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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

Migration is a key mechanism through which local labor markets adjust to economic shocks. In this paper, we analyze the migration response of American workers to two of the most important shocks that hit US manufacturing since the 1990s: Chinese import competition and the introduction of industrial robots. Exploiting plausibly exogenous variation in exposure across US local labor markets over time, we establish a new fact. Even though both shocks drastically reduced employment in the manufacturing sector, only robots led to a sizable decline in population size. We provide evidence that negative employment spillovers outside manufacturing, caused by robots but not by Chinese imports, can explain the different migration responses. We interpret our findings through the lens of a model that highlights two mechanisms: the cost savings that each shock provides and the degree of complementarity between directly and indirectly exposed industries.

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1 Introduction

Workers' geographic mobility is considered one of the key mechanisms through which labor markets adjust to local economic shocks (Blanchard and Katz, 1992). It is also viewed as a distinctive feature of the American economy: relative to their European counterparts, American workers are perceived to be more mobile and more responsive to differential economic opportunities across labor markets (Moretti, 2012). The role of migration as a re-equilibrating mechanism may have been especially important in the past twenty years, when the US manufacturing sector was hit by strong and localized shocks – most notably, Chinese import competition and the adoption of industrial robots (Abraham and Kearney, 2018).

These two shocks not only caused a steep decline in manufacturing employment, but also contributed to the rising inequality of opportunities across labor markets and to the reduction in overall employment rates (Autor et al., 2013; Abraham and Kearney, 2018; Acemoglu and Restrepo, 2020). One explanation proposed in the literature is that American workers' unusually low propensity to migrate in response to economic downturns is responsible for these persistent and regionally concentrated effects (Cadena and Kovak, 2016; Charles et al., 2019). This view is consistent with evidence that the mobility of American workers has declined in the past thirty years (Molloy et al., 2011).

At the same time, technological and trade-related structural changes are likely to keep shaping the world economy in the foreseeable future. Between 2015 and 2020, the global stock of robots nearly doubled (IFR, 2021), and recent case studies predict a three-fold increase by 2025 (BCG, 2015). The prevailing political climate in the US and Europe further suggests that trade volumes with China and other countries might change considerably in the years to come. Alongside these trends, new technologies such as Artificial Intelligence (AI) have started to transform the economy and alter labor demand patterns (Frank et al., 2019). Will local labor markets adjust smoothly to the new technological and trade-induced shocks? Or, will frictions to labor mobility prevent this from happening, possibly leading to persistent levels of unemployment and to growing regional inequality? Even in the presence of migration, will the latter be enough to fully re-equilibrate labor markets?

In this paper, we address these questions by studying the migration response to trade and technology shocks across US Commuting Zones (CZs) between 1990 and 2015. We focus on the effects of two main variables: Chinese import competition and the adoption of industrial robots. Following the existing 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 change 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 in the effects of the two shocks on migration: while industrial robots caused a sizable reduction in population size, Chinese import competition did not. Such asymmetric effects may seem particularly surprising, given the existing evidence that both shocks had a strong, negative impact on manufacturing employment (Acemoglu and Restrepo, 2020; Autor et al., 2013). 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 magnitude of our estimates is large, and implies that each new robot reduced in-migration by about four working-age individuals.

These results are robust to several checks and alternative explanations. First, we verify that our findings are not driven by differential pre-trends in population growth across regions. Second, we show that results cannot be explained by differences either in the timing of the two shocks or in CZ baseline characteristics. Third, we document that the muted migration response to Chinese imports is similar when constructing the import shock following Pierce and Schott (2016). Fourth, we show that our results are robust to adjusting standard errors for spatial correlation, and are unlikely to be driven by noise due to correlated shocks across CZs (Adao et al., 2019).

[1] In particular, we allow for time period specific differential trends in nine Census regions, along a rich set of demographic characteristics, in four broad industries, and the degree of routine-intensity and offshorability (following Autor and Dorn, 2013). We also account for potentially differential pre-trends in population growth.

[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.

In the second part of the paper, we investigate the causes of the differential migration response. 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. We begin by documenting that robots reduced employment of both low-skilled (mostly within manufacturing) and high-skilled (mostly outside manufacturing) individuals to a similar extent. However, the migration response to robots was driven by high-skilled individuals, whose migration elasticity was more than twice as large as that of low-skilled workers. Then, we compute the 1990 share of high-skilled individuals living in neighboring CZs, to proxy for potential high-skilled in-migrants that might have moved to the CZ absent the shocks. The employment effects of robots (and Chinese imports) were similar across CZs surrounded by different pools of migrants. Yet, robots reduced population growth only in areas that had a larger share of high-skilled individuals in neighboring CZs, and these effects were driven by lower in-migration, rather than by higher out-migration. Taken together, these findings indicate 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.

Turning to Chinese imports, we document that similar patterns (in the opposite direction) hold, 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

[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.

statistically significant, reduction in population in LSI CZs.

Overall, our results suggest that the migration response to local labor market shocks depends not only on the employment effect in directly exposed sectors (e.g., manufacturing), but also on that in indirectly exposed ones (e.g., non-manufacturing). This is consistent with at least two, not mutually exclusive, explanations. First, the transmission of a shock into indirectly affected sectors amplifies its initial effect, making the CZ as a whole less attractive to in-migrants. Second, indirectly hit industries may host more mobile individuals, whose migration elasticity to economic shocks is higher. Our evidence is more consistent with the latter channel.

To rationalize our empirical evidence, we introduce a quantitative spatial economic model with geographically mobile labor, where workers compete with either robots or foreign labor in the completion of tasks.[4] The goal of the model is to shed light on the factors driving the different spillovers into non-manufacturing between the two shocks – which, in turn, affect individuals' migration decisions. Combining the structure of the model with evidence from other studies, we single out two potential causes for the disparate employment effects outside manufacturing: the cost savings that each shock provides, and the degree of complementarity between directly and indirectly exposed industries. According to the model, differences in cost savings in the range of values estimated elsewhere can fully explain the different migration responses between the two shocks, through their employment effects. Instead, differences in complementarities associated with robot adoption and Chinese imports can only partially account for the differential migration response.

Our paper contributes to different strands of the literature. First, we complement recent works that examine workers' geographic mobility following local economic shocks more broadly (Cadena and Kovak, 2016; Dustmann et al., 2017; Bartik, 2018; Kearney and Wilson, 2018; Monras, 2018) by comparing the response of the same local labor markets to two simultaneous, and major shocks to US manufacturing. This comparison allows us to go beyond the estimation of migration responses to specific 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 that is independent of the type of shock hitting labor

[4] For a review on recent advances in quantitative spatial economics see Redding and Rossi-Hansberg (2017).

markets. Instead, different shocks can lead to different migration responses, depending on the set of individuals they affect in equilibrium.

Second, our findings speak to works that have studied 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). To the best of our knowledge, we are the first to compare the migration responses to the two shocks alongside one another. Closely related to our work, Greenland et al. (2019) find that Chinese import competition led to changes in CZ population. The discrepancy between our results and theirs stems from the more stringent set of controls included in our analysis, which absorb the potentially spurious correlation between import competition and other economic forces that may shape migration patterns.[5]

We expand on this literature in three ways. First, we study the impact of the two shocks not only on overall population, but also on in- and out-migration to understand the channels of adjustment. Second, we examine the heterogeneous impact of the shocks across different sub-populations to shed light on the mechanisms. In particular, we uncover a stark difference in the transmission of the two shocks to the rest of the local economy. Finally, we complement our empirical analysis with a theoretical framework that helps rationalize the economic forces behind the differential employment and migration patterns we document.

Our paper is also linked to the debate on whether workers' geographic immobility might explain the sluggish recovery of local labor markets to the shocks that hit US manufacturing in the past twenty years or so (Abraham and Kearney, 2018; Charles et al., 2019). Although the muted migration response to Chinese import competition may have exacerbated the (local and national) impact of the shock, our findings suggest that migration alone was not enough to prevent the persistence of a negative, concentrated, and large shock. Indeed, even though robot penetration led to changes in migration patterns, it nonetheless caused a long-lasting decline in employment and wages.

Finally, our findings can inform the design of specific policies to deal with future

[5] See Appendix C.2 for more details. With respect to the impact of robots, while Acemoglu and Restrepo (2020) focus on employment and wages, they also examine migration. In Table A18, they conclude: "Some of our estimates show a negative impact on population and net migration (...), though these effects are neither consistent across specifications nor precisely estimated." Table A3 below documents that the use of intercensal estimates for population and a slightly more stringent specification likely explain the difference between our results and those in Acemoglu and Restrepo (2020).

labor market shocks. For example, AI is believed to not only affect demand for unskilled workers, but to also transform occupations across the whole range of skills (Bryniolfsson et al., 2018). Recent findings in Webb (2019) indicate that high-skilled, middle-aged workers are the most exposed segment of the workforce to AI automation. Our estimates, and the heterogeneous migration elasticities in particular, might help predict the impact of AI technologies on unemployment rates, regional inequality, and local demographics in the years to come. If the geographic mobility of high skilled workers mitigates the differential employment consequences across local labor markets, the impact of AI might be qualitatively and quantitatively different from that of a trade shock, and even from that of robot adoption.

The paper is structured as follows. Section 2 describes the rise of industrial robots and Chinese import competition, and lays out the empirical strategy. Section 3 presents the data. Section 4 documents the main results for the effects of robot adoption and import competition on migration. Section 5 explores the mechanisms, and Section 6 develops a quantitative spatial economic model to rationalize the empirical evidence. Section 7 concludes.

2 Labor market shocks and empirical strategy

2.1 Labor market shocks

Our analysis focuses on two local labor market shocks that are widely considered among the most prominent causes behind the decline in employment rates since the early 2000s: industrial robots and import competition from China (Abraham and Kearney, 2018).[6]

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 1). Robot penetration was highest in the

[6] While the Great Recession likely exacerbated this longer term trend, it is probably not one of its root causes, since the decline in employment rates started already in the early 2000s, well before the crisis.

manufacturing sector, 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 (basic metals, metal products, and industrial machinery). Outside manufacturing, industrial robots are used for harvesting and the inspection of equipment and structures (Figure 2).

[Figure 1 here]

While the US added a large number of robots since the beginning of the 1990s, the origins of these changes lie outside of the country. Acemoglu and Restrepo (2021) document that global demographic trends are responsible for the introduction of robots, which are needed to replace a declining pool of young and middle-aged workers (between the ages of 21 and 55) to perform routine, manual tasks in the production process in most developed countries – from Germany to Japan to South Korea to France.[7] Even though robots are produced (and used) more heavily in aging countries, they are also exported to the rest of the world.

