and major shocks to US manufacturing. This allows us to go beyond the estimation of migration responses to single shocks taken in isolation, enriching our understanding of the drivers of migration responses more generally. Our findings suggest that the elasticity of migration with respect to economic shocks is not a fixed parameter independent of the type of shock hitting labor markets. Instead, different shocks can lead to different migration responses, depending on the characteristics of the most exposed individuals.

Our findings also speak to works on the local labor market effects of Chinese import competition and robot adoption (Autor et al., 2013; Autor et al., 2014; Dix-Carneiro, 2014; Bloom et al., 2019; Ding et al., 2019; Acemoglu and Restrepo, 2020). We expand on this literature by studying the impacts of the two shocks on migration and employment alongside one another. We examine not only their effects on overall population, but also on in- and out-migration to understand the channels of adjustment. Examining the heterogeneous effects of the two shocks, we uncover a stark difference not only in how each of them affected migration, but also how it propagated to the rest of the local economy.[5]

[4] See Faber et al. (2022), also available at `https://www.nber.org/papers/w30048`, for more details.

[5] In our longer paper (Faber et al., 2022), we also complement the empirical analysis with a theoretical framework that helps rationalize the economic forces behind the differential employment and migration patterns we document.

2 Labor market shocks and empirical strategy

In this section, we describe the labor market shocks we consider and the empirical strategy. Appendix B provides more details on the construction of the variables.

2.1 Labor market shocks

We focus on two local labor market shocks that are widely considered among the main causes behind the decline in employment since the early 2000s: industrial robots and Chinese import competition (Abraham and Kearney, 2018).

Robots. The use of industrial robots in the US and around the world has grown significantly since the early 1990s. Advances in the capabilities of robots and reductions in prices resulted in a threefold increase in the global robot stock between 1993 and 2015 (IFR, 2021). During the same period, the stock of robots increased by about 1.5 robots per 1,000 workers in the US (Figure A1). Robot penetration was highest in manufacturing, where robots typically perform tasks such as pressing, welding, packaging, assembling, painting, and sealing. Within manufacturing, the automotive industry makes the heaviest use of industrial robots, followed by plastics and chemicals, food and beverages, and the metal industries. Outside manufacturing, industrial robots are used for harvesting and the inspection of equipment and structures (Figure A2).[6]

Chinese imports. The early 1990s also marked the explosion of Chinese exports. China's share of world exports grew from 2% to more than 12% between 1990 and 2015. The rise in Chinese exports to the US was even more dramatic, with a 15-fold increase between 1991 and 2015 – from about USD 250 per American worker in 1991 to more than USD 4,000 in 2015 (Figure A1). Given China's comparative advantage, its exports were skewed towards labor-intensive industries within manufacturing. In the US, Chinese imports grew especially for electronics and electrical equipment, industrial machinery, and textiles and apparel. The least affected industries within manufacturing were transport equipment (non-automotive), paper and printing products, and food, beverages and tobacco (Figure A2).[7]

[6] See Acemoglu and Restrepo (2021) for more details on the causes of the spread of robots in the US and around the world.
[7] See Storesletten and Zilibotti (2014) and Autor et al. (2016) for more details.

2.2 Empirical strategy

We consider the 722 CZs contained in the US mainland, and stack the data from 1990 to 2015 in three periods: 1990–2000, 2000–7, 2007–15. We estimate a regression of the form:

$$\Delta \ln Y_{c,t} = \beta^r \underset{\text{robots}_{c,t}}{\text{US exposure to}} + \beta^c \underset{\text{Chinese imports}_{c,t}}{\text{US exposure to}} + \boldsymbol{X}'_{c,90}\gamma_t + \Delta \ln Y_{c,70-90} + \epsilon_{c,t} \tag{1}$$

where $Y_{c,t}$ is the number of working-age (15-64 year old) individuals living in CZ c at time t. Below, we also distinguish between in- and out-migrants, and consider other outcomes, such as employment (aggregate and by subgroup). Regressions are weighted by a CZ's 1990 size of the outcome group.[8] Standard errors allow for heteroskedasticity and arbitrary clustering by state. To allow for differential trends, we interact period dummies with: nine region dummies; and a rich vector of 1990 characteristics.[9] To account for potentially pre-existing trends, we also control for the change in the outcome variable in the pre-period (1970-90). Since we estimate stacked first difference regressions and include region-period fixed effects, the coefficients of interest, β^r and β^c, are identified from changes within the same CZ over time, as compared to other CZs in the same Census region in a given period.

As in Acemoglu and Restrepo (2020), we construct a CZ's *US exposure to robots* by interacting the 1990 employment share of each industry in a given CZ with the national change in the number of robots in a given industry within a period (relative to 1990 employment in the industry). We adjust this quantity by the overall expansion of each industry, calculated as the growth rate of an industry's output, weighted by the 1990 robot to employment ratio. Following Acemoglu and Restrepo (2020), we address endogeneity concerns by deriving an instrument for robot adoption (*exposure to robots*) that replaces: *i*) US robotization with that occurring in five European countries (Denmark, Finland, France, Italy, and Sweden); and, *ii*) the 1990 employment shares with 1970 ones.

Next, as in Autor et al. (2013), we construct a CZ's *US exposure to Chinese imports* by interacting the national growth of Chinese imports in each industry with the initial industry share of employment in a given CZ. As in Autor et al. (2013), we instrument this variable by replacing Chinese imports to the US with those to eight high-income countries, and by using lagged (rather than baseline) employment shares. We refer to the instrument as *Exposure to Chinese imports.*

[8] Cadena and Kovak (2016) show that for changes in log population size across labor markets of different sizes efficient weights must account for individuals' sampling weights to deal with inherent heteroskedasticity. These are almost perfectly correlated with initial population sizes of the outcome group.

[9] See the notes to Table 2 for the full list of controls included in $\boldsymbol{X}_{c,90}$.

3 Data and descriptive statistics

3.1 Data

In this section, we describe the key variables used in the paper. We present more details in Appendix C.

Migration. The key outcome of interest is the change in the log number of individuals of demographic group Y living in CZ c between period t and $t+1$. For the analysis of the mechanisms, we also consider changes in subgroup-specific employment as a share of total employment. When using a stacked differences dataset containing changes from 1990–2000, 2000-7 and 2007–15, we inflate changes in the two latter periods to 10-year equivalents for comparability, as in Acemoglu and Restrepo (2020) and Autor et al. (2013). We use IPUMS census samples for 1970 to 2000 and the American Community Survey (ACS) for 2007 and 2015 (Ruggles et al., 2018). We also collect data on aggregate county population from the intercensal estimates of the US Census Bureau and the county-to-county migration counts from the Internal Revenue Service (IRS), available for all years from 1990.[10] Figure 1, Panel A, plots the average net migration rates across CZs between 1992 and 2015. The map shows that there is substantial geographic variation in migration rates, which are highest in the Northwest and Southeast, and lowest in the Midwest and Northeast.

Exposure to robots. We draw on three data sources to construct exposure to robots. First, we obtain data on shipments of industrial robots by industry, country, and year from the International Federation of Robotics (IFR, 2021).[11] Second, we collect initial industry employment shares by CZ from the Integrated Public Use Microdata Series (Ruggles et al., 2018). Third, we take employment and output by industry and year for countries other than the US from the EU KLEMS dataset (Timmer et al., 2007). To construct robot penetration at the CZ level, we interact industry-level growth in different countries with initial industry employment shares in a CZ, which we take from IPUMS and the ACS.

Exposure to Chinese imports. To construct exposure to Chinese import competition, we extend the measures defined in Autor et al. (2013) to the period 2007–2015, using two data sources.[12] First, we use industry-level data on the value of Chinese imports in 2007 USD by destination country and year from the UN Comtrade database (United Nations, 2019). Second, we collect data on initial industry employment shares by CZ from the County

[10] See Appendix C.1 for more details.

[11] The IFR data has a few limitations. We deal with those identically to Acemoglu and Restrepo (2020). See Appendix C.2 for a detailed description.

[12] Our measures *US exposure to Chinese imports* and *Exposure to Chinese imports* correspond to the ΔIPW_{uit} and ΔIPW_{oit} in Autor et al. (2013), respectively.

Business Patterns (CBP; US Census Bureau, 2019), which provide county-level employment counts at the same level of granularity (4-digit classification) as the Comtrade data.[13]

3.2 Descriptive statistics

As a preliminary step, we verify that the correlation between robot exposure and Chinese import competition is sufficiently low for us to separately identify their effects. Figure 1 shows the geographic distribution of exposure to robots and to Chinese imports in Panels B and C respectively. Reassuringly, the population weighted correlation coefficient between the two shocks is as low as 0.06.[14]

Table 1 presents the summary statistics for the main variables considered in our work, reporting the average over the entire sample in column 1, and restricting attention to CZs in the upper quartile of exposure to robots and Chinese imports in columns 2 and 3, respectively. Columns 4 to 7 replicate columns 2 and 3 focusing on relative exposure to robots over Chinese imports.[15] Column 8 reports the difference between columns 7 and 4, and column 9 indicates its statistical significance.

In line with Acemoglu and Restrepo (2020) and Autor et al. (2013), CZs most exposed to either shock experienced lower than average employment growth (column 1). CZs most exposed to robots also experienced lower population growth (column 2). Column 8 compares areas especially exposed to robots with areas especially exposed to Chinese imports. This admittedly crude comparison suggests that robots and Chinese imports reduced employment to a similar extent, but that the former reduced population growth more than the latter. In the next section, we formally examine these patterns.

4 The migration response to local labor market shocks

4.1 Main results

In this section, we study the impact of robot penetration and Chinese imports on migration. We estimate equation (1) using the change in the log working-age population as dependent variable, and report 2SLS results in Table 2.[16] In column 1, we estimate a parsimonious

[13] Since the CBP data provide employment counts in brackets (i.e., lower and upper bounds), we employ the fixed-point algorithm developed by Autor and Dorn (2013) to get single numbers of employment for all such brackets.

[14] Moreover, neither shock predicts the other in population-weighted regressions that include a full set of interactions between time and census division dummies as covariates.

[15] Relative exposure to robots over Chinese imports is defined as the difference between a CZ's standardized exposure to robots (zero mean and standard deviation equal to one) and its standardized exposure to Chinese imports.

[16] First-stage regressions are presented in Panels A and B of Table A2. Both instruments are highly correlated with their respective endogenous counterparts. In some specifications, the instrument of the respective other shock has some predictive

specification that only includes interactions between time and census division dummies. The two shocks had strongly different effects on migration: while robots led to a sharp reduction in population growth, Chinese imports did not. Subsequent columns show that results are robust to an increasingly stringent set of controls. In column 2, we control for the 1970 to 1990 change in log working-age population to capture potential secular migration trends, which may be correlated with post-1990 labor market shocks. Doing so halves the coefficient on robot penetration, but leaves its precision unchanged; the effect of Chinese imports remains statistically insignificant. This suggests that, although areas more exposed to robot adoption might have been on downward trajectories for population growth, these trends cannot explain our results.

Next, we interact period dummies with 1990 CZ: demographic (column 3) and economic (column 4) characteristics; and, shares of routine and offshorable jobs (column 5).[17] Additional controls in columns 3 and 4 address the concern that initial industry shares (which we use to predict robot and Chinese import exposure) may be correlated with baseline CZ characteristics that may have influenced population growth after 1990. Column 5 aims to control for the automation of routine tasks due to the spread of computers and increased offshoring due to more general globalization trends unrelated to China. Adding this battery of controls leaves our results for robot adoption unchanged, both in terms of magnitude and in terms of precision. The coefficient on import competition remains imprecisely estimated and quantitatively small, but becomes positive from column 3 onwards.

Focusing on robot adoption, the point estimate in our most preferred specification (column 5) implies that one standard deviation increase in exposure to robots (or, 0.72 robots per 1,000 workers) reduced population growth by 0.56 percentage points per decade. That is, one additional robot per 1,000 workers reduced population growth by 0.78 percentage points, or 8.4% relative to the decadal average across CZs (9.3%).[18] These results seem puzzling, in light of the evidence that both robot adoption and Chinese imports reduced manufacturing employment (Autor et al., 2013; Acemoglu and Restrepo, 2020). In Section 5 below, we return to this point when exploring the mechanisms.

power over the endogenous variable. To rule out that the effects in Table 2 are identified from the unintended instrument, in Panels C and D, we replicate the analysis with two separate regressions for each of the shocks, including the other instrument as control. Reassuringly, results remain unchanged. In addition, Kronmal (1993) points out that using the same denominator on both sides of the equation may yield a spurious correlation and thus proposes including the denominator as a covariate. First and second stage results remain unchanged when controlling for 1990 employment in levels instead of logs.

[17] See the notes to Table 2 for the full list of controls.

[18] Acemoglu and Restrepo (2020) also find a negative effect of robots on population growth. Yet, their results are less precise. In Table A3, we verify that this difference is not due to any differences in the set of control variables. It instead results from: *i)* the use of intercensal estimates based on full counts instead of IPUMS samples (something that, we believe, increases the precision of the estimates); and *ii)* the interaction of CZ controls with period dummies (something that more flexibly accounts for potential underlying trends).

4.2 Summary of robustness checks

In Appendix D, we perform several robustness checks, which are briefly summarized here. First, we document that: *i*) neither robot exposure nor Chinese imports after 1990 are correlated with pre-period (1970 to 1990) changes in CZ population; and, *ii*) our results are insensitive to the way in which we account for pre-existing trends (Table D1). Second, we show that the muted migration response to Chinese imports is robust to using the instrument proposed by Pierce and Schott (2016) (Table D2). Third, we verify that *i*) results are unchanged when estimating long difference specifications (1990–2015 and 1990–2007, Table D3); *ii*) differences between the two shocks (over time and across CZs) cannot explain the differential migration response (Table D4); and, *iii*) results are robust to adjusting standard errors for spatial correlation (Table D5). Fourth, to address the concern that standard errors associated with Bartik instruments may be too small due to correlated shocks across observations (Adao et al., 2019), we follow Derenoncourt (2022) and perform a set of placebo checks that suggest that our findings are unlikely to be driven by noise (Figure D1). Fifth, we follow Borusyak et al. (2022), and control for migration-weighted shocks to other locations to account for the possibility of mis-specification (Table D6). Finally, we replicate the analysis for in- and out-migration by distance using different cutoffs (Tables D7 and D8).

4.3 Additional results

In-migration vs. out-migration. Lower population growth may result from either increased out-migration or reduced in-migration (or, both). On the one hand, a worker displaced by robots might choose to move to another CZ to find a new job. On the other hand, prospective in-migrants might choose not to move to a place where their chances of finding a job have deteriorated due to robots.

We examine these channels in Appendix E.1. Table E1 presents results for the log count of migrants (resp., migration rates) in Panel A (resp., Panel B), focusing on in- and out-migration in columns 1 to 3 and 4 to 6, respectively. Columns 1 and 4 document that robots reduced in-migration, but did not increase out-migration. Instead, if anything, the effect of Chinese import competition on in-migration is positive, even though not statistically significant. Table E1 (columns 2–3 and 5–6) also suggests that the reduction in in-migration stems from both close-by locations and far away regions, especially when focusing on the log count of migrants (Panel A).[19] It also shows that the positive but statistically insignificant effect of

[19] Interestingly, robot exposure had a negative and statistically significant effect on out-migration into CZs that are less than 300 miles away (column 5).

Chinese imports on in-migration flows masks substantial heterogeneity by distance. In particular, Chinese imports increased in-migration from CZs that are within 300 miles (column 2) – an effect that is statistically significant when considering log population changes (Panel A). However, this was not enough to generate a statistically significant (and quantitatively relevant) effect on overall in-migration.

