Automation, Economic Shocks, and Infant Mortality: Evidence from 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 larger job losses than men, leading to reduced household income and access to employer-provided healthcare. This economic strain forced many women into self-employment within manufacturing, 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). While the economic consequences of automation and reshoring are documented, less is known about their implications for human development—particularly infant health, which remains sensitive to changes in women's labor opportunities and household income.

Mexico provides a relevant context to study these questions. Since 1965, the *maquiladora* program has linked the Mexican economy to global production chains through factories that import materials duty-free, assemble them, and re-export final products. Employment in *maquiladoras* has been predominantly female: in 1990, women accounted for more than 50% of employment in the sector, compared to 19% in manufacturing overall. These jobs represented an important source of labor market participation for women in low-skilled manufacturing. Employment growth declined after 2000,[1] partly due to the adoption of industrial robots in the United States and the reshoring of production.[2] Prior research shows that the expansion of *maquiladoras* increased women's labor opportunities and improved child health outcomes (Atkin, 2009; Estefan, 2022).[3] Less is known about whether automation in advanced economies

[1]From 1990 to 2000, average employment growth was 11.3%, but from 2000 to 2004 it was –3.4% (INEGI, 2024a).

[2]Faber (2020) document plant reshoring in the U.S. and show that exposure to robots reduced 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

reverses these effects by reducing women's employment and affecting infant health in developing 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 exposure 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 exposure vis-à-vis those where low or null robot exposure 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 variation in *maquiladora* employment shares in 1990 as source of identifying variation, interacted with industry-level shocks from European countries. 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

mating, and improved children's health outcomes.

[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 (INEGI, 2024b).

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 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 0.66-0.74 deaths per thousand births, which translates into an increase of 4.4%-4.9% 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 granularity of the data allows me to examine whether the effect of U.S. automation on infant mortality is driven by specific groups of diseases. I classify deaths using broad categories from the International Classification of Diseases (ICD). The effects are concentrated among infectious, respiratory, and malnutrition-related diseases, which together represent about one-fifth of baseline infant deaths in Mexico. These internal causes are largely preventable under adequate living conditions for children. When focusing on external causes, most of the estimated external-cause effect is driven by accidents and aggressions, suggesting a potential link with stress-related factors.

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 mortality 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, there is more consensus on the countercyclical pattern of infant mortality (Baird et al., 2011; Bhalotra, 2010; Bozzoli and Quintana-Domeque, 2014; Panda, 2020).[6]

Most of this literature focuses on the response of infant health to transitory, aggregate economic fluctuations, leaving a gap concerning the effects of permanent shocks resulting from automation. Existing studies on the health consequences of automation focus on specific countries, such as the United States, China, and Germany, and mainly examine adult populations, considering outcomes such as substance abuse (O'Brien et al., 2022), self-reported health (Gunadi and Ryu, 2021), and transportation and workplace accidents (Gihleb et al., 2022).

This paper addresses this gap by examining the effects of income shocks on mortality in Mexico, where evidence is mixed. Following Ruhm (2000), Gonzalez and Quast (2011) find that overall mortality is procyclical with respect to changes in state-level GDP. In contrast, Cutler et al. (2002) and Arceo-Gómez (2010) report a countercyclical pattern, mainly affecting children and the elderly. This paper aligns with the latter evidence while providing additional insights into mechanisms linking income and parental time to mortality.

Second, this paper contributes to the emerging literature on cross-border effects of automation on health disparities. While previous studies show that income shocks stemming from import competition from U.S and China affect nutritional outcomes (Giuntella et al., 2020) and adult mortality in Mexico (Fernández Guerrico, 2021), U.S. automation introduces a new channel affecting health, particularly for populations largely unprotected by health insurance due to limited institutional capacity and in-

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

[6]A few exceptions are Miller and Urdinola (2010) and Charris et al. (2024) who show that for the case of Colombia and Brazil there is a procycical behaviour of infant mortality. They provide evidence that, while employment losses may reduce household income, parental time is the main input to child survival given low cost for prenatal care and other medical inputs.

formal labor markets. These findings align with models and evidence suggesting that automation reduces demand for low-skill labor in contexts of trade uncertainty (Faber et al., 2025; Firooz et al., 2025).

Third, this paper contributes to the 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 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

This section provides background on two institutional dimensions relevant for the analysis: (1) the *maquiladora* program, which has shaped labor market conditions, wages, and female employment in manufacturing; and (2) the structure of Mexico's health system, where access to services is largely determined by labor market participation. Together, these elements establish the link between employment characteristics and health coverage, which is central to the empirical analysis.

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 their proximity to the United States, *maquiladora* plants are usually located in border states,[7] specializing in labor-intensive sectors like electronics, furniture, automotive 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).

[7]The first *maquiladora* plant was in Ciudad Juarez, in the state of Chihuahua, which shares a border 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).

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,[8] 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% 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 rapid advances in health coverage, gaps in effective access to medical ser-

[8]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).

vices remain among both the insured and uninsured (Gutiérrez et al., 2014; Urquieta-Salomón and Villarreal, 2016). For instance, Urquieta-Salomón and Villarreal (2016) find that, on average, nine in ten women access prenatal care during pregnancy, with no significant differences between insured and uninsured groups. However, applying a stricter definition of effective access reveals a 20% gap between women insured through formal employment and those uninsured.[9]

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) (Bank, 2015).

3 Data

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

Unit of analysis: in line with Atkin (2016) and Faber (2020), the analysis will be 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.[10] 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 Mexican municipalities with strong ties, as measured by the frequency of commuting movements among workers across various municipalities within a *Metropolitan Zone*.[11]

[9]Urquieta-Salomón and Villarreal (2016) define crude prenatal care access as attending at least four prenatal visits with a healthcare provider. Effective prenatal care is defined as receiving the following: measurement, weight, blood pressure, general urinalysis, blood tests, blood glucose level, ultrasound, tetanus vaccine, folic acid screening, iron blood test, and syphilis detection.

[10]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.

[11]By the year 2000 Mexico had 2,443 municipalities within 32 states. The number of clustered

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.[12] 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.[13]

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,[14] 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.

Metropolitan Zones is 59, which groups 1,022 municipalities, so the remaining municipalities are independent clusters. Like Atkin (2016) and Faber (2020), I exclude Mexico 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.

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

[13]Data on birth registrations are not complete on a yearly basis, as individuals born in a given year may not be registered on their exact date of birth. Nearly 30% of reported births correspond to late registrations from previous years. To address this issue, I construct the number of births from 1998 to 2015 by collapsing the data by date of occurrence and municipality of the mother's residence, using records from 1998 through 2023, the most recent year available in the microdata.

[14]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.

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 exposure at this level (see section 4), a commonly used approach in other studies examining the impact of robots on labor markets and demographic dynamics (Acemoglu and Restrepo, 2020; Brambilla et al., 2023; Faber, 2020). Figure 1 shows that U.S. robots per worker have increased 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,[15] place of residence,

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

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.

4 Empirical strategy

4.1 Local exposure to robots

I exploit cross-variation of U.S. robot exposure at the Mexican 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 exposure per worker in the U.S. This variable leverages *maquiladora* employment composition across Mexican CZs as shares and the number of robots at the industry level as shifters.

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

Where $L^{f}_{c,i,1990}$ denotes the total *maquiladora* employment in industry i in Mexico in 1990, while $L_{c,1990}$ denotes *maquiladora* employment in commuting zone c in the same year. The shares, $\frac{L^f_{c,i,1990}}{L_{c,1990}}$, therefore represent each CZ industrial composition based on its *maquiladora* employment in 1990, approximating baseline export-oriented labor exposure.

In equation 1, $R^{US}_{i,t}$ is the number of U.S. robots in industry i at time t, which is then re-scaled by total Mexican *maquiladora* employment in each sector, $L^f_{i,1990}$ (summed across all commuting zones), and expressed per 1,000 workers.[16]This scaling ensures that the shock captures the intensity of robot adoption relative to the size of the Mexican export-oriented manufacturing sector that would be most directly affected by U.S. automation. Given the focus of the analysis, $t_0 = 2000$ and $t_1 = 2015$.

Moreover, the element O_i serves as an approximation of the extent to which certain sectors can be offshored, consequently, are more likely to compete with automation through robotics.[17] In line with Faber (2020), this measure is approximated with 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. 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,

[16]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.

[17]Note that by adding the term O_i, it is assumed that robots will not compete directly with jobs in non-tradable industries like construction or services.

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.[18]

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 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}.

[18] Details on the imputation method for robot exposure are provided in Graetz and Michaels (2018) and Appendix B.

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.[19] 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.

$$\begin{cases} \Delta robots^{US}_{c,(t_0,t_1)} = b_0 + \lambda_r + b_1 IV \Delta robots^{US}_{c,(t_0,t_1)} + \mathbf{X'}_{\mathrm{c},2000}\gamma + \Delta Y'_{c,2000-98}\rho + \epsilon_{c,(t_0,t_1)} \\ \Delta Y_{c,(t_0,t_1)} = \alpha + \theta_r + \beta \Delta \widehat{robots^{US}_{c,(t_0,t_1)}} + \mathbf{X'}_{\mathrm{c},2000}\varphi + \Delta Y'_{c,2000-98}\omega + \varepsilon_{c,(t_0,t_1)} \end{cases} \tag{3}$$

$\Delta Y_{c,t}$ denotes the change in infant mortality rate between 2000 and 2015 in CZ c. Estimates of β 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 θ_r are eight region dummies that control for broad region-specific trends. Similarly, the vector $\mathbf{X'}_{\mathrm{c},2000}$ includes base-

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

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. $\Delta Y_{c,2000-98}$ 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.[20]

Note that the estimates of β 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 should be interpreted in terms of the industry shares.[21] 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,

[20]In general, to capture the effect representative of the average infant, I weight regressions or mechanisms by the number of births at baseline. When the outcome is related to the adult population, I weight each regression by the working-age population at baseline.

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

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.