[Figure 2 here]

Chinese imports. Chinese exports skyrocketed since the early 1990s. 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 1). Given China's comparative advantage, its exports were highly skewed towards labor-intensive industries within the manufacturing sector. Specifically for the US, the growth in Chinese imports per worker was largest in electronics and electrical equipment, followed by industrial machinery as well as textiles and apparel. The least affected industries within manufacturing were transport equipment (non-automotive), paper and printing products, and food, beverages and tobacco (Figure 2).

[7] Aging also explains a large share of the cross-country variation in the development (number of automation-related patents) and adoption (number of installed robots) of robots (Acemoglu and Restrepo, 2021).

The surge of Chinese manufacturing exports since the early 1990s was caused by two main factors: China's internal, trade-promoting policies in the 1980s and 1990s; and, its accession to the World Trade Organization (WTO) in 2001. Beginning in the 1980s, China introduced several policies to boost its manufacturing exports, such as the creation of special economic zones that granted foreign investors tax breaks, lower custom duties, and relaxed labor regulations to encourage the import and final assembly of intermediate goods into final exports (Wang, 2013). It also privatized inefficient state-owned enterprises, and implemented additional measures to enhance productivity (Hsieh and Song, 2015). These reforms had a dramatic impact on Chinese exports during the 1990s (Figure 1). The upward trend was further reinforced when, in the early 2000s, China was granted Permanent Normal Trade Relations (PNTR) status by the US and joined the WTO.[8]

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. To identify the effects of industrial robots and Chinese import competition on internal migration, 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.[9] Standard errors allow for heteroskedasticity and arbitrary clustering by state. We include a rich vector of 1990 characteristics $\boldsymbol{X}_{c,90}$, interacted with period dummies, γ_t, to allow for differential trends.[10] To account for

[8] See also Storesletten and Zilibotti (2014) and Autor et al. (2016) for more details.

[9] 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.

[10] We include interactions between period dummies and: *i)* nine region dummies; and *ii)* a set of pre-determined demographic characteristics, four broad industry shares, and the shares of routine and offshorable jobs.

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.

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

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

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:

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

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:

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

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).[11] In particular, we construct

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

where $M^{CNOT}_{i,t}$ 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. [12]

Table 1, column 8, documents that CZs more exposed to either shock not only differ in their subsequent population growth, but also along a few other observable initial characteristics. For instance, CZs especially exposed to robots have a higher share of employment in mining and a lower share of workers in manufacturing and offshorable jobs. These places also have a lower share of Black individuals and lower female labor force participation. For these initial differences not to bias our results, we include them (as well as those with insignificant differences) in our subsequent analysis.[13]

3 Data and descriptive statistics

3.1 Data

Migration. 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,

[11] 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.

[12] 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.

[13] Results are robust to omitting these controls.

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.[14]

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.[15] 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.[16]

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 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.

[Figure 3 here]

[14] 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).

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

[16] 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.

Figure 3 plots the evolution of US internal migration rates between 1980 and 2015 for different geographies. During this period, both cross-county and cross-CZ migration declined – a pattern also documented in Molloy et al. (2011) among others. IRS and Current Population Survey (CPS) data show that the cross-CZ and cross-county migration rates fell by 0.8 and 1.9 percentage points, respectively, between 1992 and 2015. These trends were mirrored by similar declines in within- and across-state moves. The average reduction in migration rates, however, hides significant variation across CZs (Figure 4, Panel A). Net migration rates were highest in the Northwest and Southeast, and lowest in the Midwest and Northeast.

[Figure 4 here]

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).[17] 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. We further complement these data with industry employment and output growth rates by country and year from the EU KLEMS database.

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.[18] 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 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. Since the CBP data provide employment counts in

[17] The IFR data has a few limitations. We deal with those identically to Acemoglu and Restrepo (2020). See Appendix B.1 for a detailed description.

[18] 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.

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.

Covariates. 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).

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 4 shows the geographic distribution of the 1990-2015 exposure to robots and to Chinese imports in Panels B and C respectively. Both shocks were stronger in the eastern part of the US. However, the robot shock was largely concentrated in the Midwest, especially in the Rust Belt, while exposure to Chinese imports was more pronounced in the Southeast and in the Northeast. Reassuringly, the population weighted correlation coefficient between the two shocks is as low as 0.06.[19]

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.[20] The first quartile (column 4) thus includes CZs that were particularly exposed to Chinese imports but not to robots. Similarly, CZs in the fourth quartile (column 7) were substantially exposed to robot penetration, but not to Chinese imports. Column 8 reports the difference between columns 7 and 4, and column 9 indicates its statistical significance.

[Table 1 here]

[19] 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.

[20] 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.

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 (i.e., CZs in the first and fourth quartile with respect to the exposure to robots relative to Chinese imports). This admittedly crude comparison suggests that robots and Chinese imports reduced employment to a similar extent, but that robots affected migration patterns (i.e., reduced population growth) more than Chinese import competition. 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.[21]

[Table 2 here]

In column 1, we estimate a parsimonious 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 these results are robust to including 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

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

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 to address the concern that initial industry shares (which we use to predict robot and Chinese import exposure) may be correlated with baseline CZ demographic or economic characteristics that were also correlated with population growth after 1990.[22] Adding this battery of controls leaves our results unchanged, both in terms of magnitude and in terms of precision.

Finally, in column 5, we interact the 1990 shares of routine and offshorable jobs with period dummies, so as to capture the potentially confounding effects of two other important technology- and trade-related, contemporaneous changes. In particular, we aim 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. While the coefficient on robot exposure becomes slightly smaller in absolute value, it remains statistically significant at the 1% level. The effect of Chinese imports remains positive but not statistically different from zero.[23]

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. This implies that 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%).[24] These results seem puzzling, in light of the evidence that both robot adoption and Chinese imports reduced manufacturing employment (Autor et al., 2013; Acemoglu

[22] Demographic characteristics are: log population size, the share of men, the share of the population above 65, the share of the population with less than a college degree, the share of the population with some college or more, the population shares of Hispanics, Blacks, Whites, and Asians, and the share of women in the labor force. For economic controls, we consider shares of employment in broad industries (agriculture, mining, construction, manufacturing).

[23] Appendix C performs additional robustness checks, summarized below.

[24] 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).

and Restrepo, 2020).[25] In Section 5 below, we return to this point, and explore the mechanisms that might be responsible for the disparate migration response to the two local labor market shocks.

4.2 In-migration vs. out-migration

Lower population growth may result either from increased out-migration or from 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, 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 Table 3.

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.

[Table 3 here]

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.[26] 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.

[25] In Table 5 below, we replicate the negative effects on manufacturing employment found in the literature.

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

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.

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.[27] We deem this admittedly crude cutoff a useful approximation for within-state versus cross-state moves.[28] 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).[29] 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.

[27] 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.

[28] All results are robust to using 200 miles or 400 miles cutoffs (Tables C6 and C7).

[29] 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.

4.3 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 4, which mirrors the structure of Table 2, but uses the change in the log of the house price index as dependent variable.[30] 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 2015.[31] 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.

[Table 4 here]

4.4 Summary of robustness checks

In Appendix C, 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 C1). Second, we show that the muted migration response to Chinese imports is not due to the use of the instrument proposed by Autor et al. (2013), and we replicate the analysis with the instrument proposed by Pierce and Schott (2016) (Table C2). Third, we show that *i*) results are unchanged when estimating long difference specifications (1990–2015 and 1990–2007, Table C3); *ii*) differences between the two shocks (over time and across

[30] 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.

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

CZs) cannot explain the differential migration response (Table C4); and, *iii*) results are robust to adjusting standard errors for spatial correlation (Table C5). 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 C1). Finally, we replicate the analysis for in- and out-migration by distance using different cutoffs (Tables C6 and C7).

5 Mechanisms

In this section, we examine why, although both shocks reduced manufacturing employment (Autor et al., 2013; Acemoglu and Restrepo, 2020), only robots triggered a marked decline in population. First, we show that both shocks lowered manufacturing employment, but only robots reduced employment outside manufacturing, including in many high-skilled service industries. 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 2), 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 5, which follows the same structure as Table 2.

[Table 5 here]

As before, we start with a parsimonious specification that only includes interactions between period and census division dummies (column 1). Both robot penetration and Chinese import competition reduced manufacturing employment considerably. Both coefficients are negative and statistically significant, with the effect of Chinese imports (-5.29) being more than twice as large as that of robots (-2.06).[32] In columns 2 to 5,

[32] 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.

we gradually add more covariates to allow CZs to be on differential trends along a set of initial characteristics. Doing so results in a somewhat smaller point estimate for robots (-1.37 as opposed to -2.06) and a slightly larger one for Chinese imports (-5.36 as opposed to -5.29). However, the main take-away is unchanged.

These findings are consistent with those in Acemoglu and Restrepo (2020) and Autor et al. (2013), and show that both robots and Chinese imports considerably reduced manufacturing employment. Our preferred specification (column 5) implies that one standard deviation increase in exposure to robots and Chinese imports reduced manufacturing employment by 1.37 and 5.36% per decade, respectively.[33] These patterns seem at odds with our previous evidence, which showed that only robots, but not Chinese imports, triggered a migration response. Why should the two shocks lead to disparate migration responses, if they both reduced manufacturing employment?

Panel A of Table 5 focused on employment within the manufacturing sector. This analysis likely captures the direct effects of the two shocks, which were largely concentrated in several manufacturing industries (Figure 2). However, restricting attention to manufacturing employment may miss important margins of adjustment, such as negative demand (e.g., displaced workers consuming less) or positive productivity (e.g., firms that become more productive expanding labor demand in non-directly affected industries) spillovers into non-manufacturing industries. In Panels B and C of Table 5, we thus turn to non-manufacturing and total employment.

Panel B documents that robots had a strong, negative effect on employment outside manufacturing, similar to that prevailing within this sector. Instead, the effect of Chinese imports was entirely concentrated within manufacturing.[34] If anything, our estimates suggest that Chinese imports had a positive effect on employment outside manufacturing. One possible explanation is that trade exposure lowered input prices, inducing firms to reallocate towards services (Bloom et al., 2019; Ding et al., 2019).