House prices. In Appendix E.2, we explore the effects of robot adoption and Chinese imports on housing prices (Table E2). Consistent with the idea that lower in-migration (caused by robot adoption) reduced demand for housing, the coefficient on exposure to robots is negative and statistically significant. According to our preferred specification (column 5), one standard deviation increase in exposure to robots reduced house prices by 2.55%. In contrast, Chinese imports did not have any statistically significant effect on house prices, once CZs are allowed to be on differential trends depending on broad industry shares (columns 4 and 5). These results are consistent with the differential migration response to the two shocks documented above.

5 Mechanisms

In this section, we examine why, although both shocks reduced manufacturing employment (Autor et al., 2013; Acemoglu and Restrepo, 2020), only robots lowered population growth. First, we show that both shocks lowered manufacturing employment, but only robots reduced employment outside manufacturing. Next, we provide evidence that spillovers from manufacturing to other industries are an important mechanism for the differential migration response documented above.

5.1 Employment effects

Since both shocks were concentrated in manufacturing (Figure A2), we start by comparing their effects on employment within this sector. We estimate equation (1) using as dependent variable the change in log employment in manufacturing. We report 2SLS results in Panel A of Table 3, which follows the same structure as Table 2. We focus on our preferred specification (column 5) for brevity. Consistent with Acemoglu and Restrepo (2020) and Autor et al. (2013), both robots and Chinese imports reduced manufacturing employment considerably.[20] This seems at odds with our previous evidence, which showed that only

[20] Even if both variables are standardized, the effects are not directly comparable in an absolute sense. Coefficients merely imply that the same difference in exposure, relative to its overall distribution, resulted in a stronger reduction in manufacturing employment in response to Chinese imports than to robots.

robots triggered a migration response. Why did the two shocks lead to disparate migration responses, if they both reduced manufacturing employment?

The analysis in Panel A of Table 3 likely captures the direct effects of the two shocks, which were largely concentrated in several manufacturing industries (Figure A2). However, it may miss important margins of adjustment, such as negative demand or positive productivity spillovers into non-manufacturing industries. In Panels B and C of Table 3, we thus turn to non-manufacturing and total employment.

Panel B documents that robots had a strong, negative effect on employment outside manufacturing. Instead, the effect of Chinese imports was entirely concentrated within manufacturing.[21] If anything, our estimates suggest that Chinese imports had a positive effect on employment outside manufacturing.[22] Results in Panel C confirm those in Panels A and B: robot exposure caused an overall employment decline, while Chinese imports likely induced a reallocation of economic activity across sectors, which partly offset the employment losses in manufacturing.

Together with findings in Table 2, these patterns suggest that the negative impact of robots on migration was due to the combination of the direct effects within manufacturing and the indirect (spillover) effects outside manufacturing. Since there were no – if anything, positive – spillovers outside manufacturing for Chinese imports, the migration response was muted. In the next to sections, we provide evidence consistent with this hypothesis.

5.2 Spillovers to other industries within CZs

In Figure 2, we examine the effect of robots and Chinese imports on the employment shares in 44 industry-skill combinations.[23] We estimate our preferred specification (Table 2, column 5), using as dependent variable the change in employment in each industry-skill combination, relative to initial CZ employment. We plot coefficients on the (standardized) exposure to robots and Chinese imports in Panels A and B, respectively.

Robots reduced employment most strongly in routine, manual occupations within manufacturing (Panel A). However, these effects are visible not only in other skill groups within manufacturing, but also in industries that were not directly affected by robot penetration, such as business services, professional services, retail, and construction. The effect of Chinese imports was also strongest for manufacturing, though not only in routine, manual,

[21] These results are consistent with Acemoglu and Restrepo (2020), who find negative demand spillovers of robots into services, and Autor et al. (2013), who find no effect of Chinese imports outside manufacturing.

[22] This is consistent with the idea that trade exposure lowered input prices, inducing firms to reallocate towards services (Bloom et al., 2019; Ding et al., 2019).

[23] Skill groups are defined using the 1980 Dictionary of Occupational Titles (DOT). See Appendix C.3 for more details.

but also in abstract, cognitive occupations (Panel B). Similar to robots, the effect is visible across all occupations within the manufacturing industry. Yet, in contrast to robots, effects in industry-skill combinations outside manufacturing were mostly *positive*. These patterns reveal a stark difference in how the effects of robot penetration and Chinese import competition were transmitted within (local) labor markets. While robots likely caused negative spillovers into other industries, Chinese imports induced positive effects in other industries.

One caveat to results in Panels A and B is that, since outcomes are expressed in percentage points, initial shares in each cell may differ across areas exposed to either of the two shocks. Panels C and D provide a visual inspection of this possibility, reporting the initial share of employment in each cell, weighted by their exposure to robots and Chinese imports, respectively. Reassuringly, the distribution of the shocks across cells seems rather similar in the two panels.

5.3 Linking spillovers to migration responses

Figure 2 shows that the effects of robot adoption and Chinese imports vary substantially both across skills within manufacturing and across industries (outside manufacturing). Some of the industry-skill cells where the effects of the two shocks differ the most – such as abstract, cognitive occupations in retail or professional and business services – employ more mobile (i.e., high-skilled) workers. Such spillovers might be responsible for the negative in-migration response to robots, and the muted overall impact of Chinese imports.[24] If this were true, one should observe that robots also reduced employment of more mobile groups, and that the migration response of these groups was affected the most.

We test this hypothesis in Figure A3, where we estimate our preferred specification using the change in log employment and working-age population by subgroup (high- and low-skilled, and young, middle-aged, and old) as dependent variable.[25] The employment effects display relatively little heterogeneity across groups (Panel A). Instead, high-skilled individuals drive the migration response to robots (Panel B). This is consistent with spillovers into high-skilled occupations being, at least partly, responsible for the migration response observed in Table 2.

In Appendix E.3, we corroborate the view that our results are driven by spillovers into industries that host more skilled (and more mobile) individuals. First, in Table E3, we document that robot exposure reduces employment to a similar extent in CZs that have

[24] The lower geographic mobility of low-skilled than high-skilled workers is documented in Bound and Holzer (2000) and Topel (1986) among others.

[25] Figure A4 replicates the analysis for import competition. Detailed regression results are reported in Table A4.

different shares of "high skilled neighbors" (defined as the share of high-skilled individuals living in neighboring CZs in 1990). However, it lowers population growth only in CZs with a larger share of high skilled workers. Second, we exploit geographic variation in the effects of Chinese import competition on non-manufacturing employment (Bloom et al., 2019), augmenting our preferred specification with interactions between each measure of exposure and dummies equal to one if a CZ was, respectively, a high service intensity (HSI) or a low service intensity (LSI) area.[26] Table E4 shows that Chinese imports led to employment growth outside manufacturing in HSI CZs. Consistent with our proposed mechanism, these CZs also experienced significantly higher population growth, due to increased in-migration. In contrast, LSI CZs experienced, if anything, negative spillovers outside manufacturing. This, in turn, resulted in a negative and statistically significant overall employment response.

There exist at least two interpretations for how spillovers may foster migration. The first one is that the transmission of the shock into non-manufacturing (or any other indirectly affected sector) amplifies its initial effect, making the CZ as a whole less attractive to prospective in-migrants. The second explanation, not in contrast with the previous one, is that non-manufacturing industries that are indirectly hit host more mobile individuals, whose migration elasticity is higher. The positive migration response to Chinese imports in HSI CZs – which experienced no overall employment growth and a decline in manufacturing employment, but employment growth in non-manufacturing – is more consistent with the second interpretation.

Another way to identify spillovers to indirectly affected sectors is to compare the effects of the two shocks in the tradable and non-tradable sectors. Since both shocks were concentrated in tradable industries, employment changes in non-tradable industries are likely to reflect cross-industry spillovers. In Appendix E.4, we provide evidence consistent with our interpretation, and show that only robots reduced employment also in non-tradable industries (Table E5).

6 Conclusion

In this paper, we study the migration response to robot adoption and Chinese import competition across US CZs between 1990 and 2015. We document that, even though both shocks reduced manufacturing employment, only robots – and not import competition – negatively impacted migration. The population response to robot exposure was driven by lower in-

[26] Intuitively, services may have had higher capacity to grow in regions that were already specialized in that sector.

migration rather than by increased out-migration. Our analysis reveals that the two shocks differ in the extent to which they were transmitted from manufacturing to other sectors, not directly impacted by the shocks, in the same labor market. We offer evidence that, via these spillovers, only robots worsened employment opportunities for the most mobile individuals (i.e., high-skilled workers) who, in turn, decided to avoid labor markets affected by robots.

Our results suggest that migration may or may not be important to re-equilibrate local labor markets, depending on the set of individuals affected by the propagation of the shock across industries. They also indicate that migration alone is unlikely to entirely prevent the persistence of negative and concentrated labor market shocks, at least in the short run. We conclude by noting that our work has focused on the US, but robot penetration and trade competition are forces affecting most developed economies in the world. It would be instructive to examine how the effects of these forces vary depending on the type of labor market institutions in place. We leave this to future research.

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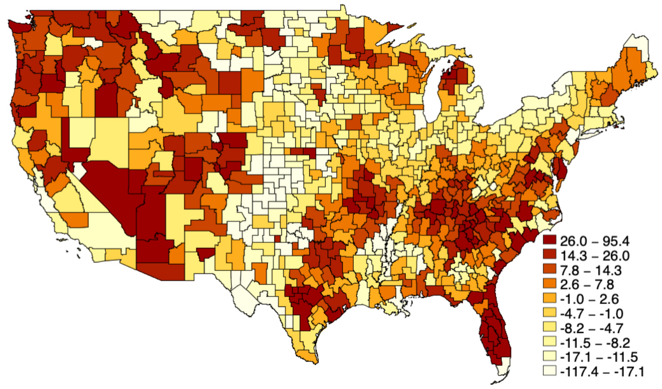
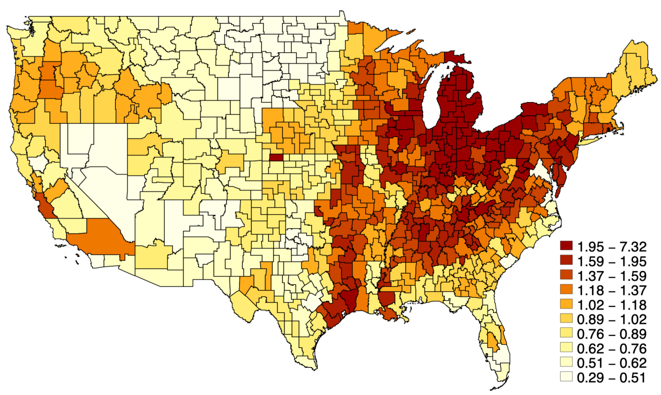
Figures and Tables

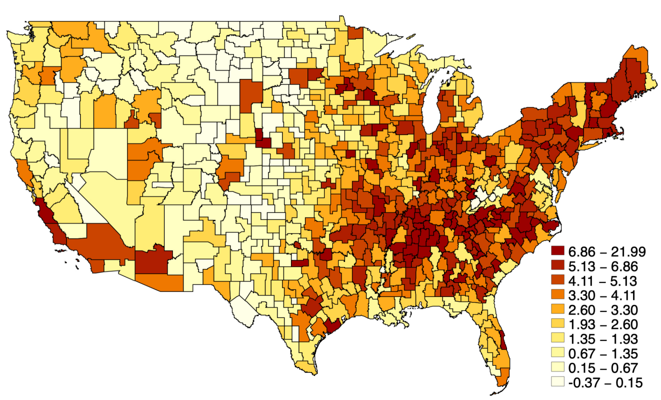
Figure 1: Geographic variation in migration and economic shocks



A. Net migration rate (1992–2015)



B. Exposure to robots (1993–2015)

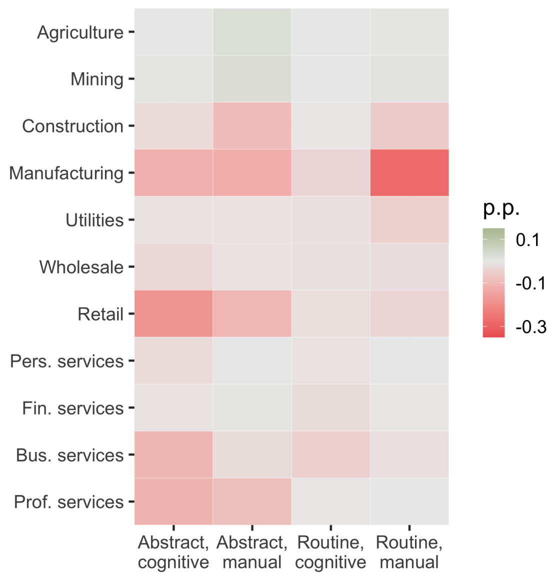


C. Exposure to Chinese imports (1991–2015)

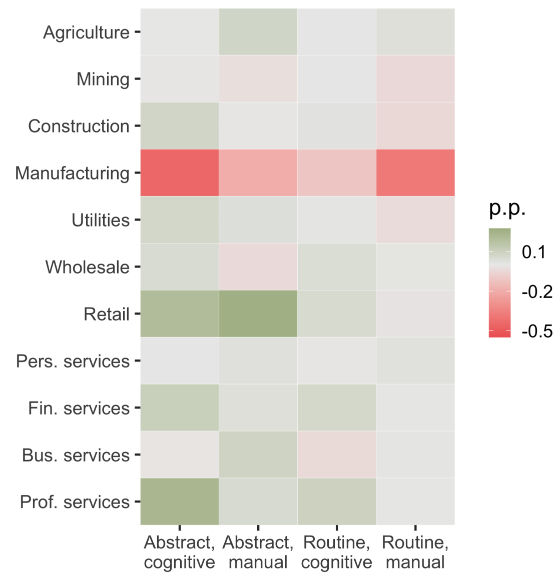
SOURCES: IFR (2021), United Nations (2019), Timmer et al. (2007), Ruggles et al. (2018), IRS (2019)

Note: Geographic variation in the net migration rate (1992–2015), exposure to robots (1993–2015), and exposure Chinese imports (1991–2015).

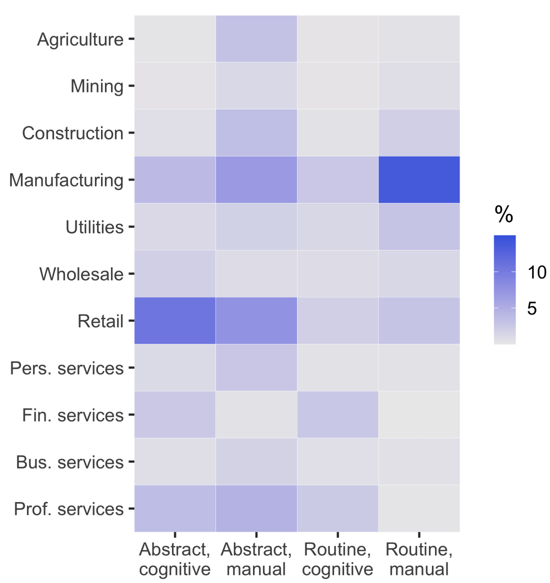
Figure 2: Industry-skill profile of robot adoption and Chinese imports



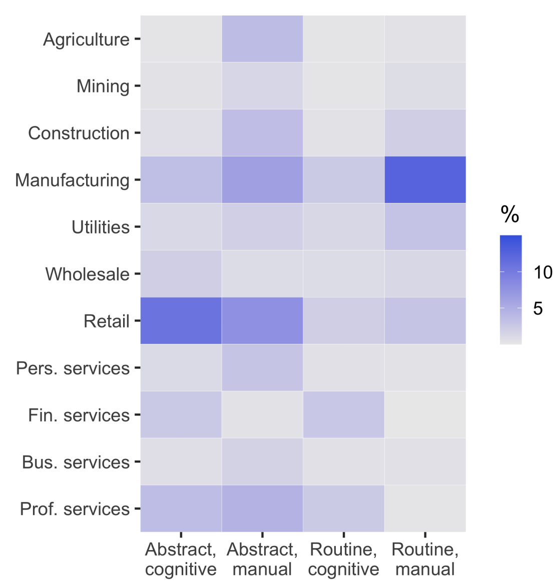
A. Exposure to robots



B. Exposure to Chinese imports



C. 1990 employment shares, weighted by exposure to robots



D. 1990 employment shares, weighted by exposure to Chinese imports

Note: Each cell in Panel A and B represents the coefficient on the (standardized) US exposure to robots and US exposure to Chinese imports, respectively, in a regression identical to the ones in column 5 of Table 2, but using the change in employment per industry-skill combination ij as a share of initial CZ employment ($(x_{cij,t+1} - x_{cij,t})/x_{c,t} \cdot 100$) as the outcome variable. All regressions are weighted by a CZ's 1990 share of national employment. Panels C and D present the 1990 shares of employment in each industry-skill combination ($x_{cij,t}/x_{c,t} \cdot 100$) weighted by the exposure to robots and Chinese imports, respectively.

