The Impact of Technology and Trade on Migration: Evidence from the US*

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December 2019

Abstract

Migration has long been considered one of the key mechanisms through which 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 have hit Western economies since the late 1990s – import competition from China and the introduction of industrial robots. Exploiting plausibly exogenous variation in exposure across US local labor markets over time, we first verify that both shocks led to a steep reduction in manufacturing employment. Next, we present our main results, and show that, on average, robots caused a sizable reduction in population size, whereas trade with China did not. The decline in population size due to robots resulted from reduced in-migration into rather than increased out-migration away from affected areas. In the second part of the paper, we explore the mechanisms behind these results. We show that the two labor market shocks differ in their propagation across industries within local labor markets: while robots caused negative spillovers to service industries, Chinese imports, if anything, favored employment growth outside of manufacturing. We provide suggestive evidence that these propagation patterns are responsible for the differential migration response.

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

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*We thank Daron Acemoglu, David Autor, Teresa Fort, Esteban Rossi-Hansberg, Kurt Schmidheiny, and the participants at UEA Summer School 2019 and WWZ Basel Economics Lunch for useful comments.

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1 Introduction

Workers' geographic mobility has long been considered one of the key mechanisms through which labor markets adjust to local economic shocks (Blanchard and Katz, 1992). It has also been described as one of the distinctive features of the American economy: relative to their European counterparts, American workers are typically perceived as being significantly more mobile and more responsive to differential economic opportunities across labor markets (Moretti, 2012). Such responsiveness is, in turn, crucial to both absorb negative economic shocks, and foster dynamism in the economy at the local and at the aggregate level.[1] The role of migration as a re-equilibrating mechanism may have been especially important in the past twenty years, when US manufacturing industries have been hit by strong and localized shocks – with Chinese import competition and industrial robots being widely considered the most important ones (Abraham and Kearney, 2018).

These two shocks have not only caused a steep decline in manufacturing employment, but also a rise in inequality of opportunities across labor markets, and a significant reduction in overall employment rates (Autor et al., 2013; Acemoglu and Restrepo, forthcoming; Abraham and Kearney, 2018). 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, regionally concentrated effects (Charles et al., 2018; Cadena and Kovak, 2016). This view is consistent with evidence showing that in the past thirty years, the mobility of American workers has displayed signs of declines (Molloy et al., 2011). At the same time, neither technological nor trade-related structural changes are likely to level off anytime soon. Recent case studies predict the global robot stock to double by 2020, and to increase by at least three-fold until 2025 (IFR, 2016; BCG, 2015). Given the current political climate in the US and many Western countries, it is also not unlikely that trade volumes with China and other countries will, again, change considerably in the years to come. Alongside these trends, new technologies such as Artificial Intelligence (AI) recently started to transform the economy and alter labor demand patterns (Frank et al., 2019). One of the key questions that policy makers face today is whether local labor markets will adjust smoothly to the new technological and trade-induced shocks or if, instead, frictions to labor mobility will prevent this from happening, leading to persistent levels of unemployment and to growing regional inequality.

[1] For example, Mundell (1961) emphasized the role of migration as an equilibrator mechanism in the context of optimal currency areas.

In this paper, we investigate this issue by studying the migration response to both trade and technology shocks across US Commuting Zones (CZs) between 1990 and 2015. Specifically, we focus on the effects of two main variables: import competition from China and the adoption of industrial robots. Following the existing literature (Autor et al., 2013; Acemoglu and Restrepo, forthcoming), we construct exogenous measures of local exposure to both shocks by combining the pre-period industrial composition of CZs with the growth in, respectively, import competition and robot adoption in other industrialized countries. These measures are highly correlated with the actual increase in import competition and robots exposure across CZs over time, but are more plausibly orthogonal to any omitted variable that might be correlated with both the shocks and changes in economic conditions prevailing in local labor markets over time.

Dividing the sample in three periods (1990-2000; 2000-2007; and 2007-2015), and using the instruments described above, we estimate stacked first difference regressions to identify the causal impact of both shocks on the change in CZ population. Specifically, our empirical strategy controls for any CZ time invariant characteristics, and allows CZs to be on differential trends depending on several baseline characteristics.[2]

We first verify that, consistent with existing studies, both shocks significantly reduce manufacturing employment, albeit the effect of robots is considerably smaller than that of Chinese imports (Acemoglu and Restrepo, forthcoming, Autor et al., 2013). Then, we turn to our main result, and show that industrial robots cause a sizable reduction in population size on average, whereas Chinese import competition does not. Exploring the potential channels of this migration response, we document that the reduction in CZ population induced by the robot shock does not arise from increased out-migration but, instead, from a decline in in-migration.[3] According to our most preferred estimates, each new robot reduces in-migration by about three working-age individuals. This migration response significantly reduces the extent to which employment losses due to robots adoption translate into lower employment *rates*.

The second part of our paper seeks to isolate the causes behind the the differential

[2] In particular, we allow for time period specific differential trends in nine broad 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.

[3] These findings are consistent with recent work by Monras (2018) for the US and Dustmann et al. (2017) for Germany, who suggest that local labor markets adjust more due to changes in the behavior of prospective migrants rather than that of incumbent workers.

migration response to the two labor market shocks. First, and in line with previous work, we document that the employment effects of robots "spill over" to industries that are not directly affected, such as business and professional services, as well as retail (Acemoglu and Restrepo, forthcoming). This pattern differs substantially from that associated with import competition, whose negative effects remain concentrated within the manufacturing sector, and, if anything, may cause positive employment effects outside of the manufacturing sector (Bloom et al., 2019; Ding et al., 2019).

Next, we offer suggestive evidence that spillovers into high-skilled industries may be responsible for the differential migration response between the two shocks. We find that robots reduce employment in both low-skilled (mostly within manufacturing) and high-skilled employment (mostly outside of manufacturing) to a similar extent, and that the migration response is largely driven by high-skilled individuals. Said differently, our results suggest 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 the effects of Chinese imports, we document that regions where non-manufacturing employment *increased* experienced a surge in population growth, due to *higher* in-migration. Specifically, we find that Chinese imports generate significantly positive employment effects outside manufacturing in regions with a high degree of specialization in services (high service intensity regions, HSI), and slightly negative, though not statistically significant, effects in regions with a low degree of specialization in services (low service intensity regions, LSI).[4] In line with these patterns, we find that import competition caused a rise in in-migration in HSI regions, and a mild (but not statistically significant) reduction in population in LSI regions. Overall, our evidence indicates that, at least in the case of robot exposure and import competition, the migration response to local labor market shocks does not depend on the overall employment effects of such shocks, but, rather, on their impact outside of manufacturing.

One alternative explanation for our results is that the two shocks coincided with different macro-economic conditions that, in turn, had differential effects across regions. In particular, the main thrust of the surge in Chinese imports happened before the Great Recession, whereas the increase in the number of robots has continued at a similar pace throughout. One may thus worry that the interaction of the robot shock with recession-

[4] This result is broadly in line with Bloom et al. (2019), who show that reallocation of employment into non-manufacturing in response to the China shock was particularly strong in regions with initially high levels of human capital.

ary conditions partly affects our results. Our stacked difference setting allows us to rule out this possibility: we show that prior to the Great Recession, the migration response to robots is not only existent but also almost identical in size. A second concern for the interpretation of our results is that differences in initial characteristics (e.g., the share of employment in the tradable sector or the share of women in the labor force) between areas exposed to robots and Chinese imports may explain the differential migration response. To rule out this possibility, we allow CZs to be on differential trends in each period according to a large number of baseline characteristics. Reassuringly, all our results are unchanged.

Our paper contributes to different strands of the literature. First, it is related to the large set of papers that have studied the local labor market effects of import competition from China and exposure to robots (Autor et al., 2013; Autor et al., 2014; Dix-Carneiro, 2014; Acemoglu and Restrepo, forthcoming; Bloom et al., 2019; Ding et al., 2019). We complement these works by analyzing the migration response to these shocks in order to understand if labor mobility acted as a re-equilibrator, or if, instead, workers' geographic immobility might be one of the mechanisms behind the sluggish recovery of local labor markets after the shocks hit. Although a recent paper by Greenland et al. (2019) has studied the migration response to import competition from China, to the best of our knowledge, we are the first to compare the migration response to import competition and robots alongside one another.[5]

Second, and more generally, our paper is related to a number of recent works that have evaluated workers' geographic mobility following specific local economic shocks (Bartik, 2018; Cadena and Kovak, 2016; Kearney and Wilson, 2018; Monras, 2018). We expand on these papers by comparing the response of the same local labor markets to two simultaneous shocks to US manufacturing. Our results suggest that the elasticity of migration with respect to economic shocks is not a fixed parameter that is independent of the type of shocks hitting labor markets. On the contrary, our findings imply that different shocks can lead to different migration responses, depending on the set of individuals they affect, and, crucially, on the extent to which they propagate to other industries in the same local labor market.

Finally, we hope that our paper can inform the design of specific policies aimed at dealing with different types of shocks in the future. For example, AI is believed to not

[5] Our results are somewhat in contrast with Greenland et al. (2019), who find that trade did lead to a population response. One possible reason for the discrepancy between our results and theirs may be the more comprehensive set of controls included in our analysis.

only affect demand for low skilled 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 work-force to AI automation. Given the large heterogeneity in migration elasticities documented in our work, we conjecture that our findings have important implications on how much AI technologies are expected to affect unemployment rates, regional inequality, and local demographics in the years to come. Specifically, the geographic mobility of high skilled workers may partly mitigate the differential employment consequences of local labor markets, and for this reason, the impact of AI on local labor markets might be both qualitatively and quantitatively different from that of a trade shock.

The paper is structured as follows. Section 2 describes the empirical context and presents the two shocks we consider in our work – that is, the rise of industrial robots and Chinese import competition. Section 3 presents the empirical strategy. Section 4 describes our data and presents descriptive statistics for the main variables of interest. Section 5 estimates the effects of industrial robots and import competition from China on employment and, crucially, on internal migration across CZs. Section 6 investigates the mechanism. Section 7 concludes.

2 Description of shocks

Our empirical analysis is focused on the two labor demand 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]

2.1 Robots

The use of industrial robots in the US and around the world has grown significantly since the beginning of the 1990s. Advances in the capabilities of robots and reductions in prices have resulted in a threefold increase of the global robot stock between 1993 and 2015 (IFR, 2016). During the same time period, the stock of robots in the US has increased by about 1.5 robots per 1,000 workers (Figure 1). The penetration of industrial robots is highest in the manufacturing sector, where robots typically perform tasks such as

[6] Another important factor may have been the Great Recession. However, the decline employment rates already started in the early 2000s, years before the crisis. It is thus likely that the Great Recession exacerbated this longer term trend, but is not necessarily a root cause of it (Abraham and Kearney, 2018). We therefore focus on the two shocks to labor demand mentioned above.

pressing, welding, packaging, assembling, painting and sealing. Within manufacturing, the automotive industry makes 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 of manufacturing, industrial robots are also used for harvesting (agriculture) and the inspection of equipment and structures (utilities) (Figure 2).

Even though the US has added a large number of robots since the beginning of the 1990s, the origins of these steep changes likely lie outside of the US. Acemoglu and Restrepo (2019) argue theoretically and document empirically that demographic trends in aging countries like Japan, South Korea, France and Germany are likely responsible for the invention of robots (Acemoglu and Restrepo, 2019). In this argument, a lack of young and middle-aged workers (between the ages of 21 and 55) that are able to perform routine, manual tasks in the production process encourages the development of technology to substitute for such workers. Acemoglu and Restrepo (2019) show empirically that aging accounts for a large part of the cross-country variation in the development (number of automation-related patents) and adoption (number of installed robots) of such automation technologies. Moreover, industrial robots are being exported from aging countries to the rest of the world. That is, demographic trends in some industrialized countries can significantly alter the technology frontier even in countries undergoing less demographic change, such as the US.

2.2 Chinese imports

The speed of the rise in China's exports to the Western world since the beginning of the 1990s is unprecedented. China's share of world exports has grown from roughly 2 percent to above 12 percent between 1990 and 2015. Even more dramatically, Chinese exports to the United States increased by more than 15-fold in the period 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, the growth in exports to Western countries was highly skewed towards labor-intensive industries within the manufacturing sector. 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 are transport equipment (non-automotive), paper and printing products, and food, beverages and tobacco (Figure 2).