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 manu-

[33] These numbers are slightly different from the effects documented in previous work (Acemoglu and Restrepo, 2020, Table A15; Autor et al., 2013, Table 5; and Bloom et al., 2019, Table 2), although the difference is not statistically significant.

[34] 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.

facturing. Relating these findings to those in Table 2, we conjecture 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 in the case of Chinese import competition there were no – if anything, positive – spillovers outside manufacturing, the migration response was muted. In what follows, we provide different pieces of evidence consistent with this hypothesis.

5.2 Spillovers to other industries within CZs

Table 5 above suggests that robot exposure and import competition triggered different spillovers to other industries within the same CZ. To get a more precise picture of the differences in spillovers, we separately examine the effect of robots and Chinese imports on the employment shares of 44 industry-skill combinations.[35] Specifically, we estimate our most stringent specification (Table 2, column 5), using as dependent variable the change in employment in each industry-skill combination, relative to initial CZ employment.

Results are presented in Figure 5, where we plot coefficients on the (standardized) exposure to robots and Chinese imports in Panels A and B respectively. Since outcomes are expressed in percentage points, it is important to rule out the possibility that the initial shares in each cell may differ from each other in areas exposed to either of the two shocks. Panels C and D provide a visual inspection of this, 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.

[Figure 5 here]

Turning to the results, Panel A documents that robots reduced employment most strongly in routine, manual occupations within manufacturing. The effects are not limited to this industry-skill combination, however. In fact, they 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,

[35] Skill groups are defined using the 1980 Dictionary of Occupational Titles (DOT). See Appendix B.2 for more details.

and construction. Panel B shows that the effect of Chinese imports was also strongest for manufacturing, though not only in routine, manual, but also in abstract, cognitive occupations. Similar to robots, the effect is visible across all occupations within the manufacturing industry. In contrast to robots, however, effects in industry-skill combinations outside manufacturing were mostly *positive*.

Figure 5 unveils 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.[36] We return to these differences in Section 6, where we present a model that shows that the different effects outside manufacturing can explain the disparate migration responses.

5.3 Linking spillovers to migration responses

Figure 5 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.[37]

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 6, where we estimate our preferred specification (Table 2, column 5) using the change in log employment and working-age population by subgroup (i.e., high- and low-skilled, and young, middle-aged, and old) as dependent variable.

Panels A and B report results for employment and migration, respectively.[38] The

[36] The positive effect of Chinese imports on employment outside manufacturing, and in particular, professional services and management, is in line with firm-level evidence of industry switching in Bloom et al. (2019). The negative effect of robots on employment in these industries is in line with demand spillovers documented in Acemoglu and Restrepo (2020).

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

[38] Figure A1 replicates the analysis for import competition. Detailed regression results are reported in Table A4.

first column from the left replicates the aggregate results of Table 2 (column 5), while the following columns present the estimated coefficients by subgroup. The employment effects display relatively little heterogeneity across groups: robots reduced low-skilled (less than college) and high-skilled (some college or more) employment to a similar extent. Middle-aged workers (31–50 years old) were the most affected of the three age groups, followed by younger individuals (18–30). However, these differences are never statistically significant at conventional levels.

[Figure 6 here]

If spillovers into high-skilled occupations are, at least partly, responsible for the migration response observed in Table 2, high-skilled individuals should feature a higher elasticity to migrate. Panel B supports this interpretation, and documents that high skilled individuals drive the migration response to robots.[39] Our estimates imply that a 1% decline in employment corresponds to a 0.60% decline in high-skilled population. This response is more than twice as strong as that of low-skilled individuals, for whom we estimate only a 0.27% decline in population size. Among the different age groups, middle-aged individuals are estimated to be the most mobile (0.57%), and somewhat surprisingly, younger people to be the least mobile (0.27%).[40]

We corroborate the view that our results are driven by spillovers into industries that host more skilled (and more mobile) individuals by performing an additional exercise. 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 6, 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

[39] Not only high-skilled individuals, but also immigrants might be highly mobile (Cadena and Kovak, 2016). We focus on immigrants in Table A4, columns 7 and 8, Panel B. However, since the employment effect of robots is close to zero for immigrants, we cannot conclude whether, also in our setting, immigrants are more likely to migrate, as shown by Cadena and Kovak (2016) for the Great Recession.

[40] In unreported results, we found that the migration elasticities of men and women were very similar.

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.

[Table 6 here]

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 7, 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.[41] The intuition is that services may have had higher capacity to grow in regions that were initially specialized in that sector.

[Table 7 here]

Table 7 reveals that Chinese imports led to employment growth outside manufacturing 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.

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

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

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.

6 Modeling the role of non-manufacturing

The previous analysis suggests that the asymmetric effects on non-manufacturing employment, via general equilibrium channels, are important for explaining the differential migration response to robot adoption and import competition. In this section, we build a quantitative spatial economic model to better understand the drivers of the employment effects of each shock in general equilibrium. The model serves two purposes. First, it uncovers the forces triggered by each shock that can cause either positive or negative employment effects and, in turn, influence migration in different directions. Second, it isolates two parameters responsible for the disparate employment effect outside manufacturing and the associated migration response: the cost savings that each shock provides, and the complementarity between directly and indirectly exposed industries. The model abstracts from many of the margins discussed above – perhaps most notably, heterogeneous migration elasticities. Since the latter mechanism has already been examined in previous work and is well understood (Borusyak et al., 2022; Bound and Holzer, 2000; Notowidigdo, 2020; Topel, 1986), we prefer to focus our attention on the asymmetric employment spillovers, which have received less attention in the literature thus far.

6.1 A two-sector model with mobile labor

The model, which is presented in more detail in Appendix D.1, builds on a recent body of research on quantitative spatial economics to incorporate the effects of automation and trade competition in a setting with geographically mobile agents.[42] We rely on Acemoglu and Restrepo (2020) and Grossman and Rossi-Hansberg (2008) to model the effects of automation and trade, respectively, and we nest these two modeling devices in an economic geography model that follows Allen and Arkolakis (2014) with a perfect

[42] For a recent review of this literature see Redding and Rossi-Hansberg (2017).

competition Armington setup (Anderson, 1979; Armington, 1969). We show that, with few additional assumptions, the two shocks can be put completely on par, facilitating their comparison from a theoretical standpoint. Such comparison highlights that the different migration responses triggered by the shocks estimated above are surprising, given their similar theoretical properties.

Trade in final vs. intermediate goods. The growth of Chinese exports led to deeper integration between the US and China in the markets for both final goods and intermediate inputs. Our model focuses on the latter, which can happen either within (via offshoring) or outside (via availability of cheaper intermediate inputs) firm boundaries. The focus on intermediate inputs is motivated by our interest in understanding the forces behind Chinese import competition that might have countervailing, positive effects on labor demand. Intermediate inputs represent precisely one such mechanism (see Bloom et al., 2019, for offshoring, and Ding et al., 2019, for availability of cheaper intermediates). As in Grossman and Rossi-Hansberg (2008), we model import competition as an increase in offshoring capabilities of US firms.[43] As noted in Grossman and Rossi-Hansberg (2008), whether tasks are carried out abroad within (offshoring) or outside (intermediate inputs) firm boundaries is largely a semantic distinction, at least at the level of abstraction used in our model. In addition, Boehm et al. (2020) show that the two forces usually go hand in hand. Since offshoring is conceptually more easily comparable with automation, we opt for this in our model.[44]

Environment. We consider an economy with $n = 1, ..., N$ CZs. Each CZ produces a unique differentiated variety of a good, and CZs are connected via a bilateral transport network under symmetric iceberg trade costs: $d_{ni} = d_{in} > 1, n \neq i$ with $d_{nn} = 1$. There is a mass $\overline{L}$ of representative consumers who are mobile across CZs and are endowed with one unit of labor that they supply inelastically with no disutility.[45] Preferences over varieties take the CES form (with elasticity σ). Hence, a consumer living in CZ n has indirect utlity $V_n = \frac{w_n}{P_n}$, where w_n and P_n are the wage and ideal price index, respectively, in that CZ.

[43] Our empirical strategy relies on a measure of Chinese imports per worker (following Autor et al., 2013), irrespective of whether these are final or intermediate goods. As noted in Autor et al. (2013), it is difficult to disentangle the effect of the two empirically, since they are highly correlated with each other.

[44] This is similar in spirit to how trade and automation are treated in Costinot and Werning (2018).

[45] An elastic labor supply is not necessary to generate endogenous labor supplies across CZs, because representative agents are geographically mobile.

There are only two sectors per CZ: a manufacturing sector that produces the tradeable variety, and a non-manufacturing sector that produces an intermediate non-tradeable input (e.g., professional services). Firms in the manufacturing sector produce each variety with a constant returns to scale technology and under perfect competition. In the quantitative exercises described below, we assume that firms can either automate or offshore some tasks in their production process, but not both.[46] A firm located in CZ i operates under:

$$Q_i^h = A_i \left[\left(\min_{\nu \in [0,1]} \left\{ \tau_i^h(\nu) \right\} \right)^{\frac{\varepsilon_i^h - 1}{\varepsilon_i^h}} + I_i^{h\,\frac{\varepsilon_i^h - 1}{\varepsilon_i^h}} \right]^{\frac{\varepsilon_i^h}{\varepsilon_i^h - 1}}, h = R, O \tag{6}$$

where I_i^h is the intermediate non-tradeable input, A_i represents the productivity of location i, and $\tau_i^h(\nu)$ represents the amount of task ν used in production out of a continuum of tasks indexed by $\nu \in [0,1]$. The parameter ε_i^h is the industry elasticity of substitution (i.e.s.), which governs the degree of substitution between manufacturing tasks and non-manufacturing inputs. This is one of the key parameters we focus on in our quantitative exercises below. The superscripts index with $h = R$ firms with tasks subject to automation, and $h = O$ firms subject to offshoring.