Table 1: Descriptive statistics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		Exposure to robots	Exposure to China	Relative exposure China			Robots		
Quartiles	All	Q4	Q4	Q1	Q2	Q3	Q4	Q4–Q1	p
N	722	181	181	180	180	181	181	361	
Change in outcomes, 1990–2015									
Log employment	23.7	14.0	15.5	21.5	31.3	23.8	18.2	–3.4	.24
Log working-age pop.	14.8	12.4	14.9	16.6	20.7	11.1	11.0	–5.6	.02
Share of employment, 1990 (in %)									
Agriculture	4.5	2.2	3.0	4.1	4.8	5.5	3.7	–0.4	.41
Construction	6.6	6.3	6.3	6.4	6.8	6.7	6.3	–0.1	.71
Mining	2.7	1.4	0.9	1.2	2.4	4.2	3.0	1.8	.00
Manufacturing	24.3	33.7	35.4	30.5	21.7	19.4	25.7	–4.8	.01
Routine jobs	28.5	30.9	30.2	29.2	28.3	27.4	29.1	–0.0	.94
Share of population, 1990 (in %)									
Men	48.9	48.5	48.6	48.8	48.9	49.2	48.9	0.1	.50
Above 65 years old	13.4	13.2	13.3	13.4	13.4	13.4	13.2	–0.2	.61
Less than college	67.1	69.6	70.4	68.5	66.2	66.3	67.5	–1.0	.34
Some college or more	28.6	26.4	25.5	27.3	29.5	29.3	28.4	1.1	.31
White	87.0	89.6	86.7	85.3	84.4	87.9	90.3	5.0	.03
Black	7.8	8.6	11.3	11.1	9.0	5.0	6.0	–5.0	.05
Hispanic	5.8	1.5	2.1	4.5	7.0	7.5	4.0	–0.4	.63
Asian	0.8	0.6	0.6	0.7	0.9	0.8	0.7	–0.1	.72
Women in labor force	43.7	43.7	44.6	44.9	44.1	43.2	42.7	–2.3	.00
Standardized index, 1990 (mean 0, sd 10)									
Offshorability	0.0	3.9	4.2	2.9	0.4	–2.8	–0.5	–3.4	.03

Note: This table reports unweighted averages of several variables across different subsets of CZs. Column 1 includes all 722 CZs in the sample. Columns 2 and 3 contain only CZs in the top quartile with respect to the average exposure to robots and Chinese imports, respectively, over the three subperiods 1993/91–2000, 2000–7 and 2007–15. Columns 4–7 group all 722 CZs into quartiles according to their relative exposure to robots and Chinese imports. To define Q1 to Q4, we first standardize both the average exposure to robots and Chinese imports variables from columns 2 and 3 to have a mean of 0 and standard deviation of one, and then compute the difference between the two. As a result, observations in Q1 and Q4 are most exposed to Chinese imports and robots, respectively, relative to the other shock. Column 8 reports the difference between the average value in Q1 and Q4 (which results from a regression of the row variable on a Q4 dummy using the data set of only observations in either Q1 or Q4). Column 9 reports the significance level of the difference in column 8 (clustering standard errors by state).

Table 2: Effects on migration, stacked differences 1990–2015 (2SLS)

	(1)	(2)	(3)	(4)	(5)
	Working-age population count				
US exposure to robots	-1.23***	-0.67***	-0.70***	-0.62***	-0.56***
	(0.43)	(0.23)	(0.18)	(0.12)	(0.12)
US exposure to Chinese imports	0.15	-0.27	0.05	0.30	0.45
	(0.97)	(0.79)	(0.78)	(0.83)	(0.78)
Kleibergen-Paap F	56.5	56.9	53.7	26.7	25.3
Region × time	✓	✓	✓	✓	✓
Pre-trends		✓	✓	✓	✓
Demographics × time			✓	✓	✓
Industry shares × time				✓	✓
Contemp. changes × time					✓

Note: The dependent variable is the change in the log count the working-age population, multiplied by 100 (i.e., $[\ln(y_{t+1}) - \ln(y_t)] \cdot 100$). There are three time periods and 722 CZs each period, resulting in N=2,166. All explanatory variables that are displayed are standardized to have a mean of 0 and a standard deviation of 1. Column 1 includes census division dummies interacted with time period dummies as covariates. Column 2 also includes the change in the outcome variable between 1970 and 1990. Column 3 also controls for 1990 demographic characteristics (i.e., log population, share of men, share of population above 65 years old, share of population with less than a college degree, share of population with some college or more, population shares of Hispanics, Blacks, Whites and Asians, and the share of women in the labor force), each interacted with time period dummies. Column 4 also includes shares of employment in broad industries in 1990 (i.e., agriculture, mining, construction, manufacturing), each interacted with time period dummies. Column 5 also includes the share of routine jobs and the average offshorability index in 1990, following Autor and Dorn (2013), each interacted with time period dummies. Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the state level (48 states). Regressions are weighted by a CZ's 1990 national share of the working-age population. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

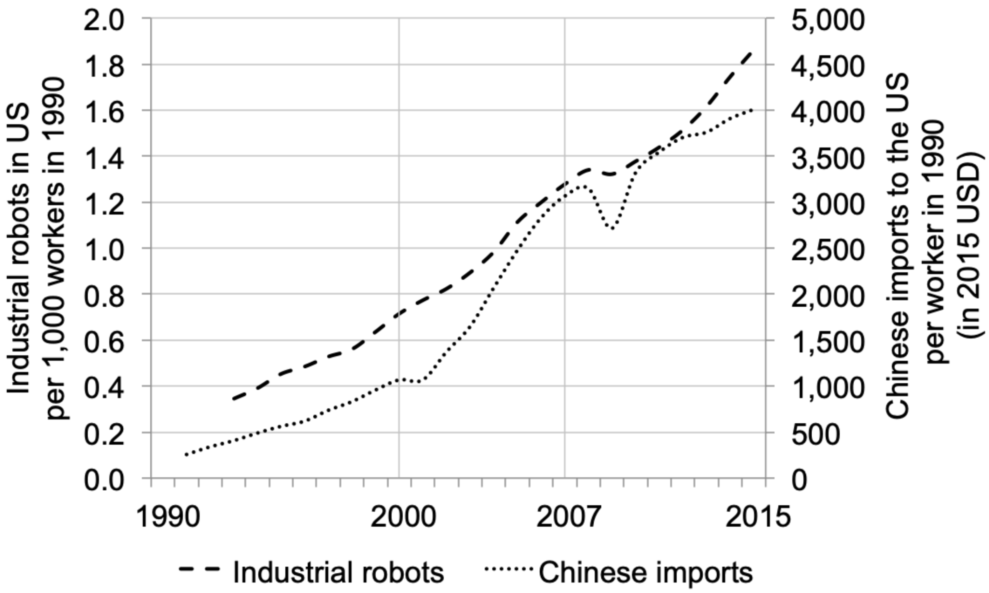
Table 3: Effects on employment, stacked differences 1990–2015 (2SLS)

	(1)	(2)	(3)	(4)	(5)
			A. Manufacturing employment		
US exposure to robots	-2.06***	-1.42***	-1.77***	-1.44***	-1.37***
	(0.61)	(0.32)	(0.36)	(0.35)	(0.37)
US exposure to Chinese imports	-5.29***	-7.30***	-6.75***	-5.38***	-5.36***
	(1.17)	(1.40)	(1.36)	(1.58)	(1.55)
			B. Non-manufacturing employment		
US exposure to robots	-1.84***	-1.62***	-1.36***	-1.49***	-1.43***
	(0.55)	(0.48)	(0.29)	(0.29)	(0.29)
US exposure to Chinese imports	1.75	1.60	1.54*	0.58	0.68
	(1.12)	(1.05)	(0.90)	(1.01)	(0.99)
			C. Total employment		
US exposure to robots	-2.42***	-1.80***	-1.67***	-1.41***	-1.37***
	(0.72)	(0.45)	(0.27)	(0.22)	(0.21)
US exposure to Chinese imports	-2.06*	-2.66***	-2.19**	-0.83	-0.79
	(1.09)	(0.95)	(0.93)	(1.01)	(0.96)
Region × time	✓	✓	✓	✓	✓
Pre-trends		✓	✓	✓	✓
Demographics × time			✓	✓	✓
Industry shares × time				✓	✓
Contemp. changes × time					✓

Note: The dependent variable in Panel A, B and C is the change in the log count of manufacturing employment, non-manufacturing employment and total employment, respectively, multiplied by 100 (i.e., $[\ln(y_{t+1})-\ln(y_t)]\cdot 100$). There are three time periods and 722 CZs each period, resulting in N=2,166. All explanatory variables that are displayed are standardized to have a mean of 0 and a standard deviation of 1. Column 1 includes census division dummies interacted with time period dummies as covariates. Column 2 also includes the change in the outcome variable between 1970 and 1990. Column 3 also controls for 1990 demographic characteristics (i.e., log population, share of men, share of population above 65 years old, share of population with less than a college degree, share of population with some college or more, population shares of Hispanics, Blacks, Whites and Asians, and the share of women in the labor force), each interacted with time period dummies. Column 4 also includes shares of employment in broad industries in 1990 (i.e., agriculture, mining, construction, manufacturing), each interacted with time period dummies. Column 5 also includes the share of routine jobs and the average offshorability index in 1990, following Autor and Dorn (2013), each interacted with time period dummies. Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the state level (48 states). Regressions are weighted by a CZ's 1990 national share of the outcome group in each panel, respectively. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

A Additional figures and tables

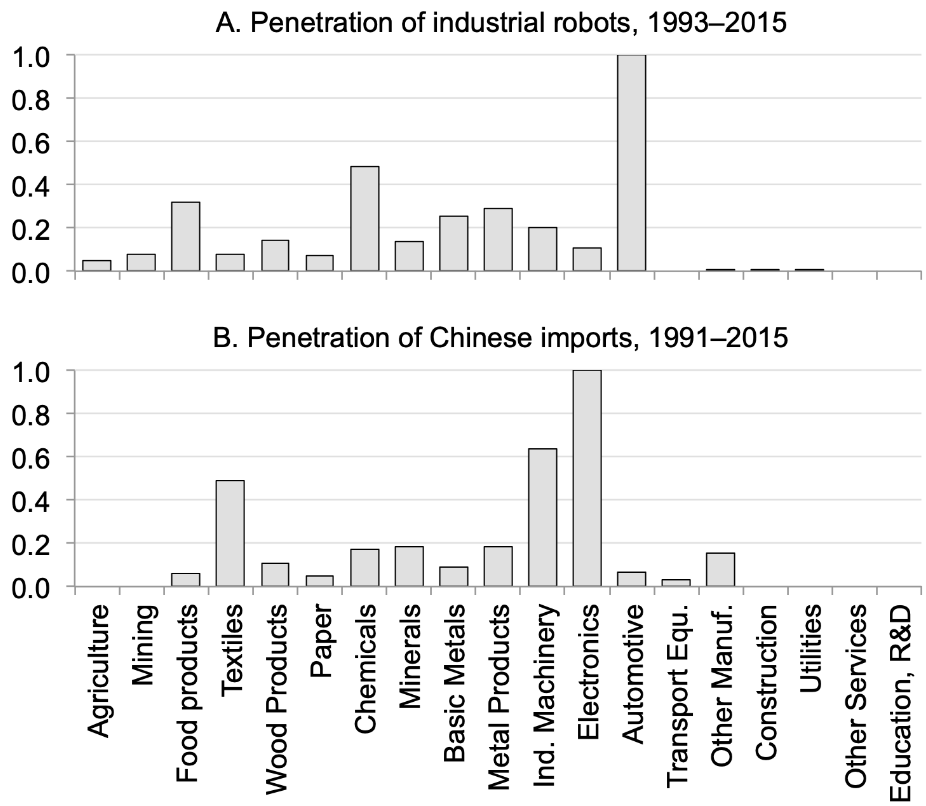
Figure A1: Temporal variation of robot adoption and Chinese imports



SOURCES: IFR (2021), United Nations (2019), Timmer et al. (2007)

Note: The dashed line represents the annual number of operational industrial robots in the US between 1993 and 2015 per 1,000 workers in 1990. The dotted line plots total annual imports from China to the US between 1991 and 2015 per worker in 1990 (in 2015 USD).

