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 lower the relative cost of domestic production and, in turn, reduce 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. 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 construct a similar measure of exposure to *foreign* robots, based on the initial geographic distribution of export-producing employment across industries, industry-level robot adoption in the US, and a US industry's initial reliance on Mexican imports. To purge results from endogeneity, I use robot adoption in the rest of the world and an index of offshoring as instruments for robot adoption in the US and the share of Mexican imports, respectively. Using these instruments, I show that US robots have a sizeable negative impact on employment in Mexico. This negative effect is stronger for men than for women, and strongest for low-educated machine operators in the manufacturing sector. Consistently with reshoring as a mechanism, I find that the employment effect is mirrored in similarly large reductions in Mexican exports and export-producing plants.

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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. Yet 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 enabling the performance of precisely these tasks at home. Despite the lack of scientific evidence for this mechanism, there is growing anecdotal evidence that advances in robot capabilities can fuel so-called 'reshoring', heralding the potential 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 with a focus on *developed* countries. Graetz and Michaels (2018) were 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 (2020) have 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 (see 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 unclear 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 may decide to not offshore or even 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 thus have the potential to fuel reshoring.

Recent examples of this reshoring process are the new proto-type "Speedfactories" of the German sportswear company Adidas. Traditionally, companies in this industry had offshored production to cheap labor locations like China, Vietnam, and Indonesia. In contrast, the new

[1] See, for example, The Economist (2013), Harvard Business Review (2014) or The Economist (2017).

[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, Puerto Rico, and the Bahamas, respectively.)

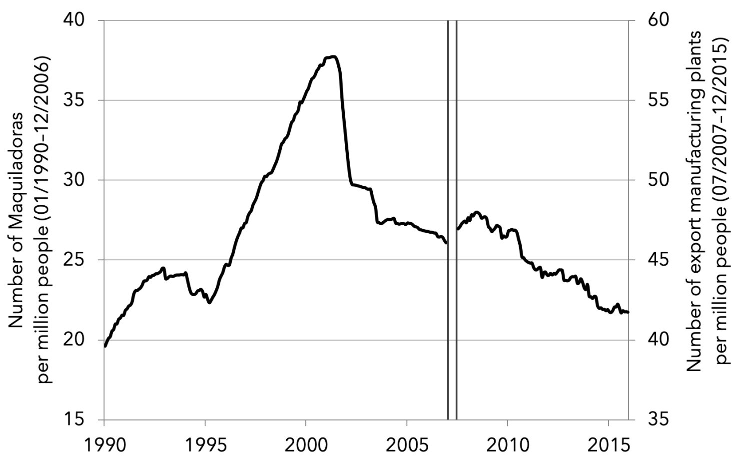
[3] Using a similar strategy, Dauth et al. (2019) conduct an analysis for Germany, and find no effect of robots on overall employment, but negative effects on manufacturing employment and, in particular, earnings of machine operators.

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

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 Speedfactories employ about 160 people locally in Ansbach and Atlanta, compared with more than 1,000 in a typical factory in an offshoring location (The Economist, 2017).

Mexico is one example of such a location, as it has relied heavily on offshoring – for the most part from the US – in recent decades. Historically, offshoring by US firms has taken the form of shipping parts and components to Mexico for assembly into final goods, which are then shipped back to the US. This division of tasks has been supported by the introduction of the so-called *Maquiladora* system in 1965, which exempts dedicated export-producing firms from tariffs on imported inputs. As a result, Maquiladoras have become an essential part of the Mexican economy, with an increase in their share of manufacturing employment from 4 percent in 1980 to 28 percent in 2002 (Hanson, 2007).

However, in recent years, the number of Maquiladoras and other export-producing factories in Mexico has been falling. Figure 1 depicts the development in the number of such factories from 1990 to 2015. Following a growth spurt after the introduction of NAFTA in 1994 and a sharp drop after the US recession of 2001, the number of factories per million people has been steadily declining since the early 2000s. One potential explanation for this is the invention of industrial robots that are also capable of assembling intermediate inputs into final goods.



SOURCE: INEGI

Figure 1: Number of export-producing factories per millon people in Mexico, 1990-2015. Data for 01/1990-12/2006 and 07/2007-12/2015 are taken from INEGI's EMIME and IMMEX data series respectively. The discontinuity in the first half of 2007 is due to a reclassification between the two data series from counting only Maquiladora plants to also including export-producing factories that are not part of the Maquiladora program.

In this paper, I estimate the effect of *domestic* and *foreign* robots on employment in Mexico. I use 1990-2015 data from Mexican local labor markets (i.e., commuting zones, CZs) as

[5] These nine other countries are Denmark, Finland, France, Germany, Italy, Norway, Spain, Sweden, and the United Kingdom – all countries for which industry-level data on annual shipments of industrial robots exists from 1993 (1996 for Denmark) onwards.

well as robot shipment data for Mexico, the US and nine other countries.[5] Similarly to Acemoglu and Restrepo (2020), 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 export-producing sector, which may be affected by US robots. I estimate the effect of US robots on local employment via a similar measure, namely, the exposure to *foreign* robots. This measure uses the US national adoption of robots in each industry, the local distribution of export-producing employment across industries, and the initial reliance of the US on imports from Mexico. These variables may suffer from endogeneity resulting from an industry's or a 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 robot stocks in Mexico and the US with robot stocks in the rest of the world (i.e., 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, contemporaneous changes to single industries (e.g., the automotive industry), or migration patterns across local labor markets driving the results and find no support for these. Notably, the negative effect of foreign robots on employment is evident and quantitatively similar in *i)* long difference specifications exploiting only differences in exposure to foreign robots across CZs within the same time period, *ii)* stacked difference specifications exploiting both the geographic and the temporal variation in CZs' exposure to foreign robots, as well as *iii)* stacked difference specifications exploiting only differences in exposure to foreign robots within the same CZ across time periods.

The estimates imply that a local labor market with an average exposure to US robots experienced a 0.43 percentage point lower growth in the employment-to-population ratio between 1990 and 2015, compared with no such exposure. At the national level, this amounts to about 270,000 fewer jobs in Mexico. This suggests that roughly 5 percent of all US robots compete with workers in Mexico. The negative effect of US robots on Mexican employment is stronger for men than for women, and strongest for low-educated machine operators in the manufacturing industry. To shed light on the mechanism behind this employment effect, I show that it is mirrored in similarly sized reductions in exports from Mexico and also reductions in export-producing plants, corroborating the view that robots foster reshoring.[6]

A number of recent studies empirically investigate the impact of robots on middle- and low-income countries. Studies drawing on variation across countries and industries find somewhat mixed results. On the one hand, Artuc et al. (2018) find that greater robot adoption in the developed world leads, on average, to a rise in imports from developing countries and an even greater increase in exports from developed ones.[7] On the other hand, Krenz et al. (2018)

[6] It is noteworthy that this may reflect either less production moving to Mexico or more production moving back to the US. Both types of effects likely have similar implications for the two countries.

[7] Crucially for this paper, this main result changes when they focus on the United States, where they find that greater robot adoption does not lead to a rise in imports from developing countries.

document a positive association between increased robot density and reshoring. Similarly, De Backer et al. (2018) find evidence for robots in developed countries reducing the rate of offshoring in recent years. Carbonero et al. (2018) also find that robots in developed countries reduce offshoring to emerging countries, and, moreover, find strong negative effects on employment in these countries.

Only recently, two studies have emerged that also exploit plausibly exogenous geographical variation in robot exposure within countries. Artuc et al. (2019) also examine the impact of US robots on Mexican local labor markets. They find that US robots reduce exports from Mexico to the US as well as manufacturing employment in areas specialized in tasks susceptible to being replaced by robots, but do not find a negative effect on overall employment. The identification strategy in this paper differs from theirs, as it relies solely on revealed comparative advantages of local labor markets prior to the advent of robots (i.e., before 1990), makes no assumption that robots differ systematically in their capabilities across industries between developed and developing countries, and exploits variation in robot exposure not only across local labor markets but also across time periods.[8] More recently, Stemmler (2019) has adopted a similar strategy for Brazil, and finds that foreign robots decrease manufacturing employment through reduced exports of final goods.

The remainder of this paper is stuctured as follows: Section 2 presents the basic model that serves as a basis for the empirical strategy, and describes how I complement this basic model with an export-producing sector to identify the effect of foreign robots on employment in Mexico. Section 3 lays out the empirical strategy and describes the instrumental variables. Section 4 reports the data sources and describes the construction of the data set. Section 5 presents the main results. Section 6 conducts several robustness checks. Sections 7 and 8 explore effect heterogeneity along several characteristics and the mechanism behind the main results, respectively. Section 9 concludes.

2 Theoretical framework

In this section, I start by briefly summarizing the main result of the theoretical model developed by Acemoglu and Restrepo (2020). Then I continue to explain how I complement this model with an export-producing sector to identify the effect of foreign robots on local employment.

2.1 Basic model

In Acemoglu and Restrepo (2020), robots compete against human labor in the completion 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

[8] In contrast, Artuc et al. (2019) rely on revealed comparative advantages in industry exports and employment in 2004 and 2000, respectively. Moreover, they instrument for foreign and domestic robots with two distinct instruments, namely increased robot density in a subset of countries in Europe for US robotization and, in Brazil, for Mexican robotization.

exposure to robots in each local labor market, which is defined by the national penetration of robots into each industry and the local distribution of employment across industries. In particular, their model in autarky yields the following general equilibrium expression for the change in employment in response to robotic automation:

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

where L_{ci} is employment in CZ c and industry i, dR_i is the change in the number of robots in industry i, $1/\eta$ is the elasticity of the supply of robots, $1/\epsilon$ is the Frisch elasticity of labor supply, $\gamma > 0$ is the relative productivity of labor, and π_c denotes the cost-saving gains from using robots instead of labor in a task.[9]

Acemoglu and Restrepo (2020) 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 equalized 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. The authors show that this model including trade between CZs results in the same reduced-form relationship between local employment and robots as in the autarky model, albeit with a more involved expression for β_c.

2.2 Incorporating foreign robots

In a world without trade *across* countries it would be sufficient to estimate the effect of robots on local employment using Equation (1) and data on employment and domestic robot installations in Mexico. However, employment in Mexico stems to a large extent from exports to the US.[10] Workers in the export-producing sector thus may not only compete with domestic, but also with foreign robots.

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, export-producing workers compete *only* with foreign robots. But also with imperfectly separable tasks and low transportation costs, importing firms are likely to install robots rather at home rather than abroad. One reason for this is the relatively high share of costs that result from the installation and maintenance of robots. This so-called *integration* is estimated to add an additional 40-150% to the costs of purchasing a robot (Hunt, 2012, p.37). Integrators "possess a unique set of expertise and knowledge (...) and specialize in various types of complex technical systems, from information and

[9] See Section A.3 in the Appendix for more details on the basic model.
[10] In 2015, Mexican exports to the United States made up roughly 30% of total Mexican GDP.

communications technology to energy distribution", skills that are likely to be found more easily in the US than in Mexico (Leigh and Kraft, 2018, p.11). Another reason is that robots may reduce the cost of production at home sufficiently to cause firms to reshore, as domestic production goes along with other strategic factors that seem to have become more important to firms in recent decades. Examples of such factors are proximity to the customer, quality control, and the possibility to do research and development on site.[11]

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 those 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 for the fact that offshorable goods are likely a specific subset of goods. They require a high degree of routine, a low degree of human interaction, and must be transportable over long distances (see Wright, 2014). I indicate whether an industry produces an offshorable or non-offshorable good with the indicator O_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 (such as construction), which seems implausible.[12]

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 $O_i = 1$ employ only labor in Mexico, and those in industries with $O_i = 0$ employ only labor in the US.[13] I allow the geographic distribution of industry employment in the export sector to differ from that in the industry as a whole, such that US firms in offshorable industries may allocate production across Mexico disproportionally to the domestic sector.[14]

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 not only compete with robots in Mexico (dR_i^d), but also with

[11] In fact, Eurofund (2019) found automation of production processes to be among the top three reasons for reshoring decisions of European firms. The other most often cited reasons were the firm's global reorganization, delivery time, poor quality of offshored products, and proximity to customers.

[12] 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.

[13] In reality, industries do not offshore all tasks, but only specific steps in the value chain. In the empirical analysis, instead of a binary indicator, I therefore use the share of offshorable tasks within an industry.

[14] This is likely to be the case if there are comparative advantages in exports production across regions, for example due to the proximity to the destination country or transportation hubs, such as roads, rivers, or the sea.

those in offshorable industries in the US ($dR_i^f O_i$), I rewrite Equation (1) as

$$d\ln L_c = \beta_c \underbrace{\sum_{i\in I} \frac{L_{ci}}{L_i}\frac{dR_i^d}{L_c}}_{\substack{\text{Exposure to}\\ \text{domestic robots}}} + \beta_c \underbrace{\sum_{i\in I} \frac{L_{ci}^f}{L_i^f}\frac{dR_i^f O_i}{L_c}}_{\substack{\text{Exposure to}\\ \text{foreign robots}}} + \epsilon_c. \tag{2}$$

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. The latter function allocates the number of US robots (dR_i^f) in each offshorable industry ($O_i = 1$) across Mexico proportional to each CZ's initial share of export-producing employment in that industry (L_{ci}^f/L_i^f). Summing up the number of allocated robots over all industries and dividing it by the total number of workers in that CZ yields the number of US robots per worker competing with Mexican labor in CZ c. For ease of exposition in the empirical analysis, I rewrite equation (2) as

$$d\ln L_c = \beta_c \sum_{i\in I} \ell_{ci}\frac{dR_i^d}{L_i} + \beta_c \sum_{i\in I} \ell_{ci}^f \frac{dR_i^f O_i}{L_i^f} + \epsilon_c, \tag{3}$$

where $\ell_{ci} = L_{ci}/L_c$ and $\ell_{ci}^f = L_{ci}^f/L_c$ denote the shares of overall industry i and the export-producing sector of industry i, respectively, of total CZ c employment.

3 Empirical strategy

Equation (3) 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

$$\begin{array}{c}\text{Exposure to}\\ \text{domestic robots}_{c,(t_0,t_1)}\end{array} \equiv \sum_{i\in I} \ell_{ci,1990}\left(\frac{R_{i,t_1}^{MX} - R_{i,t_0}^{MX}}{L_{i,1990}}\right) \qquad \text{and} \tag{4}$$

$$\begin{array}{c}\text{Exposure to}\\ \text{foreign robots}_{c,(t_0,t_1)}\end{array} \equiv \sum_{i\in I} \ell_{ci,1990}^f\left(\frac{(R_{i,t_1}^{US} - R_{i,t_0}^{US})O_{i,1992}}{L_{i,1990}^f}\right), \tag{5}$$

where $R_{i,t}^{MX}$ and $R_{i,t}^{US}$ are the (estimated) number of robots in industry i at time t in Mexico and the US, respectively.[15] $\ell_{ci,1990}$ measures the share of employment in industry i out of total CZ c employment in 1990, while $\ell_{ci,1990}^f$ is the share of *export-producing employment* in industry i out of total CZ c employment for the same year.[16] Following Acemoglu and Restrepo (2020), I keep the 1990 employment shares even when considering changes in sub-

[15] I use only US robots, as exports to the US represent the clear majority (about 80%) of overall Mexican exports between 1990 and 2015.

[16] In practice, it is difficult to identify *export-producing* employment as firms often produce for both the foreign and the domestic market. I use data on the number of employees in Maquiladoras – dedicated export manufacturing firms accounting for roughly half of Mexico's exports in 2005 – by industry and municipality in 1990 to measure $\ell_{ci,1990}^f$ and $L_{i,1990}^f$ in Equation (5). See Section A.4.2 in the Appendix for more details.

periods that start in 2000 (e.g., in stacked difference specifications), both because of data availability and to avoid endogenous and serially correlated changes in the exposure variables.

In contrast to the parameter presented in the theory, O_i is not measured as a binary variable indicating whether or not an industry-product is offshorable as a whole, but continuously, measuring what share of inputs into industry-good i are 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 $O_{i,1992} = I^{MXUS}_{i,1992}/Y^{US}_{i,1992}$ as industry i's share of Mexican imports in total US output for 1992.[17] I provide more detailed information about the sources and construction of these variables in Section 4.

The resulting exposure to domestic robots variable may, however, suffer from measurement error and endogeneity. First, there may be measurement error due to non-observed robot data for some of the years. This would cause OLS to underestimate the true effect. Second, it may be endogenous, as the decision by Mexican industries to adopt robots may directly depend on the development of labor market conditions in Mexican industries or highly specialized local labor markets. For example, if CZs highly specialized in automotive production experience tight labor markets (and thus have less room for expansion), the automotive industry in Mexico may decide to employ more robots instead. This would result in lower employment growth in local labor markets with high robot adoption, but the causality would be reversed.

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

$$\begin{matrix}\text{External exposure} \\ \text{to domestic robots}_{c,(t_0,t_1)}\end{matrix} \equiv \sum_{i \in I} \ell_{ci,1990} \left(\frac{R^{WLD}_{i,t_1} - R^{WLD}_{i,t_0}}{L_{i,1990}} \right), \tag{6}$$

where the superscript *WLD* indicates the sum over all nine countries of the robot data, except for the US and Mexico for which industry-level data exists from 1993 onwards.[18] I will from now on refer to this group of countries as the "rest of the world". The increase in robots in the rest of the world is conceivably less related to local labor market conditions in Mexico than actual robot adoption in Mexico. 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 Section 5.3.

Similarly, the close relationship between the US and Mexico 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. To

[17] 1992 is the earliest year for which data on imports from Mexico to the US by industry are available.

[18] These include Denmark, Finland, France, Germany, Italy, Norway, Spain, Sweden, and the United Kingdom. Denmark is an exception in that the IFR reported robot shipments by industry for the first time in 1996 instead of 1993.

follow the same example, if Mexican local labor markets specialized in automotive manufacturing had relatively high employment rates, and thus less room to expand, US automotive firms would have had a higher incentive to employ robots at home, and vice versa. Any such scenario would cause the OLS estimates to be biased.

Moreover, the initial share of Mexican imports in total US output may potentially 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, $\tilde{O}_{i,1990}$, 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). 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 the extent of offshoring across industries is mainly driven by an industry's task requirements and less by industry-specific skills in certain countries.