The functional form for $\tau_i^R(\nu)$ is similar to that in Acemoglu and Restrepo (2020):

$$\tau_i^R(\nu) = \begin{cases} \gamma_R R_i(\nu) + \gamma_L^R L_i^R(\nu) & \text{if} \quad \nu \leq \theta_i^R \\ \gamma_L^R L_i^R(\nu) & \text{if} \quad \nu > \theta_i^R \end{cases}, \tag{7}$$

where $R_i(\nu)$ and $L_i^R(\nu)$ are the amounts of industrial robots and human labor used in producing task ν, respectively. The parameters γ_R and γ_L^R capture their respective productivities. The intuition is that tasks below the threshold θ_i^R are subject to automation, with industrial robots being perfect substitutes for human labor, whereas tasks above θ_i^R can only be performed by human labor. We assume that firms have access to an international market for industrial robots. In each location i, firms can purchase one robot at price p_i^{R*}, which they take as given. This is consistent with the

[46] This is consistent with the low correlation (0.06) between CZs' exposures to robots and Chinese imports.

fact that US firms largely rely on imports to purchase industrial robots.[47] Denoting the domestic wage with w_i, it is easy to show that, if $1 - \frac{\gamma_L^R}{\gamma_R}\frac{p_i^{R*}}{w_i} > 0$, firms adopt robots for all tasks $\nu \leq \theta_i^R$. In our equilibrium, and from now on, we focus on this case.

To model $\tau_i^O(\nu)$, we follow Grossman and Rossi-Hansberg (2008):

$$\tau_i^O(\nu) = [\beta t(\nu)]^{-1} \gamma_L^O L_i^F(\nu) + \gamma_L^O L_i^O(\nu), \tag{8}$$

where $L_i^F(\nu)$ and $L_i^O(\nu)$ are the number of foreign and domestic workers used to perform task ν, respectively. The parameter γ_L^O captures total productivity of each form of labor, whereas $\beta t(\nu) \geq 1$ captures the higher relative productivity of domestic labor. Tasks are ordered so that $t(\nu)$ is non-decreasing. To increase the comparability of the two shocks, we further customize equation (8). Let w_i^* be the foreign wage faced by firms engaging in offshoring. Then, firms' optimization under the specification in equation (8), with $t(\nu)$ non-decreasing and $\beta t(0) w_i^* < w_i$, implies that there is a threshold below which firms offshore all tasks. However, this threshold is endogenous and changes with the model's parameters, thereby complicating the comparison to a shift in θ_i^R in equation (7). For this reason, we adopt a more specific form for the schedule $t(\cdot)$, and assume $t(\cdot) = \underline{t}$ for $\nu \leq \theta_i^O$, and $t(\cdot) = \bar{t}$, with $1 \leq \beta\underline{t} < \beta\bar{t}$. As in the case of robots, we focus on the case in which $\beta\underline{t}w_i^* < w_i < \beta\bar{t}w_i^*$. In this scenario, firms find it optimal to offshore all tasks $\nu \leq \theta_i^O$, and hire domestic labor for tasks $\nu > \theta_i^O$.

For simplicity, we assume that the non-tradeable intermediate input is produced under perfect competition with a constant returns technology given by $x_i^S = A_i^S E_i^S$, where E_i^S is non-manufacturing labor and A_i^S captures its productivity.

6.2 Equilibrium impact of the shocks

Labor mobility implies that welfare is equalized across CZs: $V_n = \overline{V}$. For the aggregate labor market to clear, it must hold that $\sum_{n=1}^{N} L_n = \overline{L}$,, where L_n is CZ n population, and we normalize $\sum_{i=1}^{N} w_i = 1$. We define a *spatial equilibrium* as a distribution of economic activity such that (a) consumers and firms make optimal choices, (b) markets clear, and (c) welfare is equalized. Appendix D.2 proves that, under some additional

[47] Out of the 28 robot supplier members in the International Federation of Robotics (IFR), only one is based in the United States (Leigh and Kraft, 2018).

assumptions on the international labor and industrial robots markets, the equilibrium exists and is unique.

We now investigate the equilibrium impact of both shocks on CZ population. Our goal is to examine: *i*) how CZ population responds to robot exposure and Chinese imports; and, *ii*) what labor market forces – within and outside manufacturing – mediate such responses.

Decomposition of employment effects. We begin by examining the forces shaping labor demand. Appendix D.2 shows that, if regions are homogeneous, in equilibrium:

$$d\ln L_i = \Omega_i d\ln E_i^M + (1-\Omega_i)\, d\ln E_i^S, \tag{9}$$

where E_i^M denotes manufacturing employment in CZ i (recall that E_i^S denotes non-manufacturing employment), and $\Omega_i = \frac{E_i^M}{L_i}$. Equation (9) shows that the proportional change in the population of CZ i is a weighted average of the (proportional) changes in manufacturing and non-manufacturing employment, with weights equal to the shares of the two types of employment. This is a straightforward result, since in this model there is no unemployment, and everyone supplies one unit of labor inelastically.

Appendix D.2 also shows that:

$$d\ln E_i^M = -\frac{d\theta_i^h}{1-\theta_i^h} - \sigma d\ln\varphi_i - \varepsilon_i^h d\ln\left[\left\{(A_i\varphi_i)^{1-\varepsilon_i^h} - \left(A_i^S\right)^{-\left(1-\varepsilon_i^h\right)}\right\}^{\frac{1}{1-\varepsilon_i^h}} / A_i\varphi_i\right] + \zeta \tag{10}$$

$$d\ln E_i^S = -\sigma d\ln\varphi_i - \varepsilon_i^h d\ln\left[\left(A_i^S\right)^{-1} / A_i\varphi_i\right] + \zeta, \tag{11}$$

where φ_i is the constant unit cost of production normalized by w_i. According to equation (10), the effect of robot penetration and Chinese import competition on labor demand for manufacturing employment can be decomposed in three different forces. The first term is a *displacement* effect: as more tasks are automated (resp., offshored), domestic labor is displaced by industrial robots (resp., foreign labor), and manufacturing employment declines. The second term is a *productivity* effect: as firms automate (resp., offshore) a larger set of tasks, they become more productive, expanding at the expense of other varieties in the economy. This also increases their demand for manufacturing labor in tasks that have not yet been automated (resp., offshored). The third term is an *industry-substitution* effect: as the manufacturing sector becomes more productive than the non-manufacturing one, labor demand shifts in favor of all manufacturing factors of production, at the expense of non-manufacturing factors of production. This also increases demand for manufacturing labor in tasks that have not yet been automated (resp., offshored).[48] The parameter ζ present in both equation (10) and equation (11) captures general equilibrium effects common to all CZs. Since these do not depend on CZ exposure to either shock, they are not captured in our empirical estimates. For simplicity, when referring to "total effects" below, we ignore the presence of ζ.

An advantage of a setup with only two sectors per CZ is that one can derive explicit expressions for both directly and *indirectly* exposed industries. Equation (11) shows that a similar decomposition can be applied to non-manufacturing employment, except for the displacement effect. This is because the latter effect has no bite for factors of production outside manufacturing. The first term in equation (11) is the productivity effect for non-manufacturing employment, which in this model is the same as that in equation (10). As manufacturing firms producing variety i become more productive, they increase their demand for all factors of production, including intermediate inputs from non-manufacturing firms. This raises non-manufacturing employment, even though the sector is not directly affected by the shocks. The second term in equation (11) captures the industry-substitution effect, which is the counterpart of that in equation (10). This is also an indirect effect, again driven by manufacturing becoming more productive in relative terms.

Sensitivity to parameter changes. To better understand the behavior of the three effects, we examine how they change when we shift two key parameters of the model: the industry elasticity of substitution (i.e.s.), and the cost savings. The i.e.s. is the parameter regulating the degree of substitution between manufacturing tasks and non-manufacturing inputs in equation (6), ε_i^h. The cost savings are given by $cs_R = \left(1 - p^{R*}\frac{\gamma_L^R}{\gamma_R}\right)$ and $cs_O = (1 - w^*\beta\underline{t})$ for industrial robots and offshoring, respectively. We focus on these parameters for two reasons. First, they are crucial drivers of spillovers into the non-manufacturing sector in the model; second, existing evidence

[48] These three forces are also present in a very similar fashion in Acemoglu and Restrepo (2020) and Grossman and Rossi-Hansberg (2008), albeit for wages in the latter. We follow their terminology as much as possible but, apart from the productivity effect, they do not coincide.

(described in detail in Appendix D.3) suggests that the two parameters differ between robots and Chinese import competition.

Figures 7 and 8 focus on the i.e.s. and the cost savings of each shock, respectively. Both figures plot each of the three effects scaled by $d \ln \theta_i^h$ and multiplied by 100 in order to ease the comparison with our quantitative results below.

[Figure 7 here]

[Figure 8 here]

Consistent with the first term in equation (10), the displacement effect on manufacturing labor does not depend on either the i.e.s. or the cost savings. Even though the displacement effect itself is zero for non-manufacturing, there is variation in the lower left panel of, for example, Figure 7. This is because the weights Ω_i shift in favor of manufacturing for higher levels of i.e.s. The same logic applies to the entire first column of Figure 8, with the difference that the weights Ω_i now increase with the level of cost savings.

The second column of the two figures shows that the productivity effect is identical across rows (as it should be, given equations (10) and (11)), and increases with both the i.e.s. and the cost savings. As non-manufacturing becomes less complementary to manufacturing, productivity gains are larger, since the lack of direct effects on non-manufacturing becomes less relevant. At the same time, higher cost savings imply that the gains are larger for a given size of the shock. The third column in the two figures shows that the industry substitution effect is positive for manufacturing and negative for non-manufacturing. The effects are again increasing in both the i.e.s. and the cost savings, for the same reason as before. Finally, the last column plots the sum of the three previous columns for the corresponding row. The bottom right graph displays the net effects for population changes. The displacement effect is always negative, while the productivity effect is always positive. However, given the different signs of the three effects involved, the total effect is ambiguous.

Quantitative implications. To assess the quantitative implications of the model, we combine evidence from other studies with our own empirical estimates $\left(\hat{\beta}^r, \hat{\beta}^c\right)$ from Section 4.1 to perform two exercises, as explained in detail in Appendix D.3.

First, we assume that equations (10) and (11) hold, and use their functional forms to link (β^r, β^c) to the i.e.s. and the cost savings. In particular, we use external information to pin down all parameters in the model except for the i.e.s. and cost savings. Then, we solve for the values of these parameters that are consistent with our 2SLS estimates of (β^r, β^c) in Table 2. This allows us to compare the model consistent i.e.s. and cost savings with the external evidence on them. Thus, we follow the existing evidence and fix the cost savings at 40% and 22.78% for the trade and the robot shock, respectively. We then solve for the i.e.s. that matches $\left(\hat{\beta}^r, \hat{\beta}^c\right) = (-0.56, 0.45)$, the estimates from our preferred specification in Table 2 (column 5). We obtain $\left(\hat{\varepsilon}^R_{model}, \hat{\varepsilon}^O_{model}\right) = (5.001, 4.33)$. This indicates that the i.e.s. consistent with the model are in line with those in Atalay (2017), in the sense that $\hat{\varepsilon}^R_{model} > \hat{\varepsilon}^O_{model}$. Moreover, in this exercise we match not only our estimates on migration $\left(\hat{\beta}^r, \hat{\beta}^c\right)$ from Table 2, but also the signs of the effects on manufacturing and non-manufacturing employment in Table 5. Hence, at these values of the cost savings and i.e.s. parameters, the model predicts a negative effect of Chinese imports on manufacturing employment, but a positive one on non-manufacturing employment and population. In contrast, all three magnitudes are negative for robots.