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 5% level. The stability of the coefficient across specifications is consistent with the assumption that baseline characteristics are not strongly correlated with the structural error term.

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 experienced 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.[22]

Taking these factors into consideration reduces somewhat the coefficient while keeping the same level of precision at 5% level, as documented in Column (4). The coefficient of 0.898 on the exposure of U.S. robots means that a one-unit increase in U.S. robot exposure will increase infant mortality by nearly 0.9 deaths per thousand live births. This implies that an average increase in U.S. robot exposure (0.74, see Table A1) will increase the infant mortality rate by 0.66 (0.898×0.74), which represents a 4.4% increase in the infant mortality rate from the baseline rate in 2000 (15.17). These results are consistent with prior research on income shocks in Mexico. For example, Cutler et al. (2002) find that infant mortality increased 6.5% following the 1995 financial crisis. Similarly, Arceo-Gómez (2010) find that a 1% increase in state GDP reduces infant mortality by 1.5% for females and 2.5% for males.

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 A2 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 examine the drivers of the main infant mortality effects by disaggregating the data into six ICD categories, as shown in Table 2: infectious and respiratory (Column 1), malnutrition (Column 2), perinatal (Column 3), congenital (Column 4), accidents or aggressions (Column 5), and other internal diseases (Column 6). Among internal causes, infectious and respiratory diseases and malnutrition are the main drivers of the results. Most of these are preventable,[23] with infectious, respiratory and malnutrition

[22]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). See Appendix B for a formal description of the variables mentioned above.

[23]For example, with adequate nutrition, sanitation, and access to basic medical care (e.g., antibiotics for pneumonia, rehydration therapy for diarrhea).

causes accounting for nearly one-fifth of deaths per thousand births at baseline.

There are no statistically significant effects of automation on perinatal conditions, suggesting that automation-related infant mortality is not driven by factors originating during gestation. Likewise, no effects are detected for other internal or congenital causes (Columns 4 and 6), which are more likely to be associated with unrelated shocks. Column (5) shows that automation increases deaths from accidents and aggressions, although this is a relatively uncommon category, representing only 4% of infant deaths at baseline. As will be shown in Section 6, a potential explanation is that industrial robot exposure is associated with working conditions that increase stress through income losses (Gihleb et al., 2022; Liu et al., 2024).

5.2 Additional robustness

I have conducted several robustness checks to probe the sensitivity of the main results. First, the estimations are robust to alternative definitions of the treatment. In Table A3, Panel A excludes the general offshorability term ($\tilde{O}_{i,1990}$). Panel B instead uses the share of Mexico's exports to the U.S. in 1990 as the interaction term. In both cases, the results remain consistent with the baseline estimates.

Next, Table A4 shows that the findings are qualitatively insensitive to different samples and specifications. Panel A documents that the estimated effect of U.S. robots on infant mortality is robust to the inclusion of domestic automation, which is consistent with evidence that Mexico's exposure to robots has been slower than in developed economies.[24]

Another concern is that outcomes during the study period could have been influenced by external shocks, particularly the Great Recession (2008–2010) through an income effect. Panel B shows that excluding the Great Recession years produces qualitatively similar results: the coefficients remain positive and statistically significant at conventional levels, and the confidence intervals overlap with the baseline estimates in

[24] Faber (2020), using a Bartik approach, finds no statistically significant effect of Mexican robots on employment. Serrano (2023), using a difference-in-differences methodology, shows that robot adoption in Mexico has not reduced employment but has instead complemented firm productivity.

Table 1. While the point estimates are somewhat larger (1.5-1.8 vs. 0.9), this difference is not statistically significant, indicating that the main findings are not driven by the recession period.

The estimates are also stable when using shorter time intervals by stacking three subperiods into a panel structure: 2000–2005, 2005–2010, and 2010–2015. Table C1 confirms that the results are similar in magnitude and precision to the baseline, suggesting that they are not driven by spurious compounding trends.[25] Finally, Panel C shows that the results remain unaffected after excluding outliers identified by Cook's distance.[26]

Bartik-style instruments are likely to suffer from correlation of residuals across regions with similar shares, which causes over-rejection of the null hypothesis ($\beta = 0$). 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 A5. The adjusted standard errors across all specifications are smaller 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.

[25]See Appendix C for details on this alternative specification.

[26]Based on this criterion, an outlier is defined if the estimated distance is higher than $4/n$.

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).[27] These labor adjustments could affect infant health by amplifying household income losses. However, there could be a substitution of employment for adult time 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 (5) 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). Although I cannot reject the null hypothesis that both coefficients are the same, the magnitude of these differences is suggestive of larger effects for women. A one-unit increase in the exposure to U.S. robots decreases female employment-to-population ratio by 0.61 percentage points. This implies that an average increase in the exposure to U.S. robots per worker (0.74) reduces female employment-to-population ratio by 0.45 percentage points (0.74×-0.61), which represents a 1.9% reduction in the female employment-to-population ratio of the observed baseline in 2000.

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

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-to-population ratio 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 0.35 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. A one-unit increase in U.S. robot exposure reduces household income by 1.7 percentage points (coefficient = -0.017). Given the average rise in robot exposure of 0.74 units, this implies that household income declined by approximately 1.3 percentage points ($-0.017 \times 0.74 = -0.013$, or -1.3%) in areas with average exposure.

Next, I explore whether there are transitions to self-employment occupations, which are likely to be informal by nature, given that these workers are not likely to be covered by labor protection through IMSS enrollment.[28] 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

[28] 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%).

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.

The transition to self-employment in manufacturing raises a question about time allocation. If self-employment offers flexible, part-time arrangements, displaced women would gain time for childcare, potentially offsetting income losses through improved parental investment (Dehejia and Lleras-Muney, 2004). Conversely, if self-employment involves intensive home-based production, women would face both reduced income and sustained time constraints. I test this using hours worked data from the 2000 and 2010 censuses.

I focus on women aged 15-35 for this analysis. Figure 4 Panel B shows that employment effects are concentrated in this age group, with larger coefficients than for older cohorts. Additionally, ages 15-35 capture Mexico's prime childbearing years (median age at first birth is 21), ensuring the analysis aligns with the population most relevant for infant mortality outcomes.

I estimate equation 3 for 2000-2010 using average hours worked as the dependent variable.[29] Table 4 presents the results. Columns (1) and (2) show null effects across all economic sectors, with point estimates near zero for both employed and self-employed women. This aggregate pattern masks sectoral heterogeneity. Columns (3) and (4) focus on manufacturing, where *maquiladora* employment is concentrated. Column (4) shows that one-unit increase in exposure to U.S. robots per thousand workers increases self-employment hours by 1.846 hours per week—a 6.5% increase from the baseline mean of 28.53 hours. Column (3) shows a statistically insignificant decline of 0.833

[29]I focus on 2000-2010 because hours worked data are only available from decennial censuses. The 2015 Intercensal Survey lacks this information.

hours for employed women, consistent with the employment reductions in Table 3.

In short, I find evidence that U.S. automation did not affect men's employment at conventional significance levels. 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).

Women resort to self-employment occupations in manufacturing as a coping mechanism. This is consistent with Bhalotra (2010) in India, who found that low-income women's labor force participation increases during difficult times, negatively impacting children's health through reduced parental time. To test whether self-employment provides time flexibility or represents time-intensive work, I examine hours worked directly. The results show that automation increases self-employment hours by 1.8 hours per week in manufacturing. Rather than gaining time for childcare, displaced women maintain or increase work hours while experiencing income losses. This creates a double burden: reduced household income (Table 3, Column (9)) and sustained or increased maternal work hours, leaving women with fewer financial resources and limited time for infant care. I next turn to examining the implications of these findings for healthcare access and utilization.

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 5 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. While self-employed workers may have enrolled in *Seguro Popular*, this does not explain away the baseline findings. Table A6 confirms that U.S. automation had no effect on enrollment in *Seguro Popular*, and the results hold after excluding CZs with high coverage under this program (Table A7).

I further validate these findings by analyzing infant mortality rates calculated separately by maternal insurance status. Using the same sample of commuting zones, I compute mortality rates specific to insured and uninsured populations. Table 6 shows in Column (2) that for births to insured mothers, 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 7 demonstrates that, on average, women in areas more exposed to automation attended fewer prenatal visits. While both income and time constraints may contribute to this decline, the increase in self-employment among women (see Figure 5, Panel B) suggests that time costs are likely a key factor. This interpretation is consistent with the fact that prenatal care in Mexico is relatively low-cost even for the uninsured, with uptake remaining above 90% throughout the analysis period. Nevertheless, the combined pressures of reduced income (Table 3, Column 9) and lost health insurance coverage (Table 5) may further discourage prenatal care utilization, particularly visits beyond the minimum recommended threshold.

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 A8 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 8 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.[30] Furthermore, I find that states 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 high-risk pregnancies.

I empirically evaluate the role of U.S. automation on birth and fetal death rates in Table A9 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.

I do find heterogeneous fertility responses: birth rates increased precisely among

[30] 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 (**?**).

mothers with the lowest and highest levels of education (Columns 3 and 6). Since these groups have, respectively, the highest and lowest baseline risks of infant mortality, these compositional shifts likely exert countervailing pressures on the observed mortality rate. Importantly, the null effect on the overall birth rate (Column 2) rules out a scale effect—automation does not systematically increase or decrease total fertility. Moreover, because the two groups experiencing fertility increases sit at opposite ends of the baseline risk distribution (lowest-educated and highest-educated mothers), their opposing effects on aggregate mortality are likely to offset one another. I therefore conclude that selection driven by fertility or fetal deaths is not a credible alternative explanation for my results.

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.