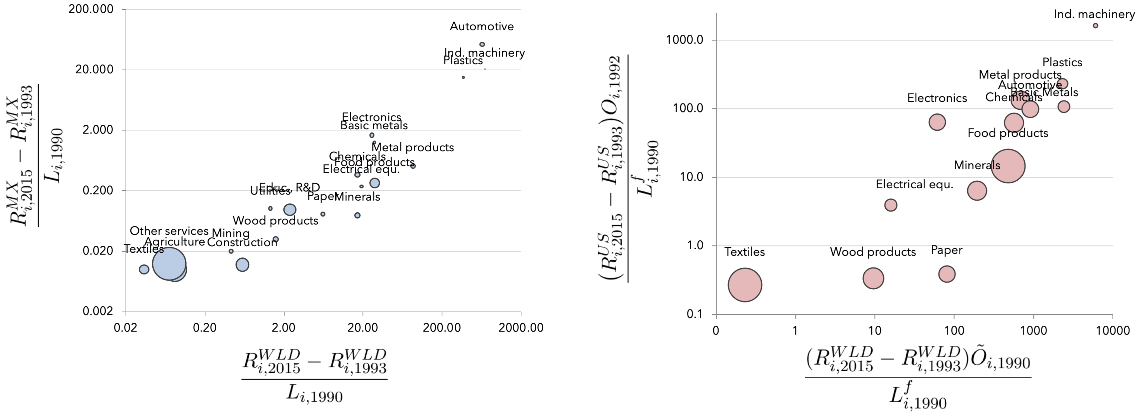
Substituting the increase in US robots with the increase in the robot stock in the rest of the world, and the initial share of Mexican imports in US output with the offshoring index defined above yields what I will refer to as *external exposure to foreign robots*:

$$\begin{array}{c}\text{External exposure}\\ \text{to foreign robots}_{c,(t_0,t_1)}\end{array} \equiv \sum_{i\in I} \ell^f_{ci,1990}\left(\frac{(R^{WLD}_{i,t_1} - R^{WLD}_{i,t_0})\tilde{O}_{i,1990}}{L^f_{i,1990}}\right). \tag{7}$$

Figure 2 depicts the first-stage relationship of the industry variation for both measures. Note that the initial employment shares $l_{ci,1990}$ and $l^f_{ci,1990}$, respectively, are not instrumented for. The instrument validity in the main specifications 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. Moreover, I also use an alternative specification that does not rely on this assumption, namely one exploiting only the temporal variation in exposure to robots within the same CZ, to bolster confidence in the results.

Figure A1 presents the geographic variation in the external exposure to domestic and foreign robots across Mexico. Note that only 251 out of 1,805 CZs have some exposure to foreign robots, as most CZs had no Maquiladora employment in 1990.[19] The correlation coefficient between the two measures is lower than 0.39 for any time period considered, thus leaving enough variation between the two measures to separately identify their effects.

[19] To ensure that the effects do not merely capture differences between Maquiladora and non-Maquiladora CZs, I also report results also using only the subset of CZs that had some Maquiladora employment in 1990.



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, 1993-2015. Panel A presents the industry-level variation between the exposure to domestic robots and 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 Panel B as they have values of zero by construction and cannot be represented on a logarithmic scale. Bubble size indicates Mexican industry employment in 1990.

The key estimating equation for identifying and quantifying the effect of robots on local employment in Mexico between t_0 and t_1 thus becomes

$$\Delta \begin{array}{c}\text{Employment-to-}\\ \text{population}\\ \text{ratio}_{c,(t_0,t_1)}\end{array} = \alpha + \beta^d \begin{array}{c}\text{Exposure}\\ \text{to domestic}\\ \text{robots}_{c,(t_0,t_1)}\end{array} + \beta^f \begin{array}{c}\text{Exposure}\\ \text{to foreign}\\ \text{robots}_{c,(t_0,t_1)}\end{array} + \boldsymbol{X}'_{c,1990}\gamma + \delta_t + \epsilon_{c,(t_0,t_1)}, \quad (8)$$

using the two *external exposure to robots*$_{c,(t_0,t_1)}$ variables as instruments. In the main results, I estimate Equation (8) using two stacked differences (1990-2000 and 2000-2015).[20] In this specification, I thus identify the effect of domestic and foreign robots using variation in exposures across 1,805 CZs and two time periods, conditional on differential trends along initial covariates $\boldsymbol{X}_{c,1990}$ and time period fixed effects δ_t. As alternative approaches, I also estimate *i)* the stacked difference specification including CZ trends, thus identifying the effect from differences in exposures within the same CZ over time, and *ii)* both short differences separately, thus identifying the effect from differences across CZs in the same time period. The latter will also provide insights as to the timing of the effect.

4 Data

To estimate Equation (8), I first construct *commuting zones* (CZs) as the unit of observation and then the key variables as described in this subsection. Summary statistics for all relevant variables are presented in Table A1 in the Appendix.

[20] As the two periods are of unequal length, all variables that measure changes are converted to 10-year equivalents in the second period.

4.1 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.[21] 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 recent literature, I thus use commuting zones (CZs) as the unit of observation.[22] 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* into 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. Third, I cluster municipalities 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 definition of local labor markets that is robust to the criticism of most alternatives: unlike states or counties, this definition features economically relevant boundaries and, unlike metropolitan areas, it includes rural regions.[23]

4.2 Employment, population and exports

The Instituto Nacional de Estadística, Geografía e Informática (INEGI) in Mexico conducted its first census at the municipality level in 1960. Since then, it has repeated the census every ten years and conducted an intercensal survey in 2015 to update the information from the 2010 census to the midpoint between the next census in 2020. Like other censuses, they contain a large number of variables for each individual, including employment status, wages, municipality of residence, municipality of workplace, 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 from IPUMS International (IPUMS, 2018).

Given the crosswalk between municipalities and CZs, I aggregate the individual-level census data by CZ to construct the main dependent variable,

$$\Delta \begin{array}{c}\text{Employment-to-}\\ \text{population ratio}_{c,(t_0,t_1)}\end{array} = \frac{L_{c,t_1}}{N_{c,t_1}} - \frac{L_{c,t_0}}{N_{c,t_0}}, \tag{9}$$

where $L_{c,t}$ is private employment (excl. self-employed and public sector employment) and $N_{c,t}$ is the working-age population in CZ c and year t.

I also consider changes in exports as an outcome variable. These come from Mexico's Tax

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

[22] Atkin (2016), Autor et al. (2015) and Acemoglu and Restrepo (2020), among others.

[23] A similar attempt by Atkin (2016) resulted in 1,808 CZs. One municipality, Nicolás Ruíz (population of approx. 3500), features only missing values in 2000, and is therefore dropped, resulting in a total of 1,805 CZs in all samples I use.

Administration Service (Servicio de Administración Tributaria, SAT) and contain data on exports by municipality between 2004 and 2014 on the HS92 product code level. These data do not contain information on the destination country, so that I cannot distinguish between exports to the US or other countries. However, given that roughly 80% of Mexico's exports are shipped to the US, it is likely that changes in exports to a large extent reflect changes in exports to the US.

4.3 Exposures to 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, 2015, 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, 2015, 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, 2015, p.31-38).

To measure the increase in robot density at the local level, I would ideally use data on actual robot installations per CZ. 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 (see Equation 4).[24] This measure is referred to as *exposure to* domestic robots, since variation is driven by CZs' initial conditions rather than by actual robot installations.

This is a good approximation of the actual number of robots installed in each CZ if each industry's robots are distributed across CZs proportional to the industry's initial share of employees in each CZ. As an illustrative example, if 5% of the Mexican automotive industry's employment were located in Saltillo in 1990, it is assumed that subsequently 5% of the automobile industry's robots have been installed in Saltillo. Acemoglu and Restrepo (2020) 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 CZs (Figure 5 and Table A8 in Acemoglu and Restrepo, 2020).

I estimate Equation (8) using two stacked differences (1990-2000, 2000-15). This requires data on the stocks of robots in Mexico, the US and the rest of the world by industry in the years 1990, 2000 and 2015. For the rest of the world, I choose the subset of countries in the IFR data for which industry-level data on robot stocks exists from the beginning of the

[24] Analogous to "US exposure to robots" in Acemoglu and Restrepo (2020).

sample.[25] For the US and Mexico, however, the IFR only started reporting robot shipments by industry in 2004 and 2011, respectively. Therefore, data on the industry distribution of robot shipments in these countries is missing in the years before. Following Acemoglu and Restrepo (2020), I therefore impute the industry distribution from all reported years on all missing years. Following the methodology used by the IFR, I then add up the (partly imputed) robot shipments of the last 12 years to obtain the robot stock for a specific year. For example, to obtain the robot stock by industry in Mexico in 2015, data on robot shipments by industry from 2004-2015 is needed. Since that breakdown is missing in the period 2004-2010, I allocate total robot shipments in these years according to their industry distribution in 2011-2015.[26]

I measure $O_{i,1992}$ 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 in 1992. In the external exposure to foreign robots measure, I instead use a more general measure of offshoring in US industries, $O_{i,1990}$, 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). 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.[27] Data on employment by SIC72 industry is taken from the County Business Patterns (CBP).

I compute 1990 employment shares by industry and CZ from publicly available census data (IPUMS, 2018). Data on Maquiladora employment come from CEPAL (1994). These data include the number of Maquiladora employees by municipality and industry. To aggregate these from the municipality to the CZ level, I apply the crosswalk described above. I then perform a few steps to make the data compatible with the industry classification used by the IFR (see Section A.4.2 for details).

4.4 NAFTA, Chinese import competition, computers and main effects

In the middle of the time period I am studying, in 1994, the North American Free Trade Agreement (NAFTA) came into effect. This led to changes in import and export tariffs for many industries. To the extent that these industry-level tariff changes are correlated with the industry variation in robots and offshorability, not accounting for NAFTA may bias the estimates. I therefore include a CZ's exposure to NAFTA as a covariate, based on its initial employment shares and NAFTA-induced tariff changes (from Hakobyan and McLaren, 2016):

$$\begin{array}{c}\text{Exposure to}\\ \text{NAFTA}_{c,1990}\end{array} \equiv \sum_{i \in I} \ell_{ci,1990} \Delta \tau_i. \tag{10}$$

[25] Except for Denmark, for which it started in 1996.

[26] The IFR data allows me to test whether the 2011-2015 industry distribution in robot shipments is a good indicator of that in 2004-2010 for 29 countries for which such data exists. Figure A2 provides visual evidence for this and shows that there is a strong positive correlation in each of those countries.

[27] See Table A9 for details on the harmonization of the different industry classifications.

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 to the United States, discounting the latter by the initial reliance of US industries on Mexican imports. It accounts for the fact that an export-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:

$$\begin{array}{c}\text{Exposure to}\\ \text{Chinese import}\\ \text{competition}_{c,(t_0,t_1)}\end{array} \equiv \sum_{i\in I} \ell_{ci,t_0} \left[\frac{\left(I^{CNMX}_{i,t_1} - I^{CNMX}_{i,t_0}\right) + O_{i,t_0}\left(I^{CNUS}_{i,t_1} - I^{CNUS}_{i,t_0}\right)}{L_{i,t_0}} \right], \tag{11}$$

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.

A third 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 censuses 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.[28]

The external exposure to foreign robots variable (Equation 7) is an interaction of several parts: in particular it contains *i)* a CZ's initial reliance on Maquiladora employment and *ii)* a CZ's initial exposure to US import reliance. To make sure that the estimated effect of foreign robots does not merely capture other shocks to Maquiladoras more generally or a change in the US's taste for Mexican imports unrelated to robots, I include the following variables as controls and refer to them as *main effects*:

$$\begin{array}{c}\text{Exposure to}\\ \text{Maquiladoras}_{c,1990}\end{array} \equiv \frac{L^f_{c,1990}}{L_{c,1990}} \quad \text{and} \quad \begin{array}{c}\text{Exposure to US}\\ \text{import reliance}_{c,1990}\end{array} \equiv \sum_{i\in I} \frac{L^f_{ci,1990}}{L_{c,1990}} \tilde{O}_{i,1990} \tag{12}$$

5 Main results

In this section, I present the empirical results on the impact of domestic and foreign robots on employment, investigate the timing of the effects, and discuss threats to identification. Then I discuss the implied magnitude of the impact of robots on employment in Mexico.

[28] 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.

5.1 The effect of domestic and foreign robots on employment

I start by estimating Equation (8) using two stacked differences (1990-2000 and 2000-2015). Reduced form results are reported in Panel A, and two-stage least squares results in Panel B of Table 1.[29] Standard errors are robust to heteroskedasticity and allow for arbitrary clustering at the CZ level in all specifications.[30] In most specifications, regressions are weighted by a CZ's 1990 share of the national working-age population.[31]

Column (1) presents the baseline specification including only dummy variables for eight broad geographic regions and two time periods as well as the main effects included in the exposure to foreign robots variable as covariates. This relatively parsimonious specification indicates that both domestic and foreign robots have a negative effect on the employment-to-population ratio. The effects of domestic and foreign robots are significant at the 10% and the 1% level, respectively. These estimates may, however, suffer from omitted variable bias, as they include only regional and time fixed effects as well as main effects as covariates.

To account for potential confounders, I allow for differential trends along a broad set of 1990 characteristics in column (2). In particular, I add a battery of demographic characteristics (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 level, respectively), broad industry employment shares (manufacturing, durable manufacturing, agriculture, construction, mining and services), and the initial conditions with respect to the outcome variable.[32] This considerably reduces the effect of domestic robots in absolute terms (-0.18 vs. -0.60) such that it becomes statistically insignificant. The effect of foreign robots becomes slightly stronger and remains significant at all conventional levels.

A few contemporaneous changes may have had an impact on employment between 1990 and 2015, and may be correlated with the exposure to robots variables. To control for the most important ones, I thus include in column (3) a CZ's exposures to NAFTA, Chinese import competition and computerization, as defined in Section 4.4. Accounting for these somewhat reduces the effect of foreign robots in absolute terms (-0.47 vs. -0.67) and leaves it significant at the 1% level.

Column (4) shows that the effect of foreign robots is almost identical in size and significance in the unweighted regression that includes the same covariates as column (3). In column

[29] In all results, the instruments are normalized to have the same mean and standard deviation as their endogenous counterparts. See Table A2 for OLS results.

[30] Adao et al. (2019) point out that with shift-share designs, there may be correlation across CZs with similar sectoral shares, independent of their geographic location. For this reason, I repeat the analysis at the industry level, which alleviates this concern. Main results remain the same and are reported in Section 6.4.

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

[32] Acemoglu and Restrepo (2020) also include the share of female employment in manufacturing. Doing so does not change the results, but 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

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

	(1)	(2)	(3)	(4)	(5)	(6)
	Change in employment-to-population ratio					
	Panel A. Reduced form					
External exposure to *domestic* robots	-0.60*	-0.18	0.34	-0.17	0.65*	-0.19
	(0.33)	(0.26)	(0.26)	(0.23)	(0.36)	(0.75)
External exposure to *foreign* robots	-0.63***	-0.67***	-0.47***	-0.49***	-0.57***	-0.53**
	(0.20)	(0.21)	(0.14)	(0.12)	(0.13)	(0.22)
	Panel B. 2SLS					
Exposure to *domestic* robots	-0.57*	-0.07	0.30	-0.17	0.58**	-0.11
	(0.33)	(0.23)	(0.24)	(0.24)	(0.29)	(0.33)
Exposure to *foreign* robots	-0.67***	-0.75***	-0.58***	-0.61***	-0.72***	-0.52**
	(0.18)	(0.19)	(0.14)	(0.16)	(0.13)	(0.23)
Kleibergen-Paap rank F	706	222	198	1318	159	104
	Panel C. First-stage, domestic					
External exposure to *domestic* robots	0.96***	1.12***	1.06***	0.93***	1.19***	2.32***
	(0.02)	(0.05)	(0.05)	(0.02)	(0.07)	(0.06)
External exposure to *foreign* robots	0.06***	0.05***	0.02	0.05***	0.02**	-0.03***
	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
	Panel D. First-stage, foreign					
External exposure to *domestic* robots	0.07*	0.14**	-0.03	0.01	0.06	-0.14
	(0.04)	(0.06)	(0.05)	(0.04)	(0.09)	(0.14)
External exposure to *foreign* robots	0.89***	0.89***	0.82***	0.79***	0.82***	1.02***
	(0.07)	(0.07)	(0.06)	(0.06)	(0.06)	(0.07)
Region, period & main effects	✓	✓	✓	✓	✓	✓
Baseline covariates		✓	✓	✓	✓	✓
Contemporaneous changes			✓	✓	✓	✓
Unweighted				✓		
Only Maquiladora CZs					✓	
CZ trends						✓
Observations	3,610	3,610	3,610	3,610	502	3,610

Notes: The dependent variable in Panels A and B is a CZ's change in the employment-to-working-age-population ratio (multiplied by 100), and in Panels C and D, the exposure to domestic and to foreign robots, respectively. Column (1) includes fixed effects for two time periods and eight broad regions in Mexico as well as the main effects from the interactions included in the external exposure to foreign robots variable (i.e., the exposures to Maquiladoras and US import reliance as described in the text). Column (2) also includes 1990 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 level, respectively), several broad 1990 industry employment shares (i.e., shares of employment in manufacturing, durable manufacturing, agriculture, construction, mining and services), and the 1990 level of the outcome variable. Column (3) also includes the share of routine jobs in 1990 following Autor and Dorn (2013), contemporaneous exposure to Chinese import competition following Autor et al. (2013), and the exposure to tariff changes from NAFTA. Column (5) includes the same controls as column (3), but excludes all CZs with no Maquiladora employment in 1990. Column (6) includes CZ trends (i.e., fixed effects in changes for all 1,805 CZs in the sample). All regressions except for column (4) are weighted by a CZ's share of the national working-age population in 1990. Standard errors are robust to heteroskedasticity and allow for arbitrary clustering at the CZ level. The coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

(5), I repeat the estimation in column (3), but now only for the subset of CZs with positive Maquiladora employment in 1990. The estimated effect of foreign robots remains negative, similar in size and significant at the 1% level, suggesting that the effect in the specifications before does not merely reflect differences between CZs with and without Maquiladora employment in 1990.[33]

Crucially, the stacked difference setting also allows me to include CZ trends, i.e., CZ fixed effects in changes. As Equation (8) is already in first differences, CZ fixed effects in levels are already accounted for. However, it remains possible that CZs exposed to domestic or foreign robots were on differential trends for reasons that are not picked up by the large battery of control variables included in columns (1)-(5). Although this is a demanding specificaton, exploiting only variation in exposure to domestic and foreign robots *within* CZs over time, and not across CZs within the same time period, results in column (6) remain almost identical. In particular, the effect of foreign robots remains significant at the 1% level and quantitatively very similar to my preferred specification in column (3) (-0.47 vs. -0.53).

