# Industrial Robots and Infant Mortality in Mexico

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**Abstract**

In this paper, I investigate the impact of increased robotics in the United States on infant mortality rates in Mexico. Using a shift-share design that leverages variations in industrial robot usage and the employment composition of export-oriented *maquiladoras*, which predominantly employ women, I find that regions with higher exposure to U.S. automation experienced a greater rise in infant mortality rates. The analysis shows that women in manufacturing faced more significant job losses than men, leading to reduced household income and access to employer-provided healthcare. This economic strain forced many women into self-employment, reducing time for childcare. Additionally, I present evidence suggesting that automation may increase risky behaviors, such as drinking and smoking, among uninsured women of childbearing age. These findings highlight the complex relationship between technological advancements and public health outcomes, emphasizing the need for policymakers to consider the cross-border effects of automation on global health and employment.

JEL Classification: I12, I15, I18, J13, J16

Keywords: industrial robots, infant mortality, *maquiladora* employment, economic shocks.

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# 1 Introduction

Over the last three decades, both developed and developing economies have experienced automation anxiety, driven by the rapid advancement of technologies such as robotics. The decrease in the relative price of capital, combined with technological progress, has made it more cost-effective for manufacturing in developed economies to integrate robots, thereby replacing routine-task jobs that were traditionally performed in labor-intensive factories in countries such as Mexico, Indonesia, Bangladesh, China, and India. This process, known as labor *reshoring*, has led advanced economies like the United States (U.S.) to rely less on *offshoring* tasks, which has negatively impacted manufacturing employment and exports in countries such as Mexico (Brambilla et al., 2023; Faber, 2020; Stemmler, 2023).

*Maquiladoras*, factories in Mexico that import materials and assemble or manufacture products on a duty-free and tariff-free basis for re-export, have been a key part of this globalized system of manufacturing. Since their creation in 1965 by the government of Mexico, *maquiladoras* have been female-dominated across various occupations: on average, female employment accounted for over 50% of total employment in 1990, compared to 19% in all manufacturing jobs, making these factories a crucial source of export-oriented labor for women in low-skilled manufacturing industries. However, *maquiladoras'* overall employment has stagnated since 2000,[1] partly due to technological advancements and the reshoring of plants through the use of industrial robots in the United States.[2] While there is evidence that women's labor and infant health outcomes improved at the onset of the *maquiladora* program in the early 1990s, due to increased labor opportunities for women (Atkin, 2009; Estefan, 2022),[3] there is a dearth of empirical support on the effects of automation on infant health in developing

[1]Over the 1990-2000 period, average employment growth was 11.3%, while for the 2000-2004 period it was -3.4%,

[2]Faber (2020) provides anecdotical evidence of increasing plant reshoring in the United States, and empirical evidence on the negative effect of U.S. robots exposure on employment in Mexico.

[3]Atkin (2009) shows that there are positive effects on children's health to increases in job opportunities for women in *maquiladora* plants. Estefan (2022) provides extensive empirical and theoretical evidence that export opportunities increased manufacturing employment for women, leading to better assortative mating, and improved children's health outcomes.

countries.

This paper fills this gap in the context of Mexico, where *maquiladoras* are a popular source of employment that is potentially susceptible to technological shocks in the United States, Mexico's leading export destination.[4]

I investigate the effect of U.S. automation on infant mortality in Mexico. To do so, I draw upon the standard trade literature to construct local labor market-specific Bartik-style measures of predicted robot adoption per worker in the United States. First, I leverage the industrial composition of *maquiladora* employment in 1990 as shares, as well as official records of industrial robot stocks and shipments from the International Federation of Robotics (IFR) as shocks. I then merge the robot intensity measure with detailed administrative records of infant mortality from *Instituto Nacional de Estadística y Geografía* (INEGI). My empirical strategy aims at making within comparisons of infant mortality rates among local labor markets highly affected by U.S. robot adoption vis-à-vis those where low or null robot adoption took place for the period 2000-2015.

Disentangling the true effect of robots on infant health is challenging due to the non-random and potentially simultaneous decision to employ robots in the U.S. To overcome these limitations, I use an instrumental variable (IV) approach that relies on the exogenous variation in maquiladora employment in 1990. This IV strategy is similar in spirit to other papers seeking to understand the effect of industrial robots on labor markets (Acemoglu and Restrepo, 2020; Brambilla et al., 2023; Dauth et al., 2021; de Vries et al., 2020; Graetz and Michaels, 2018; Stemmler, 2023).

As Goldsmith-Pinkham et al. (2020) show, the main identification threat is that the shares of *maquiladora* employment may predict infant mortality through channels other than robotics. To address this concern, I follow their recommendation and confirm that there are parallel trends in the outcome before the automation shock occurred for the period of analysis, and that there are not significant baseline correlates of the

[4]Over the period 2000-2015, exports to the United States represented on average 83% of total exports, which were comprised mainly of manufacturing products, including electronics, vehicles, and auto parts. Besides Mexico City, northern border states like Chihuahua, Baja California, Nuevo León, and Tamaulipas were the main sources of exports. Imports from the United States, on the other hand, account on average for nearly 54% of Mexico's total imports.

instrument, reassuring me the identification assumptions are met in my design.

My main results show a meaningful and statistically significant effect of U.S. robot adoption on infant mortality in areas more exposed to U.S. robots. I find that an average increase in U.S. robots per worker will increase the infant mortality rate by 0.17-0.19 deaths per thousand births, which translates into an increase of 1.2%-1.3% of the baseline mean. These results are robust to controlling for several baseline characteristics, to the inclusion of pre-trends in the outcome, and other contemporaneous shocks. Furthermore, the main results are qualitatively similar to alternative definitions of the instrument, sample restrictions, and inference methods proposed in the shift-share literature (Adão et al., 2019; Borusyak et al., 2022b).

The detailed nature of the data allows me to further explore whether the effect of U.S. automation on infant mortality is driven by specific groups of diseases. To investigate this, I divide the sample according to broad categories of the International Classification of Diseases (ICD). I find that the effects are concentrated among perinatal, infectious, respiratory, and malnutrition diseases, which together account for approximately two-thirds of baseline infant deaths in Mexico.

To shed light on potential mechanisms, I focus on examining whether there are income and substitution effects resulting from changes in the labor market. Because children's care can be considered a normal good, both income and time-intensive factors contribute to children's well-being (Becker, 1960,9). I find evidence of income-related drivers, documenting that U.S. robots negatively affect the employment-to-population ratio. These effects are predominantly concentrated among low-skilled women in manufacturing industries of childbearing age, while there are no statistically significant effects for men. Consequently, there are also statistically significant losses in real household labor income.

Employment losses among women may also decrease the opportunity cost of parental quality time (Dehejia and Lleras-Muney, 2004; Del Boca et al., 2014; Miller and Urdinola, 2010) and reduce the propensity for risky behaviors (e.g., drinking, smoking, drug abuse), thus positively affecting infant health and fertility (Ruhm, 2000). Contrary to this prediction, I find that parental time does not increase for women, as there is an increase in self-employment occupations in manufacturing as a coping mechanism for employment and income losses, which negatively impacts infant health. This suggests that the substitution between income and time is not mechanical in the case of Mexico, where many health services are not provided free of charge.

I examine the implications of these findings, reinforcing the predominance of the income effect. First, I demonstrate that job losses attributable to automation reduce women's likelihood of accessing formal health care through their employers. Second, the analysis reveals that women without health insurance are primarily driving the observed mortality outcomes, with no significant effects of automation detected among women with health insurance. Third, using data on births from Mexico's Ministry of Health, I find that children born in regions more heavily impacted by automation face a higher risk of inadequate prenatal care. However, no significant differences are found in birth outcomes such as low birth weight or preterm births. Together, these results suggest that income losses outweigh the benefits of increased parental time, indicating that automation-related increases in infant mortality are more likely to manifest in the months following birth.

Next, I rule out the possibility of other interpretations of my results. In particular, I show that there are no credible concerns of selectivity through fertility or migration. Moreover, supply-side factors such as the number of pediatricians and available beds, which might be attributed to lower income through employment losses, are not responsible for my results.

The findings of this paper speak to several strands of the literature. First, they contribute to the vast literature that evaluates the consequences of aggregate, income-related shocks on infant health.[5] Among developed countries, theoretical and empirical evidence suggests that infant health is procyclical (Dehejia and Lleras-Muney, 2004; Del Boca et al., 2014; Ruhm, 2000), and that parental time transfers to children seem to matter more than monetary transfers. Among low- and middle-income countries,

[5]See Ferreira and Schady (2009) and Bellés-Obrero and Castelló (2018) for a literature reivew.

there is more consensus on the countercyclical pattern of infant mortality (Baird et al., 2011; Bhalotra, 2010; Bozzoli and Quintana-Domeque, 2014).

However, the bulk of this literature focuses on understanding the response of infant health to transitory, aggregate fluctuations in the economy, yet there is a notable gap concerning the impact of permanent shocks resulting from automation. Most studies on the health consequences of automation are focused on specific countries like the United States, China, and Germany, but they emphasize the adult population and aim to understand the impacts on health outcomes, including substance abuse (O'Brien et al., 2022), self-reported health (Gunadi and Ryu, 2021), and incidents related to transportation and workplace accidents (Gihleb et al., 2022).

Second, this paper adds to the literature that explores the effects of income shocks on mortality in Mexico, where evidence is mixed. On one hand, following Ruhm (2000), Gonzalez and Quast (2011) show that overall mortality is procyclical to changes in state-level GDP. On the other hand, Cutler et al. (2002) and Arceo-Gómez (2010) report a countercyclical pattern of mortality, mainly affecting children and the elderly population. This paper aligns with the latter set of evidence while providing additional insights into potential mechanisms that highlight the importance of income and time. Recent empirical evidence supports this channel, as similar income shocks (e.g. trade liberalization with China) have adverse implications on adult mortality through employment losses and limited access to health insurance (Fernández Guerrico, 2021).

Third, this paper contributes to the emerging literature that examines the impact of automation on the labor market with a focus on gender. Previous studies have investigated the impact of employment opportunities for women in export-oriented sectors, particularly in contexts such as Mexico and Bangladesh (Atkin, 2009; Estefan, 2022; Majlesi, 2016; Heath, 2014; Heath and Mushfiq Mobarak, 2015). However, there is limited understanding of how labor-replacing technologies affect women's labor outcomes. Research on advanced economies indicates that the introduction of robotics has led to significant disruptions in employment and wages, with male employment being disproportionately affected by automation (Acemoglu and Restrepo, 2020). The impact of automation may differ in developing economies, suggesting that gender-specific public policy interventions may be necessary to address these disparities.

The remainder of this paper is structured as follows. To better understand the context of this paper, Section 2 outlines the characteristics of the *maquiladora* program and Mexico's health system. Section 3 describes the data sources and provides summary statistics. Section 4 details the identification strategy. Section 5 presents the empirical findings, including the robustness checks of the main results. Section 6 explores support for possible mechanisms linked to the main results. Section 7 concludes.

# 2 Context

## 2.1 The *maquiladora* program

*Maquiladoras* use free-of-tax semi-finished goods, mainly from the United States and Canada, which are then processed and returned to their owners as tariff-free finished goods. The *maquiladora* program began as a large-scale initiative by the Mexican Government, promoting job creation, capital investments, technology transfer, and the development of managerial skills.

*Maquiladoras* benefit from exemptions from value-added tax and streamlined administrative procedures, making them attractive options for foreign investors, particularly from the United States. This setup allows American companies to establish manufacturing operations in Mexico and take advantage of lower labor costs while maintaining proximity to their home market. The *maquiladora* program also provides opportunities for Mexican citizens to participate in these ventures either as workers or as partners overseeing labor-related matters. Between 1985 and 2000, *maquiladoras* contributed to half of manufacturing exports, and at its peak in 2000, *maquiladoras* represented 40% of manufacturing employment (Contreras and Munguía, 2007).

Given its proximity to the United States, *maquiladora* plants are usually located in border states,[6] specializing in labor-intensive sectors like electronics, furniture, auto-

[6]The first *maquiladora* plant was in Ciudad Juarez, in the state of Chihuahua, which shares the border

motive parts, and textiles. Since their creation, *maquiladoras* have relied heavily on female employment. Figure A1 shows the share of maquiladora employment by sex and sector in 1990. Female employment exceeds 50% across all industries except for furniture, wood, and metal products manufacturing. This trend has persisted over time. As shown in Figure A2, there is a strong, positive relationship between the share of female *maquiladora* employment in 1990 and 2006. This could be attributed to various factors, including cultural norms and perceived gender roles: some managers may view women as more adept at manual, routine tasks while reserving technical and managerial positions for men (Fussell, 2000; Villarreal and Yu, 2007).

*Maquiladora* workers also earn lower salaries compared to the overall manufacturing sector. From 1994 to 2006, the average *maquiladora* workers in the highest remuneration quantile earned less than the average manufacturing worker (Estefan, 2022). This disparity suggests that *maquiladora* firms predominantly employ workers with low skill levels and offer lower wages compared to other segments of the manufacturing sector.

## 2.2 Mexico's health system

The Mexican health system operates through three subsystems that are responsible for funding, service provision, and regulation. The first subsystem is the Social Security Scheme,[7] which is linked to the formal labor market and is financed through employers, workers, and government contributions, supporting 45% of the population. The second subsystem is the Popular Health Insurance scheme (*Seguro Popular*), which is financed through state and federal-level contributions and household out-of-pocket payments (adjusted by income capacity), covering 40% of the population (mostly uninsured through employment). The third subsystem is the private sector, which supplies 45%

with Texas. At the beginning of the program only border states were allowed to have *maquiladora* plants. After 1972, other states could host these plants, provided they did not compete in location with existing manufacturing plants (Dorocki and Brzegowy, 2014).

[7]For private employees, the main institution is the *Instituto Mexicano del Seguro Social* (IMSS). For workers in the public sector the following institutions provide health services: *Instituto de Seguridad y Servicios Sociales de los Trabajadores del Estado* (ISSSTE), *Petróleos Mexicanos* (PEMEX), *Secretaría de la Defensa* (SEDENA), and *Secretaría de Marina* (SEMAR).

of outpatient consultations and absorbs 19% of hospital care (Block et al., 2020).

