I Z A Institute of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 14623

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

Marius Faber
Andrés Sarto
Marco Tabellini

JULY 2021

I Z A Institute of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 14623

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

Marius Faber
University of Basel

Andrés Sarto
NYU Stern

Marco Tabellini
Harvard Business School, CEPR, CReAM, and IZA

JULY 2021

IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

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

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 hit US manufacturing since the late 1990s – Chinese import competition and the introduction of industrial robots. Exploiting plausibly exogenous variation in exposure across US local labor markets over time, we show that robots caused a sizable reduction in population size, while Chinese imports did not. We rationalize these results in two steps. First, we provide evidence that negative employment spillovers outside manufacturing, caused by robots but not by Chinese imports, are an important mechanism for the different migration responses triggered by the two shocks. Next, we present a model where workers are geographically mobile and compete with either machines or foreign labor in the completion of tasks. The model highlights that two key dimensions along which the shocks differ – the cost savings they provide and the degree of complementarity between directly and indirectly exposed industries – can explain their disparate employment effects outside manufacturing and, in turn, the differential migration response.

JEL Classification: J21, J23, J61

Keywords: migration, employment, technology, trade

Corresponding author:
Marco Tabellini
Harvard Business School
Boston, MA 02163
USA

E-mail: mtabellini@hbs.edu

* We thank Daron Acemoglu, David Autor, Clement Imbert, Teresa Fort, Marco Manacorda, Pascual Restrepo, Esteban Rossi-Hansberg, Kurt Schmidheiny, and participants at the UEA Summer School 2019, EEA Virtual Congress 2020, UEA Virtual 2020, NYU Stern Finance Internal Seminar, WWZ Basel Economics Lunch, and 2021 CEPR Annual Symposium in Labour Economics for useful comments. Silvia Farina and Federico Mattei provided excellent research assistance. An earlier version of this paper circulated under the title "The Impact of Technology and Trade on Migration: Evidence from the US".

1 Introduction

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

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

At the same time, neither technological nor trade-related structural changes are likely to level off anytime soon. Between 2015 and 2019, the global stock of robots increased by almost 70% (IFR, 2020). Recent case studies predict the robot stock to increase by at least three-fold by 2025 (BCG, 2015). The prevailing political climate in the US and many European countries further suggests that trade volumes with China and other countries might change considerably in the years to come. Alongside these trends, new technologies such as Artificial Intelligence (AI) have started to transform the economy and alter labor demand patterns (Frank et al., 2019). Will local labor markets adjust smoothly to the new technological and trade-induced shocks? Or, will frictions to labor mobility prevent this from happening, possibly leading to persistent levels of unemployment and to growing regional inequality? Even in the presence of migration, will the latter be enough to fully re-equilibrate labor markets?

In this paper, we address these questions by studying the migration response to trade and technology shocks across US Commuting Zones (CZs) between 1990 and 2015. We focus on the effects of two main variables: Chinese import competition and the adoption of industrial robots. Following the existing literature (Autor et al., 2013; Acemoglu and Restrepo, 2020), we construct plausibly exogenous measures of local exposure to both shocks by combining the pre-period CZ industrial composition with the growth in, respectively, import competition and robot adoption in other industrialized countries. Using these variables, and splitting the sample in three periods (1990-2000; 2000-2007; and 2007-2015), we estimate stacked first difference regressions to identify the causal impact of both shocks on the change in CZ population. Our preferred specification controls for any CZ specific, time invariant characteristics, and allows CZs to be on differential trends depending on several baseline characteristics.[1]

We find that industrial robots caused a sizable reduction in population size, whereas Chinese import competition did not. Our results are robust to accounting for pre-existing trends, to constructing the Chinese imports shock in different ways, to estimating long difference specifications, and to accounting for potentially confounding effects of the Great Recession. Examining the margin along which the migration response takes place, we document that the reduction in CZ population induced by the robot shock did not arise from increased out-migration but, instead, from lower in-migration.[2] Our estimates are quantitatively large: according to our most preferred specification, each new robot reduced in-migration by about four working-age individuals.

Next, we investigate the causes of such disparate migration responses. First, and in line with previous work, we document that the employment effects of robots "spilled over" to industries that were not directly affected, such as business and professional services, as well as retail (Acemoglu and Restrepo, 2020). This pattern differs substantially from that associated with import competition, whose negative effects remained concentrated within the manufacturing sector, and, if anything, caused positive employment effects outside manufacturing (Bloom et al., 2019; Ding et al., 2019).

Second, we provide suggestive evidence that spillovers into high-skilled industries may have been responsible for the differential migration response between the two shocks. We begin by documenting that robots reduced employment of both low-skilled (mostly within

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

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

manufacturing) and high-skilled individuals (mostly outside manufacturing) to a similar extent, but that the migration response was largely driven by high-skilled individuals. Our estimates imply that the migration elasticity of high-skilled workers was more than twice as large as that of low-skilled workers in response to robots. This suggests that at least some of the employment losses due to the introduction of robots can be accounted for by high-skill jobs that, in the absence of robots, would have been created and taken by prospective in-migrants. Next, for each CZ, we compute the share of high-skilled individuals living in neighboring CZs in 1990, to proxy for potential high-skilled in-migrants that might have moved to the CZ absent the labor market shocks. Consistent with our conjecture, the employment effects of robots (and Chinese imports) were similar across CZs surrounded by different pools of migrants. However, robots reduced population growth only in CZs with a larger share of high-skilled neighbors, and these effects were driven by lower in-migration, rather than by higher out-migration.

Turning to Chinese imports, the average effects estimated for this shock mask substantial heterogeneity, both for employment and for migration. In particular, we find that Chinese imports generated positive and statistically significant employment effects outside manufacturing in CZs with a high degree of specialization in services (high service intensity regions, HSI), and slightly negative, though not statistically significant, effects in CZs with a low degree of specialization in services (low service intensity regions, LSI).[3] Linking employment effects to migration, import competition led to higher in-migration in HSI CZs, and a mild, but not statistically significant, reduction in population in LSI CZs.

Taken together, these patterns suggest that the migration response to local labor market shocks might depend not only on their employment effects in the directly exposed sector (in this case, manufacturing), but also on that on indirectly exposed ones (in this case, non-manufacturing). This idea is consistent with at least two, non-mutually exclusive, explanations. First, the transmission of a shock into non-manufacturing (or any other indirectly affected sector) amplifies its initial effect, acting as a multiplier and making the CZ as a whole less attractive to in-migrants. Second, indirectly hit industries (in this case, non-manufacturing) may host more mobile individuals, whose migration elasticity to economic shocks is higher. The evidence described above seems more consistent with the latter channel.

The second part of the paper presents a quantitative spatial economic model with geo-

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

graphically mobile labor, where workers compete with either robots or foreign labor in the completion of tasks. The goal is to shed light on the factors driving the different spillovers into non-manufacturing between the two shocks – which might, in turn, affect individuals' decision to migrate. In the model, the migration patterns documented before are the outcomes of countervailing forces that affect labor demand in both manufacturing and non-manufacturing industries within a CZ. Combining the structure of the model with evidence from other studies, we single out two plausible causes for the disparate employment effects outside manufacturing: the cost savings that each shock provides, and the degree of complementarity between exposed and non-exposed industries. According to our model, differences in cost savings in the range of values estimated elsewhere can fully explain, through their employment effects, the different migration responses between the two shocks. Instead, even though differences in complementarities associated with robot adoption and Chinese imports account for part of the differential migration response, they cannot fully explain it.

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 the adoption of robots (Autor et al., 2013; Autor et al., 2014; Dix-Carneiro, 2014; Bloom et al., 2019; Ding et al., 2019; Acemoglu and Restrepo, 2020). To the best of our knowledge, we are the first to compare the migration responses to the two shocks alongside one another. Closely related to our work, Greenland et al. (2019) find that Chinese import competition was associated with changes in CZ population. The discrepancy between our results and theirs stems from the more stringent set of controls included in our analysis, which absorb the potentially spurious correlation between import competition and other economic forces that may shape migration patterns.[4]

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

[4] See Appendix C.2 for more details. With respect to the impact of robots, while Acemoglu and Restrepo (2020) focus on employment and wages, they also examine migration. In Table A18, they conclude: "Some of our estimates show a negative impact on population and net migration (...), though these effects are neither consistent across specifications nor precisely estimated." Table A2 below documents that the use of intercensal estimates for population and a slightly different, and more stringent, specification likely explain the difference between our results and those in Acemoglu and Restrepo (2020).

behind the differential employment and migration patterns we document.

Next, our results speak to the debate on whether workers' geographic immobility might explain the sluggish recovery of local labor markets to the shocks that hit US manufacturing in the past twenty years or so (Abraham and Kearney, 2018; Charles et al., 2019). Although the muted migration response to Chinese import competition may have exacerbated the (local and national) impact of the shock, our findings suggest that migration alone is not enough to prevent the persistence of a negative, concentrated, and large shock. Indeed, even though robot penetration triggered a substantial change in migration patterns, it nonetheless caused a long-lasting decline in employment rates and wages.[5]

Our paper also complements recent works that examine workers' geographic mobility following local economic shocks more broadly (Cadena and Kovak, 2016; Bartik, 2018; Kearney and Wilson, 2018; Monras, 2018). We expand on these papers by comparing the response of the same local labor markets to two simultaneous, and major shocks to US manufacturing. This comparison allows us to go beyond the estimation of migration responses to specific shocks taken in isolation, thus increasing our understanding of the drivers of migration responses more generally. 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. Instead, 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, our paper can inform the design of specific policies to deal with future labor market shocks. For example, AI is believed to not only affect demand for unskilled workers, but to also transform occupations across the whole range of skills (Brynjolfsson et al., 2018). Recent findings in Webb (2019) indicate that high-skilled, middle-aged workers are the most exposed segment of the workforce to AI automation. Given the heterogeneity in migration elasticities documented in our work, our findings might help predict the impact of AI technologies on unemployment rates, regional inequality, and local demographics in the years to come. Specifically, if the geographic mobility of high skilled workers mitigates the differential employment consequences across local labor markets, the impact of AI might be qualitatively and quantitatively different from that of a trade shock, and even from that of robot adoption.

[5] We suspect that the impact of robots would have been even larger in the absence of migration. Yet, the latter was not enough to re-equilibrate local labor markets, at least in the short to medium run.

The paper is structured as follows. Section 2 describes the rise of industrial robots and Chinese import competition, and lays out the empirical strategy. Section 3 introduces the data, and presents descriptive statistics for the main variables of interest. Section 4 presents the results and explores the mechanisms. Section 5 develops a quantitative spatial economic model to shed light on potential causes behind the reduced form estimates. Section 6 concludes.

2 Labor market shocks and empirical strategy

2.1 Labor market shocks

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

Robots. The use of industrial robots in the US and around the world has grown significantly since the early 1990s. Advances in the capabilities of robots and reductions in prices resulted in a threefold increase in the global robot stock between 1993 and 2015 (IFR, 2020). During the same period, the stock of robots increased by about 1.5 robots per 1,000 workers in the US (Figure 1). Robot penetration was highest in the manufacturing sector, where robots typically perform tasks such as pressing, welding, packaging, assembling, painting, and sealing. Within manufacturing, the automotive industry makes the heaviest use of industrial robots, followed by plastics and chemicals, food and beverages, and the metal industries (basic metals, metal products, and industrial machinery). Outside manufacturing, industrial robots are used for harvesting and the inspection of equipment and structures (Figure 2).

[Figure 1 here]

While the US added a large number of robots since the beginning of the 1990s, the origins of these changes lie outside of the country. Acemoglu and Restrepo (2021) document that global demographic trends are responsible for the introduction of robots, which are needed to replace a declining pool of young and middle-aged workers (between the ages of 21 and 55) to perform routine, manual tasks in the production process in most developed countries –

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

from Germany to Japan to South Korea to France.[7] Even though robots are produced (and used) more heavily in aging countries, they are also exported to the rest of the world. We exploit this feature in our empirical strategy, as we explain in detail below.

[Figure 2 here]

Chinese imports. Chinese exports skyrocketed since the early 1990s. China's share of world exports grew from 2% to more than 12% between 1990 and 2015. The rise in Chinese exports to the US was even more dramatic, with a 15-fold increase between 1991 and 2015 – from about USD 250 per American worker in 1991 to more than USD 4,000 in 2015 (Figure 1). Given China's comparative advantage, its exports were highly skewed towards labor-intensive industries within the manufacturing sector. Specifically for the US, the growth in Chinese imports per worker was largest in electronics and electrical equipment, followed by industrial machinery as well as textiles and apparel. The least affected industries within manufacturing were transport equipment (non-automotive), paper and printing products, and food, beverages and tobacco (Figure 2).

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.[8] Beginning in the 1980s, China introduced several policies to boost its manufacturing exports, such as the creation of special economic zones that granted foreign investors tax breaks, lower custom duties, and relaxed labor regulations to encourage the import and final assembly of intermediate goods into final exports (Wang, 2013). It also privatized inefficient state-owned enterprises, and implemented additional measures to enhance productivity (Hsieh and Song, 2015). These reforms had a dramatic impact on Chinese exports during the 1990s (Figure 1). The upward trend was further reinforced when, in the early 2000s, China was granted Permanent Normal Trade Relations (PNTR) status by the US and joined the WTO. As for robot adoption, to estimate the causal effects of Chinese import competition across US local labor markets, we leverage variation induced by forces that originated outside the US.

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

[8] See Storesletten and Zilibotti (2014) and Autor et al. (2016) for a discussion on the factors behind the growth of Chinese exports.

2.2 Empirical strategy

We consider the 722 CZs contained in the US mainland, and stack the data from 1990 to 2015 into three periods – 1990–2000, 2000–7, 2007–15. To identify the effects of industrial robots and Chinese import competition on internal migration, we estimate a regression of the form:

$$(1)\quad \Delta \ln Y_{c,t} = \beta^r \begin{array}{c}\text{US exposure to}\\ \text{robots}_{c,t}\end{array} + \beta^c \begin{array}{c}\text{US exposure to}\\ \text{Chinese imports}_{c,t}\end{array} + \boldsymbol{X}'_{c,1990}\gamma_t + \Delta \ln Y_{c,1970-90} + \epsilon_{c,t},$$

where $Y_{c,t}$ is the number of working-age (15-64 year old) individuals living in CZ c at time t. Throughout the paper, we also distinguish between in- and out-migrants, and consider other outcomes, such as employment (aggregate and by subgroup). Regressions are weighted by a CZ's 1990 size of the outcome group.[9] Standard errors allow for heteroskedasticity and arbitrary clustering by state. We include a rich vector of baseline characteristics $\boldsymbol{X}_{c,1990}$, interacted with period dummies, to allow for differential trends.[10] To account for potentially pre-existing trends, we also control for the change in the outcome variable in the pre-period (1970-90). Since we estimate stacked first difference regressions and include region-period fixed effects, the coefficients of interest, β^r and β^c, are identified from changes within the same CZ over time, as compared to other CZs in the same Census region in a given period.