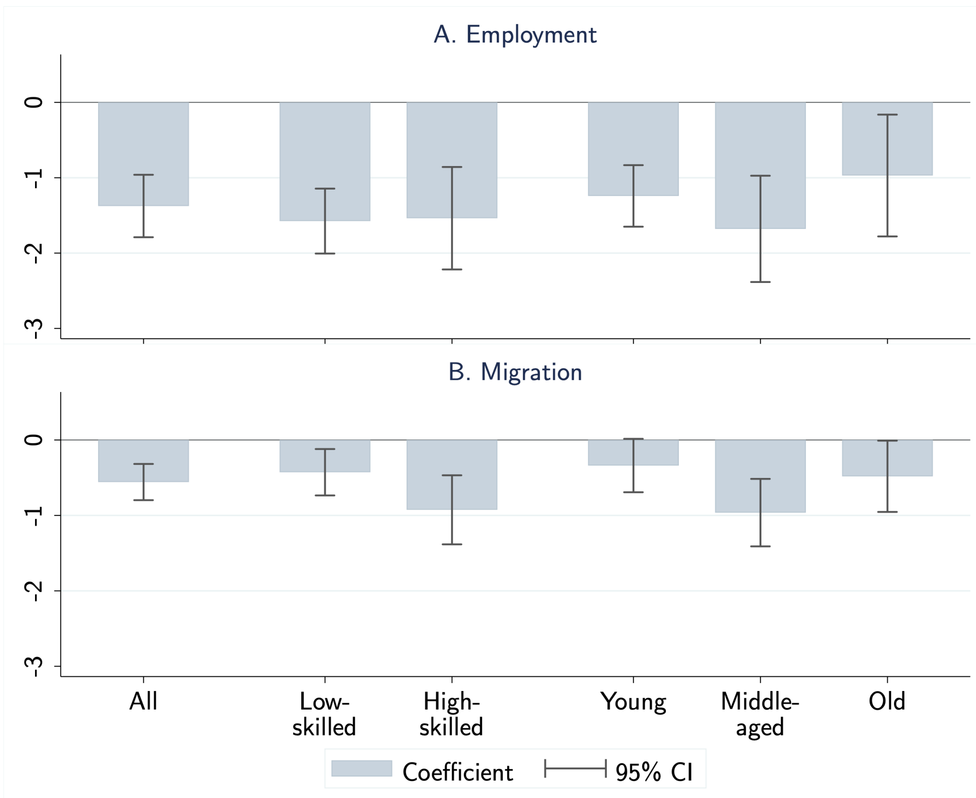
Figure A2: Industry variation of robot adoption and Chinese imports



SOURCES: IFR (2021), United Nations (2019), Timmer et al. (2007)

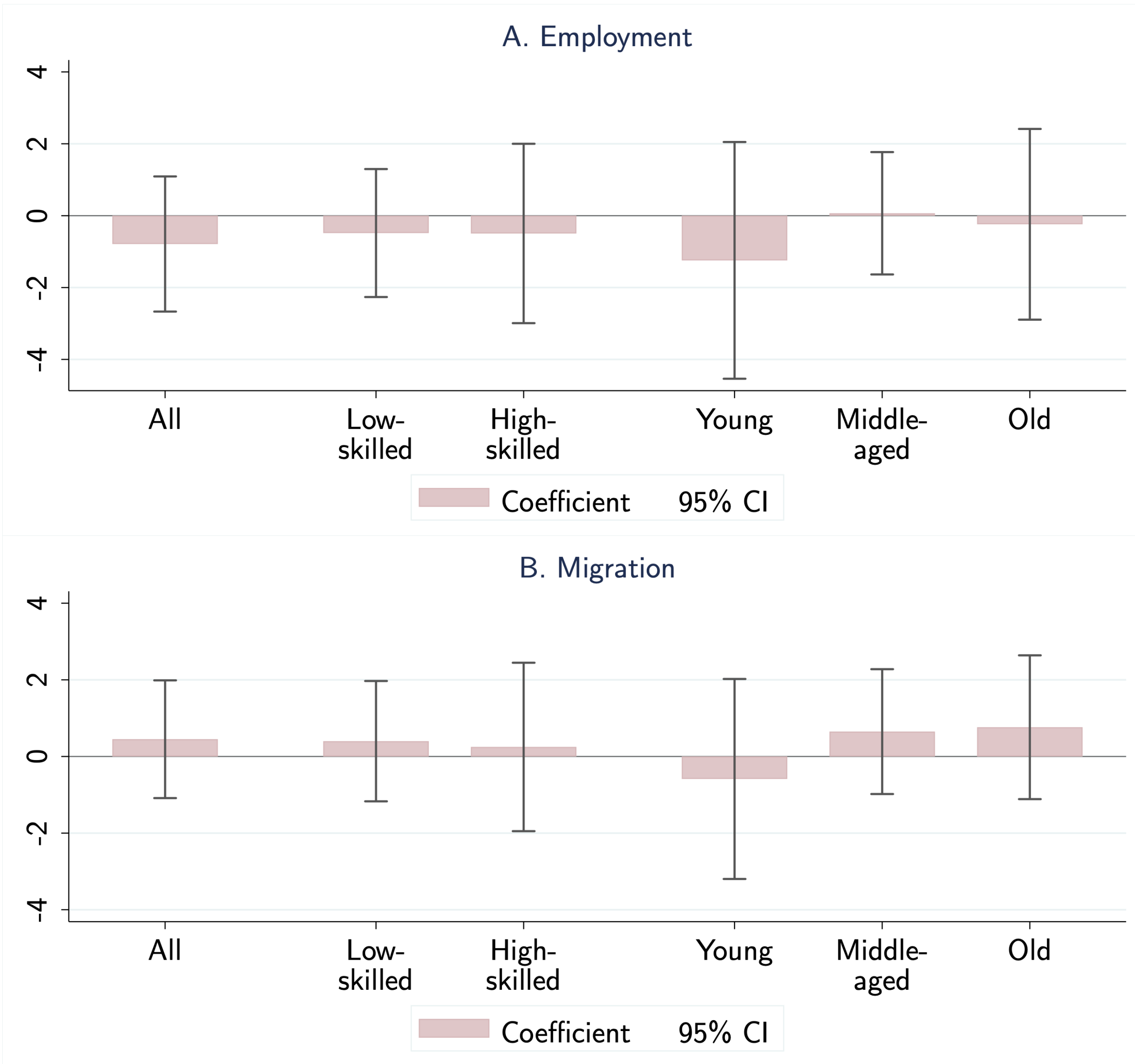
Note: Panel A presents the growth in the number of industrial robots per worker in 1990 in five European countries (Denmark, Finland, France, Italy, Sweden) between 1993 and 2015. Panel B shows the increase in imports from China to eight high-income countries (Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, Switzerland) per US worker in 1990 between 1991 and 2015. In both panels, values are normalized such that the industry with the highest growth has a value of 1, and the industries with the lowest growth has a value of zero.

Figure A3: Effect of robots on employment and migration by subgroup



Note: Panels A and B present the coefficient on the US exposure to robots in a regression identical to the one in Table 2, column 5, using log changes in subgroup-specific employment and working-age population as the outcome variable, respectively, and weighting observations by a CZ's 1990 national share of the respective outcome subgroup.

Figure A4: Effect of Chinese imports on employment and migration by subgroup



Note: Panels A and B present the coefficients on the US exposure to Chinese imports in a regression identical to the one in Table 2, column 5, using log changes in subgroup-specific employment and working-age population as the outcome variable, respectively, and weighting observations by a CZ's 1990 national share of the respective outcome subgroup.

Table A1: Effects on employment and migration (without adjustment term in (US) exposure to robots), stacked differences (2SLS)

	(1)	(2)	(3)	(4)	(5)	(6)
	Employment			Migration		
	Total	Manuf.	Non-manuf.	Pop.	In-mig.	Out-mig.
US exposure to	-1.42***	-1.08***	-1.61***	-0.62***	-1.54***	0.29
robots without adjustment	(0.33)	(0.33)	(0.47)	(0.16)	(0.40)	(0.41)
US exposure to	-0.86	-5.38***	0.56	0.42	1.61	0.48
Chinese imports	(1.00)	(1.61)	(1.01)	(0.79)	(1.12)	(1.43)

Note: The dependent variables are the log changes of the subgroup specified in each column. Columns 1–3 focus on employment and columns 4–6 on migration. In columns 1–4 and 5–6, the number of observations is N=2,166 and N=1,444, respectively. The exposure to robots and exposure to Chinese imports variables are standardized to have a mean of 0 and a standard deviation of 1. The (US) exposure to robots variables are constructed without subtracting the industry growth adjustment term as specified in Equation (2). All columns include the full set of covariates interacted with time period dummies, i.e., census division dummies, 1990 demographic characteristics (i.e., log population, share of men, share of population above 65 years old, share of population with less than a college degree, share of population with some college or more, population shares of Hispanics, Blacks, Whites and Asians, and the share of women in the labor force), 1990 shares of employment in broad industries (i.e., agriculture, mining, construction, manufacturing), and the 1990 share of routine jobs and the average offshorability index, following Autor and Dorn (2013). Moreover, they include the change in the outcome variable in the pre-period (i.e., 1970–1990 in columns 1–4 and 1992–2000 in columns 5–6). Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the state level (48 states). Regressions are weighted by a CZ's 1990 national share of the outcome group in columns 1–4 and a CZ's 1990 national share of the overall population in columns 5–6. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

Table A2: First-stages and effects on migration with partial instrumentation

	(1)	(2)	(3)	(4)	(5)
	A. First stage, US exposure to robots				
Exposure to robots	0.79***	0.79***	0.82***	0.79***	0.78***
	(0.07)	(0.07)	(0.06)	(0.07)	(0.07)
Exposure to Chinese imports	0.21***	0.21***	0.20***	0.08*	0.10*
	(0.05)	(0.05)	(0.04)	(0.05)	(0.05)
	B. First stage, US exposure to Chinese imports				
Exposure to robots	0.00	0.00	0.01	-0.03***	-0.02***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Exposure to Chinese imports	0.65***	0.65***	0.64***	0.50***	0.49***
	(0.06)	(0.06)	(0.06)	(0.07)	(0.07)
	C. Only robots instrumented (2SLS)				
US exposure to robots	-1.23***	-0.67***	-0.69***	-0.63***	-0.57***
	(0.43)	(0.23)	(0.18)	(0.13)	(0.13)
Exposure to Chinese imports	0.10	-0.18	0.03	0.15	0.22
	(0.63)	(0.51)	(0.50)	(0.42)	(0.39)
First-stage F	124.4	132.9	156.8	114.1	109.5
	D. Only Chinese imports instrumented (2SLS)				
Exposure to robots	-0.97***	-0.53***	-0.57***	-0.49***	-0.44***
	(0.26)	(0.15)	(0.14)	(0.10)	(0.10)
US exposure to Chinese imports	-0.25	-0.49	-0.17	0.21	0.34
	(0.98)	(0.82)	(0.82)	(0.85)	(0.80)
First-stage F	116.0	116.3	104.5	52.6	49.5
Region × time	✓	✓	✓	✓	✓
Pre-trends		✓	✓	✓	✓
Demographics × time			✓	✓	✓
Industry shares × time				✓	✓
Contemp. changes × time					✓

Note: The dependent variable in Panels A and B is the US exposure to robots and the US exposure to Chinese imports, respectively. The dependent variable in Panels C and D is the change in the log count of working-age individuals multiplied by 100 (i.e., $[\ln(y_{t+1}) - \ln(y_t)] \cdot 100$). There are three time periods and 722 CZs each period, resulting in N=2,166. All explanatory variables that are displayed are standardized to have a mean of 0 and a standard deviation of 1. All columns follow the same structure as Table 2. In Panel C, only US exposure to robots is instrumented for (exposure to Chinese imports included as control) and in Panel D only US exposure to Chinese imports is instrumented for (exposure to robots included as control). Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the state level (48 states). Regressions are weighted by a CZ's 1990 national share of the working-age population. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

Table A3: Estimates using controls from related literature (reduced form)

	(1)	(2)	(3)	(4)	(5)	(6)
	Employment				Population	
	Manuf.	Non-manuf.	Prof. serv.	Total	Census	IPUMS
	A. Baseline results (incl. covariates×time & pre-trends)					
Exposure to robots	-1.04***	-1.13***	-1.07***	-1.07***	-0.45***	-0.45***
	(0.29)	(0.16)	(0.22)	(0.12)	(0.10)	(0.10)
Exposure to Chinese imports	-2.79***	0.20	0.75	-0.52	0.17	-0.04
	(0.69)	(0.52)	(0.68)	(0.50)	(0.40)	(0.45)
	B. Controls from Autor et al. (2013)					
Exposure to robots	-1.88***	-1.53***	-1.22***	-1.81***	-0.65***	-0.62***
	(0.38)	(0.32)	(0.25)	(0.33)	(0.18)	(0.18)
Exposure to Chinese imports	-4.88***	-0.21	1.39	-1.82**	0.07	0.07
	(1.02)	(0.90)	(1.00)	(0.91)	(0.81)	(0.86)
	C. Controls from Acemoglu and Restrepo (2020)					
Exposure to robots	-1.44***	-1.18***	-0.65***	-1.48***	-0.24*	-0.17
	(0.31)	(0.28)	(0.18)	(0.28)	(0.13)	(0.14)
Exposure to Chinese imports	-3.90***	0.09	1.49*	-1.29*	0.45	0.50
	(0.79)	(0.74)	(0.88)	(0.68)	(0.52)	(0.56)
	D. Controls from Acemoglu and Restrepo (2020), (incl. covariates×time & pre-trends)					
Exposure to robots	-0.97***	-0.99***	-0.85***	-1.03***	-0.33***	-0.27**
	(0.29)	(0.18)	(0.19)	(0.16)	(0.12)	(0.13)
Exposure to Chinese imports	-2.52***	0.43	0.86	-0.21	0.32	0.09
	(0.65)	(0.53)	(0.72)	(0.48)	(0.39)	(0.42)

Note: The dependent variable in each column is the change in the log count of individuals in the specified subgroup, multiplied by 100. There are three time periods (1990–2000, 2000–7, 2007–15) and 722 CZs each period, resulting in N=2,166. Both explanatory variables that are displayed are standardized to have a mean of 0 and a standard deviation of 1. All outcome and displayed explanatory variables are converted to 10-year equivalents. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

Table A4: Effects on employment and migration by subgroup, stacked differences 1990–2015 (2SLS)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Education		Age			Birthplace	
	All	Low	High	Young	Middle	Old	US	Non-US
Average pop. 1990	214,245	109,259	104,986	71,658	98,253	44,334	190,697	22,101
				A. Employment				
US exposure to robots	-1.37***	-1.58***	-1.54***	-1.24***	-1.68***	-0.97**	-1.42***	0.09
	(0.21)	(0.22)	(0.35)	(0.21)	(0.36)	(0.41)	(0.24)	(0.70)
US exposure to Chinese imports	-0.79	-0.48	-0.50	-1.24	0.07	-0.24	-0.54	-1.50
	(0.96)	(0.91)	(1.27)	(1.68)	(0.87)	(1.35)	(1.17)	(3.67)
Kleibergen-Paap F	28.0	27.8	27.4	27.7	29.3	25.4	26.6	34.1
				B. Migration				
US exposure to robots	-0.56***	-0.43***	-0.93***	-0.34*	-0.96***	-0.48**	-0.75***	1.06
	(0.12)	(0.16)	(0.23)	(0.18)	(0.23)	(0.24)	(0.17)	(0.68)
US exposure to Chinese imports	0.45	0.40	0.25	-0.59	0.65	0.76	0.17	0.18
	(0.78)	(0.80)	(1.12)	(1.33)	(0.83)	(0.96)	(1.00)	(2.90)
Kleibergen-Paap F	25.3	25.7	24.8	26.3	25.9	23.7	24.6	31.1

Note: The dependent variables in Panel A and B are each subgroup's change in the log count of employment and working-age population, respectively, multiplied by 100 (i.e., $[\ln(y_{t+1}) - \ln(y_t)] \cdot 100$). There are three time periods and 722 CZs each period, resulting in N=2,166. Both explanatory variables that are displayed are standardized to have a mean of 0 and a standard deviation of 1. All columns include the full set of covariates interacted with time period dummies, i.e., census division dummies, 1990 demographic characteristics (i.e., log population, share of men, share of population above 65 years old, share of population with less than a college degree, share of population with some college or more, population shares of Hispanics, Blacks, Whites and Asians, and the share of women in the labor force), 1990 shares of employment in broad industries (i.e., agriculture, mining, construction, manufacturing), and the 1990 share of routine jobs and the average offshorability index, following Autor and Dorn (2013). Moreover, they include the change in the outcome variable between 1970 and 1990. Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the state level (48 states). Regressions are weighted by a CZ's 1990 national share of the outcome group. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

Additional Material (Not for publication)

Table of Contents

B Details on the Construction of Shocks

In this section, we explain in detail the construction of the exposure measures used in the regression analysis. First, following Acemoglu and Restrepo (2020), we define a CZ's *US exposure to robots* as a Bartik-style measure based on each industry's robot penetration in the US between t and $t+1$ (adjusted for the overall expansion of each industry) and baseline industry employment shares in CZ c. Formally, we construct

$$\begin{array}{c}\text{US exposure to}\\ \text{robots}_{c,t}\end{array} \equiv \sum_{i \in I} \ell_{ci,1990} \left(\frac{R^{US}_{i,t+1} - R^{US}_{i,t}}{L^{US}_{i,1990}} - g^{US}_{i,t:t+1} \frac{R^{US}_{i,t}}{L^{US}_{i,1990}} \right) \tag{2}$$

where $R^{US}_{i,t}$ and $L^{US}_{i,t}$ refer to the number of robots and employed people in US industry i at time t, $\ell_{ci,1990} = L_{ci,1990}/L_{c,1990}$ is the 1990 employment share of industry i in CZ c, and $g^{US}_{i,t:t+1}$ is US industry i's output growth rate between t and $t+1$.

