Do Robots Necessarily Displace Workers? Evidence from Mexican Local Labor Markets

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Abstract

This study uses the rapid rise of automation in Mexico to examine the labor market effects of industrial robot adoption in industrializing countries. I combine unique data on robot imports with administrative, survey, and economic census data. I exploit spatial and time variation in robot imports across commuting zones to estimate the impacts of automation on labor market outcomes. I find that industrial robot adoption does not negatively affect formal employment and average wages in Mexico; these results contrast with findings for developed countries. I can rule out adverse effects of a size as large as -0.7% for formal employment and -0.01% for formal wages in the short run, and I find positive effects of 6% and 3%, respectively, in the long run. I also provide evidence that these results are not due to compositional effects. Additionally, I show that after a CZ starts importing robots, its aggregated gross value added per worker increases, consistent with the productivity effect dominating or compensating for any adverse displacement effect. Despite a substantial pool of unskilled labor, automation in industrializing economies such as Mexico can yield nonnegative employment effects because of the significant productivity enhancements associated with a higher price elasticity of demand and the early stages of automation.

Keywords: Technology, Robot Adoption, Local Labor Markets, Mexico.
JEL Classification: J23, J24, J31, J46, O14, O17, R10.

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1 Introduction

Machines—from assembly lines and electric motors to computers and modern robots—have fundamentally reshaped workplaces. In 2022, a staggering 3.5 million industrial robots were operational, with a remarkable annual growth rate in this number of 31% (IFR, 2022). As robotics, artificial intelligence, and computing power advance, there is a growing fear of significant job losses (Acemoglu & Restrepo, 2020; Arntz, Gregory, & Zierahn, 2019; Frey & Osborne, 2017). These concerns prompt essential questions about the societal implications of automation. However, amid the uncertainty, this technological shift also offers the potential to boost productivity. Previous research has predominantly examined industrialized countries, demonstrating that automation reduces employment and wages, particularly among low-skilled workers engaged in routine tasks (Acemoglu & Restrepo, 2020, 2022a; Chiacchio, Petropoulos, & Pichler, 2018; Dauth, Findeisen, Suedekum, & Woessner, 2021).

Theoretically, the expected sign of the net effect of automation on outcomes is ambiguous (Acemoglu & Restrepo, 2019, 2020). On the one hand, automation replaces workers (the displacement effect), leading to declines in employment and wages in the short run. On the other hand, automation reduces production costs and allows firms to lower prices and increase sales (the productivity effect), leading to increases in employment and wages. Productivity effects in industrializing countries may be larger because automation occurs in sectors exposed to a more competitive product market such that demand is more sensitive to price changes.[1] In addition, these economies are at an early stage of automation where there is more room for large marginal gains. However, empirical evidence on the effects of automation in these economies is still lacking because it is a relatively recent process and data on robot adoption are scarce.

This paper overcomes these challenges by providing empirical evidence on the labor market effects of automation in Mexico. Mexico serves as an ideal case study for several reasons. First, the country has witnessed a remarkable surge in industrial robot adoption over the past decade, with an average annual growth rate of 40% since 2011. This transformation is especially significant within the manufacturing sector, which accounts for a large share of employment.[2] Second, Mexico provides administrative data on industrial

[1] The productivity effect will be larger, especially when product demand is relatively more elastic. In developing countries, robot adoption is more prevalent in export manufacturing, which is exposed to foreign competition, and therefore demand is arguably more elastic. Firms in this sector are more likely to invest in automation because of the relatively large fixed cost and the associated product quality upgrade, particularly when interdependence of components is a critical factor (Artuc, Bastos, Copestake, & Rijkers, 2022). Moreover, domestic consumers have relatively low incomes and are more likely to be price sensitive.

[2] Mexico is also among the most populous Latin American countries, second only to Brazil, with a pop-

robot imports, including the location and timing of robot adoption at fine geographic levels. These data measure robot adoption much more precisely in a given area than the samples in previous works, which typically rely on time series data by industry at the national level. I complement these with publicly available administrative data from the Mexican Social Security Institute (IMSS, for its Spanish acronym) to examine labor market outcomes in the formal sector, supplemented by insights from the National Occupation and Employment Survey (ENOE) on the informal sector and from Mexican economic censuses on changes in productivity and balance sheet information across all Mexican firms. These high-quality data allow a comprehensive examination of the effects of robot adoption at the local labor market level.

Identifying the causal effects of automation is challenging because of a combination of data limitations and endogeneity issues. Endogeneity concerns such as omitted variable and simultaneity biases complicate the analysis. Consider, for example, a scenario where an industry faces a negative labor supply shock and turns to automation in part to mitigate rising labor costs. Neglecting this dynamic would overestimate the negative effects of automation on employment. Conversely, if industries facing positive product-market shocks or relaxation of their financial constraints adopt robots to help them increase production, neglecting this dynamic would lead to overestimation of the positive impact of automation on employment.

To address the endogeneity issue, I employ multiple complementary strategies. My primary approach is to take advantage of timing-based event study methodologies. I identify an event as the first year in which a commuting zone (CZ) receives industrial robot imports, and then, I group CZs into cohorts based on these event years. To mitigate selection effects, I limit the sample to only CZs that import robots at some point. Therefore, the comparison group includes only CZs that import robots but do so later than the CZ under consideration. This method assumes that the timing of events is random and is not influenced by anticipation (pretreatment periods are not affected by future events) and that the outcomes for CZs importing robots and the comparison group follow parallel trends. I explore any systematic link between importation timing and observable factors to validate this assumption. Furthermore, I include granular industry-level trends to mitigate potential biases and account for industry-specific shocks, such as increasing competition. Assuming that the comparison groups and the specific fixed effects and trends account for unobservable shocks, I exploit the remaining exogenous variation arising from a combination of changes in robot supply (cost reduction and improved capa-

ulation of approximately 126 million people, 60 million of whom are of working age, among whom 62% participate in the labor force.

bilities) and exogenous variation in exposure across Mexican regions due to supply-side factors, like supply chain disruptions, random events at ports or shipping facilities, or differences in trade networks. For instance, when the cost of robots produced in Korea falls, producers with existing connections to Korean robot producers are likely to benefit first.

I find that the rapid adoption of robots in Mexico in the last decade did not lead to significant negative effects on formal employment or average real formal wages. The effect of robot adoption on employment is zero in the first year of adoption. Then, it stays stable for the first four years, with an average effect of 1.6% that is not statistically significant at the 5% level. I can rule out negative effects larger than -0.7% on formal employment and larger than -0.01% on formal wages for the average of these four years. I also provide evidence that these results do not hide compositional effects of the CZs' cohorts around the event time. This zero effect could hide potential heterogeneity across groups. However, there are, at most, minor negative effects, even among groups expected to be more exposed to the negative effects of robot adoption, based on findings from industrialized countries. These groups include workers in the manufacturing sector, workers in smaller CZs, medium-wage and prime-age workers, and workers in occupations related to industrial robots.

When I estimate the effects over an average of 5 to 8 years after the event, they consistently remain nonnegative, increase in magnitude, and achieve statistical significance. However, it is important to acknowledge that changes in composition might influence these long-term effects. This is because cohorts experience the event in different years and are observed over varying time frames after the event. Consequently, I interpret these results cautiously, concluding that automation may not lead to significant job displacement effects. This highlights that robot adoption does not necessarily harm workers and could hold transformative potential for labor market dynamics.

The main concern with my estimation method is that the adoption of robots is endogenous, and in particular could be related to positive demand shocks. To address this, I use alternative methods, such as event study approaches, triple differences (DDD), and synthetic difference-in-differences (SDD). The DDD method compares manufacturing industries that are high robot adopters with non-manufacturing non-robot adopters industries within each CZ. This allows me to net out specific shocks at the CZ level, such as positive growth trends for all the sectors in regions adopting robots first. This fact is important since, a priori, we might expect that growing CZs would adopt robots first. The SDD enables me to address potential violations of the identifying assumption of parallel trends. The method selects a different set of controls for each treated unit, composed of a weighted average of CZ that matches that unit's pre-trend. Therefore, the control group is essentially individualized, and I can investigate treatment effect heterogeneity across cohorts, relevant to analyze long-term effects avoiding compositional changes. I consistently observe the same qualitative patterns as the baseline estimates across different methods and outcome measures. In addition, I conduct a sensitivity analysis that considers varying degrees of potential violations of parallel trends in post-event periods. The results confirm the robustness of the main findings: a substantial deviation from parallel trends would be required to yield negative employment and wage estimates.

The results are also robust when employing different measures of robot adoption. One might suspect that the nonnegative effect is due to the need for a certain number of industrial robots in the CZ. Therefore, I define the event based on the cumulative value of robot imports surpassing a predefined threshold. Alternatively, I use a measure of intensity based on the cumulative number of years that a CZ receives imports. The analysis is also robust if I use alternative measures for my primary outcomes, formal employment, and average wages.

To explore potential mechanisms underlying industrial robot adoption, I employ Mexican economic censuses covering the universe of Mexican firms and balance sheet information. Within this analysis, I consistently observe that robot adoption enhances gross value added (GVA) per worker across all industries, consistent with productivity increases. The effect on the labor share is negative but imprecisely estimated. When I restrict the sample to the manufacturing sectors more likely to adopt automation, I find an increase in GVA per worker, input cost, payroll, and fixed assets, indicating increased productivity, wages, and investment. Despite these gains, the automation effects on the labor share remain negative but not statistically significant. In nonmanufacturing sectors, adopting robots generally results in statistically nonsignificant effects; however, when statistically significant, these effects tend to be small and lack a systematic pattern. These findings suggest that productivity effects dominate or compensate for potential adverse displacement effects in the case of Mexico in the short to medium run.

This study contributes to the literature on automation's impact on local labor markets, not only in developed countries (Acemoglu & Restrepo, 2020; Chen & Frey, 2021; Chiacchio et al., 2018; Dauth et al., 2021; Graetz & Michaels, 2018) but also in industrializing economies (Brambilla, César, Falcone, & Gasparini, 2023; Calì & Presidente, 2021a; Rodrigo, 2021), for which the evidence is still very limited and not conclusive.[3] Most

[3] Brambilla et al. (2023) examines the impact of domestic robots on labor markets in Argentina, Brazil,

of these papers rely on industry-level proxies of robot adoption, which assume uniformity in robot adoption within a particular industry across different districts, as implied by Bartik measures, generating potential attenuation bias. In addition, this data do not allow for exploiting variation within industry in the adoption of robots –variation that I can exploit in my setting and which allows me to control for industry–year, CZ–industry, and CZ–year specific shocks in some specifications. Because of this more granular level of variation I can control for additional shocks and therefore obtain potentially different estimates. I complement this literature by leveraging administrative data with precise information on the timing and location of domestic automation adoption, which allows me not to rely on shift-share measures and to use alternative empirical strategies.

There are several studies analyzing the impact of US automation on developing countries through trade linkages and reshoring (Artuc et al., 2022; Kugler, Kugler, Ripani, & Rodrigo, 2021; Stemmler, 2020). Two evaluate automation in Mexico (Artuc, Christiaensen, & Winkler, 2019; Faber, 2020) during 1990–2015 and include exposure to domestic automation in their analysis, using similar industry-level data, Bartik instruments, and periods. However, they arrive at different conclusions about the wage–employment effects of the increase in domestic robots, ranging from null to negative effects. My paper complements these studies by using district-level data on robot adoption, introducing a novel empirical strategy, and focusing on a more recent period marked by accelerated domestic robot adoption in Mexico. It also offers a context where domestic production of robots is minimal and firms primarily depend on imports, a scenario different from the ones in previous studies centered on countries with active domestic robot production (Acemoglu et al., 2022; Acemoglu, Lelarge, & Restrepo, 2021; Dixon, Hong, & Wu, 2019; Humlum, 2020; Koch, Manuylov, & Smolka, 2021). These contributions enrich our understanding of how automation is shaping the future of work and economic development in Mexico and beyond, offering valuable insights for policymakers.

The paper is structured as follows. Section 2 describes the data sources, including industrial robot adoption and labor market outcomes, while offering descriptive evidence that sheds light on the association between these two factors. Section 3 gives an overview of the institutional background of the labor market and the rise of automation in Mexico. Section 4 describes the empirical strategy for identifying the impact of industrial robot adoption. Section 5 presents the main results on labor market outcomes, and Section 6

and Mexico, finding increases in unemployment and informality but no statistically significant negative effect on the employment rate and wages. Rodrigo (2021) identifies positive effects on firms' productivity but no aggregate employment impact in Brazil. For Indonesia, Ing and Zhang (2022) and Calì and Presidente (2021b) observe significant productivity and employment gains from automation in manufacturing.

shows results on local mechanisms that may explain the effects of industrial robots. Section 7 presents a conceptual framework and discusses why the effects of automation could differ in developing countries such as Mexico from those found for developed countries. Section 8 concludes.

2 Data

To study the effect of robot adoption on Mexican labor markets, I compile data from multiple sources: (i) detailed administrative records on the universe of industrial robot imports in Mexico provided by the Ministry of Economy; (ii) data on formal employment, publicly accessible and released by the Mexican Social Security Institute (*Instituto Mexicano del Seguro Social*, IMSS); (iii) the Mexican employment survey (ENOE); (iv) information from the 1990 and 2000 population censuses; and (v) information from economic censuses spanning from 2003 to 2018.

I conduct the analysis at the local labor market level.[4] There are many ways of defining labor markets; generally, they are defined based on local administrative (state or municipality) boundaries, but these only sometimes coincide with economically relevant boundaries. Therefore, I use commuting zones (CZs) as the unit of observation, grouping 2438 municipalities (similar to US counties) into 1806 labor markets following Faber (2020). His algorithm follows a similar procedure designed by Atkin (2016), which clusters municipalities into CZs based on the intensity of commuting between them.[5]

[4]Identifying the relevant units of analysis is crucial for analyzing the effects of robot adoption on different outcomes. Firms that adopt robots can extend their impact to other related firms, within their industry or even within their labor market by sharing the same labor and product suppliers, consumers, and competitors (Acemoglu, Koster, & Ozgen, 2023; Acemoglu & Restrepo, 2022b; Aghion, Antonin, Bunel, & Jaravel, 2022). Making comparisons solely between robot-adopting and nonadopting firms within a single labor market could yield biased estimates of the impact of automation. To prevent this issue, one should conduct the analysis at the labor market level, capturing the direct effect of robot adopters and the indirect impact on other economic agents within the same labor market. Furthermore, supporting evidence indicates that workers do not exhibit perfect mobility across geographic regions in the US (Autor & Dorn, 2013); the case of Mexico is likely to be similar in this regard.

[5]The algorithm operates as follows: (i) clustering all municipalities within a metropolitan area into one larger municipality; (ii) computing the intensity of commuting from each municipality to any other municipality by dividing the number of people who commute by the number of residents in the origin municipality; and (iii) clustering municipalities into CZs if more than 10% of residents of either municipality commute into the other. See Faber (2020) for more details.

2.1 Robot adoption data

To measure robot adoption at the labor market level, I use information on the universe of industrial robot imports from customs data collected by the Mexican Ministry of Economy. I follow other papers that use a similar measure for developed countries (Acemoglu et al., 2023; Bessen, Goos, Salomons, & van den Berge, 2020) and define robots using the code 847950 from the international trade codes of commodities (Harmonized System, 2012), which is defined as "industrial robots, not elsewhere specified or included."[6] According to the International Standards Organizations, an "industrial robot is an actuated mechanism programmable in two or more axes, with a degree of autonomy, moving within its environment, to perform intended tasks."