Following Acemoglu and Restrepo (2020), we define a CZ's *US exposure to robots* as a Bartik-style measure based on each industry's robot penetration in the US between t and $t+1$ (adjusted for the overall expansion of each industry) and baseline industry employment shares in CZ c. Formally, we construct

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

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

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

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

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

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

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

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

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

where $M^{CNUS}_{i,t}$ is the value of Chinese imports to the US in industry i at time t. To alleviate further endogeneity concerns, we define *exposure to Chinese imports* by replacing Chinese imports to the US with those to eight high-income countries other than the US between t and $t+1$. Similar to what we do for robot penetration, we replace the initial industry employment shares in CZ c with lagged shares following Autor et al. (2013).[11] In particular, we construct

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

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

Table 1, column 8, documents that CZs more exposed to either shock not only differ in their subsequent population growth, but also along a few other observable initial characteristics. For instance, CZs especially exposed to robots have a higher share of employment in

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

mining and a lower share of workers in manufacturing and offshorable jobs. These places also have a lower share of Black individuals and lower female labor force participation. For these initial differences not to bias our results, we include them (as well as those with insignificant differences) in our subsequent analysis.[12]

3 Data and descriptive statistics

This section first describes the data used in the paper (Section 3.1), and then presents basic summary statistics (Section 3.2).

3.1 Data

Migration. The key outcome of interest in our analysis is the change in the log number of individuals of demographic group Y living in CZ c between period t and $t+1$, $\Delta \ln Y_{c,t} = \ln Y_{c,t+1} - \ln Y_{c,t}$. While our main focus is on working-age population (15-64 year old), we also consider other subgroups (e.g., by employment status, birthplace, education, and age). When examining the mechanisms, we turn to changes in subgroup-specific employment as a share of total employment, $\Delta s^{Y}_{c,t} = \frac{Y_{c,t+1} - Y_{c,t}}{L_{c,t}}$, where $Y_{c,t}$ denotes the number of workers in subgroup Y (e.g., a certain skill-industry combination such as routine, manual occupations in manufacturing), and $L_{c,t}$ denotes overall employment in CZ c at time t. When using a stacked differences dataset containing changes from 1990–2000, 2000-7 and 2007–15, we inflate changes in the two latter periods to 10-year equivalents for comparability.[13]

Most outcome variables and covariates are taken from IPUMS census samples for 1970, 1980, 1990, and 2000, and from the American Community Survey (ACS) for 2007 and 2015 (Ruggles et al., 2018). The sample size varies between 1 and 5% of the overall US population depending on the year.[14] 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.[15]

[12] Results are robust to omitting these controls.

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

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

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

We complement these data with two other sources. First, we collect data on aggregate county population from the intercensal estimates of the US Census Bureau. These have the advantage that they are based on full count census data as opposed to 1–5% samples, but the disadvantage that they do not feature detailed demographic characteristics. When using changes in aggregate (working-age) population, we rely on the intercensal estimates; instead, when examining subgroups of the population (by birthplace, education, age, employment status), we use IPUMS samples. The second additional source of data is the county-to-county migration counts from the Internal Revenue Service (IRS). These counts are based on 1040 tax return filings, which include an individual's address for every year. By tracking address changes from one year to the next, the IRS is able to report the number of in- and out-migrants of each county for all years since 1990. We aggregate this data to the CZ level, treating moves across counties but within a CZ as non-migrants.

[Figure 3 here]

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

[Figure 4 here]

Exposure to robots. We draw on three data sources to construct the exposure to robots variables. First, we obtain data on shipments of industrial robots by industry, country and year from the International Federation of Robotics (IFR, 2020).[16] Second, we collect initial industry employment shares by CZ from the Integrated Public Use Microdata Series (Ruggles et al., 2018). Third, we take employment and output by industry and year for countries other than the US from the EU KLEMS dataset (Timmer et al., 2007). To construct robot penetration at the CZ level, we interact industry-level growth in different countries with initial

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

industry employment shares in a CZ, which we take from IPUMS and the ACS. We further complement these data with industry employment and output growth rates by country and year from the EU KLEMS database.

Exposure to Chinese imports. To construct Chinese import competition, we take data from Autor et al. (2013) and extend their measures of exposure to Chinese imports per worker to the period 2007–2015.[17] To do this, we employ two data sources. First, we use industry-level data on the value of Chinese imports in 2007 USD by destination country and year from the UN Comtrade database (United Nations, 2019). Second, we collect data on initial industry employment shares by CZ from the County Business Patterns (CBP; US Census Bureau, 2019), which provide county-level employment counts at the same level of granularity (4-digit classification) as the Comtrade data. Since the CBP data provide employment counts in brackets (i.e., lower and upper bounds), we employ the fixed-point algorithm developed by Autor and Dorn (2013) to get single numbers of employment for all such brackets.

Covariates. We compute baseline CZ demographic characteristics and broad industry employment shares from the IPUMS samples. We also consider two major contemporaneous changes to the demand for specific skills as potential confounders – 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 (Autor and Dorn, 2013).

3.2 Descriptive statistics

As a preliminary step, we verify that the correlation between robot exposure and Chinese import competition is sufficiently low for us to separately identify their effects. Figure 4 shows the geographic distribution of the 1990-2015 exposure to robots and to Chinese imports in Panels B and C respectively. Both shocks were stronger in the Eastern part of the US. However, the robot shock was largely concentrated in the Midwest, especially in the Rust Belt, while exposure to Chinese imports was more pronounced in the Southeast and in the Northeast. Reassuringly, the population weighted correlation coefficient between the two is as low as 0.06.

Table 1 reports summary statistics for the main variables considered in our work. Column 1 provides the average over the entire sample. Columns 2 and 3 restrict attention to CZs in the upper quartile of exposure to robots and Chinese imports, respectively. Columns 4 to

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

7 replicate columns 2 and 3 focusing on relative exposure to robots over Chinese imports.[18] The first quartile (column 4), thus includes CZs that were particularly exposed to Chinese imports but not to robots. Similarly, CZs in the fourth quartile (column 7) were substantially exposed to robot penetration, but not to Chinese imports. Column 8 reports the difference between columns 7 and 4, and column 9 indicates its statistical significance.

[Table 1 here]

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

4 The migration response to local labor market shocks

This section first presents the effects of robot penetration and Chinese import competition on migration (Section 4.1), and then explores the mechanisms (Section 4.2).

4.1 Main results

We begin by studying the impact of robot penetration and Chinese imports on migration. We estimate equation (1) using the change in the log working-age population as dependent variable, and report 2SLS results in Table 2.[19]

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

[19] First stage regressions are presented in Panels A and B of Table A1. Both instruments are always highly correlated with their respective endogenous counterparts. In some specifications, the instrument of the respective other shock has some predictive power over the endogenous variable. To rule out that the effects in Table 2 are identified from the unintended instrument, in Panels C and D, we replicate the analysis with two separate regressions for each of the shocks, including the other instrument as control. Reassuringly, results remain unchanged.

[Table 2 here]

In column 1, we estimate a parsimonious specification that only includes interactions between time dummies and census division dummies. Despite the similar, negative effect on manufacturing employment already documented in previous work (Autor et al., 2013; Acemoglu and Restrepo, 2020), the two shocks had a strongly different impact on migration.[20] While robots led to a significant reduction in population growth, Chinese imports did not. Subsequent columns of Table 2 show that these results are robust to including an increasingly stringent set of controls.

In column 2, we control for the 1970 to 1990 change in log working-age population to capture potential secular migration trends, which may be correlated with post-1990 labor market shocks. Doing so halves the coefficient on robot penetration, but leaves its precision unchanged; the effect of Chinese imports remains statistically insignificant. This suggests that, while areas more exposed to robot adoption might have been on downward trajectories for population growth, these trends cannot explain our results.[21]

Next, we tackle the possibility that initial industry shares (which we use to predict robot and Chinese import exposure) may be correlated with baseline CZ demographic or economic characteristics that were also responsible for differential population growth after 1990. To do so, we add interactions between period dummies and 1990 CZ demographic (column 3) and economic (column 4) characteristics.[22] Adding this battery of controls leaves our results unchanged, both in terms of magnitude and in terms of precision.

Finally, in column 5, we interact the 1990 shares of routine and offshorable jobs with period dummies, so as to capture the potentially confounding effects of two other important technology- and trade-related, contemporaneous changes. In particular, we aim to control for the automation of routine tasks due to the spread of computers and increased offshoring due to more general globalization trends unrelated to China. While the coefficient on robot exposure becomes slightly smaller in absolute value, it remains statistically significant at the 1% level. The effect of Chinese imports remains positive but not statistically different from zero.

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

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

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

Focusing on robot adoption, the point estimate in our most preferred specification (column 5) implies that one standard deviation increase in exposure to robots (or, 0.72 robots per 1,000 workers) reduced population growth by 0.56 percentage points per decade. This implies that one additional robot per 1,000 workers reduced population growth by 0.78 percentage points, or 8.4% relative to the decadal average across CZs (9.3%).[23]

In-migration vs. out-migration. Lower population growth may result either from increased out-migration or from reduced in-migration (or, both). On the one hand, a worker displaced by robots might choose to move to another CZ to find a new job. On the other, prospective in-migrants might choose not to move to a place where their chances of finding a job have deteriorated due to robots. We explore these channels in Table 3.

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

[Table 3 here]

The point estimates indicate that one standard deviation increase in exposure to robots reduced the number of in-migrants by about 1.76%, or the 10-year in-migration rate by roughly 0.20 percentage points. If anything, the effect of Chinese import competition on in-migration is positive, even though not statistically significant. The coefficient on robot exposure implies that one additional robot per 1,000 workers reduced the in-migration rate by about 0.28 percentage points.[24] Since the average decadal in-migration rate during our sample period is 41%, this amounts to a 0.69% reduction in the in-migration rate.

[23] Acemoglu and Restrepo (2020) also find a negative effect of robots on population growth. Yet, their results are less precise. In Table A2, we verify that this difference is not due to any differences in the set of control variables. It instead results from: *i)* the use of intercensal estimates based on full counts instead of IPUMS samples (something that, we believe, increases the precision of the estimates); and *ii)* the interaction of CZ controls with period dummies (something that more flexibly accounts for potential underlying trends).

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

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

In columns 2–3 and 5–6, we explore in more detail where changes in in- and out-migration originated from. We split overall in- (resp. out-migrants) into those originating from (resp. moving to) places that are less and more than 300 miles away.[25] We deem this admittedly crude cutoff a useful approximation for within-state versus cross-state moves.[26] The reduction in in-migration documented in column 1 seems to stem from both close-by locations and far away regions, especially when focusing on the log count of migrants (Panel A).[27] Column 5 shows that robot exposure had a negative and statistically significant effect on out-migration into CZs that are less than 300 miles away.

Finally, columns 1–3 suggest that the positive but statistically insignificant effect of Chinese imports on in-migration flows masks substantial heterogeneity by distance. In particular, Chinese imports increased in-migration from CZs that are within 300 miles (column 2) – an effect that is statistically significant when considering log population changes (Panel A). However, this force was not strong enough to translate into a significant effect on overall in-migration. We return to the possible explanation for this pattern in Section 4.2 below, when describing the mechanisms.

House prices. One would expect lower in-migration to reduce demand for housing. If housing supply is not perfectly elastic, this should in turn reduce house prices in robot-exposed areas. We test this hypothesis in Table 4, which follows the same structure of Table

[25] 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 first group as a move within a 300 mile distance and the latter two as moves to or from more than 300 miles away.

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

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

2, but uses the change in the log of the house price index as dependent variable.[28] Since the house price index is available for a large number of CZs only from 1990 onwards, as for in- and out- migration, we estimate equation (1) for the period 2000–2015 in order to include pre-trends as a control. Consistent with our conjecture, results from our preferred specification (column 5) show that robot penetration reduced house prices. Our estimates imply that one standard deviation increase in exposure to robots reduced house prices by 2.55%. Said differently, one additional robot per 1,000 workers reduced house prices by 3.54%.[29] For comparison, US house prices grew by 58% between 2000 and 2015.[30] In contrast, Chinese imports did not have any statistically significant effect on house prices, once CZs are allowed to be on differential trends depending on broad industry shares (columns 4 and 5). These results are consistent with the differential migration response to the two shocks documented above.

[Table 4 here]

Summary of robustness checks. In Appendix C, we perform several robustness checks, which are briefly summarized here. First, we document that *i*) neither robot exposure nor Chinese import competition after 1990 are correlated with pre-period (1970 to 1990) changes in CZ population; and *ii*) our results are insensitive to the way in which we account for pre-existing trends (Table C1). Second, we show that the muted migration response to Chinese imports is not due to the use of the instrument proposed by Autor et al. (2013), and we replicate the analysis with the instrument proposed by Pierce and Schott (2016) (Table C2). Third, we show that *i*) results are unchanged when estimating long difference specifications (1990–2015 and 1990–2007, Table C3); *ii*) differences between the two shocks (over time and across CZs) cannot explain the differential migration response (Table C4); and, *iii*) results are robust to adjusting standard errors for spatial correlation (Table C5). Finally, we replicate the analysis for in- and out-migration by distance using different cutoffs (Tables C6 and C7).

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

[29] In unreported results, we find no effect on rents. This is in contrast to Acemoglu and Restrepo (2020), Table A18, which documents a reduction in rents due to robots. This discrepancy is likely due to the fact that we include interactions between baseline CZ variables and period dummies in all our specifications. One possible reason why in our setting robot exposure reduces house prices but not rents is that individuals responsible for reduced in-migration are more likely to be homeowners. Another possibility, not in contrast with the previous one, is that rents may be slower to adjust than house prices.

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

4.2 Mechanisms

In this section, we examine why, although both shocks reduced manufacturing employment (Autor et al., 2013; Acemoglu and Restrepo, 2020), only robots were associated with a significant migration response. First, we show that both shocks lowered manufacturing employment, but only robots – and not Chinese imports – reduced employment outside manufacturing, including in many high-skilled service industries. Next, we provide evidence that these spillovers (from manufacturing to other industries) are an important mechanism for the differential migration response documented above.

Employment effects. Since both shocks were concentrated in manufacturing (Figure 2), we start by comparing their effects on employment within this sector. We estimate equation (1) using as dependent variable the change in log employment in manufacturing. We report 2SLS results in Panel A of Table 5, which follows the same structure as Table 2.

[Table 5 here]

As before, we start with a parsimonious specification that only includes interactions between period and census division dummies (column 1). Both robot penetration and Chinese import competition reduced manufacturing employment considerably. Both coefficients are negative and statistically significant, with the effect of Chinese imports (-5.29) being more than twice as large as that of robots (-2.06).[31] In columns 2 to 5, we gradually add more covariates to allow CZs to be on differential trends along a set of initial characteristics. Doing so results in a somewhat smaller point estimate for robots (-1.37 as opposed to -2.06) and a slightly larger one for Chinese imports (-5.36 as opposed to -5.29) relative to those in column 1. However, the main take-away is unchanged.

Our findings are consistent with those in Acemoglu and Restrepo (2020) and Autor et al. (2013), and show that both robots and Chinese imports considerably reduced manufacturing employment. Our preferred specification (column 5) implies that one standard deviation increase in exposure to robots and Chinese imports reduced manufacturing employment by 1.37 and 5.36% per decade, respectively.[32] Since our previous analysis showed that only

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

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

robots, but not Chinese imports, triggered a migration response, this pattern seems puzzling. Indeed, *a priori*, one would expect the two shocks to induce a similar (proportional) migration response, since they both reduced manufacturing employment.