To address the concern that changes in local labor market conditions may cause robot adoption in specific industries at the national level, we replace US industries' robotization with that occurring in five European countries, and lag the baseline employment shares, $\ell_{ci,1990}$, with those of 1970:

$$\begin{array}{c}\text{Exposure to}\\ \text{robots}_{c,t}\end{array} \equiv \sum_{i \in I} \ell_{ci,1970} \frac{1}{5} \sum_{j \in EU5} \left(\frac{R^{j}_{i,t+1} - R^{j}_{i,t}}{L^{j}_{i,1990}} - g^{j}_{i,t:t+1} \frac{R^{j}_{i,t}}{L^{j}_{i,1990}} \right) \tag{3}$$

where j indicates the five European countries – Denmark, Finland, France, Italy, and Sweden.

Next, following Autor et al. (2013), we construct a CZ's *US exposure to Chinese imports*, by interacting Chinese import growth in a given industry at the national (US) level between t and $t+1$ with the initial industry employment shares in CZ c:

$$\begin{array}{c}\text{US exposure to}\\ \text{Chinese imports}_{c,t}\end{array} \equiv \sum_{i \in I} \ell_{ci,t} \left(\frac{M^{CNUS}_{i,t+1} - M^{CNUS}_{i,t}}{L^{US}_{i,t}} \right) \tag{4}$$

where $M^{CNUS}_{i,t}$ is the value of Chinese imports to the US in industry i at time t. To alleviate further endogeneity concerns, we define *Exposure to Chinese imports* by replacing Chinese imports to the US with those to eight high-income countries other than the US between t and $t+1$. Similar to what we do for robot penetration, we replace the initial industry employment shares in CZ c with lagged shares following Autor et al. (2013).[27] In particular, we construct

$$\text{(5)} \qquad \begin{array}{c}\text{Exposure to}\\ \text{Chinese imports}_{c,t}\end{array} \equiv \sum_{i \in I} \ell_{ci,t-1} \left(\frac{M_{i,t+1}^{CNOT} - M_{i,t}^{CNOT}}{L_{i,t}^{US}} \right)$$

where $M_{i,t}^{CNOT}$ is the sum of Chinese imports to eight other high-income countries (Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, Switzerland) in industry i at time t. [28]

[27] Autor et al. (2013) use (lagged) beginning-of-each-period industry employment shares, rather than fixing them at (1970) 1990, as Acemoglu and Restrepo (2020) do. For consistency, we follow Autor et al. (2013) here. Reassuringly, results (not reported for brevity) are robust to using fixed shares accordingly.

[28] The US exposure to robots and Chinese imports variables are conceptually similar, but differ in so far as the robots variables include an adjustment term to account for output growth in an industry, which may cause the adoption of robots even in the absence of technological improvements. For comparability with existing literature, we include this adjustment term in our main specifications. However, we show in Table A1 that our results remain unchanged if this term is omitted.

C Data Appendix

C.1 Data on migration and other covariates

As noted in Section 3 in the paper, the key outcome of interest in our analysis is the change in the log number of individuals of demographic group Y living in CZ c between period t and $t+1$, $\Delta \ln Y_{c,t} = \ln Y_{c,t+1} - \ln Y_{c,t}$. While our main focus is on working-age population (15-64 years old), we also consider other subgroups (e.g., by employment status, birthplace, education, and age). When examining the mechanisms, we turn to changes in subgroup-specific employment as a share of total employment, $\Delta s^{Y}_{c,t} = \frac{Y_{c,t+1} - Y_{c,t}}{L_{c,t}}$, where $Y_{c,t}$ denotes the number of workers in subgroup Y (e.g., a certain skill-industry combination such as routine, manual occupations in manufacturing), and $L_{c,t}$ denotes overall employment in CZ c at time t. When using a stacked differences dataset containing changes from 1990–2000, 2000-7 and 2007–15, we inflate changes in the two latter periods to 10-year equivalents for comparability.[29]

Most outcome variables and covariates are taken from IPUMS census samples for 1970, 1980, 1990, and 2000, and from the American Community Survey (ACS) for 2007 and 2015 (Ruggles et al., 2018). The sample size varies between 1 and 5% of the overall US population depending on the year.[30] The main advantage of this data is that it offers a rich set of covariates for each sampled individual, such as birthplace, education levels, age, employment status, industry, and occupation.[31]

We complement this dataset with two other sources. First, we collect data on aggregate county population from the intercensal estimates of the US Census Bureau. These have the advantage that they are based on full count census data as opposed to 1–5% samples, but the disadvantage that they do not feature detailed demographic characteristics. When using changes in aggregate (working-age) population, we rely on the intercensal estimates; instead, when examining subgroups of the population (by birthplace, education, age, employment status), we use IPUMS samples. The second additional source of data is the county-to-county migration counts from the Internal Revenue Service (IRS). These counts are based on 1040 tax return filings, which include an individual's address for every year. By tracking address changes from one year to the next, the IRS is able to report the number of in- and

[29] That is, we divide changes in both the dependent and explanatory variables from 2000–7 and 2007–15 by 0.7 and 0.8, respectively, as in Acemoglu and Restrepo (2020) and Autor et al. (2013).

[30] When using ACS data, we use 3-year samples to increase sample size.

[31] The lowest geographic unit available in this dataset are county groups (1970 and 1980) and Public Use Microdata Areas (PUMAs). These are combinations of counties containing at least 250,000 (1970) or 100,000 people. Since some of these overlap with more than one CZ, we employ the crosswalks used in Autor et al. (2013), which are based on a probabilistic assignment of individuals into a CZ and are available at `https://www.ddorn.net/data.htm`.

out-migrants of each county for all years since 1990. We aggregate this data to the CZ level, treating moves across counties but within a CZ as non-migrants.

Finally, we compute baseline CZ demographic characteristics and broad industry employment shares from the IPUMS samples. We also consider two major contemporaneous changes to the demand for specific skills as potential confounders: the automation of routine tasks by computers and offshoring to cheap labor locations. To control for these, we include the initial shares of routine jobs and offshorable tasks (Autor and Dorn, 2013).

C.2 Data on industrial robots

The IFR collects data on shipments and operational stocks of *industrial robots* by country and industry since 1993 "based on consolidated data provided by nearly all industrial robot suppliers world-wide" (IFR, 2021, p.25). Industrial robots are defined as "automatically controlled, reprogrammable, multipurpose manipulator[s] programmable in three or more axes, which can be either fixed in place or mobile for use in 13 industrial automation applications" (IFR, 2021, p.29). Typical applications of industrial robots are pressing, welding, packaging, assembling, painting and sealing (common in manufacturing industries), and harvesting and inspecting of equipment (prevalent in agriculture and the utilities industry) (IFR, 2021, p.31–38).

The IFR data has a few limitations. While it reports aggregate robot stocks from 1993 onwards, it only contains a breakdown by industry for the US starting in 2004. For the years before 2004, we therefore attribute the aggregate number of robots to industries proportionally to industries' shares of the overall stock in 2004 (following Acemoglu and Restrepo, 2020). Moreover, the IFR classification contains three industries that do not directly correspond to an industry covered in the US census data. These are "Other manufacturing" and "Other non-manufacturing" as well as "Unspecified". We attribute these robots according to each industry's share of robots within each of these categories.[32] Finally, robot shipments to the US also include robot shipments to Canada and Mexico before 2011. Even though this introduces measurement error, it is worth noting that the US accounts for the vast majority of robot shipments to North America (over 90%). Our IV strategy, discussed in detail in Section 2.2, should correct for this kind of measurement error.

[32] For example, robots reported as "Other manufacturing" are assigned to more specific manufacturing industries in a way that is proportional to each industry's share of precisely assigned robots in manufacturing.

C.3 Skill content of occupation groups

In Section 5, we investigate the effects of robots and Chinese imports on employment by industry-skill group. While industries are well defined, the concept of *skills* is slightly more vague. Two potential proxies for skills are education levels and occupations. We decide to use the latter, and in particular, the predominant task requirement of occupation groups. The main advantage of using occupational task requirements is that it seems more tightly connected to the capabilities of some technologies. For the same reason, the existing literature also focuses on tasks rather than education levels. In light of some of the literature's findings, using education levels may even yield misleading results. For example, automation of routine tasks may displace low-education workers performing routine occupations (machine operators), but have positive spillovers on non-routine, low-education occupations (personal services). Examining only the subgroup "low-educated" workers would miss this crucial nuance. Therefore we prefer occupational task requirements over education levels as a proxy for skills.

We follow Autor et al. (2003) in differentiating skills along four dimensions: abstract/routine and cognitive/manual. We use data from the Dictionary of Occupational Titles (DOT) from 1980 to get a proxy for the average task intensity in each of these dimensions for eight occupation groups. In particular we use the following variables from the DOT, each of which is rated from zero (low) to ten (high):

- **Abstract:** Average of *Variety & change* and *Dealing with people*
- **Routine:** *Working under specific instructions*
- **Cognitive:** *Numerical aptitude*
- **Manual:** Average of *Eye-hand-foot coordination* and *Manual dexterity*

We then compute the four products of abstract/routine and cognitive/manual, respectively, and choose the skill dimension with the largest value as an occupation's predominant skill requirement. The results of this are shown in Table C1. Using this methodology, managerial & professional as well as sales support occupations require mainly abstract, cognitive skills. Administrative support & clerical occupations are the only group requiring mainly routine, cognitive skills, and machine operators, fabricators & laborers the only one requiring mainly routine, manual skills. All remaining groups (technical support, services – such as nurses, janitors, cooks – agricultural, crafts & repair) use mostly abstract, manual abilities.

Table C1: Occupation Groups and Skill Content

	Skill dimension			
	Cognitive		Manual	
Occupation group	Abstract	Routine	Abstract	Routine
Managerial, professional	+	–	–	–
Technical support	–	–	+	–
Sales support	+	–	–	–
Administrative support	+	+	–	+
Services	–	+	+	+
Agricultural	–	–	+	+
Production, crafts, repair	+	+	+	–
Operators, laborers	–	+	–	+

Note: Skill content of occupation groups along four dimensions. Areas shaded in gray indicate the highest value for each occupation group. Plus and minus signs indicate that the score of this occupation group is above and below the median of all groups, respectively.

D Robustness Checks

D.1 Pre-trends

One potential threat to our identification strategy is that areas more exposed to robots and Chinese imports may have experienced differential migration trends prior to the treatment period. For example, if areas more exposed to robots had significantly lower population growth before the invention of robots, our results may reflect secular trends in migration patterns and not the effect of robots. Our analysis controls for potential pre-existing trends by including them as a covariate. However, to provide greater clarity on pre-existing patterns, we explore these more directly in this section.

We estimate the same regressions as before, now focusing on years 1970–1990, a time when robot technology was, if anything, still in its infancy and China had not started its surge in exports. We regress changes in the log counts of the working-age population in this pre-period on the *future* exposure to robots and Chinese imports, defined as the average exposure in the three subsequent time periods 1993/91–2000, 2000–7 and 2007–15. Results are reported in columns 1 and 2 of Table D1. In column 1, we include all the covariates from our preferred specification (Table 2, column 5), except for the contemporaneous changes, which may have played a smaller role between 1970 and 1990. In column 2, we include also the control variables for contemporaneous changes interacted with time periods, so as to replicate exactly our preferred specification. Reassuringly, coefficients are not statistically significant in either column.

In columns 1 and 2, we cannot detect any statistically significant pre-trends in overall population growth in areas exposed to robots or Chinese imports, given the standard errors of the estimates. However, the point estimates are relatively similar (e.g., –0.59 in column 2 compared to –0.56 in our preferred specification). It is thus possible that not accounting for pre-trends may bias our results. In particular, if population growth patterns are persistent, the coefficients on the exposures to robots and to Chinese imports may be biased. For this reason, we control for pre-trends in all of our results.

In columns 3–6, we again turn to the period 1990–2015 and explore how sensitive our main results are to the inclusion of pre-trends in different ways. In column 3, we repeat our main specification from column 5, Panel B of Table 2, which includes the change in the log working-age population between 1970 and 1990. Note that the effect of the pre-trends themselves is positive and statistically significant at the 1% level, suggesting that there is some persistence in population growth patterns over time. Column 4 replicates column 3 without including pre-trends. Not accounting for pre-trends changes the estimated coefficient on the exposure to robots and Chinese imports in the expected direction. Compared to our preferred specification, the effect of robots becomes slightly larger in absolute value (–0.68 vs. –0.56) and remains statistically significant at conventional levels. The effect of Chinese imports becomes more positive and appears to be marginally statistically significant (at the 10% level) when not accounting for pre-trends.

In columns 5 and 6, we probe the robustness of our findings to different strategies for accounting for pre-trends. In column 5, we interact changes in log working-age population from 1970–90 with time period dummies, thus allowing pre-existing trends to potentially dissipate over time. The effects of robots and Chinese imports remain unchanged, and there is some evidence for pre-existing patterns becoming less important over time. In column 6, we include the change in working-age population during the preceding period (rather than from 1970 to 1990). We are worried that by doing so, we might add a variable that has itself been affected by robots and Chinese imports (i.e., a "bad control" using the terminology in Angrist and Pischke, 2008). Nonetheless, it is reassuring that our main results remain unchanged also in this specification.

In sum, these results indicate that our estimates are unlikely to be influenced by pre-existing differential trends in population growth across CZs. As an additional robustness exercise, we also replicated our analysis replacing region-time dummies ($9 \times 3 = 27$) with more granular state-time dummies ($48 \times 3 = 144$), in order to account for any state-specific, time-varying unobservable characteristics. Reassuringly, results remain almost identical (i.e., -0.59** vs. -0.56*** for robots, and statistically insignificant, positive coefficients for China).

Table D1: Effects on migration, pre-trends (2SLS)

	(1)	(2)	(3)	(4)	(5)	(6)
	1970–1990		1990–2015			
US exposure to robots	-0.56	-0.59	-0.56***	-0.68***	-0.57***	-0.39**
	(0.35)	(0.36)	(0.12)	(0.23)	(0.12)	(0.16)
US exposure to Chinese imports	0.82	1.02	0.45	1.39*	0.28	0.91
	(0.83)	(0.69)	(0.78)	(0.71)	(0.78)	(0.59)
Δ_{70-90} log working-age population			0.38***			
			(0.09)			
Δ_{70-90} log working-age population × 1990–2000					0.49***	
					(0.16)	
Δ_{70-90} log working-age population × 2000–2007					0.49***	
					(0.07)	
Δ_{70-90} log working-age population × 2007–2015					0.14***	
					(0.04)	
Δ_{t-1} log working-age population						0.35***
						(0.12)
Kleibergen-Paap F	70.7	73.0	25.3	24.9	25.7	25.3
Region × time	✓	✓	✓	✓	✓	✓
Demog. × time & ind. sh. × time	✓	✓	✓	✓	✓	✓
Contemp. changes × time		✓	✓	✓	✓	✓

Note: The dependent variable is the decadal change in the log working-age population multiplied by 100 (i.e., $[\ln(y_{t+1}) - \ln(y_t)] \cdot 100$). In columns 1–2 and 3–6, there are two and three time periods and 722 CZs each period, resulting in N=1,444 and N=2,166, respectively. In columns 1–2, US exposure to robots/Chinese imports refers to the average of the changes from 1993/91–2000, 2000–7 and 2007–15. Both US exposure variables are standardized to have a mean of 0 and a standard deviation of 1. All columns includes census division dummies, initial demographic characteristics (i.e., log population, share of men, share of population above 65 years old, share of population with less than a college degree, share of population with some college or more, population shares of Hispanics, Blacks, Whites and Asians, and the share of women in the labor force) and initial shares of employment in broad industries (i.e., agriculture, mining, construction, manufacturing), each interacted with time period dummies. Columns 2–6 also include the initial share of routine jobs and the average offshorability index, following Autor and Dorn (2013), each interacted with time period dummies. Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the state level (48 states). Regressions are weighted by a CZ's initial share of the national working-age population. In columns 1–2, the initial values refer to the year 1970, in columns 3–6 to the year 1990. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

D.2 Alternative definition of Chinese imports

In contrast with our results, Greenland et al. (2019) find that Chinese imports triggered a migration response. However, their analysis differs from ours in that they rely mostly on the Pierce and Schott (2016) definition of the shock, and estimate stacked difference regressions for the time periods 1990–2000 and 2000–2010. Since we are worried about the Great Recession as a potential confounder, in our baseline specification, we chose to end our second period in 2007. In Table D2, we explicitly test whether using the Pierce and Schott (2016) treatment of the Chinese imports shock changes our results. The effect of Chinese imports on population growth is negative and statistically significant only when using a relatively parsimonious specification. However, these results are not robust to controlling for demographics, industry shares or contemporaneous changes, or to focusing on the time period before 2007. We thus interpret the discrepancy between our findings and those in Greenland et al. (2019) as due to the different (more stringent) set of controls included in our analysis.