In the second exercise, we test which margin, if any, can explain the difference between $\left(\hat{\beta}^r, \hat{\beta}^c\right)$ by itself. Appendix D.3 presents in detail the results from this exercise, which we briefly summarize here. In a nutshell, by partially reducing the cost savings associated with Chinese imports it is possible to make the estimated effect of Chinese imports on migration equal to that of robots. That is, the difference in cost savings is enough to explain the different migration responses triggered by local labor market shocks, and mediated by employment. Instead, while increasing the i.e.s. of import competition brings $\hat{\beta}^c$ closer to $\hat{\beta}^r$, the former always remains larger than the latter.

7 Conclusion

Labor mobility is an important force that can re-equilibrate labor markets after localized economic shocks. In this paper, we exploit variation in exposures to robots and Chinese imports between 1990 and 2015 across US CZs to study the migration response to these shocks alongside one another. Our main result is that only robots – and not import competition – triggered migration across CZs, even though both shocks reduced manufacturing employment. The population response to robot exposure was driven by lower in-migration rather than by increased out-migration. Stated differently, because of exposure to robots, prospective in-migrants who would have migrated to the CZ absent the shock chose not to do so. In contrast, we find no effect of robots on out-migration.

Exploring the mechanisms, we show 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. While robots caused significant employment losses also in industries not directly affected, Chinese imports, if anything, caused employment growth outside manufacturing. We offer suggestive evidence that, via these spillovers, only robots – but not Chinese imports – worsened employment opportunities for the most mobile individuals (i.e., high-skilled workers) who, in turn, decided to avoid labor markets affected by robots.

To gain more insights on the factors behind these spillovers, we develop a model where workers are geographically mobile and compete with either machines or foreign workers in the completion of tasks. Combining the model with external evidence on its parameters, we uncover two crucial causes for the disparate effects on employment outside manufacturing: cost savings generated by each shock, and the degree of complementarity between exposed and non-exposed industries. External evidence suggests that these two factors differ substantially between Chinese imports and robot penetration. In our model, the implied differences in cost savings are able to fully explain – via their effect on employment – the differential migration response we observe. Differences in complementarities can instead explain part, but not all, of it.

Findings in our paper might inform the contemporaneous political and economic debate on the future prospects of American labor markets. There are reasons to believe that the structural transformation of the US economy will continue in the years to come. By 2025, the stock of industrial robots around the world is expected to grow three to four times relative to its 2015 value (BCG, 2015), and the political climate in the US and other Western countries might lead to dramatic changes (likely reversals) in trade volumes. Alongside these trends, other potentially labor-replacing technologies, such as AI, are expected to cause further changes in labor demand patterns, particularly for individuals for which we estimate the highest elasticities to migrate (Frank et al., 2019; Webb, 2019).

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.

References

Abraham, Katharine G and Melissa S Kearney, "Explaining the decline in the US employment-to-population ratio: A review of the evidence," NBER Working Paper No. 24333, 2018.

Acemoglu, Daron and Pascual Restrepo, "Robots and Jobs: Evidence from US Labor Markets," *Journal of Political Economy*, 2020.

_ and _ , "Demographics and automation," *The Review of Economic Studies*, 2021.

Adao, Rodrigo, Michal Kolesár, and Eduardo Morales, "Shift-share designs: Theory and inference," *The Quarterly Journal of Economics*, 2019, *134* (4), 1949–2010.

AlixPartners, "2009 Manufacturing-Outsourcing Cost Index," 2009.

Allen, Treb and Costas Arkolakis, "Trade and the Topography of the Spatial Economy," *The Quarterly Journal of Economics*, 2014, *129* (3), 1085–1140.

Anderson, James E, "A Theoretical Foundation for the Gravity Equation," *American Economic Review*, March 1979, *69* (1), 106–116.

Angrist, Joshua D and Jörn-Steffen Pischke, *Mostly harmless econometrics*, Princeton university press, 2008.

Armington, Paul S., "A Theory of Demand for Products Distinguished by Place of Production," *IMF Staff Papers*, March 1969, *16* (1), 159–178.

Atalay, Enghin, "How Important Are Sectoral Shocks?," *American Economic Journal: Macroeconomics*, October 2017, *9* (4), 254–280.

Autor, David and David Dorn, "The growth of low-skill service jobs and the polarization of the US labor market," *The American Economic Review*, 2013, *103* (5), 1553–1597.

_ , _ , and Gordon H Hanson, "The China syndrome: Local labor market effects of import competition in the United States," *The American Economic Review*, 2013, *103* (6), 2121–2168.

— , **Frank Levy, and Richard J. Murnane**, "The Skill Content of Recent Technological Change: An Empirical Exploration," *The Quarterly Journal of Economics*, 2003, *118* (4), 1279.

Autor, David H, David Dorn, and Gordon H Hanson, "The China shock: Learning from labor-market adjustment to large changes in trade," *Annual Review of Economics*, 2016, *8*, 205–240.

— , — , — , **and Jae Song**, "Trade adjustment: Worker-level evidence," *The Quarterly Journal of Economics*, 2014, *129* (4), 1799–1860.

Bartik, Alexander W, "Moving Costs and Worker Adjustment to Changes in Labor Demand: Evidence from Longitudinal Census Data," 2018.

BCG, "The robotics revolution: The next great leap in manufacturing," *bcg. perspectives*, 2015.

Blanchard, Olivier and Lawrence F. Katz, "Regional evolutions," *Brookings Papers on Economic Activity*, 1992, *1992* (1), 1–75.

Bloom, Nicholas, Kyle Handley, Andre Kurman, and Phillip Luck, "The Impact of Chinese Trade on US Employment: The Good, The Bad, and The Debatable," 2019.

Boehm, Christoph E., Aaron Flaaen, and Nitya Pandalai-Nayar, "Multinationals, Offshoring, and the Decline of U.S. Manufacturing," *Journal of International Economics*, 2020, *127* (C).

Borusyak, Kirill, Rafael Dix-Carneiro, and Brian Kovak, "Understanding Migration Responses to Local Shocks," *Available at SSRN 4086847*, 2022.

Bound, John and Harry J Holzer, "Demand shifts, population adjustments, and labor market outcomes during the 1980s," *Journal of Labor Economics*, 2000, *18* (1), 20–54.

Brynjolfsson, Erik, Tom Mitchell, and Daniel Rock, "What can machines learn, and what does it mean for occupations and the economy?," in "AEA Papers and Proceedings," Vol. 108 2018, pp. 43–47.

Cadena, Brian C and Brian K Kovak, "Immigrants equilibrate local labor markets: Evidence from the Great Recession," *American Economic Journal: Applied Economics*, 2016, *8* (1), 257–90.

Charles, Kerwin Kofi, Erik Hurst, and Mariel Schwartz, "The transformation of manufacturing and the decline in US employment," *NBER Macroeconomics Annual*, 2019, *33* (1), 307–372.

Conley, Timothy G, "GMM estimation with cross sectional dependence," *Journal of Econometrics*, 1999, *92* (1), 1–45.

Costinot, Arnaud and Iván Werning, "Robots, Trade, and Luddism: A Sufficient Statistic Approach to Optimal Technology Regulation," NBER Working Papers 25103, National Bureau of Economic Research, Inc September 2018.

Derenoncourt, Ellora, "Can you move to opportunity? Evidence from the Great Migration," *American Economic Review*, 2022, *Forthcoming.*

Ding, Xiang, Teresa C Fort, Stephen J Redding, and Peter K Schott, "Structural Change Within Versus Across Firms: Evidence from the United States," Technical Report, Discussion Paper). Dartmouth College 2019.

Dix-Carneiro, Rafael, "Trade liberalization and labor market dynamics," *Econometrica*, 2014, *82* (3), 825–885.

Dustmann, Christian, Uta Schönberg, and Jan Stuhler, "Labor supply shocks, native wages, and the adjustment of local employment," *The Quarterly Journal of Economics*, 2017, *132* (1), 435–483.

Frank, Morgan R, David Autor, James E Bessen, Erik Brynjolfsson, Manuel Cebrian, David J Deming, Maryann Feldman, Matthew Groh, José Lobo, Esteban Moro et al., "Toward understanding the impact of artificial intelligence on labor," *Proceedings of the National Academy of Sciences*, 2019, *116* (14), 6531–6539.

Greenland, Andrew, John Lopresti, and Peter McHenry, "Import competition and internal migration," *Review of Economics and Statistics*, 2019, *101* (1), 44–59.

Grossman, Gene M. and Esteban Rossi-Hansberg, "Trading Tasks: A Simple Theory of Offshoring," *American Economic Review*, December 2008, *98* (5), 1978–1997.

Hsieh, Chang-Tai and Zheng Michael Song, "Grasp the large, let go of the small: the transformation of the state sector in China," NBER Working Paper No. 21006, 2015.

IFR, "World Robotics 2021," Technical Report, International Federation of Robotics 2021.

IRS, Internal Revenue Service, "Migration data," 2019.

Kearney, Melissa S and Riley Wilson, "Male earnings, marriageable men, and nonmarital fertility: Evidence from the fracking boom," *Review of Economics and Statistics*, 2018, *100* (4), 678–690.

Kronmal, Richard A, "Spurious correlation and the fallacy of the ratio standard revisited," *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, 1993, *156* (3), 379–392.

Leigh, Nancey Green and Benjamin R Kraft, "Emerging robotic regions in the United States: insights for regional economic evolution," *Regional Studies*, 2018, *52* (6), 804–815.

Molloy, Raven, Christopher L Smith, and Abigail Wozniak, "Internal migration in the United States," *Journal of Economic perspectives*, 2011, *25* (3), 173–96.

Monras, Joan, "Economic shocks and internal migration," 2018.

Moretti, Enrico, *The new geography of jobs*, Houghton Mifflin Harcourt, 2012.