Table A10 examines the effect of automation on migration by analyzing changes in the working-age population. The coefficient on robot exposure is unstable across specifications: it is negative in Column (1) (-0.019) but becomes positive once controls for pre-trends and baseline demographics are added (Columns (2)–(4): approximately $+0.017$). In the preferred specifications that control for these trends, the small positive coefficients (significant only at 10%) provide limited evidence that high-exposure areas experienced modest population inflows rather than the out-migration one might expect. However, these estimates should be interpreted with caution because migration models of this type cannot account for general equilibrium effects, as destination locations are also likely affected by automation (Borusyak et al., 2022a), which may bias the results in either direction. Overall, I find no strong evidence that selective migration substantially affects the main mortality findings.

7 Conclusion

This paper investigates the impact of U.S. automation on infant mortality in a developing country context. Mexico provides a particularly compelling setting due to its proximity to the U.S., its longstanding reliance on maquiladora employment (which predominantly involves low-skilled, female-intensive labor), and its significant rise in female labor force participation over recent decades. Yet this economic integration and growing female employment make Mexico especially vulnerable to disruptions from U.S. automation, which prior research shows 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 4.4%-4.9% 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 shifted their time towards self-employment activities in manufacturing. Furthermore, women who were more exposed to U.S. automation were less likely to access overall healthcare and prenatal care. Notably, women without health insurance were the primarily drivers of these adverse outcomes. Additionally, financially unprotected women were 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.

Lastly, to mitigate the adverse effects of cross-border automation shocks, policy should focus on decoupling health insurance from formal employment to ensure continuity of coverage for women and children following job displacement. Social safety nets, including targeted income support for displaced workers in affected regions, should be strengthened to buffer households against economic precarity. Furthermore, public health interventions, particularly those expanding postnatal and infant care resources in vulnerable communities, could help counteract the mechanisms of reduced healthcare access and increased risky behaviors identified in this paper.

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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				
$\beta : \Delta robots^{US}$	0.995**	1.021***	0.939**	0.898**
	(0.435)	(0.394)	(0.416)	(0.407)
Kleibergen-Paap F-stat	48.71	48.72	59.09	70.90
Panel B. First Stage				
$b : IV\Delta robots^{US}$	0.100***	0.100***	0.102***	0.100***
	(0.014)	(0.014)	(0.013)	(0.012)
Observations	1805	1805	1805	1805
Mean dep var	15.17	15.17	15.17	15.17
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 exposure to robots in the U.S. 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 routine 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
$\beta : \Delta robots^{US}$	0.263**	0.043**	0.360	-0.038	0.277***	-0.032
	(0.107)	(0.017)	(0.262)	(0.085)	(0.061)	(0.053)
Observations	1805	1805	1805	1805	1805	1805
Mean dep var	2.678	0.429	7.621	2.836	0.620	0.989
Region FE/industry shares	✓	✓	✓	✓	✓	✓
Outcome trends	✓	✓	✓	✓	✓	✓
Demographic trends	✓	✓	✓	✓	✓	✓
Contemporary shocks	✓	✓	✓	✓	✓	✓

Note: The dependent variables in Columns 1-6 are grouped diseases based on the International Catalogue of Diseases. Column 5 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 routine 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
$\beta : \Delta robots^{US}$	-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
P-val $\beta^{Men} = \beta^{Women}$					0.225	0.074	0.041	0.008	
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 routine 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 4: Effect of robot penetration on the change of hours worked per week for women (2000- 10)-2SLS.

	All sectors		Manufacturing	
	(1) Employed	(2) Self-employed	(3) Employed	(4) Self-employed
β : $\Delta robots^{US}$	0.022	-0.592	-0.833	1.846**
	(0.250)	(0.473)	(0.703)	(0.933)
Observations	1800	1800	1800	1800
Mean dep var	43.30	34.80	45.87	28.53
Region FE/industry shares	✓	✓	✓	✓
Outcome trends	✓	✓	✓	✓
Demographic trends	✓	✓	✓	✓
Contemporary shocks	✓	✓	✓	✓

Note: The dependent variable is the change in the number of hours worked per week for women of childbearing age (15–35). Columns (1) and (2) report the change in weekly hours worked across all sectors for employed and self-employed women, respectively. Columns (3) and (4) report the change in weekly hours worked in the manufacturing sector for employed and self-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 routine 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 health insurance coverage for women (2000- 15)-2SLS.

	(1) All	(2) Wage employment	(3) Self-employment
$\beta : \Delta robots^{US}$	-0.407**	-0.469***	0.017
	(0.177)	(0.143)	(0.069)
Observations	1804	1804	1804
Region FE/industry shares	✓	✓	✓
Demographic trends	✓	✓	✓
Contemporary shocks	✓	✓	✓

Note: The dependent variable is the change in IMSS health insurance coverage, defined as IMSS-insured women divided by total working-age female population in each CZ. Column (1) includes all employed women; Column (2) includes only wage employees; Column (3) includes only self-employed women. The denominator (total working-age women) is constant across columns; only the numerator varies. 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 routine 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 6: Effect of robot penetration on the change of infant mortality rate by insurance status (2000- 15)-2SLS.

	(1) All	(2) Insured	(3) Uninsured
$\beta : \Delta robots^{US}$	0.898**	0.012	1.025**
	(0.407)	(0.157)	(0.417)
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 routine 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 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
$\beta : \Delta robots^{US}$	-0.531***	0.090	0.002	-0.080	0.487
	(0.187)	(0.129)	(0.008)	(0.305)	(0.886)
Observations	1752	1752	1752	1752	1752
Region FE/industry shares	✓	✓	✓	✓	✓
Demographic trends	✓	✓	✓	✓	✓
Contemporary shocks	✓	✓	✓	✓	✓

Note: The dependent variables are health outcomes at birth for the period 2008-2015. Column (1) is the average number of prenatal visits per birth. Column (2) is the share of children born with low birth weight (less than 2,500 grams). Column (3) is the average Apgar score at birth. Column (4) is the share of preterm births (less than 37 weeks of gestation). Column (5) is the share of births delivered by cesarean section. 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 routine 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.

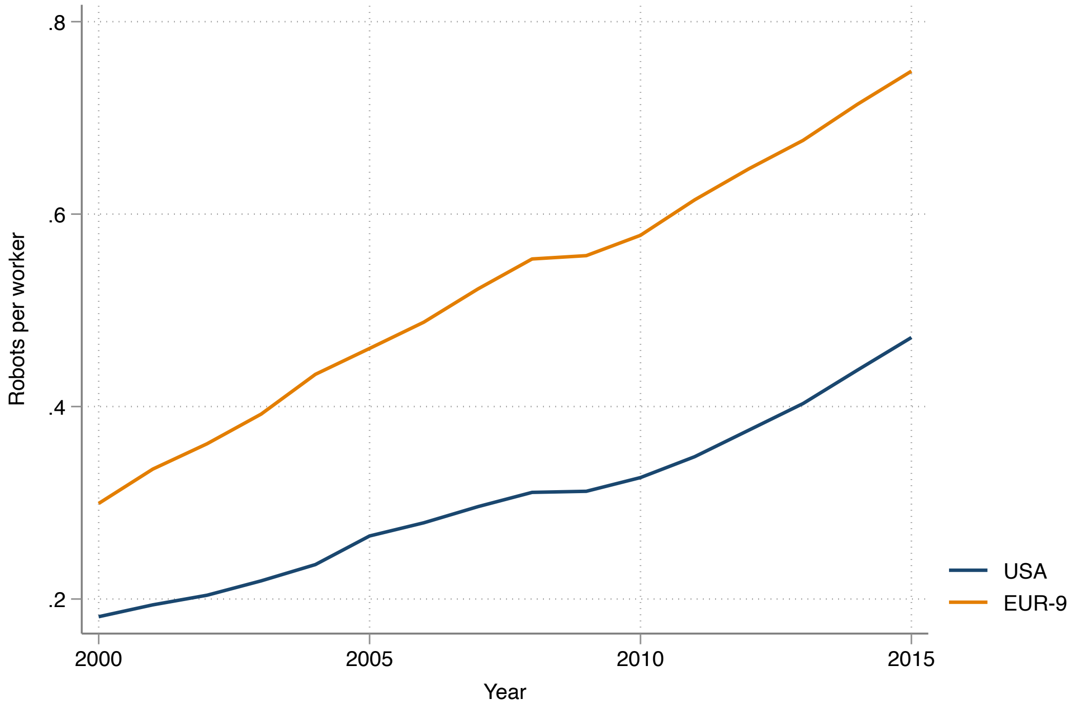
Table 8: Effect of robot penetration on the change of risk factors and women's health (2002- 2012)-2SLS.

	(1) Drinks alcohol	(2) Smokes	(3) Diabetes
Panel A. All			
$\beta : \Delta robots^{US}(2002-2012)$	-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			
$\beta : \Delta robots^{US}(2002-2012)$	-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			
$\beta : \Delta robots^{US}(2002-2012)$	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 variable is the change in the share of women of childbearing age (20-45) who regularly drink alcohol (Column 1), regularly smoke (Column 2), or have been diagnosed with diabetes (Column 3). 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.

