Robots and reshoring: Evidence from Mexican labor markets*

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Abstract

Robots in advanced economies have the potential to reduce employment in offshoring countries by fueling reshoring. Using robots instead of humans for production may reduce the relative cost of domestic production and, in turn, lower demand for imports from offshoring countries. I analyze the impact of robots on employment in an offshoring country, using data from Mexican local labor markets between 1990 and 2015. A recent literature estimates the effect of robots on local employment by regressing the change in employment on exposure to *domestic* robots in local labor markets. I similarly construct a measure of exposure to *foreign* robots, assuming that the share of US robots competing with Mexican labor is proportional to a US industry's initial share of Mexican imports. Using robot penetration in the rest of the world (i.e., neither in Mexico nor in the US) and an index of offshoring as instruments for increased robot density and the share of Mexican imports, respectively, I show that the robots in the US have a sizeable, negative impact on employment in Mexico. This effect is mirrored in lower exports to the US and fewer exports-producing factories. Preexisting trends, the automotive industry or migration patterns do not drive the results. The negative effect is strongest for low-skilled machine operators and technicians in highly robotized manufacturing industries as well as high-skilled managers and professionals in the service industry.

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1 Introduction

The debate about the impact of robots on employment focuses almost entirely on developed countries. One reason for this may be that robots are adopted mainly in advanced economies. But even though most robots are installed within the borders of the developed world, they may threaten workers outside of these borders. In response to increased offshoring, many cheap labor locations such as China, Mexico, India, Bangladesh, and Vietnam have become more specialized in low-skill, manual tasks in the past few decades. In the meantime, the invention of robots has created a cheap alternative to perform precisely these tasks at home. Despite the lack of scientific evidence for this mechansim, there is growing anecdotal evidence that advances in robot capabilities fuel so-called 'reshoring', heralding the reversal of offshoring.[1] Via this mechanism, increased use of robots in the developed world may pose a particular threat to workers in offshoring countries.

Economists have recently started to examine the impact of *industrial robots* on employment, but only for *developed* countries. Graetz and Michaels (2018) are the first to examine the effect of industrial robots across 17 highly developed countries and industries.[2] They find that robots increase labor productivity, and some evidence that they reduce the hours worked by low-skilled workers. More recently, Acemoglu and Restrepo (2017) added to this discussion by examining, both theoretically and empirically, the effect of robots on employment and wages in the United States. First, they develop a theoretical model in which robots compete against human labor in specific tasks. They show that in this class of models, the general equilibrium effect of robots can be estimated by a relatively simple regression (cf. Section 2). Second, exploiting variation in exposure to robots across US local labor markets, they find that one new robot reduces employment by six workers in the United States.[3]

In spite of these findings, it remains unanswered how robots affect employment in offshoring countries. This is despite the fact that robots may foster a recent phenomenon called *reshoring*.[4] Reshoring describes the reverse process of offshoring, namely that previously offshored tasks are moved back into the home country. One of the reasons why companies decide to reshore production is that advances in robotic automation technologies reduce their costs of production, no matter where they produce. This, in turn, increases the attractiveness of domestic production as compared to offshoring. Robots are thus likely to fuel reshoring.

Recent examples for this reshoring process are the new proto-type "Speedfactories" of German sportswear company Adidas. Traditionally, companies in this industry had offshored production to cheap labor locations like China, Vietnam, and Indonesia. In contrast, these new factories are located in Ansbach, Germany and Atlanta, US, and produce 500,000 pairs of shoes per year using mainly industrial robots. Since robots cannot perform all tasks, the

[1]cf. Economist (2013), Economist (2017), Lewis (2014).

[2]All 17 countries are in top-30 in terms of GDP per capita (excl. oil countries and very small tax haven countries such as Qatar, UAE and Puerto Rico, Bahamas, respectively.)

[3]Using a similar strategy, Dauth et al. (2017) conduct an analysis for Germany, and find no effect of robots on overall employment, but negative effects on earnings of low- and middle-skilled workers.

[4]See Rodrik (2018) for a more general discussion on the impact of new technologies on global value chains.

Speedfactories employ about 160 people locally in Ansbach and Atlanta, compared with more than a thousand in a typical factory in an offshoring location (cf. Economist, 2017).

In this paper, I estimate the effect of *domestic* and *foreign* robots on employment in an offshoring country. I use 1990–2015 data from Mexican local labor markets as well as robot shipment data for Mexico, the US and 18 other countries. Similar to Acemoglu and Restrepo (2017), I estimate the effect of Mexican robots on local employment using a local labor market's exposure to *domestic* robots. In addition, I consider an exports-producing sector, which may be affected by US robots. I estimate the effect of US robots on local employment via a similar measure – named exposure to *foreign* robots. This measure uses the US national penetration of robots into each industry, the local distribution of employment across industries, and the initial reliance of the US on imports from Mexico. Both of these variables may suffer from endogeneity resulting from an industry's or specialized local labor market's decision to adopt robots. I construct two instruments, one for each exposure to robots variable, to purge the results of such endogeneity concerns. In particular, I instrument changes in the number of Mexican and US robots per Mexican worker with changes in robot density in the rest of the world (neither US nor Mexico), and the share of Mexican imports of US output with a more general measure of offshoring as developed by Feenstra and Hanson (1999).

The IV results show that US robots reduce employment in Mexico by reducing exports to the US. I also explicitly explore alternative explanations such as preexisting trends, other changes to the automotive industry, or migration across local labor markets driving the results, and find no support for these. Two groups of workers are most affected by US robots: Low-educated machine operators and technicians in manufacturing, and highly-educated service workers in managerial and professional occupations. The estimates imply that a local labor market with an average exposure to US robots experienced a 3.5 percentage points lower growth in the employment-to-population ratio, compared with no such exposure. At the national level, this amounts to about 2 million fewer jobs in Mexico. This suggests that roughly half of all US robots compete with workers in Mexico. To explore the exact mechanism behind these employment effects, I consider exports to the US and the number of Maquiladora factories – dedicated export-manufacturing plants in Mexico – as alternative outcomes. The employment effects are mirrored in sizeable reductions in both exports and Maquiladora factories per capita, corroborating the view that robots foster reshoring.

The remainder of this paper is stuctured as follows: Section 2 presents a model, in which robots compete with human labor in different tasks. This is helpful to understand the forces at work and serves as a motivation for the empirical strategy. Section 3 describes how I complement the basic model with an exports-producing sector to identify the effect of foreign robot stocks. Section 4 lays out the empirical strategy and describes the instrumental variables. Section 5 reports the data sources and describes the construction of the data set. Section 6 presents the empirical results, conducts several robustness checks and a subgroup-analysis, and explores the mechanism behind the results. Section 7 concludes.

2 Theoretical foundation

In this section, I provide a brief summary of the model developed by Acemoglu and Restrepo (2017). In this model, robots compete against human labor in the production of different tasks. In general equilibrium, robots may increase or reduce employment and wages, depending on the relative size of countervailing effects. In this class of models, the effect of robots on local employment can be estimated by regressing the change in employment on the *exposure to robots* in each local labor market, which is defined from the national penetration of robots into each industry and the local distribution of employment across industries.

Each local labor market c (referred to as commuting zone (CZ) hereafter) maximizes aggregate consumption Y_c from several industry-specific products Y_{ci}, taking into account its relative tastes α_i for each industry-product, given by

$$Y_c = \left(\sum_{i \in I} \alpha_i Y_{ci}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}, \tag{1}$$

where $\sum_{i \in I} \alpha_i = 1$ and $\sigma > 0$ denotes the elasticity of substition across goods produced in different industries.

In autarky, each CZ consumes only its own production of each industry-good, denoted by X_{ci}, such that $X_{ci} = Y_{ci}$ for all $c \in C$ and $i \in I$. Production of a CZ's industry-good takes place by combining a set of tasks $s \in [0, 1]$ in fixed proportions so that

$$X_{ci} = A_{ci} \min_{s \in [0,1]} \{x_{ci}(s)\}, \tag{2}$$

where A_{ci} is the productivity of CZ c in industry i and $x_{ci}(s)$ is the quantity of task s utilized in the production of X_{ci}. Differences in A_{ci} thus give rise to different industry compositions across CZs.

Robots are modeled by assuming that each industry-product requires a set of tasks in fixed proportions, of which a subset $[0, M_i]$ is technologically automated, such that it can be produced by both humans and robots (cf. Figure 1). More formally,

$$x_{ci}(s) = \begin{cases} \gamma L_{ci}(s) & \text{if } s > M_i, \\ \gamma L_{ci}(s) + R_{ci}(s) & \text{if } s \leq M_i \end{cases} \tag{3}$$

where $L_{ci}(s)$ and $R_{ci}(s)$ denote labor and robots used in the production of tasks s in CZ c and industry i, respectively. The productivity of robots is normalizd to one, such that $\gamma > 0$ denotes the relative productivity of labor. Robotization takes the form of an increase in M_i (dM_i), i.e., an increase in the number of tasks in which robots can substitute for labor. Crucially, more conventional technologies (such as traditional information and communication technology) can be modeled by increasing γ, thus complementing labor.

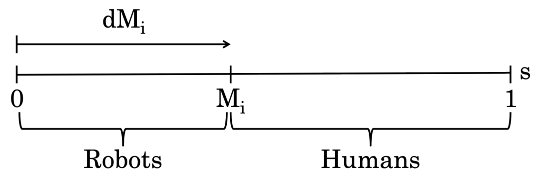


Figure 1: Automation of tasks

Finally, supply of labor L_c and robots R_c in each CZ are specified as

$$W_c = \mathcal{W}_c Y_c L_c^{\epsilon}, \quad \text{with } \epsilon \geq 0; \text{ and} \tag{4}$$

$$Q_c = \mathcal{Q}_c \left(\frac{R_c}{Y_c} \right)^{\eta}, \text{ with } \eta \geq 0 \tag{5}$$

where Q_c is the price of robots, and W_c is the wage rate, and $\mathcal{W}_c$ and $\mathcal{Q}_c$ are local supply curve shifters in commuting zone c. These specifications imply that $1/\epsilon$ is the Frisch elasticity of labor supply, while $1/\eta$ is the elasticity of the supply of robots.

Examining the change in labor demand in response to automation under autarky is helpful to understand the three different forces at work in this model:[5]

$$d \ln L_c = \underbrace{- \sum_{i \in I} \ell_{ci} \frac{dM_i}{1 - M_i}}_{\text{displacement effect}} \underbrace{- \sigma \sum_{i \in I} \ell_{ci} d \ln P_{X_{ci}}(M_i)}_{\text{price-productivity effect}} \underbrace{+ d \ln Y_c(M_i)}_{\text{scale-productivity effect}}, \tag{6}$$

where ℓ_{ci} denotes industry i's share of total employment in CZ c, $P_{X_{ci}}$ denotes the price for industry-product X_i in CZ c, and Y_c denotes CZ c's total output.

There are opposing effects on labor demand in this equation: On the one hand, the first term describes the (negative) *displacement effect*, i.e., the direct effect of robots substituting for human labor, holding prices and output constant. On the other hand, there are two opposing (positive) indirect effects: (i) the *price-productivity effect* resulting from lower prices due to higher robot usage, allowing the *industry* to expand and increase its demand for labor, and (ii) the *scale-productivity effect*, resulting from lower prices in the aggregate, allowing the *total CZ* to expand and demand more labor. Thus in principle, robotization could lead to either a reduction or an increase in labor demand in this model. This depends on whether the negative displacement effect or the positive productivity effects are larger.

An equilibrium is defined as the set of prices $\{\{P_{X_{ci}}\}_{i \in I}, W_c, Q_c\}_{c \in C}$ and the set of quantities $\{\{Y_{ci}\}_{i \in I}, L_c, R_c\}_{c \in C}$, such that in all CZs firms maximize profit, households maximize their utility, labor and robot supplies are given by (4) and (5) and the markets for final goods, labor and robots clear. For simplicity, it is assumed that it is profitable for firms to use robots in all tasks that are technologically automated. Equation (6) is in terms of robotic automation

[5]See Acemoglu and Restrepo (2017) for derivations of all steps as well as proofs of existence and uniqueness of the equilibrium presented in this subsection.

technology M_i, not the number of robots R_i. Using the facts that $1/\gamma$ is the productivity of robots relative to humans, the term $\frac{dM_i}{1-M_i} \approx \frac{1}{\gamma}\frac{dR_i}{L_i}$ when $M_i \approx 0$. This is more convenient for the empirical analysis.

Equation (6) presented changes in a CZ's labor demand in response to automation as a function of the share of automated tasks, product prices and total output. Linking these changes in prices and output to automation yields the following general equilibrium expression for the change in employment in response to robotic automation:

$$d\ln L_c = \beta_c \sum_{i \in I} \ell_{ci} \frac{dR_i}{L_i} + \epsilon_c, \text{ with } \beta_c = \left(\frac{1+\eta}{1+\varepsilon}\pi_c - \frac{1+\eta}{1+\varepsilon} \right) \frac{1}{\gamma}, \tag{7}$$

where $\pi_c = 1 - \frac{Q_c \gamma}{W_c}$ denote the cost-saving gains from using robots instead of labor in a task.