Panel B presents the 2SLS estimates from the same regressions. The pattern is very similar to the effects identified in the reduced form regressions in Panel A. My preferred specification is column (3), as it includes the full set of control variables and makes use of all CZs in the sample. The coefficient estimate of 0.58 on the exposure to foreign robots in column (3) implies a 0.17 percentage point lower decadal growth in the employment-to-population ratio for a CZ with an average exposure to foreign robots (0.30). Alternatively, a one standard deviation increase (1.34) in a CZ's exposure to foreign robots causes a 0.78 percentage point drop in the decadal growth rate of the employment-to-population ratio.

Panels C and D present the first-stage results for the exposure to domestic and foreign robots, respectively, and show that the external exposure to robots variables are relevant instruments. In both panels, the designated instruments are strongly correlated with their corresponding endogenous counterpart throughout all specifications. In my preferred specification in column (3), *only* the designated instruments predict the endogenous regressor. In the other specifications, the instrument for the exposure to foreign robots also has some explanatory power for the exposure to domestic robots, albeit comparatively little. The Kleibergen-Paap rank F-statistic is larger than 10 in all specifications, suggesting that the same instrument is not explaining both endogenous regressors (i.e., that the model is not underidentified).[34]

5.2 Effects by time period

Next, I examine the two time periods separately to understand more about the timing of the effect. I repeat the estimation of columns (3)-(5) of Table 1 for 1990-2000 and 2000-2015, respectively, in columns (1)-(3) and (4)-(6) of Table 2. Columns (1)-(3) suggest that neither

do not include this measure. Durable manufacturing includes wood products, minerals, basic metals, metal products, industrial machinery, electronics, electrical equipment and automotive industry.

[33] Column (3) already includes a CZ's exposure to Maquiladoras and thus partly alleviates this concern. Focusing on this subset of CZs is, however, a more stringent test, as it allows the effects of covariates to be distinct for the subset of Maquiladora CZs as opposed to assuming them to be identical for all CZs.

[34] Table A3 reports results with partial instrumentation. Results remain the same.

domestic nor foreign robots had a significant effect on the employment-to-population ratio from 1990-2000. This result seems plausible. Robot adoption in Mexico was very low in the 1990s (see Figure A3), consistent with no detectable effects of domestic robots before 2000. Moreover, the number and quality of robots only started to increase rapidly in the 2000s, likely explaining why any effect of foreign robots is only visible after 2000.

Columns (4)-(6) show that the negative effect of foreign robots from the previous stacked difference specification before stems from the later period, 2000-2015. The pattern is robust across all specifications and significant at the 1% level. Comparing the specifications in column (4) in Table 2 and column (3) in Table 1, the estimated effect of one additional foreign robot per thousand workers is similar in size (-0.66 vs. -0.58). In general, these patterns suggest that in the early stages of robotic automation, its effect on employment outcomes was weak.

This short difference estimation is also helpful to rule out that identification in the stacked difference relies solely on the temporal variation in a CZ's external exposure to foreign robots, which would require somewhat different identification assumptions. This analysis shows that the effect of foreign robots is qualitatively and quantitatively similar if the temporal variation is discarded and, instead, only variation across CZs in the same time period is exploited.

Finally, I present visual evidence of the correlation between the change in the employment-to-population ratio and the external exposure to foreign robots between 2000 and 2015 in Panel A of Figure 3 to bolster confidence that the results are not driven by a certain combination of covariates. The slope coefficient is negative and significant at the 1% level. Panel B shows the relationship between the two variables after all covariates from column (4) have been partialled out. The slope coefficient is therefore identical to that in column (4) of Table 2.

5.3 Identification

Identification using these Bartik 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.[35] 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 shares with the error term may thus threaten identification. I address this potential threat in several ways: First, 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).[36] It is reassuring that the averages in the first and fourth quartile are not significantly different from each other for all but four of the

[35] 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.

[36] This region-level balance test is related to the recommended industry-level balance test in Borusyak et

Table 2: Impact of exposure to robots on employment (by time period)

	(1)	(2)	(3)	(4)	(5)	(6)
	Change in employment-to-population ratio					
	1990-2000			2000-2015		
	Panel A. Reduced form					
External exposure to *domestic* robots	3.64	21.52	-0.46	0.41	-0.28	0.51**
	(5.22)	(22.60)	(7.66)	(0.30)	(0.54)	(0.20)
External exposure to *foreign* robots	-0.01	-0.30	-0.16	-0.36***	-0.33***	-0.41***
	(1.01)	(0.74)	(0.89)	(0.07)	(0.11)	(0.13)
	Panel B. 2SLS					
Exposure to *domestic* robots	3.14	19.89	-0.35	0.44	-0.27	0.56***
	(4.36)	(20.31)	(5.98)	(0.29)	(0.52)	(0.17)
Exposure to *foreign* robots	-0.02	-0.46	-0.24	-0.66***	-0.60***	-0.74***
	(1.48)	(1.29)	(1.26)	(0.13)	(0.17)	(0.21)
Kleibergen-Paap rank F	99	290	156	81	89	174
	Panel C. First-stage, domestic					
External exposure to *domestic* robots	1.16***	1.08***	1.16***	1.05***	1.02***	1.08***
	(0.02)	(0.05)	(0.01)	(0.01)	(0.01)	(0.01)
External exposure to *foreign* robots	0.00**	-0.00	0.00**	-0.01***	-0.01	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
	Panel D. First-stage, foreign					
External exposure to *domestic* robots	0.05	-0.07	0.22	0.07*	-0.00	0.13
	(0.18)	(0.20)	(0.27)	(0.04)	(0.03)	(0.08)
External exposure to *foreign* robots	0.67***	0.59***	0.65***	0.55***	0.55***	0.55***
	(0.05)	(0.02)	(0.04)	(0.04)	(0.04)	(0.03)
Region & main effects	✓	✓	✓	✓	✓	✓
Baseline covariates	✓	✓	✓	✓	✓	✓
Contemporaneous changes	✓	✓	✓	✓	✓	✓
Unweighted		✓			✓	
Only Maquiladora CZs			✓			✓
Observations	1,805	1,805	251	1,805	1,805	251

Notes: The dependent variable in Panels A and B is a CZ's change in the employment-to-working-age-population ratio (multiplied by 100), and in Panels C and D, the exposure to domestic and to foreign robots, respectively. All columns include fixed effects for two time periods and eight broad regions, the main effects from the interactions included in the external exposure to foreign robots variable (as described in main text), 1990 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 level, respectively), several broad 1990 industry employment shares (i.e., shares of employment in manufacturing, durable manufacturing, agriculture, construction, mining and services), the 1990 level of the outcome variable, and controls for contemporaneous changes (share of routine jobs in 1990 following Autor and Dorn (2013), contemporaneous exposure to Chinese import competition following Autor et al. (2013), and the exposure to tariff changes from NAFTA). Columns (2) and (5) use no weights. Columns (3) and (6) exclude all CZs with no Maquiladora employment in 1990. All regressions except for column (2) and (5) are weighted by a CZ's share of the national working-age population in 1990. Standard errors are robust to 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.

17 observable characteristics included in the full set of covariates.[37] Second, I test for pre-trends (i.e., changes in employment rates from 1970-1990, before the invention of industrial robots) in CZs exposed to domestic and foreign robots, respectively, and find no support for these. Third, I drop any single industry included in the instruments one at a time (following Goldsmith-Pinkham et al., 2018), and establish that the main result remains unchanged no matter which industry is dropped. Finally, as a strategy to deal with potential differences in unobservable characteristics directly, I estimate Equation (8) using stacked differences and including CZ time trends (i.e., fixed effects in first differences) as controls. The results remain qualitatively the same and quantitatively similar. Given these results, I conclude that unobservable characteristics of CZs with an initial industry mix giving rise to high exposures to domestic or foreign robots do not drive the results.

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 played only a minimal role in the invention of robots (Leigh and Kraft, 2018). 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 (see 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 I cannot fully rule out this possibility, the fact that Mexico exported relatively little to the nine countries used in the instrument makes this scenario somewhat unlikely.

Fourth, I assume that there has been no contemporaneous shock differentially affecting industries and time periods in the same way as robots. This scenario cannot be fully ruled out. In an attempt to control for the arguably three most important such candidates, I control for routine share intensity (computerization), Chinese import competition and exposure to NAFTA tariff changes also in the reduced form specifications from column (3) onwards. Moreover, in the robustness checks I exclude robots from each single industry from the instruments one at a time and exclude them separately as a control. The results for the effect of foreign robots remain robust, thus not lending support to this alternative explanation.

al. (2018), though here I do not compare exposure-weighted averages of region-level characteristics at the industry level, but rather region-level characteristics directly across different levels of relative exposures.

[37] Apart from region dummies and main effects. The covariates that differ at the 5% level are log population size, share of men, share of service sector workers, and the share of workers with at least a college degree.

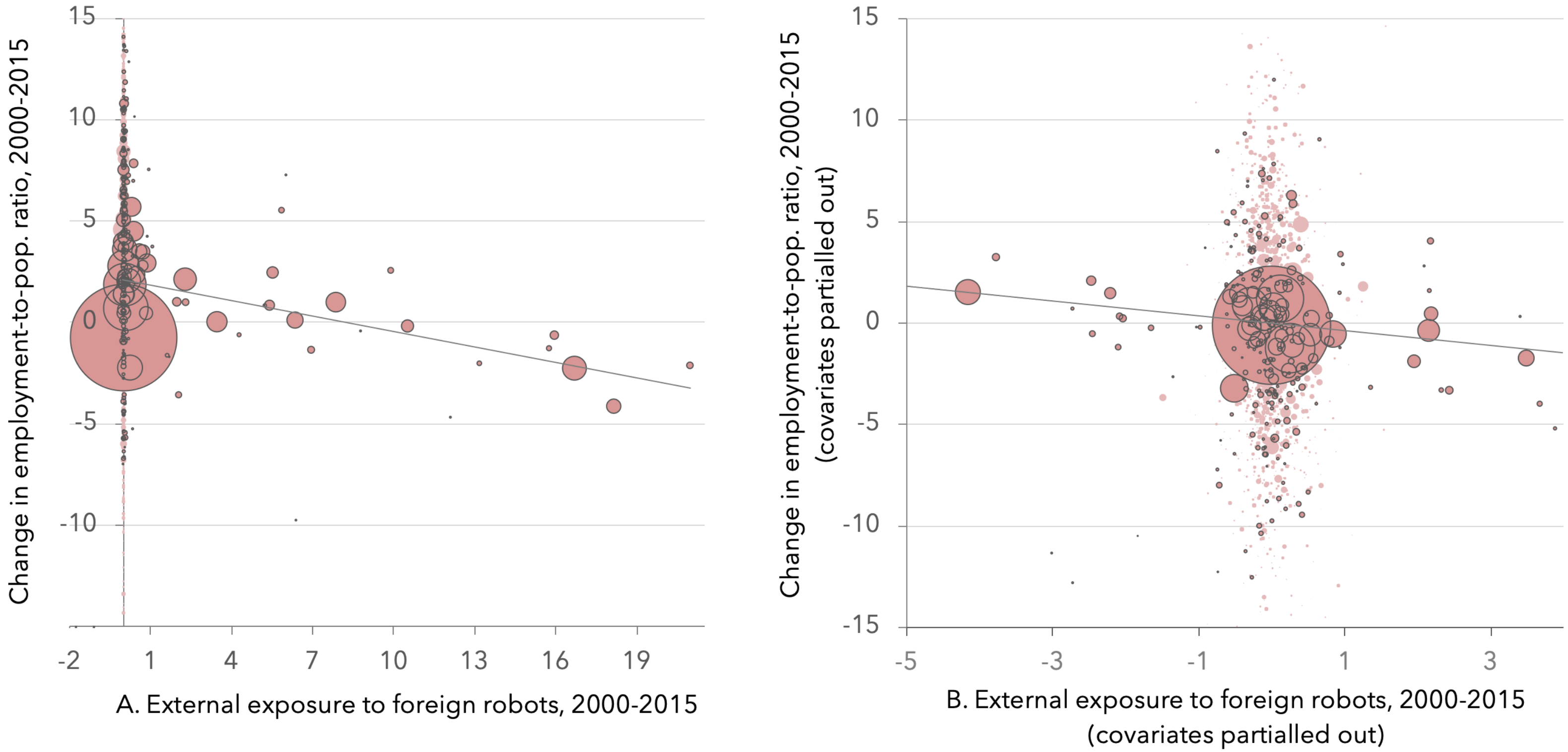


Figure 3: Relationship between employment-to-population ratio and external exposure to foreign robots, 2000-2015. Panel A plots the raw values of the change in the employment-to-population ratio and the external exposure to foreign robots. Panel B plots the values of both variables after all covariates from column (3) of Table 2 have been partialled out. Bubble size indicates a CZ's share of the overall working-age population in 1990. Borders around bubbles indicate CZs with some Maquiladora employment in 1990. The black line represents the fitted line without partialling out any covariates (Panel A) and with partialling out covariates (Panel B), using 1990 working-age population as weights.

Finally, the exclusion restriction requires that robots affect Mexican labor markets *only* via domestic or US robot adoption. Specifically, it may be that robots in other developed countries directly affect Mexican labor demand via reshoring to these countries. While this cannot be formally ruled out, it is *i)* unlikely to play a large role given Mexico's overwhelming focus on the US as an exports market and *ii)* reassuring that I cannot find significant effects of foreign robots on exports to non-US destinations at the industry-level (where I observe destination-specific exports) in Table 5.[38]

5.4 Magnitude

Next, I turn to the magnitude of the impact of robots on employment in Mexico. Note that the empirical specifications only include 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, briefly 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 derived under the assumption that these spillovers are low.[39]

My preferred specification is column (3) of Table 1, as it exploits both the geographical and the temporal variation in exposures and includes the full set of control variables. The coefficient on the exposure to foreign robots in Panel B implies that an increase in the exposure to foreign robots of one reduces the decadal employment-to-population ratio growth by 0.58 percentage points. The average value of this variable is 0.30. Therefore, a CZ with the average exposure to foreign robots experienced a 0.17 percentage point lower growth in the employment-to-population ratio per decade, or a 0.43 percentage point lower growth in the 25 years between 1990 and 2015. Aggregated to the national level (with an average working-age population of about 62 million between 1990 and 2015), this implies that foreign robots reduced employment in Mexico by about 270,000 workers between 1990 and 2015.

This estimate allows me to shed some light on the share of US robots that seem to compete with Mexican workers. Acemoglu and Restrepo (2020) find that one more robot reduces local employment in the US by about six workers. Data from the World Development Indicators from the World Bank shows that in 2015, value added per worker in manufacturing (incl. construction) was about four times as high in the US as in Mexico. Between 1993 and 2015, 234,000 robots were installed in the US. A back-of-the-envelope calculation would imply that about 5% of robots installed in the US compete with Mexican labor to account for this aggregate effect of 270,000 fewer jobs ($270,000/(234,000 \cdot 6 \cdot 4) \approx 0.05$). Similarly, this implies

[38] In 2000, 83% of total Mexican exports were shipped to the US.

[39] Acemoglu and Restrepo (2020) use the structure of their model to back out the aggregate effect. In their setup, such spillovers reduce the negative effect by about 10%.

that each robot installed in the US destroys slightly more than one job in Mexico.

6 Robustness

This section presents a number of robustness checks. First, I show that, in CZs exposed to foreign robots, there were no significant employment trends prior to the invention of robots. Second, I present evidence that robots in no single industry solely drive the effect of foreign robots on employment. Third, I show that the employment effect is also evident and robust when changes in log employment counts are used as the outcome variable. Fourth, I show that the analysis at the industry level yields qualitatively similar results. Finally, I briefly summarize more robustness checks that are provided in the Appendix.

6.1 Pre-trends

To start with, I examine the period between 1970 and 1990 to examine whether secular employment trends in industries heavily penetrated by robots or CZs heavily exposed to robots bias the main results. I therefore regress the external exposure to robots between 1993 and 2015 on changes in the employment-to-population ratio between 1970 and 1990. As the numbers of robots in Mexico and the US were likely relatively close to zero in the period before 1990 compared to today's levels, there should be no detectable effect of robots on employment between 1970 and 1990. Reduced form results are reported in Panel A of Table 3, which follows the same structure as Table 2.

It is reassuring that almost all coefficients on the exposure to domestic and foreign robots variables are insignificant. The coefficient on domestic robots is positive and significant in columns (1) and (4). However, this may reflect the ascent of Mexico as a manufacturing location for US production in this period, and is not robust across specifications. Most importantly, the effect of foreign robots is estimated to be almost precisely zero in my preferred specification in column (3). One might have expected the coefficient on the exposure to foreign robots to be positive and significant in this regression, reflecting increased offshoring from the US to Mexico during that time period. However, note that the main effect includes a CZ's exposure to Maquiladoras in 1990, likely capturing these offshoring trends. In fact, the unconditional correlation between the external exposure to foreign robots and employment-to-population ratio changes between 1970 and 1990 is positive and significant at the 1% level, as shown in Panel A of Figure 4.

In Panel B, I use another angle to test whether preexisting trends drive or bias the main results. I estimate the reduced form of the stacked differences specification again, however, now explicitly including the change in the employment-to-population ratio between 1970 and 1990 as a covariate. If the correlation between persistent trends in the outcome variable and 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 both domestic and foreign robots remains virtually unchanged, suggesting that neither of these shocks is sufficiently correlated with preexisting trends to bias the results.