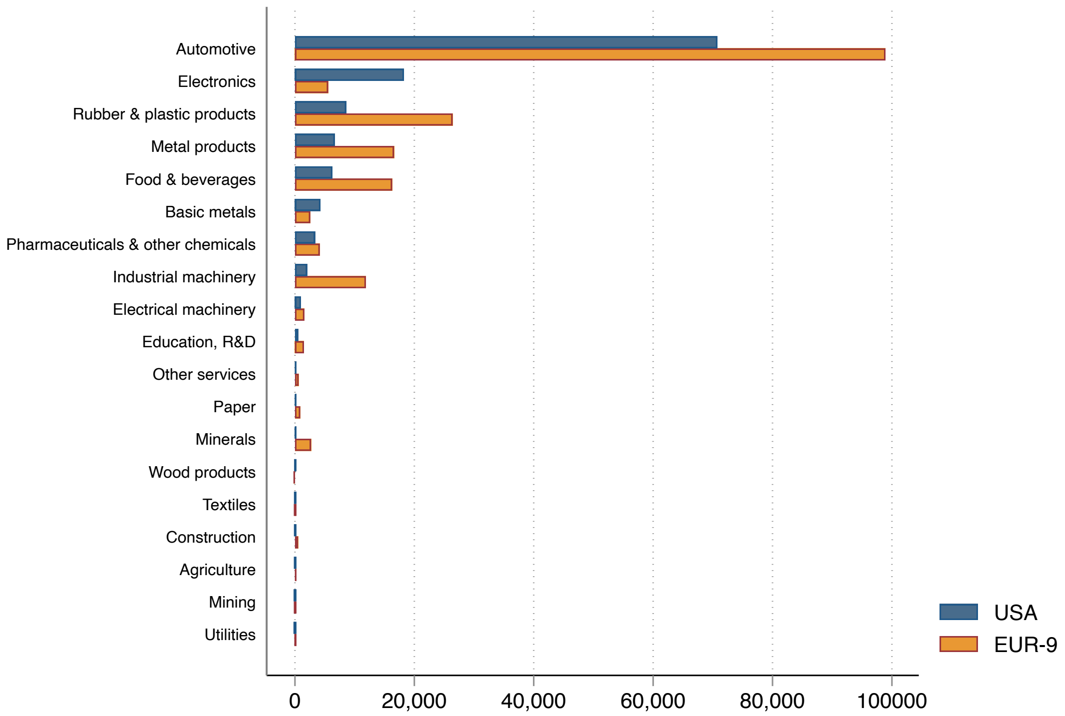
Figures

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, Norway, Sweden, United Kingdom, and Italy.

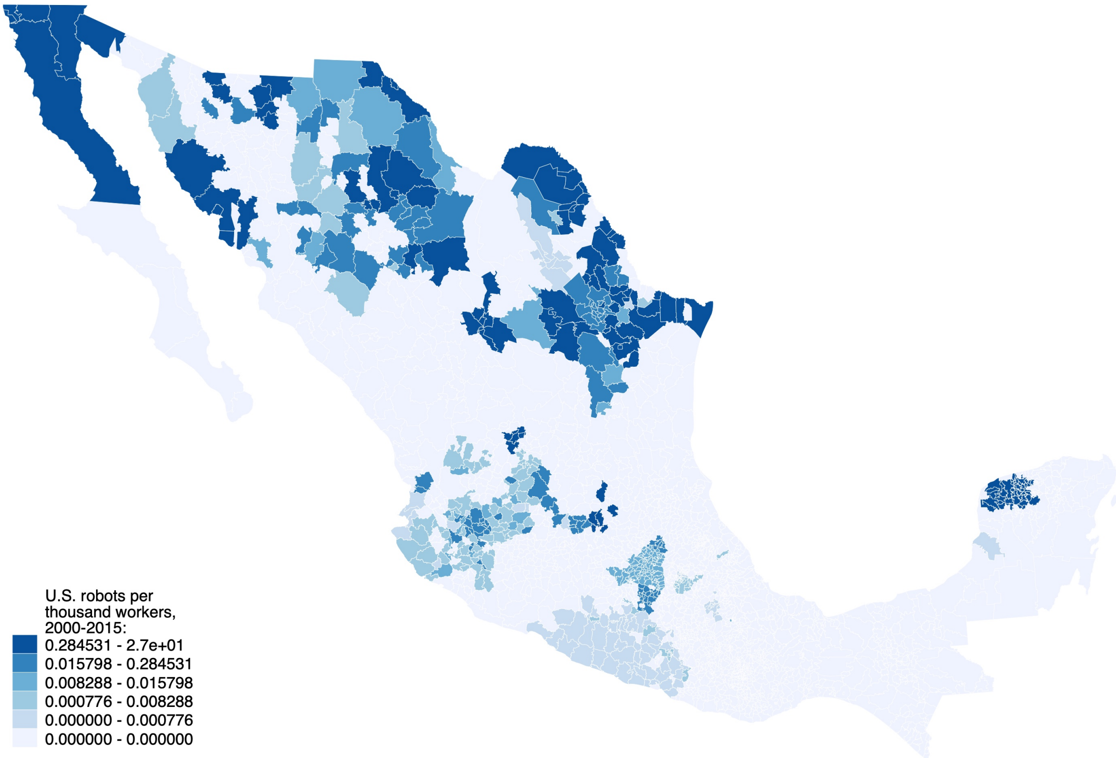
Figure 2: Change in industrial robot stock by industry, 2000-15



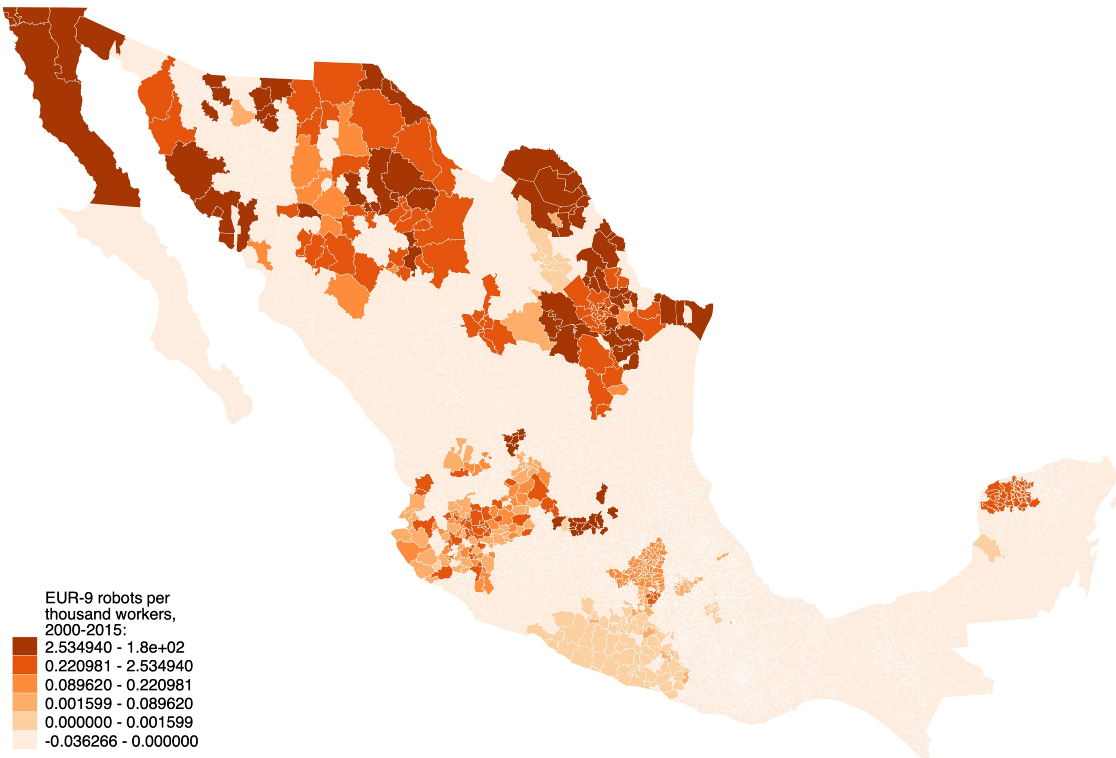
Note: Own calculation using IFR data. EUR-9 stands for European robots which is comprised by nine countries: Denmark, Spain, Finland, France, Germany, Sweden, Great Britain, and Italy.

Figure 3: Predicted spatial distribution of industrial robot exposure

(a) U.S. robot exposure



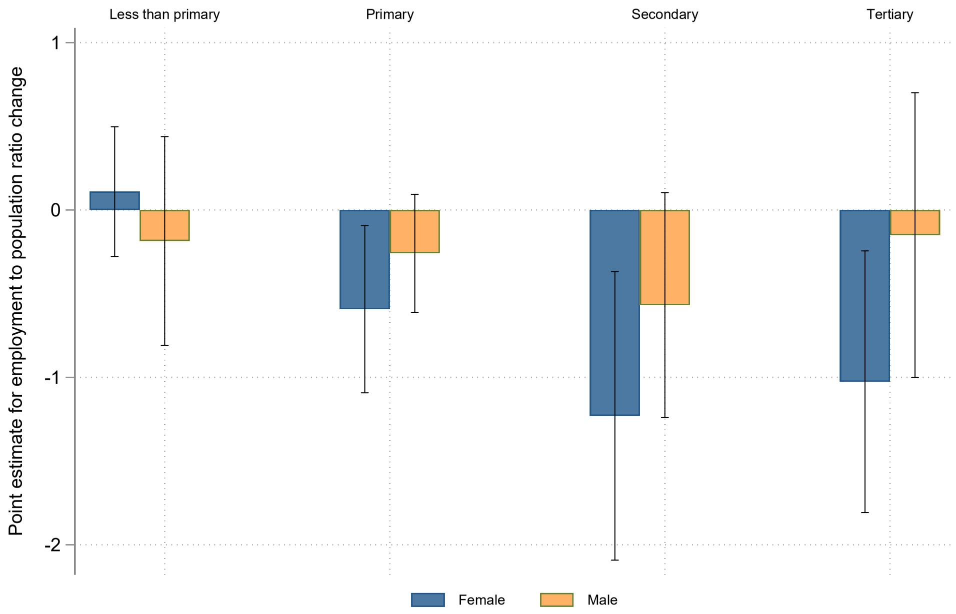
(b) EUR-9 robot exposure



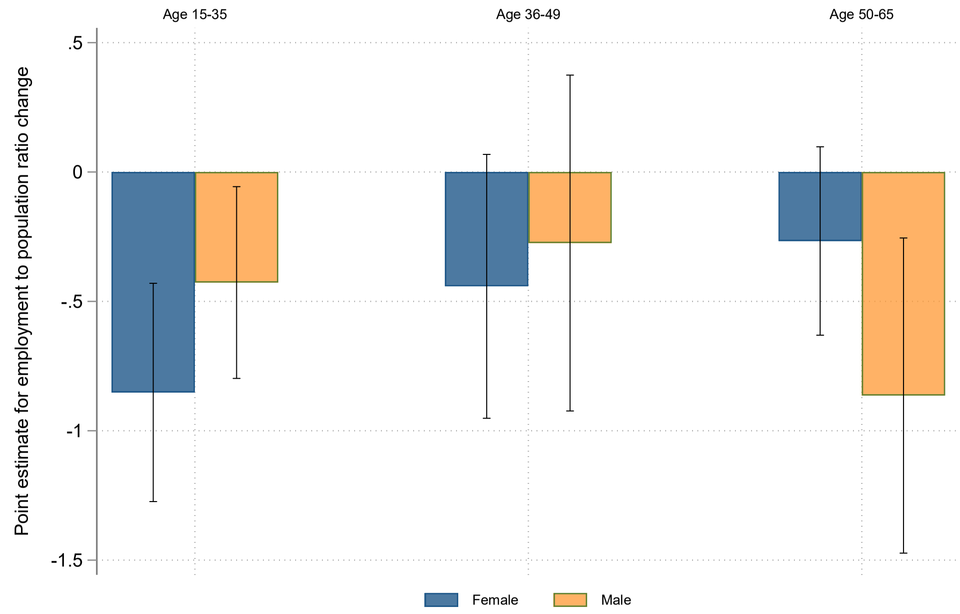
Note: The map depicts the predicted spatial distribution of U.S. and EUR-9 robots.