Notowidigdo, Matthew J, "The incidence of local labor demand shocks," *Journal of Labor Economics*, 2020, *38* (3), 687–725.

Pierce, Justin R and Peter K Schott, "The surprisingly swift decline of US manufacturing employment," *American Economic Review*, 2016, *106* (7), 1632–62.

Redding, Stephen J. and Esteban Rossi-Hansberg, "Quantitative Spatial Economics," *Annual Review of Economics*, September 2017, *9* (1), 21–58.

Ruggles, Steven, Sarah Flood, Ronald Goeken, Josiah Grover, Erin Meyer, Jose Pacas, and Matthew Sobek, "IPUMS USA: Version 8.0 [dataset]," *Minneapolis, MN: IPUMS*, 2018.

Simonovska, Ina and Michael E. Waugh, "The elasticity of trade: Estimates and evidence," *Journal of International Economics*, 2014, *92* (1), 34–50.

Storesletten, Kjetil and Fabrizio Zilibotti, "China's great convergence and beyond," *Annual Review of Economics*, 2014, *6* (1), 333–362.

Timmer, Marcel P, Mary O Mahony, Bart Van Ark et al., "EU KLEMS growth and productivity accounts: an overview," *International Productivity Monitor*, 2007, *14*, 71.

Topel, Robert H, "Local labor markets," *Journal of Political Economy*, 1986, *94* (3, Part 2), S111–S143.

United Nations, Statistics Division, "United Nations Comtrade Database," *UN Comtrade Online*, 2019.

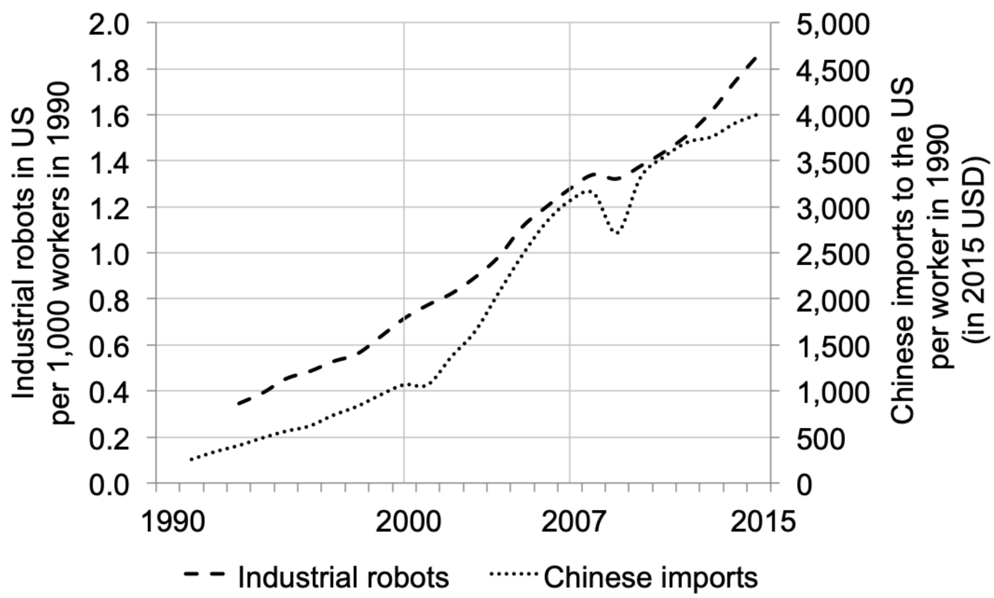
US Census Bureau, "County Business Patterns," *UN Comtrade Online*, 2019.

Wang, Jin, "The economic impact of special economic zones: Evidence from Chinese municipalities," *Journal of Development Economics*, 2013, *101*, 133–147.

Webb, Michael, "The Impact of Artificial Intelligence on the Labor Market," *Available at SSRN 3482150*, 2019.

Figures and Tables

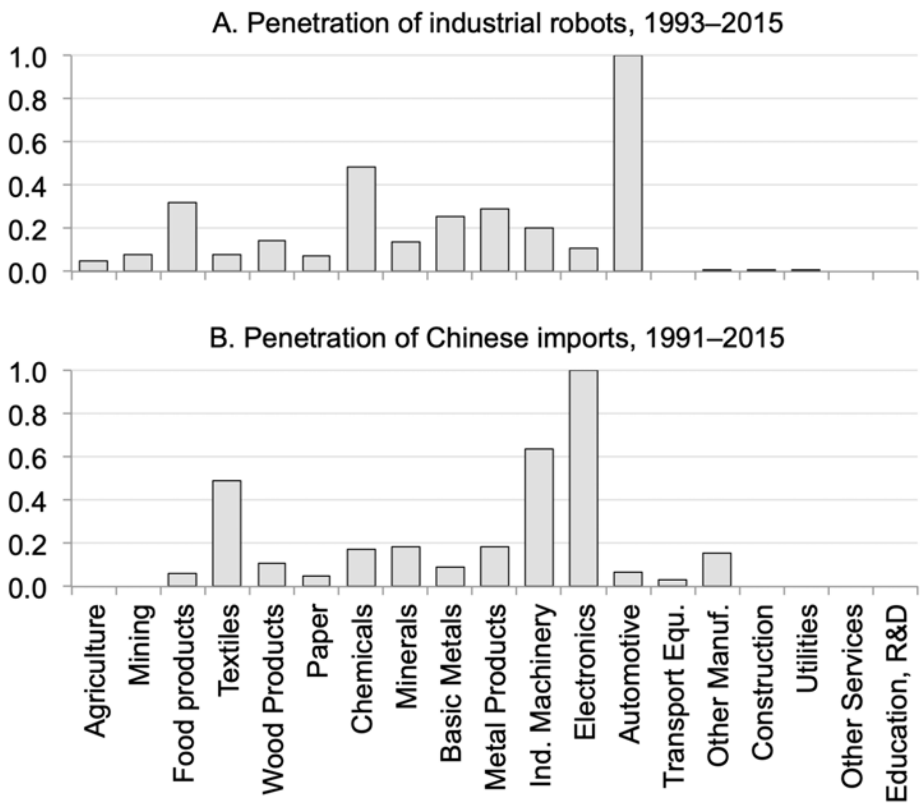
Figure 1: Temporal variation of robot adoption and Chinese imports



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).

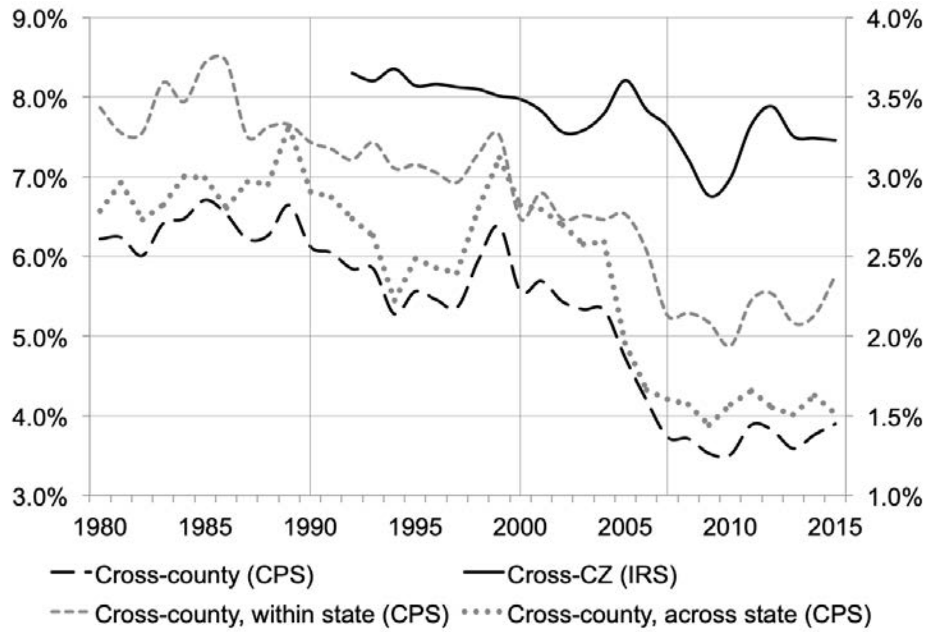
Figure 2: Industry variation of robot adoption and Chinese imports



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.

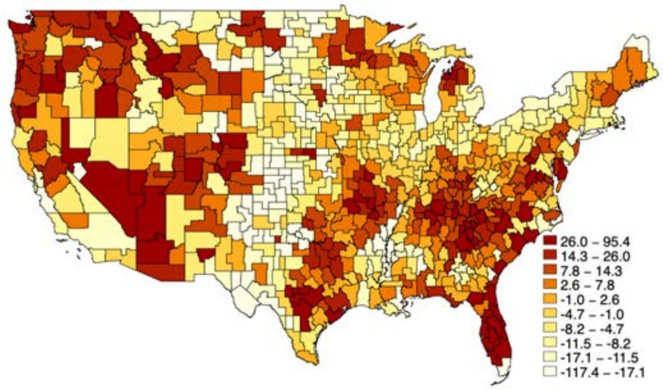
Figure 3: Evolution of US internal migration rates, 1980–2015



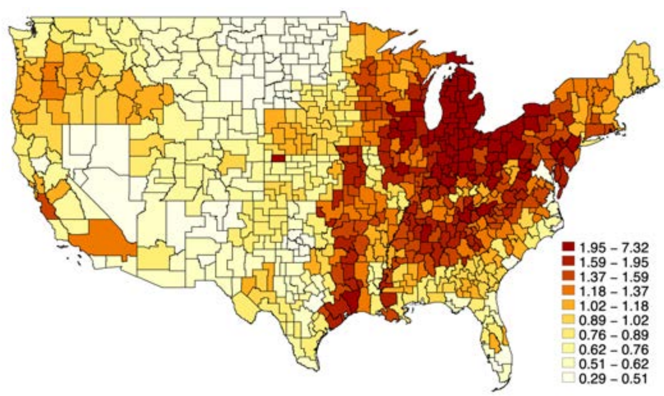
SOURCES: Current Population Survey (CPS), IRS (2019)

Note: The black lines (left axis) show the annual gross migration rates across US Commuting Zones (solid) and counties (long dashed). The gray lines (right axis) show the annual migration rates across counties, within states (dashed) and across counties, across state (dotted). IRS values for 2014 are interpolated from values in 2013 and 2015 to account for a discontinuity in the data.