The data provide information about the month and municipality in which the robots were internationally purchased, the country of origin, and the import value. In this paper, I use the publicly available version of these data, which are aggregated to the municipality–month level. The aggregated import value is available if at least three firms imported in the given period. As explained previously, I map municipalities to CZs based on the intensity of commuting flows between them. This transition from municipality–month to CZ–year aggregation allows a more comprehensive examination of the effects of automation on local labor markets. The dataset covers the period from 2006 to the present.

My data on robot imports at the municipality level allow me to measure the exposure to robot adoption more accurately than has been done in previous literature. The standard approach in the literature is to use a Bartik-type measure, which relies on national industry variation in robot shipments (based on data from the International Federation of Robots (IFR)) and the industry composition of each commuting zone (Acemoglu & Restrepo, 2020; Dauth, S Findeisen, Suedekum, & Woessner, 2018; Graetz & Michaels, 2018). This approach assumes that the same number of robots per worker are installed in each industry across all commuting zones, which may not be realistic and could generate biased estimates. In addition, in the case of Mexico, the IFR data start in 2011 and are aggregated along with the US and Canada for previous periods. My data can overcome

[6] The Harmonized System (HS) is an internationally recognized product classification system that designates unique six-digit codes for various categories and commodities. HS code 847950 specifically pertains to industrial robots not categorized under any other code. These robots are capable of autonomously performing a range of tasks, such as welding, painting, assembling, or handling material, without the need for human intervention. Industrial robots falling under this HS code encompass a variety of machines, including robotic arms employed for manipulating objects or tools in manufacturing settings and robotic vehicles designed for transporting materials or goods within warehouses or production facilities. For more information, see WCO (2013), and visit the website https://www.wcotradetools.org.

these limitations, as they capture the actual location and year of robot imports over an extended period.

My measure of robot adoption indicates whether the CZ is receiving industrial robot imports in a given year. From the data, I observe 104 different CZs receiving at least one industrial robot importation during 2006–2022. I exclude from the sample the CZs receiving imports in 2006 since this is the first year with available data and I assume that these CZs were receiving robot imports even before 2006. Figure 2 displays the geographic distribution of robot imports across CZs within the restricted sample. The robot imports are distributed across the entire territory, with the Bajío area and the northern region containing 46% of the CZs that receive robot imports, followed by the southern central region (15%) and the northeastern region (13%).[7] Within these regions, the percentage of CZs receiving imports varies from 3% to 13%, providing ample geographical variation for estimating effects.

Using custom records may have limitations; for example, it is possible that firms obtain robots from local manufacturers instead of importing them. However, this concern is insignificant in Mexico, where almost all robot adopters import them from the US, Japan, or Europe.[8] To validate the accuracy of the customs data, I compare them with national-level IFR data, finding a solid 98% correlation between the number of importing municipalities and the stock of robot installations over the period 2011–2020 (see Figure 1 for a comparison of robot adoption measures).[9,10] This distinctive feature of my research setting is advantageous because, in the developed countries studied in similar works, robot manufacturing is substantial and robot imports capture only a fraction of total robot adoptions.

Another potential concern with the use of import records is the possible concentration of robots in cities where firms' headquarters are located rather than where their plants

[7]The Bajío area includes Aguascalientes, Guanajuato, Querétaro, San Luis Potosí, and Zacatecas. The northern region comprises Baja California, Baja California Sur, Chihuahua, Durango, and Sinaloa. The southern central region encompasses Hidalgo, Puebla, Tlaxcala, and Veracruz de Ignacio de la Llave. The northeastern region includes Coahuila de Zaragoza, Nuevo León, and Tamaulipas.

[8]Global robot manufacturing is highly concentrated, with the top ten suppliers in 2021 being Japan, Germany, Italy, China, the United States, Denmark, France, South Korea, Austria, and Sweden, which accounted for 80% of total robot exports. In contrast, Mexico ranks 24th, contributing just 0.4% to global industrial robot exports, with a trade deficit in this sector.

[9]I obtain a similarly strong correlation if I compare the IFR stock of robots with the stock of the number of importing firms or the stock of the importation values.

[10]The IFR defines an industrial robot as automatically controlled (not manually operated through a joystick or pushbuttons), reprogrammable without physical alteration, multipurpose-manipulable, programmable in three or more axes, fixed in place or mobile, and for use in industrial automation applications. The definition does not include machines such as elevators, ATMs, smart washing machines, transportation tools, textile looms, software, or autonomous cars.

are situated. In Mexico, it is relatively uncommon for firms that use robots to have multiple plants. Among the firms that imported robots between 2006 and 2022, a significant majority, approximately 85%, have only one plant, and 88% operate within the same CZ. Additionally, since the automotive sector is responsible for most robot adoption in Mexico, I identify the universe of large automotive plants and verify that most are located in CZs receiving robot imports (see Figure 2).

To address the possibility that firms import machinery through domestic robot integrators specializing in installing robots at local plants, I examine the practices in Mexico to understand whether this is a significant issue. My investigation reveals that the leading robot integrators in Mexico do not import robots or any other type of machines.

2.2 Labor market outcomes

Formal labor market: To assess the impact of industrial robot adoption on formal employment, I leverage a publicly accessible administrative dataset released monthly by the IMSS. This dataset provides municipality-level information on the total count of registered (i.e., formal sector) workers and total payroll by firm size, industry (up to the 4-digit sector), gender and wage categories. The IMSS administers healthcare services to formal employees in the private sector, and because of the mandatory nature of contributions from private firms, it holds comprehensive information on their workers.

Using these data, I compute the total number of formal employees in a given CZ and 4-digit sector and the corresponding average wage by dividing the total payroll by the total number of workers. Although the frequency of the data is monthly, I focus on the information in December of each year. For the primary analysis, I do not restrict the sample by age. However, the data allow me to distinguish employee age groups and investigate potential heterogeneity.

One evident caveat of this dataset is that it does not include the public or informal sector, which is relatively large in Mexico. The informality rate in Mexico between 2005 and 2018 varied from 56% to 59% of the employed population, according to INEGI. Nevertheless, drawing from prior research, most firms that import and adopt industrial robots are more likely to be large in terms of both employees and revenues (Acemoglu et al., 2022; Koch et al., 2021) and therefore are less likely to be in the informal sector (Porta & Shleifer, 2008, 2014; Ulyssea, 2018). Another limitation of the dataset is its lack of information on hours worked, part-time or full-time employment, specific occupations or tasks, and other characteristics of workers such as educational attainment, ethnicity, and immigration status. However, the IMSS data allow me to dividing employees into different wage groups, in terms of the Mexican minimum wage level.[11]

Mexican labor force survey (ENOE). To shed light on the effects of robot adoption on transitions between the formal and informal sectors, into unemployment, and in and out of the labor force, I use the Mexican labor force survey, called ENOE. This survey is at quarterly frequency and covers most of the localities in urban centers, which I aggregate into CZs. To maintain comparability with the IMSS data, I focus on the fourth quarter of each year between 2005 and 2020. I calculate the count of formal and informal employees, unemployed individuals, and workers out of the labor force. I define formal workers as those affiliated with IMSS and informal workers as those lacking affiliation with any social security subsystems (IMSS, PEMEX, or ISSSTE). However, given ENOE's different sample of localities, I repeat my primary analysis using the IMSS data but the ENOE sample.[12]

1900, 2000, and 2015 Mexican censuses: To calculate general labor market and socioeconomic characteristics for all the Mexican CZs, I use the 1990, 2000, and 2015 population censuses conducted by the Mexican National Institute of Statistics and Geography (*Instituto Nacional de Estadística, Geografía e Informática*, INEGI). I use this information to characterize which CZ observable characteristics are associated with industrial robot import events. Additionally, for the sake of completeness and to facilitate comparisons with existing literature, I compute Bartik-type measures of robot exposure using IFR data.

Mexican economic censuses 2003–2018: I use the Mexican economic census of all firms in the country to compute measures of firm productivity and capital investment within each CZ and sector. The publicly available data are at the municipality–6-digit industry level and can be aggregated to CZ level. The most important limitation of these data is that the frequency is not yearly but every five years.

[11] Wages in the IMMS dataset are reported as daily taxable income (*salario base de cotización*), which may include various forms of compensation, including paid vacation and end-of-year bonuses. Nonetheless, they may exclude other benefits or compensation not subject to labor income taxation. Notably, wages are both bottom- and top-coded, with approximately 1.3% and 1.7% of observations falling into these categories, respectively. For further details, refer to Puggioni et al. (2022). To ensure consistency, I convert these daily wages to monthly wages by multiplying them by 365 days and dividing them by 12 months.

[12] The ENOE results could be noisier because the survey and administrative data, despite being highly correlated, differ in focus: the administrative data center on firm locations, while the survey data cover worker addresses. Despite my using representative localities, discrepancies may persist because of potential worker location differences (Puggioni et al., 2022, Gutierrez et al., 2023).

3 Institutional Background

3.1 Mexican labor markets and the manufacturing sector

Mexico provides a compelling case for studying the impact of automation on labor markets, particularly within its important manufacturing sector, a key sector for economic development and structural change. This sector is a vital component of Mexico's economy, contributing approximately 17.4% to its GDP and accounting for 30.8% of its total exports and 25.6% of total employment in 2019. Mexico manufactures many products within this sector, including automobiles, aerospace components, electronics, medical devices, textiles, apparel, footwear, and furniture.

The strong integration of Mexico into global value chains, especially with the United States, helps us understand the automation phenomenon. Firms engaged in global value chains face intense competition, particularly from China. They are also typically part of intricate production networks in which precision and reliability, which robots improve, are highly valuable. This explains why industrializing economies, including Mexico, are adopting automation, even with a labor force with relatively lower wages (Artuc et al., 2022). The competitive dynamics in Mexico's industrial landscape can imply that these firms face a higher demand elasticity in the product market, a factor affecting the size of the productivity effect of automation.

I focus the analysis on the period from 2005 to 2020, during which an increasing number of firms started importing and adopting industrial robots between 2014 and 2017 (see Figure 1). The rise of automation coincides with some national economic trends, like decreases in poverty and inequality and increases in income, GDP and foreign direct investment. The unemployment rate in Mexico is low (3% of individuals in the labor force) and remained relatively constant during my period of interest. These patterns already suggest that automation does not have a large negative effect, at least at the aggregate level. But they also suggest caution since automation coincides with potentially positive economic shocks (as noted by Brambilla et al. (2023) for Latin America), which is what my empirical strategy will address.

The sector in which automation has occurred at the largest rate is the manufacturing sector. The most potentially affected workers in this sector are not low–wage workers since 69% of these workers earn 2 to 5 times the minimum wage, and there are fewer low-wage workers than in other sectors (Figure A2, Panel A). The most common occupation in this sector (and thus most likely affected) is industrial operators (65.6%, 69% if formal), who are highly susceptible to automation and are predominantly middle-wage earners.

At the same time, professionals and managers typically earn high wages (see Panel B). Most workers in this industry are young (68% aged 20-44). Note that these groups differ from those most affected in industrialized countries, which are relatively low–wage earners in those countries. In my analysis, I will investigate the effects of automation for each of these more and less affected groups.[13]

3.2 Industrial automation in Mexico

Mexico has experienced a rapid increase in industrial robot adoption in the last decade. Figure 1 illustrates this trend, showing that the stock of operational robots surged at an average annual rate of 40% since 2011, reaching over 45,000 units by 2020. Correspondingly, the value of robot imports has surged since 2006. Simultaneously, the number of municipalities embracing industrial robot imports has risen steeply, starting at 68 in 2006 and reaching 108 by 2018.[14] A driving force behind this rapid automation is the automotive sector and other manufacturing industries, including computer, plastics, basic metals, pharmaceutical, and equipment manufacturing.

Figure A4 shows that, although Mexico's automation growth surpasses that of many nations, its level remains a fraction of that in the US or EU countries. This observation underscores Mexico's early stage of automation, wherein the incremental productivity gains from robot adoption might be comparatively larger. Other Latin American countries, such as Brazil, exhibit substantially lower automation levels that have scarcely changed since 2004.

The contribution of Mexican industry to global value chains increased substantially beginning in the mid to late 2000s, partially explained by the good performance of the automotive sector (Chiquiar, 2019; Iacovone, Muñoz Moreno, Olaberria, & De La Paz Pereira López, 2022). Sectors tightly integrated into global value chains prioritize quality due to the high costs of errors, driving automation adoption even in countries with lower labor costs (Artuc et al., 2022; Robles & Foladori, 2019; Rodrik, 2021). Sectors that adopted robots may be on different trajectories as a result. To address this, I include industry-year fixed effects, therefore only comparing firms within sectors that adopt and do not adopt robots in a given year.

[13]Panel C in Figure A2 indicates that individuals aged 25 to 45 primarily fall into the medium-wage group, with older workers enjoying higher salaries, especially in formal manufacturing. Additional details are available in Table B1, which profiles the workers in each wage category, highlighting the prevalence of industrial operators aged 20–44 among medium-wage earners in manufacturing.

[14]This growth is mirrored by the expansion in the number of firms importing robots, which surged from 304 firms in 2006 to 649 in 2018.

Then, why do some firms adopt robots within a specific industry while others do not? Aside from firm-specific shocks, most of this variation comes from supply-side shocks in the robot market. This fact could arise from differences in events at ports or shipping facilities (like accidents, strikes, or changes in regulations), exogenous supplier disruptions (like shortages of electrical and electronics components), or the history of trade ties with countries that supply robots. For example, If a new robot is developed in Japan (or if the price of Japanese robots falls), firms in CZ that have a previous trade connection with Japan are likely to benefit first. These benefits could stem from existing distribution networks, better after-sales service, preferential access, better information, etc.[15] Unfortunately, I do not observe supply chains at the firm level –in fact, my data is at the commuting zone level. So, I cannot exploit this variation. Instead, I will employ several empirical strategies to match CZ as closely as possible and assume that the remaining variation is exogenous from the point of the firm and essentially as good as random, arguing that CZ that are on similar trends have had the same demand shocks but different supply side shocks.

3.2.1 Which CZs import robots?

Previous literature studying automation at the firm level finds that importer firms are positively selected vis-à-vis nonimporters (Acemoglu et al., 2022; Bessen et al., 2020; Koch et al., 2021). Similarly, CZs that receive robot imports differ from those that do not. Table 1 shows that CZs receiving robots tend to be larger in size (population and working-age individuals) and have a higher number of formal workers who earn higher average wages. They also tend to have a larger share of their population living in urban areas and working in manufacturing. Figure A1 shows an increasing trends in formal employment and wages based on the IMSS data, which is common to every wage group and more pronounced in CZs receiving robot imports. This is a characteristic that is correlated with economic and manufacturing growth, and motivates the sample of CZs used in the empirical analysis.

Panel A of Figure 3 presents the estimated coefficients from a linear probability model where the dependent variable is a binary indicator equal to one if a CZ is importing robots and where I simultaneously include many different pre-2006 CZ characteristics. It shows many statistically significant differences between CZs receiving and not receiving robots.

[15]The importance of networks and granularity for trade has been documented by recent studies (Chaney, 2014; Gaubert & Itskhoki, 2021).