Acemoglu and Restrepo (2017) extend this basic model to allow for trade between CZs. They relax the autarky assumption by allowing each good to be consumed not only locally, but also in all other CZs. There are no transportation costs such that the price of each CZ-specific variety of an industry good is equilized across space. Market clearing then implies that the production of each CZ's industry good equals aggregate demand for this good over all CZs. Preferences across industry goods are the same as in the autarky model, but now each industry good is itself an aggregate over all CZ-varieties of that industry-good. Finally, Acemoglu and Restrepo (2017) show that this model incl. trade between CZs results in the same reduced-form relationship between local employment and robots as in the autarky model, however, with a more involed expression for β_c.

3 Incorporating foreign robots

In a world without trade *across* countries it would be sufficient to estimate the effect of robots on local employment using the above equation and data on employment and robot installations in Mexico. However, employment in offshoring countries stems to a large extent from exports to the US.[6] Workers in the exports-producing sector thus do not only compete with domestic, but also foreign robots.[7]

In an attempt to identify the effect of foreign robots on domestic employment, I complement the theoretical model above with a sector that produces exports to the US. In particular, US firms may produce certain goods using labor in Mexico. In this scenario, industry employment in Mexico (L_i) is comprised not only of workers in the sector producing goods for domestic consumption (L_i^d), but also the one producing goods for foreign consumption (L_i^f).

To identify the subset of robots in the US that compete with workers in Mexico, I assume that offshoring or trade across countries is only possible in "offshorable" goods. This is to account

[6]In 2015, Mexican exports to the United States made up roughly 30% of total Mexican GDP.

[7]In particular, assuming that the productivity and costs of robots are the same no matter where they operate, and that tasks are perfectly separable, it is never optimal for importing firms to employ robots abroad. They can always save transportation costs by employing them at home. In this extreme case, exports-producing workers compete *only* with foreign robots.

for the fact that offshorable goods are likely a specific subset of goods. They require a high degree of routineness, a low degree of human interaction, and must be transportable over long distances (cf. Wright 2014). I indicate whether an industry produces an offshorable or non-offshorable good with the indicator F_i (1 for offshorable industries, 0 for non-offshorable). It is thus only in offshorable industries that US robots compete with Mexican labor. Not accounting for this would imply, for instance, that US robots may replace Mexican labor also in non-tradeable industries, which seems implausible.[8]

In the absence of robots, US firms that produce offshorable goods can therefore decide whether to employ labor in the US or Mexico. For simplicity, I assume that it is always profitable to offshore the production of offshorable goods. Thus all US firms in industries with $F_i = 1$ employ only labor in Mexico, and those in industries with $F_i = 0$ employ only labor in the US.[9] I further assume that US firms in offshorable industries allocate production across Mexico proportional to the domestic sector, such that the geographic distribution of industry employment is the same in both sectors.

In response to automation, US firms producing offshorable goods thus replace Mexican labor with robots in all technologically automated tasks. Accounting for the fact that, in this scenario, Mexican workers do not only compete with robots in Mexico (dR_i^d), but also the ones in offshorable industries in the US ($dR_i^f F_i$), I rewrite Equation (7) as

$$d \ln L_c = \beta_c \sum_{i \in I} \ell_{ci} \frac{dR_i^d + dR_i^f F_i}{L_i} + \epsilon_c \tag{8}$$

$$\Leftrightarrow \quad d \ln L_c = \beta_c \sum_{i \in I} \ell_{ci} \frac{dR_i^d}{L_i} + \beta_c \sum_{i \in I} \ell_{ci} \frac{dR_i^f}{L_i} F_i + \epsilon_c. \tag{9}$$

Therefore, what matters in this scenario for changes in local employment in the home country are each local labor market's *exposures* to domestic and foreign robots ($\sum_{i \in I} \ell_{ci}(dR_i^d/L_i)$ and $\sum_{i \in I} \ell_{ci}(dR_i^f/L_i)F_i$, respectively). The latter is a function of the local distribution of employment across industries ($\sum_{i \in I} \ell_{ci}$) and the penetration of *foreign* robots per domestic worker into each industry (dR_i^f/L_i) conditional on this industry producing an offshorable good ($F_i = 1$).

4 Empirical strategy

Equation (9) can be taken to the data and estimated with OLS to measure the effect of domestic and foreign robots on local employment in Mexico. In particular, I define the

[8]For simplicity, I assume that offshoring is asymmetric, such that the US can offshore production to Mexico, but not vice versa. This simplifying assumption is likely innocuous given that offshoring of routine, manual work largely happens from developed to less developed countries. Results allowing for bilateral offshoring do not differ qualitatively and are available upon request.

[9]In reality, most industries do not offshore all tasks, but only specific steps in the value chain. However, note that the definition of industries in this model can be arbitrarily narrow, in which case this assumption is not implausible. In the empirical analysis, instead of a binary indicator, I use the share of offshorable tasks within a broader industry as I cannot observe such granular industries.

exposure to domestic and foreign robots variables as

$$\begin{aligned} \text{exposure to} \atop \text{domestic robots}_{c,t:t+1} &\equiv \sum_{i \in I} \ell_{ci,t} \left(\frac{R^{MX}_{i,t+1} - R^{MX}_{i,t}}{L^{MX}_{i,t}} \right) \text{ and} \qquad (10) \\ \text{exposure to} \atop \text{foreign robots}_{c,t:t+1} &\equiv \sum_{i \in I} \ell_{ci,t} \left(\frac{R^{US}_{i,t+1} - R^{US}_{i,t}}{L^{MX}_{i,t}} \right) F_{i,t}, \qquad (11) \end{aligned}$$

where $R^{MX}_{i,t}$ and $R^{US}_{i,t}$ are the (estimated) number of robots in industry i at time t in Mexico and the US, respectively. In contrast to the parameter presented in the theory, F_i is not measured as a binary variable indicating whether or not an industry-product is offshorable as a whole, but rather continuously measuring which share of inputs into industry-good i is offshorable. The reason for this is that I do not observe robots on a level granular enough to make a categorical classification into offshorable and non-offshorable. In particular, I measure $F_{i,t} = I^{MXUS}_{i,t}/Y^{US}_{i,t}$ as industry i's share of Mexican imports in total US output at time t (times 10 to make the two measures have a similar mean). I provide more detailed information about the sources and construction of these variables in Section 5.

The resulting exposure to domestic robots variable may, however, suffer from measurement error and endogeneity. First, there may be some measurement error due to the non-observed robot data for some of the years. This would cause OLS to underestimate the true effect. Second, it may be endogenous as contemporaneous shocks to certain *industries* or to certain *local labor markets* highly specialized in a certain industry may have had distinct effects on their robot and labor demand. A likely candidate for such a shock is Mexico's entry into the North American Free Trade Agreement (NAFTA) in 1994. NAFTA may have put upward pressure on specifically those industries or specialized local labor markets that already had the highest employment-to-population ratios and thus less room for expansion. Such industries or local labor markets may have then decided to employ the most robots. This would result in lower employment growth in those local labor markets with highest robot growth, but the causality would be reverse.

I apply an IV strategy to address both issues. In particular, I use the contemporaneous increase in robot density in the rest of the world as an instrument for the increase in Mexico's robot density, and name the resulting measure *external exposure to domestic robots*:

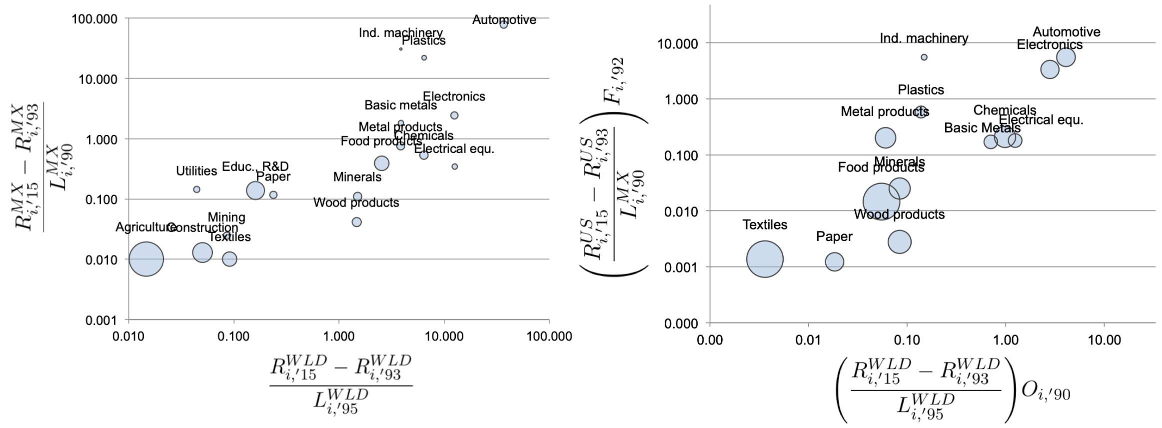
$$\text{external exposure to} \atop \text{domestic robots}_{c,t} \equiv \sum_{i \in I} \ell_{ci,t} \left(\frac{R^{WLD}_{i,'15} - R^{WLD}_{i,'93}}{L^{WLD}_{i,'95}} \right), \qquad (12)$$

where the superscript *WLD* indicates the sum over all countries in the robot data except for the US and Mexico.[10] I will henceforth refer to this group of countries as the "rest

[10] In particular, the IFR robot data includes Austria, Belgium, Czech Republic, Germany, Denmark, Spain, Finland, France, Hungary, Italy, South Korea, Netherlands, Poland, Portugal, Romania, Sweden, Slovakia and the United Kingdom. Following the recommendation of the IFR, data for Japan is excluded as it underwent a major reclassification. Data on employment by industry L^{WLD}_i is from 1995, as this is the earliest year for which industry-level employment data exists for all those 18 countries in the WORLD KLEMS database.

of the world". The increase in robot density in the rest of the world is conceivably less related to local labor market conditions in Mexico than actual robot adoption in Mexico. In particular, this instrument is likely to be unaffected by NAFTA, the most obvious cause for concern. Moreover, using the long-difference (1993–2015) industry variation also in the short-difference specifications is more robust against contemporaneous shocks affecting both robot adoption and employment in the same time period. This is a relevant instrument if quality improvements and price reductions, which affect industries across countries similarly, drive the adoption of robots. I discuss the necessary assumptions for the exclusion restriction to hold for this instrument in more detail in the discussion of the IV estimates in Section 6.1.

Similarly, the introduction of NAFTA may lead to endogeneity of the exposure to foreign robots variable. In particular, when deciding about the employment of robots, US firms may have taken into account local labor market conditions in Mexico more strongly after the free trade agreement. For example, if Mexican local labor markets specialized in automotive manufacturing had relatively low employment-to-population ratios, and thus more room to expand, US automotive firms would have had lower incentives to employ robots at home, and vice versa. Any such scenario would cause the OLS estimates to be biased.



A. First-stage for exposure to domestic robots B. First-stage for exposure to foreign robots

Figure 2: Industry-level relationship between endogenous exposure to robots variables and instruments. Panel A presents the industry-level variation between the exposure to domestic robots and the external exposure to domestic robots. Panel B presents the corresponding variation for the exposure to foreign robots and external exposure to foreign robots. All non-tradable industries are excluded from this plot as they have a value of zero by construction and cannot be represented on a logarithmic scale. Bubble size indicates Mexican industry employment in 1990.

Moreover, the initial share of Mexican imports in total US output may be correlated with unobservable characteristics of certain Mexican (large) local labor markets or industries. I therefore use a more general measure of offshoring in US industries, $O_{i,'90}$, defined as the share of imported intermediate inputs in the same industry over total non-energy intermediates in US industry i in 1990 (across all countries of origin), analogous to the (narrow) outsourcing measure developed in Feenstra and Hanson (1999).[11] Using this measure of offshoring in general as opposed to offshoring to Mexico is less likely to be correlated with unobservable characteristics of Mexican local labor markets. It is a relevant instrument if offshoring is mainly driven by lower wages abroad and an industry's task distribution and less by industry-specific skills of certain countries.

Substituting the increase in *US* robots per Mexican worker with the increase in robot density in the rest of the world, and the initial share of Mexican imports in US output with the offshoring index defined above yields what I will refer to as *external exposure to foreign robots*:

$$\begin{matrix}\text{external exposure to} \\ \text{foreign robots}_{c,t}\end{matrix} \equiv \sum_{i \in I} \ell_{ci,t} \left(\frac{R^{WLD}_{i,'15} - R^{WLD}_{i,'93}}{L^{WLD}_{i,'95}} \right) O_{i,'90}. \tag{13}$$

The first-stage relationship of the industry variation for both measures is presented in Figure 2. Note that the initial employment shares $l_{ci,t}$ are not instrumented for. The instrument validity thus rests on the assumption that the initial distribution of industries is exogenous conditional on the covariates included. I provide support for this assumption in the discussion of the main results.

Both instruments are very similar, but differ in one respect: $O_{i,'90}$, a US industry's 1990 share of imported intermediates is included only in the instrument for foreign robots. Thus not only an industry's increase in robot density matters for a Mexican local labor market's exposure to foreign robots, but also whether that industry in the US was initially highly reliant on offshoring.