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

Panel B shows that robots had a strong, negative effect on employment outside manufacturing, similar to that prevailing within this sector. Instead, the effect of Chinese imports was entirely concentrated within manufacturing.[33] If anything, our estimates suggest that Chinese imports had a positive effect on employment outside manufacturing. One possible explanation for this is that trade exposure lowered input prices, inducing firms to reallocate towards services (Bloom et al., 2019; Ding et al., 2019).

Results in Panel C confirm those in Panels A and B: robot exposure caused an overall employment decline, while Chinese imports likely induced a reallocation of economic activity across sectors, which partly offset the employment losses in manufacturing. Relating these findings to those in Table 2, we conjecture that the negative impact of robots on migration was due to the combination of the direct effects within manufacturing and the indirect (spillover) effects outside manufacturing. Since in the case of Chinese import competition there were no – if anything, positive – spillovers outside manufacturing, the migration response was muted. In what follows, we provide different pieces of evidence consistent with this hypothesis.

Spillovers to other industries within CZs. Table 5 above suggests that robot exposure and import competition triggered different spillovers to other industries within the CZ. To get a more precise picture of the differences in spillovers, we separately examine the effect of robots and Chinese imports on the employment shares of 44 industry-skill combinations.[34] Specifically, we estimate our most stringent specification (Table 2, column 5), using as de-

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

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

pendent variable the change in employment in each industry-skill combination, relative to initial CZ employment. Results are presented in Figure 5, where we plot coefficients on the (standardized) exposure to robots and Chinese imports in Panels A and B respectively. Since outcomes are expressed in percentage points, it is important to rule out the possibility that the initial shares in each cell may differ from each other in areas exposed to either of the two shocks. Panels C and D provide a visual inspection of this, reporting the initial share of employment in each cell, weighted by their exposure to robots and Chinese imports, respectively. Reassuringly, the distribution of the shocks across cells seems rather similar in the two panels.

[Figure 5 here]

Turning to the results, Panel A documents that robots reduced employment most strongly in routine, manual occupations within manufacturing. The effects are not limited to this industry-skill combination, however. In fact, they are visible not only in other skill groups within manufacturing, but also in industries that were not directly affected by robot penetration, such as business services, professional services, retail, and construction. Panel B shows that the effect of Chinese imports was also strongest for manufacturing, though not only in routine, manual, but also in abstract, cognitive occupations. Similar to robots, the effect is visible across all occupations within the manufacturing industry. In contrast to robots, however, effects in industry-skill combinations outside manufacturing were mostly *positive*.

Figure 5 unveils a stark difference in how the effects of robot penetration and Chinese import competition were transmitted throughout (local) labor markets. While robots likely caused negative spillovers into other industries, Chinese imports induced positive effects in other industries.[35] We return to these differences in Section 5, where we present a model that shows that the different effects outside manufacturing can indeed explain the disparate migration responses.

Linking spillovers to migration responses. Figure 5 shows that the effects of robot adoption and Chinese imports vary substantially both across skills within manufacturing and across industries (outside manufacturing). Since some of the industry-skill cells where the effects of the two shocks differ the most – such as abstract, cognitive occupations in

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

retail or professional and business services – employ more mobile (i.e., high-skilled) workers, these spillovers might be responsible for the negative in-migration response to robots, and the muted overall impact of Chinese imports.[36]

If this were true, one should observe that *i)* robots also reduced employment of more mobile groups; and *ii)* the migration response of these groups was affected the most. We test this conjecture in Figure 6, where we estimate our preferred specification (Table 2, column 5) using the change in log employment and working-age population by subgroup (i.e., high- and low-skilled, and young, middle-aged, and old) as dependent variable.

Panels A and B report results for employment and migration, respectively.[37] The first column from the left replicates the aggregate results of Table 2 (column 5), while the following columns present the estimated coefficients by subgroup. The employment effects display relatively little heterogeneity across demographic and skill groups: robots reduced low-skilled (less than college) and high-skilled (some college or more) employment to a similar extent. Middle-aged workers (31–50 years old) were the most affected of the three age groups, followed by younger individuals (18–30). However, these differences are never statistically significant at conventional levels.

[Figure 6 here]

If spillovers into high-skilled occupations are, at least partly, responsible for the migration response observed in Table 2, high-skilled individuals should feature a higher elasticity to migrate. Panel B supports this interpretation, and documents that high skilled individuals drive the migration response to robots.[38] Our estimates imply that a 1% decline in employment corresponds to a 0.60% decline in high-skilled population. This response is more than twice as strong as that of low-skilled individuals, for whom we estimate only a 0.27% decline in population size. Among the different age groups, middle-aged individuals are estimated to be the most mobile (0.57%), and somewhat surprisingly, younger people to be the least mobile (0.27%).[39]

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

[37] Figure A1 replicates the analysis for import competition. Detailed regression results are reported in Table A3.

[38] Not only high-skilled individuals, but also immigrants might be highly mobile (Cadena and Kovak, 2016). We focus on immigrants in Table A3, columns 7 and 8, Panel B. However, since the employment effect of robots is close to zero for immigrants, we cannot conclude whether, also in our setting, immigrants are more likely to migrate, as shown by Cadena and Kovak (2016) for the Great Recession.

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

We corroborate the view that our results are mainly driven by spillovers into industries that host more skilled (and thus, more mobile) individuals by performing a heterogeneity exercise. For each CZ, we compute the share of high-skilled individuals living in neighboring CZs in 1990. Next, we define a CZ as having either "high-skilled neighbors" (HSN) or "low-skilled neighbors" (LSN) depending on whether its neighboring CZs have a share of high-skilled individuals above or below the median, respectively. Finally, we interact such indicators with both robot exposure and Chinese import competition.

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

[Table 6 here]

Finally, to bolster confidence that differential spillovers into non-manufacturing (and not some other, potential difference between the two shocks) drive our main (migration) results, we show that similar patterns are visible for the effects of Chinese imports, once skill-industry heterogeneity across CZs is accounted for. In particular, we exploit geographic variation in the effects of Chinese import competition on non-manufacturing employment (Bloom et al., 2019). In Table 7, we augment our preferred specification with interactions between each measure of exposure and dummies equal to one if a CZ was, respectively, a high service intensity (HSI) or a low service intensity (LSI) area.[40] The idea is that regions initially specialized in services may have had a higher capacity to expand that sector.

[Table 7 here]

Table 7 reveals that Chinese imports led to employment growth outside manufacturing in areas with an initially high service intensity. Consistent with our proposed mechanism, these

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

CZs also experienced significantly higher population growth, due to increased in-migration. In contrast, CZs with initially low service employment shares experienced, if anything, negative spillovers outside manufacturing. This, in turn, resulted in a negative and statistically significant overall employment response.

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

5 A quantitative spatial economic model

The previous analysis suggests that the different employment effects outside manufacturing might explain to a large extent the disparate migration response to robot exposure and Chinese import competition. In this section, we build a quantitative spatial economic model to formalize this mechanism. Our goal is not that of modelling the migration response in general. Instead, we aim to link the employment effects (especially those outside manufacturing) to the differential migration response triggered by the two local labor market shocks.

In particular, the model serves two purposes. First, it expresses the employment-induced migration as the net of three distinct channels affecting both the manufacturing and the non-manufacturing sector within a CZ. Second, through a series of quantitative exercises, the model helps single out two forces responsible for the disparate employment effects outside manufacturing: the cost savings that each shock provides, and the complementarities of exposed industries with other, non-exposed industries. These might, in turn, influence individuals' decision to migrate.

5.1 Preliminary remarks

Theoretical contribution. From a theoretical perspective, the contribution of the model is to jointly embed the effects of automation and Chinese import competition in a setting with geographically mobile agents. The model builds on a recent body of research on quantitative spatial economics to incorporate the effects of both shocks.[41] We rely on Acemoglu and Restrepo (2020) and Grossman and Rossi-Hansberg (2008) to model the effects of automation and trade, respectively, and we nest these two modeling devices in an economic geography model that follows Allen and Arkolakis (2014) with a perfect competition Armington setup (Anderson, 1979; Armington, 1969). We show that, with few additional assumptions, the treatment of the two shocks can be put completely on par, facilitating their comparison from a theoretical standpoint. Such comparison highlights that the different migration responses triggered by the shocks (which we estimated above) are surprising, given their similar theoretical properties.

Trade in final vs. intermediate goods. The growth of Chinese exports (to the US and to many other countries) led to deeper integration between the US and China in the markets for both final goods and intermediate inputs. Our model focuses on the deeper integration with China in the intermediate inputs market, which can happen either within (via offshoring) or outside (via availability of cheaper intermediate inputs) firm boundaries.

As in Grossman and Rossi-Hansberg (2008), we model import competition as an increase in offshoring capabilities of US firms.[42] This choice is motivated by the fact that we are interested in understanding the forces behind Chinese import competition that might have countervailing, positive effects on labor demand. The intermediate inputs channel has been shown to be one mechanism for such positive effects (see Bloom et al., 2019, for offshoring, and Ding et al., 2019, for availability of cheaper intermediates). As Grossman and Rossi-Hansberg (2008) point out, whether tasks are carried out abroad within (offshoring) or outside (intermediate inputs) firm boundaries is largely a semantic distinction, at least at the level of abstraction used in our model. In addition, Boehm et al. (2020) show that the two forces usually go hand in hand. Since offshoring is conceptually more easily comparable with automation, we opt for this option in our model.[43]

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

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

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

5.2 Environment

We consider an economy with $n = 1, ..., N$ CZs. Each CZ produces a unique differentiated variety of a good, and CZs are connected via a bilateral transport network under symmetric iceberg trade costs: $d_{ni} = d_{in} > 1, n \neq i$ with $d_{nn} = 1$. There is a mass $\overline{L}$ of representative consumers who are mobile across CZs and endowed with one unit of labor that they supply inelastically with no disutility.[44]

Consumer preferences. Preferences over varieties take the constant elasticity of substitution (CES) form:

$$U_n = C_n = \left[\sum_{i=1}^{N} c_{ni}{}^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}},$$

where c_{ni} denotes consumption in CZ n of the variety produced in i, and σ denotes the elasticity of substitution across varieties. The budget constraint is given by:

$$\sum_{i=1}^{N} p_{ni} c_{ni} = w_n,$$

where w_n is the wage prevailing in CZ n and p_{ni} is the price of variety i in that CZ. The dual price index in turn is given by:

$$P_n = \left[\sum_{i=1}^{N} p_{ni}{}^{1-\sigma} \right]^{\frac{1}{1-\sigma}}.$$

Production. There are only two sectors per CZ: a manufacturing sector, subject to *location-specific* (i.e., not industry-specific) shocks, and a non-manufacturing sector that is only indirectly affected. This differs slightly from Autor et al. (2013) and Acemoglu and Restrepo (2020), who model the economy as having many industries, all of which may be affected by the shocks. There is one conceptual and one technical reason for choosing this alternative approach. Conceptually, this allows us to derive results in a parsimonious way with a minimal set of ingredients. This comes at the cost of weakening somewhat the link with our empirical strategy, which is characterized by many *industry-specific* shocks that, together, amount to an

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

average location-specific shock. However, our goal is to clarify the mechanisms at play, rather than motivating the empirical strategy. The technical reason for our modeling choice is that, in the existence and uniqueness results derived below, we follow Allen and Arkolakis (2014), who rely on mathematical results for linear operators like the celebrated Perron-Frobenius theorem. To the best of our knowledge, no equivalent result exists for economies with many industries per region and geographically mobile agents.

Firms produce each variety with a constant returns to scale technology and under perfect competition. In the quantitative exercises described below, we assume that firms can either automate or offshore some tasks in their production process, but not both.[45] In particular, the firm located in CZ i operates under:

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

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

The functional form for $\tau_i^R(\nu)$ is almost identical to the one in Acemoglu and Restrepo (2020):

$$\tau_i^R(\nu) = \begin{cases} \gamma_R R_i(\nu) + \gamma_L^R L_i^R(\nu) & \text{if } \nu \le \theta_i^R \\ \gamma_L^R L_i^R(\nu) & \text{if } \nu > \theta_i^R \end{cases}, \tag{6}$$

where $R_i(\nu)$ and $L_i^R(\nu)$ are the amounts of industrial robots and human labor used in producing task ν, respectively. The parameters γ_R and γ_L^R capture their respective productivities. The intuition is that tasks below the threshold θ_i^R are subject to automation, with industrial robots being perfect substitutes of human labor, whereas tasks above θ_i^R can only

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

be performed by human labor. The only difference with Acemoglu and Restrepo (2020) is that the threshold θ_i^R is allowed to vary by CZ rather than by industry.

We assume that firms have access to an international market for industrial robots. In each location i, firms can purchase one robot at price p_i^{R*}, which they take as given. This is consistent with the fact that US firms largely rely on imports to purchase industrial robots.[46] Denoting the domestic wage with w_i, it is easy to show that, if $1 - \frac{\gamma_L^R}{\gamma_R} \frac{p_i^{R*}}{w_i} > 0$, firms adopt robots for all tasks $\nu \leq \theta_i^R$. In our equilibrium, and from now on, we focus on this case.

The functional form of $\tau_i^O(\nu)$ is almost identical to that used in Grossman and Rossi-Hansberg (2008):

$$\tau_i^O(\nu) = [\beta t(\nu)]^{-1} \gamma_L^O L_i^F(\nu) + \gamma_L^O L_i^O(\nu), \tag{7}$$

where $L_i^F(\nu)$ and $L_i^O(\nu)$ are the number of foreign and domestic workers used to perform task ν, respectively. The parameter γ_L^O captures total productivity of each form of labor, whereas $\beta t(\nu) \geq 1$ captures the higher relative productivity of domestic labor. Tasks are ordered so that $t(\nu)$ is non-decreasing. This implies that task ν can be performed with foreign labor, but only at the cost of higher input requirements.

To increase the comparability of the two shocks, we further customize equation (7). Let w_i^* be the foreign wage faced by firms engaging in offshoring. Then, firms' optimization under the specification in equation (7), with $t(\nu)$ non-decreasing and $\beta t(0) w_i^* < w_i$, implies that there is a threshold below which firms offshore all tasks. However, this threshold is endogenous and changes with the model's parameters, thereby complicating the comparison to a shift in θ_i^R in equation (6). For this reason, we adopt a more specific form for the schedule $t(\cdot)$, and assume:

$$t(\cdot) = \begin{cases} \underline{t} & \nu \leq \theta_i^O \\ \bar{t} & \nu > \theta_i^O \end{cases},$$

with $1 \leq \beta\underline{t} < \beta\bar{t}$. As in the case of robots, we focus on the case in which $\beta\underline{t}w_i^* < w_i < \beta\bar{t}w_i^*$. In this scenario, firms find it optimal to offshore all tasks $\nu \leq \theta_i^O$, and hire domestic labor for tasks $\nu > \theta_i^O$.

In the existence and uniqueness results, we work with a slightly more general version of

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

the model by assuming that firms in all CZs operate:

$$x_i = \vec{A}_i \left[Q_i^R\right]^{\phi_i} \left[Q_i^O\right]^{1-\phi_i}, \tag{8}$$

where $\vec{A}_i = A_i \left(\phi_i\right)^{-\phi_i} \left(1-\phi_i\right)^{-(1-\phi_i)}$ and $\phi_i \in (0,1)$. The product $\left(\phi_i\right)^{-\phi_i} \left(1-\phi_i\right)^{-(1-\phi_i)}$ in $\vec{A}_i$ is just a convenient normalization. One can thus think about the quantitative exercises performed below as imposing $\vec{A}_i = A_i$ along with $\phi_i = 1$ for firms that automate some of their tasks and $\phi_i = 0$ for those that offshore them.