Various factors positively affect the predicted probability of importation: the working-age population, the share of manufacturing employment (level in 2000 and change in the 1990s), the average formal wage in 2005, and exposure to EU robots in the 1990s. Given these differences between importers and nonimporters, using an empirical strategy that uses all nonimporters as a comparison group would subject my estimates to significant biases: it would be difficult to argue that these very different CZs are on similar trends despite the considerable differences in their economic development.

3.2.2 What can explain the timing of robot imports?

An alternative approach to studying automation's effects involves keeping the CZs that receive at least one industrial robot importation during the analysis period and exploiting the variation in the import timing. Panel B of Figure 3 presents the estimated coefficients from an ordinary least square (OLS) regression where the dependent variable is the first year in which I observe a CZ receiving a robot importation. In this case, no variable except urban population share has a coefficient statistically different from zero. Despite the potential influence of unobservable factors on the timing of the first import, I find no significant and systematic relationship between import timing and relevant observable variables. Additionally, I estimate a linear probability model using the panel of CZs and sectors used in the primary analysis to investigate whether formal employment and wages affect the predicted probability of starting to import robots. Table B3 shows that, after including panel unit and year fixed effects, there is no association between the labor market variables and the event's timing. Given this result, I focus the empirical strategy on comparing CZs that receive robot imports with the ones that have yet to start importing.

4 Empirical Strategy: Event Studies

Identifying the causal effect of robot adoption on jobs and wages presents critical challenges. Given that importing and adopting robots is a decision made by the firms themselves, there is an endogeneity puzzle that necessitates a careful analysis.

On the one hand, imagine a situation where the labor supply diminishes for specific tasks, such as manual and routine ones. For instance, if a company that manufactures electronic gadgets faces a shortage of skilled manual workers who solder electronic components onto circuit boards, attach wiring, and perform quality checks, they may adopt industrial robots to handle these tasks previously performed by humans. In this scenario, it may appear that robots lead to job reductions, creating a negative bias.

On the other hand, firms could experience positive shocks in product demand. Consequently, they might adopt more robots while increasing the size of their workforce. Similarly, positive financial developments within firms might increase investments in robots and job creation. In such cases, we might erroneously deduce that robots positively affect employment when, in fact, they do not.

The approach that I employ to address this challenge involves leveraging geographical and temporal variations in robot importation while controlling for diverse unobservable factors and shocks at the CZ, 4-digit sector, and year levels. To enhance robustness, I use multiple comparison groups and various methodologies capable of addressing different potential sources of endogeneity.

The main set of strategies that I use is timing-based event study methods. I define an event as the first year in which I observe a CZ receiving industrial robot imports. Then, I can group the CZs into different cohorts by the year of this event. The strategy is to compare the labor market outcomes of CZs receiving industrial robot imports before and after the first importation, using as a comparison group the CZs that have not yet received robot imports but eventually do during the period of analysis. Following Miller (2023), I define the data structure as *timing-based* because I use only ever-treated units and the event dates vary. In this case, the underlying thought experiment is that the event timing is as good as random, implying the traditional assumptions of parallel trends and no anticipation. In this case, I rely on the fact that I find no systematic association between the timing of the importation event and economically relevant observable CZ factors.

Table 2 provides descriptive statistics on the distribution of yearly imports by CZ cohort.[16] There are 104 CZs that receive robots during 2006–2022. Most were already importing robots in 2006, so I exclude these from the sample. I also exclude from the treated sample the observations corresponding to periods after 2019, which are likely affected by the COVID-19 pandemic. After these sample restrictions, I end up with 71 CZs grouped into fourteen cohorts that, on average, imported four times during the analysis period.[17]

Two-way fixed effects model: Event-study specification. I first estimate a traditional

[16]See Figure A5 in the appendix, which shows a histogram of the events. In addition, Figure A6 shows the raw means of the number of formal workers relative to the number one year before the event for different cohorts and CZs.

[17]Note that this does not mean that on average they received four imports (i.e., a firm imported four times). It means that I observe that a CZ received robot imports in four years, regardless of whether there were many or there was just one importation within a year.

two-way fixed effect (TWFE) model. I compare the labor market outcomes of CZs receiving robot imports before and after the event, using the CZs that receive imports earlier or later as the control group. The unit of analysis is a 4-digit sector within a CZ. Therefore, the estimated model is:

$$Y_{smt} = \sum_{\tau=-10,\tau\neq-1}^{10} \beta_\tau d_{mt}^{\tau} + \gamma_{ms} + \delta_{str(m)} + \varepsilon_{mst}, \tag{1}$$

where Y_{mt} is the labor market outcome of industry s in CZ m in year t, d_{mt}^{τ} is dummies indicating the year since the CZ's first robot importation ($\tau = 0$), γ_{ms} is CZ–industry fixed effects, and $\delta_{str(m)}$ is industry–year–region fixed effects. The fixed effects are essential since they capture part of the unobservable factors causing endogeneity. For example, if possible positive demand shocks that importer firms experience happen at the 4-digit industry level, I net out that factor from the analysis.

The β_τ parameters are identified by comparing differences in Y before and after event τ for treated and not-yet-treated or already-treated units.[18] The identification assumptions underlying this approach are as follows: (i) that there is no systematic difference in how the outcomes evolve between the two groups, except the effect of the treatment (parallel trends assumption), (ii) that units do not anticipate or react to their future treatment status before the event, and (iii) that the effects are homogeneous across cohort groups. This last assumption is particularly important for settings where the analyzed treatment is staggered over time, as it prevents biases arising from comparing later-treated units with earlier-treated ones. Additionally, I cluster the standard errors at the CZ level, representing the most conservative option and corresponding to the level at which I observe robot imports.

New event-study methods. TWFE models can produce biased estimates when there are heterogeneous effects across cohorts under a staggered treatment timing, which is the setting of this study. Therefore, I implement two alternative methods—those of Callaway and Sant'Anna (2021) (CS) and Sun and Abraham (2021) (SA)—that circumvent the issue of negative weighting and the so-called bad comparisons of cohorts. Both methods consist of choosing comparison groups that are not contaminated by the treatment.

The CS method computes multiple 2-by-2 difference-in-differences estimations, avoid-

[18] To ensure identification, at least two parameter restrictions are implemented to prevent perfect multicollinearity (Borusyak, Jaravel, & Spiess, 2021; Miller, 2023; Sun & Abraham, 2021). These restrictions involve omitting the event dummy -1 and including end-cap dummy variables at the extremes, such as $d^{\tau\leq 10}mt$ and $d^{\tau\geq 10}mt$.

ing bad comparisons (i.e., not using early-treated observations as a comparison group), and then it aggregates them over event time. The building block of the estimator is $ATT(g,t)$, the average treatment effect on the treated at time t for units starting treatment at time g (cohort). Let us define $D_t = 1$ if it is treated by time t and $D_t = 0$ otherwise (not yet treated). When I use the units not yet treated by time t as the comparison group, the estimand is as follows:

$$\text{If } t \geq g: \qquad ATT(g,t) = \mathbb{E}[Y_t - Y_{g-1}|G=g] - \mathbb{E}[Y_t - Y_{g-1}|D_t = 0, G \neq g]$$
$$\text{If } t < g: \qquad ATT(g,t) = \mathbb{E}[Y_t - Y_{t-1}|G=g] - \mathbb{E}[Y_t - Y_{t-1}|D_t = 0, G \neq g]$$

For post-treatment periods, the method calculates the difference between the outcomes of treated CZs in cohort g and those of not-yet-treated CZs for the period t years after the event compared to the outcomes in the period immediately before the event (period $g-1$). This procedure implicitly controls for linear trends and accounts for unit and period fixed effects. For pretreatment periods, the method calculates the difference between the outcomes of treated CZs in cohort g and those of not-yet-treated CZs for the period t years compared to those in the period $t-1$ years before the event.

Then, I can aggregate the multiple $ATT(g,t)$ across event-time to obtain the average effect for units that have been exposed to treatment for exactly e time periods ($e = t - g$):

$$\begin{aligned}\theta(e) &= \sum_{g}^{T} \omega_e(g,t) ATT(g, g+e) \\ &= \sum_{g}^{T} \mathbb{1}\{g + e \leq T\} P(G = g | G + e \leq T) ATT(g, g+e) \qquad (2)\end{aligned}$$

The main difference between the CS and SA methods lies in the comparison group chosen in each. Both methods allow use of the not-yet-treated cohorts as the comparison group. In this context, Sun and Abraham (2021) use the last-treated cohort (cohorts that started importing robots in 2019 or later), while Callaway and Sant'Anna (2021) use all the not-yet-treated cohorts.

Synthetic DD. Synthetic difference-in-differences (SDD) is a hybrid method that combines elements from both the difference-in-differences (DD) and synthetic control (SC) approaches.[19] In an SDD analysis, we use a panel setup, balanced in calendar time, where

[19]The method described here follows the framework proposed by Arkhangelsky, Athey, Hirshberg, Imbens, and Wager (2021). Refer to their article for detailed information on estimation, inference procedures, and formal proofs of the estimator's consistency and asymptotic normality.

specific units receive treatment while others remain untreated. The goal is to assess the impact of the treatment by comparing changes in outcomes before and after treatment for both the treated units and a synthetic control group that has the same pretrends. To create the synthetic control group, the method selects units from the never-treated group (CZs that have never received robot imports during the analysis period) and time periods before the event. It assigns unit-specific weights to these untreated units and time-specific weights to the pretreatment periods. SDD capitalizes on the strengths of both the DD and SC methods. Similar to DD models, SDD allows for pretreatment differences in level outcomes between the treated and control units. Conversely, like the SC method, SDD seeks to create a control unit that mitigates the strict requirement of the parallel trends assumption.

As a result, SDD is advantageous because it can overcome common challenges encountered in implementing standard DD and SC methods. It can estimate causal relationships even when pretrends are not strictly parallel in aggregate data, which would violate a key identifying assumption for DD. Furthermore, it does not necessitate that the treated unit fall within the "convex hull" of control units, a condition imposed by the SC method.

Robustness analysis: Alternative methods. I employ a triple-differences (DDD) approach to complement my previous analysis. This method involves comparing labor market outcomes among industries that are more and less exposed to robot adoption within CZs that either receive or do not receive robot imports before and after the first robot importation event. I define more exposed industries as manufacturing industries observed to have a high rate of robot adoption in the IFR data, and low exposed as the rest of non-manufacturing industries.[20] The critical innovation of the DDD approach lies in its introducing a third difference by considering different industry exposure levels. This additional layer of differentiation allows me to effectively control for idiosyncratic labor market shocks that might otherwise confound the analysis. These shocks are a primary concern in conventional DD approaches.

I incorporate CZ–year fixed effects into the model to implement this DDD approach. These fixed effects help account for various shocks affecting a CZ labor market in a given year, such as economic downturns, local policy changes, or large-scale industry expan-

[20]More exposed industries include Transportation, Electronics, Metal products, Chemicals, Plastics, Rubber Energy and power generation, Food, and Beverages. Less exposed industries include all the non-manufacturing industries, excluding wholesale machinery trade. I exclude from the sample the rest of the manufacturing industries, i.e., Textile, Wood, Furniture, Paper, Printing, and Non-metallic mineral products.

sions. By including these fixed effects, I can isolate the impact of robot adoption within industries while minimizing the influence of external shocks or trends that might affect the outcomes. This triple-difference framework enhances the robustness of my analysis and strengthens the causal inference regarding the effects of robot adoption on labor markets.

Finally, I replicate the Bartik instrument strategy outlined in Acemoglu and Restrepo (2020). This strategy involves using an instrumental variable based on exposure to European robot adoption to instrument for exposure to domestic robot adoption. This approach provides an additional layer of validation for my analysis, as it helps isolate plausible exogenous variation in robot adoption. It assumes that European trends reflect reductions in robot costs and technological advancements and do not directly impact Mexican labor markets. Replicating this strategy enables me to compare my findings with results in the existing literature and underscores the significance of my utilizing new industrial robot data. I can improve the measurement of robot adoption and exploit variation within industries. This is crucial as it can be challenging to separate the effects of robots from industry-level shocks, particularly in this context where the automotive industry accounts for most of the phenomenon.

5 Results

5.1 Formal labor market

I begin by examining the reduced-form effects of starting to import industrial robots on CZs' formal employment and average wages for the set of CZs that eventually receive robot imports. In Figure 4 Panel (a), I visually represent the dynamic effects on the logarithmic count of formal workers, defined as individuals affiliated with IMSS in December of each year. In this figure, each dot corresponds to the estimated $\theta(e)$ event-study coefficients, calculated using equation 2, and is accompanied by a 95% confidence interval. Since outcome variables are measured in logs, the point estimates can be interpreted as semi-elasticities.

Consistent with my failing to find observable predictors of the timing of the event for the subset of not-yet-treated CZs, the pre-event coefficients consistently hover close to zero and remain statistically insignificant at the 5% significance level (the uniform confidence interval covers zero for all pre-event years). The average of the coefficients of the periods between one and five years prior to $t = 0$ is very close to zero (0.005 log points, SE = 0.004), suggesting that employment trended similarly across all CZs before the first robot importation. This finding is reassuring, as it is consistent with the validity of the parallel trends and no-anticipation assumptions.

The number of formal workers in CZs remains relatively stable during the first four years after the initial robot importation, showing an average positive effect of 1.6%, although this effect is not statistically significant at the 5% level. This result suggests that I can rule out significant short-term negative employment effects exceeding -0.7%. Subsequently, the estimated coefficients are still nonnegative. In fact, I find an increase in formal employment averaging 6.9% for five to eight years after the event, a result that is statistically significant at 1%. However, this effect might be explained by compositional changes across CZ cohorts.

The concern about compositional changes arises due to the varying duration of exposure of different cohorts. For instance, we can determine the instantaneous average effect ($t = 0$) only for the cohort of CZs that started importing robots in 2019. Conversely, for CZs that began importing in 2017, we can assess the effects at event times $t = 0, 1, 2$. While both cohorts contribute when I compute the coefficient for $t = 0$, this is not true for $t > 0$. This situation can introduce confounding dynamics and selective treatment timing among different cohorts if the impacts of robot importation systematically differ.

To mitigate this concern, I balance the sample by including only cohorts exposed to the treatment for a certain minimum number of years and examine dynamic effects within those years. Table 3 presents the results for different balanced samples, ranging from event windows of one to four years around the importation event. Encouragingly, the short-run effects remain nonnegative, allowing me to rule out negative effects within the range of [.4%–3.2%] for formal employment and [.2%–.8%] for average wages, depending on the length of exposure.

On the other hand, it is more difficult to rule out composition effects as an explanation for the positive long-run effects I document. The estimates rely on fewer and fewer units after 4 years have passed. One could in principle restrict the sample to include only units that are observed over a long period of time to estimate these long-run effects. However, there are only a handful of units that are observed for more than 4 years (for example, there are only 2 with a six-year post-period). Thus, the best estimates for these long-run effects come from the synthetic control approach. These estimates show that the effects are, in fact, the largest and most positive for these early adopters (see Figure A13).

This positive employment impact suggests that some of the productivity effects take time to emerge due to learning. The growth might also reflect that the intensity of robot use is increasing over time (for example, CZs that first adopted robots in 2011 continued to adopt more robots in subsequent years). The estimates so far only consider the impact of the first set of robots that are adopted, but in fact automation continues once the CZ starts importing robots. I investigate the effect of the intensity in the next section, and I find that the effects are more positive when the intensity is larger.