Two factors are considered the main causes behind the surge of Chinese manufacturing since the early 1990s: China's internal, trade-promoting policy changes 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. Among the most prominent ones are the creation of special economic zones that granted foreign investors tax breaks, reduced custom duties and loose labor regulations to encourage the import and final assemlby of intermediate goods into final exports (Wang, 2013) and the privatization of state-owned firms to enhance productivity (Hsieh and Song, 2015). These reforms already had a tremendous impact on Chinese exports in the 1990s (Figure 1). This upward trend was only reinforced in the early 2000s with the US granting China Permanent Normal Trade Relations (PNTR) and China's accession to the WTO. These institutional changes reduced tariffs on imported intermediate goods, and lowered uncertainty of Western firms about potential future changes in trade barriers.

3 Empirical strategy

To identify the effect of industrial robots and Chinese import competition on internal migration in the US, we estimate the following equation:

$$\Delta \ln Y_{c,t} = \beta^r \underset{\text{robots}_{c,t}}{\text{US exposure to}} + \beta^c \underset{\text{Chinese imports}_{c,t}}{\text{US exposure to}} + \boldsymbol{X}'_{c,1990}\gamma_t + \epsilon_{c,t}, \tag{1}$$

where, in our main results, $Y_{c,t}$ is the number of working-age individuals (15 to 64 year olds) living in local labor market c at time t.[7] Following the literature, we define CZs as the unit of observation.[8] Our dataset contains 722 CZs and in our main specifications we subdivide the 25 years between 1990 and 2015 into three time periods (1990–2000, 2000–7, 2007–15). 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 baseline characteristics $\boldsymbol{X}_{c,t}$ to allow for differential trends.[10] Given that

[7] When we examine the mechanism behind our main result, we also consider other outcome variables, among others employment (aggregate and by subgroup) as well as in- and out-migrants.

[8] CZs are defined as clusters of counties that feature strong commuting ties within, and weak commuting ties across CZs. Compared to alternative definitions of local labor markets (counties, states, or metropolitan areas) they represent economically relevant boundaries (unlike counties or states) and also cover rural parts of the country (unlike metropolitan areas).

[9] Cadena and Kovak (2016) show that, when examining log population size changes across labor markets of different sizes, efficient weights must account for individuals' sampling weights to account for inherent heteroskedasticity. They formally derive optimal weights and show that, in practice, these weights are almost perfectly correlated with initial population sizes of the outcome group.

[10] More precisely, 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; and the outcome variable in the pre-period (1970–90).

we estimate a regression in stacked first differences and include region-period fixed effects, our coefficients of interest, β^r and β^c, are identified from differences in the exposure to labor market shocks between CZs in a given time period and region.

We follow Acemoglu and Restrepo (forthcoming) and measure a CZ's *US exposure to robots* as a Bartik-style measure based on each industry's increase in robot density in the US between t and $t+1$ (adjusted for the overall expansion of each industry) and baseline industry employment shares in CZ c, following Acemoglu and Restrepo (forthcoming). More precisely, we construct

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

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

Local labor market conditions such as changes in population size or employment rates may directly drive the decision of US industries or specialized local labor markets to adopt robots. To circumvent such endogeneity concerns, we employ the same instrument as Acemoglu and Restrepo (forthcoming), who replace US industries' robotization with that in five European countries and the 1990 employment shares $\ell_{ci,1990}$ with those in 1970:

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

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

We construct a CZ's *US exposure to Chinese imports* identical to Autor et al. (2013). Specifically, we construct a Bartik-style measure based on Chinese import growth to the US between t and $t+1$ and initial industry employment shares in CZ c, such that

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

where $M^{CNUS}_{i,t}$ is the value of Chinese imports to the US in industry i at time t. To purge the results of endogeneity resulting from subsequent changes in US demand, we follow Autor et al. (2013) to construct the *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 $t+1$ and replace the initial industry employment shares in CZ c with lagged shares. In particular, we construct

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

where $M^{CNOT}_{i,t}$ refers to 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.

It is noteworthy that areas especially exposed to either of the shocks do not only differ in their subsequent population growth, but also in some other observable initial characteristics (Table 1, column (8)). Regions especially exposed to robots initially had a higher share of employment in mining, a lower share of workers in manufacturing, offshorable jobs and tradable industries, more whites and less blacks as well as fewer women in the labor force. For these initial differences not to bias our results, we make sure to control for them (as well as the ones with insignificant differences) in our subequent analysis.

4 Data and descriptive statistics

In this section, we introduce the various data sources we use for the construction of our outcome variables, main variables of interest – a CZ's exposures to robots and Chinese imports – as well as the covariates. Then, we provide basic descriptive statistics.

4.1 Migration

Our main outcome variable $\Delta \ln Y_{c,t:t+1} = \ln Y_{c,t+1} - \ln Y_{c,t}$ is the change in the log number of individuals belonging to subgroup Y living in CZ c between period t and $t+1$. While we mainly focus on changes in the working-age population (15-64 year olds), we also consider other subgroups (e.g., by employment status, birthplace, education, and age). For some analyses we also consider changes in subgroup-specific employment as a share of total employment, $\Delta s^{Y}_{c,t:t+1} = \frac{Y_{c,t+1} - Y_{c,t}}{L_{c,t}}$, 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 the manufacturing industry) 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.[11]

[11] 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 Acemoglu and Restrepo (forthcoming) and Autor et al. (2013) do.

We construct the majority of our outcome variables and covariates from IPUMS census samples for 1970, 1980, 1990, and 2000, as well as the American Community Survey (ACS) for 2007 and 2015. The sample size varies between 1 and 5% of the overall US population depending on the year. 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. When using ACS data, we use 3-year samples to increase sample size.[12]

We complement these data with two other sources of information on population size changes: First, we use data on aggregate population sizes of each county 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. Whenever we use changes in aggregate (working-age) population, we thus use the intercensal estimates, and when we examine subgroups of the population (by birthplace, education, age, employment status), we use IPUMS samples. Second, we use 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 4 presents the evolution of several migration rates in the US between 1980 and 2015. During this period, both cross-county and cross-CZ migration rates have been on a downward trend (as already documented in Molloy et al. (2011), for example). IRS and Current Population Survey (CPS) data shows that the cross-CZ and cross-county migration rates fell by 0.8 and 1.9 p.p., respectively, between 1992 and 2015. These falls have been accompanied by roughly proportional declines in within- and across-state moves. Despite falling migration rates in the US overall, there is considerable variation in the extent to which US Commuting Zones have grown or shrinked in terms of population size. Net migration rates have been highest in the Northwest and Southeast, and lowest in the Midwest and Northeast (Figure 3, Panel (a)).

[12] The lowest geographic unit available in this dataset is not the county, but the county *group* (1970 and 1980) and Public Use Microdata Area (PUMA). 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), that are based on a probabilistic assignment of individuals into a CZ and are available at https://www.ddorn.net/data.htm.

4.2 Exposure to robots

Following Acemoglu and Restrepo (forthcoming), we draw on three data sources to construct the exposure to robots variables: First, data on shipments of industrial robots by industry, country and year from the International Federation of Robotics (IFR, 2016); second, initial industry employment shares by CZ from the Integrated Public Use Microdata Series (IPUMS, Ruggles et al., 2018); and third, employment and output by industry and year for countries other than the US from the EU KLEMS dataset (Timmer et al., 2007).

The IFR collects data on shipments and operational stocks of *industrial robots* by country and industry since 1993 “based on consolidated data provided by nearly all industrial robot suppliers world-wide” (IFR, 2016, p.25). Industrial robots are defined as “automatically controlled, reprogrammable, multipurpose manipulator[s] programmable in three or more axes, which can be either fixed in place or mobile for use in 13 industrial automation applications” (IFR, 2016, p.29). Typical applications of industrial robots are pressing, welding, packaging, assembling, painting and sealing, all of which are common in manufacturing industries; as well as harvesting and inspecting of equipment, which are prevalent in agriculture and the utilities industry, respectively (IFR, 2016, p.31–38).

The IFR data has a few limitations: While it reports aggregate robot stocks from 1993 onwards, it only contains a breakdown by industry for the US starting in 2004. For the years before 2004, we therefore attribute the aggregate number of robots to industries proportional to the industries' shares of the overall stock in 2004. Moreover, the IFR classification contains three industries that do not directly correspond to an industry covered in the US census data. These are "Other manufacturing" and "Other non-manufacturing" as well as "Unspecified". We attribute these robots according to each industry's share of robots within each of these categories, e.g., robots reported as "Other manufacturing" are assigned to more specific manufacturing industries proportional to each industry's share of precisely assigned robots in manufacturing. Finally, robot shipments to the US also include robot shipments to Canada and Mexico before 2011. This introduces some measurement error, but should not be a large concern as the US accounts for the vast majority of robot shipments to North America (over 90%) and our IV strategy should correct for this kind of measurement error.

In the exposure to robots variables, we interact this industry-level data on robot growth in different countries with initial industry employment shares in each CZ. We calculate these initial employment shares from the IPUMS samples of census and ACS data.

Additionally, we use data on industry employment and output growth rates by country and year from the EU KLEMS database.

4.3 Exposure to Chinese imports

In the construction of the exposure to Chinese imports variables, we directly follow Autor et al. (2013) to extend their measures for the exposure to Chinese imports per worker to the period 2007–2015.[13] To do this, we employ two data sources: First, 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); and second, data on initial industry employment shares by CZ from the County Business Patterns (CBP; US Census Bureau, 2019). These provide county-level employment counts at the same level of granularity (4-digit classification) as the Comtrade data. One drawback of the CBP data is that employment counts are often only given in brackets, i.e., as lower and upper bounds. To get single numbers of employment for all such brackets, we employ the fixed-point algorithm developed by Autor and Dorn (2013).

4.4 Covariates

With regard to the covariates, we compute initial demographic characteristics and broad industry employment shares from the IPUMS samples. We also consider two major contemporaneous changes to the demand for certain skills as potential confounders, namely 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, following Autor and Dorn (2013).

4.5 Descriptive statistics

As a preliminary step, we verify that the correlation between the two shocks we consider – exposure to robots and import competition – is sufficiently low for us to separately identify their effects. Figure 3 shows the geographic distribution of the exposure to robots and to Chinese imports between 1990 and 2015. Both shocks affected mostly the East of the US, with the robot shock being largely concentrated in the Midwest and particularly the Rust Belt, and the China shock being more pronounced in the Southeast and Northeast of the country. Reassuringly, the population weighted correlation coefficient between the two is relatively low at 0.06.[14]

[13] Our measures *US exposure to Chinese imports* and *Exposure to Chinese imports* directly correspond to the ΔIPW_{uit} and ΔIPW_{oit} in Autor et al. (2013), respectively. We choose the different naming to underline the conceptual similarity to the *(US) exposure to robots* variables.

[14] A fact already documented in Acemoglu and Restrepo (forthcoming).

Table 1 reports summary statistics for the main variables considered in our work. Column (1) provides means across all 722 CZs included in our sample. Columns (2) and (3) then restrict the dataset to the upper quartile of CZs with regards to their exposure to robots and Chinese imports, respectively. Columns (4) to (7) show the same averages, but now by quartile of their *relative* exposure to robots over Chinese imports.[15] The first quartile in column (4) thus includes CZs that have been particularly exposed to Chinese imports and not robots, and vice versa for the fourth quartile in column (7). Column (8) reports the difference between columns (7) and (4) and indicates its statistical significance.

We start by examining the change in two important outcomes – log employment and log working-age population – across these different subsamples in the first two columns. In line with Acemoglu and Restrepo (forthcoming) and Autor et al. (2013), CZs most exposed to either of the two shocks have, on average, experienced weaker employment growth than the average CZ. Moreover, population growth was lower in CZs more exposed to either of the two shocks. This difference is, however, considerably more pronounced for CZs exposed to robots than those exposed to Chinese imports. Column (8) underlines this difference from a slightly different angle, comparing not areas exposed to either of the shocks to the overall average, but areas especially exposed to robots with areas especially exposed to Chinese imports. That is, we compare regions in the first and fourth quartile with respect to the exposure to robots relative to the exposure to Chinese imports. This admittedly crude comparison suggests that robots and Chinese imports reduce employment to a similar extent, but robots affect migration patterns (i.e., reduce population growth) to a significantly larger extent than Chinese import competition.