For simplicity, we assume that the non-tradeable service is produced under perfect competition with a constant returns technology given by:

$$x_i^S = A_i^S E_i^S,$$

where E_i^S is non-manufacturing labor, and A_i^S captures its productivity.

5.3 Equilibrium

The assumption of CES preferences implies that consumers' indirect utility function from living in CZ n is given by $V_n = \frac{w_n}{P_n}$. Labor mobility implies that welfare is equalized across CZs:

$$V_n = \overline{V}. \tag{9}$$

For the aggregate labor market to clear it must hold that:

$$\sum_{n=1}^{N} L_n = \overline{L}, \tag{10}$$

where L_n is CZ n population, and we normalize $\sum_{i=1}^{N} w_i = 1$. We define a *spatial equilibrium* as a distribution of economic activity such that (a) consumers and firms make optimal choices, (b) markets clear and, in particular, equation (10) holds, and (c) welfare is equalized, that is, equation (9) holds.

In this model, the purchases of robots and the offshoring of tasks imply that the economy as a whole is open, i.e., there are trade and financial transactions with the rest of the world. With no export demand, domestic income must be accompanied by a current account deficit (borrow from the rest of the world), for markets to clear. Otherwise, domestic income alone would not suffice to finance the purchase of the entire home production. In a fully dynamic model, this would be determined as part of the equilibrium. Given the static nature of our model, we need to add either exports or current account deficit in a somewhat *ad-hoc* fashion. We prefer to add a foreign demand. This is because, with exports, transactions take place within the same time period and our model is static. Thus, we assume that each variety i faces an additional export demand given by:

$$x^d_{r_n i} = \frac{d_{in}^{1-\sigma}}{d_{ir_n}^{1-\sigma}} \left(\frac{p_{r_n i}}{P_n}\right)^{-\sigma} \frac{w_n L_n}{P_n} \left(\frac{1-\kappa_n}{\kappa_n}\right), \tag{11}$$

where r_n is the foreign location associated with n, and $\kappa_n \in (0,1)$ is an exogenous parameter related to domestic labor demand that we specify in Appendix D.1. The intuition is that the resources paid by CZ n in exchange for its robots' purchases and offshored tasks are spent by recipients of those resources, according to equation (11), in all varieties i that are produced in the home country. There is one such foreign location r_n for each CZ n. The exact form of these demands is useful for proving our existence and uniqueness result, and serves no other purpose.[47]

To show the existence and uniqueness of a spatial equilibrium, we apply Theorem 1 in Allen and Arkolakis (2014), which builds on the Perron-Frobenius theorem. We assume that both the price of robots and the wages of foreign labor faced by CZ i are the product of the local wage in i and an international price and wage, respectively. That is, $p_i^{R*} = p^{R*} w_i$ and $w_i^* = w^* w_i$. Requiring that both p_i^{R*} and w_i^* depend on local economic conditions and on economic conditions in international markets seems reasonable. Since distance to those markets is also likely to influence prices, another specification might have been the following: $p_i^{R*} = p^{R*} d_{iR}^{\phi_i^d} w_i^{\phi_i^R}$ and $w_i^* = w^* d_{ic}^{\phi_i^d} w_i^{\phi_i^w}$, where d_{iR} measures the distance from CZ i to the international robots market (e.g., some of the robot producing countries in Europe), and d_{ic} measures the distance from i to China. Each margin could in turn have different weights, depending on the coefficients ϕ_i^d, ϕ_i^R and ϕ_i^w. To prove existence and uniqueness in our model, it is important that $\phi_i^R = \phi_i^w = 1$, but the condition $\phi_i^d > 0$ can be accommodated. However, given that this is not a relevant margin for our quantitative results, we set $\phi_i^d = 0$ in order to have a more parsimonious specification.

[47] Equivalent formulations, such as all export demand coming from the same foreign location, would achieve the same result with appropriate functional form adjustments.

With this, we have:

Proposition 1. *Suppose that each CZ i faces an international price of robots given by $p_i^{R*} = p^{R*}w_i$ and a foreign wage given by $w_i^* = w^* w_i$. Then:*

1. *There is a unique spatial equilibrium.*
2. *The equilibrium can be computed as the uniform limit of a simple iterative procedure.*

As with all results in this section, the proof is provided in Appendix D.1.

5.4 Equilibrium impact of the shocks

Having established the existence and uniqueness of the spatial equilibrium, we investigate the equilibrium impact of both shocks on CZ population. Our goal is to examine *i*) how CZ population responds to robot exposure and Chinese imports, and *ii*) what labor market forces, within and outside manufacturing, mediate such responses.

We begin by examining more closely the forces shaping labor demand. Given equilibrium prices and the technology in equation (8), firms face a constant unit cost of production given by:

$$\Psi_i = w_i \varphi_i$$

where:

$$\varphi_i = \frac{1}{A_i}\left(\mathbb{P}_{Q^R}\right)^{\phi_i}\left(\mathbb{P}_{Q^O}\right)^{(1-\phi_i)}$$

$$\mathbb{P}_{Q^R} = \left[\left(\frac{1-\theta_i^R\left(1-p^{R*}\frac{\gamma_L^R}{\gamma_R}\right)}{\gamma_L^R}\right)^{1-\varepsilon_i^R} + \left(\frac{1}{A_i^S}\right)^{1-\varepsilon_i^R}\right]^{\frac{1}{1-\varepsilon_i^R}}$$

$$\mathbb{P}_{Q^O} = \left[\left(\frac{1-\theta_i^O\left(1-w^*\beta\underline{t}\right)}{\gamma_L^O}\right)^{1-\varepsilon_i^O} + \left(\frac{1}{A_i^S}\right)^{1-\varepsilon_i^O}\right]^{\frac{1}{1-\varepsilon_i^O}}.$$

These objects play a crucial role in the proposition introduced next, which shows that changes in CZ population are a weighted average of changes in manufacturing and non-manufacturing employment – forces that can in turn be decomposed into three different effects. For our next result and henceforth, we specialize the environment and take $\phi_i = 1$

and $\phi_i = 0$ for a CZ subject to automation and to offshoring, respectively.[48] We denote by E_i^M manufacturing employment in CZ i (recall that E_i^S denotes non-manufacturing employment).

Proposition 2. *Suppose that all regions are homogeneous, then:*

$$d \ln L_i = \Omega_i d \ln E_i^M + (1 - \Omega_i) \, d \ln E_i^S \tag{12}$$

where, for $h = R, O$:

$$d \ln E_i^M = - \frac{d\theta_i^h}{1 - \theta_i^h} - \sigma d \ln \varphi_i - \varepsilon_i^h d \ln \left[\frac{\left\{ \left(\mathbb{P}_{Q^h} \right)^{1-\varepsilon_i^h} - \left(A_i^S \right)^{-\left(1-\varepsilon_i^h\right)} \right\}^{\frac{1}{1-\varepsilon_i^h}}}{\mathbb{P}_{Q^h}} \right] + \zeta \tag{13}$$

$$d \ln E_i^S = - \sigma d \ln \varphi_i - \varepsilon_i^h d \ln \left[\left(A_i^S \right)^{-1} / \mathbb{P}_{Q^h} \right] + \zeta \tag{14}$$

$$\Omega_i = \frac{E_i^M}{L_i}. \tag{15}$$

Remark. *Given the assumption that $d_{nn} = 1$, imposing homogeneity implies that there are no trade costs.*[49] *The reason for taking this approach is that it allows us to tie our empirical estimates to the model in the quantitative exercises performed below. At the same time, the assumption is innocuous, because the forces highlighted in Proposition 2 would still be present without it, and our focus here is not on studying differences in trade costs.*

Equations (12) and (15) show that the (proportional) change in the population of CZ i is a weighted average of the (proportional) changes in manufacturing and non-manufacturing employment, with weights equal to the shares of the two types of employment. This is a straightforward result, since in this model there is no unemployment, and everyone supplies one unit of labor inelastically.

Equation (13) shows that the effect of robot penetration and Chinese import competition on labor demand for manufacturing employment can be decomposed in three different forces. The first term is a *displacement* effect: as more tasks are automated (resp. offshored), domestic labor is displaced by industrial robots (resp. foreign labor), and manufacturing employment declines. The second term is a *productivity* effect: as firms automate (resp. offshore) a larger set of tasks, they become more productive, expanding at the expense of

[48] When the type of region is not explicitly stated, the statement applies to both.

[49] However, only the condition $d_{in} = \overline{d}$ is needed. Whether $\overline{d} = 1$ or $\overline{d} > 1$ is immaterial for our purposes.

other varieties in the economy. This also increases their demand for manufacturing labor in tasks that have not yet been automated (resp. offshored). The third term is an *industry-substitution* effect: as the manufacturing sector becomes more productive than the non-manufacturing one, labor demand shifts in favor of all manufacturing factors of production, at the expense of non-manufacturing factors of production. This also increases demand for manufacturing labor in tasks that have not yet been automated (resp. offshored).[50] Finally, the parameter ζ captures the general equilibrium effects that are identical for all CZs. These do not depend on the CZ exposure to either shock, and are thus not captured in our empirical estimates. For simplicity, we refer to "total effects" ignoring the presence of ζ.[51]

An advantage of a setup with only two sectors per CZ is that one can derive straightforward expressions for the industry that is only *indirectly* affected. Equation (14) shows that a similar decomposition can be applied to non-manufacturing employment, except for the displacement effect. This is because the latter effect has no bite for factors of production outside manufacturing. The first term in equation (14) is the productivity effect for non-manufacturing employment, which in this model is exactly the same as that in equation (13). As manufacturing firms producing variety i become more productive, they increase their demand for all factors of production, including intermediate inputs from non-manufacturing firms. This raises non-manufacturing employment, even though the sector is not directly affected by the shocks. The second term in equation (14) captures the industry-substitution effect, which is the counterpart of that in equation (13). This is also an indirect effect, again driven by manufacturing becoming more productive in relative terms.

To better understand how the three effects behave, we examine how they change when we shift two key parameters of the model: cost savings and the industry elasticity of substitution (i.e.s.). We focus on these parameters for two reasons. First, they are crucial drivers of spillovers into the non-manufacturing sector in the model; second, existing evidence (described below) suggests that the two parameters differ between robots and Chinese import competition.

Figures 7 and 8 focus on the i.e.s. and the cost savings of each shock, respectively. The cost savings are given by $cs_R = \left(1 - p^{R*}\frac{\gamma_L^R}{\gamma_R}\right)$ and $cs_O = (1 - w^*\beta\underline{t})$ for industrial robots

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

[51] For instance, we refer to the sum of the first three terms in equation (13) as the "total effect on manufacturing employment".

and offshoring, respectively. Both figures plot each of the three effects scaled by $d \ln \theta_i^h$ and multiplied by 100 in order to ease the comparison with our quantitative results below.

[Figure 7 here]

[Figure 8 here]

As the figures make clear, and consistent with the first term in equation (13), the displacement effect on manufacturing labor remains unaffected by both the i.e.s. and the cost savings. Even though the displacement effect itself is zero for non-manufacturing, there is variation in the lower left panel of, for example, Figure 7. This is because the weights Ω_i shift in favor of manufacturing for higher levels of i.e.s. The same logic applies to the entire first column of Figure 8, with the difference that, in this case, the weights Ω_i increase with the level of cost savings.

The second column of the two figures shows that the productivity effect is identical across rows (as it should be, given Proposition 2), and increases with both the i.e.s. and the cost savings. As non-manufacturing becomes less complementary to manufacturing, productivity gains are larger, since the lack of direct effects on non-manufacturing becomes less relevant. At the same time, higher cost savings imply that the gains are larger for a given size of the shock. The third column in the two figures shows that the industry substitution effect is positive for manufacturing and negative for non-manufacturing. The effects are again increasing in both the i.e.s. and the cost savings, for the same reason as before. Finally, the last column plots the sum of the three previous columns for the corresponding row. The bottom right graph displays the net effects for population changes. The displacement effect is always negative, while the productivity effect is always positive. However, given the different signs of the three effects involved, the total effect is ambiguous. The flexibility of the model is the reason why it allows us to rationalize the empirical estimates in the quantitative exercises, which we turn to next.

5.5 Quantitative exercises

In this section, we combine evidence from other studies with our own empirical estimates $\left(\hat{\beta}^r, \hat{\beta}^c\right)$ from Section 4.1 to perform different quantitative exercises. First, we assume that Proposition 2 holds, and use the functional forms above to link (β^r, β^c) to two fundamental parameters of the model: the i.e.s. and the cost savings. Using external information, we pin down all parameters in the model except for the i.e.s. and cost savings. Then, we solve for the values of these parameters that are consistent with our 2SLS estimates of (β^r, β^c) in Table 2. This allows us to compare the model consistent i.e.s. and cost savings with the external evidence on them. In line with the existing evidence, the model implies that cost savings (resp. i.e.s.) are larger for import competition (resp. robots). Moreover, by partially reducing the cost savings associated with Chinese imports, we can equate the estimated effect of robots on migration, to the effect of the Chinese imports. In other words, in this model, the difference in cost savings is enough to explain the different migration responses triggered by local labor market shocks, and mediated by employment. Instead, while increasing the i.e.s. of import competition brings $\hat{\beta}^c$ closer to $\hat{\beta}^r$, the former always remains larger than the latter (in absolute value).

Empirical evidence on cost savings and the i.e.s. As discussed above, the i.e.s. and cost savings are key in shaping the strength of each of the three effects in Proposition 2. These effects, in turn, determine the total effect on local population growth. Even though they are difficult to observe, there exists evidence, albeit imperfect, on both of them and for both shocks. BCG (2015) estimates that, between 2000 and 2015, the cost savings of US firms generated by (cheaper) Chinese imports were between 50% and 70%. Since this number does not include shipping costs, which are estimated to reduce cost savings by around 10 percentage points (AlixPartners, 2009), the total cost savings associated with Chinese imports are in the range of 40 to 60%. Acemoglu and Restrepo (2020) instead estimate that the cost savings from using robots rather than US labor are only around 30%. That is, trade with China generated substantially higher cost savings than robots, according to these estimates.

Reliable estimates for the i.e.s. are even more difficult to obtain than for cost savings, given the daunting task of measuring elasticities of substitution more generally. The fact that, in our model, the i.e.s. regulates the complementarity between manufacturing and non-manufacturing makes the measurement of the i.e.s. even harder. The most reliable estimates in the literature measure elasticities with respect to all inputs, or across all industries. For example, Atalay (2017) estimates values of around 1, on average. However, this masks heterogeneity across industries: while elasticities tend to be above one for industries most exposed to automation (e.g., automotive and chemicals), they are below one for industries most exposed to Chinese imports (e.g., textiles and electronics). Focusing exclusively on non-manufacturing, rather than all, inputs would likely yield higher values, due to the weaker linkages across sectors. This suggests that complementarity with the service sector should be higher for trade-exposed, than for robot-exposed, industries.