Panel (b) of Figure 4 plots the dynamic effects of robot adoption on the logarithmic average real monthly wage for formal workers using the same empirical approach. The patterns mirror those in Panel (a), but the effects seem less pronounced. The real monthly wage does not exhibit differential pretrends before the importation event. Then, there is no statistically significant wage increase during the first four years after the first robot importation, and there is a positive effect after $t = 5$ of 3% for all industries, which is statistically significant at 5%. If we restrict the sample to robot adopter industries within manufacturing, the effect is still nonnegative (see Table 4).

Another way of understanding whether this null effect is hiding potential effect heterogeneity is to analyze groups that are more exposed, such as manufacturing sector workers. To explore this hypothesis, Table 4 summarizes the effects for various subsamples. Indeed, when I focus the analysis on the manufacturing sector, I find that the short-term effect is still small and nonnegative but the long-term effect is larger than in the baseline, although more imprecisely estimated and potentially driven by compositional changes. The same is true for other subsamples such as workers in the manufacturing industries that have a large stock of robots according to the IFR data or the sample restricted to a balanced panel in calendar time. A consistent pattern emerges across all these different subgroups, revealing a nonnegative employment effect associated with robot adoption.[21]

Additionally, I explore whether the coefficients are more prominent for groups for which we would anticipate a significant negative effect based on the previous literature. If other groups had notably larger results, this would suggest the presence of omitted variable bias. Table 5 provides the CS model estimates, segmented by various factors such as age, wage, and firm size. This analysis confirms that all groups have the same nonnegative result in the short run. Notably, the long-term employment effects are concentrated among medium-wage and prime-age workers, both groups where industrial operators are more prevalent (see Figure A7 for the dynamic effects). Moreover, it becomes apparent that the results are most pronounced in larger firms with over 50 employees, where

[21]Note that I also consider the inclusion of never-treated CZs in the comparison group. The post-treatment effects are similar to the ones considering only the not-yet-treated sample. However, it exhibits a slightly but statistically significantly differential pretrend.

automation is more likely to occur. Panel D reveals that the employment and wage effects tend to be relatively larger in smaller CZs, which are typically more responsive to labor market shocks (see Figure A8 for further details).

The main results are consistent with Ing and Zhang's (2022) finding for Indonesia of positive employment effects for the manufacturing sector (0.113, SE = 0.038) and wages (0.068, SE = 0.040). These results are similar to this paper's findings, even though these authors consider a more general definition of automation equipment (not only industrial robots). Calì and Presidente's (2021b) employment effect for Indonesia is of the same sign but is larger in magnitude at 0.307 (SE = 0.104). Rodrigo (2021) also does not find a large statistically significant decline on employment for Brazil, and also finds positive effects on wages and productivity. These results suggest that in industrializing economies the effects are positive unlike those found for the US and Europe.

The estimates in this paper differ from those in Brambilla et al. (2023), which finds a negative effect of robot exposure on the number of formal workers in a panel of states in Brazil, Mexico, and Argentina in the periods 2004–2016. A potential source of this difference is that the study uses a shift-share instrument strategy, leveraging industry composition variation across less granular geographic units (states), and exploiting a different source of variation (only within geographic units).

5.2 Robustness checks

5.2.1 Alternative outcome measures and financial crisis

Another concern is related to the measurement of outcomes, which can have measurement errors that would decrease the precision of the estimates since I take the information from December of each year. To explore how sensitive the main results are to this issue, I calculate the labor market outcomes as a simple yearly average of the last month of each quarter (comprising March, June, October, and December). These measures may be a better indicator of what is happening in each year to the extent that they use more available information. Table B4 repeats the main table but changes how I measure the dependent variable. These results closely mirror those derived from the December data exclusively.

A second concern is related to the fact that the observed effects could be driven by firm responses to the 2009 financial crisis. To rule out this potential explanation, I re-estimate the effects excluding from the sample the cohorts that started importing robots in 2009 and 2010. Table B5 shows that the results are very similar when I exclude these cohorts.

5.2.2 Alternative methods

Figure A10 shows the dynamic coefficients of the three event-study models—TWFE, SA, and CS—for the sample of not-yet-but-eventually-treated CZs. In the case of employment, there are no significantly differential pretrends, and the postevent effect is even more pronounced than that estimated under the CS method. In the short term, the number of formal workers increases by between 3.8% and 4.1%, while in the long term, it rises to 10.7% on average. On the other hand, when I focus on average formal wages, the pre-event coefficients for the different approaches also lack statistical significance, and the effects follow the same dynamic pattern as those on employment, with more muted and less precise positive results (I can rule out negative wage effects larger than -0.8%).

While the pre-event coefficients derived from the various approaches lack statistical significance, the possibility of a modest pretrend increase in average wages emerges, particularly when I examine a timeframe extending beyond three years before the event. This possibility merits thorough investigation. To assess the significance of these pretrends, I employ a sensitivity analysis method proposed by Rambachan and Roth (2023). This analysis estimates the post-treatment effect under different assumptions of parallel trend violations, demonstrating the extent to which postevent trend differences would need to deviate from the pretrends to render the estimates negative or statistically insignificant. More precisely, I provide confidence intervals that enable the post-treatment deviation from parallel trends to reach a magnitude of up to M times the maximum pretreatment deviation, with M being a variable that can take different values. Figure A11 illustrates the results of this analysis, suggesting that if we assume that the maximum size of the pretrend persists post-treatment, the short-run and long-run estimates for employment and wages remain positive but lack statistical significance (the estimated coefficient for the employment effect in period 6 remains statistically significant when I assume that the pretrend persists but at half its size). The crucial point is that a substantial deviation of the parallel trend assumption would be necessary to yield negative employment and wage estimates.

Another way of addressing the potential violation of parallel pretrends is by controlling for CZ–time-specific idiosyncratic shocks using a DDD model. To do so, I compare the labor market outcomes of more and less exposed industries within CZs before and after the import event between treated and never-treated CZs. I define more exposed industries as those in the manufacturing sector that I observed in the IFR data adopting robots. Less exposed industries are the other, nonmanufacturing industries.[22] I further

[22] I also exclude from the less exposed industries those in educational service since it is listed as adopting

restrict the sample to CZs with a population of fewer than 500 thousand to improve comparability. Figure 5 shows that, once I control for possible deviations in the employment and wage pretrends using the less exposed group, I still find nonnegative effects on formal employment and wages of similar magnitudes to those in the previous analysis.[23]

SDD is an alternative method that directly addresses pretrend differences by construction. When I use this method, I find no statistically significant negative employment or wage effect for any industries or manufacturing sectors, as seen in Figure 6. Most of the employment and wage point estimates are positive but generally have larger confidence intervals than those for the results under the previous methods. For instance, the simple average of the employment effects across CZs is 0.07 (SD=0.30), while the average impact for wages is 0.01 (SD=0.07). Figure A13 shows the difference-in-difference graphs for a specific CZ, where there is a statistically significant positive effect in the number of workers and average wage.

To conclude the analysis, I present the results from the two-stage least squares (2SLS) method with the Bartik instrument of EU automation, using as a measure of domestic robot adoption the change in robot exposure between 2011 and 2015. Figure A14 plots the estimated coefficients and compares them with the results from Acemoglu and Restrepo (2020). Table 8 presents the 2SLS results for multiple outcomes.[24] The findings do not show any clear proof of negative effects on jobs or wages, although the standard errors are larger and not the same as those corresponding to the results under previous DD based methods. The reason might be that the Bartik method estimates the effects for a different group of units (those affected by the instrument) and relies on the assumption that if an industry adopts robots, any CZ with firms in that industry adopts robots, even if this is not the case.

Table B7 summarizes the results of all the different methods showing the average estimated coefficients during the pre-event period (averaged across four periods) and the postevent phase, further differentiating the short-run (within four years of the event) from the long-run effects (five to eight years after the event). The main finding across specifications is that there are no substantial negative employment effects of automation. After the first robot importation, there are positive but relatively small effects on the number of formal workers in the short run and larger effects in the long run. This might be consistent with the fact that integrating robots and changes in the job and task landscape

robots in the IFR data but is outside manufacturing. I further exclude the industry of wholesale trade of machinery, which likely includes robot integrators.

[23]Figure A12 shows that this conclusion holds if I use 3-digit industry codes.

[24]Table B6 presents similar results for the change between 2010 and 2015. This version implies imputing robot adoption for the year 2010, given that the IFR data for Mexico are available for years since 2011.

necessitates an adjustment period. Using event studies based on traditional TWFE, either using double or triple differences, I can rule out negative effects larger than -0.4% to -0.8%. Overall, it is encouraging that these alternative approaches support the baseline results.

5.2.3 Other robot adoption measures

Concerns may arise with respect to the relevance of defining the event of interest as a CZ's first year of industrial robot importation. It is essential to consider whether different effects emerge when alternative measures that account for import intensity are considered. To address this, I develop two alternative measures for analysis.

The first one considers the value of the robot imports and defines the event as the year in which the cumulative value of a CZ's robot imports as a share of its total 2005 manufacturing sector payroll surpasses a given threshold. To obtain this measure, I first need to impute the import value for CZs with missing data because, for confidentiality reasons, this information is observable only when more than three firms in the CZ import robots in a given period. Therefore, I impute the import values using the mean of each year–state–country supplier cell. Panel (a) of Figure A9 in the appendix shows that the imputed measure has a mean and variance similar to those of the nonimputed measure. Panel (b) compares the distribution of CZs across the time passed since the event as originally defined and the event as defined by means of the cumulative import values with a 50% threshold. Under the new definition, there are fewer CZs treated for fewer periods. Figure A15 shows the CS estimates for events based on the new definition under increasing thresholds. All the estimated coefficients for formal employment and wages are positive, regardless of the threshold. In fact, the average of the long-term coefficients is statistically significant at 1% when I use thresholds larger than 40% (i.e., the cumulative value of robot imports is larger than 40% of the total manufacturing sector wage bill). Table 6 summarizes these results.

A second possibility is to use the cumulative number of yearly imports at the CZ level. Since the Callaway and Sant'Anna (2021) method does not allow me to consider the treatment intensity, I implement this measure using the TWFE model, interacting the event-time dummies with the cumulative number of yearly imports. Table 6 shows that the employment and wage effects are similar to the baseline estimates described in the previous section.

5.3 Other margins of adjustment

To evaluate whether firms and workers use alternative margins of adjustment, I conduct an analysis of its effects on labor informality, unemployment, and labor force participation using ENOE data. Table 7 presents the results of our primary specification, using formal and informal employment measures obtained from ENOE as dependent variables. These results are compared with point estimates derived from the IMSS sample, restricting the sample to CZs for which the ENOE data are representative. It is worth noting that ENOE is representative for only a limited number of major cities. Consequently, the estimates regarding the number of formal workers, when compared to those calculated from the IMSS data, exhibit differences in precision, with the latter being less statistically robust but qualitatively consistent (showing a positive short-term effect and a more pronounced long-term effect).

Notably, our findings reveal a short-term decrease in the number of workers in the informal sector, followed by a long-term increase, potentially attributable to general-equilibrium effects. A similar pattern emerges in the case of unemployment and labor force participation. Intriguingly, there is a concurrent rise in the urban population, suggesting that there might be rural-to-urban migration.

5.3.1 Ruling out potential explanations: Plant openings

In dissecting the underlying factors behind the observed positive employment effects beyond the anticipated gains in productivity from robot adoption, I delve into the prospect that firms, buoyed by robust demand shocks, opt for expansion and open new facility establishments, potentially internationally. This sequence could subsequently trigger robot incorporation and a surge in the workforce.

To assess this, I analyze the sensitivity of the estimated robot–employment relationship to my factoring in a measure of plant openings. Leveraging the 2018 economic census, I utilize the variable tracking the commencement year of operations. This enables the calculation of establishment openings for surviving firms. I focus this analysis on specific industries and firm sizes, particularly on industries substantially exposed to automation and larger firms.

Importantly, these segments are more likely to have persisted until 2018, rendering the measure more reliable. The core point estimates remain largely unaltered upon my including this measure into the CS model (see Figure A16). Furthermore, I extend this exploration to directly evaluate the impact of robots on plant openings, finding no discernible association (see Figure 7).

In essence, this comprehensive exploration effectively narrows down the plausible drivers of potential positive employment effects, bolstering the conjecture that heightened productivity triggered by robot adoption was a significant catalyst. This fact lends further weight to the argument that the positive employment outcomes observed are rooted primarily in productivity enhancements brought about by adopting robots.

6 Mechanisms and Alternative Explanations

To analyze the effects of industrial robot adoption on productivity, output, the labor share, and capital investment, I use the Mexican economic censuses (2003, 2008, 2013, 2018). These censuses are taken every five years, which limits my ability to explore the dynamic effects of robot adoption. For this analysis, I estimate the following TWFE model:

$$Y_{smt} = \beta D_{mt}^{post} + \gamma_{sm} + \delta_{st} + \epsilon_{smt}, \tag{3}$$

where Y_{smt} represents the aggregated outcomes of firms at the six-digit sector s in CZ m in census year t and D_{mt}^{post} is an indicator variable that takes the value of one if CZ m starts or has already started to import robots in census year t. This model allows me to control for idiosyncratic shocks at a much more granular (six-digit) sector level than in the analysis with the IMSS data, where I can control for shocks only at the four-digit sector level.[25] γ_{sm} is CZ $\times$ six-digit sector fixed effects, which capture non–time-varying factors, such as product or labor market conditions. δ_{st} is six-digit sector $\times$ census year fixed effects, which capture the common trends across sectors over time. For example, some sectors may have regional policies or may experience demand shocks due to global competition or trade liberalization that affect all firms in the sector over time. By including these fixed effects, I can control for important confounding factors that may affect the relationship between robot adoption and the aggregated firm outcomes.

Table 9 presents the results and is divided into two panels: Panel (a) shows the results for all industries, and Panel (b) shows the results for a subset of manufacturing sectors that are more likely to be affected by automation (metal, machinery and equipment, plas-

[25]One example of a six-digit sector within the automotive manufacturing sector is 336111, automobile manufacturing. This sector comprises establishments primarily engaged in one or more of the following: (1) manufacturing complete automobiles (i.e., body and chassis or unibody); (2) producing automobile chassis only; (3) manufacturing automobile bodies only; or (4) manufacturing and/or assembling automobile subassemblies. This sector is part of 3361, motor vehicle manufacturing, which is part of 336, transportation equipment manufacturing.

tic and rubber, power generation, and transportation).[26] The dependent variables are the number of firms, labor share, capital per worker, ln gross value added (GVA), GVA per worker, input cost, total payroll, total fixed assets, number of workers, number of workers in production and sales, number of workers in administration, hours worked, hours worked in production and sales, and hours worked in administration.

For all industries, industrial robot adoption has a positive and significant effect on GVA and the input cost. This suggests that robot adoption may increase the productivity of firms in Mexico. However, robot adoption has no significant effect on the labor share, capital per worker, payroll, fixed assets, or employment. This suggests that robot adoption does not affect the distribution of income between labor and capital, or firm size. However, this could be result of the lack of power given the level of aggregation and the availability of observations for only few periods. The sign of the labor share is negative, and the magnitude is -1.1%, consistent with results derived from task-based frameworks for considering automation effects (Acemoglu & Restrepo, 2020).