The key estimating equation to identify and quantify the effect of robots on local employment in Mexico between t and $t + 1$ thus becomes:

$$\Delta \begin{matrix}\text{employment-to-} \\ \text{population} \\ \text{ratio}_{c,t:t+1}\end{matrix} = \alpha + \beta^d \begin{matrix}\text{exposure} \\ \text{to domestic} \\ \text{robots}_{c,t:t+1}\end{matrix} + \beta^f \begin{matrix}\text{exposure} \\ \text{to foreign} \\ \text{robots}_{c,t:t+1}\end{matrix} + \boldsymbol{X}_c'\gamma + \epsilon_c, \tag{14}$$

using the two *external exposure to robots*$_{c,t}$ variables as instruments. Standard errors are clustered by state.

5 Data

To estimate equation (14), I first construct commuting zones (CZs) as the unit of observation and then the key variables as described in this subsection. Summary statistics of all relevant variables are presented in Table A1 in the Appendix.

[11] Their measure is at the 4-digit SIC72 industry classification. To translate it to the broader IFR industry classification, I assign each SIC72 industry to one IFR industry and then calculate the employment-weighted average for each IFR industry. Data on employment by SIC72 industry is taken from the County Business Patterns (CBP). Again, I multiply $O_{i,'90}$ with 10 to make the means of both external exposure to robots variables comparable.

5.1 Commuting zones

Using local labor markets as a unit of observation is motivated by the mounting evidence that workers, and especially the low-skilled, are not perfectly mobile across space.[12] There are several potential definitions of local labor markets (counties, states, metropolitan areas). However, most of them have drawbacks: some represent political boundaries that do not necessarily coincide with economic boundaries (states, counties), others only cover urban areas (metropolitan areas).

Following a recent literature, I thus use *commuting zones* as the unit of observation.[13] CZs are clusters of municipalities that feature strong commuting ties within, and weak commuting ties across CZs. I define CZs in three steps: First, I cluster all municipalities within a *Zona Metropolitana* one larger municipality. Second, I compute the intensity of commuting from any municipality i to j (S_{ij}) by adding up the number of people commuting from i to j, and divide them by the number of residents in i. In a third step, I cluster municipalities together if more than 10% of residents of either municipality commute into the other. This results in 1,806 CZs (from 2,438 municipalities) and a defintion of local labor markets that is robust to the criticism of most alternative definitions: Unlike states or counties, this defitnition features economically relevant boundaries and, unlike metropolitan areas, it includes rural regions.

5.2 Change in employment, exports and Maquiladoras

The Instituto Nacional de Estadística, Geografía e Informática (INEGI) in Mexico conducted its first census at the municipality level in 1960. Since then, it repeated the census every ten years. Similar to other censuses, they contain a large number of variables for each individual, including employment status, wages, municipality of residence, municipality of work place, and education level. Data samples of about 1% of the population for 1960 and 1970, and 10% of the population for all the remaining censuses are available via IPUMS International (IPUMS, n.d.).

Given the cross-walk from municipalities to CZs, I aggregate the individual-level census data by CZ to construct the main dependent variable,

$$\Delta_{t:t+1} \begin{matrix}\text{employment-to-}\\ \text{population}\\ \text{ratio}_c\end{matrix} = \frac{L_{c,t+1}}{N_{c,t+1}} - \frac{L_{c,t}}{N_{c,t}},$$

where $L_{c,t}$ is private employment (excl. self-employed and public sector employment) and $N_{c,t}$ is the working-age population in commuting zone c and year t. The dependent employment variables and several control variables are constructed using census data from 1970, 1990, 2000 and 2015.

I also use two other outcomes to explore the mechanism behind the employment results, namely the change in exports and the number of Maquiladoras – Mexican export manufacturing firms exempt from tariffs on imported inputs – per capita. Data on export volumes

[12] Autor and Dorn (2013), Autor et al. (2013), Blanchard et al. (1992), Glaeser and Gyourko (2005), Malamud and Wozniak (2012)

[13] Atkin (2016), Autor et al. (2015) and Acemoglu and Restrepo (2017), among others

is not available at the municipality or CZ level. I therefore construct a Bartik-style measure of the change in exports per capita, using the initial industry employment shares across CZs from census data and industry-level changes in export volumes from Mexico to the US from the UN Comtrade database.

INEGI also provides data on the number of Maquiladoras on three levels of geographic granularity. First, at the CZ level for the 24 CZs with the most Maquiladoras per capita, second, on the state level for the 16 states with fewer ones, and third, on a national level for the remaining states with almost no Maquiladoras. To get estimates of the number of Maquiladoras per capita also for the CZs with no separate detailed information, I subdivide the remaining CZs into two groups (with information by state and by country, respectively) and allocate the respective number of Maquiladoras in a Bartik-style manner among the CZs in each group according to their initial share of manufacturing employment within that group. For example, if a state were comprised of 100 CZs, 10 of which featured detailed Maquiladora information, I allocate the state-wide data point among the 90 remaining CZs proportional to their initial share of overall manufacturing employment in those 90 CZs. This data underwent a major reclassification in 2007. Therefore I focus on the change in the number of Maquiladoras between 2007 and 2015.

5.3 Exposure to domestic robots

I construct the two main explanatory variables of interest – *exposure to domestic robots* and *exposure to foreign robots* – by combining census and trade data with robot data from the International Federation of Robotics (IFR). 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, 2014, 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, 2014, p.29).

Typical applications of industrial robots are pressing, welding, packaging, assembling, painting and sealing, all of which are common in manufacturing industries; as well as harvesting and inspecting of equipment, which are prevalent in agriculture and the utilities industry, respectively (IFR, 2014, p.31–38).

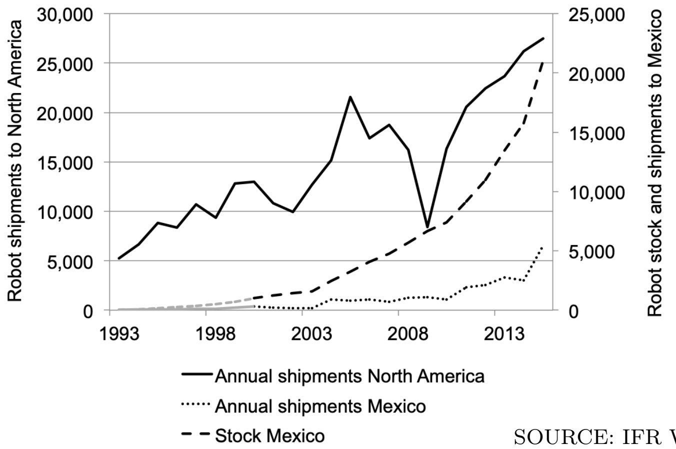
Ideally, I would use data on robot installations per CZ directly to measure increases in robot density. However, robot data on such a granular geographical level does not exist. Instead, and in line with the theory presented before, I construct a Bartik-style estimate based on the number of robots per industry and the distribution of employment across industries and CZs. I will refer to this as *exposure to domestic robots*[14]:

$$\begin{matrix}\text{exposure to} \\ \text{domestic robots}_{c,t:t+1}\end{matrix} \equiv \sum_{i \in I} \ell_{ci,t} \left(\frac{R_{i,t+1} - R_{i,t}}{L_{i,t}} \right), \tag{15}$$

[14]Analogous to "US exposure to robots" in Acemoglu and Restrepo (2017).

where $\ell_{ci,t} = L_{ci,t}/L_{c,t}$ denotes industry i's share of total employment in CZ c in year t, and $R_{i,t}$ is the stock of robots per industry i in year t. Using only the distribution of employment across CZs in the beginning of the period (and not in $t+1$) is useful to avoid any mechanical correlation with the dependent variable. This measure is referred to as *exposure to* domestic robots, since variation is driven by CZs' initial conditions rather than actual robot installations.

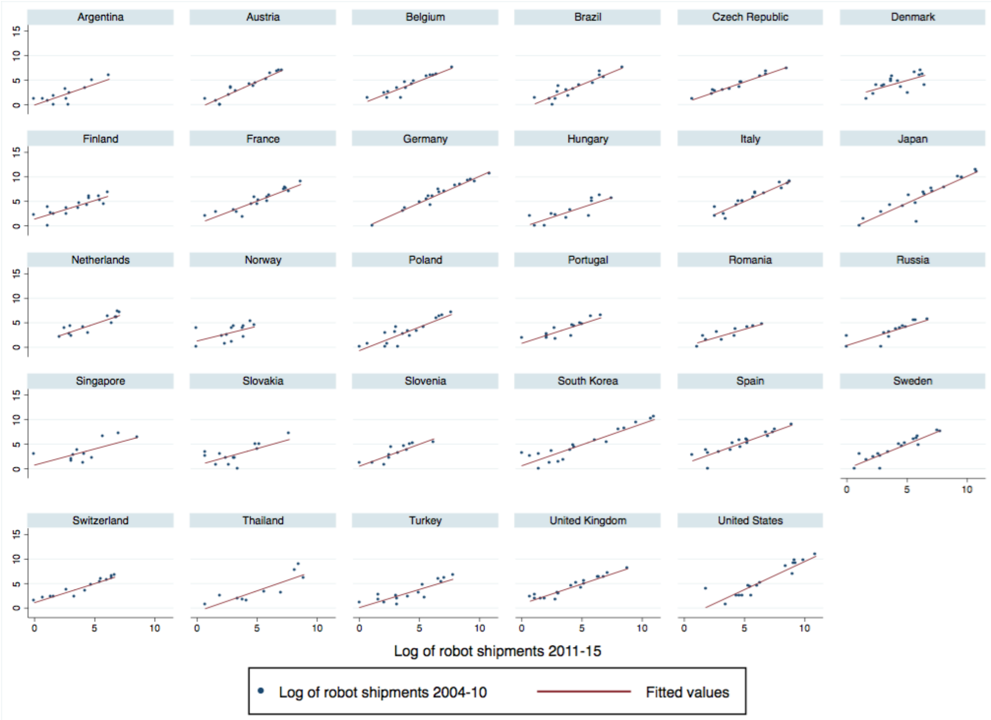
This is a good approximation of the actual number of robots employed in each CZ if each industry's robots are distributed across CZs proportional to the industry's initial share of employees in each CZ. For example, if 10% of the Mexican automotive industry's employment had been located in Saltillo in 1990, it is assumed that subsequently 10% of the automobile industry's robots have been installed in Saltillo. Acemoglu and Restrepo (2017) present some empirical evidence for the US that this is a sensible assumption. Their analogous robot exposure measure shows a strong association with both the presence and number of robot integrators in US commuting zones (cf. Figure 6 and Table A6 in their paper).



SOURCE: IFR World Robotics Database

Figure 3: Reported annual robot shipments to North America (solid) and extrapolated robot stock in Mexico (dashed), 1993–2015. The solid line shows the reported figures for annual shipments of robots to North America (left axis). The dotted line shows the corresponding values for Mexico (right axis). Based on this, Mexico's share of annual robot shipments to North America can be calculated for 2000-2015. An exponential function is then fitted through the reported shares in order to extrapolate the shares for 1993-1999. Multiplying those with the corresponding annual values of the solid line yields extrapolated annual shipments of robots to Mexico from 1993–1999. Summing up these annual shipments, and assuming an average lifetime of twelve years per robot, results in the extrapolated robot stock for Mexico (dashed line, right axis).

To estimate the long-difference specification, i.e., changes between 1990 and 2015, the initial number of robots in 1990 is required. Unfortunately, data on robot stocks in Mexico are not available for 1990. However, it seems reasonable to assume that the stock of robots was close to zero, given that (i) annual shipments of robots to North America were still relatively low in the beginning of the 1990's and (ii) Mexico's share of North American annual shipments only began its sharp rise in the late 2000's (cf. Figure 3). In fact, the IFR estimated the stock of robots in Mexico to be 301 in 2000, less than 2 percent of the value in 2015. I therefore assume that the number of robots per industry in Mexico was zero in 1990.



SOURCE: IFR World Robotics Database

Figure 4: Relationship between industries' robot shipments 2011–2015 and 2004–2010

Moreover, the IFR only started reporting Mexican robot shipments *by industry* in 2011. As they calculate their robot stock values by simply adding up robot shipments over the last twelve years, the shipments between 2004 and 2010 are missing in the reported robot stock values for 2015. This may cause a biased industry variation in Mexico's reported robot stocks if the industry variation between 2004 and 2010 was not highly correlated with the one between 2011 and 2015. Fortunately, industry-level data exists from 2004 onwards exists for 29 other countries. Figure 4 provides visual evidence about the relationship between robot shipments from 2011–2015 and their corresponding values from 2004–2010 by industry for all such 29 countries. There is a strong positive correlation in each of those countries. For this reason, I use the observed industry variation between 2011 and 2015 and impose it on the reported aggregate values between 2004 and 2010. Doing so yields a half-predicted stock of robots per industry in Mexico in 2015. This is likely to be a plausible estimate of the industry variation in robot stock growth from 1990 to 2015 and 2000 to 2015, given that Mexican robot stocks were likely zero in 1990 and less than two percent of their 2015 value in 2000.