Parameter choices. Following the trade literature (Simonovska and Waugh, 2014), we set the elasticity of substitution between tradeable varieties to $\sigma = 5$. We choose A_i^S in order to match a ratio of manufacturing to total (domestic) employment of 10%, which is consistent with the levels of this ratio for the period in our sample.[52] These values apply to both shocks.

Turning to parameter choices specific to Chinese import competition, we fix cost savings at 40% ($w^*\beta\underline{t} = 0.6$) – the lower bound of the range suggested by the external evidence described above. This value allows us to match not only $\hat{\beta}^c$ but also the signs of the effects on manufacturing and on non-manufacturing employment. When fixing the i.e.s., we set $\varepsilon^O = 0.8$, which, consistent with Atalay (2017), is slightly below 1. Since the ratio of foreign to domestic labor payroll in the model equals $\theta_i^O \left[1 - \theta_i^O\right]^{-1} w^*\beta\underline{t}$, we can pin down θ_i^O. Since data on foreign labor payroll is hard to find, we rely on the (employment-weighted) ratio of net imports from China to the US (from the UN Comtrade database) to labor compensation in the US (from the BEA) in the electronics and textiles industries in the year 2005. We focus on these two industries to mimic a hypothetical CZ that is fully "treated" with the trade shock. We choose 2005 because, in this year, both shocks are roughly half way between their 1990 and 2015 values, and it thus provides a sensible point at which to evaluate our first order approximations. Picking this value for the ratio implies $\theta_i^O = 0.619$. Finally, we set $\beta\underline{t} = 12.5$, which, together with $w^*\beta\underline{t} = 0.6$, implies $w^* = 0.048$. This, in turn, means that $w_i/w_i^* = 20.83$, which is also consistent with BCG (2015).

Turning to automation, when we fix the cost savings, we use 22.78% $\left(p^{R*}\frac{\gamma_L^R}{\gamma_R} = 0.77\right)$. We choose this value because it allows us to match not only $\hat{\beta}^r$, but also the signs of the effects on manufacturing and non-manufacturing employment. We return to this point when discussing the numerical results below. When fixing the i.e.s., we use $\varepsilon^R = 1.1$, consistent with Atalay (2017). To fix θ_i^R, we use the fact that, in the model, the ratio of industrial robots to manufacturing employment is given by $\theta_i^R \left[1 - \theta_i^R\right]^{-1} \left(\gamma_L^R/\gamma_R\right)$. Combining data from the IFR and the BEA to calculate the number of robots per worker in the automotive and chemicals industry (again, to mimic a "treated" CZ) in 2005, we get around 30 robots per 1,000 workers. This implies $\theta_i^R = 0.154$. Finally, we set $\gamma_R/\gamma_L^R = 6$, consistent with the evidence discussed in Acemoglu and Restrepo (2020).

Backing out model consistent i.e.s. and cost savings. With the parameter choices described above, we turn to the quantitative exercises. For the first part of this exercise,

[52] See https://fred.stlouisfed.org/graph/?g=Cssj.

we fix the cost savings at 40% and 22.78% for the trade and the robot shock, respectively. We then solve for the i.e.s. that matches $\left(\hat{\beta}^r, \hat{\beta}^c\right) = (-0.56, 0.45)$, the estimates from our preferred specification in Table 2 (column 5). We obtain $\left(\hat{\varepsilon}^R_{model}, \hat{\varepsilon}^O_{model}\right) = (5.01, 4.26)$. This indicates that the i.e.s. consistent with the model are in line with those in Atalay (2017), i.e. $\hat{\varepsilon}^R_{model} > \hat{\varepsilon}^O_{model}$. As noted before, it is difficult to compare the levels of the i.e.s. in our model and in Atalay (2017), because the latter measures the substitutability with a narrower set of inputs. While it is reasonable to expect the i.e.s. in our model to be larger, we lack any specific estimates to make this comparison. Nonetheless, since our goal is to compare the two shocks, the model suggests that robot affected industries have a larger i.e.s. than those affected by Chinese import competition.

In this exercise, we not only match our estimates on migration $\left(\hat{\beta}^r, \hat{\beta}^c\right)$ from Table 2, but also the signs of the effects on manufacturing and non-manufacturing employment in Table 5. For the trade shock, there is a wide range of values for the cost savings for which the model matches our point estimate for migration, $\hat{\beta}^c = 0.45$, and the signs of the effects on manufacturing (negative) and non-manufacturing employment (positive). For robots, instead, matching these objects is only possible for a small range. This is why we chose 22.78% as the parameter for robots' cost savings before.

In the second part of this exercise we fix $\left(\varepsilon^R, \varepsilon^O\right) = (1.1, 0.8)$, and solve for the model consistent cost savings. Before diving into it, note that in the previous exercise we got $\hat{\varepsilon}^R_{model} = 5.01$. This is only slightly above 5, which is the value for σ. As it turns out, in this model, to get a negative effect on non-manufacturing employment it must hold that $\varepsilon^h > \sigma$. Hence, in this second exercise – where we fix the i.e.s. at lower values following the broad estimates in Atalay (2017) – it is impossible to match the negative employment effects on non-manufacturing for automation. We nevertheless view this exercise as valuable, because it allows the model to match our empirical estimates by altering the cost savings instead of the i.e.s. The result we obtain is $(\widehat{cs}_{R_{model}}, \widehat{cs}_{O_{model}}) * 100 = (20.7\%, 25.1\%)$. This difference is lower than what the external evidence suggests. At the same time, as for the i.e.s. results obtained before, it is consistent with the external evidence in the sense that the trade shock displays higher cost savings than the robot shock.

Relative importance of i.e.s. vs. cost savings. As these results show, the model implies a higher i.e.s. for robot affected industries, but higher cost savings for Chinese import competition. We now investigate whether these margins play an equal role within the model. We first ask how much lower the cost savings would have to be for the trade shock to match an effect of $\hat{\beta}^r = -0.56$, instead of $\hat{\beta}^c = 0.45$. We take as testing point the parametrization of our first result in which $\left(\varepsilon^R, \varepsilon^O\right) = (5.01, 4.26)$ and $(cs_R, cs_O) * 100 = (22.78\%, 40\%)$.[53] We obtain a reduction from $cs_O * 100 = 40\%$ to $\overline{cs}_O * 100 = 31.16\%$. That is, reducing the cost savings for the trade shock from 40% to 31.16% is enough to move from $\hat{\beta}^c_{model} = 0.45$ to $\hat{\beta}^c_{model} = -0.56 = \hat{\beta}^r$.

We repeat the same procedure increasing the i.e.s. (rather than lowering the cost savings) of the trade shock so as to match the results obtained for robots. In this exercise, we are unable to get all the way through to $\hat{\beta}^r = -0.56$. Increasing ε^O from 4.26 to 5.01 reduces $\hat{\beta}^c_{model}$ from 0.45 to 0.04. Thus, as for the cost savings, increasing the i.e.s. helps explain the difference between automation and the trade shock. However, in contrast to the cost savings, this is not enough. In other words, even though both a higher i.e.s. for robots and a higher cost savings for Chinese imports help explain the different effects of the shocks, only cost savings are able to fully explain them.

6 Conclusion

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

Exploring the mechanisms, we show that the two shocks differ in the extent to which they were transmitted from manufacturing to other sectors, not directly impacted by the shocks, in the same labor market. While robots caused significant employment losses also in industries not directly affected, Chinese imports, if anything, caused employment growth outside manufacturing. We offer suggestive evidence that, via these spillovers, only robots – but not

[53] The same conclusions hold when using the alternative parametrization of $\left(\varepsilon^R, \varepsilon^O\right) = (1.1, 0.8)$ and $(cs_R, cs_O) * 100 = (20.7\%, 25.1\%)$.

Chinese imports – worsened employment opportunities for the most mobile individuals (i.e., high-skilled workers) who, in turn, decided to avoid labor markets affected by robots.

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

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

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

References

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

IFR, "World Robotics 2020," Technical Report, International Federation of Robotics 2020.

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

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

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

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

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

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

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

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

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

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

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

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

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

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

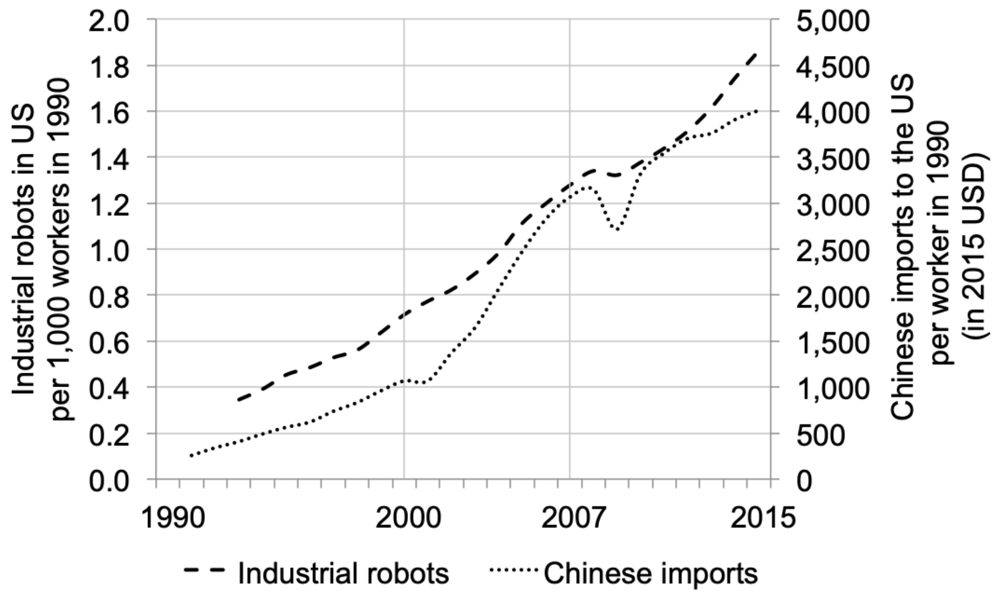
US Census Bureau, "County Business Patterns," *UN Comtrade Online*, 2019.

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

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

Figures and Tables

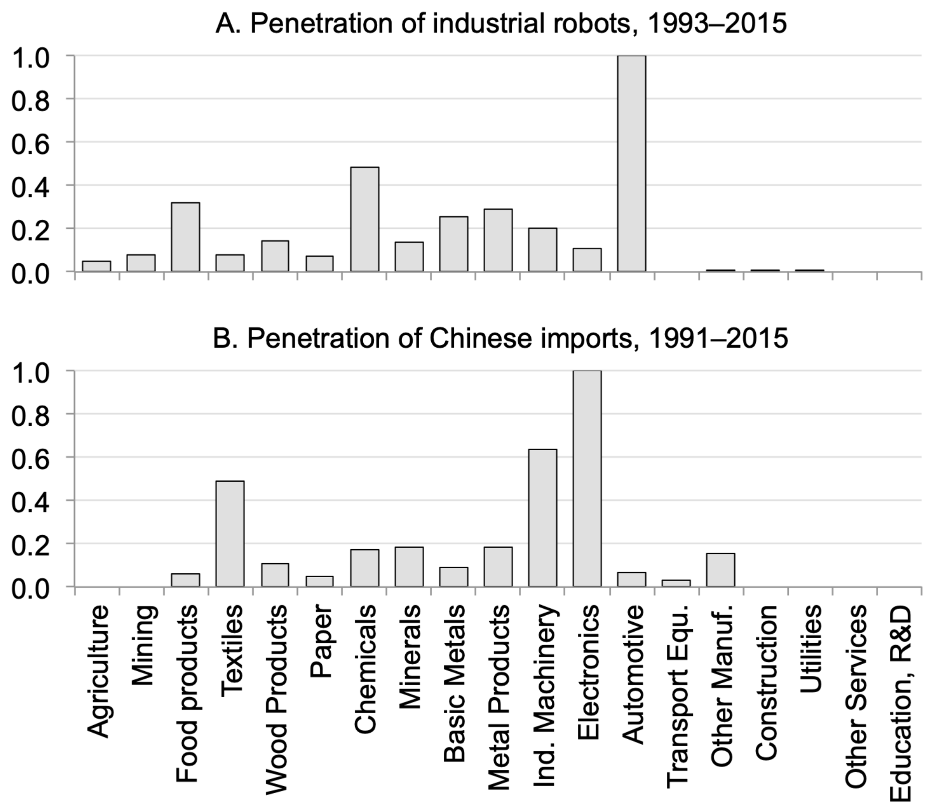
Figure 1: Temporal variation of robot adoption and Chinese imports



SOURCES: IFR (2020), United Nations (2019), Timmer et al. (2007)

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

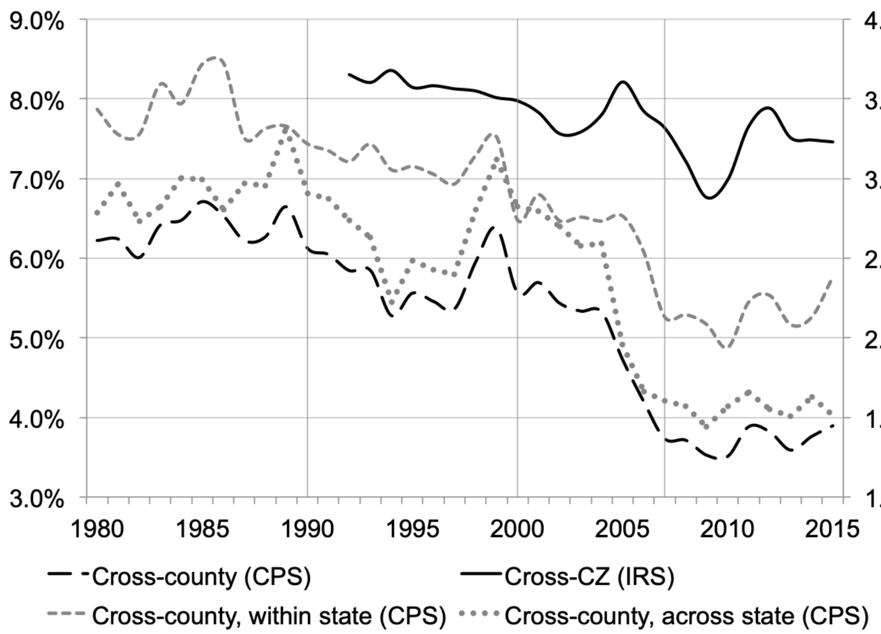
Figure 2: Industry variation of robot adoption and Chinese imports



SOURCES: IFR (2020), United Nations (2019), Timmer et al. (2007)

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

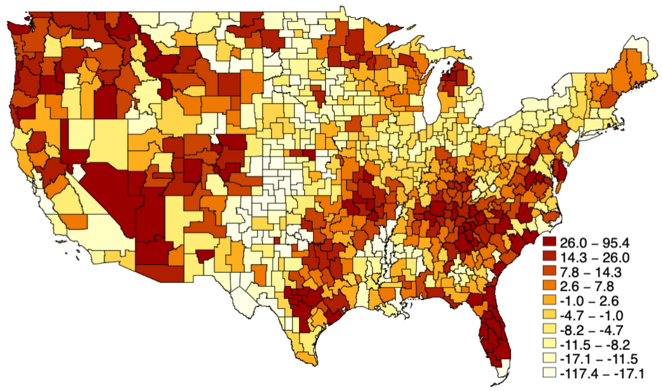
Figure 3: Evolution of US internal migration rates, 1980–2015