For the subset of manufacturing sectors that are more likely to be affected by automation, industrial robot adoption has a positive and significant effect on GVA per worker, input cost, payroll, fixed assets, and capital per worker. This suggests that robot adoption increases the productivity, efficiency, wages, and investment of firms in these sectors. However, robot adoption has no significant effect on the labor share (although the coefficient is negative and larger in magnitude than that for all industries). This suggests that robot adoption does not affect the distribution of income between labor and capital.

I find that robot adoption has a nonnegative effect not only on employment but also on hours worked. Across all industries, the effect is generally small and lacks statistical significance. However, when I narrow my focus to the manufacturing sector, the effects become more substantial and statistically significant within the balanced sample: employment shows an increase of 18.1%, while hours worked increase by 19.4%. These effects can be attributed to increased production and sales workers rather than administrative workers.[27].

For the other manufacturing sectors, the effects are either not significant or much smaller than the effects found for the manufacturing sectors that are more likely to be

[26]Tables B8 and B9 present the same results for the balanced panel in calendar time. The findings are similar to those from the unbalanced panel.

[27]The differences in the effects on production and administrative workers have been investigated by Dixon et al. (2019). They used firm-level data from Canada and found that adopting robots significantly reduces the number of managers and administrative staff, and increases productivity and wages. According to their hypothesis, robots enable companies to enhance their product and service quality, which, in turn, requires more flexible and adaptable management practices.

affected by automation. However, Panel (a) of Table 10 presents some exceptions, showing evidence for sectors such the wood, paper and chemicals industries of an increase in capital per worker (3.2%) and a reduction in employment of production and administrative workers. This finding could suggest a certain degree of reallocation of workers across sectors, depending on how much they automate and how large the productivity channel is. I find no effects for manufacturing industries with very low levels of robot adoption, such as the textile sector (see Panel (b)).

For the nonmanufacturing sectors (Panel (c) in Table 10), industrial robot adoption has a positive and significant effect on GVA, input cost, number of workers, and hours worked. However, these effects are much smaller than those for the manufacturing sectors more likely to be affected by automation. These outcomes may indicate the presence of broader, general-equilibrium effects stemming from robot adoption. Such effects can include shifts in demand or supply dynamics across various sectors, including construction, wholesale and retail trade, and manufacturing, ultimately highlighting the interconnected nature of these industries.

These findings align with the results in the literature on industrial robot adoption at the firm level, highlighting its positive impact on productivity and employment, as evidenced by significant increases in GVA per worker and number of workers (for example, Acemoglu et al. (2023) for the Netherlands, Acemoglu et al. (2022) for the US, Acemoglu et al. (2021) for France, Koch et al. (2021) for Spain, Dixon et al. (2019) for Canada, and Humlum (2020) for Denmark). These aggregate estimates might hide effects within industry since robot adopters may expand at the expense of nonadopter competitors (Acemoglu et al., 2023). However, I still find zero or positive effects on aggregate employment.

7 Discussion

7.1 Theoretical framework

To understand how industrial robot adoption may impact labor markets differently in developing countries, I summarize the key findings of a simple, competitive labor markets model in the style of Acemoglu and Restrepo (2018) where automation allows robots to substitute for workers in some tasks. Acemoglu and Restrepo (2018) develop a task-based model in which robots and human labor compete to complete various tasks. In this model, the effects of robots on wages and employment are ambiguous.

Consider a perfectly competitive economy with two sectors j: (i) manufacturing ($j =$

1) and (ii) the rest of the sectors ($j = 2$), potentially including the informal sector in the Mexican context. Production at $j = 2$ uses only workers, such that one unit of labor corresponds to one unit of output.

The representative firm in sector 1 produces a final good Q by combining a continuum unit measure of tasks, which are completed by robots and human workers. I assume that the markets for both inputs are perfectly competitive. While workers have identical productivity in all tasks, robots are as productive as workers on tasks in the range $[0, I]$ but have zero productivity at tasks $(I, 1]$. Robots can be purchased in an international competitive market at constant rental rate r. I am primarily interested in the equilibrium effects of I, that is, increased automation that allows robots to perform tasks that previously required labor.

Good 2 can be produced internally, as noted above, or imported at constant price p_2. I set this good as the numeraire in the economy: $p_2 \equiv 1$.

The manufacturing good is exported, facing isoelastic international demand:

$$Q(P_1) = \kappa P_1^{-\sigma},$$

where the constant κ is exogenous.

Turning to individual preferences, I assume that all individuals i consume only good 2, and the amount they consume is equal to the wage they receive, as the price is normalized to one. Their indirect utility is a function of their choice of employment sector ($j = 1$ or 2) and the corresponding wage, and is given by:

$$U_{ij} = \beta ln(w_j) + \epsilon_{ij},$$

where ϵ_{ij} is i.i.d. extreme value type 1 errors, indicating that workers may have a preference for one sector over the other. I denote the equilibrium wage in each sector by w_j and the cost of robots by r. Wages can be different across sectors because workers have idiosyncratic preferences for where they work. Given the assumption that production of good 2 requires one unit of labor, and that the market for good 2 is perfect competitive, it follows that $w_2 = 1$.

I assume that the cost of robots is lower than the cost of labor $r < w_1$, such that all tasks in $[0, I]$ are performed by robots while tasks in $(I, 1]$ are completed by human workers, where I represents the extent of automation. Therefore, the cost per unit is:

$$Ir + (1 - I)w_1 = P_1.$$

We obtain the labor demand by plugging the expression for P_1 into the aggregate demand for good 1:

$$Q(P_1) = \kappa[Ir + (1-I)w_1]^{-\sigma}$$

$$LD_1 = (1-I)\kappa[Ir + (1-I)w_1]^{-\sigma}.$$

Each worker with wage w_j and extreme value type 1 heterogeneity ϵ_{ij} evaluates the utility for each option and chooses the highest utility. Consequently, the aggregate labor supply of the manufacturing sector is as follows:

$$LS_1(w_1) = \frac{w_1^\beta}{w_1^\beta + w_2^\beta} = \frac{w_1^\beta}{w_1^\beta + 1} = \frac{1}{1 + w_1^{-\beta}},$$

where β corresponds to the elasticity of supply.

Equilibrium in the labor market is given by $LS_1(w_1^*) = LD_1(w_1^*)$, such that:

$$\frac{1}{1 + w_1^{-\beta}} = (1-I)\kappa[Ir + (1-I)w_1]^{-\sigma}.$$

In equilibrium, the elasticity of labor supply β affects the slope of the labor supply curve, affecting the size of the employment and wage effect but not its direction. When β is relatively low, i.e., inelastic, the effects of shifts in labor demand on employment are attenuated and wages exacerbated.

I am more interested in the direction of the effect governed by the parameter σ of labor demand, representing the price elasticity of aggregate demand for manufacturing products. Suppose that σ is relatively high. In this case, the labor demand curve shifts to the right, and there is a positive effect on employment and wages. Figure 8 graphically shows how the equilibrium depends on the parameters in a standard supply and demand model.

I next analyze how labor demand changes when the extent of automation marginally increases.

Writing the labor demand function in logs:

$$ln(LD_1(w_1)) = ln(1-I) + ln(\kappa) - \sigma ln[Ir + (1-I)w_1] \tag{4}$$

Differentiating 4 with respect to I leads to the following expression;

$$\frac{\partial LD_1(w_1)}{\partial I} = -\frac{1}{1-I} - \sigma\frac{(r-w_1)}{Ir+(1-I)w_1}.$$

Given the assumption $r < w_1$, I can rewrite this as:

$$\frac{\partial LD_1(w_1)}{\partial I} = \underbrace{-\frac{1}{1-I}}_{\text{Displacement effect}} + \underbrace{\sigma\frac{w_1-r}{Ir+(1-I)w_1}}_{\text{Productivity effect}}.$$

According to this result, extending automation has an ambiguous effect on labor demand. On the one hand, there is a displacement effect, which is always negative, $-\frac{1}{1-I} < 0$.[28] On the other hand, there is a productivity or scale effect that is positive under the assumption that $r < w_1$. This latter effect crucially depends on the size of the elasticity of labor demand σ. The larger σ is, the larger the productivity effect, which may more than compensate for the negative displacement effect.

Automation drives the substitution of labor with capital when capital can perform specific tasks more efficiently at the margin. The productivity effect rises because of a reduction in production costs, which translates into a reduction in prices for goods, increasing real income for consumers and consumer demand. In turn, this increases labor demand within nonautomated tasks or sectors yet to undergo automation. This is why, if consumers are more price sensitive, there could be a larger increase in demand and the productivity effect might offset any adverse effect.

7.2 Why might the productivity effect be larger in industrializing than in rich countries?

To understand whether the positive productivity effects of automation are more likely to be larger in industrializing economies such as Mexico, it is helpful to analyze where the productivity gains from robot adoption come from. As explained in Section 7.1, the productivity gains from automation do not result from capital and labor becoming more productive in tasks that they were already performing—they are a consequence of firms' abil-

[28]In Acemoglu and Restrepo (2020), the formula for the cost savings from using robots in labor market c is in terms of relative prices: $\pi_c = 1 - \frac{\gamma_L}{W_c}\frac{R_c^M}{\gamma_M}$, where γ is factor productivity and W and R^M the prices of labor and capital, respectively. The greater the productivity of capital in automated tasks relative to the rental rate of capital, and the smaller the productivity of labor in these tasks relative to wages, the greater are the productivity gains from automation.

ity to use cheaper capital in functions previously performed by human workers. Therefore, the productivity effect that arises is proportional to the cost savings.

However, the productivity effect also depends on the size of the elasticity of labor demand σ. If the elasticity is large enough, with all else held constant, the productivity effects could offset or even more than compensate for the displacement effect and increase labor demand. Are there reasons why the elasticity of demand for goods in Mexico be different from that in the US?

Automation in Mexico happens mostly in specific manufacturing industries that are generally concentrated on labor-intensive tasks (assembly) and producing tradable goods for export. Firms in these sectors often face foreign competition, leading to price reductions through automation, creating a competitive advantage and boosting output.[29] On the other hand, US firms might face low competition from abroad since they could be more interested in satisfying domestic demand and consumers may prefer US goods. Consumers in the US also have higher earnings, so they might be less price-sensitive than Mexican consumers.

Alternative explanations are related to different type of industrial robots being adopted depending on the automation stage. Acemoglu and Restrepo (2020) maintain that the predominant negative displacement effect in the US aligns with the prevalence of low-productivity automation technology (referred to as *so-so automation*), which is sufficiently productive that firms adopt it in the presence of factors such as tax code distortions but not inherently more cost-effective than the processes that it supplants.[30] Consistent with this idea, Graetz and Michaels (2018) and Calì and Presidente (2021b) suggest that the positive productivity effect could be larger in developing countries because of diminishing marginal gains from automation. This implies that, as robot density increases, the corresponding productivity gains become increasingly smaller. Furthermore, negative displacement effects might be smaller in Mexico than in the US, given that the labor displaced and early-stage automation might have higher productivity.

[29]For example, Harasztosi and Lindner (2019) find that the tradable sector and exporting firms have larger responses to minimum wage increases because they are more exposed to foreign competitors and have a higher price elasticity of demand.

[30]In the context of so-so automation, the technology's productivity only marginally surpasses that of labor ($\frac{\gamma_L}{W_c} \approx \frac{R_c^M}{\gamma_M}$). Nonetheless, in Mexico, the likelihood of $\frac{\gamma_M}{R_c^M} \gg \frac{\gamma_L}{W_c}$ is heightened, particularly considering that so-so automation tends to emerge at later industrialization stages.

8 Conclusion

This study sheds light on the impact of industrial robot adoption on labor markets in developing countries, with Mexico serving as a compelling case study. The findings offer evidence to support an optimistic narrative: the rapid adoption of robots in Mexico over the last decade has not yielded substantial negative effects on formal employment or average real formal wages. Instead, it sets a favorable transitional phase, with far-reaching implications. While the immediate impact may appear modest, there is evidence of a potential positive effect in the long run, underlining the gradual labor market adjustments linked to automation.

These findings suggest possible policy considerations for industrializing countries such as Mexico. Policymakers can explore the potential of promoting automation to increase productivity and growth, especially in the tradable manufacturing sector. However, the equitable distribution of these benefits is a crucial aspect that needs attention. Facilitating technology transfer from automating to non-automating sectors through partnerships and collaborations could be a viable strategy. Policymakers can adopt a forward-thinking approach, anticipating a future where automation plays a significant role in the economy. This approach could involve planning for investments in education and training for jobs in automated industries, developing infrastructure to support automation, and formulating regulations to guide the ethical use of these technologies. Adopting such a long-term perspective could ensure a smooth and beneficial transition to a more automated economy.

In conclusion, this study contributes to the emerging body of evidence on automation's impact on industrializing economies and suggests promising avenues for future research. Further investigations using firm- and establishment-level data can provide a deeper understanding of the mechanisms and dynamics underlying the observed effects. Exploring worker-level effects will enable a more nuanced assessment of reallocation effects and of which workers might be beneficiaries and which might be adversely affected, offering valuable insights for public policy interventions. Comparative studies across regions and countries hold the potential to reveal the nuanced impact of automation across different contexts, facilitating more targeted and effective policy responses. As we navigate the transformative era of automation, continued research in these directions will be essential to inform evidence-based policymaking and ensure inclusive and sustainable economic development.