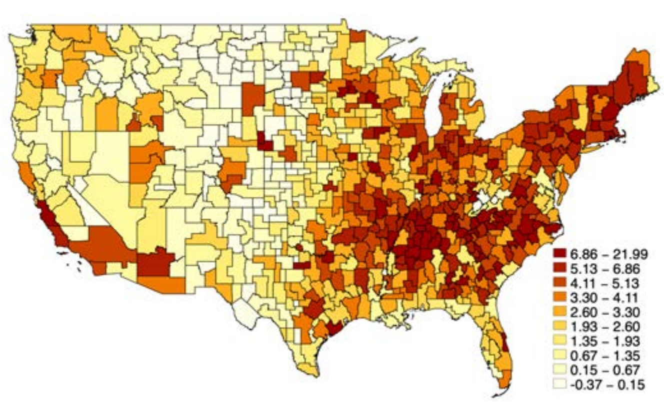
Figure 4: Geographic variation in migration and economic shocks



A. Net migration rate (1992–2015)



B. Exposure to robots (1993–2015)

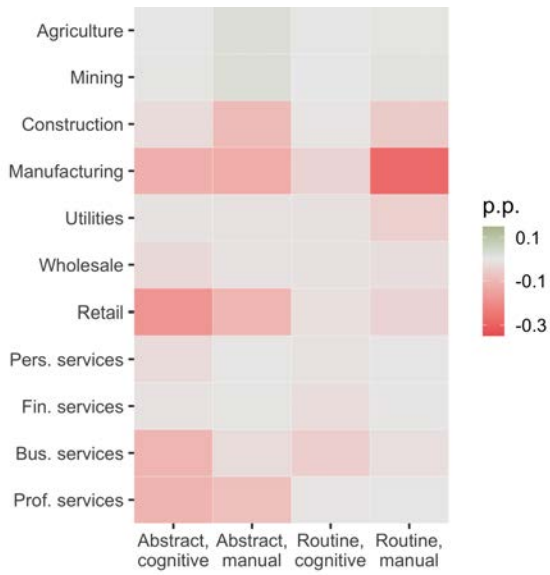


C. Exposure to Chinese imports (1991–2015)

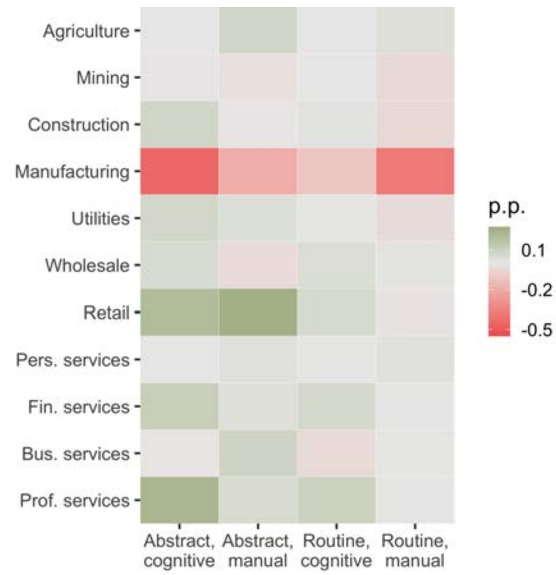
SOURCES: IFR (2021), United Nations (2019), Timmer et al. (2007), Ruggles et al. (2018), IRS (2019)

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

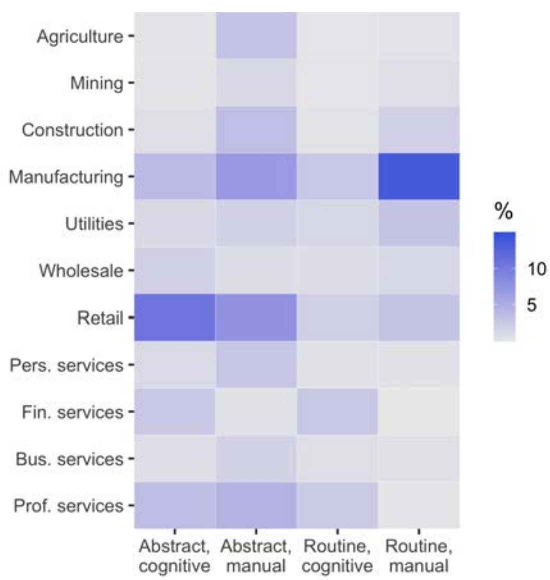
Figure 5: Industry-skill profile of robot adoption and Chinese imports



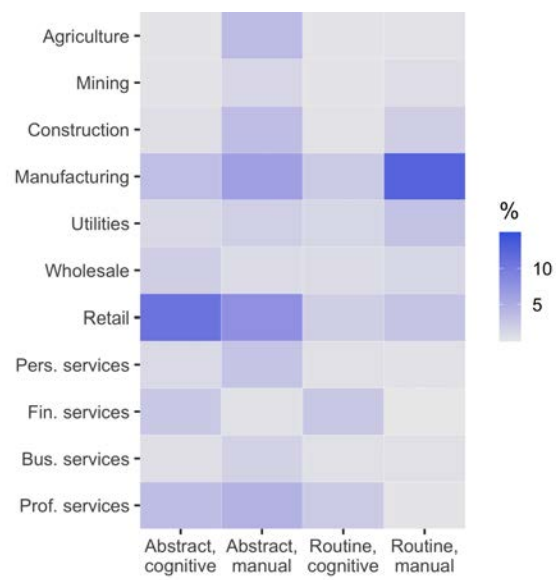
A. Exposure to robots



B. Exposure to Chinese imports



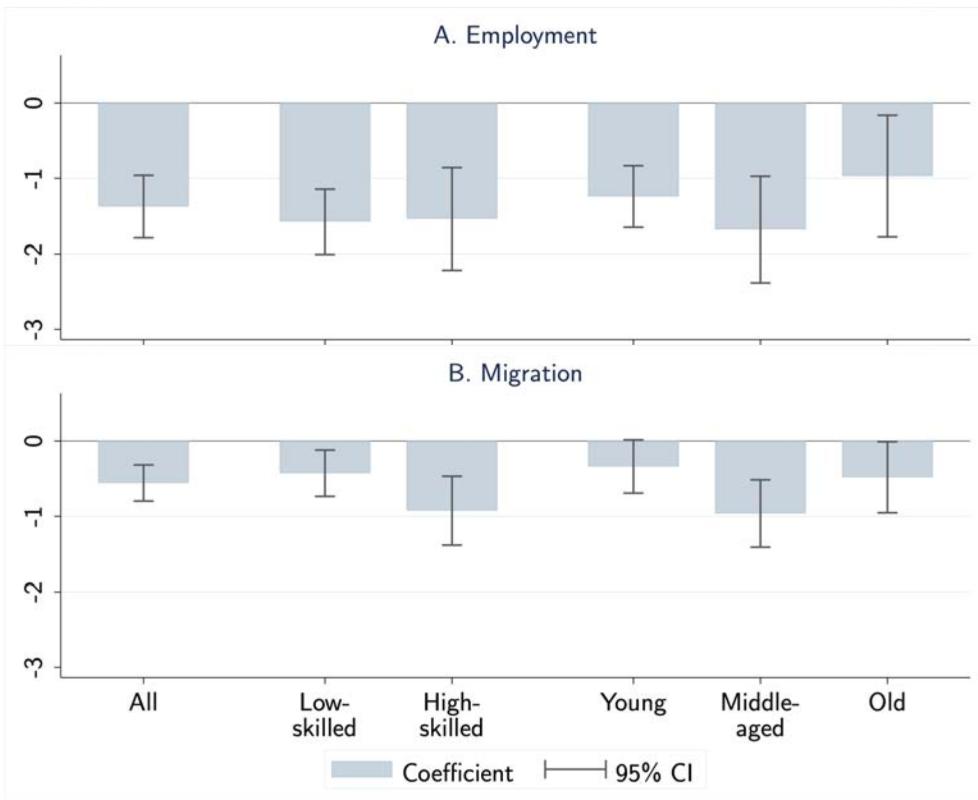
C. 1990 employment shares,
weighted by exposure to robots



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

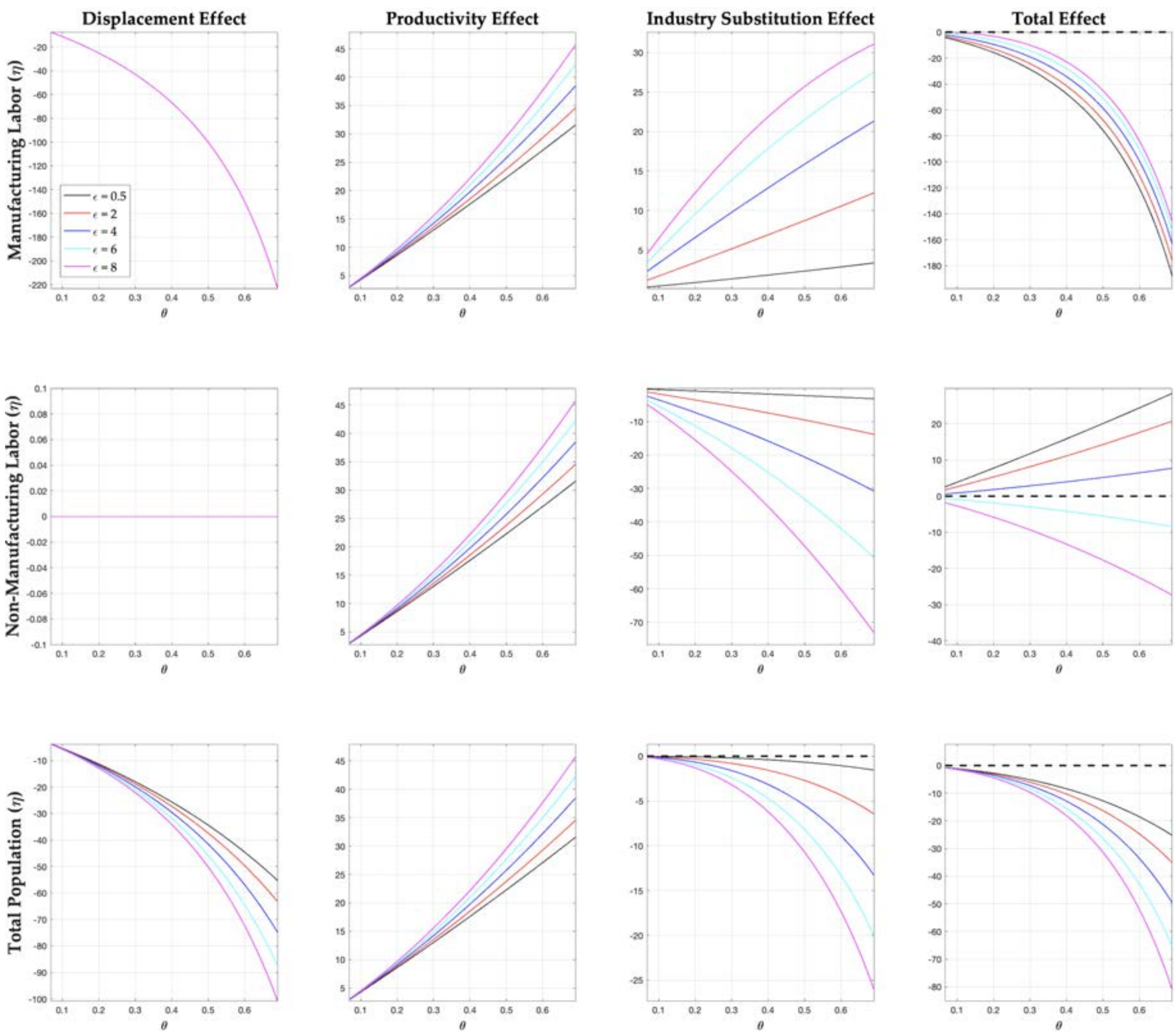
Note: Each cell in Panel A and B represents the coefficient on the (standardized) US exposure to robots and US exposure to Chinese imports, respectively, in a regression identical to the ones in column 5 of Table 2, but using the change in employment per industry-skill combination ij as a share of initial 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.