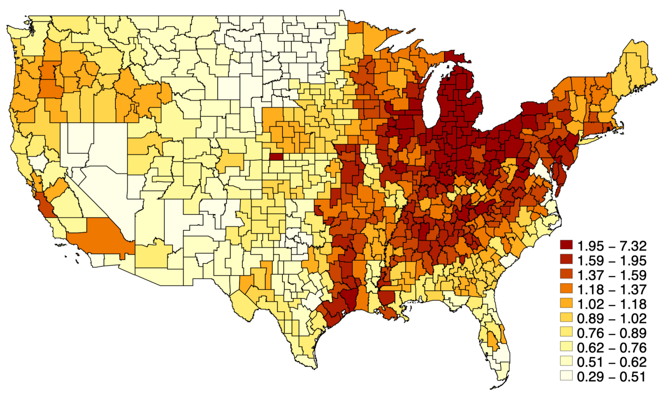
SOURCES: Current Population Survey (CPS), IRS (2019)

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

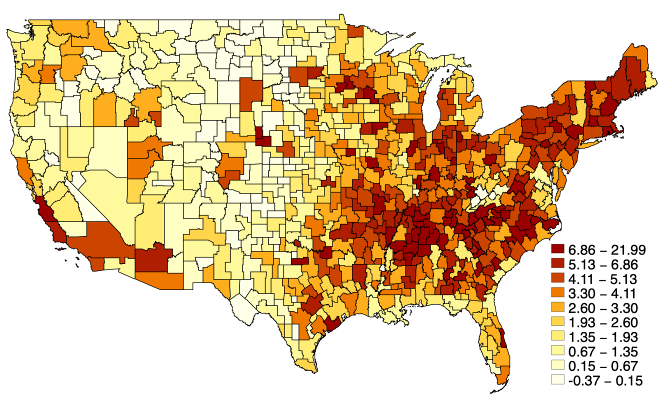
Figure 4: Geographic variation in migration and economic shocks



A. Net migration rate (1992–2015)



B. Exposure to robots (1993–2015)

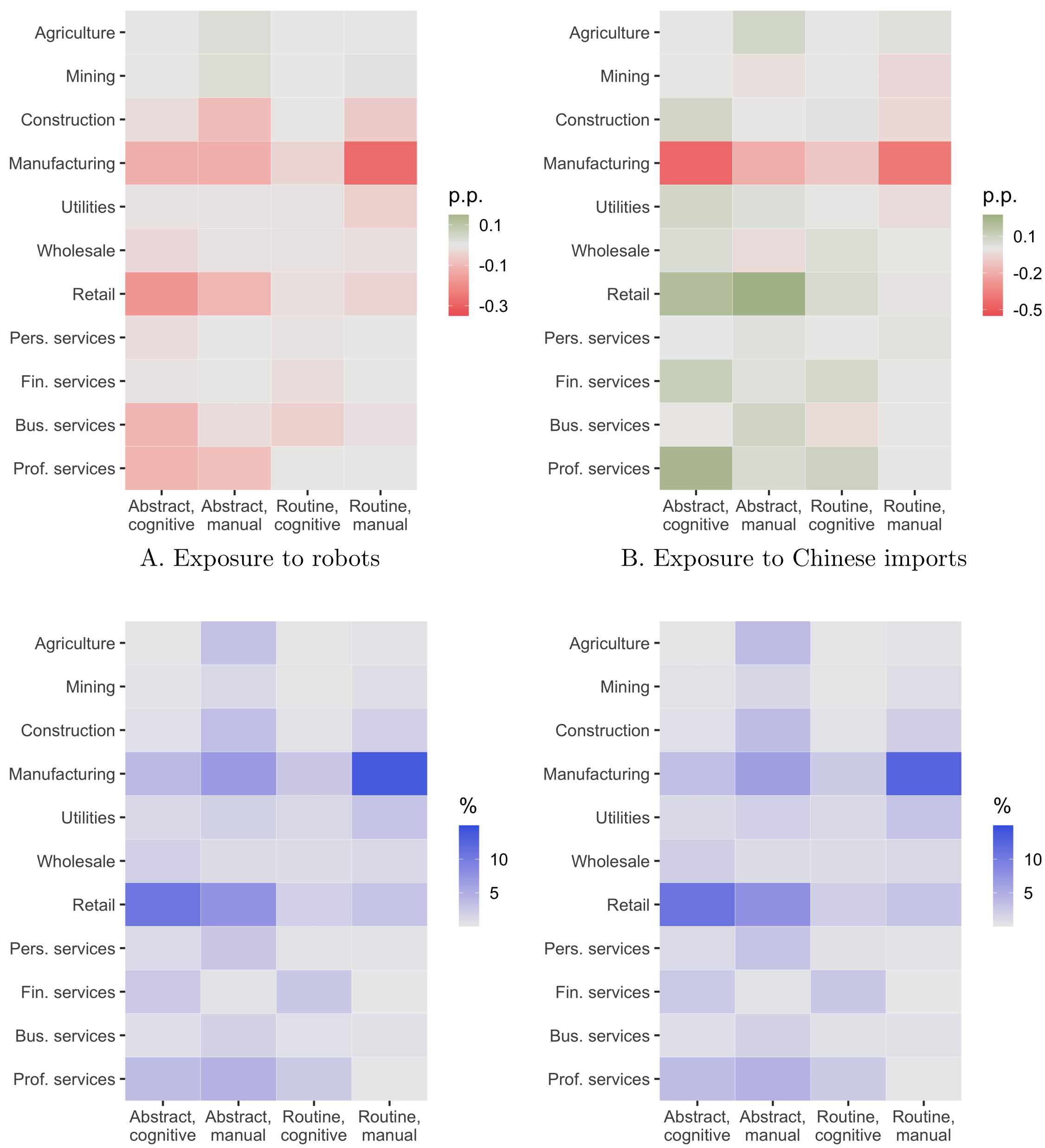


C. Exposure to Chinese imports (1991–2015)

SOURCES: IFR (2020), United Nations (2019), Timmer et al. (2007), Ruggles et al. (2018), IRS (2019)

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

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



A. Exposure to robots

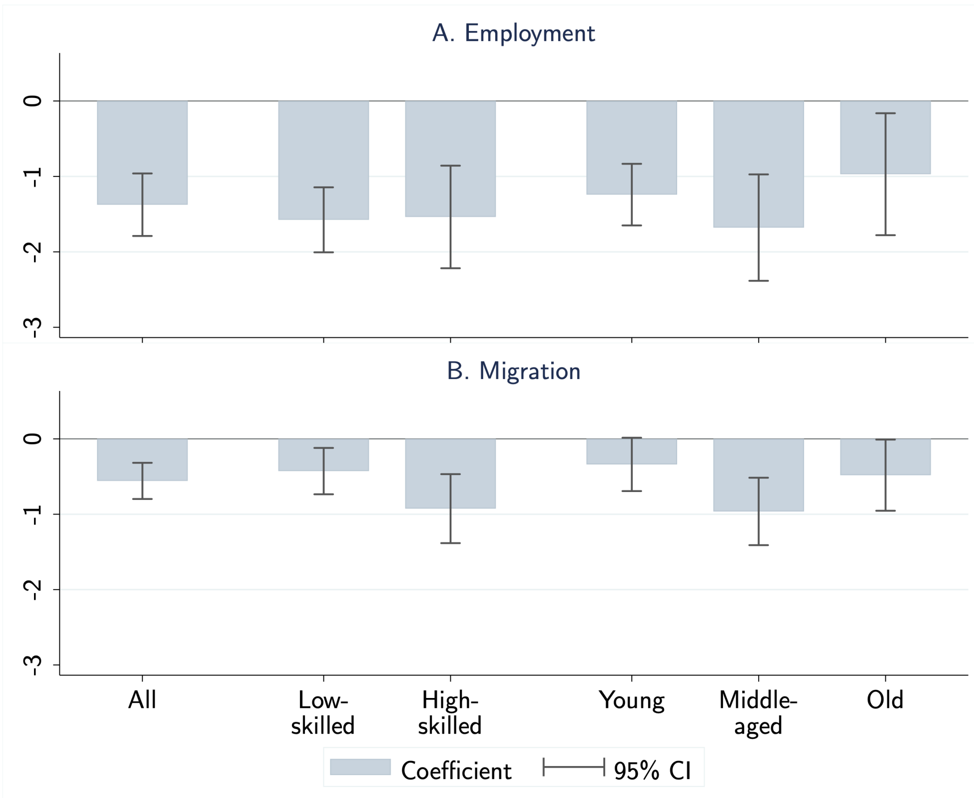
B. Exposure to Chinese imports

C. 1990 employment shares, weighted by exposure to robots

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

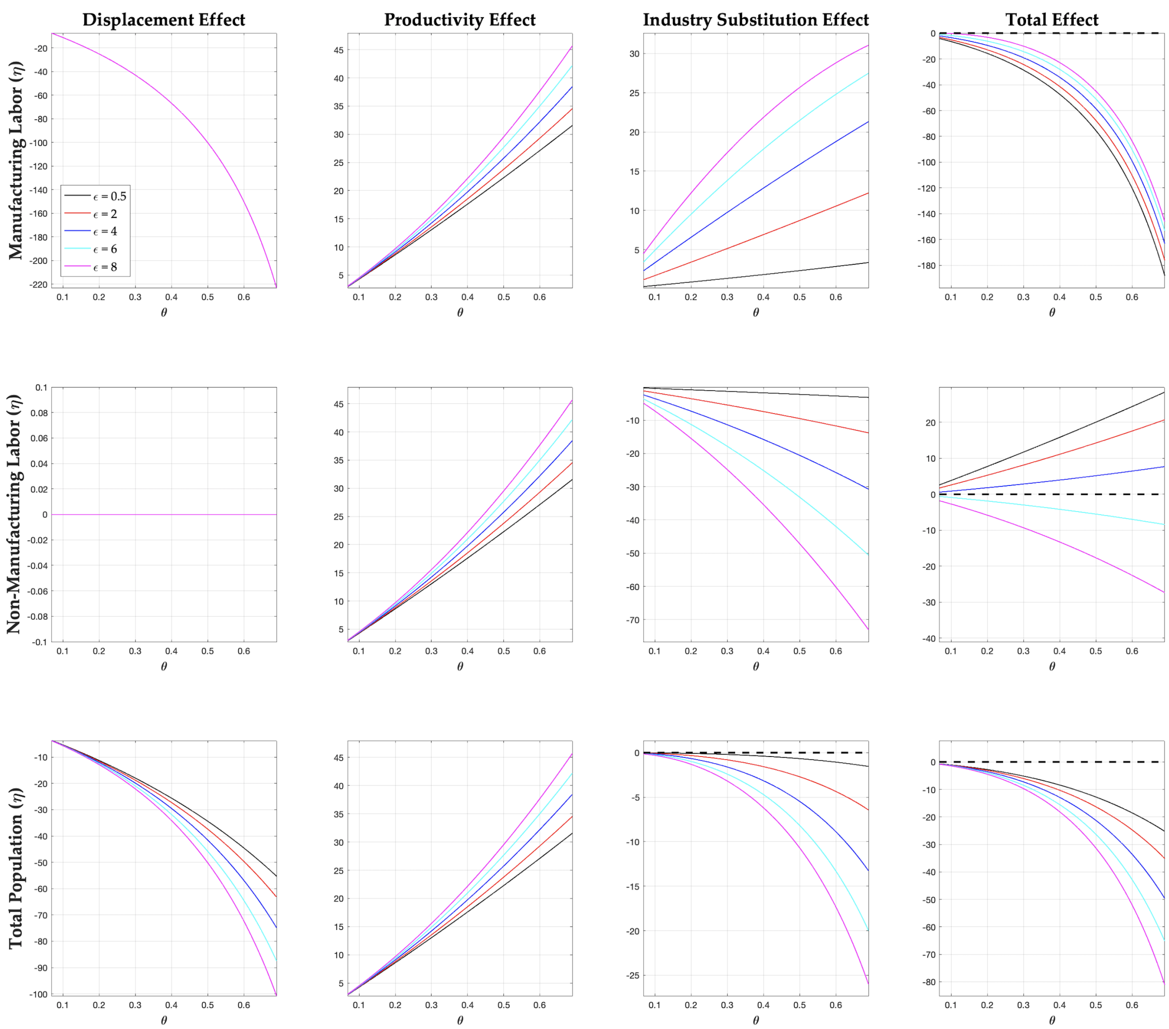
Note: Each cell in Panel A and B represents the coefficient on the (standardized) US exposure to robots and US exposure to Chinese imports, respectively, in a regression identical to the ones in column 5 of Table 2, but using the change in employment per industry-skill combination ij as a share of initial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

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



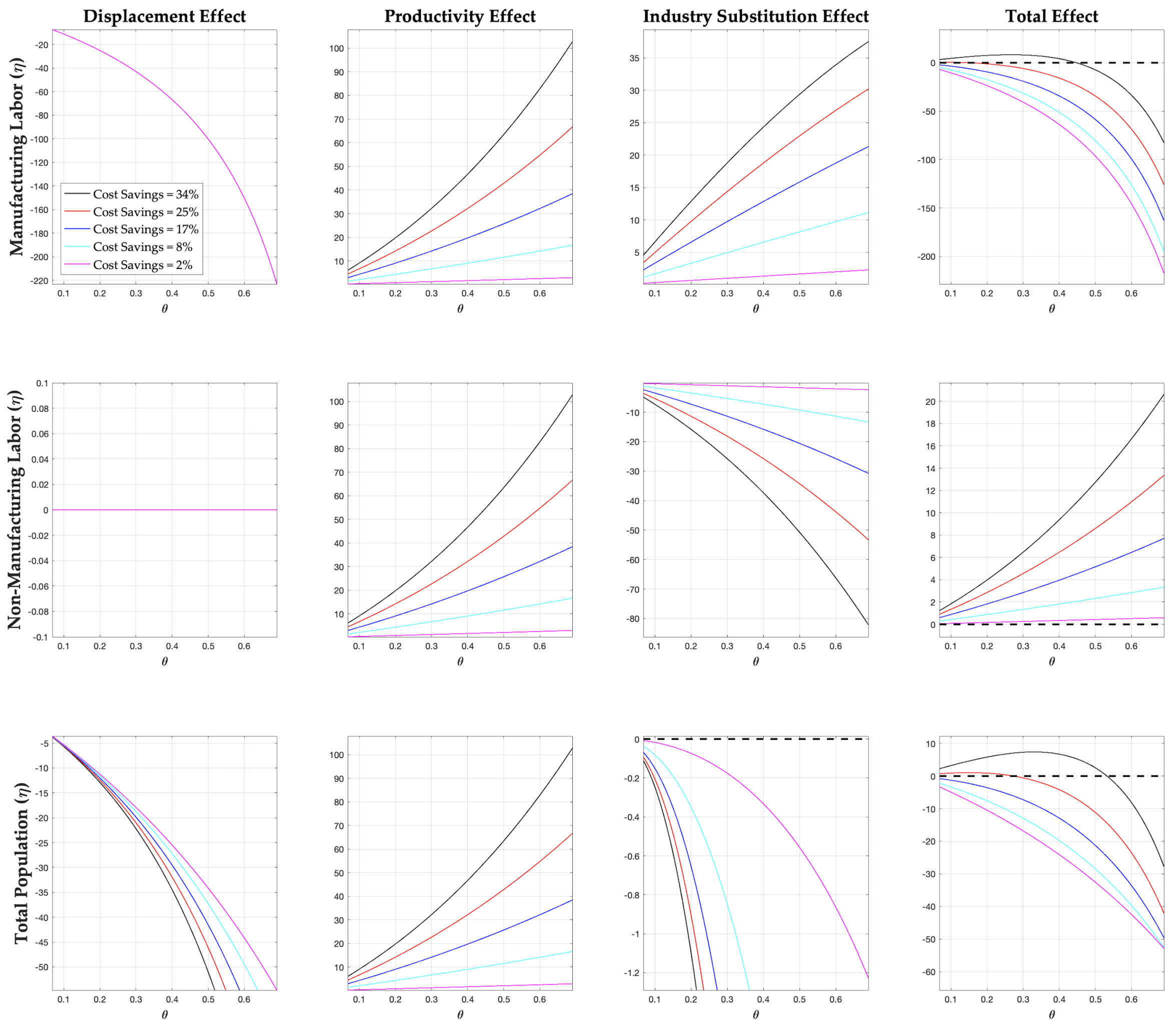
Note: Panels A and B present the coefficient on the US exposure to robots in a regression identical to the one in Table 2, column 5, using log changes in subgroup-specific employment and working-age population as the outcome variable, respectively, and weighting observations by a CZ's 1990 national share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