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

	(1)	(2)	(3)	(4)	(5)
	Change in employment-to-population ratio				
	Panel A. 1970-1990				
External exposure to *domestic* robots, 1993-2015	2.17***	0.78	0.33	2.08***	0.38
	(0.71)	(0.49)	(0.42)	(0.71)	(0.27)
External exposure to *foreign* robots, 1993-2015	-0.15	0.05	0.02	0.18	0.05
	(0.21)	(0.11)	(0.06)	(0.14)	(0.03)
Observations	1,805	1,805	1,805	1,805	251
	Panel B. 1990-2015 (controlling for pre-trends)				
External exposure to *domestic* robots	-0.55*	-0.19	0.33	-0.18	0.71*
	(0.32)	(0.25)	(0.25)	(0.23)	(0.36)
External exposure to *foreign* robots	-0.63***	-0.67***	-0.47***	-0.50***	-0.57***
	(0.20)	(0.21)	(0.14)	(0.12)	(0.13)
Change in employment-to-population ratio, 1970-1990	-0.01	0.02***	0.02*	-0.01*	-0.04*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Observations	3,576	3,576	3,576	3,576	502
Region & main effects	✓	✓	✓	✓	✓
Baseline covariates		✓	✓	✓	✓
Contemporaneous changes			✓	✓	✓
Unweighted				✓	
Only Maquiladora CZs					✓

Notes: The dependent variable in Panels A and B is a CZ's change in the employment-to-working-age-population ratio (multiplied by 100) from 1970-1990 and 1990-2000/2000-2015, respectively. Column (1) includes fixed effects for eight broad regions as well as the main effects from the interactions included in the external exposure to foreign robots variable (i.e., the exposures to Maquiladoras and US import reliance as described in the text). 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 level, respectively), several broad baseline industry employment shares (i.e., shares of employment in manufacturing, durable manufacturing, agriculture, construction, mining and services), and the baseline level of the outcome variable. Column (3) also controls for the 1990 share of routine jobs following Autor and Dorn (2013), exposure to Chinese import competition from 1990-2015 following Autor et al. (2013), and the 1990 exposure to tariff changes from NAFTA. Column (5) includes the same controls as column (3), but excludes all CZs with no Maquiladora employment in 1990. All regressions except for column (4) are weighted by a CZ's share of the national working-age population in 1990. Standard errors are robust to heteroskedasticity and allow for arbitrary clustering at the state level (31 states) in Panel A and at the CZ level in Panel B. All columns in Panel B also include time period dummies. The coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

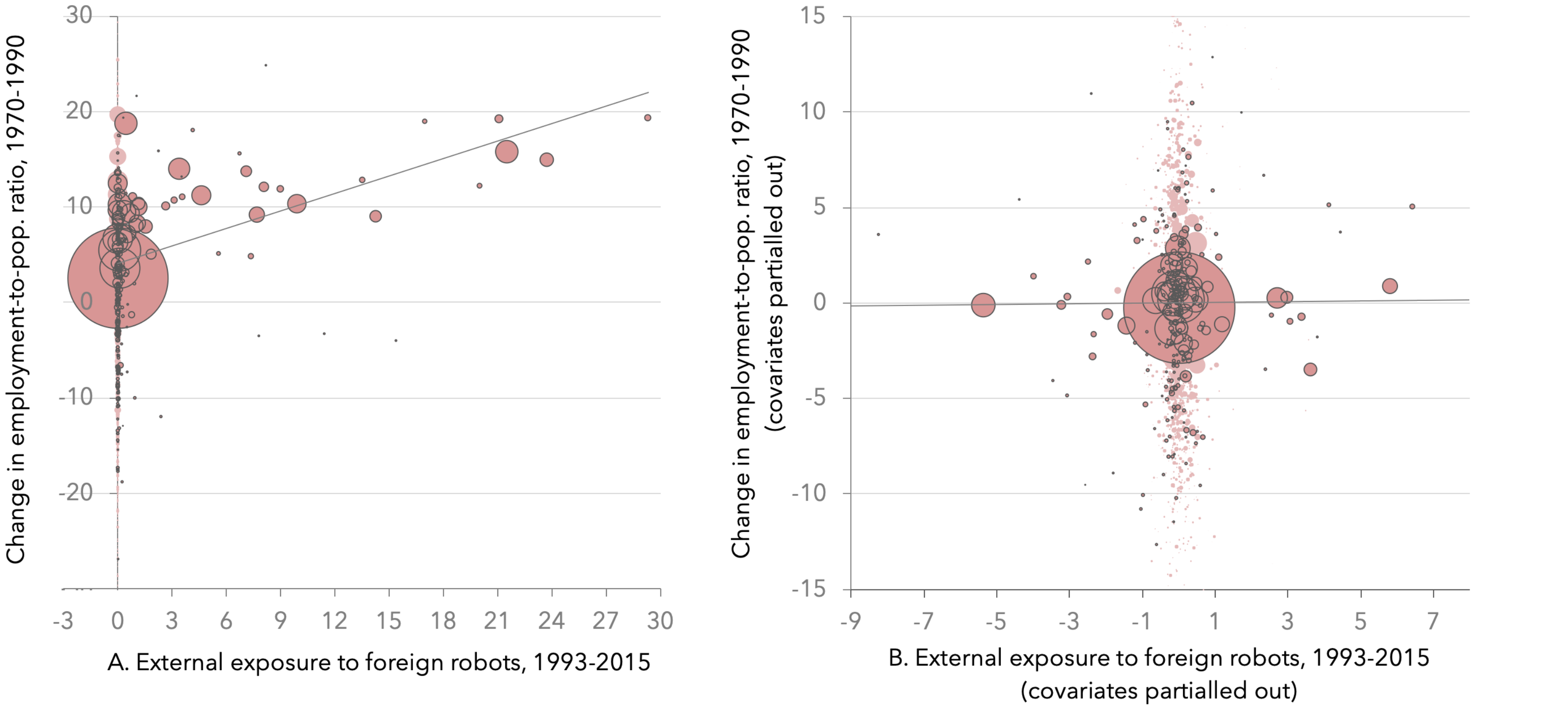


Figure 4: Relationship between employment-to-population ratio from 1970-1990 and the future external exposure to foreign robots (1993-2015). Panel A plots the raw values of the change in the employment-to-population ratio and the external exposure to foreign robots. Panel B plots the values of both variables after all covariates from column (3) of Table 3 have been partialled out. Bubble size indicates a CZ's share of the overall working-age population in 1990. Borders around bubbles indicate CZs with some Maquiladoras in 1990. The black line represents the fitted line without partialling out any covariates (Panel A) and with partialling out covariates (Panel B), using 1990 working-age population as weights.

6.2 Shocks to single industries

The use of robots per worker has increased more in some industries than in others. For example, the automotive industry uses robots most heavily and therefore drives a large part of the variation in both of the exposure to robots variables. It is possible that much of the effect of robots found before is, in reality, due to some other shock that affected the automotive industry (or other single industries) in the same period. To test for this, I exclude robots used in automotive manufacture from both external exposure to robots variables, and include them as two separate measures named *exposure to domestic/foreign robots in automotive industry*. If other shocks to the automotive industry indeed drove the results so far, the two new variables, *exposure to domestic/foreign robots in other industries*, should show no effect. I estimate this model 19 times, dropping one industry in the IFR data at a time. Results are reported in Figure 5. Panel A shows the results for domestic robots, and Panel B those for foreign robots. Dots indicate the estimates coefficient on the respective variables, and the capped lines show the 95% confidence intervals.

The effect of domestic robots is highly sensitive to the inclusion of robots in the automotive industry, and remains insignificant independent of which industry is dropped from the instrument. In contrast, the effect of foreign robots remains significant at the 5% level no matter which single industry is dropped from the instrument. The point estimate appears to be most sensitive to the exclusion of robots in the electronics industry and the automotive industry, which is to be expected as these are the two largest sectors in terms of both Mexican exports and the number of robots in the US. I conclude that the effect of foreign robots is not confounded by unrelated shocks to any of the industries included in the shift-share instrument.

6.3 Employment and population

The dependent variable in all specifications so far was the change in the employment-to-population ratio, 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 (log) employment. It is therefore useful to test the model's prediction by estimating it using the log employment count and the log working-age population as dependent variables. This is done in Panels A and B of Table 4, respectively. The table follows the same structure as Table 1.[40]

In line with the results so far, the effect of foreign robots on log employment is negative and significant at the 1% level in almost all specifications. In my preferred specification in column (3), an increase in a CZ's exposure to foreign robots by one (the variable's mean is 0.30 and the standard deviation is 1.34) is estimated to cause employment growth to fall by about 4.6 percent. This effect becomes smaller and insignificant in the unweighted regression. However, I do not prefer this specification as it is both less informative about the aggregate effect on employment in Mexico and less efficient in this case (see Cadena and Kovak, 2016).

[40] See Table A4 in the Appendix for results from the equivalent exercise for the time period 2000-2015.

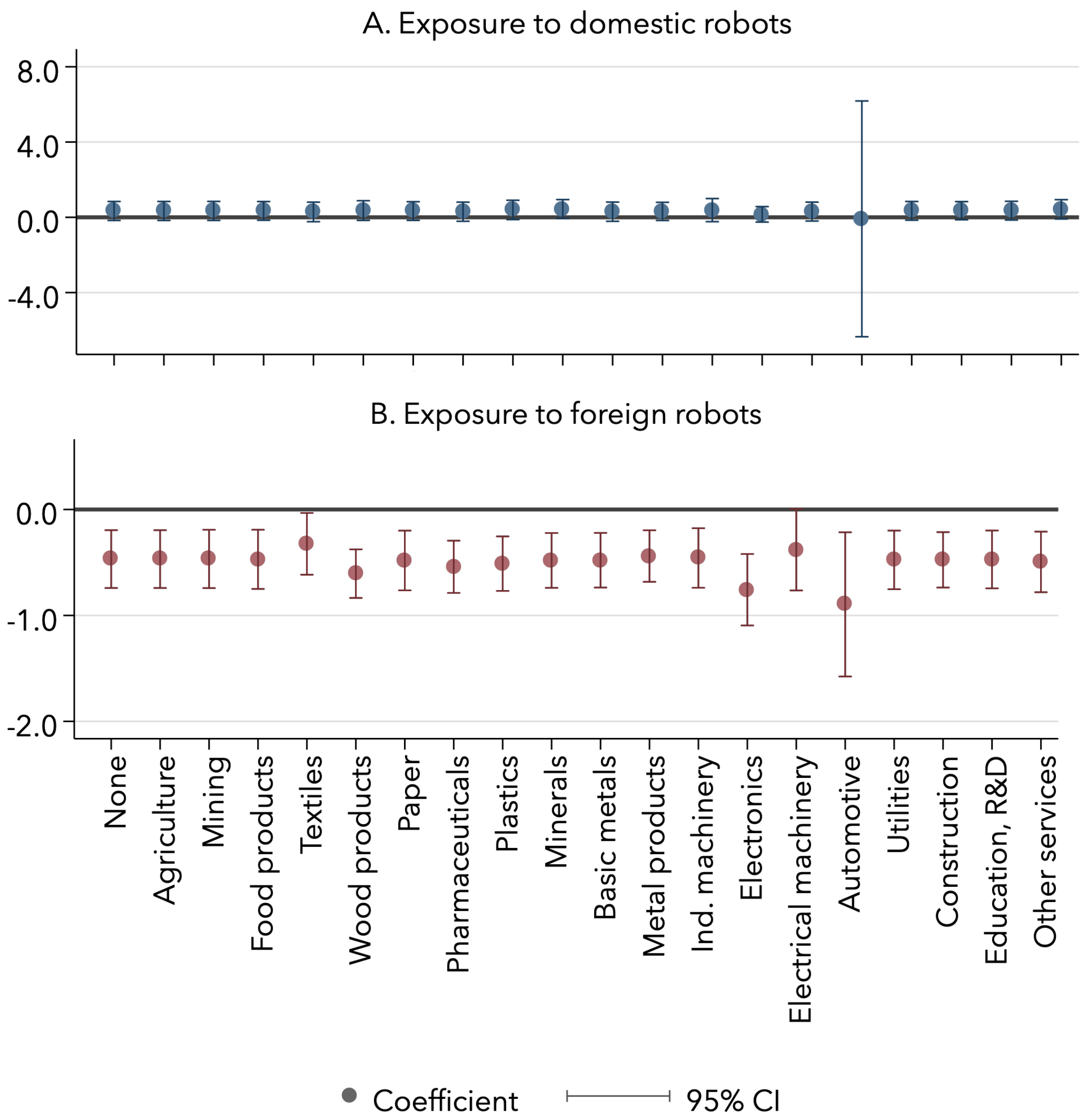


Figure 5: Sensitivity of external exposure to domestic and foreign robots to dropping single industries. Panels A and B show the coefficient estimates (dots) and 95% confidence intervals (capped lines) of the external exposure to domestic and foreign robots variable, respectively. Regressions are identical to those in Table 1, Panel A, column (3), but excluding robots from each single industry at a time from both instruments and including them separately. As a reference, the leftmost point estimate reports the result when including robots from all industries.

Table 4: Impact of exposure to robots on log employment and migration (stacked differences, 2SLS)

	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A. Log employment count			
Exposure to *domestic* robots	5.12**	-0.00	0.81	6.81	3.61*	-1.30
	(2.42)	(2.26)	(2.35)	(6.32)	(1.85)	(1.98)
Exposure to *foreign* robots	-5.50***	-4.52***	-4.61***	-1.77	-5.86***	-3.07**
	(0.99)	(0.92)	(0.84)	(3.24)	(0.89)	(1.46)
			Panel B. Log population count			
Exposure to *domestic* robots	9.80***	-0.50	0.31	1.12	1.81	-4.39**
	(3.06)	(1.67)	(1.77)	(2.13)	(1.57)	(2.17)
Exposure to *foreign* robots	-5.35***	-3.45***	-3.43***	-1.88	-4.07***	-1.28
	(1.09)	(0.81)	(0.70)	(2.81)	(0.70)	(1.33)
Region, period & main effects	✓	✓	✓	✓	✓	✓
Baseline covariates		✓	✓	✓	✓	✓
Contemporaneous changes			✓	✓	✓	✓
Unweighted				✓		
Only Maquiladora CZs					✓	
CZ trends						✓
Observations	3,610	3,610	3,610	3,610	502	3,610

Notes: The dependent variable in Panels A and B is a CZ's change in the log employment count and log working-age population (each multiplied by 100), respectively. Column (1) includes fixed effects for two time periods and eight broad regions in Mexico as well as the main effects from the interactions included in the external exposure to foreign robots variable (i.e., the exposures to Maquiladoras and US import reliance as described in the text). Column (2) also includes 1990 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 level, respectively), several broad 1990 industry employment shares (i.e., shares of employment in manufacturing, durable manufacturing, agriculture, construction, mining and services), and the 1990 level of the outcome variable. Column (3) also includes the share of routine jobs in 1990 following Autor and Dorn (2013), contemporaneous exposure to Chinese import competition following Autor et al. (2013), and the exposure to tariff changes from NAFTA. Column (5) includes the same controls as column (3), but excludes all CZs with no Maquiladora employment in 1990. Column (6) includes CZ trends (i.e., fixed effects in changes for all 1,805 CZs in the sample). All regressions except for column (4) are weighted by a CZ's share of the national working-age population in 1990. Standard errors are robust to heteroskedasticity and allow for arbitrary clustering at the CZ level. The coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

Panel B presents the results from estimating Equation 8 using the change in log working-age population size as the dependent variable. The effect of foreign robots is negative and significant in many specifications. These suggest a strong migration response to deteriorated labor market conditions due to foreign robots. This effect is, however, not robust to the inclusion of CZ trends in column (6). While it should therefore be interpreted with caution, it may reflect either reduced in-migration into affected CZs due to reduced job opportunities (in line with Faber et al., 2019) or increased out-migration to other CZs within Mexico or the United States. This may have somewhat mitigated the equilibrium effect on the employment-to-population ratio, which would have decreased by more in the absence of a negative migration response.

6.4 Industry-level correlations

I perform the main analysis at the CZ level for three main reasons. First, CZs are units that, by construction, are largely isolated from one another because they feature limited flows of individuals between units. This is useful to properly capture equilibrium effects that play out at a local level. Second, I can exploit geographic variation in revealed comparative advantages in exports (e.g., being located close to the border, the sea, or good infrastructure), which is not possible using, for example, industry variation. Third, as a more practical matter, the number of observations is considerably larger, as Mexico features 1,805 CZs whereas data on robot shipments by the IFR includes 19 detailed industries (see Table A9).

Nonetheless, I repeat the main analysis at the industry level in this subsection. There are two main advantages to doing so. First, it is a useful robustness check if the error terms are potentially correlated across CZs that are geographically far apart but share a similar initial industry mix (as pointed out in Borusyak et al., 2018). In that case, clustering standard errors by state, for example, does not solve this issue. Performing the analysis at the industry level, however, alleviates this concern. Second, data on exports by destination are only available at the industry level. Therefore, only the analysis at this level allows for testing one potential violation of the exclusion restriction, namely whether robots outside of Mexico affect Mexican employment only via US robots, or also directly via robots in other destinations of Mexican exports.

Table 5 presents the results of the industry-level exercise analogous to that shown in Table 1 at the CZ level.[41] Panels A, B and C present the correlations between the penetration of robots variables and changes in log employment, log exports to the US, and log exports to non-US destinations, respectively. Main results are in line with the analysis at the CZ level. There is a significant, negative correlation between the penetration of foreign robots and employment growth in most specifications. In my preferred specification in column (3), it is significant at the 5% level. In other words, employment in industries that have experienced high robot growth *and* have been initially highly offshorable have had lower employment growth, conditional on the covariates included. This correlation becomes insignificant when

[41] Section A.4.3 explains in detail how I construct the industry-level penetration of domestic and foreign robots variables.

industry trends (i.e., fixed effects in changes) for all 19 industries in the sample are included in column (6). However, this is a very demanding specification, especially given the small number of cross-sectional units. Notably, the point estimate remains identical to column (3). There is a positive correlation between the penetration of domestic robots and employment growth.

In Panel B, I repeat the same analysis, now using the change in log exports to the US as an outcome variable. Results are again in line with those from the CZ level analysis. There is a negative and significant correlation between the penetration of foreign robots and export growth to the US in my preferred specification in column (3) as well as the majority of remaining specifications. Similar to the correlations for employment in Panel A, the penetration of domestic robots shows a positive correlation also for growth in exports to the US.