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

(a) Skill level



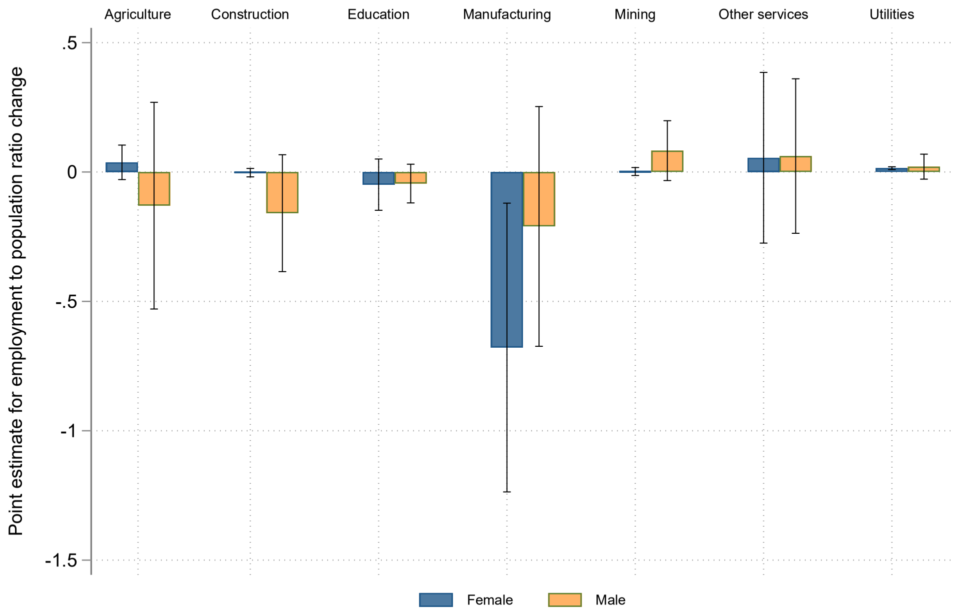
(b) Age



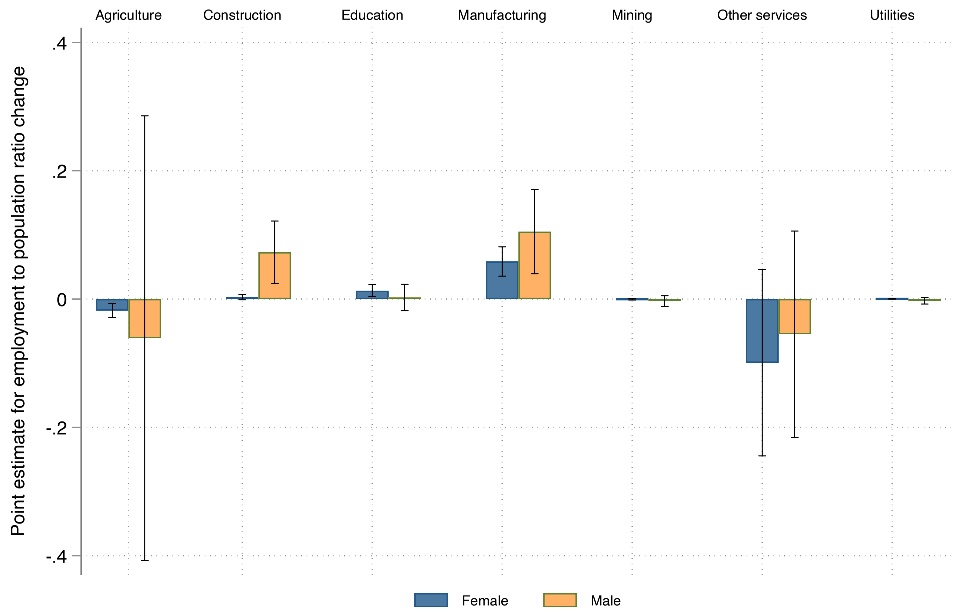
Note: Figure shows the 2SLS results of the estimated effects of U.S. robots on employment by skill level, age and sex. Each specification controls for the sum of shares in *maquiladora* employment, eight broad region dummies, the pretrend in outcomes; baseline demographic outcomes measured in 2000: the 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 routine 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 U.S. robot exposure on employment and self-employment by sex and economic sector. Each specification 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 routine 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.

Online Appendix

A Supplementary Figures and Tables

Table A1: Summary statistics

	Mean	SD	p10	Median	p90
A. Main outcome					
Change infant mortality rate 2000-15	-3.231	10.547	-9.203	-4.138	5.208
B. Treatment/IV					
$\Delta robots^{US}$	0.740	3.049	0.000	0.000	0.549
$IV\Delta robots^{US}$	4.872	20.521	0.000	0.001	3.893
C. Controls					
Sum of maquiladora employment 1990	0.020	0.079	0.000	0.000	0.013
Infant mortality rate 1998-00	-2.044	5.707	-6.309	-2.218	1.950
Ln of population	12.998	2.407	9.932	12.993	16.811
Share of male	0.487	0.012	0.475	0.486	0.504
Share of working-age population	0.601	0.049	0.524	0.617	0.653
Share of pop. with primary completed	0.524	0.069	0.437	0.546	0.584
Share of pop. with secondary completed	0.143	0.063	0.043	0.164	0.208
Share of pop. with tertiary completed	0.070	0.039	0.014	0.075	0.117
China trade exposure	0.086	0.089	0.010	0.059	0.184
Share of routine occupations 1990	0.222	0.096	0.071	0.254	0.312
Exposure to NAFTA	-0.017	0.012	-0.037	-0.013	-0.006

Note: The table shows descriptive statistics of the main outcome variable (Panel A), the change of treatment variable and its instrumental variable for the period 2000-15 (Panel B), and baseline controls (Panel C). Observations are weighted by the count of births at the start of the analysis period in 2000. See Appendix B for a definition of the following variables: China trade exposure, share of routine occupations in 1990, and exposure to NAFTA.

Table A2: Effect of robot penetration on the change of infant mortality rate (2000-15)-OLS .

	(1)	(2)	(3)	(4)
$\beta : \Delta robots^{US}$	0.849**	0.883**	0.813**	0.784*
	(0.396)	(0.384)	(0.388)	(0.400)
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 routine 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: Alternative instruments

	(1)	(2)	(3)	(4)
Panel A. No offshorability term				
$\beta : \Delta robots^{US}$	1.020**	1.091**	1.050**	1.078**
	(0.495)	(0.492)	(0.466)	(0.487)
Observations	1805	1805	1805	1805
Kleibergen-Paap F-stat	16.93	16.92	16.67	19.20
Panel B. Export share interaction				
$\beta : \Delta robots^{US}$	1.039**	1.052***	0.963**	0.921**
	(0.429)	(0.394)	(0.418)	(0.406)
Observations	1805	1805	1805	1805
Kleibergen-Paap F-stat	46.60	46.67	56.33	67.35
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 U.S. as the interaction term. Column (1) controls for the sum of shares in *maquiladora* employment and eight broad Mexican region dummies. Column (2) adds the change in infant mortality rate for the period 1998-2000 (outcome pre-trend). Column (3) adds baseline demographic 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, and the share of workers with completed primary, secondary, and tertiary schooling. Column (4) adds contemporary shocks: the local exposure to imports from China, the share of routine jobs in 1990, and the exposure to NAFTA. Robust standard errors are clustered at the state level and reported in parentheses. Significance: *** p<0.01, ** p<0.05, * p<0.10.

Table A4: Robustness

	(1)	(2)	(3)	(4)
Panel A. Controlling for Domestic robots				
$\Delta robots^{MX}$	-1.258*	-1.189	-0.787	-0.940
	(0.735)	(0.764)	(0.556)	(0.893)
$\beta : \Delta robots^{US}$	1.111***	1.130***	1.035**	0.948**
	(0.419)	(0.386)	(0.439)	(0.435)
Observations	1805	1805	1805	1805
Panel B. Removing recession years				
$\beta : \Delta robots^{US}$	1.737***	1.754***	1.654**	1.542**
	(0.531)	(0.528)	(0.648)	(0.653)
Observations	1805	1805	1805	1805
Panel C. No outliers				
$\beta : \Delta robots^{US}$	1.212***	1.229***	1.146***	1.186***
	(0.426)	(0.381)	(0.343)	(0.359)
Observations	1610	1610	1610	1610
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 removes observations based on Cook's distance using the common threshold $4/n$. Column (1) controls for the sum of shares in *maquiladora* employment and eight broad Mexican region dummies. Column (2) adds the change in infant mortality rate for the period 1998-2000 (outcome pre-trend). Column (3) adds baseline demographic 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, and the share of workers with completed primary, secondary, and tertiary schooling. Column (4) adds contemporary shocks: the local exposure to imports from China, the share of routine 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 infant mortality rate, using Adão et al. (2019) standard errors (2000-2015) -2SLS.