5.4 Exposure to foreign robots

In light of the large share of exports-producing employment in Mexico and the emergence of reshoring, it is important to include the exposure to *foreign* robots when examining the impact of robots in employment in Mexico. Motivated by Equation (9), I construct a measure of exposure to *foreign* robots as:

$$\begin{matrix}\text{exposure to} \\ \text{foreign robots}_{c,t:t+1}\end{matrix} \equiv \sum_{i \in I} \ell_{ci,t} \left(\frac{R^{US}_{i,t+1} - R^{US}_{i,t}}{L_{i,t}} \right) F_{i,t} \tag{16}$$

Note that I only use US robots, as exports to the US represent the majority, or about 80% of overall Mexican exports between 1990 and 2015. I measure $F_{i,t}$ by dividing imports from Mexico to the US (from the UN Comtrade database) by total US output (from the US Bureau of Labor Statistics) in industry i at time t. A CZ's exposure to foreign robots is thus high if it was highly specialized in industries where (a) US industries have employed many robots per Mexican worker and (b) US output relied heavily on Mexican imports intially.

5.5 Computers and Chinese import competition

A contemporaneous shock that might affect the results is the replacement of routine jobs by computers (computerization). Data on routine task intensity does not exist on the occupation classification level used in Mexican censuses. As a workaround, I use occupation-level data on routine task intensity in the US from Autor and Dorn (2013). As the occupation classifications used in the US and Mexican census vary from one another, I first aggregate occupations to common occupation groups. In a second step, I use the arithmetic means of routine task intensity across the various occupations within an occupation group.[15]

Another relevant contemporaneous shock that I control for is the increase in import competition from China both at home and abroad. I use data on trade flows – most importantly Chinese imports to Mexico and the US – from the UN Comtrade Database. Starting in 1992, this database contains data on trade flows from China to Mexico and the US by 6-digit HS industry classification. The control variable *exposure to Chinese import competition* takes into account changes in Chinese imports to Mexico as well as the United States, discounting the latter by the initial reliance of US industries on Mexican imports. It accounts for the fact that an exports-oriented country not only competes with Chinese imports at home, but also in foreign markets. It is constructed as a Bartik-style measure equivalent to the *domestic plus international exposure to Chinese imports* in Autor et al. (2013), namely:

$$\begin{matrix}\text{exposure to} \\ \text{Chinese import} \\ \text{competition}_{c,t:t+1}\end{matrix} \equiv \sum_{i \in I} \ell_{ci,t} \left[\frac{\left(I^{CNMX}_{i,t+1} - I^{CNMX}_{i,t}\right) + F_{i,t}\left(I^{CNUS}_{i,t+1} - I^{CNUS}_{i,t}\right)}{L_{i,t}} \right],$$

where $I^{CNMX}_{i,t}$ and $I^{CNUS}_{i,t}$ indicate the value of imports from China to Mexico and the US, respectively, in industry i at time t.

6 Empirical results

In this section, I present the empirical results along with robustness checks. Moreover, I discuss the implied magnitude of the impact of robots on employment in Mexico, and break

[15] This implicitly assumes that each occupation within an occupation group has equal weight. While this may not be perfectly precise, it seems to be the best approximation given the available data.

it down by subgroups. Finally, I shed light on the mechanisms by examining more outcomes, in particular export values and number of Maquiladora factories.

6.1 Main results

The results from the OLS estimation of Equation (9) in Section 3 are shown in Table 1. Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the state level in all specifications.[16]

Panel A presents results for the long difference, 1990–2015. The baseline specification in column (1) includes only dummy variables for eight broad geographic regions as covariates. It shows a positive, insignificant coefficient for exposure to *domestic* robots and a negative, significant one for exposure to *foreign* robots. In particular, the estimates imply a 2.7 percentage points smaller increase in the employment-to-population ratio between 1990 and 2015 for a CZ with an average exposure to foreign robots (0.97). This estimate is significant at the 5% significance level. The results may, however, suffer from omitted variable bias, as they include only regional fixed effects as covariates.

To account for this bias and allow for differential trends along several characteristics, I start by adding baseline demographic characteristics and broad industry shares in column (2). In particular, I add log population size, share of males, share of working-age population, share of population 65 or more years old, and the shares of people with primary, secondary and tertiary education as their highest degree, respectively, and the initial shares of employment in manufacturing, durable manufacturing (defined as the wood products, minerals, basic metals, metal products, industrial machinery, electronics, eletrical equipment and automotive industry), agriculture, construction, mining and services.[17] This slightly reduces the effect of foreign robots in absolute terms, and does not alter its significance.

As mentioned before, a few contemporaneous changes may have had an impact on employment between 1990 and 2015 while being correlated with the exposure to robots variables. To control for the most important ones, I thus include in column (3) the initial share of routine tasks as a measure of a CZ's exposure to computerization, and the exposure to contemporaneous Chinese import competition, and a measure of exposure to US import reliance, which is defined as the main effect of the interaction term included in the exposure to foreign robots variable. The latter is to rule out that changes in US import demand, which may have changed for other reasons, drive the results. Accounting for these contemporaneous changes does not alter the qualitative results, but increases the absolute size of the effect of foreign robots from 2.3 to 3.2. This likely accounts for the fact that as the exposure to foreign robots variable includes initial trade shares, it is important to account for the most

[16] Abadie et al. (2017) show that in models without fixed effects, a necessary condition for clustering standard errors is clustering in the assignment of a treatment. Figure A1 suggests that there is some geographical clustering in the treatment intensity.

[17] Acemoglu and Restrepo (2017) also include the share of female employment in manufacturing. Doing so does not change the results, however, shrinks the sample by more than 10% as some CZs had no manufacturing employment in 1990, and thus the share of female employment in manufacturing is not computable. I therefore do not include this measure.

Table 1: Impact of exposure to robots on employment (OLS)

	(1)	(2)	(3)	(4)	(5)
			Panel A. 1990–2015		
Exposure to *domestic* robots,	1.157	1.157	1.306	1.071	1.533*
1993–2015	(1.197)	(0.998)	(0.845)	(0.674)	(0.810)
Exposure to *foreign* robots,	-2.768**	-2.317**	-3.224***	-2.940***	-2.776***
1993–2015	(1.175)	(0.945)	(1.025)	(0.833)	(0.980)
Observations	1,806	1,806	1,806	1,806	1,793
R^2	0.424	0.498	0.517	0.557	0.473
			Panel B. 1990–2000		
Exposure to *domestic* robots,	-8.293	-3.549	-3.112	-6.053	9.182
1990–2000	(9.090)	(8.807)	(8.809)	(8.767)	(10.689)
Exposure to *foreign* robots,	1.870	1.620	2.240	2.902	-1.441
1990–2000	(1.789)	(1.639)	(1.628)	(1.768)	(2.291)
Observations	1,805	1,805	1,805	1,805	1,792
R^2	0.087	0.144	0.149	0.176	0.140
			Panel C. 2000–2015		
Exposure to *domestic* robots,	0.797	0.413	3.882**	3.205	2.822
2000–2015	(0.692)	(0.750)	(1.866)	(1.917)	(1.979)
Exposure to *foreign* robots,	-1.412***	-1.257***	-2.996***	-2.552**	-2.279**
2000–2015	(0.288)	(0.288)	(0.972)	(1.011)	(1.047)
Observations	1,805	1,805	1,805	1,805	1,792
R^2	0.469	0.515	0.526	0.601	0.400
Region dummies	✓	✓	✓	✓	✓
Baseline covariates		✓	✓	✓	✓
Computers, China trade & import reliance of US			✓	✓	✓
Initial conditions				✓	
Remove top 0.5%					✓

Notes: The dependent variable in Panels A, B and C is the change in the employment-to-working-age-population ratio per CZ from 1990–2015, 1990–2000 and 2000–2015, respectively. Column (1) includes fixed effects for eight broad regions in Mexico. Column (2) also includes baseline CZ demographics (i.e., log population size, share of men, share of working-age people, share of people 65 years or older, and the shares of people with primary, secondary and tertiary education as their highest degree, respectively) and several broad baseline industry employment shares (i.e., shares of employment in manufacturing, durable manufacturing, agriculture, construction, mining and services). Column (3) also controls for the share of routine jobs in the baseline year following Autor and Dorn (2013), contemporeaneous exposure to Chinese import competition from following Autor et al. (2013), and the initial exposure to US Mexican-import reliance (i.e., the main effect of the interaction in the exposure to foreign robots variable). Column (4) also includes the baseline employment-to-population ratio. Column (5) includes the same controls as column (3), but excludes the top 0.5% of observations with regards to each of the exposure to robots variables. All regressions are weighted by working-age population in 1990. Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the state level (31 states). The coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

important drivers of trade integration during this period, i.e., NAFTA and the opening up of China, which have put upward pressure on employment on some of the industries that have simultaneously been robotized.

In column (4), I include the initial employment-to-population ratio to check for robustness against mean reversion. The data generating process of employment-to-population ratios may be mean-reverting. In that case, any CZs with temporarily high initial values would likely feature falling employment-to-population ratios in the subsequent years, and vice versa. If these variations were correlated with the exposure to robots variables, the results may in reality be driven by mean reversion. Adding the initial conditions would capture such mean-reverting dynamics. Doing so also does not alter the qualitative or quantitative results. Thus I conclude that mean reversion seems not to be the driving force behind the results.

Finally, I run the same regression as in column (3) again, but exclude the top 0.5 percent of all observations with regards to each of the exposure to robots variables in column (5). This is to rule out that only a few observations at the very top of the distribution drive this result. Doing so does not significantly alter the result, except that the effect of domestic robots has become larger and slightly significant.

Next, I examine two shorter time periods, 1990–2000 and 2000–2015, to understand more about the timing of these estimated effects. The results are reported in Panels B and C, respectively. Panel B suggests that domestic robots had no effect on the employment-to-population ratio between 1990 and 2000. While measurement error in the exposure to robots variables for this period may also partly explain this result, it seems plausible. Robot adoption in Mexico was very low in the 1990s (cf. Figure 3), which is consistent with no detectable effects of domestic robots before 2000. Moreover, the number and quality of robots started their rapid increase only in the 2000s, potentially explaining why any robust effects of domestic and foreign robots are only visible after 2000.

The effect of foreign robots, though insignificant, is now positive in most specifications. One potential explanation for the non-negative effect of foreign robots from 1990 to 2000 is that in the middle of this period, in 1994, NAFTA came into effect, leading to an increase in exports to the US. As Mexican exports are concentrated in similar industries as US robots, this may have counteracted any negative effect US robots may have had.

Panel C shows that the results from the long-difference specification before stem from the later period, 2000–2015. The pattern is similar to and slightly more robust than the one shown in Panel A. In this later period, there is some evidence for a positive effect of domestic robots on employment, although it is not robust across specifications. In general, these patterns suggest that in the early stages of robotic automation, its effect on employment outcomes was weak.

The effect in the long-difference estimation seems to stem from the later period, 2000–2015. For this reason, and to better purge the results from contemporaneous effects due to NAFTA, I focus on that period from now on. Next, I run the reduced form and two stage least squares regressions, using the *external exposure to robots* variables as described before. The results are presented in Table 2. The main goal of using these variables is to rule out potential endogeneity caused by contemporaneous shocks to Mexican and US industries, or highly specialized Mexican commuting zones. The reduced form results are shown in Panel A, and are qualitatively similar to the OLS results. Again, there is a robust, negative, detectable effect of foreign robots, and some evidence for a positive effect of domestic robots on employment. However, the positive effect of domestic robots seems to be largely driven by a few observations at the top of the distribution, as evident in the coefficient becoming much smaller and turning insignificant in column 5.

Panel B presents the estimates from the two stage least squares IV estimation using the external exposure to robots variables as instruments. Panels C and D report the corresponding first-stage results. The IV results show an almost identical pattern as the OLS and reduced form estimations. The effect of foreign robots on employment remains negative and robust across all specifications. Accounting for other contemporaneous changes, in particular trade shocks, still seems to be quantitatively important. Moreover, there is still some evidence for domestic robots having a positive effect on employment. The first-stage results show that the external exposure to robots variables are relevant instruments. In Panels C and D, the designated instruments are stongly correlated with their corresponding endogenous counterpart throughout all specifications. In columns (3) to (5), *only* the designated instruments predict the endogenous regressor.[18] The Kleibergen-Paap rank F-statistic is larger than 10 in all specifications, suggesting that it is not the same instrument explaining both endogenous regressors (i.e., that the model is not underidentified).

The fact that the IV results are relatively similar to the OLS results may have been anticipated as the endogenous exposure variables were already Bartik-style measures, which already abstract from variation caused by specific local conditions. Moreover, Panel B of Figure 2 suggests that the industry variation of US robots is very similar to that in the rest of the world, and thus does not seem to be particularly affected by Mexican labor market conditions. The results therefore suggest that endogeneity concerns affecting industry variation seem not to cause a large bias in the prior results. The raw residual plot of the change in the employment-to-population ratio and external exposure to foreign robots is shown in Figure 5 to bolster confidence that this result is not driven by a few outliers or a certain combination of covariates.

Identification using these instruments rests on a few assumptions: First, and most importantly, local initial employment shares in the industries driving the difference between both exposure to robots variables are assumed to be uncorrelated with the error term.[19] In the instruments of both exposure to robots variables, I do not instrument for the initial employment shares, although they drive part of the variation. Any correlation of the initial

[18] In columns (1) and (2), both instruments predict both endogenous regressors, but even in these, the designated instrument is related to its endogenous counterpart more significantly than the remaining instrument.

[19] As discussed and formally shown in Goldsmith-Pinkham et al. (2018), the key identifying assumption using Bartik-style instruments is best stated in terms of initial shares.