Although significant efforts have been made in expanding coverage and improving service provision with the introduction of *Seguro Popular* in 2004—evidenced by the increase in the population's insurance coverage from 42% in 2000 to 82% in 2015—income-related barriers remain that disproportionately affect the most vulnerable populations. For instance, the share of out-of-pocket expenditure for health services in Mexico is relatively high compared to economies with similar levels of development in the Latin America and Caribbean (LAC) region (see Figure A3). Additionally, due to long waiting times, underfunding, and limited capacity in the public sector, many individuals turn to private healthcare providers, which often require substantial upfront payments.

Despite the rapid advances in health coverage, effective access to medical services for those needing them has significant gaps among the insured and uninsured (Gutiérrez et al., 2014; Urquieta-Salomón and Villarreal, 2016). For example, Urquieta-Salomón and Villarreal (2016) show that although, on average, 9 in 10 women have access to prenatal care during pregnancy—with no significant differences among insured and uninsured—there is a 20% difference between the population insured with formal jobs and those uninsured if a more stringent definition of effective access is applied.[8]

Mexico's average infant mortality rate for the period 2000-2015 was 18.1. While this figure is slightly below than the average for Latin American countries (20.4), Mexico's average infant mortality rate was twice as high as that of OECD countries for the same period (8.6).

# 3 Data

This section summarizes the data I use to investigate the causal relationship between automation through robot adoption and infant mortality in Mexico.

**Unit of analysis:** in line with Atkin (2016) and Faber (2020), the analysis will be

[8] Urquieta-Salomón and Villarreal (2016) define crude prenatal care access as women having attended at least four prenatal visits with a healthcare provider. On the other hand, effective prenatal care is defined as women reporting having received: measurement, weight, blood pressure, general urinalysis, blood tests, blood glucose level, ultrasound, tetanus vaccine, folic acid screen, blood test for iron level and syphilis detection.

conducted at the commuting zones (CZ) level. It is an important distinction in contrast to other studies that use other geographic areas (e.g., counties, municipalities, states) as their unit of analysis for two reasons. First, it mitigates concerns about attenuation bias arising from highly disaggregated and potentially unconnected geographic units. Conventional geographic boundaries (e.g., states or municipalities) do not necessarily coincide with economic boundaries.[9] Second, workers are not necessarily mobile across geographic units, especially those at the bottom of the skill distribution (Patt et al., 2021; Villarreal, 2016). In this specific context, CZs are defined as clusters of municipalities with strong ties, as measured by the frequency of commuting movements among workers across various municipalities within a *Metropolitan Zone*.[10] Thus, a CZ is defined as a condition in which at least 10% of residents of a given municipality commute to the other within the same zone. The resulting number of CZs is approximately 1,806.

**Mortality and infant health data:** data on infant mortality come from the universe of annual death certificates of children younger than one year old.[11] I have access to the microdata files from *Instituto Nacional de Estadística y Geografía* (INEGI), which contain comprehensive information about the date of death, the cause of death based on the International Classification of Diseases (ICD), the gender of the child, whether the child (mother) had any insurance coverage, as well as the mother's municipality of residence. Collectively, the dataset encompasses approximately 580,000 infant deaths recorded during the 1998-2015 period. Using individual microdata, I compute counts of infant deaths for each CZ-year cell. To derive infant mortality rates expressed per 1,000 live births, I normalize the infant mortality counts by the aggregated count of live births at the CZ-year level, information that is likewise accessible through INEGI.

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[9]See Lindo (2015) for a discussion about geographic aggregation and its impact on the relationship between area shocks and health outcomes in the U.S..

[10]By the year 2000 Mexico had 2,443 municipalities within 32 states. The number of clustered Metropolitan Zones is 59, which groups 1,022 municipalities, so the remaining municipalities are independent clusters. Like Atkin (2016) and Faber (2020), I exclude México City. Given its own size (over 570 squared miles) and economic importance, it is unlikely that workers commute outside of the city on a regular basis.

[11]Data are collected by INEGI through Mexico's Ministry of Health, from its state-wide regional branches.

In addition, I utilize two sources of administrative records from Mexico's Ministry of Health. First, for the period 2008-2015, I draw on comprehensive birth records from public hospitals. These data provide detailed information on births, including the gestational week at birth, birth weight in grams, Apgar scores,[12] and basic maternal information such as municipality and state of residence, education level, age, and type of health coverage. Second, for the period 2001-2015, I use data on human and physical resources, which include the number of pediatricians, newborn cribs, and delivery rooms available in healthcare facilities.

**Robot usage:** the stock of robots by industry and country is collected by the International Federation of Robotics (IFR), following, albeit not with absolute precision, the International Standard Industrial Classification. These data are compiled from supplier surveys from 75 countries for the period 2000-2015, accounting for over 90% of the market of industrial robots. The IFR defines a robot as an "automatically controlled, reprogrammable, and multipurpose machine"(IFR, 2015). Thus, robots are autonomous machines that need little to no human supervision and can be programmed to perform several tasks like packaging, carrying materials, assembling, welding, and painting. These features are distinct from other machines like tractors and sewing machines, as they cannot be programmed, perform other specific tasks, or both.

There are some limitations with the IFR data. First, for the United States, industry-by-year information is only available after 2004, and North America is recorded as one entity, even though over 90% of robot shipments have been sent to the United States since 1993. Therefore, I follow the proposed perpetual inventory method by Graetz and Michaels (2018) to estimate robot stock, assuming a depreciation rate of 5% to impute missing robots. Another limitation is the lack of CZ-level robot data, so I use a Bartik-style approach to predict robot adoption at this level (see section 4), a commonly used approach in other studies examining the impact of robots on labor markets and demographic dynamics. Figure 1 shows that U.S. robots per worker have increased

[12]The Apgar score goes from 0 to 10 points and assesses the immediate health status of the newborn. It has five components: color, heart rate, reflexes, muscle tone, respiration. Each component is given a score of 0, 1, or 2.

dramatically since 2000, though the pace is lower than that of European countries. The sectoral composition documented in Figure 2 highlights that robots in the automotive sector are particularly important, followed by the electronics, rubber (plastic), and metal industries.

**Census microdata:** I employ individual-level 10% IPUMS samples from Mexico's population census for the years 1990 and 2000, as well as the latest intercensal survey in 2015 (Ruggles et al., 2015). These data contain detailed demographic characteristics including age, education attainment, type of health insurance,[13] place of residence, and economic information related to labor income, sector, and occupation in main employment, which are then collapsed at the CZ level. I use the data from the 1990 and 2000 census samples to compute initial demographic characteristics. When evaluating potential mechanisms, I study the changes in employment, self-employment, health access, and household labor income between census (intercensal) years between 2000 and 2015. I focus on employment, unemployment, self-employment to population ratios, and household real labor income at the CZ level.

**Other data:** I used the digitized sample of employment in *maquiladoras* at the CZ-by-sector level in 1990 available from CEPAL (1994), provided by Faber (2020), to construct the shares of the Bartik treatment and instruments. To further explore mechanisms, I use cross-sectional data from *Encuesta Nacional de Salud* (ENSA) in 2000 and *Encuesta Nacional de Nutrición y Salud* (ENSANUT) in 2012. These surveys collect information about nutrition and infant care. ENSA and ENSANUT are representative at the state level, therefore I compute measures of the prevalence of risky behaviors (e.g. smoking, drinking) at this level of aggregation.

[13]Data about health insurance is not available in 1990.

# 4 Empirical strategy

## 4.1 Local exposure to robots

I exploit cross-variation of robot adoption at the CZ level, following Faber (2020) and Acemoglu and Restrepo (2020). Equation 1 shows the treatment variable, which is a shift-share measure of the change in robot adoption per worker in the United States. This variable leverages *maquiladora* employment composition across CZs as shares and the number of robots at the industry level as shifters.

$$\Delta robots_{c,t}^{US} = \sum_{i \in I}^{I} \frac{L_{c,i,1990}^{f}}{L_{c,1990}} \left( \frac{(R_{i,t_1}^{US} - R_{i,t_0}^{US}) O_{i,1992}}{L_{i,1990}^{f}/1,000} \right) \tag{1}$$

In equation 1, $R_{i,t}^{US}$ is the number of U.S. robots in industry $i$ at time $t$, which is then re-scaled by employment in each sector, $L_{i,1990}^{f}$.[14] Given the focus of the analysis, $t_0 = 2000$ and $t_1 = 2015$. It is worth noting that labor shares vary due to the distinct nature of their impacts: U.S. robots exert a more direct influence on industries oriented towards exports from Mexico. To approximate baseline export-orienting labor, $\frac{L_{c,i,1990}^{f}}{L_{c,1990}}$ is the share of employment in *maquiladoras* in CZ $c$ and industry $i$, relative to total CZ employment in 1990. Moreover, the element $O_i$ serves as an approximation of the degree of sectoral employment *offshorability*, denoting the share of Mexican imports within industry $i$ in relation to U.S. output in 1992.

The treatment variable is meant to capture the degree of exposure to U.S. robots in Mexico. Thus, CZs with high (low) *maquiladora* employment will have high (low) U.S. robot exposure. Note, however, that the industrial composition of robots is common across CZs. Panel A of Figure 3 describes the spatial distribution of the treatment variable, where, unsurprisingly, a greater intensity is found across northern Mexican states, consistent with the importance of *maquiladora* employment close to the U.S.

[14] The IFR data record 19 separate industries. Given that *maquiladoras* are concentrated in the manufacturing sector, the number of industries I effectively exploit are 14: food and beverages, textiles, wood products, paper products, pharmaceutical and chemicals, rubber and plastic products, minerals, basic metals, electronics except for machinery, electrical machinery, industrial machinery, automotive and parts, other services.

border.

## 4.2 Identification

In an ideal case, I would observe how randomly assigned CZs specialize in sectors more (or less) prone to automation, and subsequently compare their infant health outcomes. However, this is not feasible: regional-level robot adoption is nonrandom, so exposure to U.S. robots is potentially endogenous on multiple fronts, leading to potentially biased estimations.

First, there could be measurement error, as the IFR sectoral data offer country-specific breakdowns within the North American region only after 2011. Consequently, I impute and construct the stock of robots for the U.S. based on available shipments.[15] Second, omitted variable bias could arise, due to unobserved local demand shocks which may affect the treatment variable as well as labor and health outcomes. Third, owing to their geographical proximity, the likelihood of reverse causality emerges, where either the U.S. or Mexico might adopt robotics in response to the automation initiatives of the other.

To account for these limitations, I follow an instrumental variable approach in the spirit of Faber (2020) and Acemoglu and Restrepo (2020). I instrument the above-mentioned treatment variable (equation 1) with external robot usage from other high-income countries other than the U.S.:

$$\Delta IVrobots_{c,t}^{US} = \sum_{i \in I}^{I} \frac{L_{c,i,1990}^{f}}{L_{c,1990}} \left( \frac{(R_{i,t_1}^{EUR-9} - R_{i,t_0}^{EUR-9})\tilde{O}_{i,1990}}{L_{i,1990}^{f}/1,000} \right) \tag{2}$$

Equation 2 follows a similar structure as equation 1. Instead of using the share of imports from Mexico in total U.S. output, $\tilde{O}_i$ is a more general outsourcing measure defined as the share of imported intermediate inputs in the same industry over total non-energy intermediates in U.S. industry $i$ in 1990 (Faber, 2020).

I draw upon the plausibly exogenous robot adoption, $R_i^{EUR-9}$, across nine European

[15]See Graetz and Michaels (2018) for details on the imputation method

countries: Denmark, Finland, France, Germany, Italy, Norway, Spain, Sweden, and the United Kingdom. These countries provide comprehensive sectoral-level data on the number of robots throughout the period of analysis that do not need to be imputed. Panel B of Figure 3 shows the geographical distribution of the instrument. Since this measure uses the same shares as the treatment variable, the geographical layout is similar, while changes come from the intensity of $R_i^{EUR-9}$.

The rationale behind the relevance of the instrument hinges on the fact that European countries have assumed a pioneering role in the realm of robot adoption, marked by advancements in terms of pricing, accessibility, and technological sophistication. These supply shifters, according to Acemoglu and Restrepo (2022), are mostly attributed to a demographic transition of aging European countries. Moreover, Mexico's trade with the U.S. comprises around 80% of Mexico's exports, while trade with European economies in sectors linked with *maquiladoras* is minimal.[16] Therefore, any correlation between robot adoption patterns in the U.S. and those in Europe is unlikely to stem from factors associated with exports or labor demand in Mexico. Figure A4 shows that there is a strong, positive relationship between U.S. robot exposure and the instrument, which aligns well with Acemoglu and Restrepo (2022), to the extent that U.S. robots were absorbed by the U.S. while European countries acted as robot supply shifters.

## 4.3 Estimation

To quantify the effect of robots on infant mortality, my results are based on 2SLS estimates using the following system of equations, where I instrument the predicted U.S. robot exposure with robot exposure from nine European countries.

$$\begin{cases} \Delta robots^{US}_{c,(t_0,t_1)} = b_0 + \lambda_r + b_1 IV \Delta robots^{US}_{c,(t_0,t_1)} + \mathbf{X}'_{c,2000}\gamma + \Delta Y'_{c,2000-98}\rho + \epsilon_{c,t} \\ \Delta Y_{c,(t_0,t_1)} = \alpha + \theta_r + \beta \widehat{\Delta robots^{US}_{c,(t_0,t_1)}} + \mathbf{X}'_{c,2000}\varphi + \Delta Y'_{c,2000-98}\omega + \varepsilon_{c,t} \end{cases} \tag{3}$$

[16]Mexican exports to Europe account for less than 5% of Mexico's total exports.

$\Delta Y_{c,t}$ denotes the change in infant mortality rate between 2000 and 2015 in CZ $c$. Estimates of $\beta$ identify within variation in robot adoption at the CZ level for the period 2000-2015, so every CZ represents one data point. Given that equation 3 is in first differences, location fixed effects are accounted for, and $\theta_r$ are eight region dummies that control for broad region-specific trends. Similarly, the vector $\mathbf{X}'_{c,2000}$ includes base-period characteristics (measured in 2000), meant to account for secular demographic trends.

I include the initial sum of shares of *maquiladora* employment in total employment in 1990, so the variation in U.S. robots is driven by the initial industrial composition.[17] $\Delta Y_{c,2000-98}$ controls for pre-existing trends in the outcome variable. Combined; these controls ensure that I am comparing outcomes with similar baseline, while accounting for potential confounding factors. I weight each cell by the start of the period number of births and allow standard errors to be clustered at the state level.