5 Main results

This section presents our main results. First, consistent with existing work from Autor et al. (2013) and Acemoglu and Restrepo (forthcoming), Section 5.1 documents that both import competition and exposure to robots reduced manufacturing employment. Next, Section 5.2 shows that, despite similar employment effects, only exposure to robots – but not that to trade – reduced CZ population. Unpacking the margins behind the migration response to robots, Section 5.3 shows that the reduction in CZ population was due to lower in-migration rather than to higher out-migration. Finally, Section 5.4 performs a variety of robustness checks.

[15] Relative exposure to robots over Chinese imports is defined as the difference between a CZ's standardized exposure to robots (mean of 0, sd of 1) and its standardized exposure to Chinese imports.

5.1 Manufacturing employment

Our main focus is to understand how migration responds to changes in employment opportunities driven by local exposure to robots and import competition. Since both shocks are concentrated within manufacturing (Figure 2), we start our analysis by comparing their effects on manufacturing employment. We estimate Equation (1) using as dependent variable the change in log employment in the manufacturing sector, and report 2SLS results in Panel A of Table 2.[16]

In column (1), we only include interactions between time period and census division dummies as covariates. Already this relatively parsimonious specification indicates that both shocks reduce manufacturing employment considerably. Both coefficients are negative and statistically significant at conventional levels, with the effect of Chinese imports being more than twice as large as that of robots (–5.57 vs. –2.33). In columns (2) to (5), we gradually add more covariates to allow for differential trends along a set of observable initial characteristics.

We start by including the outcome variable between 1970 and 1990 (in this case, the change in log manufacturing employment) to capture secular labor market trends as a potential confounder. Doing so somewhat reduces the magnitude of the coefficient and the standard error on the effect of robots, whereas the effect of Chinese imports becomes larger (in absolute value). These changes suggest that manufacturing might have been on a downward trend in areas exposed to robots, and on an upward trend in areas exposed to Chinese imports, though not pronounced enough to explain the majority of the effect.

Columns (3) and (4) add interactions between period dummies and several 1990 characteristics – in particular, a set of demographic characteristics (log population size, the share of men, the share of the population above 65 years old, 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) and shares of employment in broad industries (agriculture, mining,

[16] Results from the first stage regressions are presented in Panels A and B of Table A3. Both instruments are highly correlated with their respective endogenous counterparts in all specifications. In some specifications, also the instrument of the respective other shock has some predictive power over the endogenous variable. To rule out that the effects in Panel A of Table 2 are identified from the unintended instrument, we run the same regression again in Panels C and D, but now as two separate IV regressions for each of the shocks (including the other instrument as a control variable). Results remain almost identical.

construction, manufacturing). Adding this battery of controls leaves the effect of robots unchanged and somewhat reduces the (negative) effect of Chinese imports; in both cases, however, results remain quantitatively large and statistically significant at the 1% level.

Finally, in column (5), we include the shares of routine and offshorable jobs in 1990, both interacted with period dummies, so as to capture the potentially confounding effects of other contemporaneous changes. In particular, we aim to control for the automation of routine tasks through the spread of computers and increased offshoring to cheap labor locations due to reduced trade costs. Once again, the inclusion of additional controls leaves the precision and the magnitude of both point estimates virtually unchanged.

In sum, the evidence documented thus far confirms findings in Acemoglu and Restrepo (forthcoming) and Autor et al. (2013) and shows that both robots and Chinese imports considerably reduce manufacturing employment. The point estimates in our preferred specification in column (5) imply that one standard deviation increase in exposure to robots and Chinese imports reduces employment by 1.52 and 5.49 percent per decade, respectively. These are slightly smaller in absolute terms than the effects identified in previous work (Acemoglu and Restrepo, forthcoming, Table A15; Autor et al., 2013, Table 5; and Bloom et al., 2019, Table 2) but not statistically significantly different from these. This negligible difference might arise from our more conservative set of covariates, and in particular, interactions between pre-determined characteristics and period dummies.

5.2 Migration

Having confirmed the pronounced, negative effects of robots and Chinese imports on manufacturing employment documented in previous work (Acemoglu and Restrepo, forthcoming; Autor et al., 2013), we move to our main analysis, and study the impact of robots and Chinese imports on migration. To do so, we estimate Equation (1) using the change in log working-age population as dependent variable. Results are reported in Panel B of Table 2.[17]

As before, we start with a parsimonious specification, which only includes interactions between period and census division dummies (column (1)). Results are striking: despite the similar, negative effect on manufacturing employment, the two shocks have a

[17] See Panels A and B of Table A4 for first-stage results of these specifications. As in Table A3, both instruments are highly correlated with their respective endogenous counterparts in all specifications. Again, in some specifications, also the instrument of the respective other shock has some predictive power over the endogenous variable. Panels C and D show that this does not change our results.

strongly different impact on migration. In particular, while robots lead to a significant reduction in population growth, Chinese imports have no detectable effect on population size. As in Panel A, we sequentially add more covariates in columns (2) to (5). Compared to Panel A, we now add pre-trends with respect to migration (rather than employment), but all remaining covariates are the same as before. The pattern that only robots induce a migration response remains unchanged when adding pre-trends, initial demographic characteristics, broad industry shares and contemporaneous changes as control variables. Adding this battery of control variables reduces the size of the effect of robots by more than 50%, but leaves it significant at least at the 1% level in all specifications.[18] The effect of Chinese imports is not statistically different from zero in any of the specifications.

The point estimate in our most preferred specification (column 5) implies that one standard deviation increase in exposure to robots reduces population growth by 0.62 percentage points per decade. Since one standard deviation change in robot exposure corresponds to an increase of roughly 0.87 robots per thousand workers, our estimates imply that one additional robot per thousand workers reduces population growth by 0.71 percentage points. Given an average population growth of 9.3 percent per decade across all CZs, this implies that one more robot per thousand workers causes population growth to fall by 7.7 percent.[19]

In contrast with our results, Greenland et al. (2019) find that the China shock triggered a migration response. However, their analysis differs from ours in that they rely mostly on the Pierce and Schott (2016) definition of the China shock, and estimate stacked difference regressions for the time periods 1990–2000 and 2000–2010. Since we are worried about the Great Recession as a potential confounder, in our baseline specification, we chose to end our second period in 2007. In Table A6, we explicitly test whether using the Pierce and Schott (2016) treatment of the China shock changes our results. The effect of Chinese imports on population growth is negative and statistically significant only when using a relatively parsimonious specification. However, these results appear

[18] Acemoglu and Restrepo (forthcoming) also find evidence for a negative migration response to robots, although their coefficient is less precisely estimated. Table A5 shows that this difference is not due to any differences in the set of control variables, but due to *i)* using intercensal estimates based on full counts instead of IPUMS samples and *ii)* interacting controls with time period dummies.

[19] While we prefer the stacked difference specification as it allows us to more flexibly control for potential, contemporaneous changes during the time periods we observe, we also estimate the corresponding long difference (1990–2015 and 1990–2007) specifications in the Appendix (Table A2). The results are unchanged.

to be non-robust to controlling for demographics, industry shares or contemporaneous changes, or to focusing on the time period before 2007. We thus interpret the discrepancy between our findings and those in Greenland et al. (2019) as due to the different (more stringent) set of controls included in our analysis.

5.3 In-migration vs. out-migration

Lower population growth in a region may result from increased migration out of or reduced migration into it. On the one hand, a worker displaced by robots might choose to move to another location to find a new job. On the other, it is possible that *prospective* in-migrants choose not to move to a place where their chances of finding a job have deteriorated due to robots.

We explore these two potential channels explicitly in Table 3. The dependent variables are the log counts of migrants in columns (1) to (3), and migration rates in columns (4) to (6). Panel A focuses on in-migrants, whereas Panel B turns to out-migrants. Since IRS migration data only starts in 1990, Equation (1) is estimated only for the period 2000–2015 in order to include pre-trends as a control. Results show that robots reduce in-migration, and do not lead to increased out-migration. The point estimates in columns (3) and (6) imply that one standard deviation increase in exposure to robots reduces the number of in-migrants by about 1.74 percent, or the 10-year in-migration rate by roughly 0.20 percentage points.

To interpret the magnitude of this effect, our estimates imply that one additional robot per thousand workers reduces the in-migration rate by about 0.23 percentage points (0.20/0.87). Since the average decadal in-migration rate during our sample period is 41 percent, this implies a 0.56 percent reduction in the in-migration rate. Extrapolating these numbers at the national level to illustrate the magnitudes, our estimates would imply that one additional robot per thousand workers lowers migration flows by 370,000 working-age individuals. One additional robot per thousand workers is equivalent to 120,000 more robots in the US. Thus, our estimates imply that each additional robot reduces in-migration flows by three working-age individuals. Between 1993 and 2015, the number of robots in the US has increased by almost 190,000, implying a reduction in in-migration flows of 570,000 working-age people.[20]

In Table 4, we explore in more detail where this reduction in in-migrants originates from. Columns (1) and (4) replicate our results with full controls from Table 3. Next, in

[20] Of course, one should not interpret these number literally, since we are not accounting for general equilibrium effects.

columns (2)–(3) and (5)–(6), we split up overall in-/out-migrants into those originating from/moving to places that are less and more than 300 miles away.[21] The reduction seems to stem from both closeby locations and far away regions. From these results, it is not clear which of the two forces is stronger. In column (5), we also estimate a *negative* effect of robots on out-migration into closeby regions. This is likely due to the fact that the robot shock is clustered geographically (Figure 3) and thus reduced in-migration from nearby locations inevitably comes from areas that are also highly affected by robots, too.

Columns (1)–(3) also suggest that the insignificant effect of Chinese imports in in-migration masks substantial heterogeneity by distance. In column (2), we find some evidence for Chinese imports increasing in-migration from nearby regions, though not strongly enough to translate into a significant effect on overall in-migration. These may be explained by the partly positive employment effect of Chinese imports in industries housing highly mobile individuals (Bloom et al., 2019). We return to this point in Section 6 below.

We conclude that prospective in-migrants avoid places that suffered due to robots. The effect is visible for in-migrants from both close and distant labor markets. Moreover, since the robot shock is highly clustered, this reduced in-migration is also associated with reduced out-migration from nearby areas. Most importantly, we find no evidence for existing residents or displaced workers actively leaving affected areas.[22] Perhaps surprisingly, given their stronger, direct negative effect on manufacturing employment, we find no evidence for Chinese imports reducing population growth. Before further exploring the mechanisms behind our results, in the next section, we verify that our results are not affected by pre-existing trends correlated with either of the two labor market shocks.

[21] One drawback of the IRS migration data is that it only contains exact numbers of county-to-county migration flows 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 former group as a move within a 300 mile distance and the latter two as moves to/from more than 300 miles away.

[22] The importance of inflows rather than outflows as an adjustment mechanism is in line with Dustmann et al. (2017), who find that reduced employment of natives due to a labor supply shock in Germany is mainly driven by reduced inflows into employment, and Monras (2018), who shows that population adjustments in response to the Great Recession are mainly due to disproportionate decreases in in-migration.

5.4 House prices

Lower in-migration should result in lower demand for housing. In turn, if housing supply is not perfectly elastic, this should lead to reduced house prices in robot-exposed areas. We empirically test this hypothesis in Table 5, which follows the same structure as Table 2 now focusing on the change in the log house price index (using data from the Federal Housing Finance Agency on house prices by county covering 414 out of 722 CZs in 1990) as the dependent variable.

We estimate Equation (1) for the period 2000–2015 in order to include pre-trends as a control for a large number of CZs. Results in our preferred specification (column 5) show that robots reduce house prices significantly.[23] In contrast, Chinese imports do not have any significant effect on house prices once we allow CZs to be on differential trends depending on broad industry shares (columns 4 and 5). These results are consistent with the differential migration response to both shocks documented before. Our estimates imply that a one standard deviation increase in exposure to robots reduces house prices by 2.52 percent, or that one additional robot per thousand workers reduces house prices by 2.90 (2.52/0.87) percent.