Finally, in Panel C, I use exports to destinations other than the US as an outcome variable. The coefficient on the penetration of foreign robots becomes insignificant in column (3) and most other columns. While the exclusion restriction cannot be tested directly, it is reassuring that exports to countries other than the US have not significantly decreased in industries that have been robotized and had a high initial offshorability.[42]

6.5 Other robustness checks

The Appendix reports additional robustness checks. First, I show that results are similar when excluding outliers from the sample. Table A5 reports results if either the top 1% of CZs (on average over the two time periods) or the top 1% of observations (in either of the two time periods) with some exposure to foreign robots that have been most exposed to foreign robots are excluded.

Second, Table A6 reports results if alternative instruments are used. In Panel A, I use the set of five European countries that are used in Acemoglu and Restrepo (2020) (i.e., Denmark, Finland, France, Italy, and Sweden). Panel B reports results if the interaction with initial offshorability ($\tilde{O}_i$) from the external exposure to foreign robots is dropped. Panel C reports results if Mexico's exports to the US as a share of total Mexican exports (X_i) instead of the initial offshorability are used as an interaction term. Results remain the same using any of these alternative approaches.

Third, Table A7 shows that results remain robust if fixed effects for 31 states are used instead of eight broad regions. Finally, Table A8 uses a two-step LASSO procedure for the selection of covariates (following Belloni et al., 2014), leaving results qualitatively and quantitatively almost identical.

[42] While not providing direct evidence for it, these insignificant estimates also do not rule out the possibility that foreign robots reduced exports to countries other than the US. However, this is likely of limited importance quantitatively, given the high share of Mexican exports to the US (83% in 2000). It is also possible that robots in these other countries compete with Mexican workers via the US, by causing the US to substitute demand away from Mexico and to these other countries. These caveats leave reduced form results unaffected, but may lead to a slight overstatement in the quantification of the effect of US robots in Section 5.4.

Table 5: Industry-level correlations of employment and exports with penetration of robots

	(1)	(2)	(3)	(4)	(5)	(6)
			A. Employment			
Penetration of *domestic* robots	0.08	0.34***	0.40**	0.48*	0.46**	0.31
	(0.09)	(0.08)	(0.15)	(0.23)	(0.19)	(0.37)
Penetration of *foreign* robots	0.03	-0.39***	-0.47**	-0.59*	-0.56*	-0.47
	(0.14)	(0.11)	(0.22)	(0.34)	(0.29)	(0.51)
Observations	38	38	38	38	28	38
			B. Exports to the US			
Penetration of *domestic* robots	0.52***	0.51***	1.48**	1.09*	1.42*	3.52
	(0.11)	(0.10)	(0.60)	(0.54)	(0.71)	(3.13)
Penetration of *foreign* robots	-1.23***	-1.08***	-2.62**	-1.85*	-2.45**	-5.49
	(0.27)	(0.22)	(0.95)	(0.86)	(1.07)	(4.47)
Observations	28	28	28	28	26	28
			C. Exports to non-US destinations			
Penetration of *domestic* robots	0.19*	0.14	0.90	0.06	0.85	0.27
	(0.09)	(0.09)	(0.67)	(0.55)	(0.66)	(0.36)
Penetration of *foreign* robots	-0.52*	-0.49	-1.67	-0.05	-1.66	-1.55**
	(0.27)	(0.31)	(1.15)	(0.84)	(1.15)	(0.53)
Observations	28	28	28	28	26	28
Period dummies & main effects	✓	✓	✓	✓	✓	✓
Baseline conditions		✓	✓	✓	✓	✓
Broad industry dummies		✓	✓	✓	✓	✓
Contemporaneous changes			✓	✓	✓	✓
Unweighted				✓		
Only manufacturing					✓	
Industry trends						✓

Notes: The dependent variable in Panels A, B and C is the change in the log employment count, log exports value to the US and log exports value to countries other than the US in each industry, multiplied by 100. There are 19 industries and two time periods. Column (1) includes period dummies as well as the main effects that are part of the penetration of foreign robots variable (see main text) as covariates. Column (2) also includes the 1990 log value of the outcome variable as well as dummy variables for the durable manufacturing and service sectors. Column (3) also includes the penetration of Chinese imports, the 1990 share of routine jobs and the exposure to NAFTA tariff changes. Column (4), (5) and (6) include the same covariates as column (3) but use no weights, only the subset of manufacturing industries and include industry trends, respectively. All regressions except column (4) are weighted by each industry's 1990 share of the national total of the outcome variable. Standard errors are robust to heteroskedasticity and serial correlation at the industry level. The coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

7 Effects by gender, education, occupation and industry

In the following, I break down the effect for the aggregate into subgroups of workers. In particular, I reestimate the 2SLS specification column (3), Panel B of Table 1, but now with subgroup-employment-to-population ratios as the dependent variable. Figure 6 presents the results of this exercise. The blue and red thick bars represent point estimates of the coefficient on exposure to domestic and foreign robots, respectively. The thin lines on top of each bar correspond to its standard error. Panel A presents estimates by gender, Panel B by education, Panel C by occupation and Panel D by industry.

I focus on the effect of foreign robots (red bars) as I cannot rule out that the effect of domestic robots merely reflects contemporaneous developments in the automotive sector. The effect of foreign robots is more pronounced for men than for women, and strongest for those with primary school education as their highest level. This is in line with results in Acemoglu and Restrepo (2020), who also find the strongest effect for low-educated men. With respect to occupations, the effect stems almost entirely from machine operators, with considerably smaller negative effects on supervisors and clerical workers also. This seems plausible, given the specialization of robots in manufacturing assembly. There is a positive effect on crafts workers (i.e., manufacturing workers working without machines), which might reflect some take-up of displaced workers within the manufacturing industry. Moreover, there seems to be a small take-up of displaced workers also outside of manufacturing, namely in retail, laborers and other service occupations. The effects across industries paint a similar picture, with a pronounced negative effect in the manufacturing sector and a much smaller negative effect in construction.[43] The slight increase in employment in the education industry potentially reflects heightened demand for (high school) teachers, which make up the majority of workers in this industry.[44]

8 Mechanism

If the reduction in employment due to foreign robots is indeed driven by reshoring, one should see a similar response in exports. To test for this also at the CZ level, I use the change in exports between 2004 and 2014 per worker (in 2000) as a dependent variable in Panel A of Table 6. The results 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 and significant in most specifications, in particular my preferred specification in column (3).

The point estimate of -2.61 implies that a CZ with an average exposure to foreign robots between 2000 and 2015 (0.61) experienced an export reduction of about USD 1,600 per worker between 2004 and 2014. On average, exports per worker increased by roughly USD 8,200 in

[43] See Figure A4 for the detailed breakdown by subindustry within manufacturing. The negative effect of foreign robots stems mostly from electronics, automotive and other manufacturing.

[44] This would correspond to the reverse mechanism of Atkin (2016), i.e., reduced opportunity costs of staying in school for prospective high school dropouts due to worsened labor market conditions from lower offshoring activities.

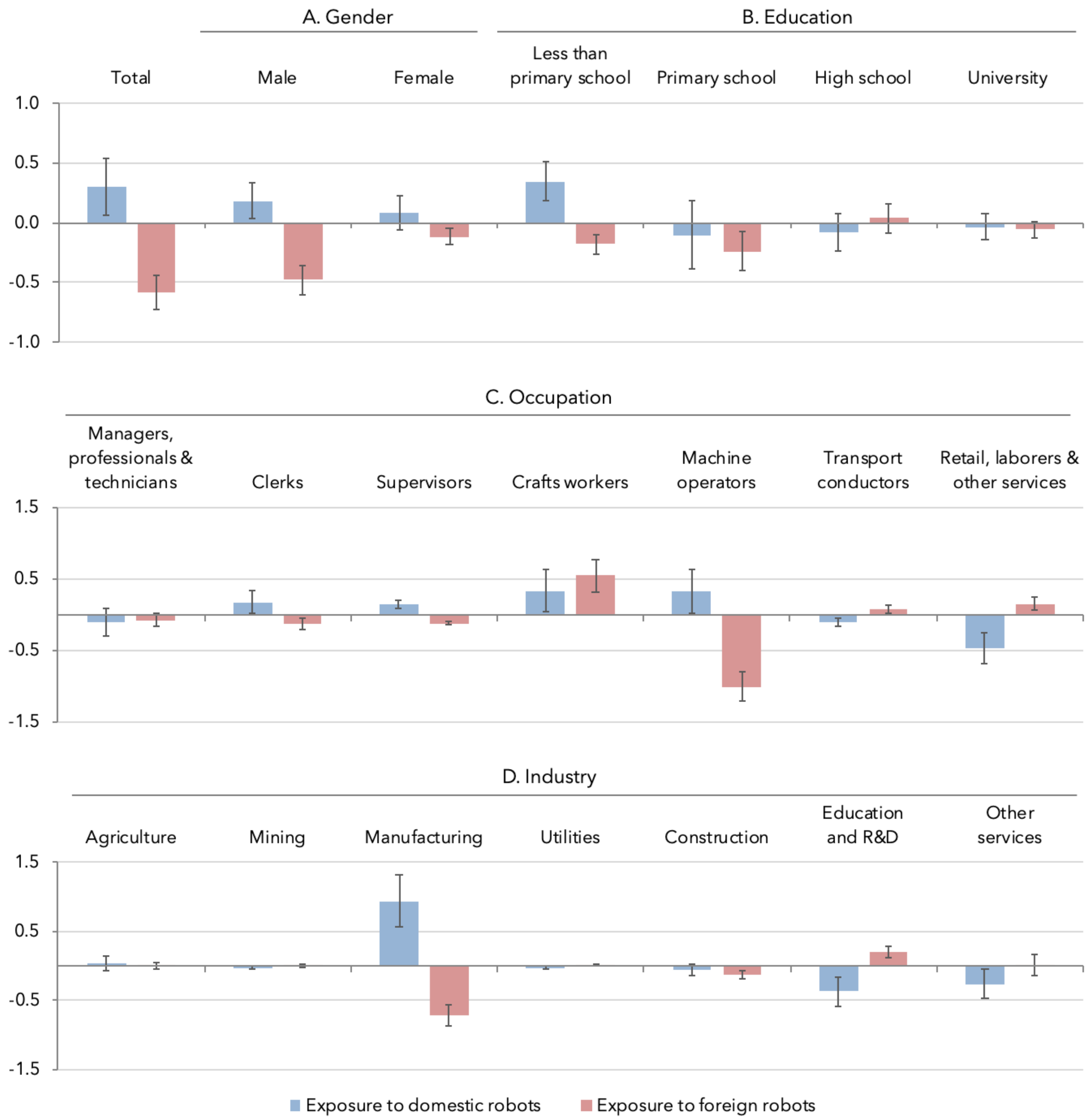


Figure 6: Impact of exposure to robots on employment by gender, education, occupation and industry. This figure plots the point estimates (thick bars) and standard errors (thin bars) of the exposure to domestic (blue) and foreign robots (red) on different employment-to-population ratios. The specification is identical to the estimation in column (3), Panel B of Table 1, 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.

Table 6: Impact of exposure to robots on exports (2004-2014, 2SLS)

	(1)	(2)	(3)	(4)	(5)
	Panel A. Change in exports value per worker				
Exposure to	5.23***	3.44	2.84	4.30*	-1.17
domestic robots, 2000-2015	(1.87)	(2.89)	(3.03)	(2.24)	(3.06)
Exposure to	-4.07***	-3.15***	-2.61**	0.56	-1.31
foreign robots, 2000-2015	(1.06)	(1.07)	(1.03)	(1.15)	(1.07)
Kleibergen-Paap rank F	57	120	116	90	167
	Panel B. Change in exporting plants per worker				
Exposure to	0.15***	0.02	0.05	-0.03	0.01
domestic robots, 2000-2015	(0.05)	(0.06)	(0.05)	(0.03)	(0.09)
Exposure to	-0.40***	-0.14***	-0.13***	-0.04	-0.10***
foreign robots, 2000-2015	(0.08)	(0.04)	(0.04)	(0.03)	(0.04)
Kleibergen-Paap rank F	57	58	69	96	106
Region & main effects	✓	✓	✓	✓	✓
Baseline covariates		✓	✓	✓	✓
Contemporaneous changes			✓	✓	✓
Unweighted				✓	
Only Maquiladora CZs					✓
Observations	1,805	1,805	1,805	1,805	251

Notes: The dependent variable in Panel A and B is a CZ's change in exports value per capita (divided by 1000) and the number of exporting plants per capita between 2004 and 2014, respectively. Column (1) includes fixed effects for eight broad regions in Mexico as well as the main effects from the interactions included in the external exposure to foreign robots variable (i.e., the exposures to Maquiladoras and US import reliance as described in the text). Column (2) also includes 1990 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 level, respectively), several broad 1990 industry employment shares (i.e., shares of employment in manufacturing, durable manufacturing, agriculture, construction, mining and services), and the 1990 level of the outcome variable. Column (3) also controls for the share of routine jobs in 1990 following Autor and Dorn (2013), contemporaneous exposure to Chinese import competition following Autor et al. (2013), and the exposure to tariff changes from NAFTA. Column (5) includes the same controls as column (3), but excludes all CZs with no Maquiladora employment in 1990. All regressions except for column (4) are weighted by a CZ's share of the national employment in 2000. Standard errors are robust to 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.

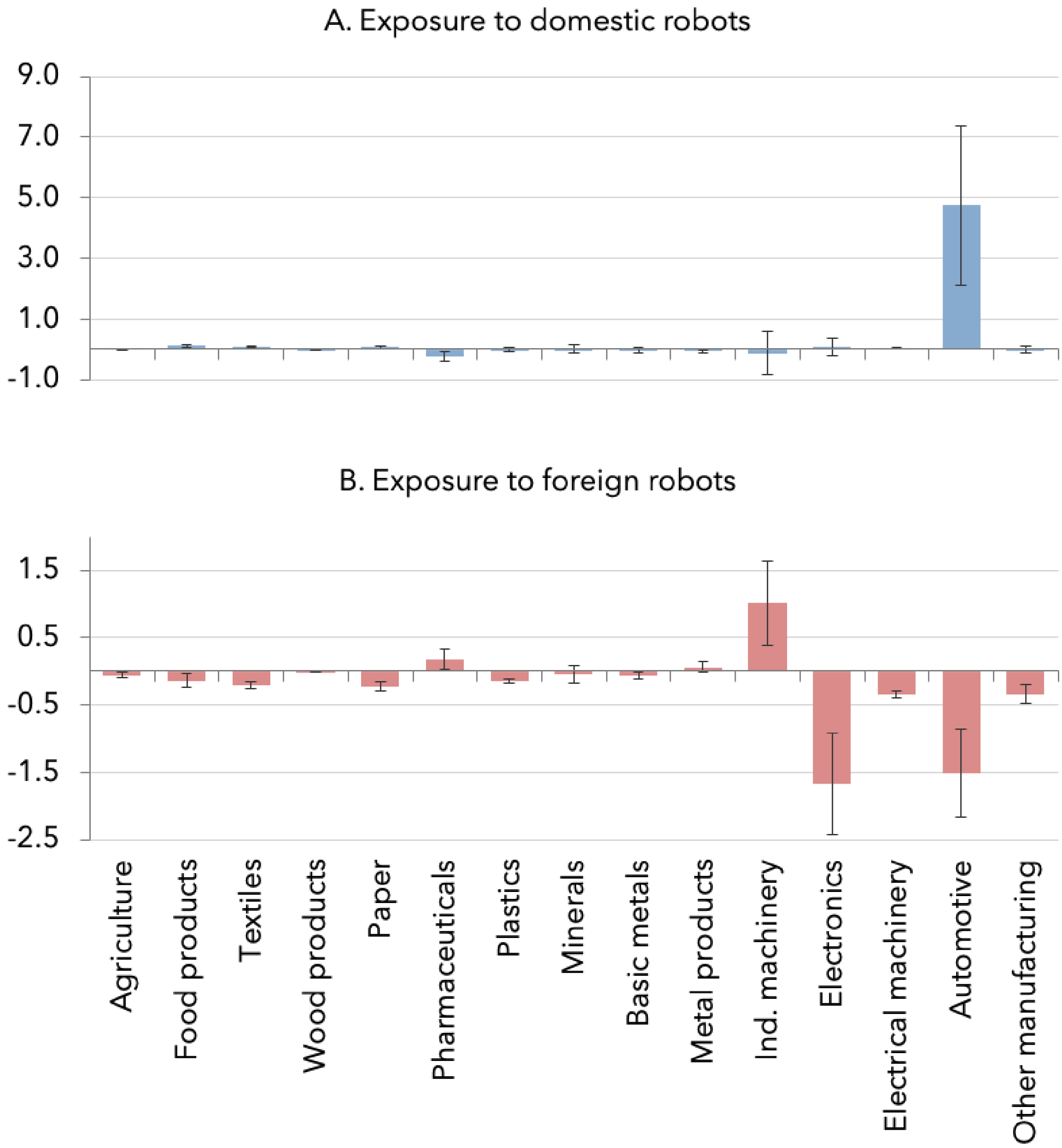


Figure 7: Effect of domestic and foreign robots on exports per worker by industry. Panels A and B show the coefficient estimates (dots) and standard errors (capped lines) of the exposure to domestic and the exposure to foreign robots variable, respectively, in regressions identical to that in column (3) of Table 6, but using industry-specific exports per worker as the dependent variable.

this time period. Thus foreign robots reduced export growth in this time period by roughly 20%. Given that the total number of workers in export-producing plants was about 2 million between 2007 and 2015, a 20% reduction in output may correspond to about 400,000 fewer workers.[45]

This number is of similar magnitude to that from estimating the effects on employment directly. While the overall effect of 270,000 fewer workers is somewhat smaller, it is crucial to note that this also includes take-up of displaced workers by other industries or occupations in equilibrium. It is, of course, difficult to disentangle the direct and indirect effects. However, one simple approach is to look at the size of the effect on occupations and industries one would expect to be directly affected by robots. The impact on manufacturing, for example, is about 122% of the total effect (see Figure 6). In this case, the size of the direct effect would be 330,000 fewer workers due to foreign robots. This, however, may still hide some take-up occurring within manufacturing. Focusing on only machine operators instead results in an estimate of the direct effect of 172% of the total effect, implying 470,000 fewer workers due to foreign robots, which is slightly higher than the 400,000 fewer workers estimated from reduced exports. I therefore conclude that the effect of foreign robots on exports is large enough in magnitude to rationalize the employment effects found before.