D.3 Alternative mechanisms

We now explore the possibility that the two shocks may differ systematically along key dimensions, and for this reason led to differential migration responses. Broadly, we view these alternative explanations as falling in two (non-mutually exclusive) categories: first, the two shocks may differ in the time period during which they affected the economy; second, the set of regions exposed to either shock may differ according to some pre-existing characteristics.

Affected time periods. First, the two shocks may differ from each other in terms of the time period, and thus the macroeconomic conditions, during which they hit the economy. This may in turn affect the transmission of a shock throughout the economy and, in particular, whether or not it induces a migration response. For instance, it is conceivable that prospective in-migrants are more cautious in their location choice when labor markets are slacker at the national level. In the case of the two shocks we consider, the surge in Chinese imports had largely flattened out before the Great Recession, whereas the introduction of robots steadily continued at a similar speed during and after the crisis. However, in what follows, we document that differences in the macro-economic environment pre-post the Great Recession cannot explain the differential effects estimated above.

First, we estimate the migration response to both shocks now omitting the post-2007 period. Results are reported in Panel A of Table D4, which follows the same structure of Table 2. The pattern is almost identical to our initial results that included the post-2007 period: throughout all specifications, robots have a significant, negative impact on

Table D2: Effects on migration, Pierce and Schott (2016) Chinese import shock (reduced form)

	(1)	(2)	(3)	(4)	(5)	(6)
	1990–2015			1990–2007		
	A. Interacting baseline controls with time dummies					
Exposure to robots	-0.46***	-0.50***	-0.46***	-0.36***	-0.36***	-0.34***
	(0.13)	(0.11)	(0.10)	(0.12)	(0.11)	(0.10)
NTR Gap × post-2000	-1.14***	0.18	-0.15	-0.65	0.19	-0.22
	(0.32)	(0.61)	(0.49)	(0.50)	(0.72)	(0.60)
	B. Not interacting baseline controls with time dummies					
Exposure to robots	-0.34***	-0.41***	-0.36***	-0.31**	-0.33**	-0.28**
	(0.12)	(0.11)	(0.10)	(0.12)	(0.13)	(0.12)
NTR Gap × post-2000	-0.98***	-0.20	-0.43	-0.38	0.00	-0.20
	(0.36)	(0.61)	(0.56)	(0.54)	(0.52)	(0.50)
Region dummies & pre-trends	✓	✓	✓	✓	✓	✓
Demographics & industry shares		✓	✓		✓	✓
Contemp. changes			✓			✓

Note: The dependent variable is the change in the log working-age population. In columns 1–3 there are three time periods (1990–2000, 2000–7 and 2007–15) and 722 CZs each period, resulting in N=2,166. In columns 4–6, the time period 2007–15 is dropped, resulting in N=1,444. All explanatory variables that are displayed are standardized to have a mean of 0 and a standard deviation of 1. Columns 1 and 4 include census division dummies, time period dummies, and the outcome variable between 1970 and 1990 as covariates. Columns 2 and 5 also control for demographic characteristics (i.e., log population, share of men, share of population above 65 years old, share of population with less than a college degree, share of population with some college or more, population shares of Hispanics, Blacks, Whites and Asians, and the share of women in the labor force) and 1990 shares of employment in broad industries (i.e., agriculture, mining, construction, manufacturing). In Panel A, census division dummies, demographic characteristics, broad industry shares and contemporaneous changes are interacted with time period dummies. Columns 3 and 6 also include the share of routine jobs and the average offshorability index in 1990, following Autor and Dorn (2013), each interacted with time period dummies. Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the state level (48 states). Regressions are weighted by a CZ's 1990 national share of the working-age population. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

population growth, whereas Chinese imports have no effect. As before, the effect of robots roughly halves in size after including a more stringent set of covariates. According to our preferred specification (column 5), the magnitude of the effect is almost identical to that estimated including the post-2007 period (–0.56 vs. –0.62). Given their standard errors, these are not statistically different from each other. Moreover, even in this pre-2007 period we do not detect any migration response to Chinese imports in any of the specifications.

Second, in Panel B of Table D4, we return to the full sample (incl. post-2007), but now add interactions between shocks and a post-2007 dummy. We are particularly interested in the coefficient on the interaction between exposure to robots and the post-2007 period dummy. If recessionary conditions mediate the migration response to robots, the coefficient on the interaction should be significant (negative or positive, depending on the direction of the effect of the Great Recession). Results from our most preferred specification (column 5) show that this is not the case. The coefficient on the interaction term is negative but not statistically significant, suggesting that the size of the migration response to robots does not significantly differ between the pre- and post-crisis period.

Affected regions. Even if regions affected by robots and by Chinese imports are relatively similar, one may be worried that some differences exist between them along a few variables (Table 1). To address this concern, we include all such variables as controls in our preferred specification to account for potential confounding effects along these characteristics. However, one may still be worried that the mediation of the employment effect (and in particular, whether it causes a migration response) depends on some of these characteristics. For example, it is possible that the same shock only causes a migration response in areas with a large share of college-educated individuals. If areas affected by robots housed significantly more college-educated workers, the reason for the differential migration response between the two shocks might partly lie in the initial characteristics of the affected regions, rather than in the shocks themselves. To rule out this possibility, we run a battery of tests (unreported) in which we interact each of the shocks with the initial covariates that significantly differ between the regions affected by the two shocks (as in Table 1, column 8). Reassuringly, none of these results support the view that differences in initial, observable characteristics of affected regions explain the differential migration response associated with the two shocks.

Table D3: Effects on migration, long differences (2SLS)

	(1)	(2)	(3)	(4)	(5)
			A. 1990–2015		
US exposure to robots	-1.28***	-0.70***	-0.73***	-0.85***	-0.77***
	(0.44)	(0.24)	(0.20)	(0.16)	(0.16)
US exposure to Chinese imports	0.25	-0.36	-0.22	-0.40	-0.48
	(0.64)	(0.47)	(0.51)	(0.58)	(0.58)
Kleibergen-Paap F	160.5	153.3	110.8	59.1	54.4
			B. 1990–2007		
US exposure to robots	-1.37**	-0.66**	-0.64***	-0.74***	-0.66***
	(0.54)	(0.26)	(0.25)	(0.19)	(0.20)
US exposure to Chinese imports	-0.11	-0.56	-0.30	-0.59	-0.54
	(0.98)	(0.80)	(0.80)	(0.85)	(0.86)
Kleibergen-Paap F	54.5	53.7	42.3	22.3	19.8
Region dummies	✓	✓	✓	✓	✓
Pre-trends		✓	✓	✓	✓
Demographics			✓	✓	✓
Industry shares				✓	✓
Contemp. changes					✓

Note: The dependent variable in Panel A and B is the 1990–2015 and 1990–2007 change in the log count of the working-age population, respectively, multiplied by 100 (i.e., $[\ln(y_{t+1}) - \ln(y_t)] \cdot 100$). There are N=722 CZs. All explanatory variables that are displayed are standardized to have a mean of 0 and a standard deviation of 1. Column 1 includes census division dummies as covariates. Column 2 also includes the change in the log count of the working-age population between 1970 and 1990. Column 3 also controls for 1990 demographic characteristics (i.e., log population, share of men, share of population above 65 years old, share of population with less than a college degree, share of population with some college or more, population shares of Hispanics, Blacks, Whites and Asians, and the share of women in the labor force). Column 4 also includes shares of employment in broad industries in 1990 (i.e., agriculture, mining, construction, manufacturing). Column 5 also includes the share of routine jobs and the average offshorability index in 1990, following Autor and Dorn (2013). Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the state level (48 states). Regressions are weighted by a CZ's 1990 national share of the working-age population. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

Table D4: Effects on migration, different time periods (2SLS and reduced form)

	(1)	(2)	(3)	(4)	(5)
			A. 1990–2007		
US exposure to robots	-1.11***	-0.49***	-0.53***	-0.48***	-0.42***
	(0.41)	(0.19)	(0.19)	(0.12)	(0.12)
US exposure to Chinese imports	-0.53	-0.83	-0.33	-0.17	0.01
	(1.18)	(1.03)	(0.93)	(1.07)	(1.01)
Kleibergen-Paap F	41.0	41.6	38.4	17.3	16.3
			B. 1990–2015 (with post-2007 interactions)		
Exposure to robots	-0.87***	-0.47***	-0.49***	-0.42***	-0.36***
	(0.25)	(0.15)	(0.15)	(0.10)	(0.10)
Exposure to Chinese imports	-0.46	-0.52	-0.20	0.04	0.12
	(0.67)	(0.57)	(0.54)	(0.43)	(0.40)
Exposure to robots	-0.25	-0.15	-0.19	-0.22	-0.23
× post-2007	(0.19)	(0.20)	(0.13)	(0.15)	(0.16)
Exposure to Chinese imports	1.11**	0.77*	0.30	0.20	0.16
× post-2007	(0.47)	(0.45)	(0.29)	(0.25)	(0.23)
Region × time	✓	✓	✓	✓	✓
Pre-trends		✓	✓	✓	✓
Demographics × time			✓	✓	✓
Industry shares × time				✓	✓
Contemp. changes × time					✓

Note: The dependent variable is the change in the log count of the working-age population multiplied by 100 (i.e., $[\ln(y_{t+1}) - \ln(y_t)] \cdot 100$). All explanatory variables that are displayed are standardized to have a mean of 0 and a standard deviation of 1. Panel A only includes two time periods (1990–2000, 2000–7) and Panel B includes all three (also 2007–15), resulting in N=1,444 and N=2,166, respectively. Column 1 includes only time period and census division dummies as covariates. Column 2 also includes the change in the outcome variable between 1970 and 1990. Column 3 also controls for 1990 demographic characteristics (i.e., log population, share of men, share of population above 65 years old, share of population with less than a college degree, share of population with some college or more, population shares of Hispanics, Blacks, Whites and Asians, and the share of women in the labor force). Column 4 also includes shares of employment in broad industries in 1990 (i.e., agriculture, mining, construction, manufacturing). Column 5 also includes the share of routine jobs and the average offshorability index in 1990, following Autor and Dorn (2013). Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the state level (48 states). Regressions are weighted by a CZ's 1990 national share of employment (Panel A) and the working-age population (Panel B). Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

D.4 Standard errors correction

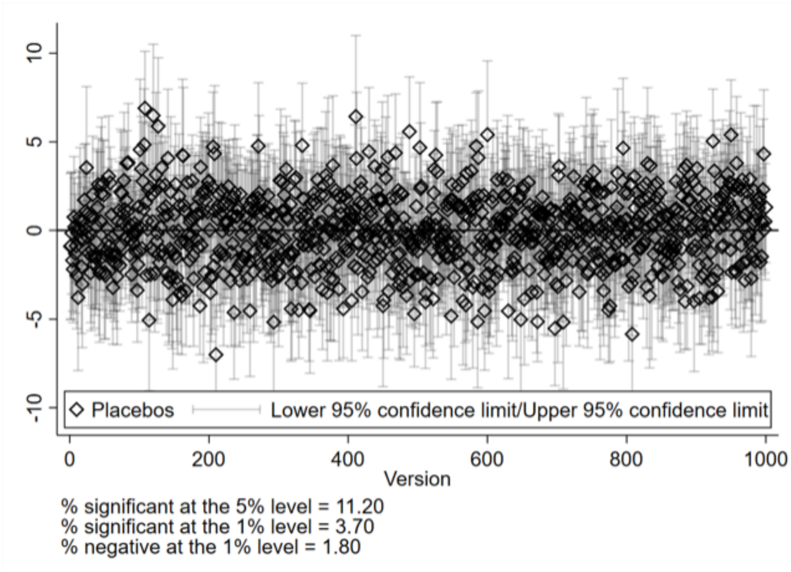
In our main results, standard errors allow for arbitrary clustering at the state level (48 states). It is, however, possible that errors are clustered not only within state borders, but across space more generally. For this reason, we perform a robustness exercise in Table D5, where we repeat the estimation of our preferred specification (column 5 in Table 2), estimating standard errors using the method proposed by Conley (1999). In particular, we allow for arbitrary spatial correlation with CZs that lie within varying distances, from less than 100 miles away (column 1) to less than 500 miles away (column 5). Reassuringly, although standard errors become slightly larger as we increase the radius, results remain unchanged.

In addition to spatial correlation, one concern with Bartik-style instruments is that standard inference procedures may deliver excessively small standard errors, if errors are correlated across observations that are geographically far apart but have similar employment shares (Adao et al., 2019). We address this issue by performing a set of placebo checks suggested by Adao et al. (2019). Similar to Derenoncourt (2022), we interact the employment shares used to construct the instruments for robots and Chinese imports with industry-specific shocks drawn from a random normal distribution.

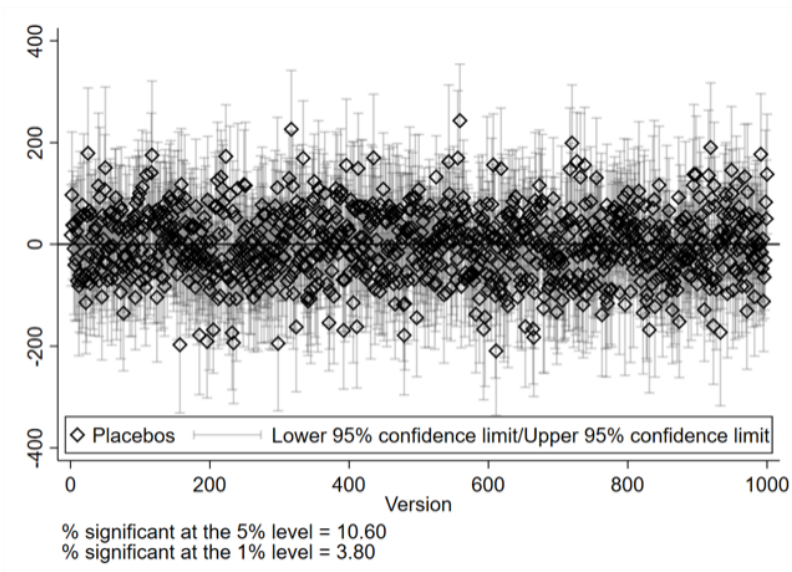
We iterate this procedure 1,000 times, and report the share of iterations for which results (for exposure to robots and to Chinese imports, respectively) are statistically significant at the 5% and 1% level. Panels A and B of Figure D1 document that the coefficients on the placebo instruments for exposure to robots and to Chinese imports are statistically significant at the 5% level 11.2% and 10.6% of the times, respectively. This is more than 5 times lower compared to the application shown in Adao et al. (2019), where the placebo shocks are statistically significant at the 5% level 55% of the times. Moreover, our placebo shocks are statistically significant at the 1% level only about 3.8% of the times.