Note that the estimates of $\beta$ are not intended to capture the *total* effect of robot adoption on infant health. General equilibrium effects or additional spillover forces might disproportionally affect CZs at the same time. What I do aim to identify are *relative* effects of automation on infant mortality, as I leverage cross-CZ variation in robot adoption (Dix-Carneiro and Kovak, 2023).

## 4.4 Validity of research design

In practice, shift-share instruments need an element of exogeneity to be able to provide consistent estimates of automation on infant health. Goldsmith-Pinkham et al. (2020) show that 2SLS estimates with Bartik-like instruments are numerically equivalent to a generalized method of moments (GMM) estimator, using the industry shares as instruments and a weighting matrix coming from the shock part of the instrument. In this setting, identification can be attained from local differences in exposure to common shocks in robot adoption, so the exogeneity condition of the instrument

[17] This is equivalent to rescaling the shares to sum one, when the underlying task is to distinguish the relevant cross-sectional identifying variation from other sources of variation (Borusyak et al., 2022b).

should be interpreted in terms of the industry shares.[18] Moreover, if pre-period data are available, this empirical strategy resembles a difference-in-difference design.

I proceed to test for the parallel trends assumption in two steps. First, following Goldsmith-Pinkham et al. (2020), I calculate the Rotemberg weights (RW) (Rotemberg, 1983), which assign relative importance to the shares, and help identify which industry-specific instruments are worth testing. In my data, the highest RW is for automotive (0.8); followed by electronics (0.05), pharmaceutical and chemicals (0.03), rubber and plastic (0.027), and industrial machinery (0.025). Second, for each pre-analysis year available (e.g. 1998 to 2000), I regress the infant mortality rate on the *maquiladora* industry shares. I weigh each regression by the number of births in 2000 and cluster the standard error by state. Each regression result is plotted by year for each of the top 5 RW industry shares, and the mean of all industries.

Figure A5 shows that, in general, there is no evidence of pre-trends. This supports the identification assumption that predetermined shocks do not predict infant health outcomes through unobserved channels coming from the main industries driving the variation in the instrument. Figure A6 also provides evidence that at the CZ-level, there are not baseline characteristics that correlate with the instrument, other than the share of working-age men. This is expected given the natural composition of *maquiladora* employment. Therefore, it is reasonable to assume that the identifying variation stemming from the shares is as-good-as random.

# 5 Results

In this section, I present the empirical results on the impact of U.S. robots on infant mortality, investigate possible threats to identification, and present several robustness tests. The magnitude of the estimated effects is also discussed.

[18]Conditional on having a large number of shocks, Borusyak et al. (2022b) show that identification can be achieved in terms of the shocks.

## 5.1 Baseline results

I start by estimating equation 3 for the period 2000-15. In Table 1, the results for the second stage are reported in Panel A, and the first stage is reported in Panel B. Standard errors are robust to heteroskedasticity, allowing for clustering at the state level. In all specifications, I weight observations by the number of births at the start of the period (2000).

Column (1) of Panel A presents the basic specification, including the sum of *maquiladora* employment shares and eight broad region indicators as controls. This parsimonious specification indicates that U.S. robot adoption, as a proxy for automation of external export-oriented manufacturing, causes an increase in the infant mortality rate, significant at the 5% level. This specification, however, may be biased by other omitted factors.

While the infant mortality rate in Mexico exhibited a downward trend between 2000 and 2015, regional differences across CZs could potentially obscure the true effect. To address this, and in line with the approach of Dix-Carneiro and Kovak (2017), I control for the predetermined change in the infant mortality rate between 1998 and 2000. The results presented in Column (2) remain consistent in both precision and magnitude.

To account for differential demographic trends, I include a set of baseline demographic characteristics measured in 2000: the logarithm of population, the share of male population, the share of working-age population, and the share of working-age individuals with primary, secondary, or tertiary education. Column (3) shows a slightly lower effect, precisely estimated at the 1% level. These results also imply that baseline characteristics are independent of the error of the 2SLS estimator, which is of no concern even if there are any observable imbalances that correlate with the instrumental variable (Borusyak et al., 2022b).

Several other contemporaneous factors could be correlated with both robots in the U.S. and infant mortality rates. First, the entry of China into the World Trade Organization (WTO) in 2001 impacted manufacturing employment in Mexico by increasing competition to business schemes like *maquiladoras*, therefore reducing employment and operating plants in Mexico (Iacovone et al., 2013; Utar and Ruiz, 2013). Second, since 1994, Mexico has come from a strong tariff liberalization with the signing of the North American Free Trade Agreement (NAFTA), in which the margin of adjustment has been progressive, strengthening the commercial ties between Mexico and the signing countries (Canada and the U.S.) over time (Caliendo and Parro, 2015; Juhn et al., 2014; Robertson and Dutkowsky, 2002). Third, similar shocks to U.S. robots could be influential in the period of analysis related to the extent that jobs might be *offshorable* by automation and trade.[19]

Taking these factors into consideration reduces somewhat the coefficient while keeping the same level of precision at 1% level, as documented in Column (4). The coefficient of 1.36 on the exposure of U.S. robots implies that an average increase in U.S. robot adoption will increase infant mortality by 0.17 deaths per thousand births ($1.36 \times 0.13$), which represents a 1.2% increase in infant mortality rate to the baseline rate in 2000 (14.02). It also implies that such simultaneous shocks are orthogonal to automation stemming from U.S. robot exposure in Mexico.

Panel B presents the first-stage results, showing that the instrument is relevant across all specifications in Columns (1) to (4). The Kleibergen-Paap rank $F$-statistic is larger than the usual threshold of 10, indicating that the instrument does not pose the problem of weak instruments (Staiger and Stock, 1994; Stock and Yogo, 2005). OLS results reported in Table A1 likely underestimate the true effect of automation on infant mortality. Thus, given the latent endogeneity bias, I refer primarily to the 2SLS results.

**Causes of death:** Using my most demanding specification (Column (4) of Table 1), I next investigate the drivers of the main effects of infant mortality by breaking the data into six independent ICD categories, as shown in Table 2: infectious and respiratory (Column 1), malnutrition (Column 2), prenatal (Column 3), congenital (Column 4), accidents or aggressions (Column 5), and other internal diseases (Column 6). Among the internal causes, infectious and respirator, perinatal, and malnutrition diseases are

[19]Like in Faber (2020), I controlled for the share of routine jobs in 1990, which was constructed by Autor and Dorn (2013). To account for CZ-level China imports, I followed Autor et al. (2013)'s exposure measure. The measure for NAFTA exposure follows closely the Bartik-style approach proposed by Hakobyan and McLaren (2016).

the ones driving the main results. Most of these diseases are preventable; being perinatal, bacterial, and infectious diseases the most prevalent at baseline, accounting for two-thirds of total infant deaths.

There are no detected effects for other internal or congenital factors (Columns 4 and 6); diseases that are likely to be associated with other types of shocks, unrelated to automation. Column (5) shows that automation increases accidents and aggressions, which is an uncommon cause of death, accounting for 4% of total deaths at baseline.[20]

## 5.2 Additional robustness

I have carried out several robustness checks to probe the sensitivity of my main results. To start with, the main estimations are robust to alternative definitions of the treatment. In Table A2, Panel A, I exclude the general offshorability term ($\tilde{O}_{i,1990}$). Panel B includes the share of Mexico's exports to the U.S. in 1990 as the interaction term instead of the offshorability term. The main results remain similar with these alternative instruments.

Next, Table A3 shows that the results remain qualitatively insensitive to different samples and specifications. Panel A documents that the results that evaluate the effect of U.S. robots on infant mortality are robust to the inclusion of domestic automation, which is not surprising given that Mexico's exposure to robots has not been as rapid as in developed economies.[21] Another concern is that outcomes during the period of analysis might be influenced by other factors, particularly by events like the Great Recession (2008-2010) through an income effect. Panel B confirms that after excluding the Great Recession period, the results remain stable. Panel C shows that the main results are unaffected if I drop the top 1% of U.S. robot exposure, or if I include only CZs with nonzero employment in *maquiladoras* (Panel D).

Bartik-style instruments are likely to suffer from correlation of residuals across regions with similar shares, which causes over-rejection of the null hypothesis ($\beta = 0$).

[20]A potential reason could be that industrial robot exposure is associated with workers' job safety, thus affecting mental stress (Gihleb et al., 2022; Liu et al., 2024)

[21]Faber (2020), following a Bartik approach shows that the effect of Mexican robots on employment is not statistically significant. Serrano (2023), using a difference-in-difference methodology finds that the adoption of Mexican robots has not had an effect on employment, but rather complements firm productivity.

Thus, clustering standard errors at the state level might not be sufficient. I follow Adão et al. (2019)'s adjustment procedure and report the results in Table A4. The adjusted standard errors across all specifications are more conservative than those reported in Table 1, confirming the initial significance of my estimates.

Lastly, I employ a non-parametric permutation test following the approach of Dell et al. (2019). In Figure A7, I randomized equation 2 and ran the first stage (Panel A) and the reduced-form regression (Panel B) 1,000 times. The share of estimates that are larger than the 'true' estimate (Table 1, Column 4) act as $p$-values. If automation affected infant mortality rates, then my baseline estimates should lie on the right-hand side of the empirical distribution. Both the estimates of the first stage and the reduced-form estimates are in the right tail of the empirical distribution with $p$-values lower than 5%. Thus, these results support the conclusion that my results were driven by automation and not by mere chance.

# 6 Potential channels

In this section, I investigate the potential influence of income and adult time on changes in infant mortality rates. First, I analyze the impact of automation on shifts in employment, unemployment, and self-employment by gender, as well as its effect on overall household real income. I then assess how automation influences access to health services and its implications for the consumption of harmful goods.

## 6.1 Labor market effects: income and parental time

The most direct mechanism through which industrial robot penetration impacts infant mortality is labor. Previous work on Mexico and several Latin American countries has found that automation hurts employment (Brambilla et al., 2023; Faber, 2020; Stemmler, 2023).[22] These labor adjustments could affect infant health by amplifying household income losses. However, there could be a substitution of employment for adult time

[22]For Mexico in particular, the *offshoring* of employment from Mexico to the U.S via lower exports is the main channel (Faber, 2020).

allocated to children's care. I investigate below how this substitution (or lack thereof) relates to the estimated increase in infant mortality reported above.

Table 3 presents the results using equation 3. Columns (1) and (4) look at changes in private employment-to-population ratios for men and women separately, showing that the estimated change in total employment for women is more precise than that for men at conventional levels. These estimates show that employment losses for women were almost twice as high as those for men (-0.61 compared to -0.35). This implies that an average increase in U.S. robots per worker (0.13) reduces female employment by 0.07 percentage points (0.13×-0.61), which represents a 1% reduction in the female employment-to-population ratio of the observed baseline in 2000.

The estimated results hide substantial heterogeneity. Figure 4 provides a breakdown of the same estimation by skill level (Panel A) and age (Panel B), allowing for a more nuanced understanding of the findings. U.S. robots impacted female employment across all skill levels, particularly for women with secondary education and those of childbearing age (15-49 years old). This is reassuring given that, by construction, the portion of employment most at risk of automation comes from *maquiladoras*, where young, unskilled women are disproportionately employed across industries and CZs (Dorocki and Brzegowy, 2014).

Another possible transition for individuals facing labor market disruptions is to either exit the labor force entirely or continue searching for employment. For men, there are no observed movements statistically distinguishable from zero—Table 3, Columns (3) and (4). For women, on the other hand, I find that the increase of one U.S. robot per thousand workers raises the unemployment-to-population ratio by 0.02 percentage points, and the portion of women out of the labor force by 0.33 percentage points, although the latter coefficient is only significant at the 10% level. Importantly, Column (9) shows that greater exposure to U.S. robots is associated with household income losses: an average increase in U.S. robot penetration lowers household income by 0.22% percentage points (1.74×0.13).

Next, I explore whether there are transitions to self-employment occupations, which are likely to be informal by nature.[23] In Table 3, Columns (2) and (6) reveal that overall, on average, neither men nor women move to self-employment occupations. Since there could be heterogeneity across sectors, I break down by economic sector the estimates presented in Table 3 for employment and self-employment-to-population ratios. Figure 5, Panel A, shows that female employment losses are concentrated in the manufacturing sector, while the estimated effects for men are not different from zero. Panel B documents that women resort to self-employment occupations as a response to employment losses in that sector. Several reasons could explain this result: (i) women who were employed in *maquiladoras* may have had valuable training in manufacturing occupations (e.g., apparel and shoe making) which led them to remain in the manufacturing sector; (ii) these occupations may offer flexible options to cope with household income losses. My data are limited to further explore these hypotheses within the manufacturing industry.

In short, I find evidence that U.S. automation did not affect men's employment. For women, however, there are employment losses primarily driven by the manufacturing sector, while a small proportion continued to actively seek employment. More importantly, there are significant household labor income losses due to the changes in female labor participation. While one could hypothesize that there could be more time available for children's care resulting from employment losses, income losses may not be easily offset, especially in the context of *maquiladora* workers, who are generally more likely to be financially constrained, relatively young, and unskilled. This defies conventional wisdom, particularly in developed economies, where it has been shown that the opportunity cost of time decreases in hard economic times (Dehejia and Lleras-Muney, 2004; Miller and Urdinola, 2010).

In contrast, I find that women resort to self-employment occupations in the manufacturing industries as a copying mechanism. This is consistent with Bhalotra (2010) in India, who found that low-income women's labor force participation increases during

[23] According to the population census, self-employed workers comprise one-quarter of the employed population. Those who reported being self-employed are likely to be informal at baseline (2000), as measured by the proportion of workers not contributing to a health plan (76%).

difficult times, negatively impacting children's health via less parental time. I next turn to examining the implications of these findings.

### 6.2 Access to health services

Women who exited the labor market may have encountered barriers to accessing health-enhancing services, such as prenatal care or baby stimulation advice. I investigate the impact of automation on healthcare access in two ways. First, using population census data, I calculate the percentage of women with employer-provided insurance, specifically those covered through the Mexican Social Security Institute (IMSS). Table 4 reveals that automation is negatively associated with access to health insurance in the formal sector, and is particularly driven by overall and wage employment (Columns 1 and 2), whereas, by definition, this is not the case for self-employed occupations. I further validate these findings by analyzing infant mortality data, separating the sample into insured and uninsured women. Table 5 shows in Column (2) that for women with health insurance, the effect of U.S. automation on infant mortality is minimal and statistically insignificant. In contrast, the baseline results are primarily driven by uninsured women, as evident when comparing the estimates in Column (1) to those in Column (3).