Table 2: Impact of exposure to robots on employment (reduced form and 2SLS)

	(1)	(2)	(3)	(4)	(5)
			Panel A. Reduced form		
External exposure to *domestic* robots	0.588	0.426	2.657*	3.320**	1.941
	(0.886)	(0.862)	(1.315)	(1.341)	(1.210)
External exposure to *foreign* robots	-2.644**	-2.421**	-5.830***	-6.557***	-4.316**
	(1.229)	(1.158)	(2.045)	(2.052)	(1.856)
			Panel B. 2SLS		
Exposure to *domestic* robots	1.050	1.004	4.196**	5.288***	3.252*
	(1.034)	(1.009)	(1.891)	(1.985)	(1.922)
Exposure to *foreign* robots	-1.507***	-1.474***	-3.113***	-3.507***	-2.410**
	(0.407)	(0.403)	(0.958)	(0.980)	(0.974)
Kleibergen-Paap rank F	12.64	19.81	26.99	27.28	19.07
			Panel C. First-stage, domestic		
External exposure to *domestic* robots	1.040***	1.096***	0.548***	0.551***	0.499***
	(0.176)	(0.132)	(0.122)	(0.123)	(0.134)
External exposure to *foreign* robots	-0.786***	-0.809***	0.058	0.055	0.139
	(0.239)	(0.171)	(0.180)	(0.181)	(0.204)
			Panel D. First-stage, foreign		
External exposure to *domestic* robots	0.334***	0.457***	-0.115	-0.116	-0.131
	(0.116)	(0.112)	(0.128)	(0.129)	(0.138)
External exposure to *foreign* robots	1.207***	1.091***	1.951***	1.952***	1.979***
	(0.163)	(0.156)	(0.191)	(0.191)	(0.214)
Region dummies	✓	✓	✓	✓	✓
Baseline covariates		✓	✓	✓	✓
Computers, China trade & import reliance of US			✓	✓	✓
Initial conditions				✓	
Remove top 0.5%					✓
Observations	1,805	1,805	1,805	1,805	1,792

Notes: The dependent variable in Panels A and B is the change in the employment-to-working-age-population ratio per CZ from 2000–2015, and in Panels C and D the exposure to domestic and foreign robots per CZ from 2000–2015, respectively. Column (1) includes fixed effects for eight broad regions in Mexico. Column (2) also includes baseline CZ demographics (i.e., log population size, share of men, share of working-age people, share of people 65 years or older, and the shares of people with primary, secondary and tertiary education as their highest degree, respectively) and several broad baseline industry employment shares (i.e., shares of employment in manufacturing, durable manufacturing, agriculture, construction, mining and services). Column (3) also controls for the share of routine jobs in the baseline year following Autor and Dorn (2013), contemporeaneous exposure to Chinese import competition following Autor et al. (2013), and the initial exposure to US import reliance (i.e., the main effect of the interaction in the external exposure to foreign robots variable). Column (4) also includes the baseline employment-to-population ratio. Column (5) includes the same controls as column (3), but excludes the top 0.5% of observations with regards to each of the exposure to robots variables. All regressions are weighted by working-age population in 1990. Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the state level (31 states). The coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

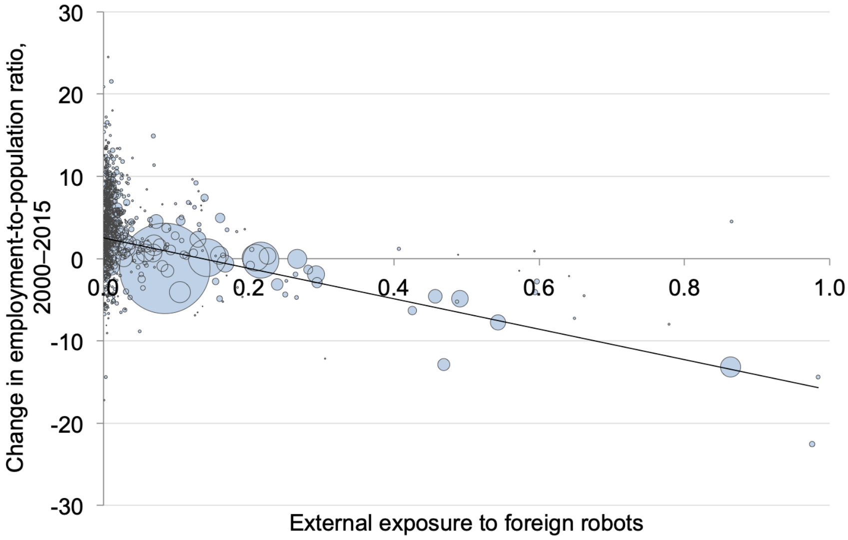


Figure 5: Relationship between employment-to-population ratio and external exposure to foreign robots, 2000–2015. This figure presents the residual plot of the change in the employment-to-population ratio and the external exposure to foreign robots. Bubble size indicates a CZ's share of the overall working-age population in 1990. The black line represents the fitted line without partialling out any covariates, using 1990 working-age population as weights.

shares with the error term may thus threaten identification. While it is impossible to test for their correlation with unobservables, one can at least test whether CZs that have the largest difference in the exposure to domestic relative to foreign robots have similar observable characteristics. Columns Q1 to Q4 in Table A1 report summary statistics of selected covariates used in the specifications, ranging from the quartile of CZs relatively most exposed to foreign robots (Q1) to the one relatively most exposed to domestic robots (Q4). It is reassuring that the averages in the first and fourth quartile are not significantly different from each other for all but two of the 17 observable characteristics I include, namely the share of males and the exposure to Chinese import competition.

Second, the *invention* of robots is assumed to be unrelated to local labor market conditions in Mexico. In reality, firms can decide whether they invest in the invention of automation technology or offshore production to save labor costs. As Mexico is an open economy taking part in global trade, firms in robot-inventing countries may take labor market conditions in Mexico into account in their decision. In that case, this assumption may be violated. However, Mexico trades mostly with the United States, which has not been at the forefront of the invention of robots. In fact, there is evidence that the invention of robots is largely driven by demographic trends in countries such as Germany, South Korea and Japan, which are geographically far away from Mexico and have never been highly reliant on Mexican production (cf. Acemoglu and Restrepo (2018)).

Third, the *adoption* of robots in countries outside of Mexico and the US is assumed to be unrelated to local labor market conditions in Mexico. In reality, industries across countries are in competition with one another. Local labor market conditions in Mexico may thus affect Mexican and US robot adoption, which in turn may affect world robot adoption. In this story, the reverse causality would carry all the way through to the instrument. While it is certainly true that industries are in competition with each other across countries, the fact that Mexico exported relatively little to the 18 countries used in the instrument makes this scenario somewhat unlikely.

Fourth, I assume that there has been no global shock differentially affecting industries across the world in the same way as robots. This scenario cannot be fully ruled out. In an attempt to control for the arguably two most important such candidates, I control for routine share intensity (computerization) and Chinese import competition also in the reduced form specifications from column (4) onwards. Moreover, I include robots in the most highly-robotized industry, automotive, separately in the robustness checks below. The results for the effect of foreign robots are robust against this, thus not lending support to this alternative explanation.

6.2 Robustness checks

In this subsection, I perform robustness checks against some alternative explanations. To start with, I examine the period between 1970 and 1990 to rule out that long-run negative employment trends in precisely those industries that had the largest increase in robot usage abroad drive these results. I therefore estimate the identical regressions as in Table 1, only that now the dependent variable is the 1970–1990, and not the 1990–2015 change in the employment-to-population ratio. I present the OLS and reduced form results alongside each other. As I argued before, the numbers of robots in Mexico and the US were likely close to zero in the period before 1990. Thus there should be no detectable effect of robots on employment between 1970 and 1990.

The OLS and reduced form results are reported in Panels A and B of Table 3, respectively. It is reassuring that almost all coefficients on the exposure to foreign robots variables are insignificant. However, the OLS coefficients in columns (1) and (3) in Panel A are positive and slightly significant. This has a plausible explanation: If the exposure to foreign robots captures any effects of *reshoring*, it is likely to capture the effects of *offshoring* in the pre-period. In the late 1960s, Mexico introduced their *Maquiladora* program, which allowed the duty-free import of materials for assembly and subsequent export of the manufactured goods, and is to a large extent responsible for Mexico's status as a typical manufacturing offshoring country today. The positive coefficient on the exposure to foreign robots thus likely captures the effects of that program. Figure 6 presents the residual plot of changes in the employment-to-population ratio between 1970 and 1990 and the external exposure to foreign robots between 1993 and 2015. It becomes visible that the industries most affected by foreign robots had been, if at all, on the *opposite* trend prior to robotization. The results of this exercise thus lend no support to the view that preexisting trends are responsible for the results.

Table 3: Impact of exposure to robots on employment (pre-tends)

	(1)	(2)	(3)	(4)	(5)
	Change in employment-to-population ratio, 1970–1990				
	Panel A. OLS				
Exposure to *domestic* robots, '93–'15	-0.317	0.277	-0.229	-0.569	0.263
	(1.022)	(0.736)	(0.640)	(0.467)	(1.440)
Exposure to *foreign* robots, '93–'15	2.090**	0.630	1.534**	0.880	0.813
	(0.851)	(0.680)	(0.743)	(0.591)	(1.763)
	Panel B. Reduced form				
External exposure to *domestic* robots, '93–'15	3.916**	2.017**	0.561	1.147	0.340
	(1.449)	(0.846)	(0.712)	(0.689)	(0.995)
External exposure to *foreign* robots, '93–'15	-2.945	-1.512	1.115	-0.596	1.567
	(1.876)	(1.155)	(1.006)	(0.886)	(1.372)
	Change in employment-to-population ratio, 2000–2015				
	Panel C. OLS				
Exposure to *domestic* robots	0.741	0.442	4.214**	3.939*	3.176
	(0.708)	(0.764)	(1.904)	(2.052)	(2.018)
Exposure to *foreign* robots	-1.368***	-1.286***	-3.180***	-2.951**	-2.470**
	(0.299)	(0.292)	(0.994)	(1.090)	(1.069)
Change in employment–to–population ratio, '70–'90	-0.026	0.032	0.045	0.109***	0.058**
	(0.028)	(0.031)	(0.027)	(0.026)	(0.026)
	Panel D. Reduced form				
External exposure to *domestic* robots	0.612	0.445	2.820**	3.811**	2.132*
	(0.894)	(0.853)	(1.307)	(1.388)	(1.216)
External exposure to *foreign* robots	-2.639**	-2.474**	-6.114***	-7.371***	-4.631**
	(1.230)	(1.140)	(2.036)	(2.153)	(1.875)
Change in employment–to–population ratio, '70–'90	-0.027	0.030	0.041	0.108***	0.055**
	(0.028)	(0.030)	(0.028)	(0.027)	(0.027)
Region dummies	✓	✓	✓	✓	✓
Baseline covariates		✓	✓	✓	✓
Computers, China trade & import reliance of US			✓	✓	✓
Initial conditions				✓	
Remove top 0.5%					✓
Observations	1,788	1,788	1,788	1,788	1,775

Notes: The dependent variable is the change in the employment-to-working-age-population ratio from 1970–1990 in Panels A and B and from 2000–2015 in Panels C and D. Column (1) includes fixed effects for eight broad regions in Mexico. Column (2) also includes the same baseline CZ demographics and broad baseline industry employment shares as in Table 1. Column (3) also controls for the share of routine jobs in 1990 following Autor and Dorn (2013), exposure to Chinese import competition from 1990–2015 in Panels A and B, and 2000–2015 in Panel C and D, following Autor et al. (2013), and the initial exposure to US import reliance. Column (4) also includes the baseline employment-to-population ratio. Column (5) includes the same controls as column (3), but excludes the top 0.5% of observations with regards to each of the exposure to robots variables. All regressions are weighted by working-age population in 1990. Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the state level (31 states). The coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

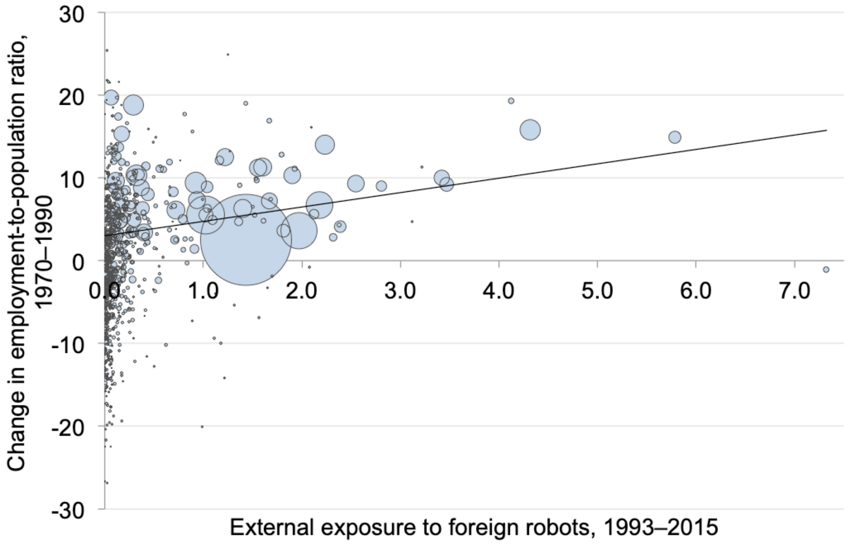


Figure 6: Relationship between changes in the employment-to-population ratio in the pre-period and external exposure to foreign robots. This figure presents the residual plot of the change in the employment-to-population ratio, 1970–1990 and the external exposure to foreign robots, 1993–2015. Bubble size indicates a CZ's share of the overall working-age population in 1990. The black line represents the fitted line without partialling out any covariates, using 1990 working-age population as weights.