	(1)	(2)	(3)	(4)
$\beta : \Delta robots^{US}$	0.995	1.021	0.939	0.898
	(0.166)***	(0.170)***	(0.141)***	(0.140)***
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 routine 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 *Seguro Popula*r enrollment (2004-09)-2SLS.

	(1)	(2)	(3)	(4)
$\beta : \Delta robots^{US}$	0.665	0.681	0.129	-0.143
	(1.105)	(1.088)	(1.235)	(1.155)
Observations	1805	1805	1805	1805
Region FE/industry shares	✓	✓	✓	✓
Outcome trends		✓	✓	✓
Demographic trends			✓	✓
Contemporary shocks				✓

Note:. The dependant variable is the change in Seguro popular enrollment for the period 2004 to 2009. Columns control 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 routine 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 infant mortality rate, restricted sample (2000- 15)-2SLS.

	(1)	(2)	(3)	(4)
$\beta : \Delta robots^{US}$	1.041**	1.070***	0.849**	0.837**
	(0.438)	(0.399)	(0.376)	(0.389)
Observations	1493	1493	1493	1493
Region FE/industry shares	✓	✓	✓	✓
Outcome trends		✓	✓	✓
Demographic trends			✓	✓
Contemporary shocks				✓

Note:. The dependent variable is the change in infant mortality, excluding CZs with an enrollment rate higher than 15% on the *Seguro Popular* program. Columns control 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 routine 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 A8: Effect of robot penetration on the change of public health provision (2001-2015) -2SLS.

	(1) Pediatricians	(2) Incubators	(3) Newborn cribs	(4) Delivery rooms
$\beta : \Delta robots^{US}$	0.167*	0.029	0.051	-0.031
	(0.088)	(0.054)	(0.149)	(0.037)
Observations	1622	1622	1622	1622
Region FE/industry shares	✓	✓	✓	✓
Demographic trends	✓	✓	✓	✓
Contemporary shocks	✓	✓	✓	✓

Note: The dependent variables are changes in public health infrastructure measures for the period 2001-2015: the number of pediatricians (Column 1), incubators (Column 2), newborn cribs (Column 3), and delivery rooms (Column 4) per CZ. 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 routine 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 A9: 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
$\beta : \Delta robots^{US}$	0.205	0.793	1.260***	0.085	0.928	0.719***	0.716	-0.058
	(0.362)	(0.799)	(0.308)	(0.256)	(1.192)	(0.235)	(0.740)	(0.080)
Observations	1805	1804	1804	1804	1804	1804	1804	1804
Mean dep var	10.51	108.5	23.91	31.02	41.96	7.246	98.52	8.381
Region FE/industry shares	✓	✓	✓	✓	✓	✓	✓	✓
Outcome trends	✓	✓	✓	✓	✓	✓	✓	✓
Demographic trends	✓	✓	✓	✓	✓	✓	✓	✓
Contemporary shocks	✓	✓	✓	✓	✓	✓	✓	✓

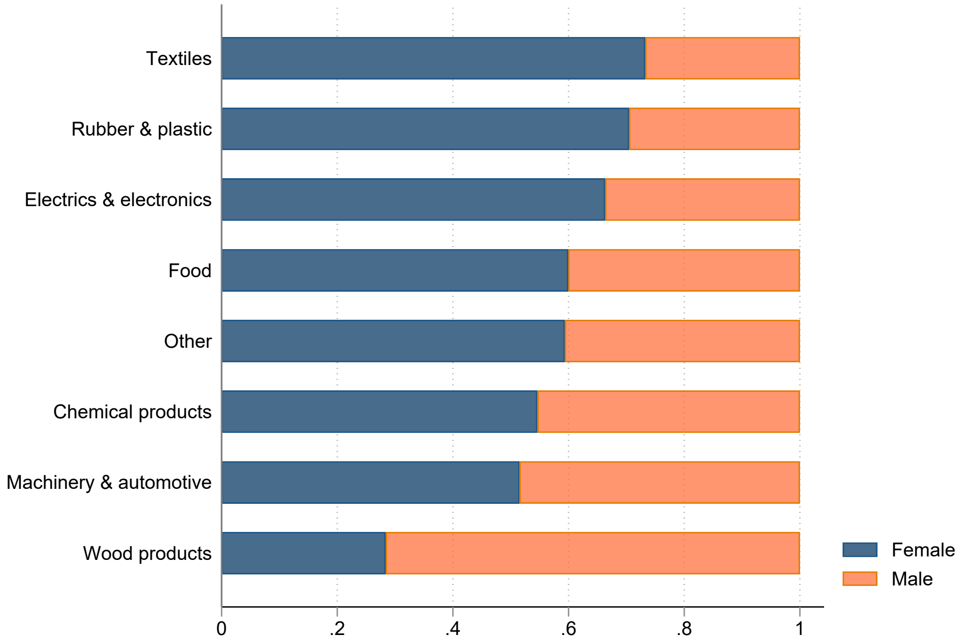
Note:. The dependent variable is the change in fetal deaths (Column (1). Column (2) is the overall birth rate. Columns (3) to (6) are the birth rate by education level. Columns (7) and (8) are the birth rate by age brackets. Each column controls for the sum of shares in *maquiladora* employment, eight 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 routine 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 A10: Effect of robot penetration on the change of the logarithm of working-age population (2000- 15)-2SLS.

	(1)	(2)	(3)	(4)
$\beta : \Delta robots^{US}$	-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				✓

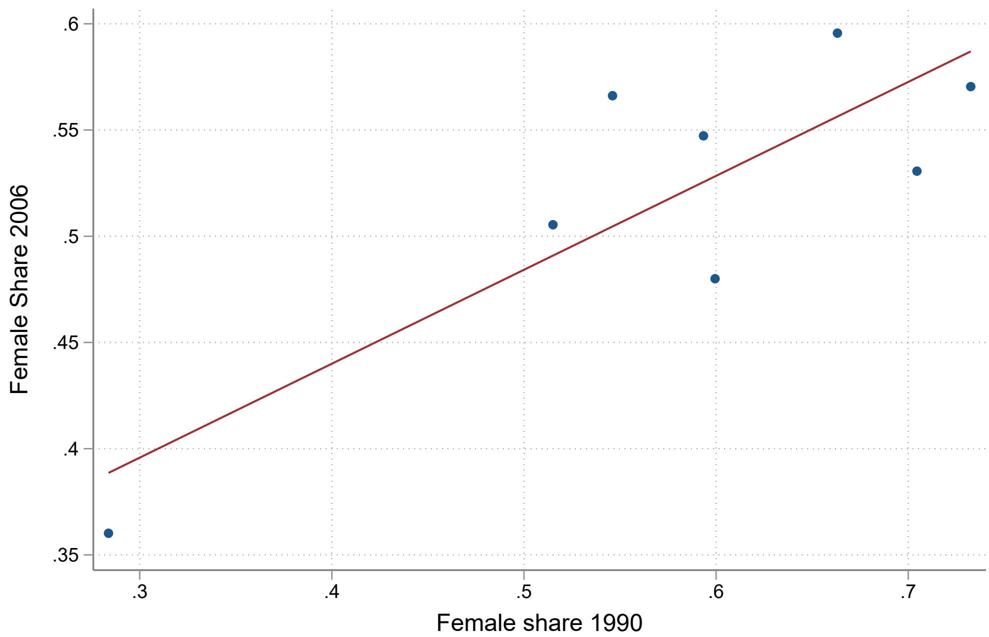
Note: The dependent variable is the change of the logarithm of working-age population. Column (1) controls for the sum of shares and eight broad Mexican regions. Column (2) includes the change in infant mortality rate for the period 1998-2000. Column (3) includes baseline controls measured in 2000: the 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 routine 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.

Figure A1: Mexican employment shares by sector in 1990



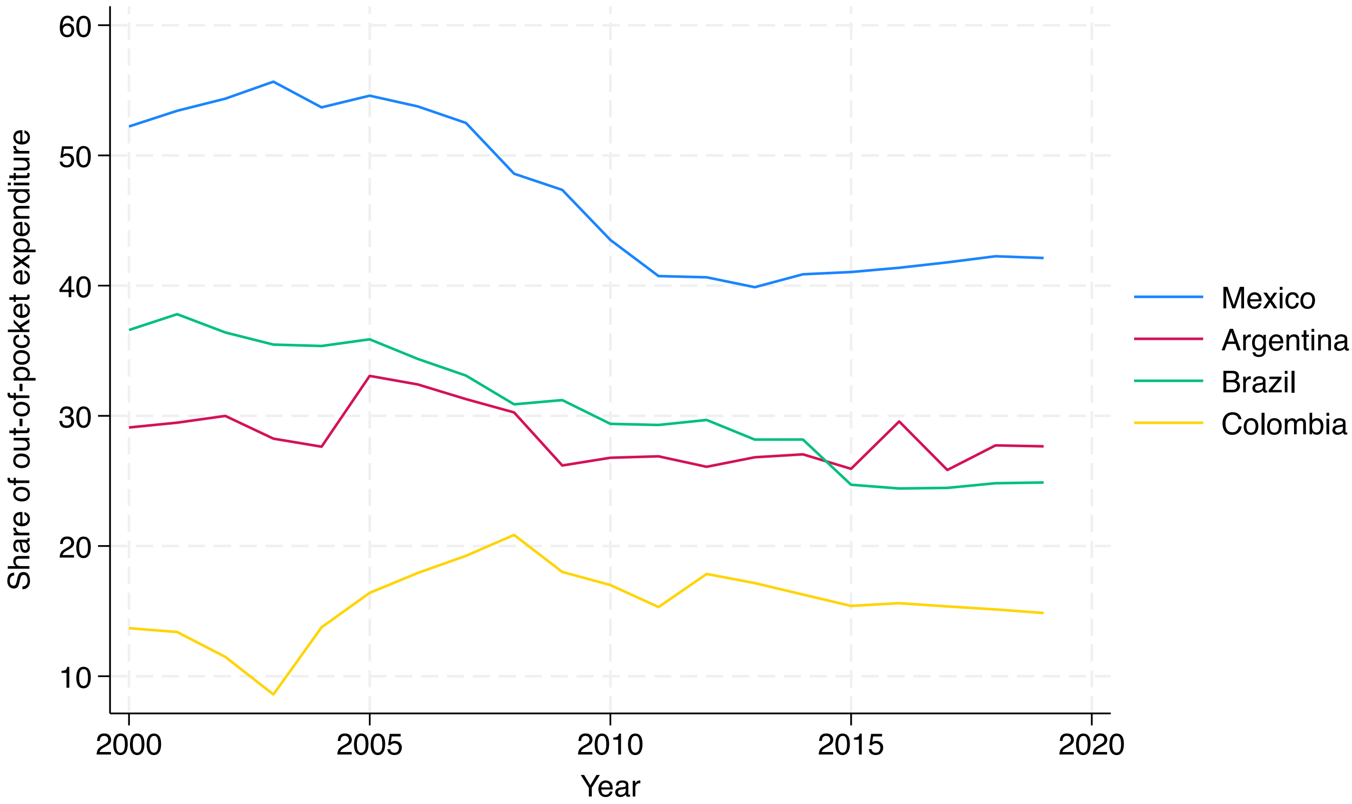
Note: This figure shows the share of employment by gender in eight *maquiladora*, manufacturing industries. Source: *Estadística de la Industria Maquiladora de Exportación*.