Results in Panel B repeat this exercise, but now using the change in the number of export-producing plants per worker as the dependent variable. Results are in line with those found for export values in Panel A, and suggest that US robots affect export-producing businesses in Mexico not only via the internal margin, but also via the external margin.[46]

Results so far have shown the effect of foreign robots on aggregate exports. However, it is also important to understand which industries have experienced the largest drop in exports in response to this shock. For this reason, I repeat the analysis in column (3) of Table 6 by industry and report results in Figure 7. Foreign robots have reduced exports in the electronics and automotive industries, in line with the results on employment by manufacturing subindustry in Figure A4. There is also a small positive effect on industrial machinery exports, though it is not significant at any conventional level.

9 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 increasing anecdotal evidence for reshoring, this is the first empirical analysis of the effect of robots on employment in offshoring countries.

[45] Number of workers in export manufacturing based on INEGI IMMEX data.

[46] In principle, it is possible that single firms report exporting several products. This may lead to multiple counts of a single firm when summing over all products in a municipality. Changes in this variable may thus not only result from plant openings and closures, but also from changes in the range of products firms export. Given that it is not obvious how this may be correlated with the external exposure variables, and results are in line with Panel A, which does not suffer from this potential issue, I do not view this as a major concern.

Following 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*. In light of the emergence of reshoring, I also consider an export-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 export employment, and the foreign industry's initial reliance on imports from the home country.

So far unexploited data on 1990 Maquiladora employment by municipality and industry from CEPAL, as well as data on robot shipments from the IFR and employment from Mexican censuses allow me to construct empirical counterparts to these theoretical measures. In principle, these direct counterparts may suffer from endogeneity due to the decision of US and Mexican industries to adopt robots. 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 the number of robots 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.

In the main specification, I regress changes in the employment-to-population ratio from 1990-2000 and 2000-2015 on these exposure to robots variables via two-stage least squares. Using this methodology, I find a large negative and robust effect of US robots on Mexican employment. This effect stems from the later period in the sample, 2000-2015, and is not visible in the period 1990-2000. It is robust to allowing for differential trends regarding a number of covariates, including region dummies, CZ demographics, broad industry shares, tariff changes from NAFTA, Chinese import competition, computerization, and even CZ trends.

These results are also robust to several alternative explanations. First, preexisting trends in industries in which robots are most heavily used are not 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 solely driven by contemporaneous shocks to a single industry (e.g., automotive). Third, the effect is indeed driven by reduced employment rather than any underlying increases in population size. The negative employment effect is stronger for men than for women, and strongest for low-educated machine operators in the manufacturing sector. With regard to the magnitude of this effect, my preferred estimates imply that a local labor market with an average exposure to foreign robots experienced a 0.43 percentage point lower growth in the employment-to-population ratio between 1900 and 2015, compared with no such exposure. At the national level, this amounts to roughly 270,000 fewer jobs in Mexico, implying that roughly 5 percent of all US robots seem to compete with Mexican labor. This sizeable employment effect is mirrored in similar reductions in export values and in the number of export-producing plants, corroborating the view that robots foster reshoring.

This analysis, however, does not take into account potential countervailing spillover effects across local labor markets resulting from lower prices for consumers and higher capital gains for robot owners. Alternative strategies for estimating the aggregate implications of robots on reshoring, such as cross-country and cross-industry comparisons utilizing more granular data on robot adoption are complementary to this within-country comparison approach. Moreover, well-identified within-country studies on other offshoring countries will help gain an understanding of the extent to which these results are driven by the specific patterns of initial comparative advantage of the US and Mexico, or developed and offshoring countries more generally. Finally, similar analyses for other labor-saving or even labor-augmenting technologies are crucial to understanding the interplay between automation and reshoring more broadly.

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 higher in 2025 than in 2015, 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 may pose a threat to labor markets and, in turn, political stability, in the developing world. This paper offers first insights into potential causes of such instabilities. These may help inform the debate on how to prevent or at least mitigate such effects.

References

Acemoglu, Daron and Pascual Restrepo, "Demographics and Automation," *NBER Working Paper No. 24421*, 2018.

_ and _ , "Robots and Jobs: Evidence from US Labor Markets," *Journal of Political Economy*, 2020.

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

Artuc, Erhan, Luc Christiaensen, and Hernan Jorge Winkler, "Does Automation in Rich Countries Hurt Developing Ones?: Evidence from the US and Mexico," *Policy Research Working Paper; No. 8741. World Bank, Washington, DC*, 2019.

_ , Paulo Bastos, and Bob Rijkers, "Robots, Tasks and Trade," *Policy Research Working Paper; No. 8674. World Bank, Washington, DC*, 2018.

Atkin, David, "Endogenous Skill Acquisition and Export Manufacturing in Mexico," *The American Economic Review*, 2016, *106* (8), 2046–2085.

Autor, David and David Dorn, "The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market," *The American Economic Review*, 2013, *103* (5), 1553–1597.

_ , _ , and Gordon H Hanson, "The China Syndrome: Local Labor Market Effects of Import Competition in the United States," *The American Economic Review*, 2013, *103* (6), 2121–2168.

_ , _ , and _ , "Untangling Trade and Technology: Evidence from Local Labour Markets," *Economic Journal*, 2015, *125* (584), 621–46.

_ , _ , Gordon Hanson, and Kaveh Majlesi, "Importing political polarization? the electoral consequences of rising trade exposure," *NBER Working Paper No. 22637*, 2016.

Backer, Koen De, Timothy DeStefano, Carlo Menon, and Jung Ran Suh, "Industrial Robotics and the Global Organisation of Production," 2018.

BCG, "The Robotics Revolution: The Next Great Leap in Manufacturing," *bcg. perspectives*, 2015.

Belloni, Alexandre, Victor Chernozhukov, and Christian Hansen, "High-dimensional Methods and Inference on Structural and Treatment Effects," *Journal of Economic Perspectives*, 2014, *28* (2), 29–50.

Blanchard, Olivier, Lawrence F. Katz, Robert E. Hall, and Barry Eichengreen, "Regional Evolutions," *Brookings papers on economic activity*, 1992, *1992* (1), 1–75.

Borusyak, Kirill, Peter Hull, and Xavier Jaravel, "Quasi-experimental Shift-Share Research Designs," *NBER Working Paper No. 24997*, 2018.

Cadena, Brian and Brian Kovak, "Immigrants Equilibrate Local Labor Markets: Evidence from the Great Recession," *American Economic Journal: Applied Economics*, 2016, *8* (1), 257–90.

Carbonero, Francesco, Ekkehard Ernst, Enzo Weber et al., "Robots Worldwide: The Impact of Automation on Employment and Trade," *ILO Research Department Working Paper*, 2018, *36*, 23–37.

CEPAL, "Mexico: La Industria Maquiladora," Technical Report, United Nations Comisión Económica para América Latina y el Caribe 1994.

Dauth, Wolfgang, Sebastian Findeisen, Jens Suedekum, and Nicole Woessner, "The Adjustment of Labor Markets to Robots," 2019.

Eurofund, "Reshoring in Europe: Overview 2015–2018," *Publications Office of the European Union*, 2019.

Faber, Marius, Andres Sarto, and Marco Tabellini, "The Impact of Technology and Trade on Migration: Evidence from the US," *Harvard Business School BGIE Unit Working Paper*, 2019, (20-071).

Feenstra, Robert C and Gordon H Hanson, "The Impact of Outsourcing and High-Technology Capital on Wages: Estimates for the United States, 1979–1990," *The Quarterly Journal of Economics*, 1999, *114* (3), 907–940.

Glaeser, Edward L and Joseph Gyourko, "Urban Decline and Durable Housing," *Journal of Political Economy*, 2005, *113* (2), 345–375.

Goldsmith-Pinkham, Paul, Isaac Sorkin, and Henry Swift, "Bartik Instruments: What, When, Why, and How," *NBER Working Paper No. 24408*, 2018.

Graetz, Georg and Guy Michaels, "Robots at Work," *Review of Economics and Statistics*, 2018, *100* (5), 753–768.

Hakobyan, Shushanik and John McLaren, "Looking for Local Labor Market Effects of NAFTA," *Review of Economics and Statistics*, 2016, *98* (4), 728–741.

Hanson, Gordon H, "Globalization, Labor Income, and Poverty in Mexico," in "Globalization and poverty," University of Chicago Press, 2007, pp. 417–456.

Harvard Business Review, "Robots Are Starting to Make Offshoring Less Attractive," Harvard Business Review 2014. [Online; accessed March 16, 2017].

Hunt, V Daniel, *Robotics sourcebook*, Elsevier, 2012.

IFR, "World Robotics 2015," Technical Report, International Federation of Robotics 2015.

IPUMS, "Minnesota Population Center. Integrated Public Use Microdata Series, International: Version 7.1 [dataset]. Minneapolis, MN: IPUMS, 2018," 2018.

Krenz, Astrid, Klaus Prettner, and Holger Strulik, "Robots, Reshoring, and the Lot of Low-Skilled Workers," *CEGE Discussion Papers*, 2018, (351).

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

Malamud, Ofer and Abigail Wozniak, "The Impact of College on Migration: Evidence from the Vietnam Generation," *Journal of Human resources*, 2012, *47* (4), 913–950.

Rodrik, Dani, "New Technologies, Global Value Chains, and Developing Economies," *NBER Working Paper No. 25164*, 2018.

Stemmler, Henry, "Does Automation Lead to De-Industrialization in Emerging Economies? Evidence from Brazil," *CEGE Discussion Papers*, 2019, (382).

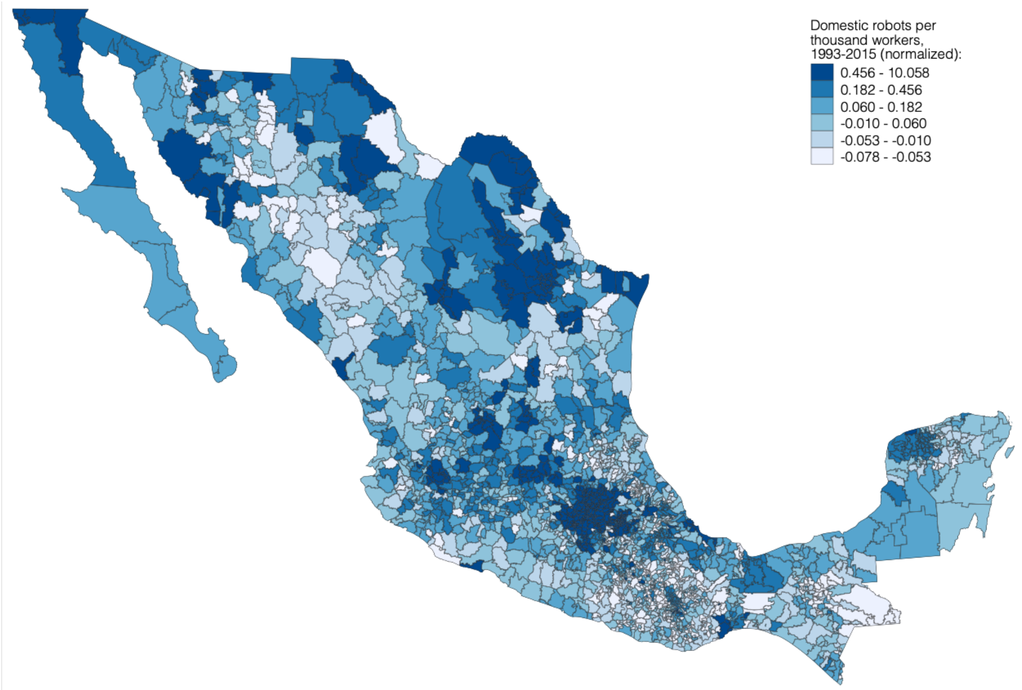
The Economist, "Coming home," 2013. [Online; accessed March 16, 2017].

_ , "Adidas's High-Tech Factory Brings Production Back to Germany," 2017. [Online; accessed Oct 12, 2018].

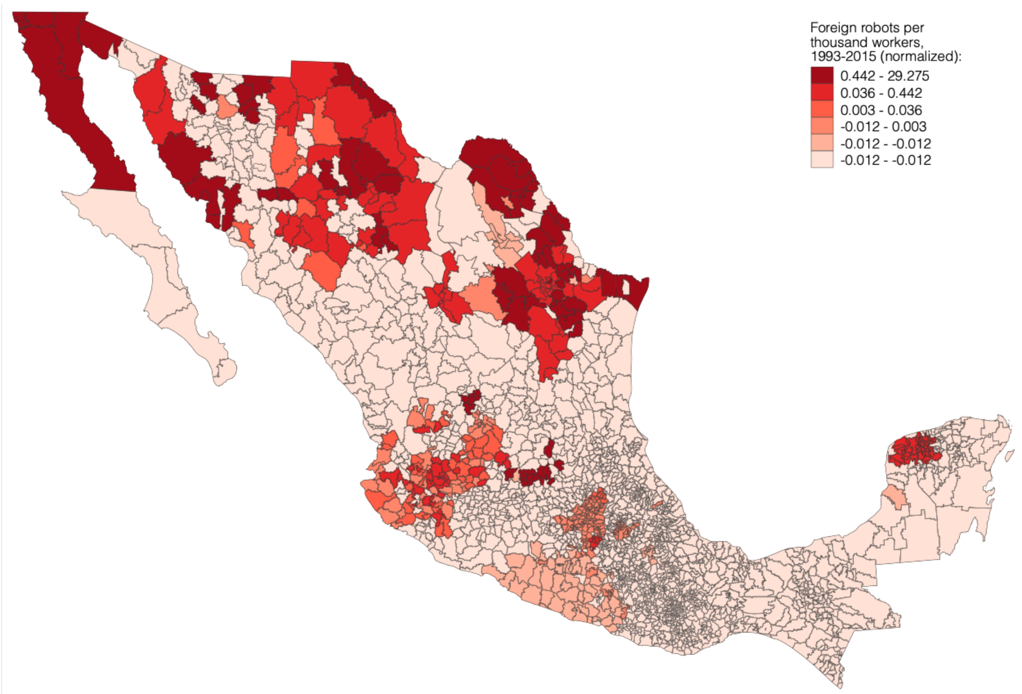
Wright, Greg C, "Revisiting the Employment Impact of Offshoring," *European Economic Review*, 2014, *66*, 63–83.

A Appendix

A.1 Figures

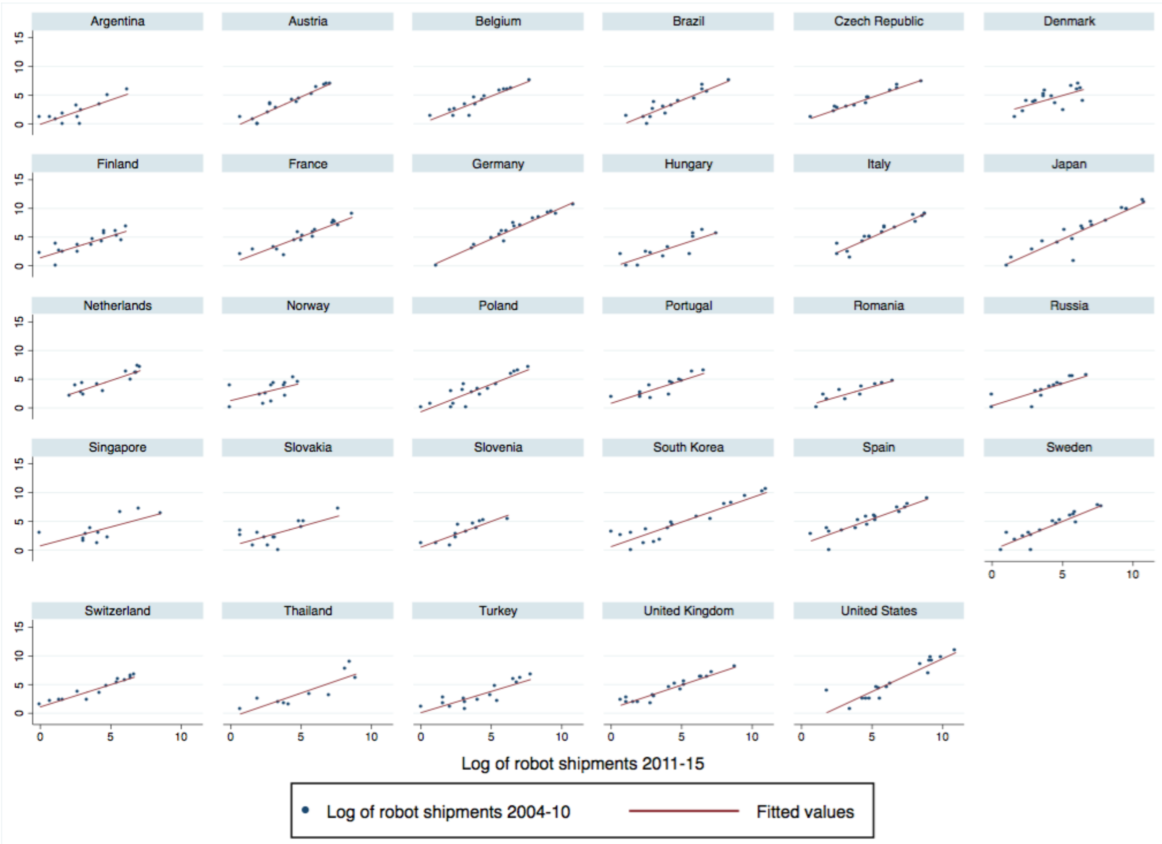


(a) External exposure to domestic robots, 1993-2015



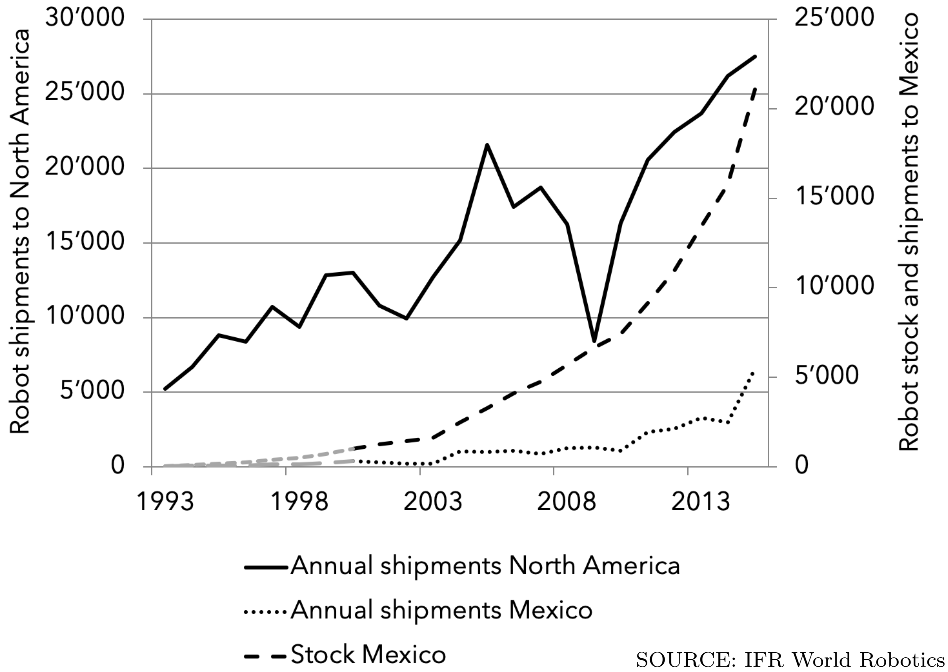
(b) External exposure to foreign robots, 1993-2015

Figure A1: Commuting zone-level variation in external exposure to domestic and foreign robots, 1993-2015. Values are normalized to have the same mean and variance as the endogenous counterparts.