Second, using birth record data, I assess the impact of automation on the time women dedicate to prenatal care, specifically evaluating the frequency of prenatal visits. I also evaluate the role of automation on children's health at birth by computing the share of children born prematurely (within less than 37 seven weeks), the share of children with low weight at birth (less than 2,500 grams), the number of children born using a cesarian section, and their Apgar score.

Table 6 demonstrates that, on average, women in areas more exposed to automation attended fewer prenatal visits. This finding underscores the significance of time constraints, likely intensified by the rise in self-employment among women (see Figure 5, Panel B), despite the fact that prenatal visit uptake remained above 90% throughout the analysis period. Columns (2) to (5) indicate that automation does not have significant effects on infant health outcomes at birth.

To further explore whether birth outcomes are influenced by supply-side constraints in infrastructure, potentially due to income losses in CZs more affected by automation, I leverage administrative data on hospital resources from the Ministry of Health. Table A5 shows that automation has no discernible impact on public health provisions such as the availability of pediatricians, newborn cribs, incubators, and delivery rooms.

Taken together, these results suggest that (i) automation-induced employment losses restrict women's access to healthcare, (ii) prenatal visits may be constrained by income or time-related factors, and (iii) the observed increase in infant mortality is more likely attributable to postnatal conditions rather than perinatal factors alone.

## 6.3 Risky behaviors

Another implication of employment and income losses relates to the consumption of harmful substances by both mothers and children. Although alcohol, tobacco, and narcotic drugs are typically considered normal goods, their consumption might actually increase in response to negative income shocks due to heightened stress and despair during difficult times (Adda and Fawaz, 2020; Lang et al., 2019; Pierce and Schott, 2020).

Table 7 presents the 2SLS results analyzing the impact of automation on risky behaviors among women of childbearing age. As noted, the ENSA and ENSANUT datasets are not representative at the CZ level; thus, the data were aggregated at the state level for the period between 2002 and 2012. The analysis includes the full sample of women aged 20-45 (Panel A), as well as subgroups of insured (Panel B) and uninsured women (Panel C).

Columns (1) to (3) document the effect of automation on potential risk factor for infant health development such as alcohol drinking (Column 1), smoking (Column 2), diabetes (Column 3). The results for the full sample and for those insured show that automation is associated with an increase in the prevalence of diabetes, Mexico's leading cause of mortality.[24] Furthermore, I find that CZs more affected by automation have a higher prevalence of smoking among the uninsured population (Column 1, Panel C), which is related to infant-related risk factors, such as low birth weight, respiratory infections, cardiovascular complications, and sudden infant death syndrome (Knopik, 2009; O'Leary et al., 2013; Pereira et al., 2017). At a broad level, I interpret this evidence as being consistent with the notion that income and stress are plausible mechanisms explaining the main results.

## 6.4 Selection

### 6.4.1 Selective fertility and fetal deaths

Automation can impact the opportunity cost of having children, introducing a potential selection bias to the main estimations, since it could affect children's likelihood of survival. During hard times, families may delay having children until the economy recovers, while others may take advantage of the fact that children are time-consuming, thus increasing fertility due to increased time availability resulting from job losses . Additionally, the composition of births may change due to the increase in fetal deaths, miscarriages, or stillbirths coming from low quality pregnancies.

I empirically evaluate the role of U.S. automation on birth and fetal death rates in Table A6 using equation 3. I compute the birth rate as number of births divided by the number of women in childbearing age using census data, while the fetal death rate is calculated dividing the number of fetal deaths by the number of births. Columns (1) and (2) show that CZs relatively more exposed to U.S. automation did not see an increase in fetal deaths or overall birth rate, respectively. The granularity of the data also allows me to explore the heterogeneity of the effect by education levels and age brackets.

Columns (3) to (6) present the results broken down by the latest school grade attained by the mother. The estimated coefficient for mothers with less than primary

[24] Diabetes among pregnant women increases the risk of cesarian section deliveries in Mexico (Herrera-Almanza et al., 2024), which in turn is associated with poorer infant health compared with vaginal births (Costa-Ramón et al., 2018).

education (Column 3) is positive and precisely estimated; however, the effect size is small: an average increase in U.S. robots increases the birth rate by 0.19 births per thousand women (1.449× 0.13), which represents a 0.5% increase relative to the baseline mean. There is also a precisely estimated increase in birth rates among high-skilled women (Column 6) that represents an increase of 1.2% relative to the baseline mean (1.2%≈ (0.13×0.68/7.1)×100). There are not observed effects for women with primary, secondary education (Columns 4 and 5), nor across age brackets (Columns 7 and 8).

I conclude that selection due to fertility and fetal deaths is unlikely to drive my results. While these results may imply an upward bias of my baseline estimations, the role of automation on fertility is, at best, minimal.

### 6.4.2 Selective migration

Since U.S. robot penetration affected employment, a possible bias could arise from selective migration, with some families moving away from CZs more affected by automation. The concern appears if the non-movers were systematically different from those who decided to move. In Table A7, I find that areas with higher U.S. robot adoption experienced a larger change in the working-age population, though the evidence is limited under different specifications, as the point estimates are significant only at the 10% level. Note, however, that these types of models may not accurately identify the effect of automation on migration responses because destination places are also likely to be affected by automation (Borusyak et al., 2022a), which I do not account for. Therefore, caution is needed when interpreting these results.

## 7 Conclusion

This paper investigates the impact of U.S. automation on infant mortality in a developing country context. Mexico provides a particularly compelling case study due to its proximity to the U.S. and its longstanding reliance on maquiladora employment, which predominantly involves low-skilled, female-intensive labor. Additionally, Mexico has witnessed a significant rise in female labor force participation over the past few decades, mirroring trends observed in other similarly developed countries. However, both anecdotal and empirical evidence suggest that automation, particularly through the adoption of industrial robots, adversely affects manufacturing employment by increasing the capital share in production at the expense of labor demand (Acemoglu and Restrepo, 2020; Faber, 2020).

I exploit variation in the baseline composition of maquiladora employment and the sectoral distribution of industrial robots in the U.S. Identification is derived from the arguably exogenous share of maquiladora employment in 1990 and the stock of robots from nine European countries. My findings indicate that U.S. automation is associated with an increase in infant mortality. The magnitude of my estimates suggests that an average increase in U.S. robots per worker raises infant mortality by 1.2%-1.3% of the baseline mean in 2000. These results align with the understanding that infant mortality follows a countercyclical pattern in Mexico (Arceo-Gómez, 2010) and other developing countries (Baird et al., 2011).

While men are generally unaffected by automation, low-skilled women in manufacturing industries are disproportionately displaced from their jobs. My analysis reveals that losses in female employment and household income are not easily mitigated by the increased parental time associated with unemployment. Instead, I find evidence that affected women shift their time towards self-employment activities in manufacturing. Furthermore, women who are more exposed to U.S. automation are less likely to access overall healthcare and prenatal care. Notably, women without health insurance are primarily driving these adverse outcomes. Additionally, financially unprotected women are more likely to engage in risky behaviors such as drinking and smoking. Collectively, this evidence suggests that income and time constraints are the primary drivers of increased infant mortality. I find limited support for alternative explanations, including selective migration, fertility changes, or supply-side factors related to public health provision.

It is important to note that the estimates presented in this paper are not intended to capture the total effect of automation on infant mortality. Other underlying mechanisms related to the general equilibrium conditions of the economy may also contribute to my findings. Instead, the framework I employ aims to capture the relative effect of automation. Further research is necessary to explore the aggregate impact of automation on infant health.

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# Figures and tables

## Tables

Table 1: Effect of robot penetration on the change of infant mortality rate (2000- 15)- 2SLS.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| **Panel A. 2SLS** | | | | |
| $\Delta robots^{US}$ | 1.505** | 1.493*** | 1.384*** | 1.358*** |
| | (0.629) | (0.565) | (0.528) | (0.511) |
| Kleibergen-Paap F-stat | 48.05 | 48.17 | 57.41 | 68.02 |
| **Panel B. First Stage** | | | | |
| $IV\Delta robots^{US}$ | 0.100*** | 0.100*** | 0.102*** | 0.100*** |
| | (0.014) | (0.014) | (0.013) | (0.012) |
| Observations | 1805 | 1805 | 1805 | 1805 |
| Mean dep var | 14.02 | 14.02 | 14.02 | 14.02 |
| Region FE/industry shares | ✓ | ✓ | ✓ | ✓ |
| Outcome trends | | ✓ | ✓ | ✓ |
| Demographic trends | | | ✓ | ✓ |
| Contemporary shocks | | | | ✓ |

*Note:* The dependent variable in Panel A is the change in infant mortality rate, and in Panel B the change in predicted exposure to robots in the US. Column (1) controls for the sum of shares in *maquiladora* employment and eight broad Mexican region dummies. Column (2) includes the change in infant mortality rate for the period 1998-2000. Column (3) includes baseline controls measured in 2000: the share of male workers, the logarithm of population, the share of working age population (18-65 years old), the share of workers older than 65, the share of workers with completed primary, secondary, and tertiary schooling. Column (4) includes contemporary shocks: the local exposure to imports from China, the share of routinary jobs in 1990, and the exposure to NAFTA. Robust standard errors are clustered at the state level and reported in parentheses. Regressions are weighted by the number of births in 2000. Significance: *** p<0.01, ** p<0.05, * p<0.10.

Table 2: Effect of robot penetration on the change of infant mortality rate by source (2000-15)-2SLS.

| | (1) Infectious/respiratory | (2) Malnutrition | (3) Perinatal | (4) Congenital | (5) Accidents/aggressions | (6) Other |
|---|---|---|---|---|---|---|
| $\Delta robots^{US}$ | 0.306** | 0.058*** | 0.574** | 0.054 | 0.318*** | 0.009 |
| | (0.127) | (0.020) | (0.284) | (0.086) | (0.077) | (0.041) |
| Observations | 1805 | 1805 | 1805 | 1805 | 1805 | 1805 |
| Mean dep var | 2.475 | 0.397 | 7.044 | 2.621 | 0.573 | 0.914 |
| Region FE/industry shares | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Outcome trends | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Demographic trends | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Contemporary shocks | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

*Note:* The dependent variables in Columns 1-7 are grouped diseases based on the International Catalogue of Diseases. Column 6 groups accidents (including transport) and aggressions. The dependent variables in Columns 1-7 are grouped diseases based on the International Catalogue of Diseases. Column 6 groups accidents (including transport) and aggressions. Each column controls for the sum of shares in *maquiladora* employment, eight broad region dummies, the pretrend in outcomes; baseline demographic outcomes measured in 2000: the share of male workers, the logarithm of population, the share of working age population (18-65 years old), the share of workers older than 65, the share of workers with completed primary, secondary, and tertiary schooling; and contemporary shocks: the local exposure to imports from China, the share of routinary jobs in 1990, and the exposure to NAFTA. Robust standard errors are clustered at the state level and reported in parentheses. Regressions are weighted by the number of births in 2000. Significance: *** p<0.01, ** p<0.05, * p<0.10.

Table 3: Effect of robot penetration on labor market outcomes-2SLS.

| | Men | | | | Women | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) Employment | (2) Self-employment | (3) Unemployment | (4) OLF | (5) Employment | (6) Self-employment | (7) Unemployment | (8) OLF | (9) Household income |
| $\Delta robots^{US}$ | -0.354* | 0.120 | 0.000 | 0.054 | -0.612*** | -0.030 | 0.020*** | 0.353* | -0.017** |
| | (0.184) | (0.213) | (0.016) | (0.145) | (0.220) | (0.067) | (0.004) | (0.193) | (0.008) |
| Observations | 1804 | 1804 | 1804 | 1804 | 1804 | 1804 | 1804 | 1804 | 1804 |
| Mean dep var | 50.717 | 20.730 | 1.190 | 19.430 | 23.383 | 7.630 | 0.325 | 64.206 | |
| Region FE/industry shares | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Outcome trends | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Demographic trends | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Contemporary shocks | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

*Note:* The dependent variables are labor market outcomes split by sex. Columns (1) through (8) are rates of employment, self-employment, unemployment, and out of the labor force (OLF) over population. Column (9) is the average household labor income. Each column controls for the sum of shares in *maquiladora* employment, eight broad region dummies, the pretrend in outcomes; baseline demographic outcomes measured in 2000: the share of male workers, the logarithm of population, the share of working age population (18-65 years old), the share of workers older than 65, the share of workers with completed primary, secondary, and tertiary schooling; and contemporary shocks: the local exposure to imports from China, the share of routinary jobs in 1990, and the exposure to NAFTA. Robust standard errors are clustered at the state level and reported in parentheses. Regressions are weighted by the number of births in 2000. Significance: *** p<0.01, ** p<0.05, * p<0.10.

Table 4: Effect of robot penetration on the change of health insurance coverage for women (2000- 15)-2SLS.

| | (1)<br>All | (2)<br>Wage employment | (3)<br>Self-employment |
|---|---|---|---|
| $\Delta robots^{US}$ | -0.405** | -0.465*** | 0.015 |
| | (0.179) | (0.146) | (0.069) |
| Observations | 1804 | 1804 | 1804 |
| Region FE/industry shares | ✓ | ✓ | ✓ |
| Demographic trends | ✓ | ✓ | ✓ |
| Contemporary shocks | ✓ | ✓ | ✓ |

*Note:* The dependent variable is the change of the percentage of women with health insurance in the formal sector (IMSS). Column (1) groups all employed women. Column (2) groups only those in private employment. Column (3) groups only sellf-employed women. Each column controls for the sum of shares in *maquiladora* employment, eight broad region dummies, baseline demographic outcomes measured in 2000: the share of male workers, the logarithm of population, the share of working age population (18-65 years old), the share of workers older than 65, the share of workers with completed primary, secondary, and tertiary schooling; and contemporary shocks: the local exposure to imports from China, the share of routinary jobs in 1990, and the exposure to NAFTA. Robust standard errors are clustered at the state level and reported in parentheses. Regressions are weighted by the working-age population in 2000. Significance: *** p<0.01, ** p<0.05, * p<0.10.