In Panels C and D, I use another angle to test whether preexisting trends drive the results. I reestimate the OLS and reduced form specifications for the period between 2000 and 2015, however, now controlling for the change in the employment-to-population ratio between 1970 and 1990. If persistent trends in the outcome variable correlated with any of the exposure to robots variables drove the results, directly controlling for these trends should make the effect of this variable insignificant. It is reassuring that this is not the case. The effect of foreign robots remains essentially unchanged, while the effect of domestic robots becomes slightly less significant.

The use of robots per worker has increased the most in the automotive industry. It is therefore possible that much of the effect of robots found before is, in reality, due to some other shock that has affected the automotive industry in the same period. To test for this, I exclude robots used in automotive manufacture from both exposure to robots variables (and their external counterparts), and include them as a separate measure named *exposure to robots in automotive industry.*[20] If other shocks to the automotive industry indeed drove the results so far, the new *exposure to robots in other industries* variables should show no effect.

Table 4 presents the results of this estimation. Panel A presents the OLS results and Panel B the reduced form results. In the OLS results, the coefficient of the *exposure to domestic robots in other industries* is not significantly different from zero in any of the specifications. The

[20]Note that in this setting, it is impossible to separately estimate coefficients for the exposure to domestic and foreign robots in the automotive industry, as they only differ by the factor $F_{i,t}$ (or $O_{i,'90}$) and are thus collinear.

Table 4: Impact of exposure to robots on employment (controlling for automotive industry)

	(1)	(2)	(3)	(4)	(5)
			Panel A. OLS		
Exposure to *domestic*	-4.649	2.159	-2.114	-1.580	-2.948
robots in other industries	(4.434)	(4.323)	(3.700)	(3.457)	(3.922)
Exposure to *foreign*	-1.090***	-1.323***	-3.722***	-3.133**	-2.968**
robots in other industries	(0.312)	(0.264)	(1.041)	(1.142)	(1.093)
Exposure to robots	-1.950***	-2.158***	-2.204***	-1.980***	-1.780***
in automotive industry	(0.195)	(0.276)	(0.255)	(0.268)	(0.252)
			Panel B. Reduced form		
External exp. to *domestic*	0.223	1.182	2.188*	3.179**	1.774
robots in other industries	(1.413)	(1.309)	(1.199)	(1.185)	(1.220)
External exp. to *foreign*	-2.347	-3.016**	-6.098***	-6.636***	-4.449**
robots in other industries	(1.519)	(1.347)	(2.144)	(2.186)	(1.974)
Exposure to robots	-2.070***	-2.239***	-2.451***	-2.187***	-1.858***
in automotive industry	(0.186)	(0.259)	(0.335)	(0.327)	(0.336)
Region dummies	✓	✓	✓	✓	✓
Baseline covariates		✓	✓	✓	✓
Computers, China trade			✓	✓	✓
& import reliance of US					
Initial conditions				✓	
Remove top 0.5%					✓
Observations	1,805	1,805	1,805	1,805	1,792

Notes: The dependent variable in both Panels is the change in the employment-to-working-age-population ratio from 2000–2015. Column (1) includes fixed effects for eight broad regions in Mexico. Column (2) also includes the same baseline CZ demographics and broad baseline industry employment shares as in Table 1. Column (3) also controls for the share of routine jobs in the baseline year following Autor and Dorn (2013), contemporeaneous exposure to Chinese import competition following Autor et al. (2013), and the initial exposure to US import reliance (i.e., the main effect of the interaction in the respective exposure to foreign robots variables used). Column (4) also includes the baseline employment-to-population ratio. Column (5) includes the same controls as column (3), but excludes the top 0.5% of observations with regards to each of the exposure to robots variables. All regressions are weighted by working-age population in 1990. Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the state level (31 states). The coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

reduced form estimates still show a significant effect of domestic robots in columns (3) and (4), however, it becomes undetectable once a few observations at the top of the distribution are excluded. I can therefore not rule out that other shocks to the automotive industry drive the effect of domestic robots on employment found before. The coefficient of the *exposure to foreign robots in other industries* variable, however, remains negative and significant throughout all specifications in both the OLS and the reduced form estimation.[21] It is, reassuringly,

[21] Following the procedure explained in Goldsmith-Pinkham et al. (2018), I calculate the Rotemberg weights for each of the external exposure to robots variables (see Table A2). The Rotemberg weight of the automotive industry ranges from 0.58 to 1.50 across specifications for domestic robots, and from 0.16 to 0.56 for foreign robots. Another industry with high weight in the external exposure to foreign robots is electronics, ranging from 0.17 to 0.82. Conducting the equivalent robustness check for the electronics industry slightly reduces the effect of external exposure to foreign robots to –4.27 (p=0.02) in the specification in column (4).

similar in absolute size to the ones on the previous variables including automotive robots. This suggests that robots are, in fact, a similar technology across industries, without much variation in their relative productivity and that robots in different industries are substitutes for Mexican workers to a similar degree.

Table 5: Impact of exposure to robots on employment and migration

	(1)	(2)	(3)	(4)	(5)	(6)
	Δ log employment, 2000–2015			Δ log working-age, 2000–2015		
			Panel A. OLS			
Exposure to *domestic* robots	0.131	0.092	0.087	0.044	0.042	0.022
	(0.081)	(0.080)	(0.081)	(0.049)	(0.050)	(0.039)
Exposure to *foreign* robots	-0.106**	-0.082**	-0.073*	-0.034	-0.033	-0.016
	(0.040)	(0.040)	(0.042)	(0.024)	(0.024)	(0.020)
			Panel B. Reduced form			
External exposure to *domestic* robots	0.099	0.116*	0.061	0.052	0.051	0.031
	(0.067)	(0.057)	(0.062)	(0.040)	(0.040)	(0.039)
External exposure to *foreign* robots	-0.211**	-0.227**	-0.134	-0.093	-0.092	-0.049
	(0.099)	(0.086)	(0.096)	(0.059)	(0.059)	(0.059)
Region dummies & baseline covariates	✓	✓	✓	✓	✓	✓
Computers, China trade & import reliance of US	✓	✓	✓	✓	✓	✓
Initial conditions		✓			✓	
Remove top 0.5%			✓			✓
Observations	1,805	1,805	1,792	1,805	1,805	1,792

Notes: The dependent variable in columns 1–3 is the change in the log of the employment count between 2000 and 2015, in columns 4–6 the change in the log of the working-age population between 2000 and 2015. Columns (1) and (4) include fixed effects for eight broad regions in Mexico, 2000 CZ demographics (i.e., log population size, share of men, share of working-age population, share of people 65 years or older, and the shares of people with primary, secondary and tertiary education as their highest degree, respectively), 2000 industry employment shares (i.e., shares of employment in manufacturing, durable manufacturing, agriculture, mining, construction and services), exposure to US import reliance (i.e., the main effect of the interaction in the respective exposure to foreign robots variable used), the share of routine jobs in 2000 following Autor and Dorn (2013) and exposure to Chinese import competition from 2000–2015, following Autor et al. (2013). Column (2) and (5) also control for the initial conditions with respect to the outcome variable. Columns (3) and (6) are the same specifications as columns (1) and (4), but exclude the top 0.5% of observations with respect to each of the exposure to robots variables. All regressions are weighted by working-age population in 1990. Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the state level (31 states). The coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

The dependent variable in all specifications so far was the change in the employment-to-population ratio, as this is the standard measure used in this literature. In principle, changes in this ratio may arise from changes in employment or changes in the working-age population. The model predicts changes in employment, and the use of CZs is motivated by low rates of migration across CZs. It is therefore useful to test the model's prediction of changes in log employment and implicit assumption low migration across CZs by estimating the model using the log employment count and the log working-age population as the dependent variable, respectively. This is done in columns (1)–(3) and (4)–(6) of Table 5, respectively. The results show that the negative effect of foreign robots on the employment-to-population ratio stems, in fact, from changes in employment and not in the working-age population. The positive effect of domestic robots found in some specifications before is not detectable any-more when using the log count of employment as opposed to the employment-to-population ratios. Moreover, columns (4)–(6) suggest that neither domestic nor foreign robots triggered a significant migration response, lending support to the view that CZs are a useful unit of observation.

6.3 Magnitude

Next, I turn to the magnitude of the impact of robots on employment in Mexico. Note that the empirical specifications include only a CZ's *exposure to* robots, not the number of installed robots directly. Thus the clean interpretation of the coefficients only allows for conclusions about employment-to-population ratio growth in CZs initally *specialized* in certain industries, not about the number of workers each robot substitutes for directly. I will, however, shortly discuss the implied magnitudes for the latter, for the hypothetical scenario that the exposure to robots variables perfectly measure a CZ's actual number of robots competing with labor. Moreover, note that these estimates only measure the effect of robots on *local* employment. In particular, they do not account for positive spillovers resulting from reductions in the overall price level from the use of robots in other CZs. The aggregate implications stated here are thus under the assumption that these spillovers are low.[22]

I run the two-stage least squares counterpart to Table 2, but now using the change in the *engagement*-to-population ratio as the dependent variable (i.e., including self-employed and public sector employees) to assess the magnitude of the effect of foreign robots on overall engagement. This broader measure allows for take-up of displaced employed workers as self-employed workers, laborers or public administrators, and is more informative to gauge the magnitude of the aggregate effect. Table 6 presents the results of this estimation. I focus on the results for foreign robots as I cannot rule out that the ones for domestic robots are purely driven by the automotive industry.

My preferred specification is column (4) as it includes the most control variables and uses information of all commuting zones. The coefficient in this specification implies that an increase in the exposure to foreign robots of one reduces the employment-to-population ratio growth by 2.5 percentage points. The average value of this variable is around 1.4. Therefore, a CZ with the average exposure to foreign robots experienced a 3.5 percentage points lower growth in the employment-to-population ratio. This implies that foreign robots reduced engagement in Mexico by about 2 million workers between 2000 and 2015.

This estimate allows me to shed some light on the share of US robots that seem to compete with Mexican labor. Acemoglu and Restrepo (2017) find that one robot reduces employment in the US by about 6 workers, and data from the World Development Indicators from the

[22]Acemoglu and Restrepo (2017) use the structure of their model to back out the aggregate effect. In their setup, such spillovers reduce the negative effect by about 10%.

Table 6: Impact of exposure to robots on engagement (2SLS)

	(1)	(2)	(3)	(4)	(5)
Exposure to *domestic* robots	6.037**	3.554***	5.360**	5.102**	5.569**
	(2.353)	(1.335)	(2.316)	(2.260)	(2.622)
Exposure to *foreign* robots	-2.341***	-1.709***	-2.609**	-2.464**	-2.787**
	(0.862)	(0.479)	(1.065)	(1.025)	(1.243)
First-stage F-statistics					
- *domestic*	321.8	522.9	1093.1	1107.0	339.3
- *foreign*	8779.3	10858.8	5832.2	5852.1	1790.0
- Kleibergen-Paap rank	12.64	19.81	26.99	27.41	19.07
Region dummies	✓	✓	✓	✓	✓
Baseline covariates		✓	✓	✓	✓
Computers, China trade & import reliance of US			✓	✓	✓
Initial conditions				✓	
Remove top 0.5%					✓
Observations	1,805	1,805	1,805	1,805	1,792

Notes: The dependent variable is the change in the engagement-to-working-age-population ratio from 2000–2015. Column (1) includes fixed effects for eight broad regions in Mexico. Column (2) also includes the same baseline CZ demographics and broad baseline industry employment shares as in Table 1. Column (3) also controls for the share of routine jobs in the baseline year following Autor and Dorn (2013), contemporeaneous exposure to Chinese import competition following Autor et al. (2013), and the initial exposure to US import reliance (i.e., the main effect of the interaction in the external exposure to foreign robots variable). Column (4) also includes the baseline employment-to-population ratio. Column (5) includes the same controls as column (3), but excludes the top 0.5% of observations with regards to each of the exposure to robots variables. All regressions are weighted by working-age population in 1990. Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the state level (31 states). The coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

World Bank shows that in 2015, the value added per worker in manufacturing (incl. construction) was about four times as high in the US as in Mexico. Between 2000 and 2015, 145,000 robots have been installed in the US. Given the differences in productivity described above, this implies that roughly half of all robots installed in the US must compete with Mexican labor to account for this aggregate effect of 2 million fewer jobs.

6.4 Subgroup analysis

In the following I break down the effect for the aggregate into subgroups of workers. In particular, I reestimate the IV specification column (4), Panel B of Table 2, but now with subgroup-employment-to-population ratios as the dependent variable. Figure 7 presents the results of this exercise. The thick bars represent point estimates of the coefficient on exposure to foreign robots. The thin lines on top of each bar correspond to its standard error. The upper panel presents estimates by gender and education, the middle one by occupation and the lower one by industry.