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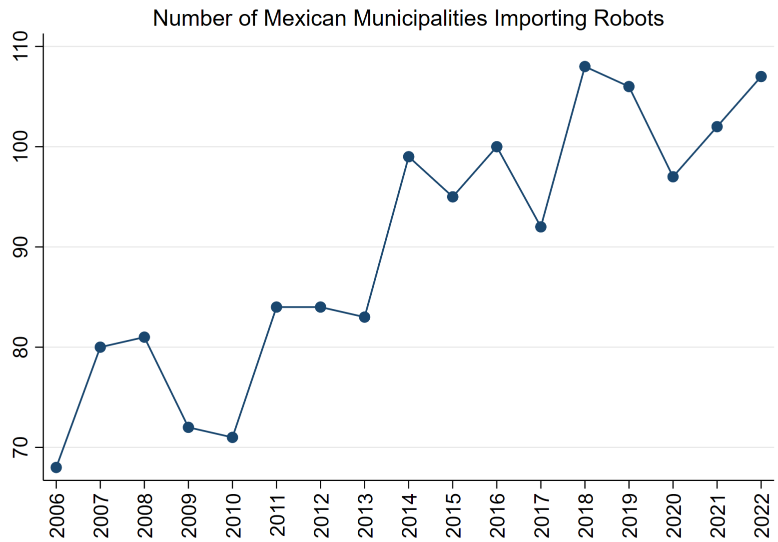
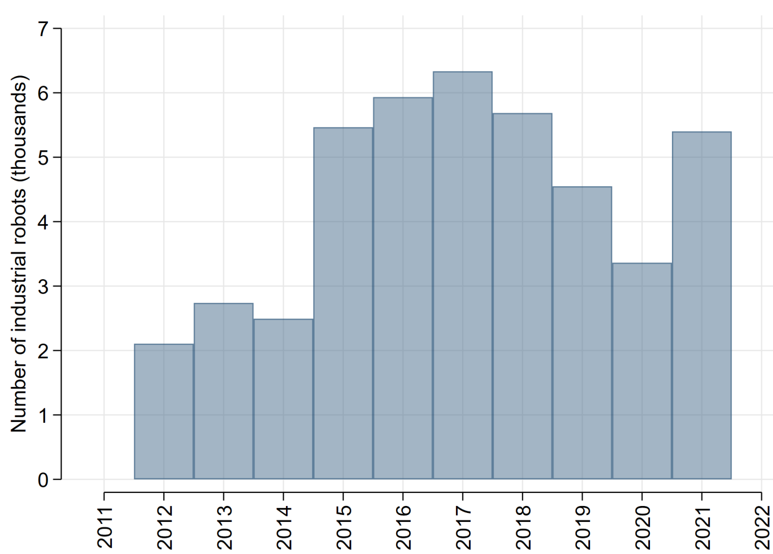
Figures and tables

FIGURE 1: ROBOT ADOPTION IN MEXICO



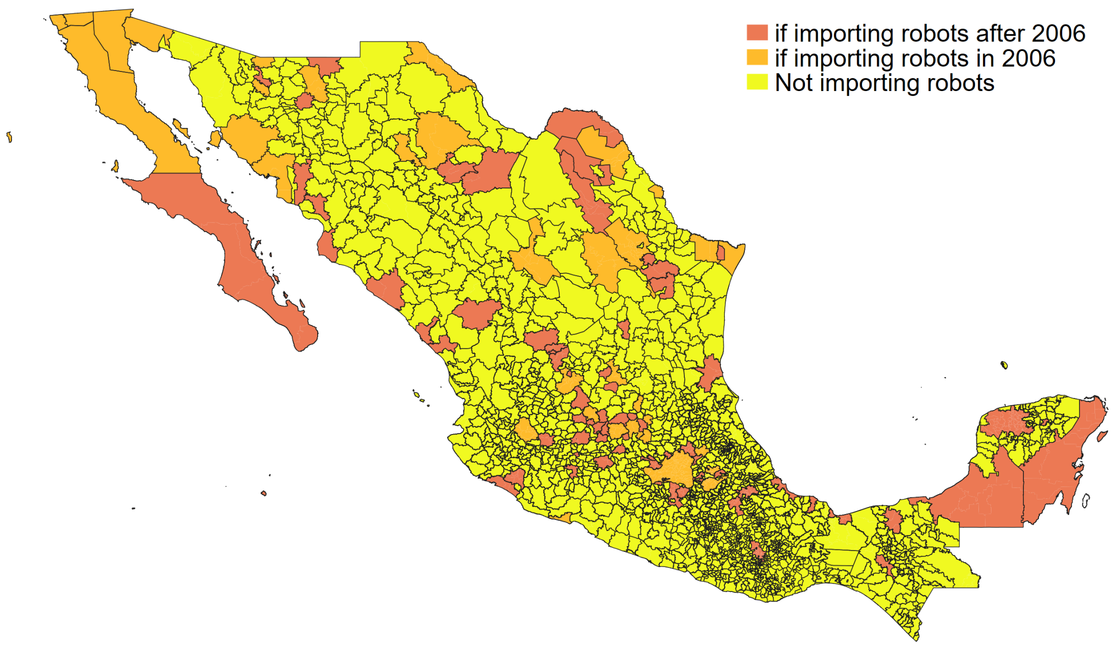
(a) Robot imports from customs records



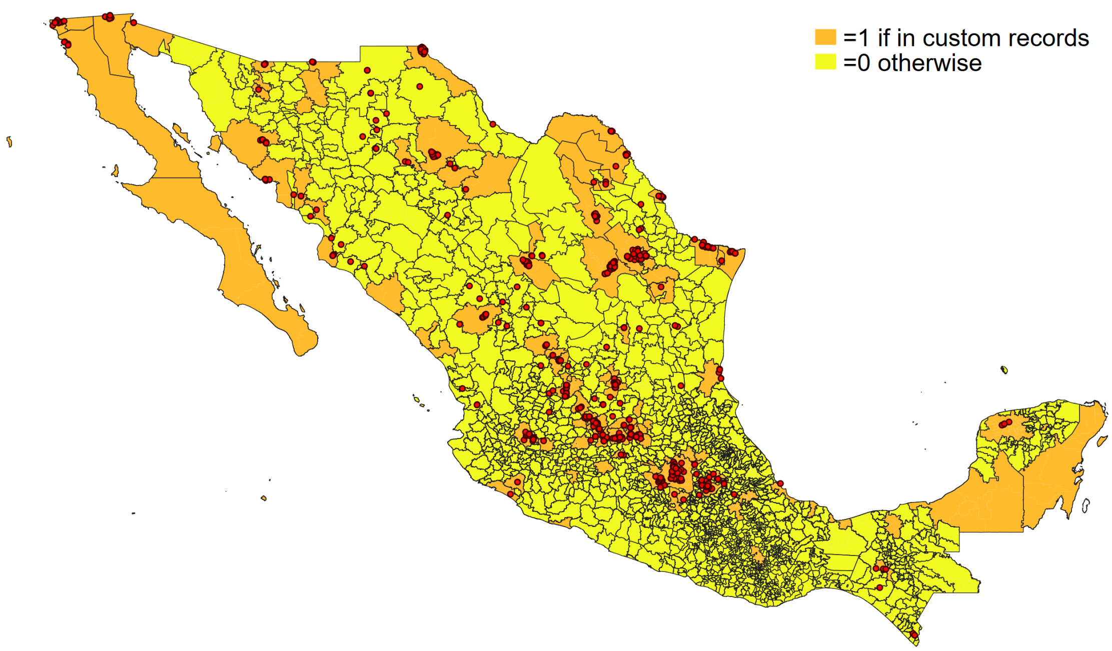
(b) Flow of industrial robots from IFR data

Notes: Panel (a) of Figure 1 depicts the flow evolution of the number of Mexican municipalities (similar to US counties) importing robots between 2006 and 2022. Panel (b) shows the evolution of the flow of industrial robots adopted in Mexico according to IFR data. *Data sources*: Mexican customs records from Secretaría de Economía, own calculations based on IFR World Robotics Database.

Figure 2: Automation geography: robot imports across commuting zones



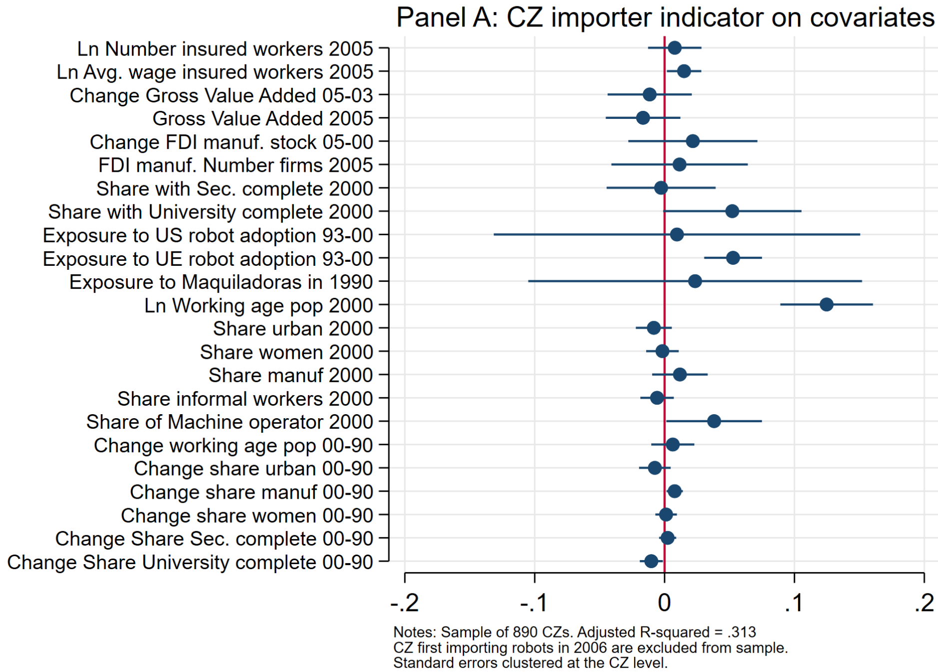
(a) Sample of commuting zones

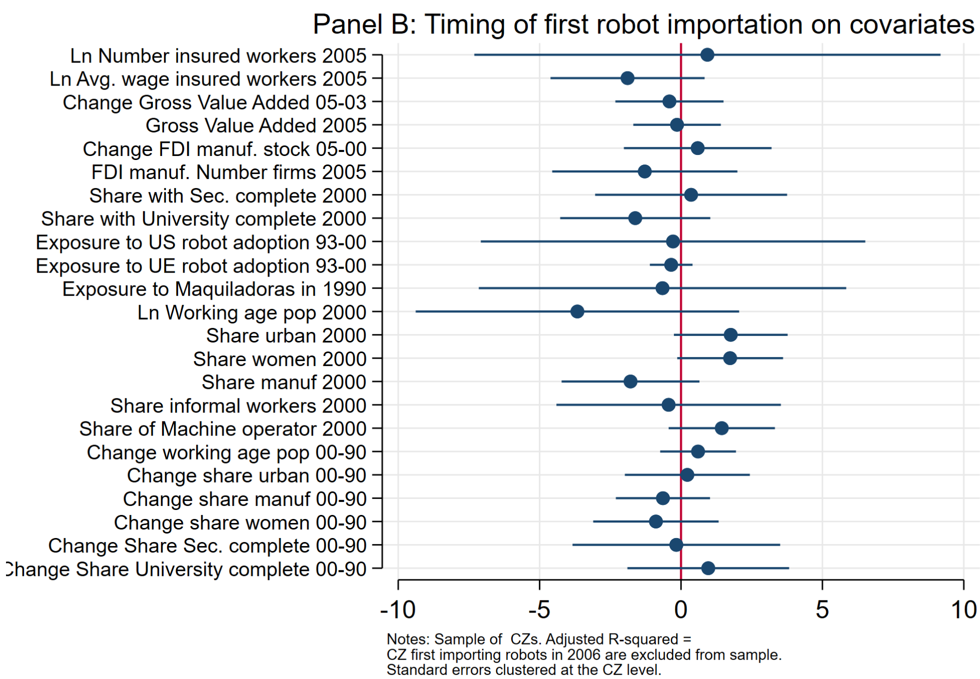


(b) Including large plants in the transportation manufacturing subsector

Notes: Figure 2 depicts the geographic distribution of robot imports across commuting zones. Darker shades indicate commuting zones with any robot imports during 2006–2022. The location of importation refers to the exact municipality where purchasing companies are legally registered, as determined by their fiscal address. This registration location may not necessarily coincide with the physical location of the production plant. Red dots correspond to the location of 991 large plants, defined as establishments with more than 250 employees, in transportation equipment manufacturing (NAICS 336). *Data sources*: Mexican customs records from Secretaría de Economía. National Statistical Directory of Economic Units (DENUE, 2020).

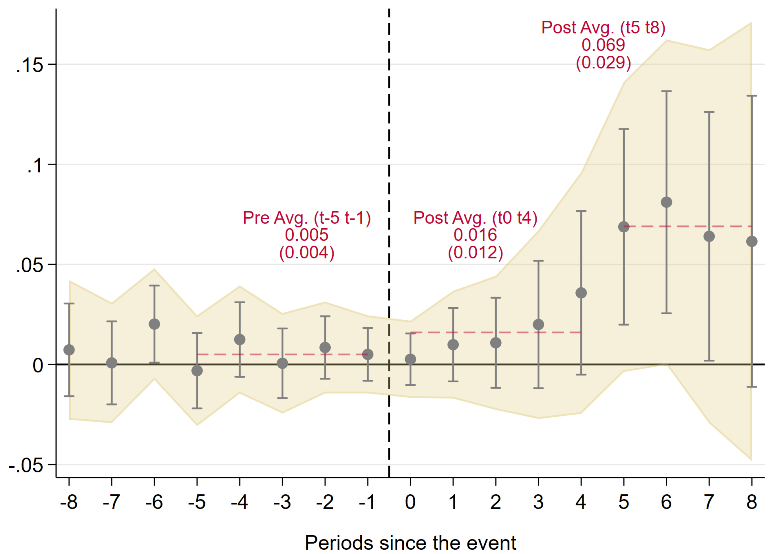
FIGURE 3: PREDICTING WHO IMPORTS ROBOTS AND WHEN



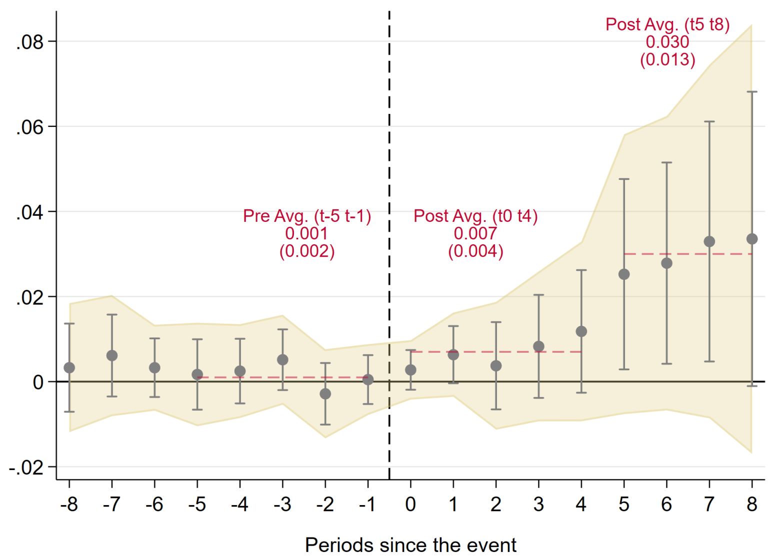


Notes: Panel (a) in Figure 3 displays the estimated OLS coefficients along with the corresponding 95% confidence interval of a linear probability model. In this model, the dependent variable indicates whether the CZ received robot imports between 2006 and 2022. Panel (b) illustrates the estimated OLS coefficients of a model with the year of the first robot importation event as the dependent variable. CZs that began importing robots in 2006 are excluded from the sample. The standard errors are clustered at the CZ level. *Data sources*: Mexican customs records from Secretaría de Economía. IMMS public data. Mexican 1990 and 2000 censuses.