Table 5: Effect of robot penetration on the change of infant mortality rate by insurance status (2000- 15)-2SLS.

| | (1) All | (2) Insured | (3) Uninsured |
|---|---|---|---|
| $\Delta robots^{US}$ | 1.358*** | 0.279 | 1.153** |
| | (0.511) | (0.229) | (0.481) |
| Observations | 1805 | 1805 | 1805 |
| Region FE/industry shares | ✓ | ✓ | ✓ |
| Outcome trends | ✓ | ✓ | ✓ |
| Demographic trends | ✓ | ✓ | ✓ |
| Contemporary shocks | ✓ | ✓ | ✓ |

*Note:* The dependent variable is the change of infant mortality rate split by insurance coverage. Column (1) uses the full sample. Column (2) uses the population insured. Column (3) uses the population uninsured. Each column controls for the sum of shares in *maquiladora* employment, eight broad region dummies; baseline demographic outcomes measured in 2000: the share of male workers, the logarithm of population, the share of working age population (18-65 years old), the share of workers older than 65, the share of workers with completed primary, secondary, and tertiary schooling; and contemporary shocks: the local exposure to imports from China, the share of routinary jobs in 1990, and the exposure to NAFTA. Robust standard errors are clustered at the state level and reported in parentheses. Regressions are weighted by the number of births in 2000. Significance: *** p<0.01, ** p<0.05, * p<0.10.

Table 6: Effect of robot penetration on prenatal care and health outcomes at birth (2008-15)-2SLS.

| | (1) Prenatal visits | (2) Low birth weight | (3) Apgar | (4) Preterm birth | (5) C-section |
|---|---|---|---|---|---|
| $\Delta robots^{US}$ | -0.521*** | 0.095 | 0.002 | -0.104 | 0.531 |
| | (0.191) | (0.133) | (0.008) | (0.327) | (0.933) |
| Observations | 1752 | 1752 | 1752 | 1752 | 1752 |
| Region FE/industry shares | ✓ | ✓ | ✓ | ✓ | ✓ |
| Demographic trends | ✓ | ✓ | ✓ | ✓ | ✓ |
| Contemporary shocks | ✓ | ✓ | ✓ | ✓ | ✓ |

*Note:* The dependent variable is the average number of prenatal visits (Column 1), the average of children born with low birth weight (Column 2), the Apgar score at birth (Column 3), the average number of preterm births (Column 4), and the average of cesarian section deliveries (Column 5). Each column controls for the sum of shares in *maquiladora* employment, eight broad region dummies, baseline demographic outcomes measured in 2000: the share of male workers, the logarithm of population, the share of working age population (18-65 years old), the share of workers older than 65, the share of workers with completed primary, secondary, and tertiary schooling; and contemporary shocks: the local exposure to imports from China, the share of routinary jobs in 1990, and the exposure to NAFTA. Robust standard errors are clustered at the state level and reported in parentheses. Regressions are weighted by the number of births in 2000. Significance: *** p<0.01, ** p<0.05, * p<0.10.

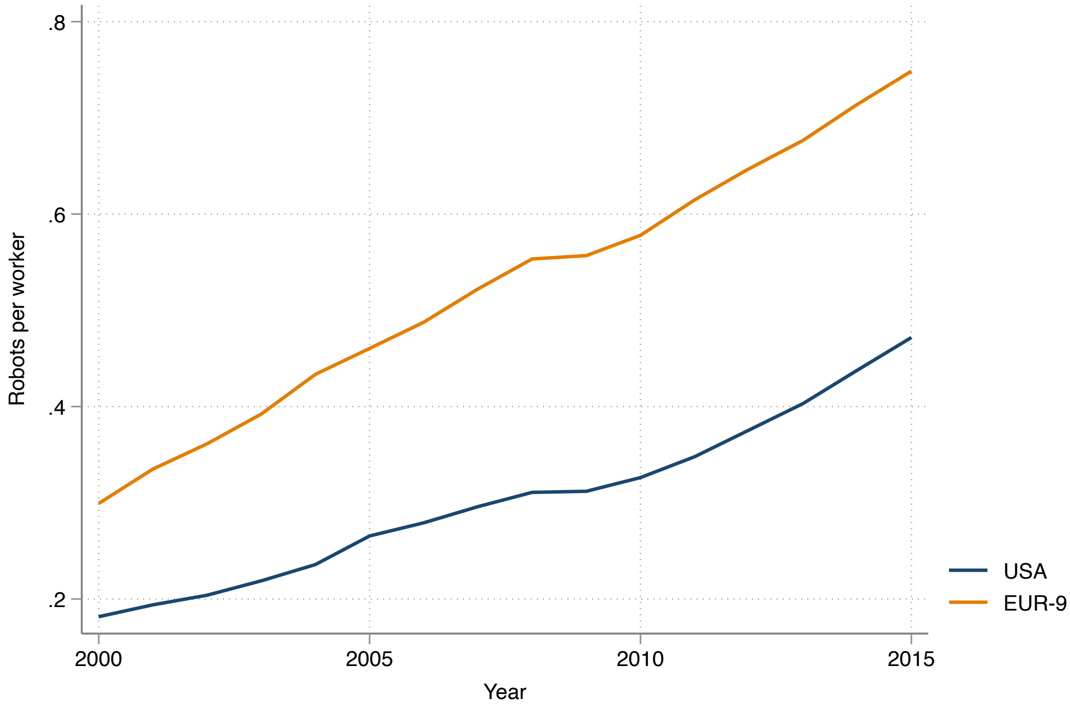
Table 7: Effect of robot penetration on the change of preventive health services and women's health (2002- 2012)-2SLS.

| | (1) Drinks alcohol | (2) Smokes | (3) Diabetes |
|---|---|---|---|
| **Panel A. All** | | | |
| $\Delta robots^{US}(2002-2012)$ | -0.502 | 0.631 | 0.166*** |
| | (0.449) | (0.429) | (0.057) |
| Observations | 31 | 31 | 31 |
| Mean dep var | 61.35 | 14.99 | 2.050 |
| **Panel B. Insured** | | | |
| $\Delta robots^{US}(2002-2012)$ | -0.981** | 0.248 | 0.286** |
| | (0.469) | (0.271) | (0.132) |
| Observations | 31 | 31 | 31 |
| Mean dep var | 62.53 | 18.49 | 2.919 |
| **Panel C. Uninsured** | | | |
| $\Delta robots^{US}(2002-2012)$ | 0.916** | 0.814* | 0.264* |
| | (0.396) | (0.422) | (0.140) |
| Observations | 31 | 31 | 31 |
| Mean dep var | 60.57 | 13.56 | 2.397 |

*Note:* The dependent variables is the change of prenatal visits (Column 1), the share of women who regularly drink (Column 2); the share of women who regularly smoke (Column 3); the share of women with diabetes and hypertension (Columns 4 and 5), for the population of women in childbearing age (20-45). Panel A includes all women. Panel B includes only insured population. Panel C includes only uninsured population. Regressions control for the sum of share in maquiladora employment and the baseline of the outcome variable. Regressions are weighted by population between 20 and 45 years old. Robust standard errors are reported in parentheses. Significance: *** p<0.01, ** p<0.05, * p<0.10.

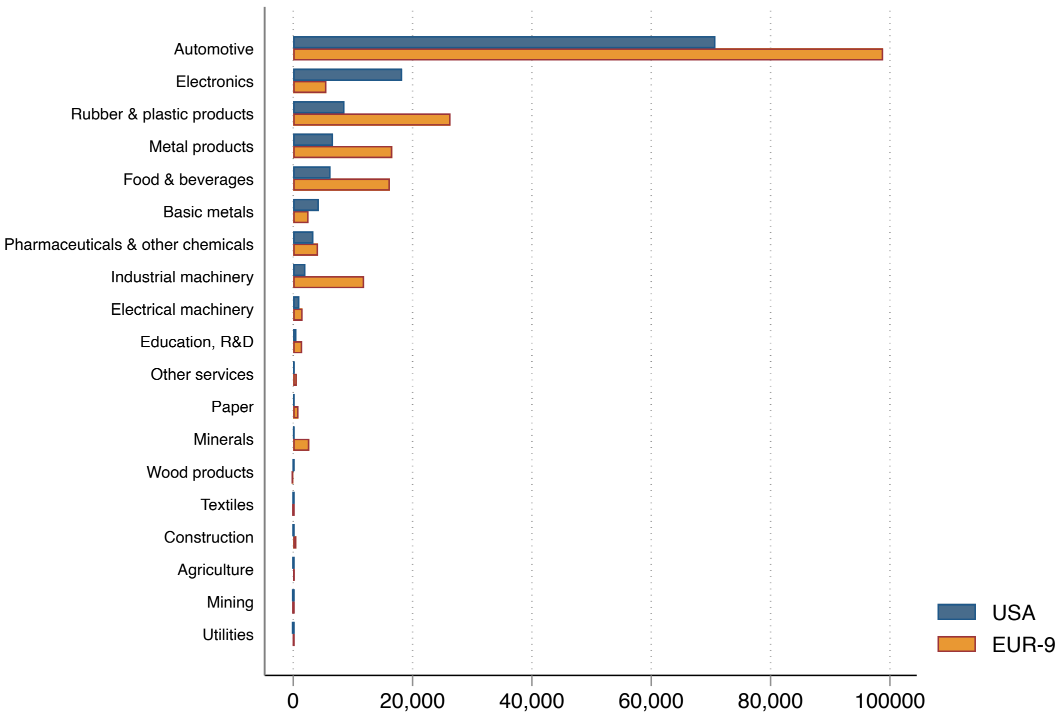
## Figures

Figure 1: Industrial robots per worker, 2000-15




*Note:* Own calculation using IFR data. EUR-9 stands for European robots which is comprised by nine countries: Denmark, Spain, Finland, France, Germany, Sweden, Great Britain, and Italy.

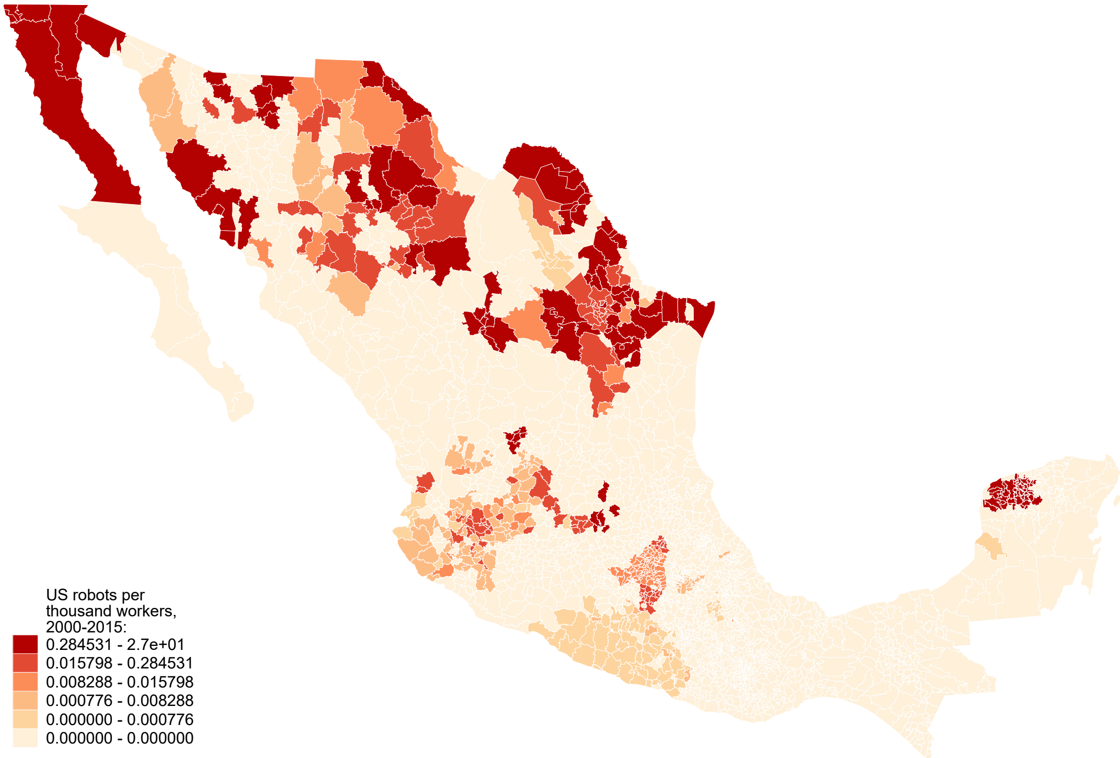
Figure 2: Change in industrial robot stock by industry, 2000-15



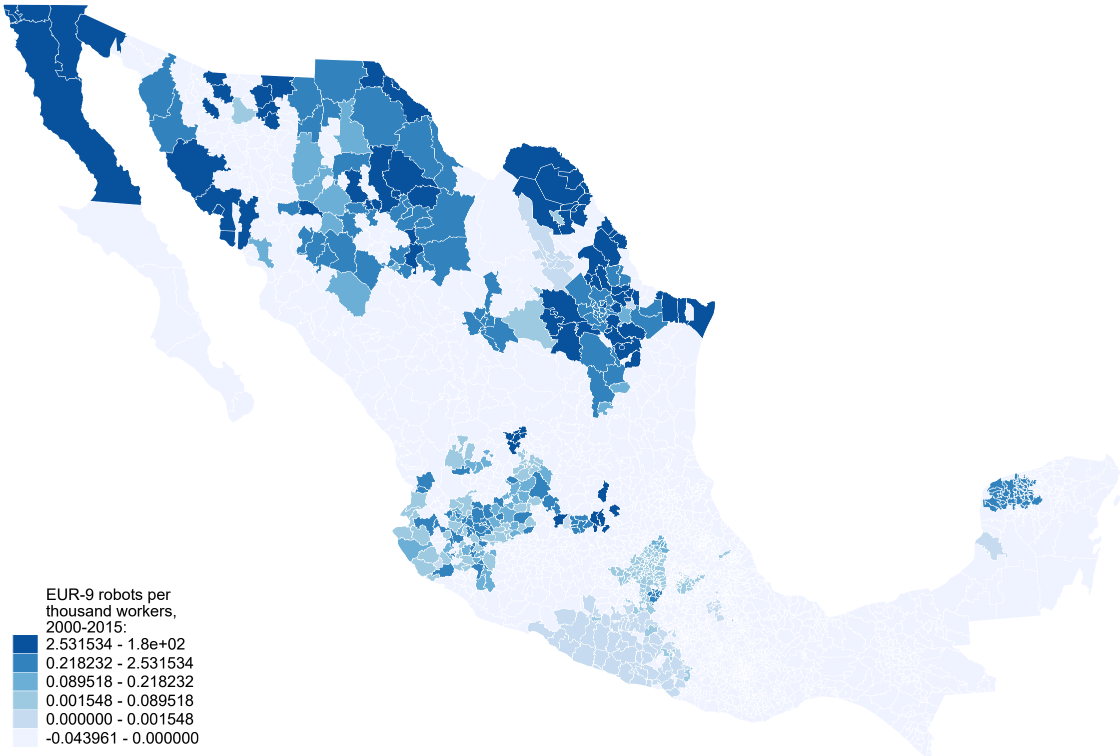

*Note:* Own calculation using IFR data. EUR-9 stands for European robots which is comprised by nine countries: Denmark, Spain, Finland, France, Germany, Sweden, Great Britain, and Italy.