Figure A2: Relationship between *maquiladora* employment in 1990 and 2006



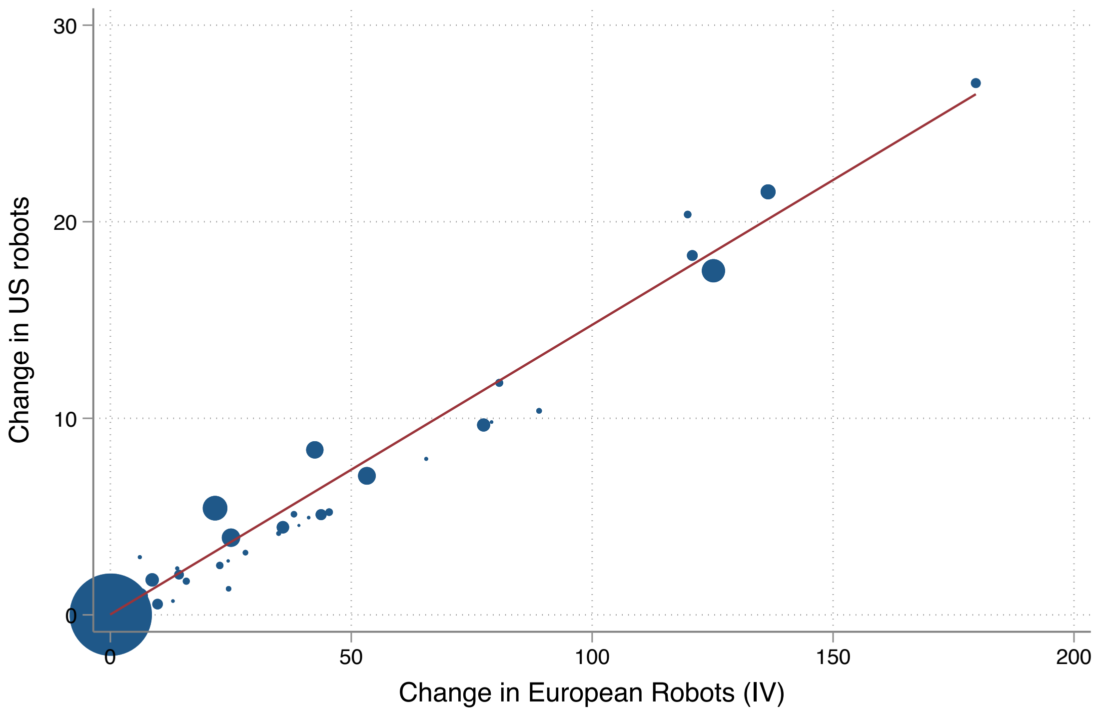
Note: This figure shows the relationship between female share employment in *maquiladoras* by industry in 2006 and 1990. Data source: *Estadística de la Industria Maquiladora de Exportación*.

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. Source: Our World in Data.

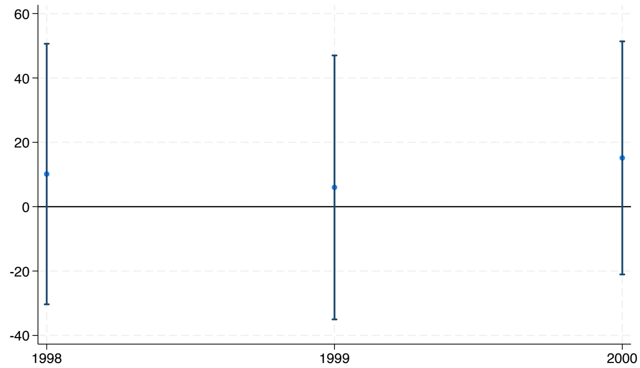
Figure A4: First-stage relationship



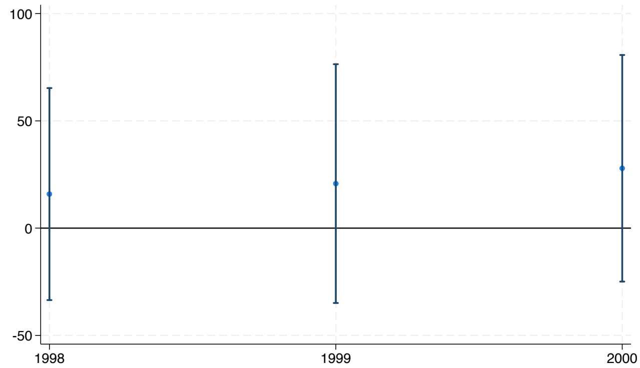
Note This figure shows that relationship between the change of U.S. robots and the change of European Robots for the period 2000-15. The size of the dots are the number of baseline births in 2000.

Figure A5: Pre-trends test

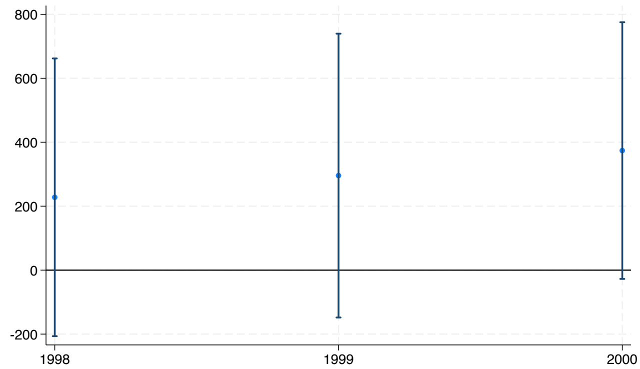
(a) Automotive



(b) Electronics



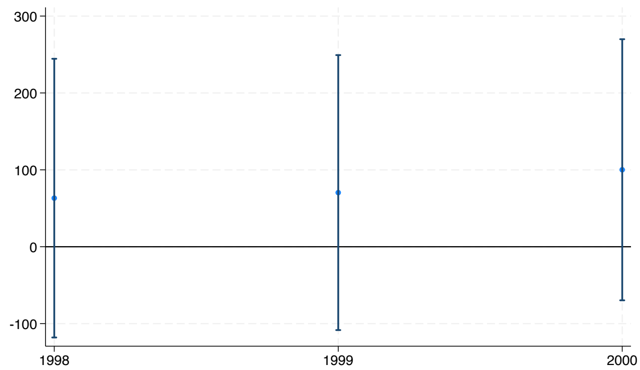
(c) Pharmaceuticals and chemicals



(d) Rubber and plastic

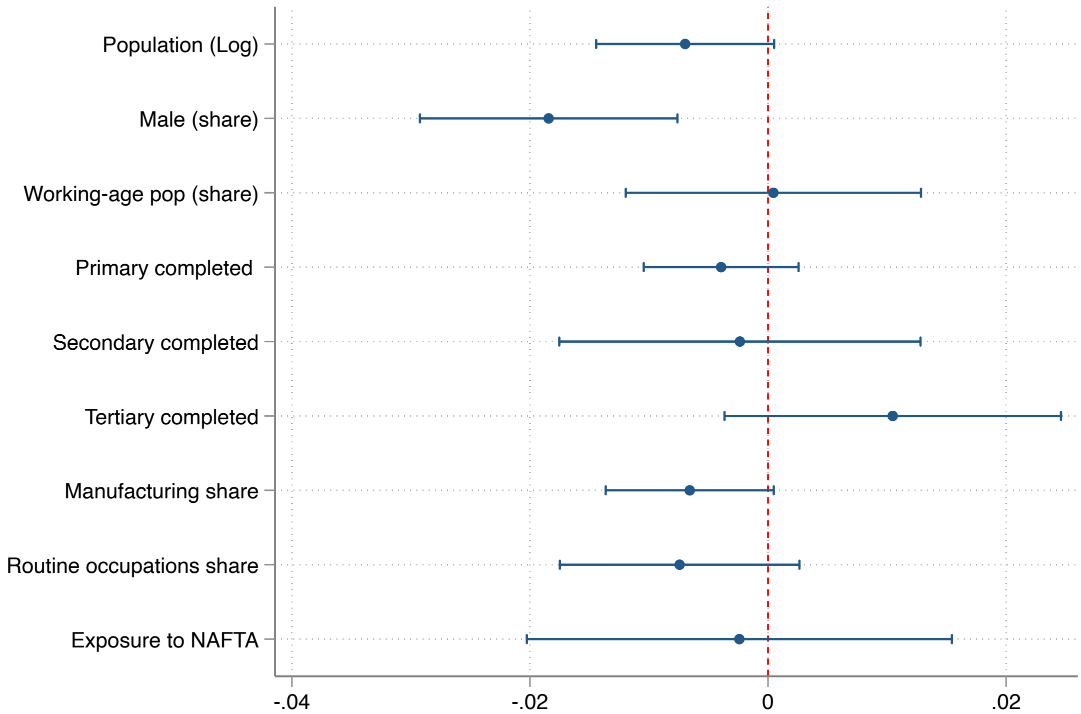
(e) Industrial machinery

(f) Average of all industries



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.