SOURCE: IFR World Robotics Database

Figure A2: Relationship between industries' robot shipments 2011-2015 and 2004-2010



SOURCE: IFR World Robotics Database

Figure A3: 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).

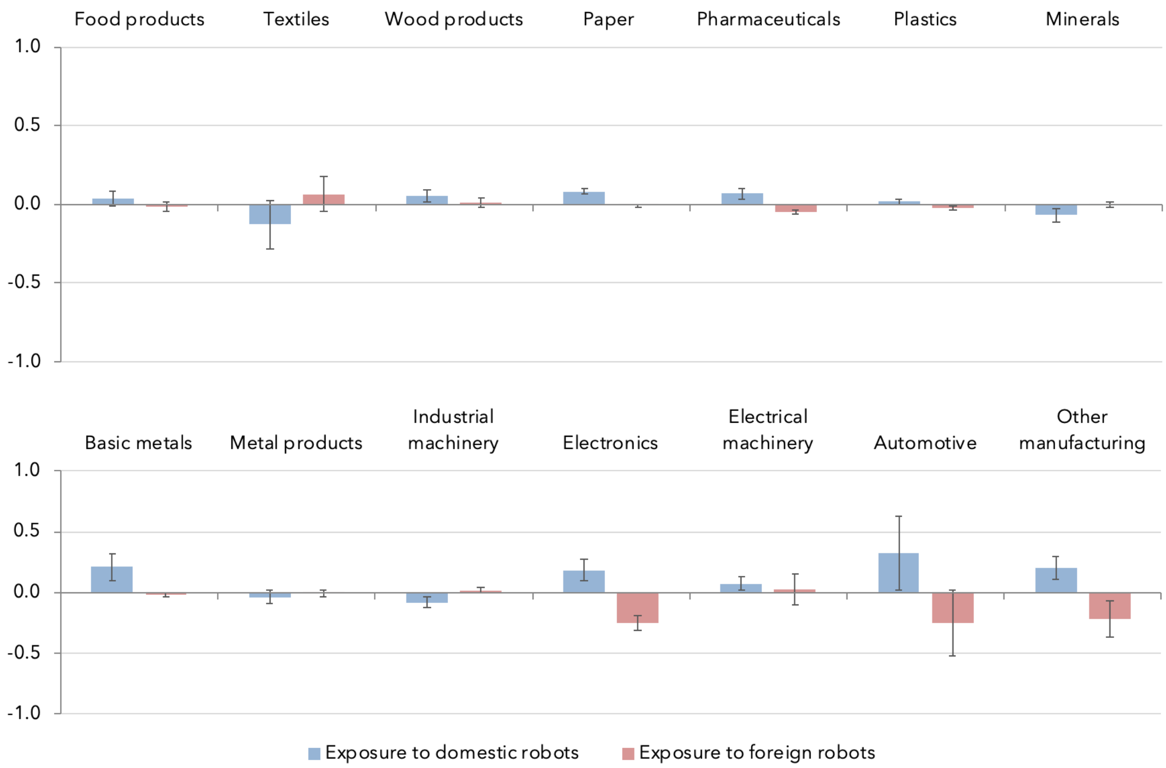


Figure A4: Impact of exposure to robots on employment by manufacturing subindustry. This figure plots the point estimates (thick bars) and standard errors (thin bars) of the exposure to domestic (blue) and foreign robots (red) on different subindustry-employment-to-population ratios. The specification is identical to estimation in column (3), Panel B of Table 1, with the only difference that the dependent variables are now subgroup-specific employment-to-population ratios. For example, the dependent variable in the second column in the upper panel is the change in employment in the textiles industry over the entire working-age population in a CZ.

A.2 Tables

Table A1: Summary statistics

	All CZs	Difference between standardized exposure to domestic and foreign robots Q1	Q2	Q3	Q4
		Panel A. Outcomes			
Change in outcome (1990-2015)					
Employment-to-population ratio ×100	6.53	5.65	7.41	8.59	6.07
	[3.91]	[4.10]	[5.67]	[3.94]	[3.50]
Log employment count ×100	71.7	77.16	74.06	82.40	68.30
	[29.21]	[44.24]	[50.39]	[34.94]	[21.21]
Log working-age population ×100	49.76	55.38	32.62	47.37	50.99
	[22.11]	[29.71]	[27.01]	[31.81]	[16.35]
		Panel B. Explanatory variables			
Exposure to robots (1993-2015)					
Domestic	0.63	0.93	0.01	0.11	0.77
	[0.70]	[0.99]	[0.01]	[0.23]	[0.68]
Foreign	0.81	8.22	0.01	0.51	0.08
	[3.39]	[8.62]	[0.02]	[1.75]	[0.19]
CZ demographics (1990)					
Share of men	0.49	0.50	0.50	0.49	0.49
	[0.01]	[0.01]	[0.02]	[0.01]	[0.01]
Working-age share	0.58	0.58	0.51	0.54	0.59
	[0.05]	[0.06]	[0.03]	[0.04]	[0.04]
Share with primary education*	0.49	0.48	0.33	0.41	0.52
	[0.10]	[0.16]	[0.09]	[0.08]	[0.06]
Share with secondary education*	0.11	0.09	0.03	0.07	0.13
	[0.05]	[0.06]	[0.02]	[0.04]	[0.04]
Share with tertiary education*	0.05	0.04	0.01	0.02	0.06
	[0.03]	[0.02]	[0.01]	[0.02]	[0.02]
Broad industry shares (1990)					
Manufacturing	0.19	0.20	0.06	0.09	0.22
	[0.10]	[0.14]	[0.06]	[0.05]	[0.08]
Durable manufacturing	0.06	0.07	0.02	0.03	0.07
	[0.04]	[0.05]	[0.02]	[0.03]	[0.04]
Agriculture	0.24	0.31	0.69	0.44	0.14
	[0.25]	[0.35]	[0.12]	[0.20]	[0.16]
Construction	0.07	0.06	0.04	0.07	0.07
	[0.03]	[0.03]	[0.04]	[0.03]	[0.02]
Initial conditions (1990)					
Employment-to-population ratio ×100	31.53	31.46	16.88	24.62	34.35
	[8.89]	[14.59]	[7.32]	[7.62]	[5.57]
Contemporaneous changes					
Share of routine jobs (1990)	0.23	0.21	0.07	0.16	0.26
	[0.09]	[0.12]	[0.04]	[0.07]	[0.06]
Chinese import comp. (1992-2015)	3.01	5.57	0.21	0.34	3.50
	[3.40]	[5.69]	[0.29]	[0.23]	[3.00]

Note: The first line for each variable represents the mean (weighted by 1990 working-age population), and the second line, the corresponding standard deviation in brackets. To define Q1-Q4, I first standardized both external 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. Therefore, the CZs included in Q1 and Q4 are relatively most exposed to foreign and domestic robots, respectively.

*As highest level obtained.

Table A2: OLS results for exposure to robots and employment (stacked differences)

	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A. Employment-to-population ratio			
Exposure to *domestic* robots	-0.54**	-0.31	0.03	-0.57	0.50	-0.10
	(0.26)	(0.23)	(0.24)	(0.50)	(0.34)	(0.34)
Exposure to *foreign* robots	-0.70***	-0.75***	-0.54***	-0.46***	-0.68***	-0.43*
	(0.16)	(0.17)	(0.15)	(0.12)	(0.15)	(0.23)
			Panel B. Log employment count			
Exposure to *domestic* robots	2.43	-0.99	-0.80	2.48	0.82	-3.34
	(1.93)	(1.85)	(1.99)	(3.55)	(2.05)	(2.32)
Exposure to *foreign* robots	-4.83***	-4.27***	-4.25***	-1.71	-5.29***	-3.36***
	(1.06)	(1.01)	(0.91)	(1.91)	(0.92)	(1.30)
Region, period & main effects	✓	✓	✓	✓	✓	✓
Baseline covariates		✓	✓	✓	✓	✓
Contemporaneous changes			✓	✓	✓	✓
Unweighted				✓		
Only Maquiladora CZs					✓	
CZ trends						✓
Observations	3,610	3,610	3,610	3,610	502	3,610

Notes: The dependent variable in Panel A and B is a CZ's change in the employment-to-working-age-population ratio and the log employment count (each multiplied by 100), respectively. Column (1) includes fixed effects for two time periods and eight broad regions in Mexico as well as the main effects from the interactions included in the external exposure to foreign robots variable (i.e., the exposures to Maquiladoras and US import reliance as described in the text). Column (2) also includes 1990 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 level, respectively), several broad 1990 industry employment shares (i.e., shares of employment in manufacturing, durable manufacturing, agriculture, construction, mining and services), and the 1990 level of the outcome variable. Column (3) also includes the share of routine jobs in 1990 following Autor and Dorn (2013), contemporaneous exposure to Chinese import competition following Autor et al. (2013), and the exposure to tariff changes from NAFTA. Column (5) includes the same controls as column (3), but excludes all CZs with no Maquiladora employment in 1990. Column (6) includes CZ trends (i.e., fixed effects in changes for all 1,805 CZs in the sample). All regressions except for column (4) are weighted by a CZ's 1990 share of the national working-age population and national employment in Panels A and B, respectively. Standard errors are robust to heteroskedasticity and allow for arbitrary clustering at the CZ level. The coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

Table A3: Impact of exposure to robots on employment, partial instrumentation (stacked differences)

	(1)	(2)	(3)	(4)	(5)	(6)
	Change in employment-to-population ratio					
	Panel A. 2SLS, only domestic robots instrumented					
Exposure to *domestic* robots	-0.63*	-0.16	0.32	-0.18	0.55*	-0.08
	(0.34)	(0.23)	(0.24)	(0.25)	(0.29)	(0.32)
External exposure to *foreign* robots	-0.59***	-0.66***	-0.47***	-0.48***	-0.59***	-0.53**
	(0.20)	(0.21)	(0.14)	(0.12)	(0.13)	(0.22)
First-stage F statistic	1830	456	407	3753	312	1500
	Panel B. 2SLS, only domestic robots instrumented					
External exposure to *domestic* robots	-0.55*	-0.08	0.32	-0.16	0.69**	-0.26
	(0.31)	(0.25)	(0.26)	(0.23)	(0.35)	(0.77)
Exposure to *foreign* robots	-0.71***	-0.75***	-0.57***	-0.62***	-0.70***	-0.52**
	(0.18)	(0.19)	(0.14)	(0.16)	(0.13)	(0.23)
First-stage F statistic	160	178	175	172	192	213
Region, period & main effects	✓	✓	✓	✓	✓	✓
Baseline covariates		✓	✓	✓	✓	✓
Contemporaneous changes			✓	✓	✓	✓
Unweighted				✓		
Only Maquiladora CZs					✓	
CZ trends						✓
Observations	3,610	3,610	3,610	3,610	502	3,610

Notes: The dependent variable in both Panels is a CZ's change in the employment-to-working-age-population ratio (multiplied by 100). Column (1) includes fixed effects for two time periods and eight broad regions in Mexico as well as the main effects from the interactions included in the external exposure to foreign robots variable (i.e., the exposures to Maquiladoras and US import reliance as described in the text). Column (2) also includes 1990 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 level, respectively), several broad 1990 industry employment shares (i.e., shares of employment in manufacturing, durable manufacturing, agriculture, construction, mining and services), and the 1990 level of the outcome variable. Column (3) also includes the share of routine jobs in 1990 following Autor and Dorn (2013), contemporaneous exposure to Chinese import competition following Autor et al. (2013), and the exposure to tariff changes from NAFTA. Column (5) includes the same controls as column (3), but excludes all CZs with no Maquiladora employment in 1990. Column (6) includes CZ trends (i.e., fixed effects in changes for all 1,805 CZs in the sample). All regressions except for column (4) are weighted by a CZ's share of the national working-age population in 1990. Standard errors are robust to heteroskedasticity and allow for arbitrary clustering at the CZ level. The coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

Table A4: Impact of exposure to robots on log employment and migration (2000-2015, 2SLS)

	(1)	(2)	(3)	(4)	(5)
			Panel A. Log employment count		
Exposure to *domestic* robots	3.22	1.29	1.84	-0.11	2.60**
	(1.98)	(1.90)	(1.92)	(1.99)	(1.27)
Exposure to *foreign* robots	-3.03***	-2.66***	-2.87***	1.11	-4.04***
	(0.75)	(0.87)	(0.76)	(2.39)	(1.05)
			Panel B. Log population count		
Exposure to *domestic* robots	5.79***	0.64	0.68	0.77	1.92***
	(2.05)	(1.59)	(1.46)	(1.99)	(0.72)
Exposure to *foreign* robots	-2.95***	-1.49*	-1.01*	3.03	-2.07***
	(0.70)	(0.77)	(0.58)	(2.08)	(0.72)
Region & main effects	✓	✓	✓	✓	✓
Baseline covariates		✓	✓	✓	✓
Contemporaneous changes			✓	✓	✓
Unweighted				✓	
Only Maquiladora CZs					✓
Observations	1,805	1,805	1,805	1,805	251

Notes: The dependent variable in Panels A and B is a CZ's change in the log employment count and log working-age population (each multiplied by 100) from 2000-2015, respectively. Column (1) includes fixed effects for eight broad regions in Mexico as well as the main effects from the interactions included in the external exposure to foreign robots variable (i.e., the exposures to Maquiladoras and US import reliance as described in the text). Column (2) also includes 1990 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 level, respectively), several broad 1990 industry employment shares (i.e., shares of employment in manufacturing, durable manufacturing, agriculture, construction, mining and services), and the 1990 level of the outcome variable. Column (3) also controls for the share of routine jobs in 1990 following Autor and Dorn (2013), contemporaneous exposure to Chinese import competition following Autor et al. (2013), and the exposure to tariff changes from NAFTA. Column (5) includes the same controls as column (3), but excludes all CZs with no Maquiladora employment in 1990. All regressions except for column (4) are weighted by a CZ's share of the national working-age population in 1990. Standard errors are robust to 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.

Table A5: Impact of exposure to robots on employment (excl. CZs/observations with high exposure)

	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A. Excludes top-1% of CZs with non-zero exposure to foreign robots			
External exposure to *domestic* robots	-0.57*	-0.12	0.39	-0.15	0.80**	-0.33
	(0.32)	(0.25)	(0.27)	(0.23)	(0.38)	(0.75)
External exposure to *foreign* robots	-0.32*	-0.39**	-0.27*	-0.46***	-0.35**	-0.54*
	(0.16)	(0.19)	(0.16)	(0.14)	(0.14)	(0.30)
			Panel B. Excludes top-1% of observations with non-zero exposure to foreign robots			
External exposure to *domestic* robots	-0.58*	-0.15	0.37	-0.16	0.78**	-0.34
	(0.32)	(0.25)	(0.27)	(0.24)	(0.37)	(0.76)
External exposure to *foreign* robots	-0.40*	-0.45*	-0.35*	-0.49***	-0.43**	-0.69**
	(0.20)	(0.24)	(0.19)	(0.18)	(0.17)	(0.34)
Region, period & main effects	✓	✓	✓	✓	✓	✓
Baseline covariates		✓	✓	✓	✓	✓
Contemporaneous changes			✓	✓	✓	✓
Unweighted				✓		
Only Maquiladora CZs					✓	
CZ trends						✓
Observations	3,604	3,604	3,604	3,604	496	3,604

Notes: The dependent variable in Panel A and B is a CZ's change in the employment-to-working-age-population ratio and the log employment count (each multiplied by 100), respectively. Panel A exludes the CZs Ciudad Acuña, Matamoros and Ciudad Juárez in both periods (1990-2000 and 2000-2015). Panel B excludes the CZs Ciudad Acuña, Matamoros, Ciudad Juárez, Nogales, Agua Prieta and Sabinas Hidalgo/Bustamante, all in the second period (2000-2015). Column (1) includes fixed effects for two time periods and eight broad regions in Mexico as well as the main effects from the interactions included in the external exposure to foreign robots variable (i.e., the exposures to Maquiladoras and US import reliance as described in the text). Column (2) also includes 1990 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 level, respectively), several broad 1990 industry employment shares (i.e., shares of employment in manufacturing, durable manufacturing, agriculture, construction, mining and services), and the 1990 level of the outcome variable. Column (3) also includes the share of routine jobs in 1990 following Autor and Dorn (2013), contemporaneous exposure to Chinese import competition following Autor et al. (2013), and the exposure to tariff changes from NAFTA. Column (5) includes the same controls as column (3), but excludes all CZs with no Maquiladora employment in 1990. Column (6) includes CZ trends (i.e., fixed effects in changes for all 1,805 CZs in the sample). All regressions except for column (4) are weighted by a CZ's share of the national working-age population in 1990. Standard errors are robust to heteroskedasticity and allow for arbitrary clustering at the CZ level. The coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

Table A6: Impact of exposure to robots on employment (using alternative instruments)