The effect of foreign robots is slightly more pronounced for men than for women, and strongest for those with primary school and university education. There is a small but insignificant positive effect on individuals with a high-school diploma. This may reflect the reverse mechanism

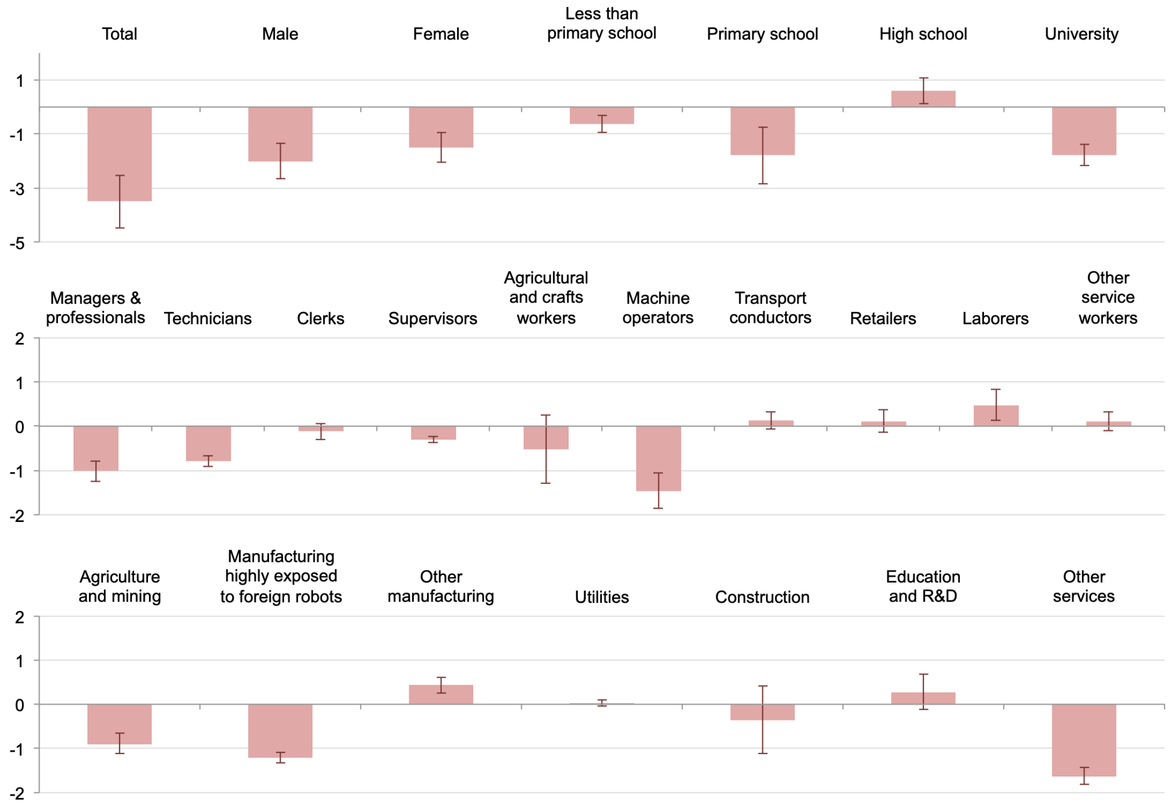


Figure 7: Impact of exposure to robots on employment by gender, education, occupation and industry. This figure plots the point estimates (thick bars) and standard errors (thin bars) of the exposure to foreign robots variable on different employment-to-population ratios. The specification is identical to the IV estimation in column (4), Panel B of Table 2, with the only difference that the dependent variables are now subgroup-specific employment-to-population ratios. The upper panel presents estimates by gender and education, the middle panel by occupation, and the lower panel by industry. For example, the dependent variable in the second column in the upper panel is the change in male employment over the entire working-age population in a CZ between 2000 and 2015.

of Atkin (2016), i.e., lower opportunity costs of staying in school for prospective high-school dropouts due to worsened labor market conditions from reduced offshoring activities. In terms of occupations, the effect stems mostly from machine operators, and the effect on university-educated workers is reflected in the estimates for managers and professionals. There is also a significant, negative effect on employment of technicians. The small, positive effect on employment of laborers may reflect some take-up of displaced machine operators. The effects across industries paint a similar picture, with the strongest negative effects in manufacturing industries that were highly exposed to US robots (i.e., automotive, electronics, metal products and minerals) and services, and small negative effects in agriculture and mining. The small positive effect on laborers is mirrored in a small increase in the employment in other, less robotized manufacturing industries.

While it is easy to imagine that robots have an effect on less-educated machine operators and technicians, it is not as clear why it should have such a strong effect on university-educated workers in managerial and professional occupations. Potential reasons for this are either above average employment of university-educated people and managers in the exports-producing sector or positive spillovers into such sectors. Cañas et al. (2013) provide some support for the latter, i.e., that Maquiladora production has particularly strong spillovers into the service sector (in particular transportation, finance, insurance, real-estate, legal and accounting).

Overall, the results from this analysis suggest that two groups of workers were negatively affected by foreign robots: First, less-educated machine operators and technicians in the manufacturing sector, and second, highly-educated managers and professionals in the service industry. From these results, it seems that the former group may have more successfully managed to sort into related occupations (laborers in less robotized manufacturing industries) than the latter.

6.5 Mechanism

If the reduction in employment due to foreign robots is indeed driven by reshoring, one should see a similar response in exports from Mexico to the US. To check for this, I use a Bartik-style measure of the change in Mexican exports to the US per worker between 2000 and 2015 as a dependent variable in columns (1)–(3) of Table 7. The results strongly support the narrative that foreign robots reduce the volume of exports, and thereby employment in the affected CZs. The effect of foreign robots is negative in all specifications, both in the OLS and IV estimations. On a national level, the estimates from the IV estimation in column (2) suggest that annual exports were roughly USD 51 billion lower as a result of foreign robots. On average between 2007 and 2015, a Maquiladora – a Mexican export manufacturing firm exempt from tariffs on imported inputs, and a main driver of Mexico's status as an offshoring country[23] – produced USD 15 million worth of exports utilizing about 380 employees.[24] Therefore, each employee contributed roughly USD 40,000 worth of exports. The estimated reduction of USD 51 billion in exports thus translates into about 1.3 million fewer employees, or about 65% of the total effect found for employment directly. This magnitude seems reasonable, considering the spillovers from reduced exports production into the domestic sectors shown in Section 6.4. Note, however, that the standard errors in this specification must be interpreted with caution, as both the dependent and explanatory variables of interest are based on the same initial employment shares.

In another attempt to test whether the effect of foreign robots indeed works via reshoring, I next consider the change in the number of Maquiladora factories per capita as the outcome variable. Maquiladoras are especially interesting to examine in this context as they are specialized in similar tasks as robots (assembly and processing of raw materials), produce only exports and make up about half of overall trade from Mexico to the US. Thus if robots in the US indeed fuel reshoring, their effect is likely to be visible in reduced numbers of Maquiladoras. Columns (4)–(6) of Table 7 therefore use the change in the number of Maquiladoras per 1,000 working-age people between 2007 and 2015 as the dependent variable. Both the OLS and the IV estimates confirm the negative effect of foreign robots found before in the

[23] Maquiladoras made up about 45% of Mexican exports in 2006

[24] Based on INEGI EMIME data.

Table 7: Impact of exposure to robots on exports to the US and Maquiladoras

	(1)	(2)	(3)	(4)	(5)	(6)
	Δ Exports per cap., 2000–2015			Δ Maq.'s per cap., 2007–2015		
			Panel A. OLS			
Exposure to *domestic* robots	4.442***	5.316***	4.323***	0.034***	0.047***	0.044**
	(0.319)	(0.280)	(0.341)	(0.011)	(0.015)	(0.017)
Exposure to *foreign* robots	-0.676***	-1.465***	-0.610***	-0.013**	-0.019**	-0.020**
	(0.024)	(0.024)	(0.020)	(0.040)	(0.040)	(0.042)
			Panel B. 2SLS			
Exposure to *domestic* robots	4.765***	5.704***	4.683***	0.050**	0.060***	0.048*
	(0.564)	(0.606)	(0.605)	(0.021)	(0.023)	(0.027)
Exposure to *foreign* robots	-0.814***	-1.654***	-0.758***	-0.020**	-0.025**	-0.022
	(0.270)	(0.334)	(0.290)	(0.009)	(0.011)	(0.014)
Region dummies & baseline covariates	✓	✓	✓	✓	✓	✓
Computers, China trade & import reliance of US	✓	✓	✓	✓	✓	✓
Initial conditions		✓			✓	
Remove top 0.5%			✓			✓
Observations	1,805	1,805	1,792	1,805	1,805	1,792

Notes: The dependent variable in columns (1)–(3) is a Bartik-style measure of the change in exports to the US in thousand USD between 2000 and 2015 per worker in 2000, and in columns (4)–(6) the change in the number of Maquiladora factories between 2007 and 2015 per working-age person in 2000. Columns (1) and (4) include fixed effects for eight broad regions in Mexico, the same 2000 CZ demographics and industry employment shares as in Table 5, exposure to US import reliance (i.e., the main effect of the interaction in the respective exposure to foreign robots variable used), the share of routine jobs in 2000 following Autor and Dorn (2013) and exposure to Chinese import competition from 2000–2015, following Autor et al. (2013). Column (2) and (5) also control for the initial conditions with respect to the outcome variable. Columns (3) and (6) are the same specifications as columns (1) and (4), but exclude the top 0.5% of observations with respect to each of the exposure to robots variables. All regressions are weighted by working-age population in 1990. Standard errors are robust against heteroskedasticity and allow for arbitrary clustering at the state level (31 states). The coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

employment regressions. The effect is significant throughout all specifications, except for column (3) in the IV estimation, where it becomes slightly insignificant (p=0.11). Areas more exposed to foreign robots thus experienced a significant fall in the number of Maquiladoras per person. The magnitude of the IV estimates in column (2) implies that a CZ with an average exposure to foreign robots experienced a decline in its number of Maquiladoras of 1.14, or 40%. Nationally, this translates into 2000 fewer such factories. Given that the average Maquiladora employs roughly 380 workers, this reduction between 2007 and 2015 seems to account for about 760,000 of the 2 million fewer jobs between 2000 and 2015.

7 Conclusion

In this paper, I investigate the impact of industrial robots on employment in an offshoring country, using the example of Mexico. Robots may have a distinct impact on employment in offshoring countries, as they potentially fuel reshoring by reducing the relative cost of domestic production in developed countries. Despite an increasing anecdotal evidence for reshoring, this is the first empirical analysis of the effect of robots on employment in offshoring countries.

Following a recent literature, I use a model in which robots compete against human labor to analyze the effect of both *domestic* and *foreign* robots on employment. In the basic model without trade across countries, the effect of domestic robots on employment in a local labor market depends linearly on its *exposure to domestic robots*. This exposure is defined by the penetration of domestic robots into each industry, weighted by its initial share of the respective industry's national employment. In light of the emergence of reshoring, I also consider an exports-producing sector, which may be affected by foreign robots. The effect of foreign robots on employment in a local labor market is identified via its *exposure to foreign robots*, defined by the penetration of foreign robots into each industry, weighted by its initial share of the respective industry's national employment, and the foreign industries' initial reliance on imports from the home country.

Data from the IFR and Mexican censuses allow me to construct empirical counterparts to these theoretical measures. In the baseline specification, I regress changes in the employment-to-population ratio between 1990 and 2015 on these exposure to robots variables. Using this methodology, I find a large, negative and robust effect of foreign robots on employment. This effect stems from the later period in the sample, 2000–2015, and is not visible in the period from 1990–2000. It is robust to allowing for differential trends regarding a number of covariates, including region dummies, CZ demographics, broad industry shares, computerization, Chinese import competition, US import reliance, as well as initial conditions.

In principle, these results may suffer from endogeneity caused by contemporaneous shocks to US and Mexican industries or specialized local labor markets, such as the introduction of NAFTA. To purge the analysis of bias caused by such endogeneity or measurement error, I apply an instrumental variable strategy. In particular, I instrument changes in the number of Mexican and US robots per Mexican worker with changes in robot density the rest of the world (neither US nor Mexico), and the share of Mexican imports of US output with a more general measure of offshoring. Doing so confirms the OLS results, suggesting that these endogeneity and measurement error concerns do not cause a large bias.

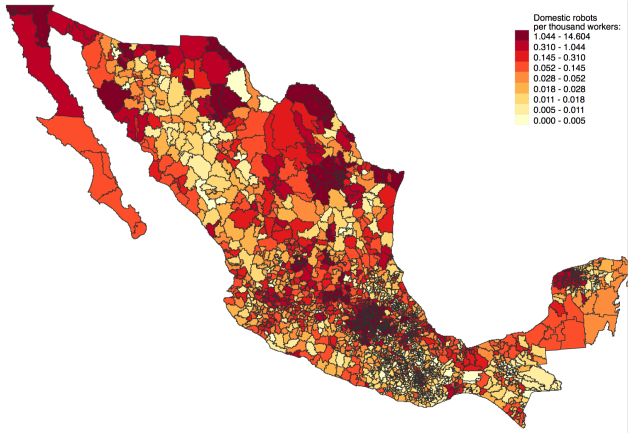
Moreover, I perform robustness checks to rule out alternative explanations. First, preexisting trends in industries in which robots are most heavily used seem not to be the driving force. A pre-period analysis, looking at the period 1970–1990, does not provide evidence for this alternative explanation. Second, the results for the effect of foreign robots are not only driven by the automotive industry, the industry robots are most prevalent in. Third, the effect is indeed driven by reduced employment, not any underlying migration patterns. The most affected groups of this negative effect are low-educated machine operators and technicians in manufacturing, and highly-educated service workers in managerial and professional occupations.