Figure 6: Effect of robots on employment and migration by subgroup



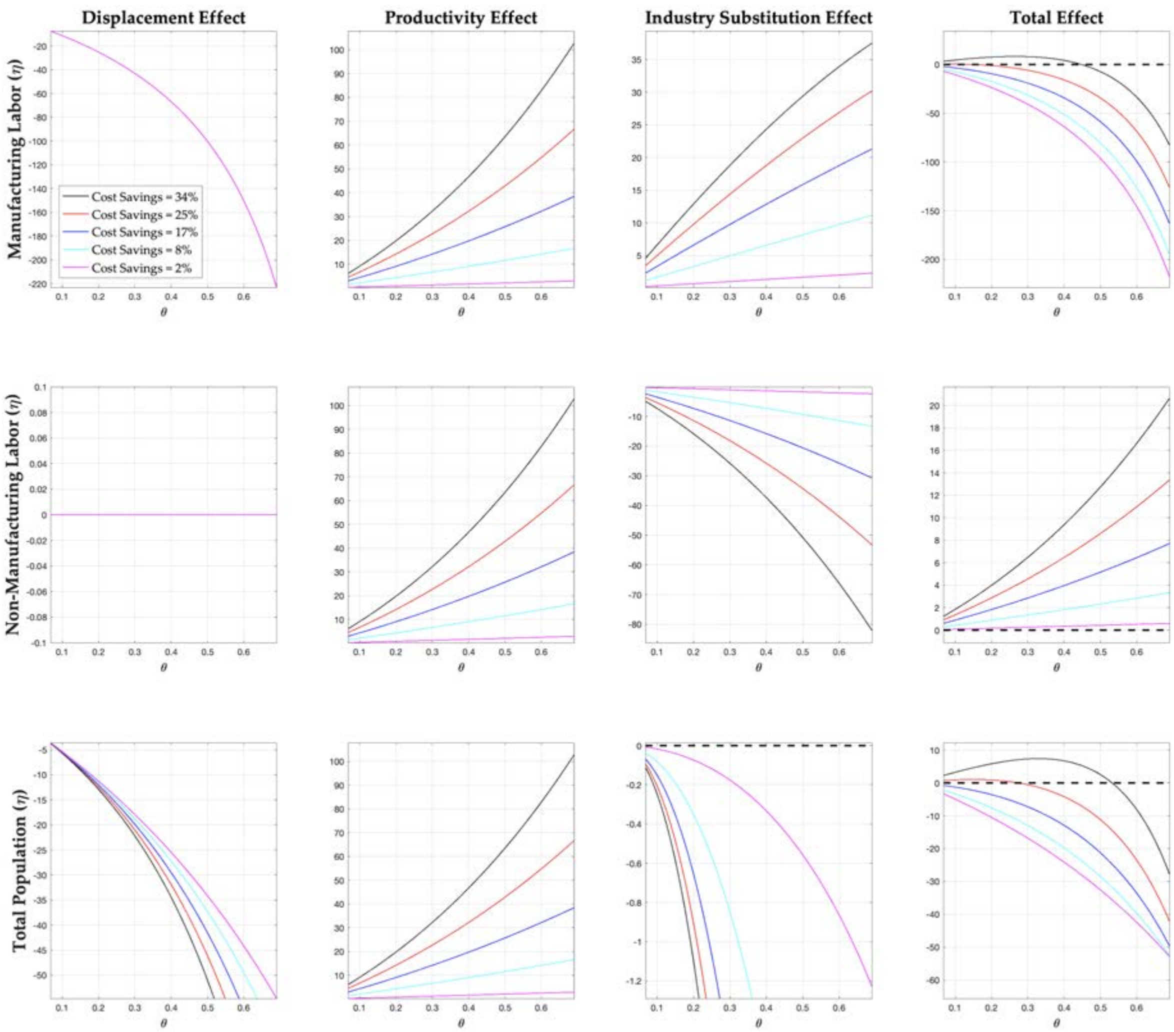
Note: Panels A and B present the coefficient on the US exposure to robots in a regression identical to the one in Table 2, column 5, using log changes in subgroup-specific employment and working-age population as the outcome variable, respectively, and weighting observations by a CZ's 1990 national share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

Figure 7: Variation in the employment and population effects for different levels of the i.e.s



Note: Variation in displacement, productivity, industry substitution and total effects for different levels of i.e.s. (ϵ) in manufacturing and non-manufacturing employment, and in total population.

Figure 8: Variation in the employment and population effects for different levels of cost savings



Note: Variation in displacement, productivity, industry substitution and total effects for different levels of cost savings in manufacturing and non-manufacturing employment, and in total population.

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 zero 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 zero 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 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 zero 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 4: 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 zero 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 5: 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 zero 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.

Table 6: 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 zero 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.

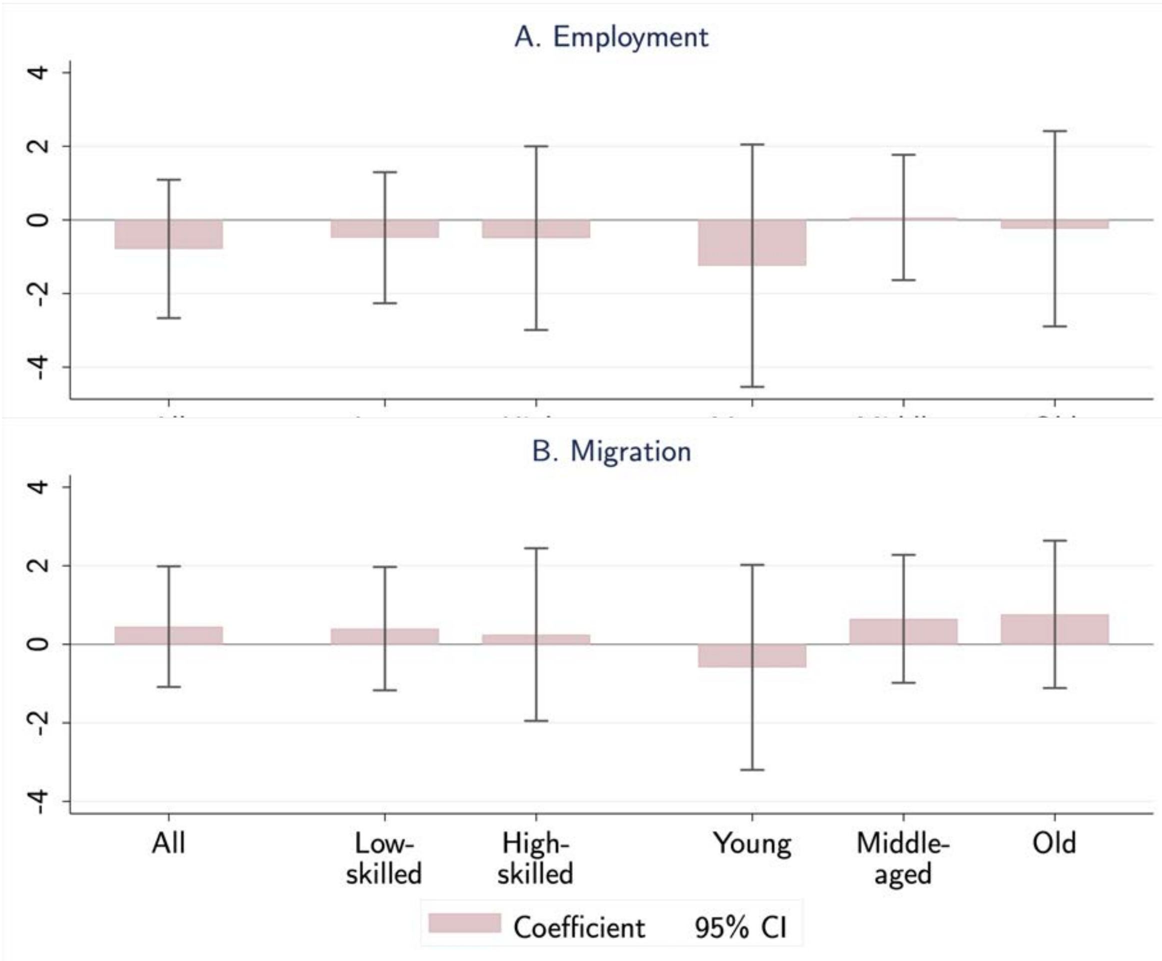
Table 7: Heterogeneity of effects by initial service intensity, stacked differences (reduced form)

	(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 zero 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.

A Additional figures and tables

Figure A1: Effect of Chinese imports on employment and migration by subgroup



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 zero 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 zero 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 zero and a standard deviation of 1. All outcome and displayed explanatory variables are converted to 10-year equivalents.

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 zero 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.