Taken together, results in Figure D1 suggest that, even though standard errors may be too small due to the presence of correlated shocks, the estimated effects of robot exposure and Chinese import competition are unlikely to be driven by noise.

Figure D1: Placebo industry-level shocks



A. Exposure to robots



B. Exposure to Chinese imports

Note: This figure plots the coefficients on exposure to robots (Panel A) and exposure to Chinese imports (Panel B) in 1,000 separate reduced form regressions with randomly generated industry-level shocks. The specification is identical to column 5 in Table 2.

Table D5: Adjusting standard errors for spatial correlation following Conley (1999)

	(1)	(2)	(3)	(4)	(5)
	100 mi.	200 mi.	300 mi.	400 mi.	500 mi.
			A. Migration		
US exposure to robots	-0.56***	-0.56***	-0.56***	-0.56***	-0.56**
	(0.13)	(0.18)	(0.19)	(0.20)	(0.23)
US exposure to Chinese imports	0.45	0.45	0.45	0.45	0.45
	(0.76)	(0.73)	(0.74)	(0.76)	(0.77)
			B. House prices		
US exposure to robots	-2.55***	-2.55**	-2.55*	-2.55*	-2.55*
	(0.94)	(1.14)	(1.32)	(1.32)	(1.31)
US exposure to Chinese imports	0.49	0.49	0.49	0.49	0.49
	(2.94)	(2.78)	(2.69)	(2.43)	(2.67)
			C. In-migration		
US exposure to robots	-1.76***	-1.76***	-1.76***	-1.76***	-1.76***
	(0.54)	(0.57)	(0.61)	(0.67)	(0.65)
US exposure to Chinese imports	1.65	1.65	1.65	1.65	1.65
	(1.10)	(1.26)	(1.27)	(1.34)	(1.22)
			D. Out-migration		
US exposure to robots	-0.01	-0.01	-0.01	-0.01	-0.01
	(0.58)	(0.52)	(0.51)	(0.60)	(0.53)
US exposure to Chinese imports	0.43	0.43	0.43	0.43	0.43
	(1.46)	(1.54)	(1.51)	(1.63)	(1.61)

Note: The dependent variable in Panel A is the change in the log count of working-age individuals (15-64), in Panel B the change in the log house price index (see Section 4.1 for details), and in Panels C and D the log count of in-migrants and out-migrants, respectively. There are three time periods in Panel A, and two time periods in Panels B, C and D, and 722 CZs each period, resulting in N=2,166 and N=1,444, respectively. All explanatory variables that are displayed are standardized to have a mean of 0 and a standard deviation of 1. All columns include the full set of covariates interacted with time period dummies, i.e., census division dummies, 1990 demographic characteristics (i.e., log population, share of men, share of population above 65 years old, share of population with less than a college degree, share of population with some college or more, population shares of Hispanics, Blacks, Whites and Asians, and the share of women in the labor force), 1990 shares of employment in broad industries (i.e., agriculture, mining, construction, manufacturing), and the 1990 share of routine jobs and the average offshorability index, following Autor and Dorn (2013). Moreover, they include the change in the outcome variable in the pre-period (1970-1990 in Panel A, 1990/92-2000 in Panels B, C and D). Standard errors allow for arbitrary spatial correlation with CZs within 100 mi., 200 mi., 300 mi., 400 mi., and 500 mi. in columns 1, 2, 3, 4, and 5, respectively. Regressions are weighted by a CZ's 1990 national share of the outcome group in each Panel, respectively. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

D.5 Misspecification of conventional migration regression

Borusyak et al. (2022) show that conventional migration regressions may be misspecified due to the bilateral nature of location choices – if one CZ gains an individual, another CZ loses one. They show that one way to account for this possibility is to control for the migration-weighted shock to other locations, where weights reflect a CZ's intensity of migration flows between itself and each other CZ. In Table D6, we follow that advice and estimate the same regressions as in Table 2, but now controlling for migration-weighted exposures to robots and Chinese imports in other CZs. The weighted exposures to connected CZs are, in fact, positively correlated with own exposures, with population-weighted correlation coefficients of 0.32 for robots and 0.47 for Chinese imports. However, and crucially, this correlation cannot explain our results. In particular, even with these controls, results remain virtually identical to the ones in Table 2.

Table D6: Effects on migration (controlling for exposures to shocks in other CZs), stacked differences 1990–2015 (2SLS)

	(1)	(2)	(3)	(4)	(5)
	Working-age population count				
US exposure to robots	-0.93**	-0.46**	-0.68***	-0.63***	-0.55***
	(0.44)	(0.22)	(0.22)	(0.18)	(0.17)
US exposure to Chinese imports	-0.28	-0.53	-0.14	0.02	0.01
	(0.74)	(0.65)	(0.57)	(0.68)	(0.69)
Kleibergen-Paap *F*	61.8	61.8	56.9	26.8	25.1
Region × time	✓	✓	✓	✓	✓
Pre-trends		✓	✓	✓	✓
Demographics × time			✓	✓	✓
Industry shares × time				✓	✓
Contemp. changes × time					✓

Note: The dependent variable is the change in the log count the working-age population, multiplied by 100 (i.e., $[\ln(y_{t+1}) - \ln(y_t)] \cdot 100$). There are three time periods and 722 CZs each period, resulting in N=2,166. All explanatory variables that are displayed are standardized to have a mean of 0 and a standard deviation of 1. All columns control for *i)* the migration-weighted exposure to robots in other CZs, and *ii)* the migration-weighted exposure to Chinese imports in other CZs. Column 1 includes census division dummies interacted with time period dummies as covariates. Column 2 also includes the change in the outcome variable between 1970 and 1990. Column 3 also controls for 1990 demographic characteristics (i.e., log population, share of men, share of population above 65 years old, share of population with less than a college degree, share of population with some college or more, population shares of Hispanics, Blacks, Whites and Asians, and the share of women in the labor force), each interacted with time period dummies. Column 4 also includes shares of employment in broad industries in 1990 (i.e., agriculture, mining, construction, manufacturing), each interacted with time period dummies. Column 5 also includes the share of routine jobs and the average offshorability index in 1990, following Autor and Dorn (2013), each interacted with time period dummies. Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the state level (48 states). Regressions are weighted by a CZ's 1990 national share of the working-age population. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

D.6 In- and out-migration robustness checks

In Table E1, we define "close" and "far" moves using a threshold of 300 miles. This admittedly arbitrary cutoff is a convenient proxy for within-state and across-state moves. To verify that results are insensitive to the specific value chosen, we replicate the analysis using cutoffs of 200 miles and 400 miles, respectively. Results, reported in Tables D7 and D8, remain the same.

Table D7: Effects on in- and out-migration by distance, stacked differences 2000–2015 (2SLS)

	(1)	(2)	(3)	(4)	(5)	(6)
	In-migration			Out-migration		
	Overall	<200 mi.	>200 mi.	Overall	<200 mi.	>200 mi.
	A. Log count of migrants					
US exposure to robots	-1.76***	-2.10***	-1.84***	-0.01	-1.94***	0.41
	(0.53)	(0.51)	(0.69)	(0.55)	(0.49)	(0.81)
US exposure to Chinese imports	1.65	2.94**	0.06	0.43	1.45	0.56
	(1.12)	(1.20)	(1.52)	(1.43)	(1.35)	(1.74)
	B. Migration rate					
US exposure to robots	-2.03*	-0.11	-2.11**	-0.16	-1.11*	0.83
	(1.20)	(0.90)	(1.06)	(1.12)	(0.57)	(1.05)
US exposure to Chinese imports	4.40	2.23	1.02	-1.35	-1.12	-0.04
	(4.52)	(3.52)	(4.85)	(4.44)	(1.64)	(3.97)

Note: The dependent variables in Panels A and B are the log count of migrants and migration rate, respectively. Columns 1–3 focus on in-migration and columns 4–6 on out-migration. The log counts of migrants and migration rates are multiplied by 100 and 1000, respectively, and converted to 10-year equivalents. There are two time periods (2000–7 and 2007–15) and 722 CZs each period, resulting in N=1,444. All explanatory variables that are displayed are standardized to have a mean of 0 and a standard deviation of 1. All columns include the full set of covariates interacted with time period dummies, i.e., census division dummies, 1990 demographic characteristics (i.e., log population, share of men, share of population above 65 years old, share of population with less than a college degree, share of population with some college or more, population shares of Hispanics, Blacks, Whites and Asians, and the share of women in the labor force), 1990 shares of employment in broad industries (i.e., agriculture, mining, construction, manufacturing), and the 1990 share of routine jobs and the average offshorability index, following Autor and Dorn (2013). Moreover, they include the change in the outcome variable between 1992 and 2000. Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the state level (48 states). Regressions are weighted by a CZ's 1990 national share of the working-age population. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

Table D8: Effects on in- and out-migration by distance, stacked differences 2000–2015 (2SLS)

	(1)	(2)	(3)	(4)	(5)	(6)
	In-migration			Out-migration		
	Overall	<400 mi.	>400 mi.	Overall	<400 mi.	>400 mi.
	A. Log count of migrants					
US exposure to robots	-1.76***	-2.17***	-1.62**	-0.01	-1.42***	0.51
	(0.53)	(0.47)	(0.70)	(0.55)	(0.48)	(0.79)
US exposure to Chinese imports	1.65	2.96**	0.13	0.43	0.97	0.28
	(1.12)	(1.25)	(1.58)	(1.43)	(1.43)	(1.77)
	B. Migration rate					
US exposure to robots	-2.03*	-0.45	-1.47*	-0.16	-1.11**	0.76
	(1.20)	(0.94)	(0.88)	(1.12)	(0.56)	(0.91)
US exposure to Chinese imports	4.40	3.07	0.09	-1.35	-0.47	-1.21
	(4.52)	(3.80)	(4.48)	(4.44)	(1.90)	(3.45)

Note: The dependent variables in Panels A and B are the log count of migrants and migration rate, respectively. Columns 1–3 focus on in-migration and columns 4–6 on out-migration. The log counts of migrants and migration rates are multiplied by 100 and 1000, respectively, and converted to 10-year equivalents. There are two time periods (2000–7 and 2007–15) and 722 CZs each period, resulting in N=1,444. All explanatory variables that are displayed are standardized to have a mean of 0 and a standard deviation of 1. All columns include the full set of covariates interacted with time period dummies, i.e., census division dummies, 1990 demographic characteristics (i.e., log population, share of men, share of population above 65 years old, share of population with less than a college degree, share of population with some college or more, population shares of Hispanics, Blacks, Whites and Asians, and the share of women in the labor force), 1990 shares of employment in broad industries (i.e., agriculture, mining, construction, manufacturing), and the 1990 share of routine jobs and the average offshorability index, following Autor and Dorn (2013). Moreover, they include the change in the outcome variable between 1992 and 2000. Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the state level (48 states). Regressions are weighted by a CZ's 1990 national share of the working-age population. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

E Additional Results

E.1 In-migration vs. out-migration

As discussed in the main paper (Section 4.3), the negative effect of robots on population growth may result either from increased out-migration or from reduced in-migration (or, both). On the one hand, displaced workers might move to another CZ searching for better opportunities. On the other hand, prospective in-migrants might decide not to move to places with high robot exposure that offer limited job opportunities. In Table E1, we test these ambiguous predictions.

The dependent variable is the log count of migrants in Panel A, and migration rates in Panel B. We focus on in- and out-migrants in columns 1 to 3 and columns 4 to 6, respectively. Since IRS migration data starts in 1990, equation (1) is estimated only for the period 2000–2015, in order to include pre-trends as a control. For brevity, we focus on the most stringent specifications (Table 2, column 5). Columns 1 and 4 show that robots reduced in-migration, but did not lead to increased out-migration. That is, robot penetration slowed down population growth mainly by discouraging prospective migrants from moving into a CZ, rather than by inducing displaced workers to relocate elsewhere. Instead, if anything, the effect of Chinese import competition on in-migration is positive, even though not statistically significant.

According to our estimates, one standard deviation increase in exposure to robots reduced the number of in-migrants by about 1.76%, or the 10-year in-migration rate by roughly 0.20 percentage points. The coefficient on robot exposure implies that one additional robot per 1,000 workers reduced the in-migration rate by about 0.28 percentage points.[33] Since the average decadal in-migration rate during our sample period is 41%, this amounts to a 0.69% reduction in the in-migration rate.

Extrapolating these numbers to the national level, our estimates imply that one additional robot per 1,000 workers lowered (internal) migration flows by 460,000 working-age individuals. Given that one additional robot per 1,000 workers is equivalent to 120,000 more robots in the US, our results suggest that each extra robot reduced in-migration flows by almost four working-age individuals. Between 1993 and 2015, the US adopted almost 190,000 robots. According to our estimates, this would have reduced in-migration flows by 730,000 working-age people over the period. While one should not take these numbers literally, since they abstract from general equilibrium effects, they can be nonetheless useful to put our effects into perspective.

[33] This number is obtained by first scaling the coefficient in column 6 by 10 (so as to express the effect of robot exposure in percent), and then dividing it by the standard deviation of robot exposure (0.72).

In columns 2–3 and 5–6, we explore in more detail where changes in in- and out-migration originated from. We split overall in- (resp., out-migrants) into those originating from (resp., moving to) places that are less and more than 300 miles away.[34] We deem this admittedly crude cutoff a useful approximation for within-state versus cross-state moves.[35] The reduction in in-migration documented in column 1 seems to stem from both close-by locations and far away regions, especially when focusing on the log count of migrants (Panel A).[36] Column 5 shows that robot exposure had a negative and statistically significant effect on out-migration into CZs that are less than 300 miles away.

Finally, columns 1–3 suggest that the positive but statistically insignificant effect of Chinese imports on in-migration flows masks substantial heterogeneity by distance. In particular, Chinese imports increased in-migration from CZs that are within 300 miles (column 2) – an effect that is statistically significant when considering log population changes (Panel A). However, this was not enough to generate a statistically significant (and quantitatively relevant) effect on overall in-migration.

E.2 House prices

In this section, we present more details for the analysis summarized in Section 4.3 of the main paper, where we examine the relationship between robot exposure (and Chinese imports) and house prices.

One would expect lower in-migration to reduce demand for housing. If housing supply is not perfectly elastic, this should in turn reduce house prices in robot-exposed areas. We test this hypothesis in Table E2, which mirrors the structure of Table 2, but uses the change in the log of the house price index as dependent variable.[37] Since the house price index is available for a large number of CZs only from 1990 onwards, as for in- and out-migration, we estimate equation (1) for the period 2000–2015 in order to include pre-trends as a control. Our preferred specification (column 5) documents that robot penetration had a negative and statistically significant effect on house prices.

Our estimates imply that one standard deviation increase in exposure to robots reduced house prices by 2.55%. Said differently, one additional robot per 1,000 workers reduced house prices by 3.54%. For comparison, US house prices grew by 58% between 2000 and

[34] The IRS migration data only contains exact numbers of county-to-county migrants for combinations with at least ten moves from one county to the other. If there are less than ten moves, they are reported as "Other flows - same state", "Other flows – different state" or "Other flows – foreign". We treat the first group as a move within a 300 mile distance and the latter two as moves to or from more than 300 miles away.