5.5 Pre-trends

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

We estimate the same regressions as before, but now using the time period 1970–1990, a time when robot technology was, if anything, still in its infancy and China had not started its surge in exports. We regress changes in the log counts of the working-age

[23] Instead, we do not detect any significant effect on rents. This is in contrast to Acemoglu and Restrepo (forthcoming), who find a reduction in rents in response to robots. This difference is due to the fact that we include interactions between control and period dummies in all of our specifications. One possible reason why robot exposure in our setting reduces house prices and not rents is that individuals responsible for reduced in-migration are more likely to be homeowners. Another possibility is that rents may be slower to adjust than house prices.

population in this pre-period on the *future* exposure to robots and Chinese imports, defined as the average exposure in the three subsequent time periods 1993/91–2000, 2000–7 and 2007–15. The results are shown in columns (1) and (2) of Table 6. In column (1), we include all the covariates from our preferred specification in column (5) of Table 2, except for the contemporaneous changes, which may have played a smaller role between 1970 and 1990. Next, we include also the control variables for contemporaneous changes interacted with time periods, in an attempt to exactly mimic our preferred specification, only now for the period 1970–1990. Reassuringly, neither of the two shocks' coefficients is statistically significant in either of the two columns.

In columns (1) and (2), we cannot detect any statistically significant pre-trends in overall population growth in areas exposed to robots or Chinese imports, given the standard errors of the estimates. However, the point estimates are relatively large (e.g., –0.50 in column (2) compared to –0.62 in our preferred specification). It is thus possible that not accounting for pre-trends may bias our results. In particular, assuming population growth patterns are persistent, it may bias the coefficient on the exposure to robots and China to be more negative and positive, respectively. For this reason, we specifically control for pre-trends in all of our reported results.

In columns (3)–(6), we again turn to the period 1990–2015 and explore how sensitive our main results are to the inclusion of pre-trends in different ways. In column (3), we repeat our main specification from column (5), Panel B of Table 2, which includes the change in the log working-age population between 1970 and 1990. Note that the effect of the pre-trends themselves is positive and significant at the 1% level, suggesting that there is some persistence in population growth patterns over time. Column (4) is almost identical, only that it does not account for pre-trends in any way. Not accounting for pre-trends adjusts the estimated coefficient on the exposure to robots and Chinese imports in the expected direction. Compared to our preferred specification, the effect of robots becomes slightly larger in absolute terms (-0.77 vs. –0.62) and remains significant at all conventional levels. The effect of Chinese imports becomes more positive and appears to be slightly significant (at the 10% level) when not accounting for pre-trends.

In columns (5) and (6), we test whether alternative ways of accounting for pre-trends affect our main results. In column (5), we interact changes in log working-age population from 1970–90 with time period dummies, thus allowing pre-existing trends to potentially dissipate over time. The effects of robots and Chinese imports remain unchanged, and there is some evidence for pre-existing patterns becoming less important over time. In column (6), we include the change in working-age population not from 1970–90, but from the directly preceding period. We are worried that by doing so, we might add a variable that has itself been affected by robots and Chinese imports (i.e., a "bad control"). Nonetheless, it is reassuring that our main results remain unchanged also in this specification.

In sum, these results show that there are no significant pre-trends in population growth in areas exposed to either robots or Chinese imports, and that accounting for such pre-trends in several ways nonetheless does not alter our main conclusion.[24]

6 Mechanism

In this section, we seek to reconcile the seemingly counter-intuitive result that, although both shocks reduced manufacturing employment, only robots were associated with a significant migration response.[25] To do so, we analyze the employment effects of the two shocks in more detail, testing how each of them affected employment outside the manufacturing sector.

6.1 Effects on non-manufacturing and total employment

Our analysis so far has focused only on the effects of robots and import competition on employment within the manufacturing sector. This analysis likely identifies the direct effects of the two shocks, as both the growth of robots and of Chinese imports is largely concentrated in several manufacturing industries (Figure 2). However, solely focusing on manufacturing employment may miss important aspects of the adjustment mechanism, such as demand spillovers or labor reallocation into non-manufacturing industries.

We now turn to the effects of both shocks on non-manufacturing and on total employment. Table 7 presents results from this exercise. To ease comparisons, Panel A repeats results for manufacturing employment reported before. Then, Panels B and C show results for non-manufacturing and total employment, respectively. Robots have similarly strong, negative effect on employment both within and outside of manufacturing

[24] It remains possible that another, unobserved factor that may be correlated with the exposure variables gives rise to population growth patterns that are mildly different in the pre-period and strongly different in the treatment period. We estimate our preferred specification again, but now including not region-time dummies ($9 \times 3 = 27$) but instead more granular state-time dummies ($48 \times 3 = 144$) to account for any state-specific unobservable characteristics. Reassuringly, our results remain almost identical (i.e., -0.68** vs. -0.62*** for robots, and insignificant, positive coefficients for China).

[25] This pattern is even more puzzling given that the direct effect of robots on employment (i.e., within manufacturing) was considerably smaller, in absolute value, than that of Chinese imports.

(panels A and B). These findings suggest that in the case of robots, indirect effects are quantitatively large and potentially important in understanding the transmission of this shock into migration responses.

In contrast with the patterns documented for robots, the effect of Chinese imports remains entirely concentrated within manufacturing.[26] If anything, our estimates suggest that Chinese imports may have a positive effect on employment outside of manufacturing. One possible explanation for this might be that trade exposure lowered physical input prices and induced firms to reallocate towards services (Bloom et al., 2019; Ding et al., 2019).

Consistent with the previous two panels, Panel C shows that robots caused overall employment to decline, while Chinese imports likely induced a reallocation of economic activity across sectors, which offset the employment losses within manufacturing.

6.2 Spillovers to other industries within CZ

We interpret any effects of these shocks outside of their industries of origin (within manufacturing) as *indirect* effects, such as negative demand spillovers (e.g., displaced workers consuming less) or positive productivity spillovers (e.g., firms that become more productive expanding labor demand in non-directly affected domains) from manufacturing to other industries in the same CZ.

Our previous results indicate that the two shocks differ substantially in the spillovers they create outside manufacturing. To get a more precise picture of the differences in spillovers, we separately estimate the effect of robots and Chinese imports on the employment shares of 44 industry-skill combinations.[27] Results are presented in Figure 5. Each cell in Panels (a) and (b) plots the coefficient on the (standardized) exposure to robots and Chinese imports, respectively, in a regression identical to the ones in column (5) of Table 2, but using the change in employment per corresponding industry-skill combination as a share of initial CZ employment as the outcome variable. Since outcomes are expressed in percentage points, it is important to rule out that the underlying initial shares in each cell significantly differ from one another in areas affected by the two shocks. Panels (c) and (d) provide visual inspection of this, reporting the initial share

[26] These results are also consistent with Acemoglu and Restrepo (forthcoming), who find negative demand spillovers of robots into service industries, and Autor et al. (2013), who find no significant negative employment effect of Chinese imports on non-manufacturing.

[27] See Section A.1 for details on how we define skill groups using data from the 1980 Dictionary of Occupational Titles (DOT).

of employment in each cell, weighted by their exposure to robots and Chinese imports, respectively.

Panel (a) documents that robots most strongly reduce employment in routine, manual occupations in the manufacturing industry. The effect is not limited to this industry-skill combination, but is also visible in other skill groups within manufacturing and, most notably, also in industries that were not directly affected, such as business services, professional services, retail, and construction. Panel (b) shows that the effect of Chinese imports is 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, there are *positive* effects on employment in almost all industry-skill combinations outside of manufacturing. These results suggest that there is a stark difference in how each of these shocks was transmitted throughout the economy. While robots' negative effect likely caused negative (potentially demand) spillovers into other industries, Chinese imports induced positive (potentially productivity) effects in other industries.[28]

6.3 Heterogeneous elasticities to migrate

Figure 5 shows that a defining difference between these two shocks is the extent to which they spill over into industry-skill groups that were not directly affected, such as abstract, cognitive occupations in retail or professional and business services. Given that these are also the industry-skill cells that tend to employ more mobile (i.e., high-skilled) workers, these spillovers might potentially also be the cause of the negative in-migration response to robots.

If this conjecture were true, one should observe that *i)* robots reduce employment of more mobile groups; and *ii)* precisely these groups are most affected in their migration response. We explore this possibility by estimating the same specification as in column (5) of Table 2, but now using the change in log employment and working-age population by subgroup (i.e., high- and low-skilled, and young, middle-aged, and old). Results of this exercise are presented in Figure 6 for employment and migration in Panels A and B respectively.[29] The first column replicates the aggregate results of column (5) of Table 2, while the following columns present the estimated coefficients by subgroup. Consistent

[28] The positive effect of Chinese imports on employment outside of manufacturing, and in particular, professional services and management, is in line with firm-level evidence of industry switching in Bloom et al. (2019).

[29] See Figure A1 for the corresponding results for China, and Table A7 for detailed regression results.

with Acemoglu and Restrepo (forthcoming), employment effects display relatively little heterogeneity across demographic and skill groups: robots reduce low-skilled (less than college) and high-skilled (some college or more) employment to a similar extent. Middle-aged workers (31–50 years old) are the most affected of the three age groups, followed by younger individuals (18–30). However, these differences are never statistically significant.

If spillovers into high-skilled occupations such as business and professional services indeed drove the migration response, high-skilled individuals should also feature a higher elasticity to migrate. Panel B supports this interpretation, and documents that high skilled individuals mainly drive the migration response to robots.[30] Our estimates imply that a 1 percent decline in employment corresponds to a 0.60 percent decline in population size among the high-skilled sub-group of the population. Notably, this response is more than twice as strong as that of low-skilled individuals, who only respond with a 0.28 percent decline in population size. Among the different age groups, middle-aged individuals are estimated to be the most mobile (0.56 percent), and somewhat surprisingly, younger people to be the least mobile (0.29 percent).

To bolster confidence that differential spillovers into non-manufacturing (and not some other, potential difference between the two shocks) drive our main results, we next show that the same patterns are also visible for the China shock once effect heterogeneity across regions is accounted for. To do so, we exploit the substantial variation across regions in the effects of Chinese import competition on non-manufacturing employment (Bloom et al., 2019). In Table 8, we re-estimate our preferred specification, augmenting it with interactions between each exposure variable and dummies equal to one if a CZ was, respectively, a high service intensity (HSI) or a low service intensity (LSI) area.[31] In columns (1)–(3), we examine the impact on total, manufacturing, and non-manufacturing employment, and in columns (4)–(6) the impact on overall population growth, in-migration and out-migration, respectively.

Results show that Chinese imports lead to employment growth outside manufacturing in areas with an initially high service intensity. Consistent with our proposed mechanism, these CZs also experience significantly higher population growth, due to increased in-migration. In contrast, our estimates suggest that CZs with initially low service

[30] In addition to high-skilled individuals, one might have expected immigrants to be relatively mobile, too, as shown in Cadena and Kovak (2016). We explicitly explore this in Table A7, columns (7) and (8), Panel B. Our results cannot speak to this, as the effect of robots on employment of immigrants is estimated to be close to zero.

[31] We base our sample split using the CZ 1990 share of employment in services.

employment shares experience, if anything, negative spillovers into non-manufacturing, resulting in a significantly negative employment response overall. Results on Chinese imports in columns (1), (3) and (4) also indicate that what matters for the migration response is not the effect of a shock on overall employment, but specifically the effect on non-manufacturing. We believe this is an important result, which can have relevant implications for the design of government policies aimed at smoothing local economic shocks.

6.4 Alternative mechanisms

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

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

First, we estimate the migration response to both shocks now omitting the post-2007 period. Results are reported in Panel A of Table 9, which follows the same structure of Table 2. The pattern is almost identical to our initial results that included the post-2007 period: throughout all specifications, robots have a significant, negative impact on population growth, whereas Chinese imports have no effect. As before, the effect of robots roughly halves in size after including a more stringent set of covariates. According to most our preferred specification (column 5), the magnitude of the effect is almost identical to that estimated including the post-2007 period (–0.56 vs. –0.62). Given their standard errors, these are not statistically different from each other. Moreover, even in this pre-2007 period we do not detect any migration response to Chinese imports in any of the specifications.