Figure 3: Predicted spatial distribution of industrial robots

(a) US robots



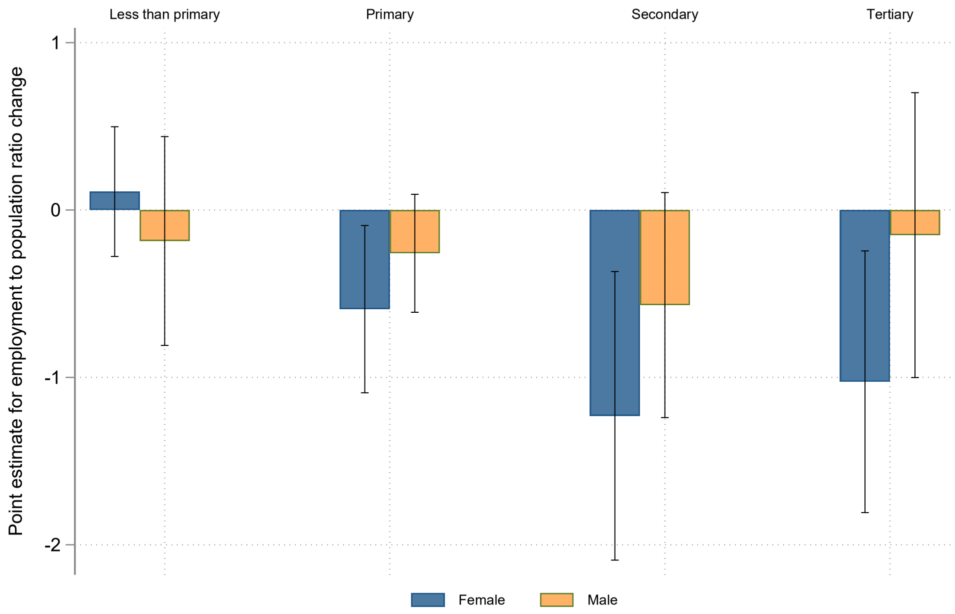

(b) EUR-9 robots



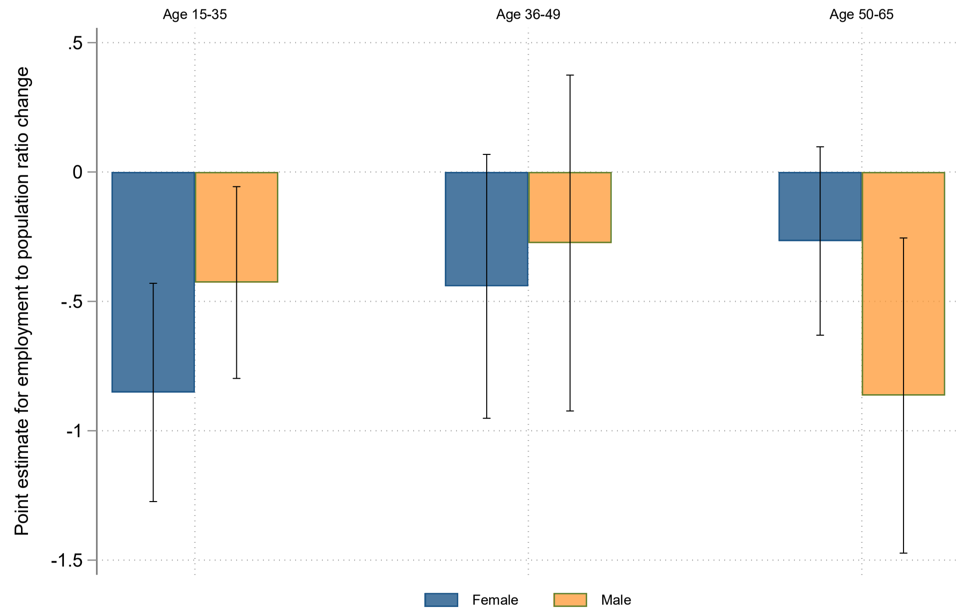

*Note:* The map depicts the predicted spatial distribution of US and EUR-9 robots.

Figure 4: Effect of robot penetration on employment by skill level and age

(a) Skill level



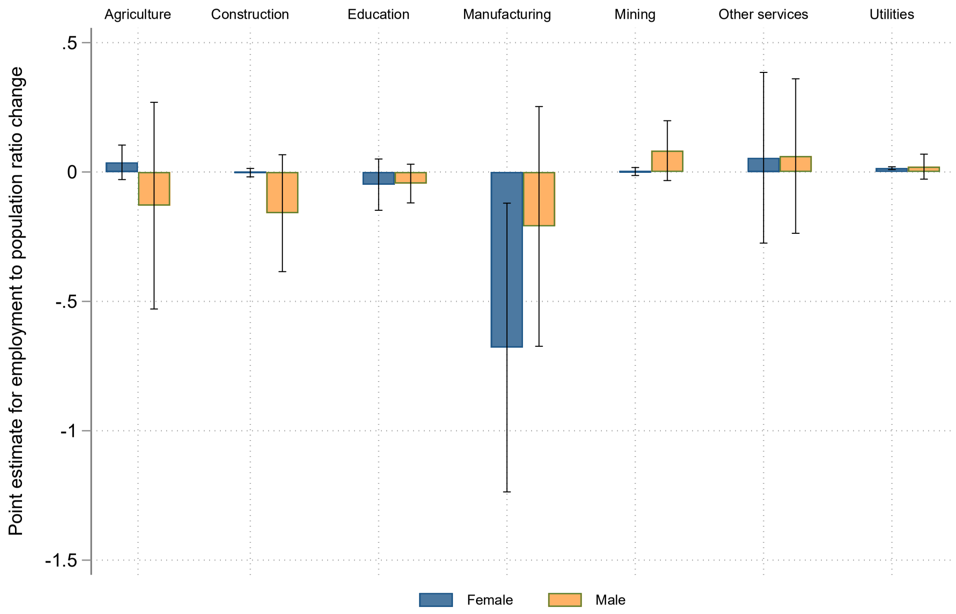

(b) Age



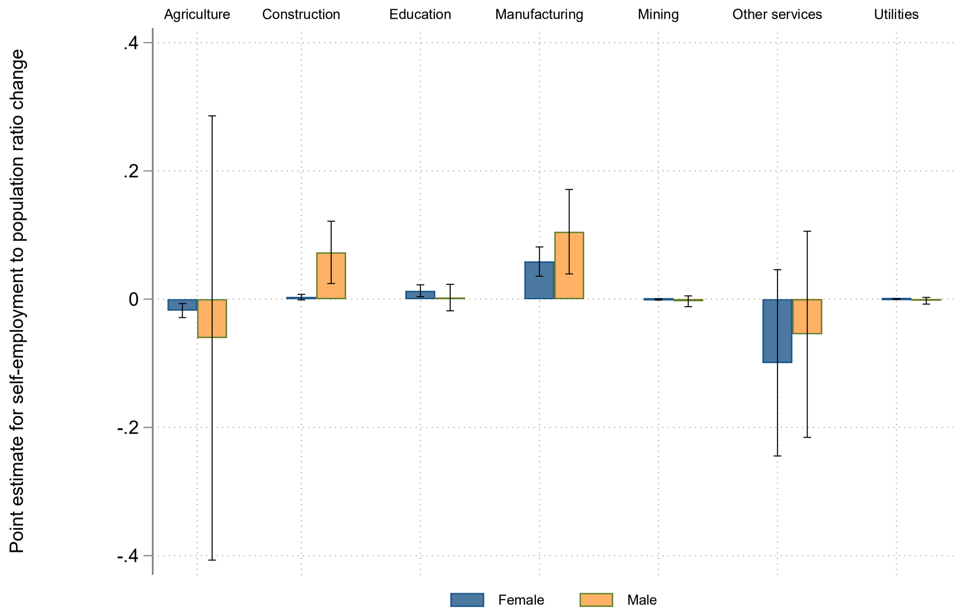

*Note:* Figure shows the 2SLS results of the estimated effects of US robots on employment by skill level, age and sex. Each column controls for the sum of shares in *maquiladora* employment, eight broad region dummies, the pretrend in outcomes; baseline demographic outcomes measured in 2000: the share of male workers, the logarithm of population, the share of working age population (18-65 years old), the share of workers older than 65, the share of workers with completed primary, secondary, and tertiary schooling; and contemporary shocks: the local exposure to imports from China, the share of routinary jobs in 1990, and the exposure to NAFTA. Robust standard errors are clustered at the state level. Regressions are weighted by the number of births in 2000. Whiskers show 95% confidence intervals.

Figure 5: Effect of robot penetration on employment and self-employment by economic sector

(a) Employment




(b) Self-employment




*Note:* Figure shows the 2SLS results of the estimated effects of US robot exposure on employment and self-employment by sex and economic sector. Each column controls for the sum of shares in *maquiladora* employment, eight broad region dummies, the pretrend in outcomes; baseline demographic outcomes measured in 2000: the share of male workers, the logarithm of population, the share of working age population (18-65 years old), the share of workers older than 65, the share of workers with completed primary, secondary, and tertiary schooling; and contemporary shocks: the local exposure to imports from China, the share of routinary jobs in 1990, and the exposure to NAFTA. Robust standard errors are clustered at the state level. Regressions are weighted by the number of births in 2000. Whiskers show 95% confidence intervals.

## Appendix Tables

Table A1: Effect of robot penetration on the change of infant mortality rate (2000-15)-OLS .

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| $\Delta robots^{US}$ | 1.160** | 1.182** | 1.080** | 1.068** |
| | (0.500) | (0.477) | (0.447) | (0.446) |
| Observations | 1805 | 1805 | 1805 | 1805 |
| Region FE/industry shares | ✓ | ✓ | ✓ | ✓ |
| Outcome trends | | ✓ | ✓ | ✓ |
| Demographic trends | | | ✓ | ✓ |
| Contemporary shocks | | | | ✓ |

*Note:* The dependent variable is the change in infant mortality rate. Column (1) controls for the sum of shares in *maquiladora* employment and eight broad Mexican region dummies. Column (2) includes the change in infant mortality rate for the period 1998-2000. Column (3) includes baseline controls measured in 2000: the share of male workers, the logarithm of population, the share of working age population (18-65 years old), the share of workers older than 65, the share of workers with completed primary, secondary, and tertiary schooling. Column (4) includes contemporary shocks: the local exposure to imports from China, the share of routinary jobs in 1990, and the exposure to NAFTA. Robust standard errors are clustered at the state level and reported in parentheses. Regressions are weighted by the number of births in 2000. Significance: *** p<0.01, ** p<0.05, * p<0.10.

Table A2: Alternative instruments

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| **Panel A. No offshorability term** | | | | |
| $\Delta robots^{US}$ | 1.212** | 1.307** | 1.226** | 1.275** |
| | (0.577) | (0.566) | (0.495) | (0.506) |
| Observations | 1805 | 1805 | 1805 | 1805 |
| Kleibergen-Paap F-stat | 17.27 | 17.29 | 17.09 | 19.44 |
| **Panel B. Export share interaction** | | | | |
| $\Delta robots^{US}$ | 1.563** | 1.540*** | 1.421*** | 1.400*** |
| | (0.633) | (0.572) | (0.538) | (0.515) |
| Observations | 1805 | 1805 | 1805 | 1805 |
| Kleibergen-Paap F-stat | 45.67 | 45.83 | 54.34 | 64.05 |
| Region FE/industry shares | ✓ | ✓ | ✓ | ✓ |
| Outcome trends | | ✓ | ✓ | ✓ |
| Demographic trends | | | ✓ | ✓ |
| Contemporary shocks | | | | ✓ |

*Note:*. The dependent variable is the change in infant mortality rate. Panel A excludes the offshorability term from the main instrument $\tilde{O}_{i,1990}$. Panel B includes the share of Mexican exports in 1990 to the US as interaction term. Column (1) controls for the sum of shares and eight broad Mexican regions. Column (2) includes baseline controls measured in 2000: the share of male workers, the logarithm of population, the share of working age population (18-65 years old), the share of workers older than 65, the share of workers with completed primary, secondary, and tertiary schooling. Column (3) includes contemporary shocks: the local exposure to imports from China, the share of routinary jobs in 1990, and the exposure to NAFTA. Robust standard errors are clustered at the state level and reported in parentheses. Regressions are weighted by the number of births in 2000. Significance: *** p<0.01, ** p<0.05, * p<0.10.