FIGURE 4: ROBOT ADOPTION AND FORMAL LABOR MARKET



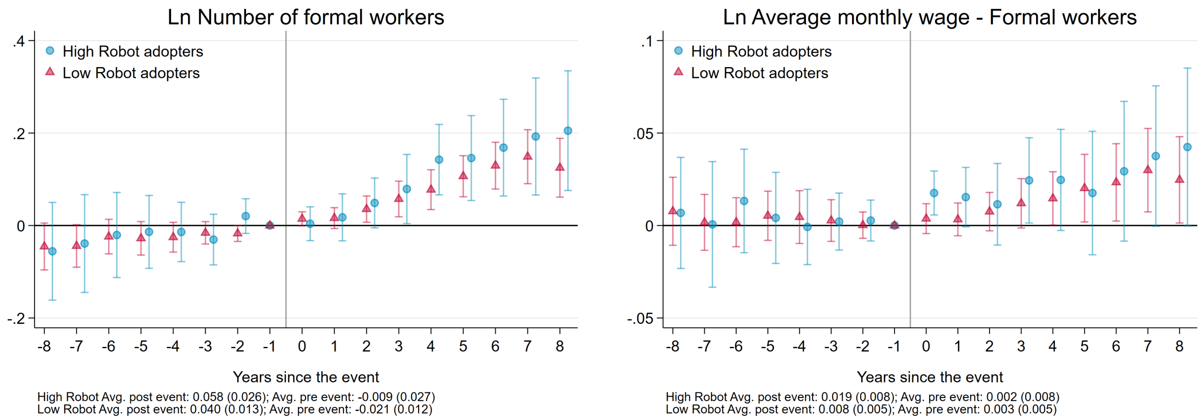
(a) Ln Number of formal workers



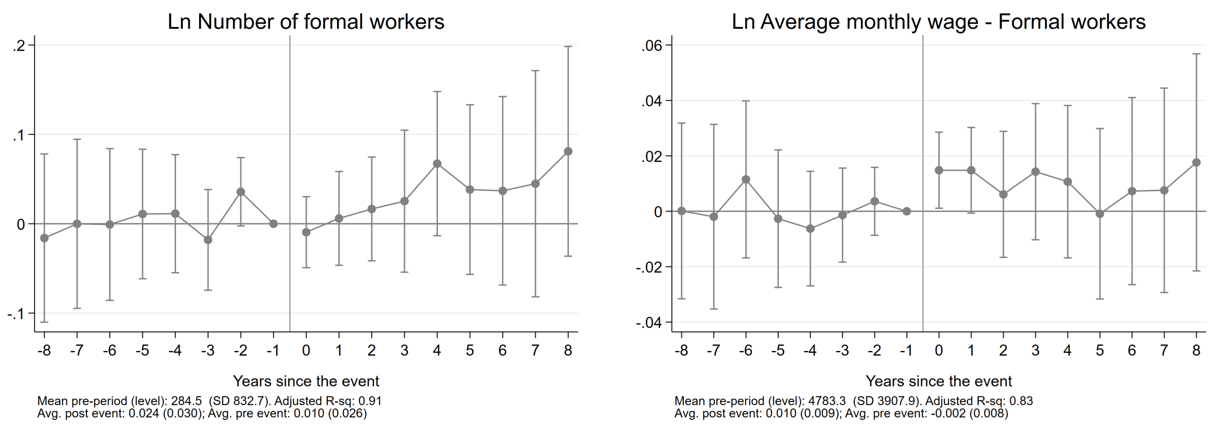
(b) Ln Average monthly wage – formal workers

Notes: Figure 4 plots the estimated $\theta(e)$ event-study coefficients using equation 2 (Callaway and Sant'Anna (2021) method). The outcome variable is, in turn, the log number of formal workers (Panel (a)) and log average real monthly wage for formal workers, deflated to constant 2010 pesos using Mexican consumer price index (CPI) (Panel (b)). The event is defined as a first-time industrial robot importation. The vertical lines reflect the 95% pointwise confidence intervals, while the shadowed area reflects the 95% uniform confidence intervals, which are robust to multiple hypothesis testing. Horizontal lines show the simple average estimated coefficient for different periods: pre-event refers to years -5 to -1; postevent short run refers to years 0 to 4; long-run refers to years 5 to 8. The clustering of standard errors is at the CZ level. Sample of not-yet-but-eventually-treated CZs for 2005–2019, including cohorts that started importing robots during 2007–2022. The unit of observation is CZ–4-digit industry (N=100,619; 71 CZs). *Data sources*: Mexican customs records from Secretaría de Economía. IMMS public data.

FIGURE 5: TWFE MODELS: DD & DDD



(a) DD estimates. CZ–4-dig. industry level

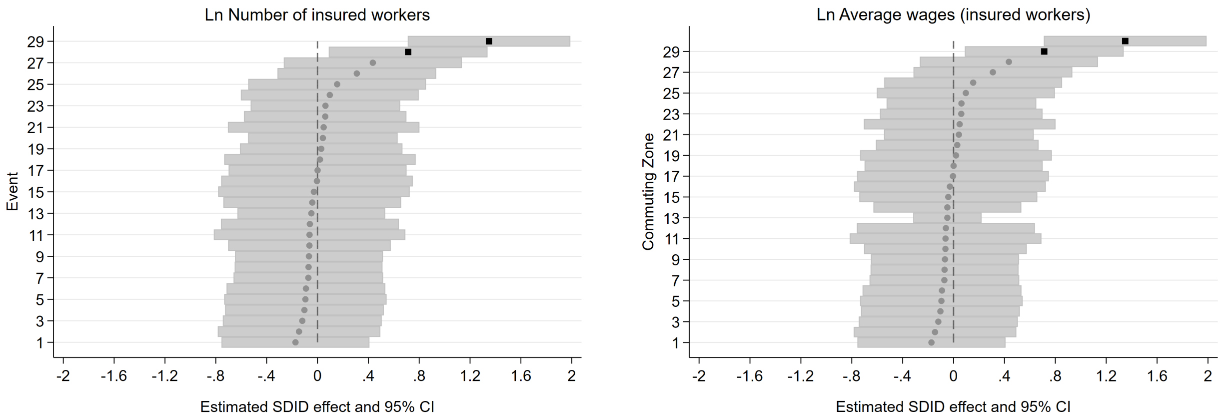


(b) DDD estimates. CZ–4-dig. industry level

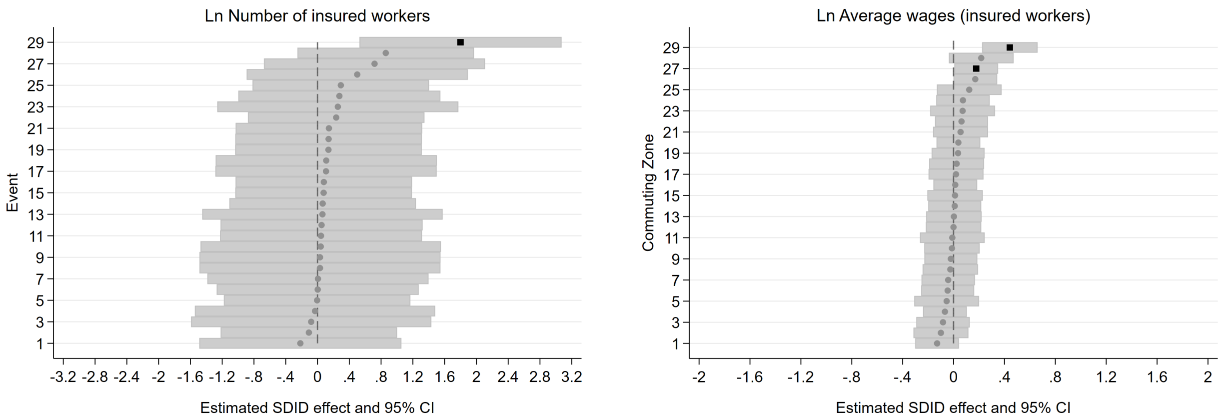
Notes: Figure 5 displays the estimated event-study coefficients obtained using equation 2, a TWFE model. In Panel (a), the results of the difference-in-differences specification are presented, showing overlapping estimates from two different subsamples: "high robot adopters", comprising manufacturing industries with higher rates of robot adoption observed in the IFR data, and "low robot adopters", which include the remaining nonmanufacturing industries. Panel (b) shows estimates from the triple difference-in-differences specification, where the third difference is introduced by contrasting high and low robot adopters. The outcome variable is, in turn, the log number of formal workers and log average real monthly wage for formal workers, deflated to constant 2010 pesos using Mexican CPI. The event is defined as a first-time industrial robot importation. The clustering of standard errors is at the CZ level. Sample of CZs with fewer than 500 thousands inhabitants for the period 2005–2019, including cohorts that started importing robots during 2007–2022. *Data sources*: Mexican customs records from Secretaría de Economía. IMMS public data.

Figure 6: SDD ESTIMATES FOR EACH CZ FROM COHORTS 2010–2016

(a) Sample: All industries

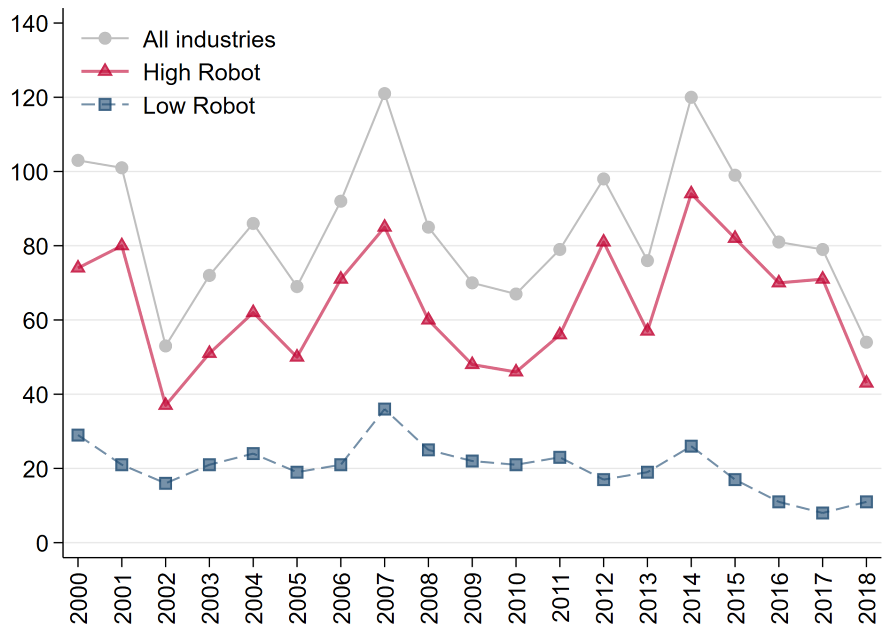


(b) Sample: Manufacturing industries

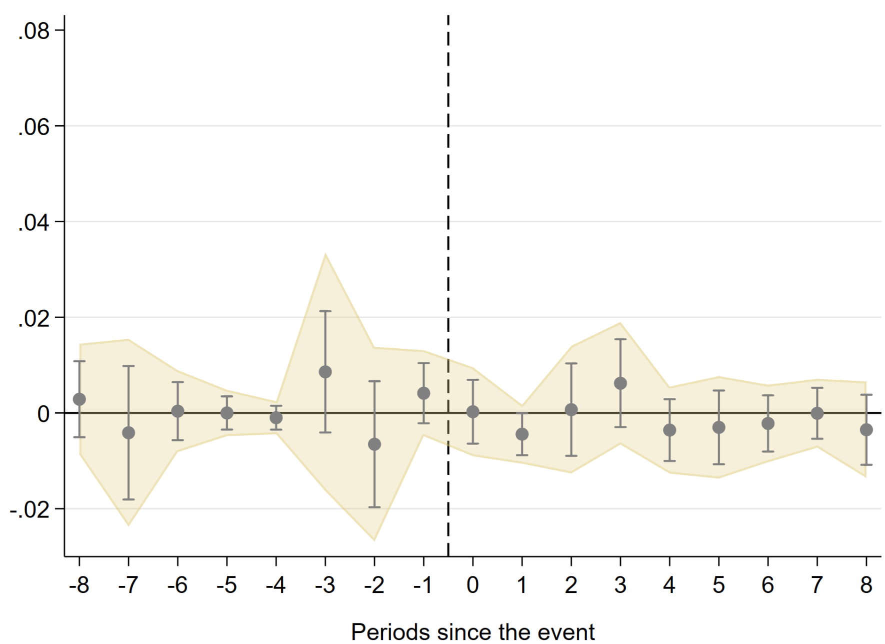


Notes: Figure 6 exhibits the estimated treatment effects using the synthetic difference-in-difference model as outlined by Arkhangelsky et al. (2021). In this figure, each dot represents the estimated effect for individual CZs belonging to cohorts from 2010 to 2016, and the gray bars indicate the corresponding 95% confidence intervals. The comparison group for these estimates is derived from the pool of all CZs that have never been treated, and it employs optimal weighting of units and pre-event periods in its construction. The dataset comprises a panel of CZs, balanced in calendar time, spanning from 2005 to 2019. Panel (a) presents the results for the aggregate of all industries, while Panel (b) focuses specifically on the results for the sample of aggregate manufacturing industries. The outcome variables are the logarithm of the number of formal workers and the logarithm of the average real monthly wage for formal workers, adjusted to constant 2010 pesos using Mexican CPI. The event is defined as a first-time industrial robot importation. *Data sources*: Mexican customs records from Secretaría de Economía. IMMS public data.

Figure 7: ROLE OF LARGE PLANT OPENINGS



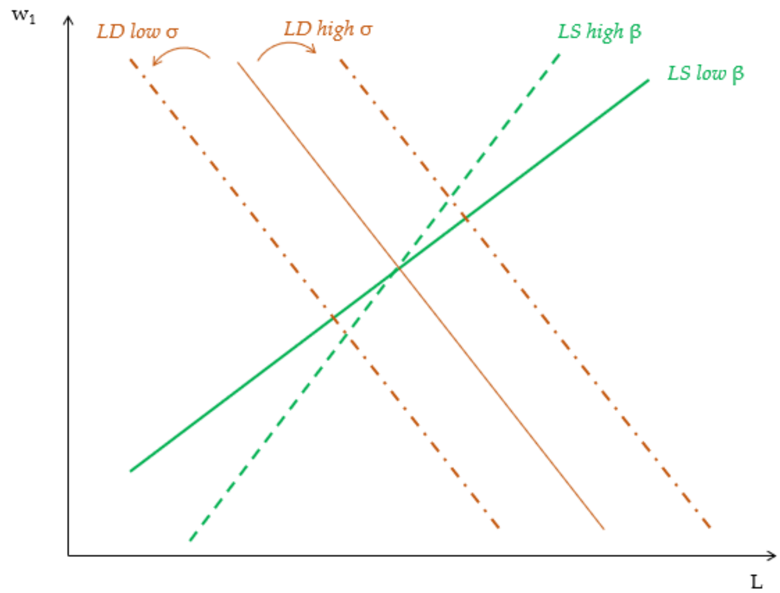
A. Number of large plant openings conditional on the plants' surviving until 2018



B. Effect of first robot importation on the number of large plant openings

Notes: The first graph in Figure 7 illustrates the number of firms in the manufacturing sector (SCIAN codes 31–33) observed in the 2018 census by opening year. The sample is further divided into four groups based on two criteria: firm size (distinguishing between firms with more or fewer than 250 workers) and the extent of robot adoption (classified as high or low robot adopters, as determined by IFR data and described in the notes for Figure 5). The second graph displays the estimated OLS coefficient derived from an event-study specification utilizing a TWFE model (equation 2). The output is the number of large manufacturing firms that opened in period t across CZs. The clustering of standard errors is at the CZ level. The event is defined as a first-time industrial robot importation. *Data sources*: Mexican customs records from Secretaría de Economía. IMMS public data. Mexican economic census 2018.

FIGURE 8: EQUILIBRIUM IN THE LABOR MARKET



Notes: In Figure 8, I visually represent the equilibrium in the labor market and how it depends on given parameters. In equilibrium, the elasticity of labor supply (β) influences the slope of the labor supply curve, affecting the magnitude of employment and wage changes while not altering their direction. When β is relatively low (indicating inelastic labor supply), shifts in labor demand have a muted effect on employment and a heightened impact on wages. The direction of these effects is determined by the parameter σ representing the price elasticity of aggregate demand for manufacturing products. A higher σ results in a rightward shift of the labor demand curve, positively affecting employment and wages.