Second, in Panel B of Table 9, we return to the full sample (incl. post-2007), but now add interactions between shocks and a post-2007 dummy. We are particularly interested in the coefficient on the interaction between exposure to robots and the post-2007 period dummy. If recessionary conditions mediate the migration response to robots, the coefficient on the interaction should be significant (negative or positive, depending on the direction of the effect of the Great Recession). Results from our most preferred specification (column 5) show that this is not the case. The coefficient on the interaction term is negative but not statistically significant, suggesting that the size of the migration response to robots does not significantly differ between the pre- and post-crisis period.

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

6.5 Discussion

Our findings suggest that the different propagation across industries within local labor markets is a key mechanism for why otherwise similar negative shocks to *manufacturing* employment generate such disparate migration responses. In what follows, we describe a conceptual framework to explain when a shock to a given sector can propagate to others, in turn triggering a "stabilizing" migration response.

A framework to study spillovers. As suggested in Acemoglu and Restrepo (forthcoming), robots represent a new factor (e.g., machines) that replaces a subset of tasks previously performed by human labor. The equilibrium response at the industry-CZ level can be decomposed into a *i)* a displacement effect, *ii)* a composition effect, and *iii)* a productivity effect. The displacement effect captures the direct impact of the shock: robots take over tasks previously performed by workers. The composition effect captures the surge in demand for labor in non-automated tasks, and acts as a positive (within-industry) spillover. The productivity effect captures a general equilibrium reaction at the CZ level. When robots replace human labor, the cost of production falls, and, due to complementarities in production across industries, demand for labor increases in unaffected industries. Said differently, the productivity effect exerts positive spillovers to other industries within a local labor market (i.e., a CZ).

In contrast to robots, import competition can not only replace tasks, but also cause entire firms to disappear. However, existing evidence indicates that plant closures from firm deaths are unlikely to have played a major role in the US manufacturing decline (Bloom et al., 2019; Ding et al., 2019; Fort et al., 2018; Pierce and Schott, 2016). According to this literature, trade with China likely represented not only a threat to US firms, but also an opportunity to offshore production tasks, in turn reducing the cost of production. Hence, the China shock might be conceived as Chinese workers, rather than robots, substituting for US workers in the production of certain tasks in a given industry. Thus, a model as Grossman and Rossi-Hansberg (2008), where offshoring and trade in tasks play a central role, offers a fruitful framework to analyze the effects of the China shock. Specifically, Grossman and Rossi-Hansberg (2008) decompose the response to an "offshoring shock" in three different effects, which parallel those described previously for robots from Acemoglu and Restrepo (forthcoming).

Equating the terminology in Grossman and Rossi-Hansberg (2008) with that in Acemoglu and Restrepo (forthcoming), the displacement effect corresponds to the labor-supply effect, the composition effect to the relative-price effect, and the productivity effect shares the same name. For simplicity, we stick to the terminology of Acemoglu and Restrepo (forthcoming). In both frameworks, the effects of the respective shocks – robots in Acemoglu and Restrepo (forthcoming) and trade in Grossman and Rossi-Hansberg (2008) – can be decomposed into the same forces in terms of direct effects at the industry level (displacement), spillover effects within the industry (composition), and spillover effects at the CZ level (productivity).

We focus on the difference that the productivity effect plays in the transmission of the two shocks to other industries in the same CZ. While the other two forces might be relevant as well, we conjecture that the productivity effect is the key driver of the differential effects observed in our context.[32] In our setting, a large productivity effect in manufacturing may cause employment growth in non-manufacturing, whereas a low productivity effect may not offset negative demand spillovers from the displacement effect. In our context, two factors can influence the size of the productivity effect: *cost savings* and *complementarities*.

Cost savings. As noted above, cost savings result from using the new rather than the old technology. Clearly, higher cost savings are associated with a larger productivity effect. Existing evidence indicates that offshoring to China is likely to generate higher cost savings than the introduction of robots: according to BCG (2018), the cost savings enjoyed by US firms from using Chinese instead of US labor were as high as 75% between 2000 and 2007. Instead, the estimates obtained in Acemoglu and Restrepo (forthcoming) suggest that the cost savings from using robots instead of US labor are only around 30%. That is, trade with China was associated with cost savings that were more than twice as large as those associated with robots. We speculate that one reason for the different propagation patterns we observe may be the lower productivity gains that firms achieved when introducing robots, compared to moving production to China.

Complementarities. Another force governing the strength of the productivity effect is the degree to which industries are complements to one another. This may affect how much other industries are able to expand due to productivity improvements in directly affected industries. As Figure 2 shows, the bulk of the impact of the robots shock was concentrated in the automotive industry, whereas the China shock was concentrated mainly in the electronics industry. Notably, the automotive industry relies on intermediate inputs from the service sector to a much lower degree than the electronics industry. For example, in 2011, 37% of intermediate inputs in the electronics industry were accounted for by services. In contrast, this number was as low as 8% in the automotive industry.[33] Thus, higher complementarities of China-exposed industries with the service sector may be a second factor behind the different propagation patterns estimated above.

Other explanations: geographic clustering. Yet another feature that may have

[32] In companion work, we plan to analyze in more detail potential differences in the other two effects.

[33] These numbers are publicly available in the input-output accounts of the Bureau of Economic Analysis (BEA).

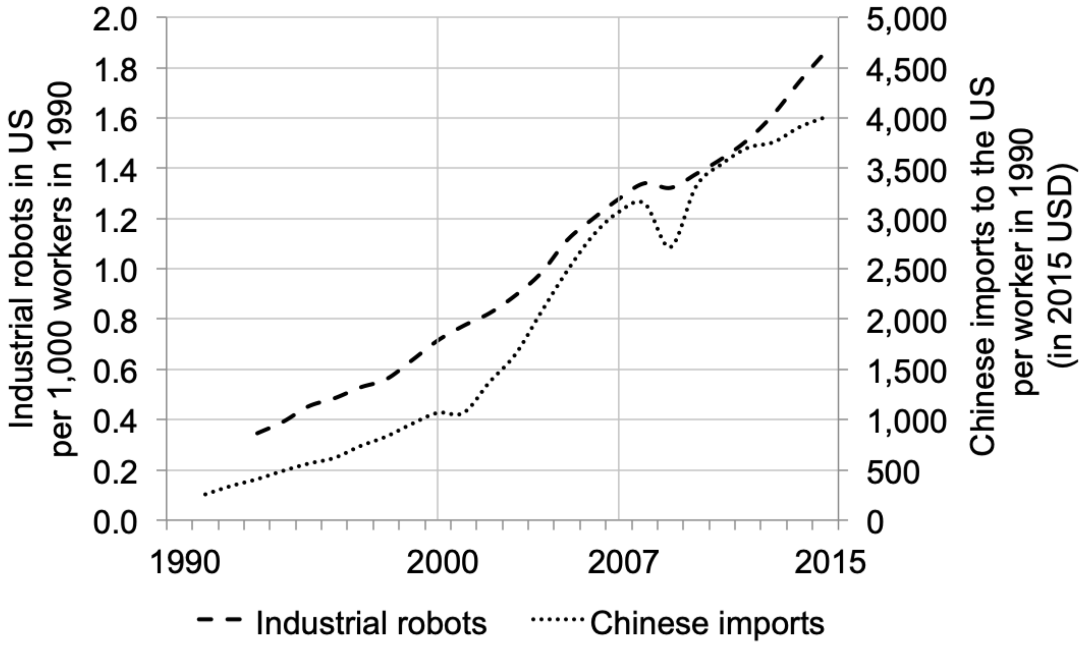
contributed to the migration response we observe is the different level of geographical clustering of the two shocks. Figure 3 shows that exposure to robots is far more geographically clustered than exposure to Chinese imports. Geographical clustering may partly govern the migration response for two reasons. First, a high geographical concentration of a shock may exacerbate any negative demand spillovers not only within but also between regions. Stated differently, the negative spillovers triggered by a shock would be lower, the lower the geographical clustering of such shock. It is possible that higher clustering of robot exposure, by amplifying the magnitude of spillovers, likely acted as a multiplier for the migration response we estimated. Second, geographic concentration may also affect migration directly, as the decision to migrate into or out of a CZ likely depends not only on the labor market conditions in a given CZ, but also on those prevailing in neighboring CZs. Prospective in- or out-migrants may use positive labor market conditions in surrounding CZs as an insurance for a potential job loss or for finding a new job, respectively. Due to the high geographical concentration of the exposure to robots, this insurance mechanism may have been less pronounced in response to robots.

7 Conclusion

Labor mobility is an important force that can re-equilibrate local labor markets after an adverse economic shock. In this paper, we exploit variation in US CZs' exposures to robots and Chinese imports between 1990 and 2015 to study the migration response to these two labor demand shocks alongside one another. Our main result is that, on average, although both import competition and robots adoption cause large declines in manufacturing employment, only robots – and not import competition – trigger a migration response across CZs. Decomposing the margins of the population response to robot exposure, we find that results are driven by reduced 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. Conversely, we find no effect of robots on out-migration.

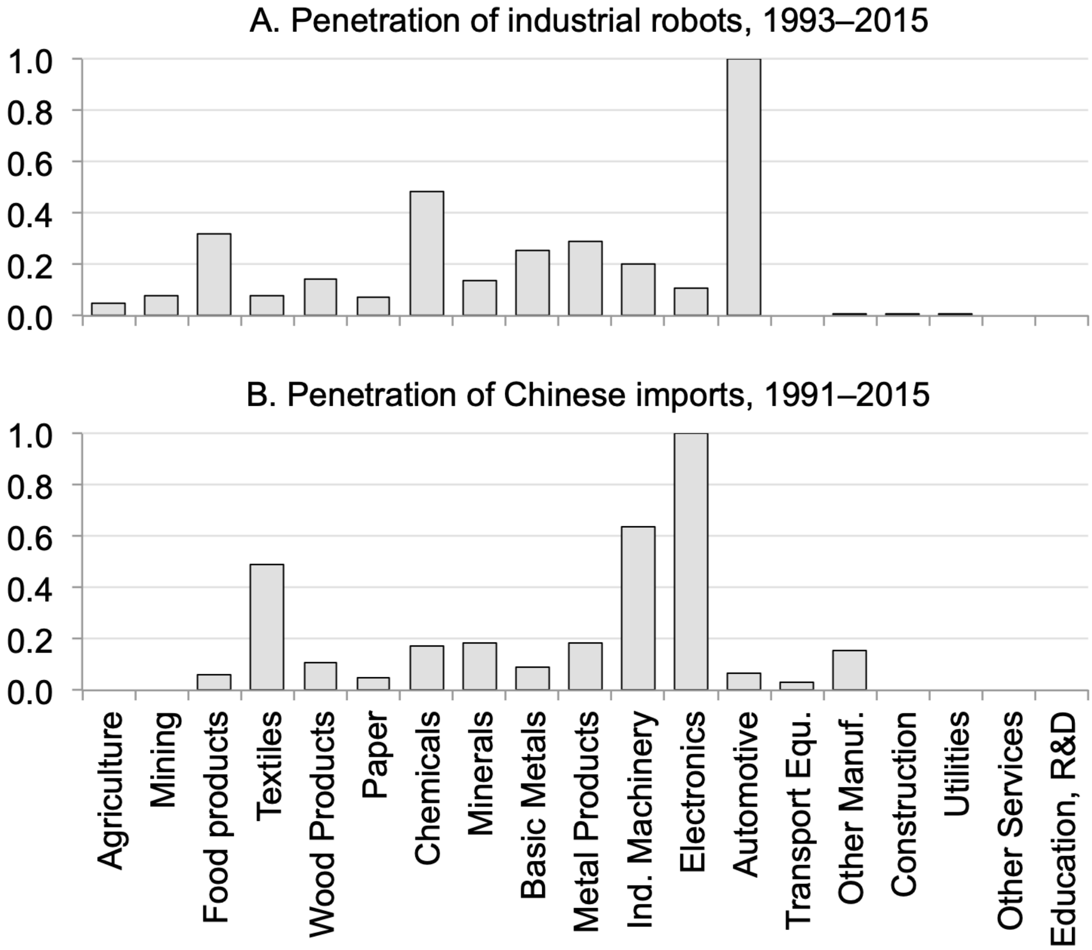
The second part of the paper explores the mechanisms behind these results. It shows that the two shocks differ in how the initial employment effects are transmitted from manufacturing to other industries and sectors – not originally impacted by the shocks – in the same labor market. While robots cause significant employment losses also in industries not directly affected, Chinese imports, if anything, cause employment growth outside of manufacturing. We offer suggestive evidence that via these spillovers, only robots – but not Chinese imports – worsen employment opportunities for the most mobile individuals (i.e., high-skilled workers) who, in turn, decide to avoid labor markets affected by robots. Furthermore, we rule out that these different migration responses are due to other differences between the two shocks, such as their timing or the initial characteristics of affected areas. Finally, we offer several potential explanations for why the two shocks may cause opposite spillovers to other industries.