Table A3: Robustness

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| **Panel A. Controlling for Domestic robots** | | | | |
| $\Delta robots^{MX}$ | -1.890** | -1.858** | -1.113* | -1.281 |
| | (0.765) | (0.787) | (0.609) | (0.941) |
| $\Delta robots^{US}$ | 1.682*** | 1.668*** | 1.518*** | 1.428*** |
| | (0.582) | (0.525) | (0.534) | (0.527) |
| Observations | 1805 | 1805 | 1805 | 1805 |
| **Panel B. Removing recession years** | | | | |
| $\Delta robots^{US}$ | 1.652*** | 1.604*** | 1.561*** | 1.568*** |
| | (0.425) | (0.486) | (0.541) | (0.554) |
| Observations | 1804 | 1804 | 1804 | 1804 |
| **Panel C. Nonzero maquiladora employment** | | | | |
| $\Delta robots^{US}$ | 1.244** | 1.207*** | 0.727** | 0.770** |
| | (0.575) | (0.443) | (0.355) | (0.358) |
| Observations | 251 | 251 | 251 | 251 |
| **Panel D. No outliers** | | | | |
| $\Delta robots^{US}$ | 1.835** | 1.733** | 1.644** | 1.544** |
| | (0.784) | (0.724) | (0.736) | (0.737) |
| Observations | 1801 | 1801 | 1801 | 1801 |
| Region FE/industry shares | ✓ | ✓ | ✓ | ✓ |
| Outcome trends | | ✓ | ✓ | ✓ |
| Demographic trends | | | ✓ | ✓ |
| Contemporary shocks | | | | ✓ |

*Note:*. The dependent variable is the change in infant mortality rate. Panel A controls for domestic robots for the period 2000-2015. Panel B shows the regressions for the period 2000-2007. Panel C only leaves nonzero employment in *maquiladoras*. Panel D removes the 1% in the distribution of US robot exposure. Column (1) controls for the sum of shares and eight broad Mexican regions. Column (2) includes baseline controls measured in 2000: the share of male workers, the logarithm of population, the share of working age population (18-65 years old), the share of workers older than 65, the share of workers with completed primary, secondary, and tertiary schooling. Column (3) includes contemporary shocks: the local exposure to imports from China, the share of routinary jobs in 1990, and the exposure to NAFTA. Robust standard errors are clustered at the state level and reported in parentheses. Regressions are weighted by the number of births in 2000. Significance: *** p<0.01, ** p<0.05, * p<0.10.

Table A4: Effect of robot penetration on the change of infant mortality rate, using Adão et al. (2019) standard errors (2000-2015) -2SLS.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| $\Delta robots^{US}$ | 1.497 | 1.483 | 1.375 | 1.349 |
| | (0.256)*** | (0.254)*** | (0.216)*** | (0.220)*** |
| Observations | 1805 | 1805 | 1805 | 1805 |
| Region FE/Industry shares | ✓ | ✓ | ✓ | ✓ |
| Outcome trends | | ✓ | ✓ | ✓ |
| Demographic trends | | | ✓ | ✓ |
| Contemporary shocks | | | | ✓ |

*Note:*The dependent variable is the change in infant mortality rate. Column (1) controls for the sum of shares in *maquiladora* employment and eight broad Mexican region dummies. Column (2) includes the change in infant mortality rate for the period 1998-2000. Column (3) includes baseline controls measured in 2000: the share of male workers, the logarithm of population, the share of working age population (18-65 years old), the share of workers older than 65, the share of workers with completed primary, secondary, and tertiary schooling. Column (4) includes contemporary shocks: the local exposure to imports from China, the share of routinary jobs in 1990, and the exposure to NAFTA. Robust standard errors are clustered at the state level and reported in parentheses. Regressions are weighted by the number of births in 2000. Significance: *** p<0.01, ** p<0.05, * p<0.10. .

Table A5: Effect of robot penetration on the change of public health provision (2001-2015) -2SLS.

| | (1)<br>Pediatricians | (2)<br>Incubators | (3)<br>Newborn cribs | (4)<br>Delivery rooms |
|---|---|---|---|---|
| $\Delta robots^{US}$ | 0.234 | 0.057 | 0.029 | 0.035 |
| | (0.150) | (0.066) | (0.121) | (0.023) |
| Observations | 1622 | 1622 | 1622 | 1622 |
| Region FE/industry shares | ✓ | ✓ | ✓ | ✓ |
| Demographic trends | ✓ | ✓ | ✓ | ✓ |
| Contemporary shocks | ✓ | ✓ | ✓ | ✓ |

*Note:*The dependent variable is the change in infant mortality rate.Each column controls for the sum of shares in *maquiladora* employment, eight broad region dummies, baseline demographic outcomes measured in 2000: the share of male workers, the logarithm of population, the share of working age population (18-65 years old), the share of workers older than 65, the share of workers with completed primary, secondary, and tertiary schooling; and contemporary shocks: the local exposure to imports from China, the share of routinary jobs in 1990, and the exposure to NAFTA. Robust standard errors are clustered at the state level and reported in parentheses. Regressions are weighted by the number of births in 2000. Significance: *** p<0.01, ** p<0.05, * p<0.10.

Table A6: Effect of robot penetration on the change of fetal deaths and birth rates by mother skill level (2000- 15)-2SLS.

| | | Birth rate | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) Fetal deaths | (2) All | (3) Less than primary | (4) Primary | (5) Secondary | (6) Tertiary | (7) 15-35 | (8) 36-45 |
| $\Delta robots^{US}$ | 0.356 | -0.001 | 1.450*** | -0.164 | 0.127 | 0.679*** | -0.565 | -0.164* |
| | (0.418) | (0.001) | (0.450) | (0.286) | (1.204) | (0.245) | (0.656) | (0.095) |
| Observations | 1805 | 1804 | 1804 | 1804 | 1804 | 1804 | 1804 | 1804 |
| Mean dep var | 9.715 | 0.128 | 34.11 | 32.47 | 40.90 | 7.116 | 106.6 | 9.710 |
| Region FE/industry shares | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Outcome trends | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Demographic trends | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Contemporary shocks | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

*Note:*. The dependent variable is the change in fetal deaths (Column (1). Column (2) is the overall birth rate. Columns (3) to (6) are the birth rate by education level. Columns (7) and (8) are the birth rate by age brackets. Each column controls for the sum of shares in *maquiladora* employment, eight broad region dummies, the pretrend in outcomes; baseline demographic outcomes measured in 2000: the share of male workers, the logarithm of population, the share of working age population (18-65 years old), the share of workers older than 65, the share of workers with completed primary, secondary, and tertiary schooling; and contemporary shocks: the local exposure to imports from China, the share of routinary jobs in 1990, and the exposure to NAFTA. Robust standard errors are clustered at the state level and reported in parentheses. Regressions are weighted by the number of births in 2000. Significance: *** p<0.01, ** p<0.05, * p<0.10.

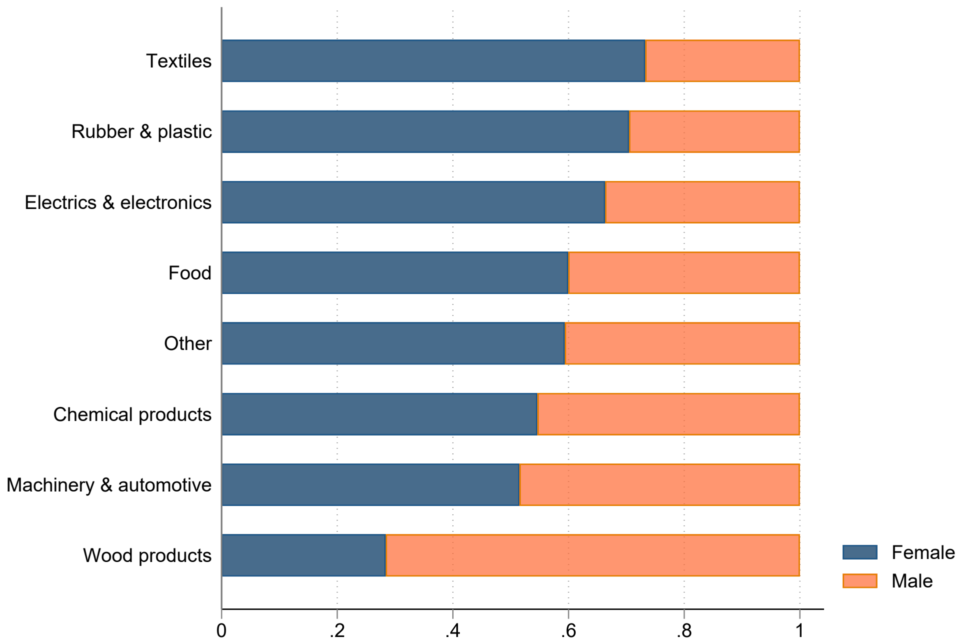
Table A7: Effect of robot penetration on the change of the logarithm of working-age population (2000- 15)-2SLS.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| $\Delta robots^{US}$ | -0.019* | 0.017* | 0.016* | 0.017* |
| | (0.011) | (0.009) | (0.009) | (0.009) |
| Observations | 1804 | 1804 | 1804 | 1804 |
| Region FE/industry shares | ✓ | ✓ | ✓ | ✓ |
| Outcome trends | | ✓ | ✓ | ✓ |
| Demographic trends | | | ✓ | ✓ |
| Contemporary shocks | | | | ✓ |

*Note:* The dependent variable is the change of the logarithm of working-age population. Column (1) controls for the sum of shares and eight broad Mexican regions. Column (2) includes the change in infant mortality rate for the period 1998-2000. Column (3) includes baseline controls measured in 2000: the share of male workers, the logarithm of population, the share of working age population (18-65 years old), the share of workers older than 65, the share of workers with completed primary, secondary, and tertiary schooling. Column (4) includes contemporary shocks: the local exposure to imports from China, the share of routinary jobs in 1990, and the exposure to NAFTA. Robust standard errors are clustered at the state level and reported in parentheses. Regressions are weighted by the number of births in 2000. Significance: *** p<0.01, ** p<0.05, * p<0.10.

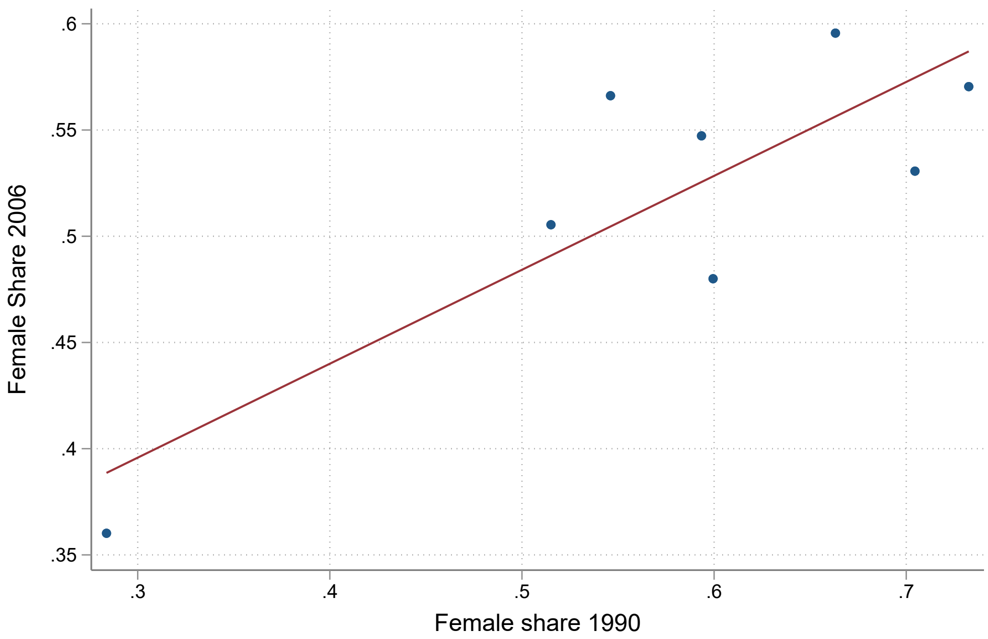
## Appendix Figures

Figure A1: Employment shares by sector in 1990



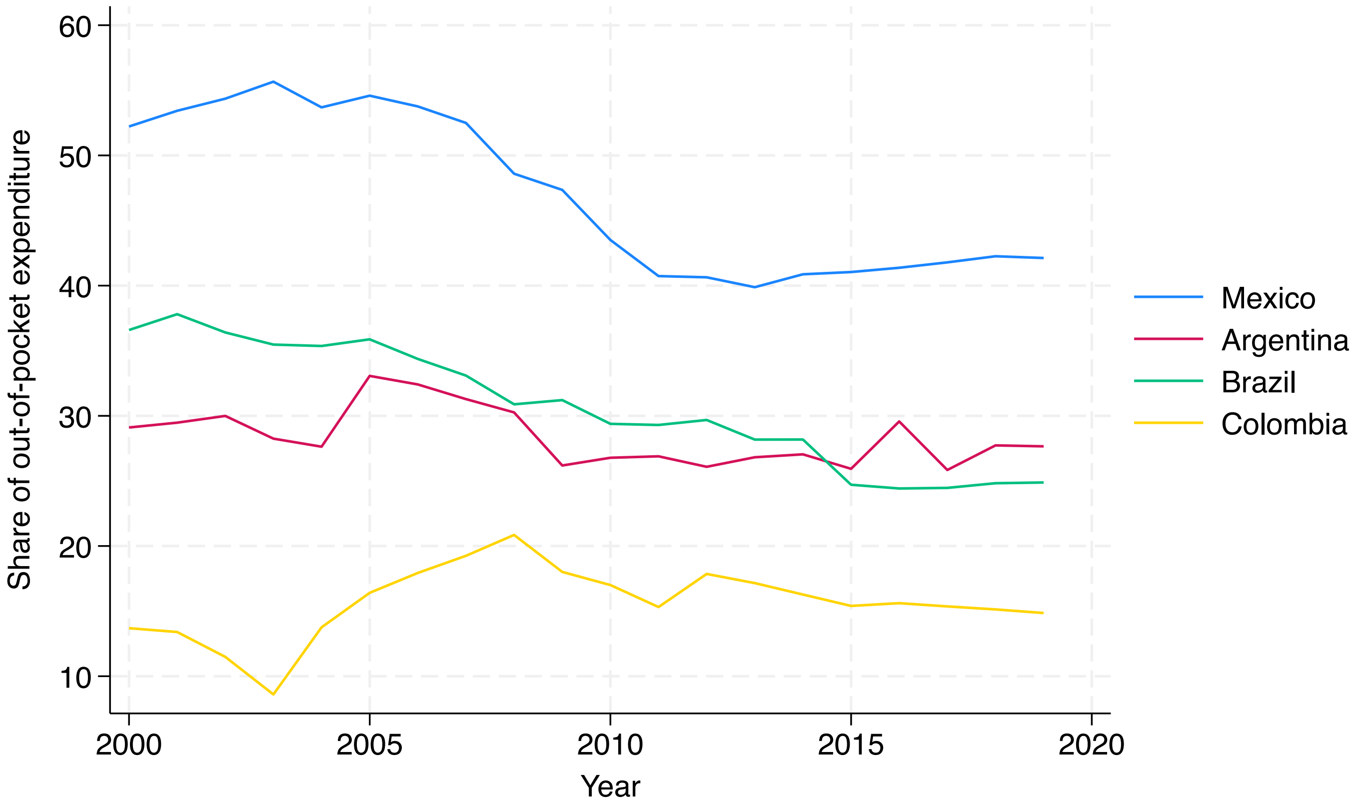

*Note:* This figure shows the share of employment by gender in 8 *maquiladora*, manufacturing industries.