[35] All results are robust to using 200 miles or 400 miles cutoffs (Tables D7 and D8).

[36] When considering migration rates (Panel B), the coefficient on robot exposure is marginally significant and quantitatively larger only for further places (column 3). However, this difference is not statistically significant at conventional levels.

[37] Data on house prices are available at the county level, and are taken from the Federal Housing Finance Agency. Since data are not available for all counties in the earlier years, when aggregating them at the CZ level, we are able to cover 414 out of 722 CZs in 1990.

2015.[38] In contrast, Chinese imports did not have any statistically significant effect on house prices, once CZs are allowed to be on differential trends depending on broad industry shares (columns 4 and 5). These results are consistent with the differential migration response to the two shocks documented above.

E.3 Additional analysis linking spillovers to migration

As explained in Section 5.3, we perform an additional exercise to support the notion that spillovers into industries that host more skilled (and more mobile) individuals are an important mechanism for our results. We proceed as follows. For each CZ, we compute the share of high-skilled individuals living in neighboring CZs in 1990. Next, we define a CZ as having either "high-skilled neighbors" (HSN) or "low-skilled neighbors" (LSN) depending on whether its neighboring CZs have a share of high-skilled individuals above or below the median, respectively. Finally, we interact such indicators with both robot exposure and Chinese import competition.

Results are reported in Table E3, where we consider total, manufacturing, and non-manufacturing employment in columns 1 to 3, and overall population growth, in-migration, and out-migration in columns 4 to 6, respectively. Results are consistent with the idea that more skilled individuals are responsible for the migration response to robots. While robot exposure reduces employment to a similar extent in HSN and LSN CZs (columns 1 to 3), it lowers population growth only in the former (column 4). Moreover, results are driven by lower in-migration (column 5), rather than by higher out-migration (column 6). Notably, the difference in coefficients for in-migration between HSN and LSN CZs is statistically significant at the 1% level. When focusing on import competition, no clear pattern of heterogeneity emerges.

Finally, to bolster confidence that differential spillovers into non-manufacturing (and not some other, potential difference between the two shocks) drive our main migration results, we show that similar patterns are visible for the effects of Chinese imports, once skill-industry heterogeneity across CZs is accounted for. We exploit geographic variation in the effects of Chinese import competition on non-manufacturing employment (Bloom et al., 2019). In Table E4, we augment our preferred specification with interactions between each measure of exposure and dummies equal to one if a CZ was, respectively, a high service intensity (HSI) or a low service intensity (LSI) area.[39] The intuition is that services may have had higher capacity to grow in regions that were initially specialized in that sector.

Table E4 reveals that Chinese imports led to employment growth outside manufactur-

[38] See `https://fred.stlouisfed.org/series/USSTHPI`.

[39] The sample split is based on the 1990 CZ share of employment in services.

ing in areas with an initially high service intensity. Consistent with our proposed mechanism, these CZs also experienced significantly higher population growth, due to increased in-migration. In contrast, CZs with initially low service employment shares experienced, if anything, negative spillovers outside manufacturing. This, in turn, resulted in a negative and statistically significant overall employment response.

E.4 Employment in tradable vs. non-tradable industries

In Table 3, we examine the employment effects of both shocks in manufacturing and non-manufacturing. We find that only robots reduced employment outside manufacturing. This suggests that there were negative spillovers to indirectly affected sectors only in response to robots, and not to Chinese imports.

Another way to test for spillovers is to separately look at the effects of robot adoption and Chinese imports on employment in tradable and non-tradable industries. Since both shocks directly hit tradable industries, employment effects in non-tradable industries are likely the result of spillovers. We classify industries in either tradable or non-tradable depending on their geographic industry concentration in 1990, following Mian and Sufi (2014). More specifically, we categorize an industry as non-tradable if its geographic concentration was in the bottom tercile (least concentrated) of the distribution in 1990, and as tradable if it was in the top tercile (most concentrated).

In Table E5, we then replicate our preferred specification focusing on employment in tradable (Panel A) and non-tradable (Panel B) industries. Results indicate that, in line with findings in Table 3, only robots caused negative spillovers to indirectly affected industries. Indeed, while both shocks lowered employment growth in tradable industries, only robots also had negative effects on employment in non-tradable industries.

Table E1: Effects on in- and out-migration by distance, stacked differences 2000–2015 (2SLS)

	(1)	(2)	(3)	(4)	(5)	(6)
	In-migration			Out-migration		
	Overall	<300 mi.	>300 mi.	Overall	<300 mi.	>300 mi.
			A. Log count of migrants			
US exposure to robots	-1.76***	-2.18***	-1.67**	-0.01	-1.86***	0.62
	(0.53)	(0.47)	(0.70)	(0.55)	(0.48)	(0.80)
US exposure to Chinese imports	1.65	3.38***	-0.02	0.43	1.05	1.00
	(1.12)	(1.27)	(1.65)	(1.43)	(1.34)	(1.87)
			B. Migration rate			
US exposure to robots	-2.03*	-0.34	-1.69*	-0.16	-1.29**	0.90
	(1.20)	(0.93)	(0.92)	(1.12)	(0.57)	(0.95)
US exposure to Chinese imports	4.40	2.82	-0.05	-1.35	-1.72	0.57
	(4.52)	(3.72)	(4.67)	(4.44)	(1.54)	(3.97)

Note: The dependent variables in Panels A and B are the log count of migrants and migration rate, respectively. Columns 1–3 focus on in-migration and columns 4–6 on out-migration. The log counts of migrants and migration rates are multiplied by 100 and 1000, respectively, and converted to 10-year equivalents. There are two time periods (2000–7 and 2007–15) and 722 CZs each period, resulting in N=1,444. All explanatory variables that are displayed are standardized to have a mean of 0 and a standard deviation of 1. All columns include the full set of covariates interacted with time period dummies, i.e., census division dummies, 1990 demographic characteristics (i.e., log population, share of men, share of population above 65 years old, share of population with less than a college degree, share of population with some college or more, population shares of Hispanics, Blacks, Whites and Asians, and the share of women in the labor force), 1990 shares of employment in broad industries (i.e., agriculture, mining, construction, manufacturing), and the 1990 share of routine jobs and the average offshorability index, following Autor and Dorn (2013). Moreover, they include the change in the outcome variable between 1992 and 2000. Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the state level (48 states). Regressions are weighted by a CZ's 1990 national share of the working-age population. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

Table E2: Effects on house prices, stacked differences 2000–2015 (2SLS)

	(1)	(2)	(3)	(4)	(5)
	House price index				
US exposure to robots	-5.78***	-5.26**	-4.43***	-2.71***	-2.55***
	(1.86)	(2.05)	(1.01)	(0.67)	(0.67)
US exposure to Chinese imports	-7.72***	-7.62**	-5.34**	1.17	0.49
	(2.84)	(2.98)	(2.08)	(2.58)	(3.25)
Region × time	✓	✓	✓	✓	✓
Pre-trends		✓	✓	✓	✓
Demographics × time			✓	✓	✓
Industry shares × time				✓	✓
Contemp. changes × time					✓

Note: The dependent variable is the change in the log house price index (using data from the Federal Housing Finance Agency on house prices by county covering 414 CZs) multiplied by 100 (i.e., $[\ln(y_{t+1}) - \ln(y_t)] \cdot 100$) and converted to 10-year equivalent changes. There are two time periods and 414 CZs each period, resulting in N=828. All explanatory variables that are displayed are standardized to have a mean of 0 and a standard deviation of 1. Column 1 includes census division dummies interacted with time period dummies as covariates. Column 2 also includes the change in the log house price index between 1990 and 2000. Column 3 also controls for 1990 demographic characteristics (i.e., log population, share of men, share of population above 65 years old, share of population with less than a college degree, share of population with some college or more, population shares of Hispanics, Blacks, Whites and Asians, and the share of women in the labor force), each interacted with time period dummies, as well as the 1990 log house price index. Column 4 also includes shares of employment in broad industries in 1990 (i.e., agriculture, mining, construction, manufacturing), each interacted with time period dummies. Column 5 also includes the share of routine jobs and the average offshorability index in 1990, following Autor and Dorn (2013), each interacted with time period dummies. Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the state level (48 states). Regressions are weighted by a CZ's 1990 national share of the working-age population. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

Table E3: Heterogeneity of effects by neighboring CZs' initial skill intensity, stacked differences (reduced form)

	(1)	(2)	(3)	(4)	(5)	(6)
	Employment			Migration		
	Total	Manuf.	Non-manuf.	Pop.	In-mig.	Out-mig.
Exposure to robots	-1.23***	-1.12***	-1.27***	-0.61***	-2.05***	-0.56
× HSN	(0.14)	(0.33)	(0.17)	(0.10)	(0.41)	(0.34)
Exposure to robots	-0.89***	-1.01*	-1.03***	-0.29	-0.45	-0.39
× LSN	(0.34)	(0.53)	(0.38)	(0.31)	(0.68)	(0.71)
Exposure to Chinese imports	-0.29	-2.88***	0.38	0.09	0.37	0.01
× HSN	(0.74)	(0.90)	(0.75)	(0.58)	(0.65)	(0.90)
Exposure to Chinese imports	-0.74	-2.63***	-0.01	0.29	0.85	0.57
× LSN	(0.48)	(0.78)	(0.53)	(0.33)	(0.64)	(0.65)
P(HSN=LSN):						
– Exposure to robots	0.26	0.80	0.52	0.27	0.00	0.78
– Exposure to Chinese imports	0.53	0.80	0.63	0.74	0.53	0.53

Note: The dependent variables are the log changes of the subgroup specified in each column. Columns 1–3 focus on employment and columns 4–6 on migration. In columns 1–4 and 5–6, the number of observations is N=2,166 and N=1,444, respectively. The exposure to robots and exposure to Chinese imports variables are standardized to have a mean of 0 and a standard deviation of 1. HSN (acronym for "high-skilled neighbors") and LSN ("low-skilled neighbors") are indicators for CZs with neighboring CZs that had above and below average shares of workers with some college or more in 1990. All columns include the full set of covariates interacted with time period dummies, i.e., census division dummies, 1990 demographic characteristics (i.e., log population, share of men, share of population above 65 years old, share of population with less than a college degree, share of population with some college or more, population shares of Hispanics, Blacks, Whites and Asians, and the share of women in the labor force), 1990 shares of employment in broad industries (i.e., agriculture, mining, construction, manufacturing), and the 1990 share of routine jobs and the average offshorability index, following Autor and Dorn (2013). Moreover, they include the change in the outcome variable in the pre-period (i.e., 1970–1990 in columns 1–4 and 1992–2000 in columns 5–6) and a main effect of the HSN indicator variable. The last two rows report the p-value of a t-test for equality of the coefficients for HSN and LSN regions for the indicated variables. Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the state level (48 states). Regressions are weighted by a CZ's 1990 national share of the outcome group in columns 1–4 and a CZ's 1990 national share of the working-age population in columns 5–6. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

Table E4: Heterogeneity of effects by initial service intensity, stacked differences (reduced form)

	(1)	(2)	(3)	(4)	(5)	(6)
	Employment			Migration		
	Total	Manuf.	Non-manuf.	Pop.	In-mig.	Out-mig.
Exposure to robots	-1.03***	-1.07***	-1.08***	-0.39***	-1.43***	0.11
× HSI	(0.13)	(0.28)	(0.17)	(0.11)	(0.41)	(0.40)
Exposure to robots	-1.09***	-1.02*	-1.17***	-0.53***	-0.81	-0.54
× LSI	(0.29)	(0.54)	(0.26)	(0.19)	(0.73)	(0.72)
Exposure to Chinese imports	0.52	-3.01***	1.22*	1.03**	1.61*	0.97
× HSI	(0.52)	(0.84)	(0.63)	(0.50)	(0.85)	(0.95)
Exposure to Chinese imports	-1.16**	-2.69***	-0.53	-0.41	-0.17	-0.28
× LSI	(0.54)	(0.91)	(0.52)	(0.40)	(0.54)	(0.75)
P(HSI=LSI):						
– Exposure to robots	0.84	0.91	0.76	0.48	0.34	0.25
– Exposure to Chinese imports	0.02	0.79	0.02	0.01	0.04	0.19

Note: The dependent variables are the log changes of the subgroup specified in each column. Columns 1–3 focus on employment and columns 4–6 on migration. In columns 1–4 and 5–6, the number of observations is N=2,166 and N=1,444, respectively. The exposure to robots and exposure to Chinese imports variables are standardized to have a mean of 0 and a standard deviation of 1. HSI and LSI are indicators for CZs with above and below average shares of workers in the service industry in 1990. All columns include the full set of covariates interacted with time period dummies, i.e., census division dummies, 1990 demographic characteristics (i.e., log population, share of men, share of population above 65 years old, share of population with less than a college degree, share of population with some college or more, population shares of Hispanics, Blacks, Whites and Asians, and the share of women in the labor force), 1990 shares of employment in broad industries (i.e., agriculture, mining, construction, manufacturing), and the 1990 share of routine jobs and the average offshorability index, following Autor and Dorn (2013). Moreover, they include the change in the outcome variable in the pre-period (i.e., 1970–1990 in columns 1–4 and 1992–2000 in columns 5–6) and a main effect of the HSI indicator variable. The last two rows report the p-value of a t-test for equality of the coefficients for HSI and LSI regions for the indicated variables. Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the state level (48 states). Regressions are weighted by a CZ's 1990 national share of the outcome group in columns 1–4 and a CZ's 1990 national share of the overall population in columns 5–6. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

Table E5: Effects on employment, stacked differences 1990–2015 (2SLS)

	(1)	(2)	(3)	(4)	(5)
			A. Employment in tradable sectors		
US exposure to robots	-3.89***	-2.87***	-2.65***	-2.13***	-2.07***
	(0.95)	(0.58)	(0.41)	(0.44)	(0.41)
US exposure to Chinese imports	-6.86***	-7.48***	-7.65***	-3.62**	-3.95**
	(1.49)	(1.08)	(1.34)	(1.50)	(1.54)
			B. Employment in non-tradable sectors		
US exposure to robots	-1.98**	-1.62**	-1.50***	-1.43***	-1.32***
	(0.85)	(0.72)	(0.30)	(0.25)	(0.24)
US exposure to Chinese imports	0.56	0.16	1.32	1.16	1.61
	(1.30)	(1.13)	(1.19)	(1.19)	(1.12)
Region × time	✓	✓	✓	✓	✓
Pre-trends		✓	✓	✓	✓
Demographics × time			✓	✓	✓
Industry shares × time				✓	✓
Contemp. changes × time					✓

Note: The dependent variable in Panels A and B are the change in the log count of employment in tradable and non-tradable sectors, respectively, multiplied by 100 (i.e., $[\ln(y_{t+1})-\ln(y_t)]\cdot 100$). There are three time periods and 722 CZs each period, resulting in N=2,166. All explanatory variables that are displayed are standardized to have a mean of 0 and a standard deviation of 1. Column 1 includes census division dummies interacted with time period dummies as covariates. Column 2 also includes the change in the outcome variable between 1970 and 1990. Column 3 also controls for 1990 demographic characteristics (i.e., log population, share of men, share of population above 65 years old, share of population with less than a college degree, share of population with some college or more, population shares of Hispanics, Blacks, Whites and Asians, and the share of women in the labor force), each interacted with time period dummies. Column 4 also includes shares of employment in broad industries in 1990 (i.e., agriculture, mining, construction, manufacturing), each interacted with time period dummies. Column 5 also includes the share of routine jobs and the average offshorability index in 1990, following Autor and Dorn (2013), each interacted with time period dummies. Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the state level (48 states). Regressions are weighted by a CZ's 1990 national share of the outcome group in each panel, respectively. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.