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 their value in 2015 (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 findings suggest that migration might or might not play an important role in re-equilibrating local labor markets, depending both on the "type" of individuals affected by the shocks and on the propagation mechanisms across industries generated by such shocks.



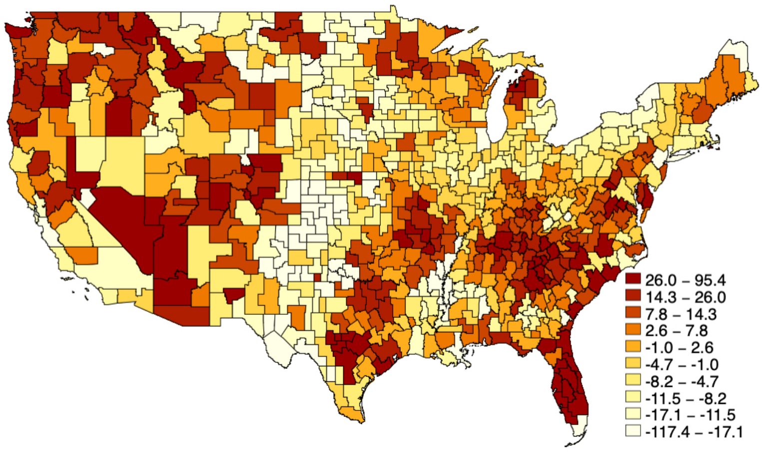
SOURCES: IFR (2016), United Nations (2019), Timmer et al. (2007)

Figure 1: Temporal variation of robot and China shock. 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).

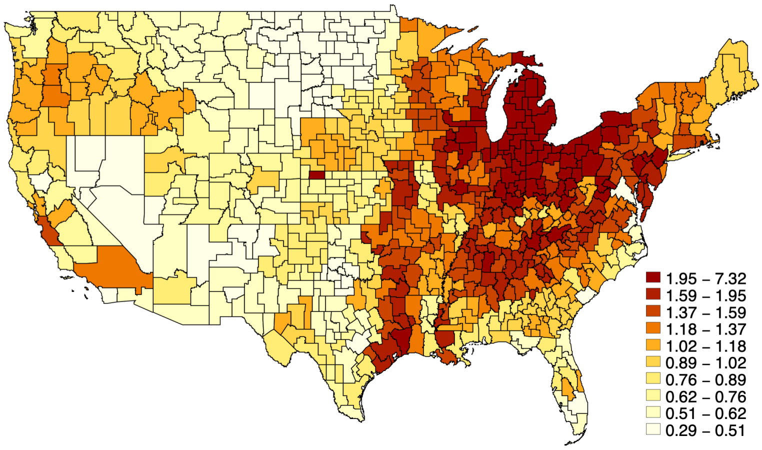


SOURCES: IFR (2016), United Nations (2019), Timmer et al. (2007)

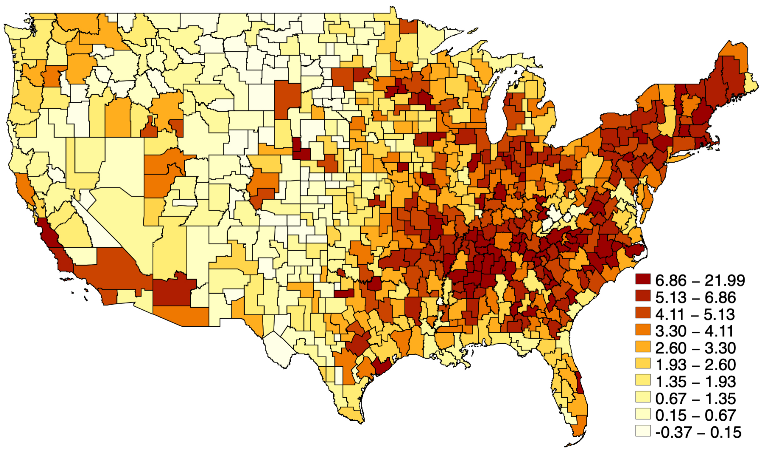
Figure 2: Industry variation of robot and China shock. Panel A presents the growth in the number of industrial robots per worker in 1990 in five European countries (Denmark, Finland, France, Italy, Sweden) between 1993 and 2015. Panel B shows the increase in imports from China to eight high-income countries (Autralia, 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.



(a) Net migration rate

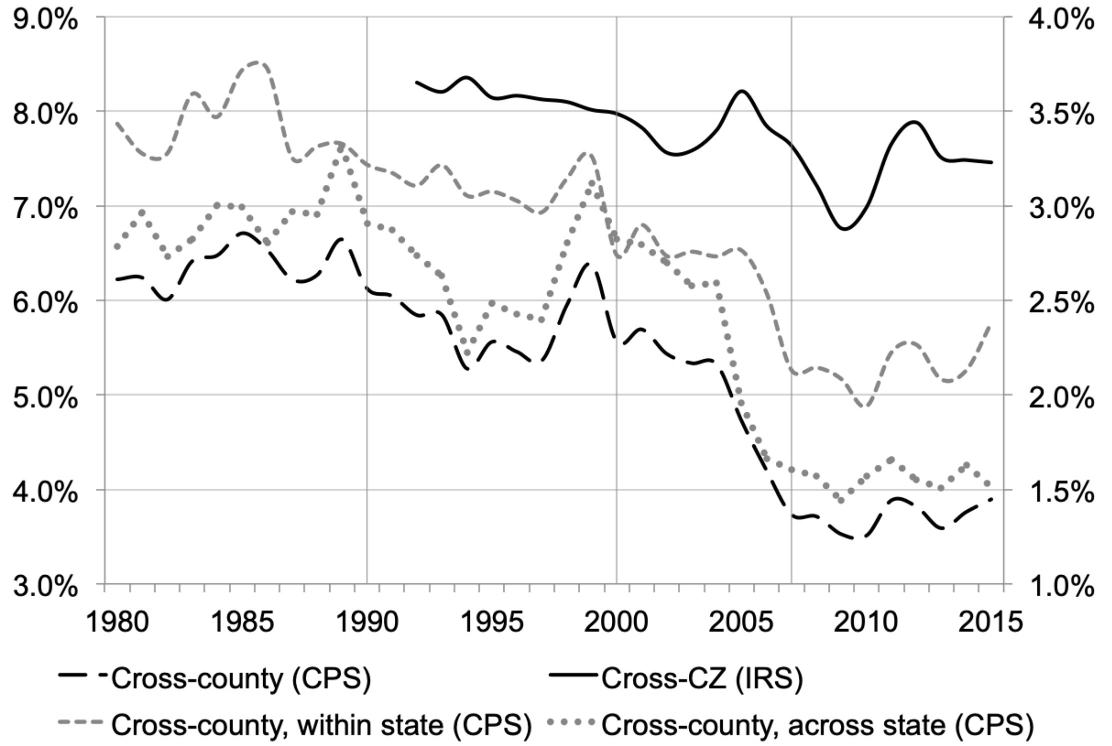


(b) Exposure to robots



(c) Exposure to Chinese imports

Figure 3: Geographic variation in the net migration rate (1992–2015), exposure to robots (1993–2015), and exposure Chinese imports (1991–2015)



SOURCES: Current Population Survey (CPS), Internal Revenue Service (IRS)

Figure 4: Evolution of US migration rates, 1980–2015. 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.

(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

Figure 5: Industry-skill profile of robot shock and China shock. 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.

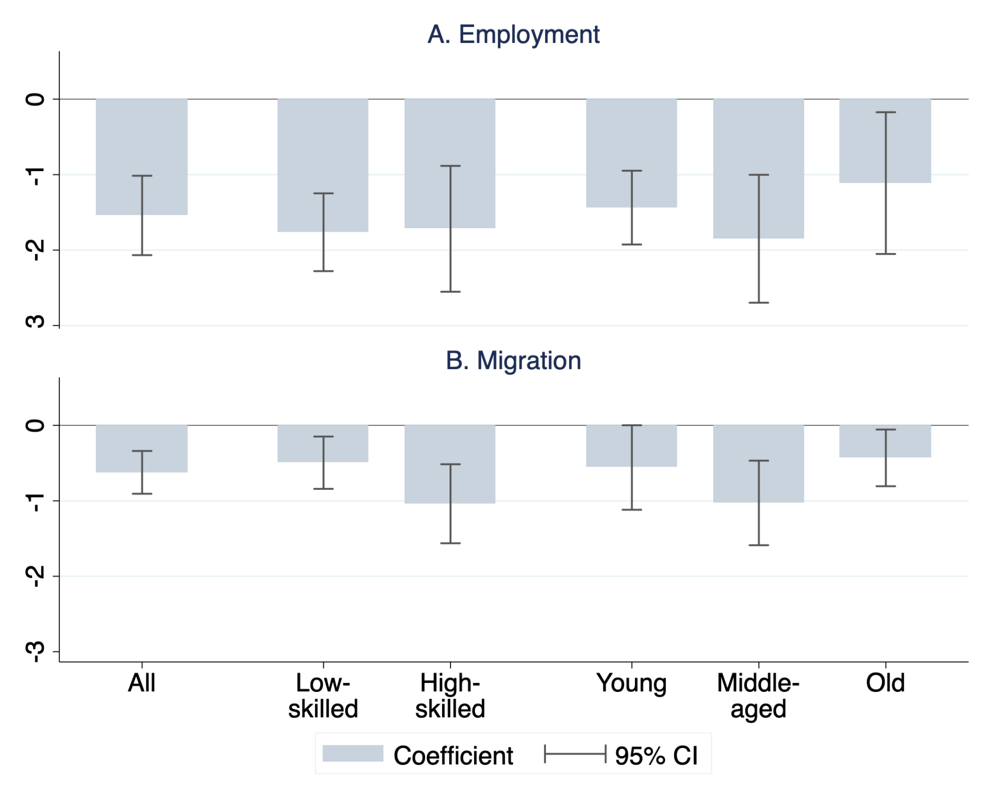


Figure 6: Effect of robots on employment and migration by subgroup. Panels A and B present the coefficient on the US exposure to robots in a regression identical to the one in Table 2, column (5), using log changes in subgroup-specific employment and working-age population as the outcome variable, respectively, and weighting observations by a CZ's 1990 national share of the respective outcome subgroup.

Table 1: Descriptive statistics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Exposure to robots	Exposure to China	Relative exposure China			Robots	
Quartiles	All	Q4	Q4	Q1	Q2	Q3	Q4	Q4–Q1
N	722	181	181	180	180	181	181	361
Change in outcomes, 1990–2015								
Log employment	23.7	14.2	15.5	22.1	30.3	23.8	18.5	–3.6
Log working-age population	14.8	12.5	14.9	17.1	19.8	11.4	11.1	–5.9**
Share of employment, 1990 (in %)								
Agriculture	4.5	2.2	3.0	4.1	4.8	5.5	3.6	–0.5
Construction	6.6	6.3	6.3	6.4	6.8	6.7	6.3	–0.1
Mining	2.7	1.4	0.9	1.2	2.4	4.1	3.1	1.9***
Manufacturing	24.3	33.7	35.4	30.3	21.8	19.6	25.7	–4.6**
Routine jobs	28.5	30.9	30.2	29.1	28.3	27.4	29.1	0.0
Share of population, 1990 (in %)								
Men	48.9	48.6	48.6	48.8	48.9	49.2	48.9	0.1
Above 65 years old	13.4	13.2	13.3	13.3	13.5	13.4	13.2	–0.2
Less than college	67.1	69.5	70.4	68.5	66.2	66.2	67.6	–0.9
Some college or more	28.6	26.5	25.5	27.2	29.6	29.4	28.2	1.0
White	87.0	89.7	86.7	85.2	84.3	88.1	90.2	5.0**
Black	7.8	8.3	11.3	11.0	9.2	4.8	6.1	–4.9*
Hispanic	5.8	1.6	2.1	4.9	6.5	7.5	4.2	–0.8
Asian	0.8	0.7	0.6	0.7	0.9	0.8	0.7	–0.1
Women in labor force	43.7	43.7	44.6	44.9	44.2	43.1	42.7	–2.2***
Standardized indeces, 1990 (mean 0, sd 10)								
Offshorability	0.0	4.0	4.2	2.8	0.5	–2.8	–0.4	–3.2**
Tradability	0.0	4.5	5.4	3.4	–1.1	–1.7	–0.6	–4.0***

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 along with its significance level (which results from a regression of the row variable on a Q4 dummy using the dataset of only observations in either Q1 or Q4, clustering standard errors by state. Differences with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively).