Figure A2: Relationship between maquiladora employment in 1990 and 2006



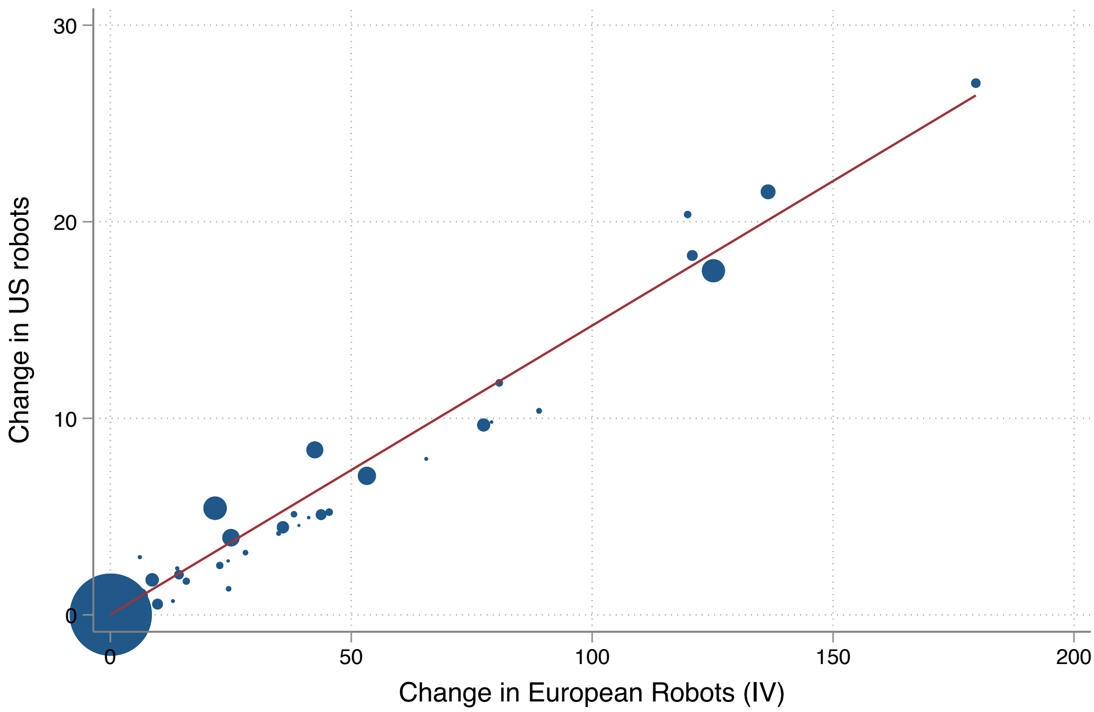

*Note:* This figure shows the relationship between female share employment in *maquiladoras* by industry in 2006 and 1990.

Figure A3: Share of out-of-pocket expenditure by country



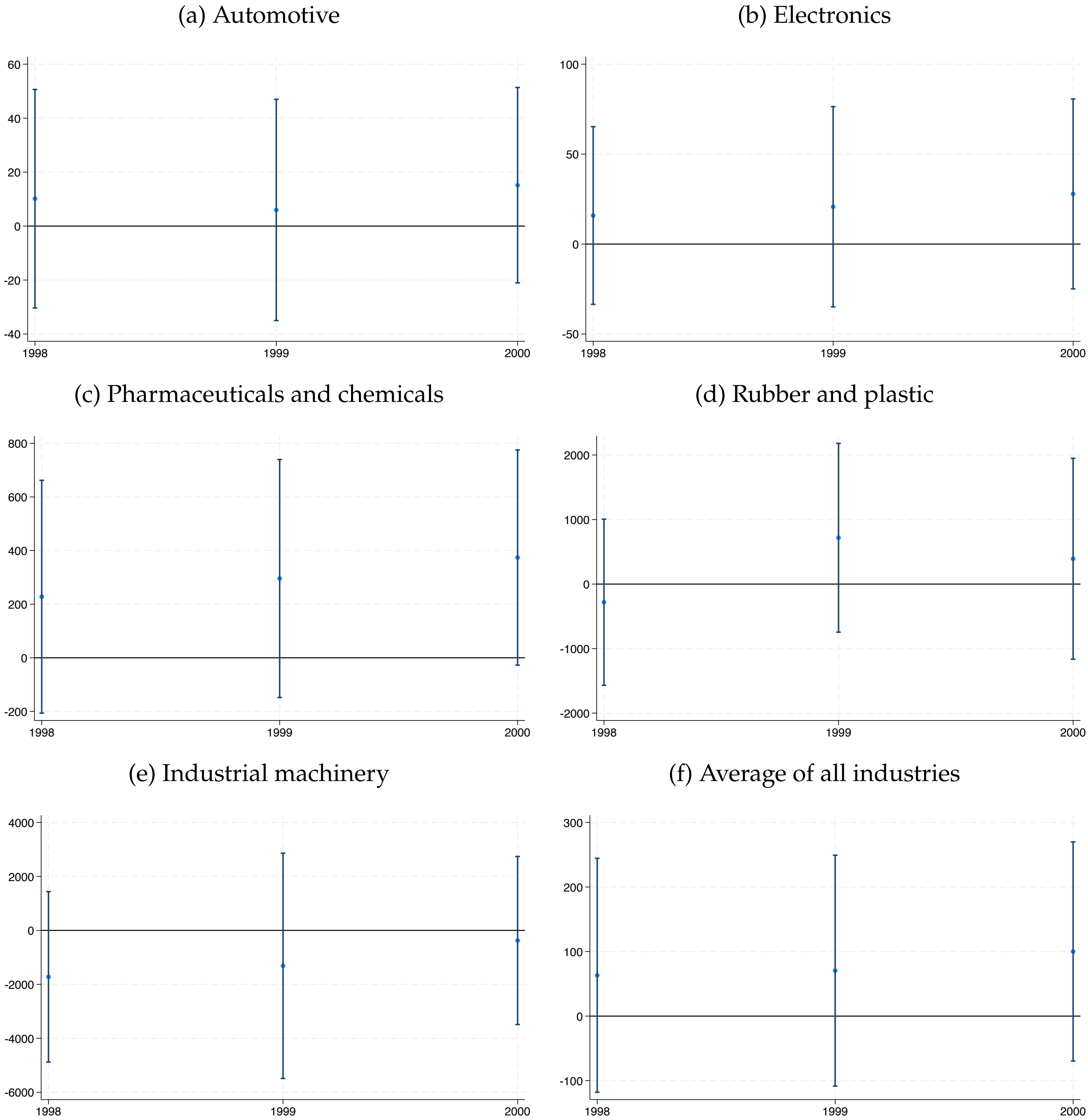

*Note* This figure shows the evolution of the share of out-of-pocket health expenditure in Mexico, Argentina, Brazil, and Colombia.

Figure A4: First-stage relationship



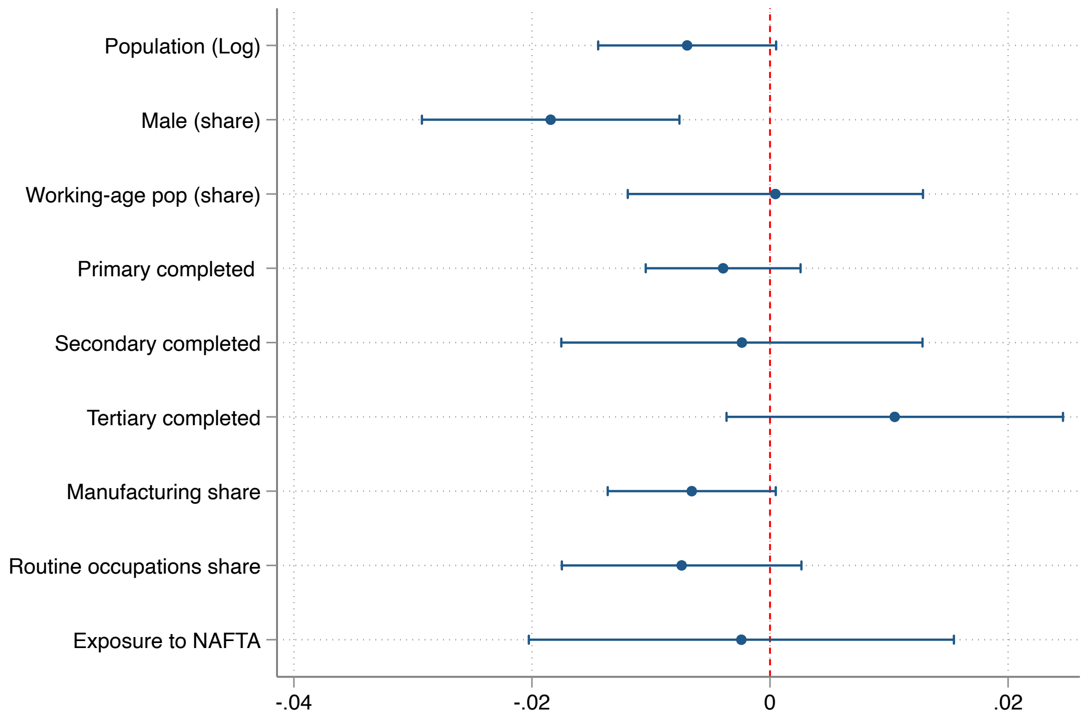

*Note* This figure shows that relationship between the change of US robots and the change of European Robots for the period 2000-15. The size of the dots are the number of baseline births in 2000.

Figure A5: Pre-trends test




*Note:* The figure shows the estimated coefficient and the 95% confidence intervals for separate regressions of infant mortality rates on maquiladora industry shares. Column (F) shows the average of all industries. Each regression is weighted by the number of births in 2000, and the standard errors are clustered at the state level.

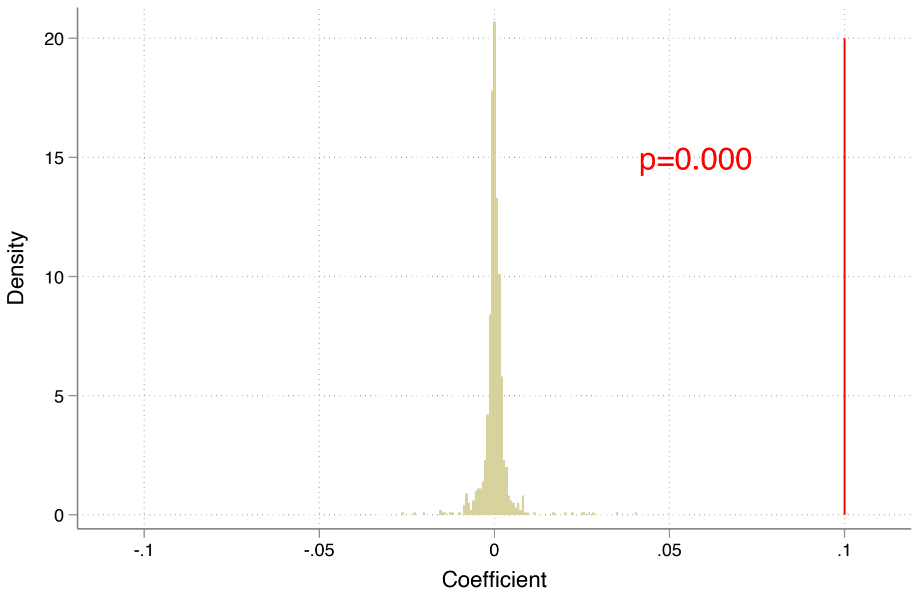
Figure A6: Location-level balance test



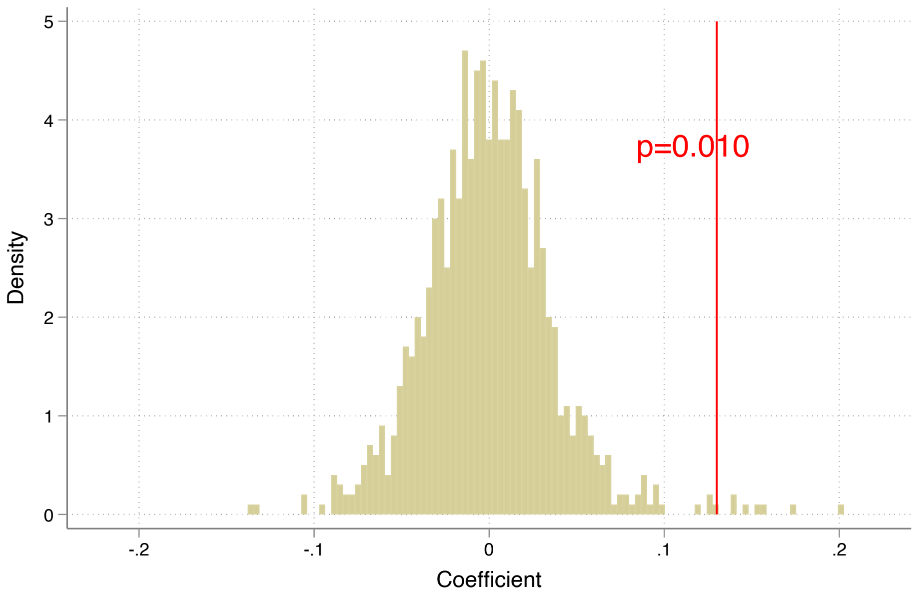

*Note:* This figure shows the separate regression of each characteristic on the column on US robot adoption, controlling for the sum of shares in *maquiladora* employment. All regressions are weighted by births in 2000.

Figure A7: Permutation test

(a) First stage




(b) Reduced form




*Note:* This figure shows the distribution of coefficients that randomized the assignment of european robots exposure (IV) at the CZ level. There were in total 1,000 iterations (regressions) on each Panel. Panel A shows the estimates for the first stage, and Panel B shows the estimates for the reduced-form regression. The vertical lines are the estimated "true" coefficients, using the main specification. The $p$-values refer to the number of observations that are greater than the true value.