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



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

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



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

Table 1: Descriptive statistics

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

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

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

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

Note: The dependent variable is the change in the log count the working-age population, multiplied by 100 (i.e., $[\ln(y_{t+1})-\ln(y_t)]\cdot 100$). There are three time periods and 722 CZs each period, resulting in N=2,166. All explanatory variables that are displayed are standardized to have a mean of zero and a standard deviation of 1. Column 1 includes census division dummies interacted with time period dummies as covariates. Column 2 also includes the change in the outcome variable between 1970 and 1990. Column 3 also controls for 1990 demographic characteristics (i.e., log population, share of men, share of population above 65 years old, share of population with less than a college degree, share of population with some college or more, population shares of Hispanics, Blacks, Whites and Asians, and the share of women in the labor force), each interacted with time period dummies. Column 4 also includes shares of employment in broad industries in 1990 (i.e., agriculture, mining, construction, manufacturing), each interacted with time period dummies. Column 5 also includes the share of routine jobs and the average offshorability index in 1990, following Autor and Dorn (2013), each interacted with time period dummies. Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the state level (48 states). Regressions are weighted by a CZ's 1990 national share of the 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 by distance, stacked differences 2000–2015 (2SLS)

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

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

Table 4: Effects on house prices, stacked differences 2000–2015 (2SLS)

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

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

Table 5: Effects on employment, stacked differences 1990–2015 (2SLS)

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

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

Table 6: Heterogeneity of effects by neighboring CZs' initial skill intensity, stacked differences (reduced form)

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

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

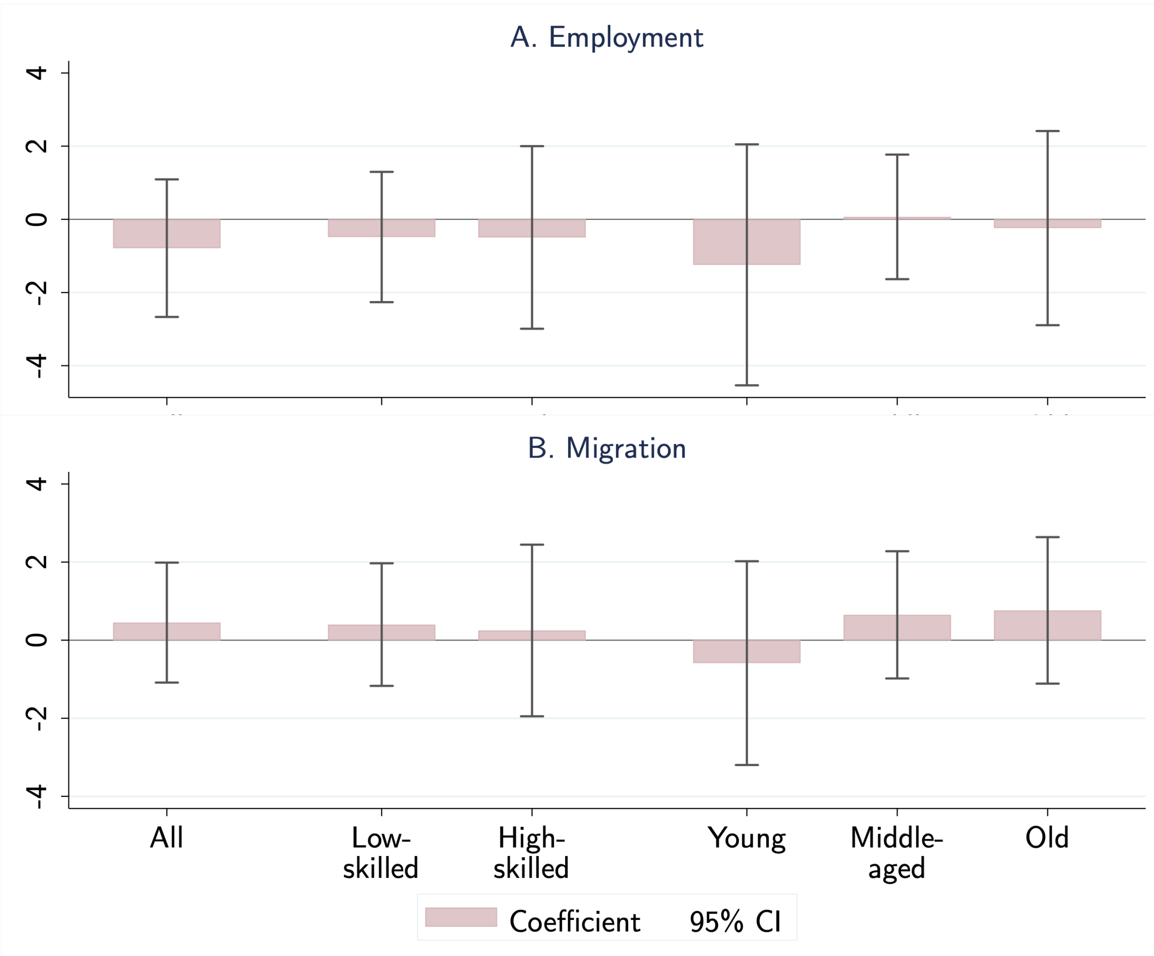
Table 7: Heterogeneity of effects by initial service intensity, stacked differences (reduced form)

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

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

A Additional figures and tables

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



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

Table A1: First-stages and effects on migration with partial instrumentation

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

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

Table A2: Estimates using controls from related literature (reduced form)

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

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

Table A3: Effects on employment and migration by subgroup, stacked differences 1990–2015 (2SLS)

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

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

Additional Material (Not for publication)

Table of Contents

B Data Construction

B.1 Data on industrial robots

The IFR collects data on shipments and operational stocks of *industrial robots* by country and industry since 1993 "based on consolidated data provided by nearly all industrial robot suppliers world-wide" (IFR, 2020, 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, 2020, p.29). Typical applications of industrial robots are pressing, welding, packaging, assembling, painting and sealing (common in manufacturing industries), and harvesting and inspecting of equipment (prevalent in agriculture and the utilities industry) (IFR, 2020, p.31–38).

The IFR data has a few limitations. While it reports aggregate robot stocks from 1993 onwards, it only contains a breakdown by industry for the US starting in 2004. For the years before 2004, we therefore attribute the aggregate number of robots to industries proportionally to industries' shares of the overall stock in 2004 (following Acemoglu and Restrepo, 2020). Moreover, the IFR classification contains three industries that do not directly correspond to an industry covered in the US census data. These are "Other manufacturing" and "Other non-manufacturing" as well as "Unspecified". We attribute these robots according to each industry's share of robots within each of these categories.[54] Finally, robot shipments to the US also include robot shipments to Canada and Mexico before 2011. Even though this introduces measurement error, it is worth noting that the US accounts for the vast majority of robot shipments to North America (over 90%). Our IV strategy, discussed in detail in Section 2.2, should correct for this kind of measurement error.

B.2 Skill content of occupation groups

In Section 4.2, we investigate the effects of robots and Chinese imports on employment by industry-skill group. While industries are well defined, the concept of *skills* is slightly more vague. Two potential proxies for skills are education levels and occupations. We decide to use the latter, and in particular, the predominant task requirement of occupation groups. The main advantage of using occupational task requirements is that it seems more

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

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 B1. Using this methodology, managerial & professional as well as sales support occupations require mainly abstract, cognitive skills. Administrative support & clerical occupations are the only group requiring mainly routine, cognitive skills, and machine operators, fabricators & laborers the only one requiring mainly routine, manual skills. All remaining groups (technical support, services – such as nurses, janitors, cooks – agricultural, crafts & repair) use mostly abstract, manual abilities.

Table B1: Occupation Groups and Skill Content

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

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

C Robustness Checks

C.1 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 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 C1. 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 similar (e.g., –0.59 in column 2 compared to –0.56 in our preferred specification). It is thus possible that not accounting for pre-trends may bias our results. In particular, 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 (-0.68 vs. –0.56) 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.[55]

[55] 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., -0.59** vs. -0.56*** for robots, and insignificant, positive coefficients for China).

Table C1: Effects on migration, pre-trends (2SLS)

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

Note: The dependent variable is the decadal change in the log working-age population multiplied by 100 (i.e., $[\ln(y_{t+1}) - \ln(y_t)] \cdot 100$). In columns 1–2 and 3–6, there are two and three time periods and 722 CZs each period, resulting in N=1,444 and N=2,166, respectively. In columns 1–2, US exposure to robots/Chinese imports refers to the average of the changes from 1993/91–2000, 2000–7 and 2007–15. Both US exposure variables are standardized to have a mean of 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 initial share of the national working-age population. In columns 1–2, the initial values refer to the year 1970, in columns 3–6 to the year 1990. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

C.2 Alternative definition of Chinese imports

In contrast with our results, Greenland et al. (2019) find that Chinese imports triggered a migration response. However, their analysis differs from ours in that they rely mostly on the Pierce and Schott (2016) definition of the shock, and estimate stacked difference regressions for the time periods 1990–2000 and 2000–2010. Since we are worried about the Great Recession as a potential confounder, in our baseline specification, we chose to end our second period in 2007. In Table C2, we explicitly test whether using the Pierce and Schott (2016) treatment of the Chinese imports shock changes our results. The effect of Chinese imports on population growth is negative and statistically significant only when using a relatively parsimonious specification. However, these results appear 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.

Table C2: Effects on migration, Pierce and Schott (2016) Chinese import shock (reduced form)

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

Note: The dependent variable is the change in the log working-age population. In columns 1–3 there are three time periods (1990–2000, 2000–7 and 2007–15) and 722 CZs each period, resulting in N=2,166. In columns 4–6, the time period 2007–15 is dropped, resulting in N=1,444. All explanatory variables that are displayed are standardized to have a mean of 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 contemporaneous changes are interacted with time period dummies. Columns 3 and 6 also include the share of routine jobs and the average offshorability index in 1990, following Autor and Dorn (2013), each interacted with time period dummies. Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the state level (48 states). Regressions are weighted by a CZ's 1990 national share of the working-age population. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

C.3 Alternative mechanisms

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

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

First, we estimate the migration response to both shocks now omitting the post-2007 period. Results are reported in Panel A of Table C4, 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 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 C4, we return to the full sample (incl. post-2007), but now add interactions between shocks and a post-2007 dummy. We are particularly interested in the coefficient on the interaction between exposure to robots and the post-2007 period dummy. If recessionary conditions mediate the migration response to robots, the coefficient on the interaction should be significant (negative or positive, depending on the direction of the effect of the Great Recession). Results from our most preferred specification (column 5) show that this is not the case. The coefficient on the interaction term is negative but not statistically significant, suggesting that the size of the migration response to robots does not significantly differ between the pre- and post-crisis period.

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

Table C3: Effects on migration, long differences (2SLS)

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

Note: The dependent variable in Panel A and B is the 1990–2015 and 1990–2007 change in the log count of the working-age population, respectively, multiplied by 100 (i.e., $[\ln(y_{t+1}) - \ln(y_t)] \cdot 100$). There are N=722 CZs. All explanatory variables that are displayed are standardized to have a mean of 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 C4: Effects on migration, different time periods (2SLS and reduced form)

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

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

C.4 In- and out-migration robustness checks

In our main results (Tables 2, 3, and 4), standard errors allow for arbitrary clustering at the state level (48 states). It is, however, possible that errors are clustered not only within state borders, but across space more generally. For this reason, we perform a robustness exercise in Table C5, where we repeat the estimation of our preferred specification (column 5 in Table 2), estimating standard errors using the method proposed by Conley (1999). In particular, we allow for arbitrary spatial correlation with CZs that lie within varying distances, from less than 100 miles away (column 1) to less than 500 miles away (column 5). Reassuringly, although standard errors become slightly larger as we increase the radius, results remain unchanged.

In Table 3, we define "close" and "far" moves using a threshold of 300 miles. This admittedly arbitrary cutoff is a convenient proxy for within-state and across-state moves. To verify that results are insensitive to the specific value chosen, we replicate the analysis using cutoffs of 200 miles and 400 miles, respectively. Results, reported in Tables C6 and C7, remain the same.

Table C5: Adjusting standard errors for spatial correlation following Conley (1999)

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

Note: The dependent variable in Panel A is the change in the log count of working-age individuals (15-64), in Panel B the change in the log house price index (see Section 4.1 for details), and in Panels C and D the log count of in-migrants and out-migrants, respectively. There are three time periods in Panel A, and two time periods in Panels B, C and D, and 722 CZs each period, resulting in N=2,166 and N=1,444, respectively. All explanatory variables that are displayed are standardized to have a mean of 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 in the pre-period (1970-1990 in Panel A, 1990/92-2000 in Panels B, C and D). Standard errors allow for arbitrary spatial correlation with CZs within 100 mi., 200 mi., 300 mi., 400 mi., and 500 mi. in columns 1, 2, 3, 4, and 5, respectively. Regressions are weighted by a CZ's 1990 national share of the outcome group in each Panel, respectively. Coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

Table C6: Effects on in- and out-migration by distance, stacked differences 2000–2015 (2SLS)

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

Note: The dependent variables in Panels A and B are the log count of migrants and migration rate, respectively. Columns 1–3 focus on in-migration and columns 4–6 on out-migration. The log counts of migrants and migration rates are multiplied by 100 and 1000, respectively, and converted to 10-year equivalents. There are two time periods (2000–7 and 2007–15) and 722 CZs each period, resulting in N=1,444. All explanatory variables that are displayed are standardized to have a mean of 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 C7: Effects on in- and out-migration by distance, stacked differences 2000–2015 (2SLS)

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

Note: The dependent variables in Panels A and B are the log count of migrants and migration rate, respectively. Columns 1–3 focus on in-migration and columns 4–6 on out-migration. The log counts of migrants and migration rates are multiplied by 100 and 1000, respectively, and converted to 10-year equivalents. There are two time periods (2000–7 and 2007–15) and 722 CZs each period, resulting in N=1,444. All explanatory variables that are displayed are standardized to have a mean of 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 C8: 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	-2.21***	-1.85***	-1.76***	-5.86***	-1.82	-2.03*
	(0.68)	(0.52)	(0.53)	(1.43)	(1.14)	(1.20)
US exposure to Chinese imports	0.53	1.22	1.65	-0.72	2.04	4.40
	(1.05)	(1.04)	(1.12)	(4.34)	(4.01)	(4.52)
			B. Out-migration			
US exposure to robots	-0.72	-0.31	-0.01	-1.95	-0.60	-0.16
	(0.76)	(0.55)	(0.55)	(1.64)	(1.19)	(1.12)
US exposure to Chinese imports	0.44	1.00	0.43	-1.93	-0.32	-1.35
	(1.08)	(1.37)	(1.43)	(3.61)	(4.54)	(4.44)
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.