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

	(1)	(2)	(3)	(4)	(5)
			A. Manufacturing employment		
US exposure to robots	-2.33***	-1.60***	-1.96***	-1.60***	-1.52***
	(0.71)	(0.37)	(0.40)	(0.38)	(0.41)
US exposure to Chinese imports	-5.57***	-7.50***	-7.04***	-5.50***	-5.49***
	(1.24)	(1.48)	(1.44)	(1.64)	(1.61)
Kleibergen-Paap F	69.3	58.5	63.1	36.5	33.1
			B. Migration		
US exposure to robots	-1.40***	-0.76***	-0.77***	-0.69***	-0.62***
	(0.51)	(0.27)	(0.21)	(0.14)	(0.14)
US exposure to Chinese imports	-0.02	-0.36	-0.06	0.27	0.41
	(0.99)	(0.81)	(0.81)	(0.85)	(0.80)
Kleibergen-Paap F	58.2	58.6	52.8	26.5	25.1
Region $\times$ time	✓	✓	✓	✓	✓
Pre-trends		✓	✓	✓	✓
Demographics $\times$ time			✓	✓	✓
Industry shares $\times$ time				✓	✓
Contemp. changes $\times$ time					✓

Note: The dependent variable in Panel A and B is the change in the log count of manufacturing employment and the 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. 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 3: Effects on in- and out-migration, stacked differences 2000–2015 (2SLS)

	(1)	(2)	(3)	(4)	(5)	(6)
	Log count of migrants			Migration rates		
			A. In-migration			
US exposure to robots	-2.18***	-1.83***	-1.74***	-5.86***	-1.82	-2.03*
	(0.68)	(0.52)	(0.54)	(1.46)	(1.14)	(1.20)
US exposure to Chinese imports	0.14	1.06	1.49	-1.69	1.87	4.20
	(1.14)	(1.03)	(1.10)	(4.37)	(3.98)	(4.49)
			B. Out-migration			
US exposure to robots	-0.71	-0.29	0.00	-1.97	-0.58	-0.15
	(0.77)	(0.55)	(0.54)	(1.66)	(1.18)	(1.12)
US exposure to Chinese imports	0.32	0.97	0.43	-2.24	-0.37	-1.36
	(1.10)	(1.35)	(1.42)	(3.63)	(4.48)	(4.39)
Region × time & pre-trends	✓	✓	✓	✓	✓	✓
Demographics × time & industry shares × time		✓	✓		✓	✓
Contemp. changes × time			✓			✓

Note: The dependent variables in columns (1)–(3) and (4)–(6) are the log count of migrants and migration rate, respectively. Panel A focuses on in-migration and Panel B on out-migration. For example, the log count of in-migrants in columns (1)–(3) of Panel A is defined as the log of the sum of in-migrants in all the years of the subperiod (e.g., 2000–2007). 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. Columns (1) and (4) include interactions between census division and time period dummies, and the change in the outcome variable between 1992 and 2000. Columns (2) and (5) also control for demographic characteristics (i.e., log population, share of men, share of population above 65 years old, share of population with less than a college degree, share of population with some college or more, population shares of Hispanics, Blacks, Whites and Asians, and the share of women in the labor force) and 1990 shares of employment in broad industries (i.e., agriculture, mining, construction, manufacturing), each interacted with time period dummies. Columns (3) and (6) also include the share of routine jobs and the average offshorability index in 1990, following Autor and Dorn (2013), each interacted with time period dummies. Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the state level (48 states). Regressions are weighted by a CZ's 1990 national share of the working-age population. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

Table 4: 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	-1.74***	-2.14***	-1.68**	0.00	-1.83***	0.63
	(0.54)	(0.47)	(0.71)	(0.54)	(0.49)	(0.78)
US exposure to Chinese imports	1.49	3.17***	-0.18	0.43	0.87	1.06
	(1.10)	(1.17)	(1.68)	(1.42)	(1.33)	(1.88)
	B. Migration rate					
US exposure to robots	-2.03*	-0.33	-1.70*	-0.15	-1.27**	0.91
	(1.20)	(0.93)	(0.92)	(1.12)	(0.57)	(0.93)
US exposure to Chinese imports	4.20	2.78	-0.22	-1.36	-1.85	0.66
	(4.49)	(3.71)	(4.69)	(4.39)	(1.55)	(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 5: Effects on house prices, stacked differences 2000–2015 (2SLS)

	(1)	(2)	(3)	(4)	(5)
US exposure to robots	-5.75***	-5.25**	-4.43***	-2.67***	-2.52***
	(1.90)	(2.08)	(1.02)	(0.67)	(0.67)
US exposure to Chinese imports	-8.82***	-8.63***	-6.25***	0.93	0.25
	(2.66)	(2.81)	(2.14)	(2.54)	(3.28)
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 outcome group in each Panel, respectively. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

Table 6: Effects on migration, pre-trends (2SLS)

	(1)	(2)	(3)	(4)	(5)	(6)
	1970–1990		1990–2015			
US exposure to robots	-0.48	-0.50	-0.62***	-0.77***	-0.63***	-0.44**
	(0.39)	(0.38)	(0.14)	(0.28)	(0.14)	(0.18)
US exposure to Chinese imports	1.03	1.04	0.41	1.34*	0.25	0.88
	(0.75)	(0.65)	(0.80)	(0.72)	(0.80)	(0.60)
Δ_{70-90} log working-age population			0.38***			
			(0.09)			
Δ_{70-90} log working-age population $\times$ 1990–2000					0.49***	
					(0.16)	
Δ_{70-90} log working-age population $\times$ 2000–2007					0.49***	
					(0.07)	
Δ_{70-90} log working-age population $\times$ 2007–2015					0.14***	
					(0.04)	
Δ_{t-1} log working-age population						0.35***
						(0.12)
Kleibergen-Paap F	57.6	71.2	25.1	72.9	25.5	17.8
Region $\times$ time	✓	✓	✓	✓	✓	✓
Demog. $\times$ time & ind. sh. $\times$ time	✓	✓	✓	✓	✓	✓
Contemp. changes $\times$ time		✓	✓	✓	✓	✓

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

Table 7: Effects on employment, stacked differences 1990–2015 (2SLS)

	(1)	(2)	(3)	(4)	(5)
			A. Manufacturing employment		
US exposure to robots	-2.33***	-1.60***	-1.96***	-1.60***	-1.52***
	(0.71)	(0.37)	(0.40)	(0.38)	(0.41)
US exposure to Chinese imports	-5.57***	-7.50***	-7.04***	-5.50***	-5.49***
	(1.24)	(1.48)	(1.44)	(1.64)	(1.61)
			B. Non-manufacturing employment		
US exposure to robots	-2.08***	-1.82***	-1.52***	-1.67***	-1.61***
	(0.66)	(0.57)	(0.36)	(0.37)	(0.37)
US exposure to Chinese imports	1.48	1.37	1.32	0.49	0.58
	(1.15)	(1.10)	(0.95)	(1.06)	(1.03)
			C. Total employment		
US exposure to robots	-2.73***	-2.03***	-1.86***	-1.58***	-1.54***
	(0.85)	(0.54)	(0.33)	(0.27)	(0.27)
US exposure to Chinese imports	-2.41**	-2.91***	-2.46**	-0.92	-0.89
	(1.11)	(1.02)	(1.00)	(1.07)	(1.02)
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 8: 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	-1.06***	-1.09***	-1.12***	-0.40***	-1.43***	0.11
× HSI	(0.13)	(0.28)	(0.18)	(0.11)	(0.41)	(0.40)
Exposure to robots	-1.10***	-1.03*	-1.19***	-0.55***	-0.79	-0.48
× LSI	(0.30)	(0.55)	(0.27)	(0.20)	(0.73)	(0.72)
Exposure to Chinese imports	0.51	-3.01***	1.21*	1.03**	1.63*	0.96
× HSI	(0.52)	(0.84)	(0.63)	(0.50)	(0.85)	(0.95)
Exposure to Chinese imports	-1.17**	-2.69***	-0.54	-0.41	-0.18	-0.28
× LSI	(0.54)	(0.91)	(0.52)	(0.40)	(0.54)	(0.75)
P(HSI=LSI):						
– Exposure to robots	0.89	0.90	0.81	0.46	0.32	0.29
– 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. 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 9: Effects on migration, different time periods (2SLS and reduced form)

	(1)	(2)	(3)	(4)	(5)
			A. 1990–2007		
US exposure to robots	-1.48***	-0.66***	-0.69***	-0.63***	-0.56***
	(0.58)	(0.26)	(0.25)	(0.16)	(0.16)
US exposure to Chinese imports	-0.56	-0.77	-0.35	-0.21	-0.05
	(1.07)	(0.92)	(0.84)	(0.95)	(0.90)
Kleibergen-Paap F	41.1	41.6	38.1	16.8	16.0
			B. 1990–2015 (with post-2007 interactions)		
Exposure to robots	-0.89***	-0.49***	-0.51***	-0.43***	-0.38***
	(0.26)	(0.15)	(0.15)	(0.10)	(0.10)
Exposure to Chinese imports	-0.46	-0.52	-0.19	0.04	0.11
	(0.67)	(0.56)	(0.54)	(0.43)	(0.40)
Exposure to robots	-0.26	-0.16	-0.19	-0.22	-0.23
× post-2007	(0.19)	(0.19)	(0.13)	(0.16)	(0.16)
Exposure to Chinese imports	1.11**	0.77*	0.29	0.20	0.16
× post-2007	(0.47)	(0.45)	(0.29)	(0.25)	(0.24)
Region × time	✓	✓	✓	✓	✓
Pre-trends		✓	✓	✓	✓
Demographics × time			✓	✓	✓
Industry shares × time				✓	✓
Contemp. changes × time					✓

Note: The dependent variable is the change in the log count of the working-age population multiplied by 100 (i.e., $[\ln(y_{t+1}) - \ln(y_t)] \cdot 100$). All explanatory variables that are displayed are standardized to have a mean of zero and a standard deviation of 1 when considering the full sample of three time periods and 722 CZs. Panel A only includes two time periods (1990–2000, 2000–7) and Panel B includes all three (also 2007–15), resulting in N=1,444 and N=2,166, respectively. Column (1) includes only time period and census division dummies as covariates. Column (2) also includes the change in the outcome variable between 1970 and 1990. Column (3) also controls for 1990 demographic characteristics (i.e., log population, share of men, share of population above 65 years old, share of population with less than a college degree, share of population with some college or more, population shares of Hispanics, Blacks, Whites and Asians, and the share of women in the labor force). Column (4) also includes shares of employment in broad industries in 1990 (i.e., agriculture, mining, construction, manufacturing). Column (5) also includes the share of routine jobs and the average offshorability index in 1990, following Autor and Dorn (2013). Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the state level (48 states). Regressions are weighted by a CZ's 1990 national share of employment (Panel A) and the working-age population (Panel B). Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

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A Appendix

A.1 Skill content of occupation groups

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

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

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

We then compute the four products of abstract/routine and cognitive/manual, respectively, and choose the skill dimension with the largest value as an occupation's predominant skill requirement. The results of this are shown in Table A1. Using this methodology, managerial & professional as well as sales support occupations require mainly abstract, cognitive skills. Administrative support & clerical occupations are the only group requiring mainly routine, cognitive skills, and machine operators, fabricators & laborers the only one requiring mainly routine, manual skills. All remaining groups (technical support, services (e.g., nurses, janitors, cooks), agricultural, crafts & repair) use mostly abstract, manual abilities.