	(1)	(2)	(3)	(4)	(5)	(6)
	Stacked differences		1990-2000		2000-2015	
	Panel A. EU5 countries instead of rest of the world					
External exposure to *domestic* robots	0.00	0.56*	-0.05	0.01	0.29	0.42
	(0.30)	(0.33)	(0.12)	(0.15)	(0.32)	(0.36)
External exposure to *foreign* robots	-0.81**	-0.60***	-0.10	-0.11	-0.28**	-0.41***
	(0.34)	(0.22)	(0.36)	(0.35)	(0.11)	(0.11)
	Panel B. No interaction with offshorability ($\tilde{O}_i$)					
External exposure to *domestic* robots	-0.12	0.39	1.68	4.79	0.27	0.43
	(0.25)	(0.26)	(3.91)	(4.91)	(0.27)	(0.31)
External exposure to *foreign* robots	-0.72***	-0.52***	-0.03	-0.04	-0.19	-0.32**
	(0.22)	(0.14)	(0.04)	(0.04)	(0.13)	(0.12)
	Panel C. Exports share (X_i) instead of offshorability ($\tilde{O}_i$)					
External exposure to *domestic* robots	-0.22	0.34	0.72	3.64	0.26	0.41
	(0.27)	(0.26)	(4.12)	(5.36)	(0.27)	(0.30)
External exposure to *foreign* robots	-0.58***	-0.41***	-0.00	0.02	-0.21***	-0.32***
	(0.21)	(0.13)	(0.33)	(0.32)	(0.07)	(0.07)
Region & main effects	✓	✓	✓	✓	✓	✓
Baseline covariates	✓	✓	✓	✓	✓	✓
Contemporaneous changes		✓		✓		✓
Period dummies	✓	✓				
Observations	3,610	3,610	1,805	1,805	1,805	1,805

Notes: The dependent variable is a CZ's change in the employment-to-population ratio (multiplied by 100). In Panel A, the external exposure measures are computed using the same five EU countries as in Acemoglu and Restrepo (2020); in Panel B, it leaves out the interaction with an industry's 1990 offshorability $\tilde{O}_i$; and in Panel C, it uses an industry's 1990 share of total Mexican exports instead of 1990 offshorability $\tilde{O}_i$. Columns (1) and (3) include fixed effects for eight broad regions in Mexico as well as the main effects from the interactions included in the external exposure to foreign robots variable (i.e., the exposures to Maquiladoras and US import reliance as described in the text). Columns (2) and (4) also include 1990 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 level, respectively), several broad 1990 industry employment shares (i.e., shares of employment in manufacturing, durable manufacturing, agriculture, construction, mining and services), and the 1990 level of the outcome variable. Columns (3) and (6) also control for the share of routine jobs in 1990 following Autor and Dorn (2013), contemporaneous exposure to Chinese import competition following Autor et al. (2013), and the exposure to tariff changes from NAFTA. Columns (3)-(6) also include time period dummies. All regressions are weighted by a CZ's share of the national working-age population in 1990. Standard errors are robust to heteroskedasticity and allow for arbitrary clustering at the state level (31 states) in columns (1)-(3) and the CZ level in columns (4)-(6). The coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

Table A7: The impact of exposure to robots on employment (incl. state fixed effects)

	(1)	(2)	(3)	(4)	(5)
	Change in employment-to-population ratio				
	Panel A. Stacked differences				
External exposure to *domestic* robots	-0.65*	-0.19	0.30	-0.06	0.59
	(0.34)	(0.25)	(0.23)	(0.26)	(0.45)
External exposure to *foreign* robots	-0.73***	-0.76***	-0.53***	-0.51***	-0.66***
	(0.17)	(0.18)	(0.14)	(0.11)	(0.14)
Observations	3,610	3,610	3,610	3,610	502
	Panel B. 1990-2000				
External exposure to *domestic* robots	-6.85	-0.23	0.05	20.30	-0.35
	(7.69)	(5.34)	(4.77)	(22.97)	(9.34)
External exposure to *foreign* robots	-0.14	-0.02	-0.11	-0.42	-0.30
	(1.12)	(1.30)	(1.26)	(0.74)	(1.13)
Observations	1,805	1,805	1,805	1,805	251
	Panel C. 2000-2015				
External exposure to *domestic* robots	-0.26	0.27	0.33	-0.36	0.36
	(0.37)	(0.33)	(0.34)	(0.52)	(0.31)
External exposure to *foreign* robots	-0.33**	-0.36***	-0.41***	-0.45*	-0.61***
	(0.13)	(0.13)	(0.08)	(0.22)	(0.15)
Observations	1,805	1,805	1,805	1,805	251
State & main effects	✓	✓	✓	✓	✓
Baseline covariates		✓	✓	✓	✓
Contemporaneous changes			✓	✓	✓
Unweighted				✓	
Only Maquiladora CZs					✓

Notes: The dependent variable is a CZ's change in the employment-to-working-age-population ratio (multiplied by 100). Column (1) includes fixed effects for 31 states in Mexico as well as the main effects from the interactions included in the external exposure to foreign robots variable (i.e., the exposures to Maquiladoras and US import reliance as described in the text). 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 level, respectively), several broad baseline industry employment shares (i.e., shares of employment in manufacturing, durable manufacturing, agriculture, construction, mining and services), and the baseline level of the outcome variable. Column (3) also controls for the 1990 share of routine jobs following Autor and Dorn (2013), exposure to Chinese import competition from 1990-2015 following Autor et al. (2013), and the 1990 exposure to tariff changes from NAFTA. Column (5) includes the same controls as column (3), but excludes all CZs with no Maquiladora employment in 1990. All regressions except for column (4) are weighted by a CZ's share of the national working-age population in 1990. Standard errors are robust to heteroskedasticity and allow for arbitrary clustering at the CZ level in Panel A and the state level (31 states) in Panels B and C. The coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

Table A8: The impact of exposure to robots on employment (using LASSO for covariate selection)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Stacked differences			1990-2000			2000-2015		
	Panel A. Reduced form								
External exposure to *domestic* robots	0.33	0.02	0.73**	5.71	27.76	4.11	0.52*	-0.48	0.12
	(0.25)	(0.24)	(0.32)	(6.44)	(22.89)	(4.47)	(0.27)	(0.47)	(0.27)
External exposure to *foreign* robots	-0.48***	-0.49***	-0.56***	-0.05	-0.40	0.07	-0.51***	-0.23	-0.45***
	(0.13)	(0.12)	(0.14)	(0.83)	(1.03)	(0.78)	(0.13)	(0.15)	(0.07)
	Panel B. 2SLS								
Exposure to *domestic* robots	0.26	0.02	0.41*	5.05	22.17	-5.36	0.47**	-0.12	0.25
	(0.24)	(0.26)	(0.22)	(5.07)	(20.70)	(8.20)	(0.24)	(0.39)	(0.21)
Exposure to *foreign* robots	-0.59***	-0.61***	-0.68***	-0.25	-0.49	0.13	-0.88***	-0.36	-0.80***
	(0.14)	(0.16)	(0.13)	(1.24)	(1.73)	(1.16)	(0.16)	(0.24)	(0.13)
LASSO-selected covariates	✓	✓	✓	✓	✓	✓	✓	✓	✓
Unweighted		✓			✓			✓	
Only Maquiladora CZs			✓			✓			✓
Observations	3,610	3,610	502	1,805	1,805	251	1,805	1,805	251

Notes: The dependent variable is the change in the employment-to-population ratio (multiplied by 100). All columns include covariates selected by LASSO, following Belloni et al. (2014). Columns (1) and (4), all CZs are included and regressions are weighted by a CZ's share of the national working-age population in 1990. In columns (2) and (5), regressions are unweighted. In columns (3) and (6), only CZs with some Maquiladora employment in 1990 are included. Standard errors are robust to heteroskedasticity and allow for arbitrary clustering at the state level (31 states) in columns (1)-(3) and the CZ level in columns (4)-(6). The coefficients with ***, **, and * are significant at the 1%, 5% and 10% confidence level, respectively.

A.3 Theoretical foundation (Acemoglu and Restrepo, 2020)

This section, provides a brief summary of the model developed by Acemoglu and Restrepo (2020). 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 by 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

$$Y_c = \left(\sum_{i \in I} \alpha_i Y_{ci}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}, \tag{13}$$

where $\sum_{i \in I} \alpha_i = 1$ and $\sigma{>}0$ denotes the elasticity of substitution 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

$$X_{ci} = A_{ci} \min_{s \in [0,1]} \{x_{ci}(s)\}, \tag{14}$$

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 (see Figure A5). More formally,

$$x_{ci}(s) = \begin{cases} \gamma L_{ci}(s) & \text{if } s > M_i, \\ \gamma L_{ci}(s) + R_{ci}(s) & \text{if } s \leq M_i \end{cases} \tag{15}$$

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.

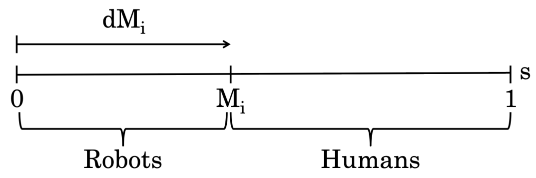


Figure A5: Automation of tasks

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

$$W_c = \mathcal{W}_c Y_c L_c^{\epsilon}, \quad \text{with } \epsilon \geq 0; \text{ and} \tag{16}$$

$$Q_c = \mathcal{Q}_c \left(\frac{R_c}{Y_c}\right)^{\eta}, \text{ with } \eta \geq 0 \tag{17}$$

where Q_c is the price of robots, W_c is the wage rate, and $\mathcal{W}_c$ and $\mathcal{Q}_c$ are local supply curve shifters in CZ 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 in understanding the three different forces at work in this model:[47]

$$d\ln L_c = \underbrace{-\sum_{i\in I}\frac{L_{ci}}{L_c}\frac{dM_i}{1-M_i}}_{\text{displacement effect}} \underbrace{-\sigma\sum_{i\in I}\frac{L_{ci}}{L_c}d\ln P_{X_{ci}}(M_i)}_{\text{price-productivity effect}} \underbrace{+\,d\ln Y_c(M_i)}_{\text{scale-productivity effect}}, \tag{18}$$

where $P_{X_{ci}}$ 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 (16) and (17) and the markets for final goods, labor and robots clear. For simplicity, it is assumed that it is profitable for firms to use

[47] See Acemoglu and Restrepo (2020) for derivations of all steps as well as proofs of existence and uniqueness of the equilibrium presented in this subsection.

robots in all tasks that are technologically automated. Equation (18) is in terms of robotic automation *technology* M_i, not the number of robots R_i. Using the fact 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 (18) 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:

$$d\ln L_c = \beta_c \sum_{i \in I} \frac{L_{ci}}{L_i}\frac{dR_i}{L_c} + \epsilon_c, \text{ with } \beta_c = \left(\frac{1+\eta}{1+\varepsilon}\pi_c - \frac{1+\eta}{1+\varepsilon}\right)\frac{1}{\gamma}, \tag{19}$$

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

Acemoglu and Restrepo (2020) 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 equalized 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 (2020) show that this model including 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.

A.4 Data construction

A.4.1 Industry crosswalks

The International Federation of Robotics (IFR) uses its own industry classification. To match the data at the industry level with employment and trade data, I apply several crosswalks from other classifications. Table A9 presents all crosswalks that I implement in this paper.

A.4.2 Maquiladora employment

To compute the number of people employed in Maquiladoras by CZ and industry, I rely on non-digitized data from CEPAL (1994) (p.129ff). Figure A6 presents one example page from the original document. In a first step, I match each municipality in the CEPAL (1994) data to a unique CZ, using the crosswalk resulting from the exercise described in Section 4.1.

Moreover, I perform three steps to make the data compatible with the industry classification used by the IFR: First, the Maquiladora data reports on the electronics and electrical machinery industries, which are separate in the IFR data, as one combined industry. I therefore allocate employment in this combined industry to the two more detailed industries according to the relative size of each of these in the respective CZ in the census data. Second, the data contains dedicated industry information only for the eight most important Maquiladora industries (covering 80% of total Maquiladora employment in 1990), the remainder being reported in the residual category "other industries".[48] I allocate these into the remaining IFR manufacturing industries according to their relative size in the respective CZ in the census data. Third, the industry breakdown is missing entirely for some municipalities. In these cases, I allocate the reported total according to each industry's share of total Maquiladora employment from all CZs for which this data exists.

A.4.3 Penetration of robots at industry level

In Section 6.4, I perform a similar analysis as the main analysis, but at the industry level instead of the CZ level. For this, I construct the industry-level counterparts of the external exposures to domestic and foreign robots. I refer to these as the *penetration of domestic robots* and *penetration of foreign robots*, respectively (analogous to the wording used in Acemoglu and Restrepo, 2020). More precisely, I define

$$\begin{array}{c}\text{Penetration of}\\ \text{domestic robots}_{i,(t_0,t_1)}\end{array} \equiv \left(\frac{R^{WLD}_{i,t_1} - R^{WLD}_{i,t_0}}{L_{i,1990}}\right), \qquad \text{and} \tag{20}$$

$$\begin{array}{c}\text{Penetration of}\\ \text{foreign robots}_{i,(t_0,t_1)}\end{array} \equiv \frac{L^f_{i,1990}}{L_{i,1990}} \left(\frac{(R^{WLD}_{i,t_1} - R^{WLD}_{i,t_0})\tilde{O}_{i,1990}}{L^f_{i,1990}}\right). \tag{21}$$

Analogous to the CZ-level external exposure measure, an industry's penetration of foreign robots is thus high, if *i)* many foreign robots have been installed per Maquiladora worker

[48] Detailed industries are food products, textiles, wood products, chemicals, metal products, electronics, automotive, and other services. "Other industries" contains paper, plastics, basic metals, and industrial machinery.

(term in big brackets) and *ii)* Maquiladora employment made up a large share of overall industry employment to start with.

Table A9: Industry crosswalks

Industry name	IFR code	SIC87	HS92	Mexican census data		
				1990	2000	2015
Agriculture	A-B	.	1-15	10001-10999	110-119	1110-1199
Mining	C	.	.	20001-20999	210-212	2110-2199
Manufacturing industries						
Food products & beverages	10-12	2000-2199	16-24	31001-31099	310-311	3110-3120
Textiles & apparel	13-15	2200-2399, 3100-3199	41-43, 50-67	31101-31211	312-315	3130-3160
Wood products	16	2400-2599	44-47	31301-31399	320, 336	3210, 3370
Paper & printing	17-18	2600-2799	48-49	32001-32099, 32199	321-322	3220-3230
Pharmaceuticals & other chemicals	19-21	2800-2819, 2830-2999	27-38	32101-32132, 32199	323-324	3240-3250
Rubber & plastic products	22	2820-2829, 2000-3099	39-40	32141-32152	325	3260
Minerals	23	3200-3299	25-26, 68-71	32201-32299	326	3270
Basic metals	24	3300-3399	72, 7401-7406, 7501-7504, 7601-7603, 7801-7802, 7901-7903, 8001-8002, 81	32301-32399	330	3310
Metal products	25	3400-3499	73, 7407-7419, 7505-7508, 7604-7616, 7803-7806, 7904-7907, 8003-8007, 82-83	32401-32404	331	3320
Industrial machinery	28	3500-3569, 3580-3599	84	32411	332	3330
Computers & electronics	26-27 (except 271)	3570-3579, 3650-3679	8508-8510, 8517-8548 32422-32423	32412-32413,	333	3340
Electrical equipment & machinery	271	3600-3649, 3680-3699	8501-8507, 8511-8516	32421	334	3350
Automotive & transport equipment	29-30	3700-3799	86-89	32431-32441	335	3360
Utilities	E	.	.	41000-41999	220-222	2210-2222
Construction	F	.	.	42001-42999	230-239	2361-2399
Education, R&D	P	.	.	82001-82099	540-541, 610	6111-6199
Other services	90	.	.	82101-85999	430-539, 550-564, 620-939	4310-5620, 6211-9399

Cuadro 5

MEXICO: INDUSTRIA MAQUILADORA UBICADA EN CIUDAD JUAREZ

(Diciembre de 1990)

	Número de plantas		Personal ocupado		Tamaño de planta		Sueldos, salarios y prestaciones		Valor agregado		Salario mensual por persona ocupada	
	Unidad	%	Unidad	%		%	Miles de pesos	%	Miles de pesos	%	Pesos	%
Total	275	100.0	123,046	100.0	447	100.0	162,559	100.0	266,641	100.0	1,321,124	100.0
Equipo de transporte	30	10.9	40,442	32.9	1,348	301.3	54,612	33.6	89,475	33.6	1,350,378	102.2
Materiales eléctricos y electrónicos	84	30.5	36,430	29.6	434	96.9	51,281	31.5	88,046	33.0	1,407,659	106.6
Aparatos eléctricos y electrónicos	21	7.6	12,450	10.1	593	132.5	15,663	9.6	25,119	9.4	1,258,072	95.2
Prendas de vestir	27	9.8	7,648	6.2	283	63.3	12,428	7.6	15,324	5.7	1,625,000	123.0
Servicios	17	6.2	7,440	6.0	438	97.8	6,790	4.2	9,584	3.6	912,634	69.1
Otras industrias	32	11.6	6,837	5.6	214	47.8	8,643	5.3	15,640	5.9	1,264,151	95.7
Muebles de madera y metal	29	10.5	6,684	5.4	230	51.5	7,968	4.9	13,217	5.0	1,192,101	90.2
Productos químicos	10	3.6	2,506	2.0	251	56.0	2,670	1.6	4,153	1.6	1,065,443	80.6
Calzado y cuero	13	4.7	1,123	0.9	86	19.3	1,164	0.7	2,057	0.8	1,036,509	78.5
Herramientas y equipo no eléctricos	5	1.8	787	0.6	157	35.2	852	0.5	1,465	0.5	1,082,592	81.9
Preparacion de alimentos	6	2.2	670	0.5	112	25.0	475	0.3	2,532	0.9	708,955	53.7
Juguetes y artículos deportivos	1	0.4	29	0.0	29	6.5	13	0.0	29	0.0	448,276	33.9

Fuente: CEPAL sobre la base de cifras del Instituto Nacional de Estadística, Geografía e Informática.

SOURCE: CEPAL (1994)

Figure A6: Number of employees (*personal ocupado*) in Maquiladoras by industry in Ciudad Juarez, December 1990