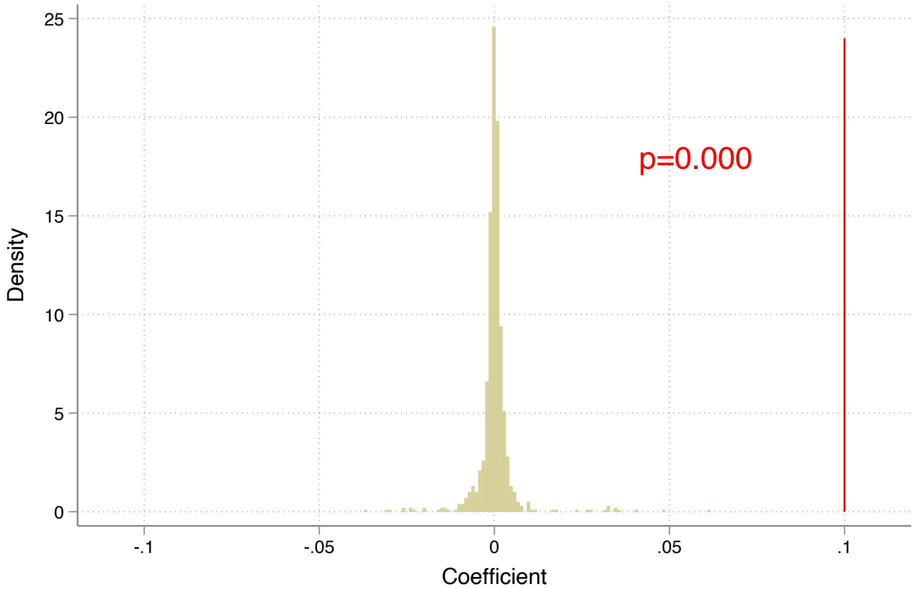
Figure A6: Location-level balance test



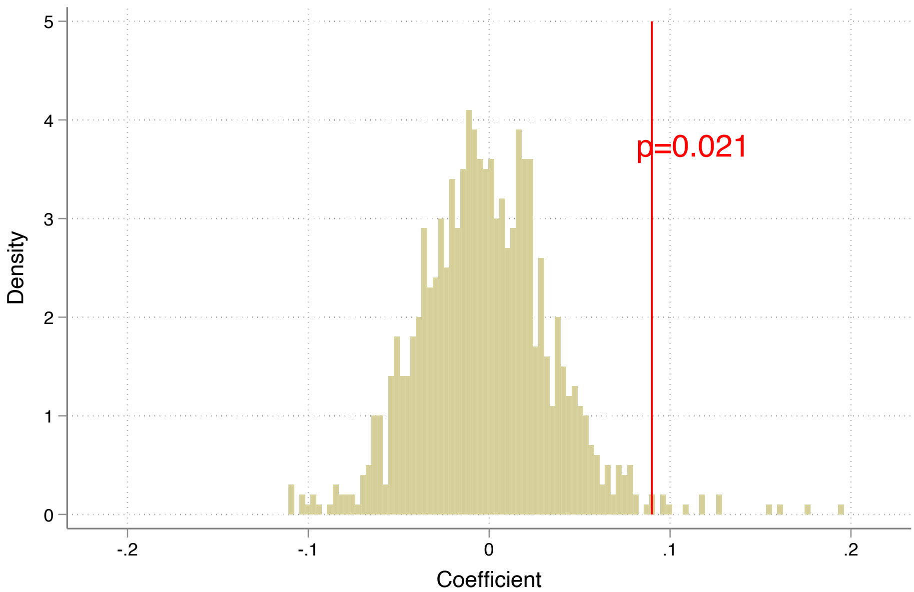
Note: This figure shows the results of separate regressions of each baseline characteristic (measured in 2000) on the instrumental variable (EUR-9 robot exposure), controlling for the sum of shares in *maquiladora* employment. Each regression is weighted by births in 2000.

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) used to construct the results 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 share of observations that are greater than the true value.

B Data Appendix

Robot exposure adjustment: Data on robot adoption in the United States and Mexico are available at the industry level only after 2004 and 2011, respectively. Before 2004, shipments were aggregated into the North American region under the "unspecified" category. Following Graetz and Michaels (2018), I construct comparable data on robot shipments for Mexico and the U.S. To impute industry-level robot shipments for the full analysis period (2000–2015), I distribute the number of robots classified as "unspecified" across industries using the average industry share of total shipments observed in the years with available data (up to 2015). This procedure is applied only to countries lacking information for the relevant years in the analysis; countries used in the construction of the IV instrument are excluded. As a second step, Graetz and Michaels (2018) propose a perpetual inventory method to account for capital use at a constant depreciation rate, which I fix at 5%.

China's import competition exposure: I rely on Autor et al. (2013) to calculate the predicted exposure to Chinese import competition. The idea is that Mexico (as an exporting country) competes not only directly with China but also indirectly with Chinese imports entering the U.S. market. Formally, for each commuting zone (CZ) c, l_{c,i,t_0} is the employment share of industry i in 1990, using the 6-digit Harmonized System (HS) industrial classification. $\frac{\Delta^{CNUS}_{i,t_0,t_1}}{L_{i,t_0}}$ and $\frac{\Delta^{CNMX}_{i,t_0,t_1}}{L_{i,t_0}}$ represent change in real import flows per worker in industry i from China to the U.S. and from China to Mexico, respectively from 1990 to 2000.

$$\text{Imports}\,^{\text{China}}_{c,(t_0,t_1)} = \sum_{i \in I}^{I} l_{c,i,t_0} \left[\frac{\Delta M^{CNUS}_{i,(t0,t1)} + \Delta M^{CNMX}_{i,(t0,t1)}}{L_{i,t_0}} \right]$$

NAFTA exposure: Based on NAFTA-induced tariff changes between 1990 and 2000 from Hakobyan and McLaren (2016), and the employment shares of industry i in commuting zone (CZ) c, I compute the predicted local exposure to NAFTA. This measure is relevant because tariff reductions under NAFTA affected industries, and potentially local labor markets in the long run, depending on their initial industry composition.

$$NAFTA_{c,1990} = \sum_{i \in I}^{I} l_{i,1990} \left[\tau_i^{2000} - \tau_i^{1990}\right]$$

C Alternative Specifications

As an alternative specification, I estimate a two-stage least squares (2SLS) system in stacked five-year first differences (2000–2005, 2005–2010, 2010–2015). Stacking increases the number of effective observations and allows me to exploit variation across multiple shorter periods. The first stage relates the change in U.S. robot adoption in commuting zone c over period t, $\Delta robots_{c,t}^{US}$, to its instrument, $IV\Delta robots_{c,t}^{US}$, while including region-by-year fixed effects ($\theta_{r,t}$), baseline commuting-zone characteristics in 2000 interacted with time dummies ($X'_{c,2000}$), and lagged changes in the outcome between 1998 and 2000 ($\Delta Y_{2000-98}$):

$$\Delta robots_{c,t}^{US} = b_0 + b_1 IV\Delta robots_{c,t}^{US} + \theta_{r,t} + X'_{c,2000}\gamma_t + \Delta Y_{2000-98}\rho + \varepsilon_{c,t}.$$

The inclusion of region-by-year fixed effects absorbs any common shocks within broad regions in a given period, ensuring that identification comes from differential robot adoption across commuting zones within the same region and year.

In the second stage, I regress the change in infant mortality, $\Delta Y_{c,t}$, on the fitted values of robot adoption, $\widehat{\Delta robots}_{c,t}^{US}$, while including the same set of controls:

$$\Delta Y_{c,t} = \alpha + \theta_{r,t} + \beta\widehat{\Delta \text{robots}}_{c,t}^{US} + X'_{c,2000}\varphi_t + \Delta Y'_{c,2000-98}\omega + \varepsilon_{c,t}$$

This alternative design leverages repeated shorter-term changes and flexibly controls for slow-moving confounders and region-specific shocks.

Table C1: Effect of robot penetration on the change of infant mortality rate (stacked regressions-2SLS).

	(1)	(2)	(3)	(4)
$\beta : \Delta robots^{US}$	1.181***	1.202***	0.746***	0.996**
	(0.445)	(0.418)	(0.260)	(0.396)
Observations	5418	5418	5415	5415
Region × time	✓	✓	✓	✓
Outcome trends		✓	✓	✓
Demographic trends × time			✓	✓
Contemporary shocks × time				✓

Note: The dependent variable is the change in the infant mortality rate. Column (1) controls for the sum of shares in *maquiladora* employment and eight broad Mexican region dummies interacted with time fixed effects in three stacked periods: 2000–2005, 2005–2010, and 2010–2015. Column (2) additionally includes the change in the infant mortality rate for the period 1998–2000. Column (3) adds baseline controls measured in 2000, each interacted with time dummies: the share of male workers, the logarithm of population, the share of the working-age population (18–65 years old), the share of workers older than 65, and the shares of workers with completed primary, secondary, and tertiary schooling. Column (4) includes contemporary shocks interacted with time dummies: local exposure to imports from China, the share of routine jobs in 1990, and 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 levels: *** p<0.01, ** p<0.05, * p<0.10.