With regard to the magnitude of this effect, a local labor market with an average exposure to foreign robots experienced a 3.5 percentage points lower growth in the employment-to-population ratio, compared with no such exposure. At the national level, this amounts to roughly 2 million fewer jobs in Mexico, implying that roughly half of all US robots seem to compete with Mexican labor. This sizeable employment effect is mirrored in similar reductions in the export volume and the number of Maquiladoras, Mexican exports-manufacturing factories. This analysis, however, does not take into account potential countervailing spillover effects resulting from lower prices due to the use of robots. Moreover, alternative strategies to estimate the aggregate implications of robots on reshoring, such as cross-country comparisons, are obviously complementary to this within-country comparison approach. Moreover, a cross-country approach will help to gain an understanding to what extent these results are driven by the initial comparative advantage of the US and Mexico, or developed and offshoring countries in general.

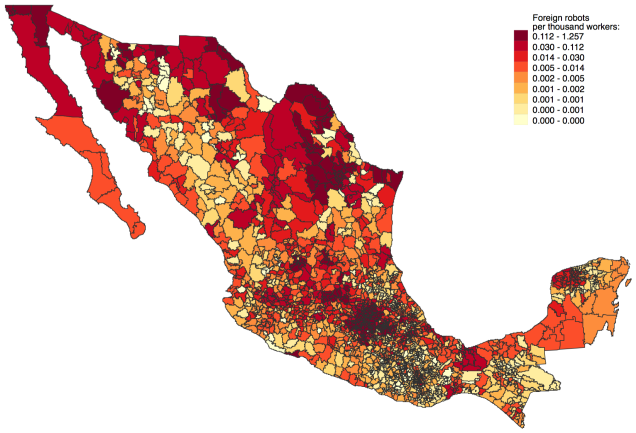
These limitations notwithstanding, the empirical results of this paper are at least worrying for offshoring and developing countries. Robot stocks in the developed world are expected to be three times as high as today by 2025, which will likely fuel reshoring further (BCG, 2015, p.7). Such rapid changes in employment patterns have been shown to foster political polarization in the United States (Autor et al., 2016). Given offshoring countries' combined population of about 3 billion, or 40% of the world's population, robots in developed countries seems to pose a threat to labor markets and, in turn, political stability, in the developing world. This paper offers first insights about potential causes of such instabilities. These may help to inform the debate about how to prevent or at least mitigate such effects.

A Appendix

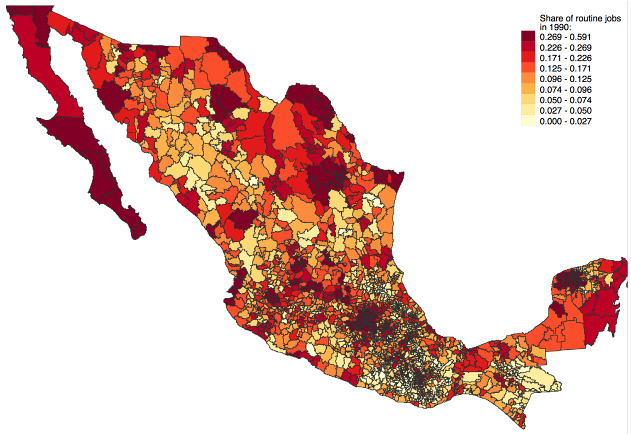
A.1 Figures and tables



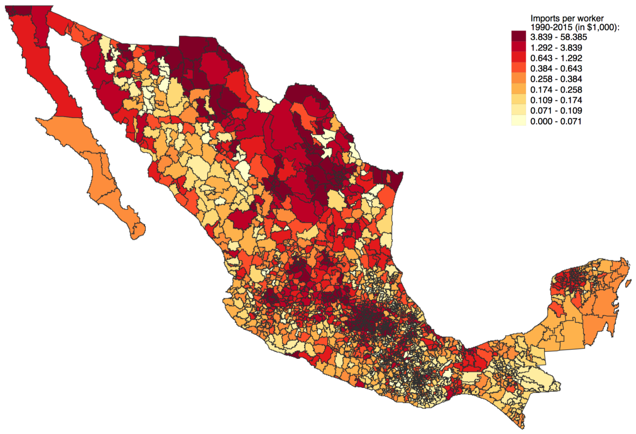
(a) Exposure to domestic robots, 1993–2015



(b) Exposure to foreign robots, 1993–2015



(c) Share of routine jobs, 1990



(d) Exposure to Chinese import competition, 1992–2015

Figure A1: Commuting Zone-level variation in exposures to domestic and foreign robots, computerization and Chinese import competition

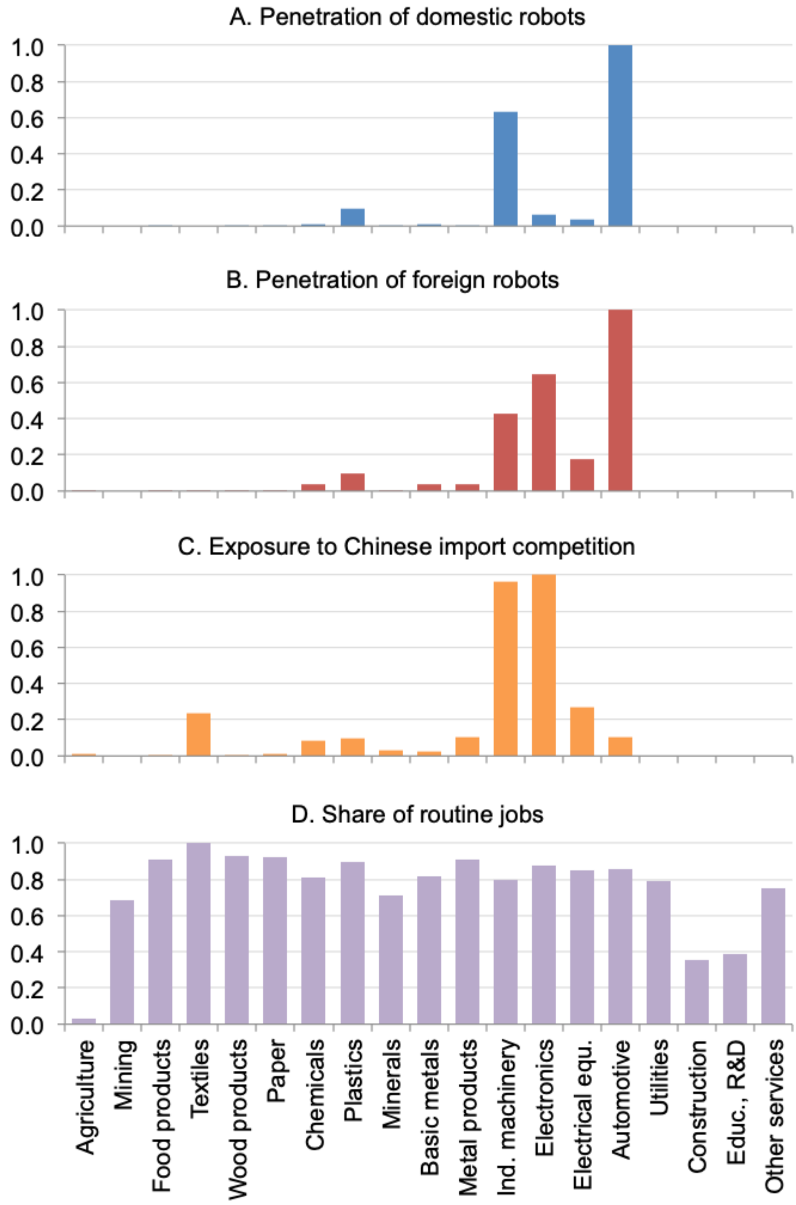


Figure A2: Industry-level variation in increase in domestic robots, foreign robots, US exports and Chinese imports per worker, and offshorability and computerization. Panel A presents the 2000–2015 increase in robots per worker in Mexico. Panel B shows the 2000–2015 increase in robots in the US per Mexican worker multiplied by each US industry's reliance on Mexican imports in 2000. Panel C presents the 2000–2015 increase in Chinese imports per worker (as defined in the text above). Panel D presents the share of routine jobs per industry in 2000 (following Autor and Dorn (2013)). All variables are normalized such that the industry with the highest value gets a value of one and the lowest gets a value of zero.

Table A1: Summary statistics

		Difference between standardized exposure to domestic and foreign robots			
	All CZs	Q1	Q2	Q3	Q4
		Panel A. Outcomes			
Change in outcome (2000–15)					
Employment-to-population ratio	0.796	0.336	2.718	3.914	0.041
	[4.125]	[4.588]	[4.635]	[4.190]	[3.008]
Log employment count	0.307	0.325	0.387	0.406	0.253
	[0.201]	[0.172]	[0.324]	[0.266]	[0.150]
Log working-age population	0.267	0.302	0.263	0.252	0.244
	[0.124]	[0.113]	[0.166]	[0.180]	[0.097]
		Panel B. Explanatory variables			
Exposure to robots (2000–15)					
Domestic minus foreign	-0.106	-0.399	0.011	0.021	0.074
	[0.430]	[0.602]	[0.002]	[0.003]	[0.131]
Domestic	0.550	0.768	0.048	0.040	0.597
	[0.857]	[1.104]	[0.123]	[0.032]	[0.717]
Foreign	1.427	2.317	0.111	0.080	1.301
	[2.223]	[3.025]	[0.284]	[0.074]	[1.523]
CZ demographics (2000)					
Share of men	0.487	0.489	0.491	0.487	0.484
	[0.011]	[0.011]	[0.015]	[0.016]	[0.009]
Working-age share	0.608	0.619	0.563	0.571	0.624
	[0.045]	[0.037]	[0.048]	[0.046]	[0.039]
Share with primary education*	0.530	0.542	0.462	0.479	0.546
	[0.061]	[0.050]	[0.078]	[0.066]	[0.046]
Share with secondary education*	0.150	0.153	0.093	0.101	0.171
	[0.060]	[0.049]	[0.064]	[0.058]	[0.054]
Share with tertiary education*	0.075	0.077	0.040	0.046	0.086
	[0.038]	[0.036]	[0.035]	[0.035]	[0.033]
Broad industry shares (2000)					
Manufacturing	0.181	0.215	0.093	0.091	0.192
	[0.094]	[0.102]	[0.073]	[0.056]	[0.071]
Durable manufacturing	0.064	0.08	0.093	0.091	0.192
	[0.047]	[0.052]	[0.073]	[0.056]	[0.071]
Agriculture	0.179	0.150	0.429	0.355	0.110
	[0.210]	[0.169]	[0.255]	[0.228]	[0.158]
Construction	0.079	0.084	0.073	0.085	0.076
	[0.028]	[0.023]	[0.039]	[0.040]	[0.024]
Exposure to contemporaneous changes					
Share of routine jobs (2000)	0.241	0.259	0.158	0.176	0.260
	[0.073]	[0.066]	[0.077]	[0.073]	[0.056]
Chinese import comp. (2000–15)	2.322	3.966	0.411	0.316	1.867
	[2.639]	[3.630]	[0.464]	[0.257]	[0.982]
Initial conditions (2000)					
Employment-to-population ratio	36.138	39.221	26.525	27.923	37.555
	[9.156]	[8.564]	[11.037]	[9.890]	[6.107]

Note: To define Q1 to Q4, I first standardized both exposure to robots variables to have a mean of zero and standard deviation of one, and then computed the difference of the standardized exposures to domestic minus foreign robots.

*As highest degree obtained.

Table A2: Top Rotemberg weights for exposure to robots variables, 2000–2015

	(0)	(1)	(2)	(3)
	A. External exposure to domestic robots			
Automotive	0.579	1.500	1.500	1.438
Agriculture	0.353	0.121	0.110	0.141
Electronics	0.092	–1.681	–1.677	–1.697
Electrical equipment	0.066	1.168	1.161	1.317
Construction	0.010	0.001	0.000	0.009
Mining	0.004	–0.004	–0.004	–0.003
	B. External exposure to foreign robots			
Automotive	0.559	0.158	0.155	0.195
Agriculture	0.312	–0.030	–0.028	–0.035
Electronics	0.171	0.812	0.817	0.759
Electrical equipment	0.034	–0.158	–0.159	–0.170
Construction	0.010	–0.001	0.000	–0.002
Food and beverages	0.004	0.393	0.390	0.403
Region dummies		✓	✓	✓
Baseline covariates & contemp. changes		✓	✓	✓
Initial conditions			✓	
Remove top 0.5%				✓

Notes: This table presents the six industries with the highest Rotemberg weights in a specification without covariates for each external exposure to robots variable, following the procedure described in Goldsmith-Pinkham et al. (2018). Panels A and B present the Rotemberg weights for the external exposure to domestic and foreign robots between 2000 and 2015, respectively. Column (0) includes no covariates. Column (1), (2) and (3) include all covariates included in columns (3), (4) and (4) of Table 2, respectively.

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