D Theoretical results

D.1 Proofs

In this subsection we provide the proofs for Propositions 1 and 2.

PROOF OF PROPOSITION 1: From firm's i cost minimization problem we get:

$$\gamma_L^R L_i^R = Q_i^R \left\{ \frac{\frac{w_i\left\{1-\theta_i^R\left(1-p^{R*}\frac{\gamma_L^R}{\gamma_R}\right)\right\}}{\gamma_L^R}}{\mathcal{P}_{Q^R}} \right\}^{-\varepsilon_i^R} \tag{D.1}$$

$$I_i^R = Q_i^R \left\{ \frac{p_i^S}{\mathcal{P}_{Q^R}} \right\}^{-\varepsilon_i^R} \tag{D.2}$$

where:

$$Q_i^R = x_i \frac{\phi_i}{A_i} \frac{\left(\mathcal{P}_{Q^R}\right)^{\phi_i}\left(\mathcal{P}_{Q^O}\right)^{(1-\phi_i)}}{\mathcal{P}_{Q^R}} \tag{D.3}$$

$$\mathcal{P}_{Q^R} = \left[\left\{ \frac{w_i\left\{1-\theta_i^R\left(1-p^{R*}\frac{\gamma_L^R}{\gamma_R}\right)\right\}}{\gamma_L^R} \right\}^{1-\varepsilon_i^R} + \left(p_i^S\right)^{1-\varepsilon_i^R} \right]^{\frac{1}{1-\varepsilon_i^R}} \tag{D.4}$$

$$\mathcal{P}_{Q^O} = \left[\left\{ \frac{w_i\left\{1-\theta_i^O\left(1-w^*\beta\underline{t}\right)\right\}}{\gamma_L^O} \right\}^{1-\varepsilon_i^O} + \left(p_i^S\right)^{1-\varepsilon_i^O} \right]^{\frac{1}{1-\varepsilon_i^O}}. \tag{D.5}$$

Similarly, we also get:

$$\gamma_L^O L_i^O = Q_i^O \left\{ \frac{\frac{w_i\left\{1-\theta_i^O\left(1-w^*\beta\underline{t}\right)\right\}}{\gamma_L^O}}{\mathcal{P}_{Q^O}} \right\}^{-\varepsilon_i^O} \tag{D.6}$$

$$I_i^O = Q_i^O \left\{ \frac{p_i^S}{\mathcal{P}_{Q^O}} \right\}^{-\varepsilon_i^O} \tag{D.7}$$

with:

$$Q_i^O = x_i \frac{(1-\phi_i)}{A_i} \frac{\left(\mathcal{P}_{Q^R}\right)^{\phi_i}\left(\mathcal{P}_{Q^O}\right)^{(1-\phi_i)}}{\mathcal{P}_{Q^O}}. \tag{D.8}$$

These in turn imply a constant unit cost given by:

$$\Psi_i = \frac{1}{A_i} \left(\mathcal{P}_{Q^R}\right)^{\phi_i} \left(\mathcal{P}_{Q^O}\right)^{(1-\phi_i)}. \tag{D.9}$$

Now, total labor demand in commuting zone i is given by:

$$\begin{aligned} L_i^D &= \left[1-\theta_i^R\right] L_i^R + \left[1-\theta_i^O\right] L_i^O + \frac{1}{A_i^S}\left(I_i^R + I_i^O\right) \\ &= x_i \kappa_i \underbrace{\frac{\left(\mathbb{P}_{Q^R}\right)^{\phi_i}\left(\mathbb{P}_{Q^O}\right)^{(1-\phi_i)}}{A_i}}_{=\varphi_i}, \end{aligned} \tag{D.10}$$

where:

$$\begin{aligned} \kappa_i \coloneqq \phi_i & \left(\frac{\left[\frac{1-\theta_i^R}{\gamma_L^R}\right] \left(\frac{1-\theta_i^R\left(1-p^{R*}\frac{\gamma_L^R}{\gamma_R}\right)}{\gamma_L^R} \right)^{-\varepsilon_i^R} + \left(\frac{1}{A_i^S}\right)^{1-\varepsilon_i^R}}{\mathbb{P}_{Q^R}^{1-\varepsilon_i^R}} \right) \\ + (1-\phi_i) & \left(\frac{\left[\frac{1-\theta_i^O}{\gamma_L^O}\right] \left(\frac{1-\theta_i^O(1-w^*\beta\underline{t})}{\gamma_L^O} \right)^{-\varepsilon_i^O} + \left(\frac{1}{A_i^S}\right)^{1-\varepsilon_i^O}}{\mathbb{P}_{Q^O}^{1-\varepsilon_i^O}} \right). \end{aligned}$$

Moreover, given the CES form of preferences we also have:

$$\begin{aligned} c_{ni} &= \left(\frac{p_{ni}}{P_n}\right)^{-\sigma} C_n \\ C_n &= \frac{w_n}{P_n}. \end{aligned}$$

Hence, market clearing in commuting zone i labor market requires:

(D.11)

$$L_i\left(\kappa_i\right)^{-1} = \varphi_i \left\{ \sum_{n=1}^{N} d_{in} \left[\left(\frac{p_{ni}}{P_n}\right)^{-\sigma} \frac{w_n L_n}{P_n} \right] + \sum_{n=1}^{N} d_{ir_n} \left[\frac{d_{in}^{1-\sigma}}{d_{ir_n}^{1-\sigma}} \left(\frac{p_{r_n i}}{P_n}\right)^{-\sigma} \frac{w_n L_n}{P_n} \left(\frac{1-\kappa_n}{\kappa_n}\right) \right] \right\}.$$

Given the assumption of perfect competition, the final price of a good produced in i and sold in any location n equals the marginal cost of production and shipping:

$$p_{ni} = w_i \varphi_i d_{in}.$$

So we can rewrite (D.11) as:

$$L_i (\kappa_i)^{-1} = \varphi_i \sum_{n=1}^{N} d_{in} \left[\left(\frac{w_i \varphi_i d_{in}}{P_n} \right)^{-\sigma} \frac{w_n L_n (\kappa_n)^{-1}}{P_n} \right]. \tag{D.12}$$

If we substitute P_n using $V_n = \frac{w_n}{P_n}$ and manipulate somewhat the expression we get:

$$w_i^{\sigma} L_i (\kappa_i)^{-1} = \sum_{n=1}^{N} \left[(\varphi_i d_{in})^{1-\sigma} V_n^{1-\sigma} w_n^{\sigma} L_n (\kappa_n)^{-1} \right]. \tag{D.13}$$

Moreover, using the expression for the price index P_n together with $V_n = \frac{w_n}{P_n}$ and equilibrium prices yields:

$$P_n = \left[\sum_{i=1}^{N} {p_{ni}}^{1-\sigma} \right]^{\frac{1}{1-\sigma}}$$

$$\frac{w_n}{V_n} = \left[\sum_{i=1}^{N} (w_i \varphi_i d_{in})^{1-\sigma} \right]^{\frac{1}{1-\sigma}}. \tag{D.14}$$

If we impose welfare equalization in (D.13) and (D.14) we get:

$$w_i^{\sigma} L_i (\kappa_i)^{-1} = V^{1-\sigma} \sum_{n=1}^{N} \left[(\varphi_i d_{in})^{1-\sigma} w_n^{\sigma} L_n (\kappa_n)^{-1} \right] \tag{D.15}$$

$$w_n^{1-\sigma} = V^{1-\sigma} \left[\sum_{i=1}^{N} (\varphi_i d_{in})^{1-\sigma} w_i^{1-\sigma} \right]. \tag{D.16}$$

Both (D.15) and (D.16) are linear operators with the same eigenvalue, $V^{\sigma-1}$, and with eigenvectors $w_n^{\sigma} L_n (\kappa_n)^{-1}$ and $w_i^{1-\sigma}$, respectively. Following Theorem 1 in Allen and Arkolakis (2014), we can apply the celebrated Perron-Frobenius theorem to conclude there is a unique (up to scale) positive eigenvector, for each of (D.15) and (D.16), associated with a positive real eigenvalue. Moreover, given that the matrices that describe these operators are the transpose of each other, we know the eigenvalues coincide. Following the arguments in Allen and Arkolakis (2014) we can show there is a simple iterative procedure that converges to the solution. Finally, using the normalization $\sum_{i=1}^{N} w_i = 1$ and aggregate market clearing in the labor market, $\sum_{i=1}^{N} L_i = \overline{L}$, we pin down the scales. $\blacksquare$

PROOF OF PROPOSITION 2: Imposing homogeneity and differentiating (D.15) and (D.16) yields:

$$d\ln L_i = d\ln\kappa_i + (\sigma-1)\, d\ln\varphi_i^{-1} + \zeta. \tag{D.17}$$

To ease notation, we work with a commuting zone subject to automation for the rest of this proof. The exact same arguments apply to a region subject to offshoring. Using (D.1)-(D.9) we can write:

$$\begin{aligned} E_i^M &= \left[1-\theta_i^R\right] L_i^R = \frac{x_i}{A_i}\left(\frac{1-\theta_i^R}{\gamma_L^R}\right)\left(\frac{\left(\gamma_L^R\right)^{-1}\left[1-\theta_i^R\left(1-p^{R*}\frac{\gamma_L^R}{\gamma_R}\right)\right]}{\mathbb{P}_{Q^R}}\right)^{-\varepsilon_i^R} \\ E_i^S &= \left(A_i^S\right)^{-1} I_i^R = \frac{x_i}{A_i}\left(A_i^S\right)^{-1}\left(\frac{\left(A_i^S\right)^{-1}}{\mathbb{P}_{Q^R}}\right)^{-\varepsilon_i^R}. \end{aligned}$$

If we differentiate these expressions we get:

$$d\ln E_i^M = d\ln x_i + d\ln\left(\frac{1-\theta_i^R}{\gamma_L^R}\right) - \varepsilon_i^R d\ln\left(\frac{\left(\gamma_L^R\right)^{-1}\left[1-\theta_i^R\left(1-p^{R*}\frac{\gamma_L^R}{\gamma_R}\right)\right]}{\mathbb{P}_{Q^R}}\right) \tag{D.18}$$

$$d\ln E_i^S = d\ln x_i - \varepsilon_i^R d\ln\left(\frac{\left(A_i^S\right)^{-1}}{\mathbb{P}_{Q^R}}\right). \tag{D.19}$$

If we impose equilibrium in (D.10) and differentiate we can express:

$$d\ln L_i = d\ln x_i + d\ln\varphi_i + d\ln\kappa_i, \tag{D.20}$$

so if we combine (D.17) and (D.20) we get:

$$d\ln x_i = -\sigma d\ln\varphi_i + \zeta.$$

Hence, if we substitute in (D.18) and (D.19) we get:

$$d \ln E_i^M = d \ln \left(\frac{1-\theta_i^R}{\gamma_L^R} \right) - \sigma d \ln \varphi_i - \varepsilon_i^R d \ln \left(\frac{\left(\gamma_L^R\right)^{-1} \left[1-\theta_i^R \left(1-p^{R*}\frac{\gamma_L^R}{\gamma_R}\right)\right]}{\mathbb{P}_{Q^R}} \right) + \zeta \tag{D.21}$$

$$d \ln E_i^S = -\sigma d \ln \varphi_i - \varepsilon_i^R d \ln \left(\frac{\left(A_i^S\right)^{-1}}{\mathbb{P}_{Q^R}} \right) + \zeta. \tag{D.22}$$

Equation (D.22) is the one given in the text. Using the fact that:

$$d \ln \left(\frac{1-\theta_i^R}{\gamma_L^R} \right) = -\frac{d\theta_i^R}{1-\theta_i^R}$$

in (D.21) gives (13).

Finally, using (D.10) again we know:

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

which gives (12) and (15) in the text. ■

D.2 Additional information on the quantitative exercises

The quantitative exercises use Proposition 2 to tie the effects in the model to the empirical estimates in Section 4.1. However, given that the quantities $d\ln\theta_i^h$ are unobservable, the connection between the two requires an additional step. For the case of automation, the empirical results measure the exposure as:

$$\textit{exposure to robots}_i = \frac{d\,(\textit{machines}_i)}{\textit{labor}_i} - \frac{dY_i}{Y_i}\frac{\textit{machines}_i}{\textit{labor}_i}.$$

Thus, in order to connect the elasticities within the model with the ones from our empirical estimates we need to translate changes in $\ln\theta_i^h$ to this exposure measure. After some algebra, one can show that:

$$\begin{aligned}
&\frac{d\,(\textit{machines}_i)}{\textit{labor}_i} - \frac{dY_i}{Y_i}\frac{\textit{machines}_i}{\textit{labor}_i} \\
&= \left(\frac{\left(\frac{1-\theta_i^R\left(1-p^{R*}\frac{\gamma_L^R}{\gamma_R}\right)}{\gamma_L^R}\right)^{1-\varepsilon_i^R} + \left(\frac{1}{A_i^S}\right)^{1-\varepsilon_i^R}\left[\frac{1+\theta_i^R\left(1-p^{R*}\frac{\gamma_L^R}{\gamma_R}\right)(\varepsilon_i^R-1)}{1-\theta_i^R\left(1-p^{R*}\frac{\gamma_L^R}{\gamma_R}\right)}\right]}{\left(\frac{1-\theta_i^R\left(1-p^{R*}\frac{\gamma_L^R}{\gamma_R}\right)}{\gamma_L^R}\right)^{1-\varepsilon_i^R} + \left(\frac{1}{A_i^S}\right)^{1-\varepsilon_i^R}} \right) \\
&* \frac{\textit{machines}_i}{\textit{labor}_i}d\ln\theta_i^R.
\end{aligned} \tag{D.23}$$

For our results on the China trade shock, we rely on the same relationship (replacing the appropriate robot parameters in (D.23) for their offshoring counterparts). Even though the trade shock lacks the output growth normalization of this exposure measure, we still think this is the best way to do the match for two reasons. First, the estimates we obtain are coming from a 2SLS strategy, that has at the core the intention of capturing the pure technological changes from the shock, as opposed to any scale changes that might be happening simultaneously. Ideally, using the variation coming from other developed countries achieves this. Second, treating the data symmetrically allows us to rule out any differences coming from small changes on how we decide to match the shocks in the model with the estimates.