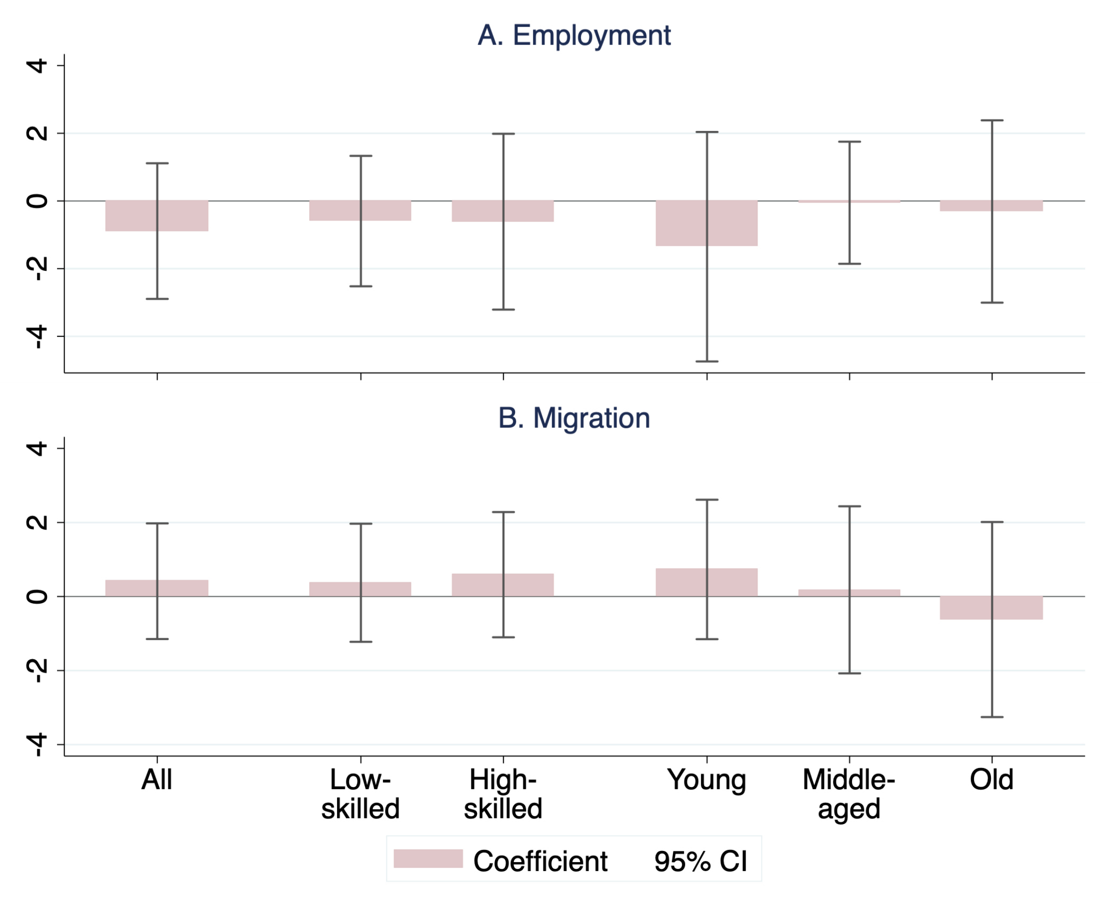

Figure A1: Effect of Chinese imports on employment and migration by subgroup. Panels A and B present the coefficient on the US exposure to Chinese imports in a regression identical to the one in Table 2, column (5), using log changes in subgroup-specific employment and working-age population as the outcome variable, respectively, and weighting observations by a CZ's 1990 national share of the respective outcome subgroup.

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

Table A1: Skill content of occupation groups along four dimensions. Areas shaded in gray indicate the highest value for each occupation group. Plus and minus signs indicate that the score of this occupation group is above and below the median of all groups, respectively.

Table A2: Effects on migration, long differences (2SLS)

	(1)	(2)	(3)	(4)	(5)
			A. 1990–2015		
US exposure to robots	-1.28***	-0.69***	-0.72***	-0.76***	-0.76***
	(0.46)	(0.25)	(0.20)	(0.16)	(0.16)
US exposure to Chinese imports	0.18	-0.41	-0.26	-0.53	-0.53
	(0.64)	(0.48)	(0.51)	(0.58)	(0.58)
Kleibergen-Paap F	158.1	150.7	107.5	54.9	54.9
			B. 1990–2007		
US exposure to robots	-1.41**	-0.68**	-0.66**	-0.68***	-0.68***
	(0.57)	(0.27)	(0.26)	(0.21)	(0.21)
US exposure to Chinese imports	-0.14	-0.58	-0.32	-0.57	-0.57
	(0.99)	(0.80)	(0.80)	(0.86)	(0.86)
Kleibergen-Paap F	53.4	52.7	41.5	19.9	19.9
Region dummies	✓	✓	✓	✓	✓
Pre-trends		✓	✓	✓	✓
Demographics			✓	✓	✓
Industry shares				✓	✓
Contemp. changes					✓

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

Table A3: First-stages and effects on manufacturing employment with partial instrumentation, stacked differences 1990–2015

	(1)	(2)	(3)	(4)	(5)
			A. First stage, US exposure to robots		
Exposure to robots	0.74***	0.76***	0.78***	0.76***	0.75***
	(0.06)	(0.05)	(0.05)	(0.05)	(0.06)
Exposure to Chinese imports	0.12***	0.07**	0.05*	0.04	0.06**
	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)
			B. First stage, US exposure to Chinese imports		
Exposure to robots	0.00	0.01	0.01	-0.02**	-0.02**
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
Exposure to Chinese imports	0.65***	0.62***	0.60***	0.49***	0.49***
	(0.05)	(0.06)	(0.05)	(0.06)	(0.06)
			C. Only robots instrumented (2SLS)		
US exposure to robots	-2.33***	-1.70***	-2.09***	-1.47***	-1.40***
	(0.72)	(0.39)	(0.43)	(0.38)	(0.40)
Exposure to Chinese imports	-3.60***	-4.68***	-4.23***	-2.73***	-2.70***
	(0.77)	(0.82)	(0.77)	(0.70)	(0.68)
First-stage F	143.6	215.6	226.4	183.3	166.8
			D. Only Chinese imports instrumented (2SLS)		
Exposure to robots	-6.01***	-7.67***	-7.21***	-5.63***	-5.69***
	(1.20)	(1.45)	(1.42)	(1.63)	(1.63)
US exposure to Chinese imports	-1.72***	-1.22***	-1.52***	-1.21***	-1.15***
	(0.44)	(0.27)	(0.27)	(0.28)	(0.29)
First-stage F	138.0	116.1	126.6	73.0	65.5
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 A4: First-stages and effects on migration with partial instrumentation, stacked differences 1990–2015

	(1)	(2)	(3)	(4)	(5)
	A. First stage, US exposure to robots				
Exposure to robots	0.71***	0.72***	0.75***	0.72***	0.72***
	(0.08)	(0.07)	(0.07)	(0.08)	(0.08)
Exposure to Chinese imports	0.10***	0.10***	0.08***	0.05*	0.06**
	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)
	B. First stage, US exposure to Chinese imports				
Exposure to robots	0.00	0.00	0.01	-0.03***	-0.03***
	(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	-1.40***	-0.77***	-0.77***	-0.70***	-0.64***
	(0.51)	(0.28)	(0.21)	(0.15)	(0.15)
Exposure to Chinese imports	-0.01	-0.24	-0.04	0.14	0.21
	(0.64)	(0.52)	(0.51)	(0.43)	(0.40)
First-stage F	84.1	88.1	106.5	80.6	76.5
	D. Only Chinese imports instrumented (2SLS)				
Exposure to robots	-0.99***	-0.55***	-0.58***	-0.50***	-0.45***
	(0.27)	(0.16)	(0.14)	(0.10)	(0.10)
US exposure to Chinese imports	-0.24	-0.48	-0.17	0.20	0.34
	(0.98)	(0.82)	(0.81)	(0.85)	(0.80)
First-stage F	116.0	116.3	104.4	52.5	49.9
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 A5: Estimates using controls used 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	-1.50***	-1.31***	-1.04***	-1.28***	-0.35***	-0.35**
	(0.28)	(0.22)	(0.23)	(0.17)	(0.09)	(0.14)
Exposure to Chinese imports	-3.01***	-0.03	0.49	-0.71	-0.03	-0.16
	(0.82)	(0.62)	(0.77)	(0.61)	(0.44)	(0.55)
	B. Controls from Autor et al. (2013)					
Exposure to robots	-1.93***	-1.59***	-1.26***	-1.87***	-0.69***	-0.66***
	(0.39)	(0.33)	(0.26)	(0.34)	(0.19)	(0.19)
Exposure to Chinese imports	-4.87***	-0.21	1.39	-1.81**	0.07	0.07
	(1.01)	(0.90)	(1.00)	(0.90)	(0.81)	(0.86)
	C. Controls from Acemoglu and Restrepo (forthcoming)					
Exposure to robots	-1.51***	-1.25***	-0.68***	-1.55***	-0.29**	-0.20
	(0.31)	(0.28)	(0.18)	(0.29)	(0.14)	(0.15)
Exposure to Chinese imports	-3.90***	0.09	1.49*	-1.29*	0.44	0.50
	(0.79)	(0.74)	(0.88)	(0.68)	(0.52)	(0.56)
	D. Controls from Acemoglu and Restrepo (forthcoming), (incl. covariates×time & pre-trends)					
Exposure to robots	-1.01***	-1.02***	-0.86***	-1.05***	-0.34***	-0.28**
	(0.29)	(0.19)	(0.19)	(0.16)	(0.12)	(0.13)
Exposure to Chinese imports	-2.52***	0.43	0.85	-0.21	0.31	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 A6: Effects on migration, Pierce and Schott (2016) China shock treatment (reduced form)

	(1)	(2)	(3)	(4)	(5)	(6)
	1990–2015			1990–2007		
	A. Interacting baseline controls with time dummies					
Exposure to robots	-0.48***	-0.51***	-0.47***	-0.38***	-0.37***	-0.35***
	(0.13)	(0.11)	(0.10)	(0.13)	(0.11)	(0.10)
NTR Gap × post-2000	-1.14***	0.18	-0.15	-0.64	0.18	-0.23
	(0.32)	(0.61)	(0.49)	(0.50)	(0.72)	(0.60)
	B. Not interacting baseline controls with time dummies					
Exposure to robots	-0.38***	-0.45***	-0.39***	-0.33***	-0.35***	-0.30**
	(0.12)	(0.10)	(0.10)	(0.13)	(0.13)	(0.12)
NTR Gap × post-2000	-0.97***	-0.20	-0.43	-0.37	0.00	-0.20
	(0.36)	(0.60)	(0.56)	(0.54)	(0.52)	(0.50)
Region dummies & pre-trends	✓	✓	✓	✓	✓	✓
Demographics & industry shares		✓	✓		✓	✓
Contemp. changes			✓			✓

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

Table A7: 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	-1.54***	-1.76***	-1.72***	-1.44***	-1.85***	-1.11**	-1.58***	-0.07
	(0.27)	(0.26)	(0.43)	(0.25)	(0.43)	(0.48)	(0.29)	(0.80)
US exposure to Chinese imports	-0.89	-0.59	-0.61	-1.35	-0.05	-0.31	-0.63	-1.54
	(1.02)	(0.98)	(1.33)	(1.73)	(0.92)	(1.37)	(1.23)	(3.75)
Kleibergen-Paap F	27.7	27.5	27.1	27.4	29.0	25.2	26.4	34.8
				B. Migration				
US exposure to robots	-0.62***	-0.49***	-1.03***	-0.43**	-1.04***	-0.56*	-0.82***	1.05
	(0.14)	(0.18)	(0.29)	(0.19)	(0.27)	(0.29)	(0.20)	(0.75)
US exposure to Chinese imports	0.41	0.37	0.18	-0.62	0.59	0.73	0.13	0.31
	(0.80)	(0.81)	(1.15)	(1.34)	(0.86)	(0.96)	(1.03)	(2.97)
Kleibergen-Paap F	25.1	25.5	24.5	26.1	25.7	23.6	24.4	31.7

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.