TABLE 1: COMPARISON OF CZS WITH AND WITHOUT ROBOT IMPORTS

	CZs importing robots				CZs not importing robots			
	All CZ		Excluding 2006 cohort		Balanced sample		Not balanced	
	Mean	s.d.	Mean	s.d.	Mean	s.d.	Mean	s.d.
Number of CZs	104		71		924		1612	
Number of CZs with manufacturing	104		71		730		733	
Number of CZs with manufacturing	82		52		134		134	
IMSS data (levels in 2005)								
Formal workers	1094	(6825)	423	(1468)	65	(509)	65	(508)
Monthly real wage	5350	(3950)	4739	(3697)	3487	(2560)	3487	(2558)
Formal workers in manuf.	879	(3526)	250	(791)	53	(237)	53	(237)
Monthly real wage in manuf.	5191	(3350)	4383	(3041)	3031	(1753)	3031	(1753)
Formal workers in automotive	2059	(4829)	473	(886)	145	(413)	145	(413)
Monthly real wage in automotive	6958	(4273)	5321	(3621)	3130	(1624)	3130	(1624)
Census 2000								
Population (thou.)	591.9	(2004.6)	255.6	(258.1)	33.5	(54.6)	21.9	(43.8)
Working age population (thou.)	373.6	(1307.9)	157.3	(163.4)	19.1	(33.1)	12.4	(26.4)
Share urban	76.9	(18.9)	72.3	(20.2)	42.9	(28.5)	29.7	(31.2)
Share women	51.1	(1.3)	51.2	(1.3)	51.0	(1.8)	51.1	(2.0)
Share manufacturing industry	22.3	(10.6)	19.8	(10.8)	12.1	(8.5)	10.5	(9.4)
Share automotive industry	1.9	(3.1)	1.3	(2.8)	0.3	(1.6)	0.2	(1.3)
Share agriculture industry	14.5	(11.6)	17.6	(12.2)	41.7	(17.3)	51.4	(21.0)
Share service industry	43.3	(9.9)	42.4	(11.2)	29.0	(10.6)	22.8	(12.2)
Share informal workers	26.6	(6.1)	28.1	(6.0)	43.0	(14.7)	52.9	(20.2)
Number in manuf. occupation	12.2	(3.4)	11.9	(3.5)	10.1	(6.6)	9.2	(8.2)
Share secondary complete	14.5	(4.7)	13.5	(5.0)	7.5	(4.1)	5.7	(4.2)
Share superior ed. complete	6.6	(3.2)	6.1	(3.4)	2.8	(2.1)	2.1	(2.0)
Percentage change censuses 1990–2000 (%)								
Population	24.2	(15.9)	21.3	(16.3)	8.7	(15.6)	6.9	(16.8)
Working age population	31.6	(16.9)	29.2	(18.0)	15.9	(17.4)	12.9	(18.8)
Share urban	5.4	(12.1)	6.8	(13.8)	5.8	(22.1)	3.1	(19.7)
Share women	0.5	(1.6)	0.8	(1.5)	1.0	(3.4)	1.3	(4.7)
Share manufacturing industry	18.7	(48.7)	23.3	(56.8)	42.9	(112.8)	57.2	(161.5)
Share automotive industry	189.6	(429.6)	215.0	(499.3)	39.9	(497.1)	20.6	(364.2)
Share agriculture industry	-32.6	(23.2)	-31.8	(22.3)	-24.0	(17.3)	-18.8	(29.3)
Share service industry	14.6	(17.1)	18.6	(18.1)	68.4	(71.4)	102.8	(190.6)
Number in manuf. occupation	73.2	(52.6)	77.6	(60.9)	140.6	(233.7)	158.4	(324.7)
Share secondary complete	46.0	(28.1)	50.5	(31.2)	104.1	(118.8)	114.5	(156.7)
Share superior ed. complete	72.5	(54.8)	80.1	(62.8)	141.0	(208.3)	117.6	(203.7)

Notes: Table 1 provides descriptive statistics comparing CZs that received robot imports during 2006–2022 (treated) to those that did not (never treated). For the treated sample, the table includes sample averages and standard deviations for all CZs. It also presents statistics for a subsample obtained by excluding the always-treated CZs, i.e., the 2006 cohort. The table also shows results for the never-treated sample for balanced and unbalanced calendar time samples. Average real monthly wage for formal workers is measured in constant 2010 pesos (adjusted using Mexican CPI). *Data sources*: IMMS public data. Mexican customs records from Secretaría de Economía. Mexican censuses 1990 and 2000.

Table 2: Summary statistics of import events by event cohort in CZs

Cohort	# CZs	Mean	SD	Min	Max
2006	33	13.9	5.3	1	17
2007	13	8.4	3.9	1	15
2008	6	7.3	5.3	2	14
2009	2	3.5	0.7	3	4
2010	5	5.0	2.9	1	9
2011	6	3.8	3.2	1	10
2012	5	4.0	3.1	1	8
2013	4	2.5	1.9	1	5
2014	3	2.7	1.5	1	4
2015	5	3.8	1.6	1	5
2016	6	3.0	1.4	1	5
2018	7	2.0	1.2	1	4
2019	3	1.3	0.6	1	2
2020	2	1.0	0.0	1	1
2021	2	1.0	0.0	1	1
2022	2	1.0	0.0	1	1

Notes: Table 2 provides summary statistics for robot import events within each treated cohort available in the data. For instance, six different CZs began receiving industrial robot imports in 2011 (2011 cohort). On average, these CZs received imports for approximately 3.8 years, considering CZs that received imports only once (minimum) or for up to ten years (maximum). *Data sources*: Mexican customs records from Secretaría de Economía.

TABLE 3: RULING OUT COMPOSITIONAL EFFECTS

	Pre-event	Postevent
	(1)	(2)
A. Log Number formal workers		
1-year window	0.002	0.010
	(0.008)	(0.007)
2-year window	0.009	0.011
	(0.006)	(0.008)
3-year window	0.007	0.006
	(0.005)	(0.014)
4-year window	0.007	0.011
	(0.006)	(0.023)
B. Log average wage – formal workers		
1-year window	0.001	0.004
	(0.003)	(0.003)
2-year window	-0.000	0.004
	(0.002)	(0.003)
3-year window	-0.001	0.007
	(0.002)	(0.005)
4-year window	-0.001	0.006
	(0.002)	(0.007)

Notes: Table 3 shows the simple average of the estimated $\theta(e)$ event-study coefficients using equation 2 for different periods. The samples are restricted to cohorts included in samples balanced in event-time for different window lengths and that are observed during those periods. The event is defined as a first-time industrial robot importation. Sample of not-yet-but-eventually-treated CZs for the period 2005–2019, including cohorts that started importing robots during 2007–2022. Clustering of standard errors is at the CZ level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. *Data sources*: Mexican customs records from Secretaría de Economía. IMMS public data.

Table 4: Main estimates for different samples

	Pre-event	Postevent short run	Postevent long run
	(1)	(2)	(3)
A. Log Number formal workers			
Baseline	0.005	0.016	0.069***
	(0.004)	(0.012)	(0.029)
Balanced sample	0.005	0.005	0.058**
	(0.004)	(0.011)	(0.029)
Manufacturing	0.009	0.012	0.073
	(0.008)	(0.018)	(0.049)
Manufacturing robot adopters	0.011	0.017	0.103*
	(0.009)	(0.023)	(0.059)
Never treated	0.012***	0.041***	0.108***
	(0.004)	(0.010)	(0.021)
B. Log Average wage – formal workers			
Baseline	0.001	0.007	0.030**
	(0.002)	(0.004)	(0.013)
Balanced sample	0.002	0.005	0.027**
	(0.002)	(0.004)	(0.013)
Manufacturing	0.003	0.000	0.024
	(0.002)	(0.008)	(0.020)
Manufacturing robot adopters	0.001	0.007	0.040*
	(0.003)	(0.010)	(0.024)
Never treated	0.001	0.006	0.026***
	(0.001)	(0.004)	(0.008)

Notes: Table 4 shows the simple average of the estimated $\theta(e)$ event-study coefficients using equation 2 for different periods. Pre-event: years -5 to -1; postevent short run: years 0 to 4; long run: years 5 to 8. The outcome variable is, in turn, log number of formal workers (Panel (a)) and log average real monthly wage for formal workers, deflated to constant 2010 pesos using Mexican CPI (Panel (b)). The event is defined as a first-time industrial robot importation. The baseline sample includes not-yet-but-eventually-treated CZs for 2005–2019, including cohorts that started importing robots during 2007–2022. The manufacturing sample is a subset of the baseline sample, focusing only on CZs within the manufacturing sector (3-digit SCIAN codes ranging from 311 to 339). The robot-adopter sample further narrows the selection to manufacturing sectors that adopt robots in the IFR dataset. Finally, the never-treated sample is an extension of the baseline sample encompassing CZs that did not receive robot imports during the analyzed period, which serves as a comparison group. Clustering of standard errors is at the CZ level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. *Data sources*: Mexican customs records from Secretaría de Economía. IMMS public data.

Table 5: Heterogeneities

	Log Number Formal Workers			Log Average Wage		
	Pre-event	Postevent short run	Postevent long run	Pre-event	Postevent short run	Postevent long run
	(1)	(2)	(3)	(4)	(5)	(6)
A. By age group						
Aged 15–19	0.006	0.004	0.032	-0.000	-0.004	0.001
	(0.007)	(0.027)	(0.044)	(0.002)	(0.007)	(0.012)
Aged 20–34	0.006	0.011	0.071**	-0.000	0.004	0.029***
	(0.004)	(0.012)	(0.035)	(0.002)	(0.004)	(0.012)
Aged 35–49	0.006*	0.001	0.028	0.000	0.007*	0.026**
	(0.003)	(0.012)	(0.026)	(0.002)	(0.004)	(0.013)
Aged 50–64	0.007***	0.016	0.085***	0.005***	-0.007	0.008
	(0.003)	(0.011)	(0.023)	(0.002)	(0.007)	(0.015)
Age >64	0.009*	0.006	0.007	0.007	-0.003	0.029
	(0.005)	(0.015)	(0.040)	(0.004)	(0.010)	(0.027)
B. By wage group						
Low-wage group	0.002	0.003	0.035	0.002*	-0.002	0.009
	(0.004)	(0.011)	(0.031)	(0.001)	(0.004)	(0.011)
Middle-wage group	0.002	0.019	0.070*	0.001	0.002	0.007
	(0.005)	(0.017)	(0.037)	(0.001)	(0.002)	(0.005)
High-wage group	0.003	-0.006	0.024	-0.002*	0.001	0.002
	(0.006)	(0.018)	(0.036)	(0.001)	(0.003)	(0.009)
C. By firm Size						
1–5 workers	0.006*	0.005	0.037	0.002	0.003	0.027**
	(0.003)	(0.011)	(0.024)	(0.002)	(0.006)	(0.013)
6–50 workers	-0.003	-0.003	0.023	0.001	-0.003	0.017
	(0.003)	(0.011)	(0.021)	(0.001)	(0.005)	(0.012)
51–250 workers	0.007	0.004	0.041	-0.003	-0.003	-0.006
	(0.005)	(0.018)	(0.030)	(0.003)	(0.007)	(0.022)
>250 workers	-0.001	0.028*	0.023	0.002	-0.007	0.014
	(0.005)	(0.015)	(0.038)	(0.003)	(0.008)	(0.020)
D. By CZ size						
Excluding >500k hab.	0.004	0.022	0.096***	0.002	0.012**	0.038***
	(0.003)	(0.014)	(0.034)	(0.002)	(0.005)	(0.016)
Excluding >150k hab.	0.004	0.017	0.133**	0.002	0.023***	0.049***
	(0.005)	(0.022)	(0.057)	(0.002)	(0.008)	(0.020)

Notes: See notes in Table 4. Sample of not-yet-but-eventually-treated CZs for the period 2005–2019, including cohorts that started importing robots during 2007–2022. Clustering of standard errors is at the CZ level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. *Data sources*: Mexican customs records from Secretaría de Economía. IMMS public data.

Table 6: Other robot adoption measures

	Pre-event	Postevent short run	Postevent long run
	(1)	(2)	(3)
A. Log Number formal workers			
Baseline CS	0.005	0.016	0.069***
	(0.004)	(0.012)	(0.029)
Import value event	<0.001	0.028	0.383***
	(0.007)	(0.025)	(0.071)
Baseline DD	-0.003	0.033*	0.100***
	(0.011)	(0.019)	(0.043)
DD with intensity	-0.001	0.031*	0.066***
	(0.016)	(0.016)	(0.026)
B. Log Average wage – formal workers			
Baseline CS	0.001	0.007	0.030**
	(0.002)	(0.004)	(0.013)
Import value event	-0.001	-0.001	0.067**
	(0.002)	(0.010)	(0.030)
Baseline DD	-0.007	0.017	0.046
	(0.008)	(0.013)	(0.030)
DD with intensity	-0.014**	0.017***	0.035***
	(0.007)	(0.006)	(0.010)

Notes: Table 6 shows the event-study estimates using different robot adoption measures. *Baseline CS* corresponds to the main specification in Table 4. *Import value event* refers to the same model but defines the event as the period when the cumulative total value of robot imports is larger than 50% of the CZ's 2005 total wage bill (refer to Figure A15 to see estimates under different thresholds). *Baseline DD* refers to the estimation of a TWFE model defining the event as first-time receipt of industrial robot imports. *DD with intensity* refers to *Baseline DD* interacting the event with a measure of robot importation intensity, the cumulative number of years receiving robot imports. Pre-event: years -5 to -1; postevent short run: years 0 to 4; long run: years 5 to 8. The outcome variable is, in turn, log number of formal workers (Panel (a)) and log average real monthly wage for formal workers, deflated to constant 2010 pesos using Mexican CPI (Panel (b)). Sample of not-yet-but-eventually-treated CZs for the period 2005–2019, including cohorts that started importing robots during 2007–2022. Clustering of standard errors is at the CZ level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. *Data sources*: Mexican customs records from Secretaría de Economía. IMMS public data.

TABLE 7: ADDITIONAL LABOR MARKET OUTCOMES FROM ENOE DATA

	Mean	Pre-event	Event year	Postevent short run	Postevent long run
	(1)	(2)	(3)	(4)	(5)
A. Formal employment and earnings					
Log number workers (IMSS)	54122.5	0.014***	0.003	0.044**	0.118
		(0.006)	(0.008)	(0.020)	(0.076)
Log number workers (ENOE)	46452.3	0.042	-0.054	0.036	0.300
		(0.035)	(0.072)	(0.086)	(0.224)
Log average wage (IMSS)	208.6	<0.001	0.008*	0.008	0.012
		(0.003)	(0.004)	(0.008)	(0.016)
Log hours worked	49.4	<0.001	0.016	-0.013	-0.031*
		(0.003)	(0.017)	(0.009)	(0.018)
B. Informal employment					
Log number informal workers	84293.8	0.033*	-0.139**	-0.043	0.169*
		(0.018)	(0.061)	(0.070)	(0.099)
Informality rate	60.2	0.163	-2.111**	-1.016	1.600
		(0.451)	(1.043)	(1.423)	(2.068)
C. Unemployment					
Log number unemployed	6235.5	0.018	-0.497	-0.203	0.313
		(0.095)	(0.308)	(0.246)	(0.329)
Unemployment rate	0.04	-0.001	-0.003	0.000	-0.002
		(0.001)	(0.004)	(0.004)	(0.005)
D. Educational attainment					
Log number less than primary	27473.5	-0.030	0.063	0.054	0.199
		(0.039)	(0.200)	(0.260)	(0.248)
Log number primary complete	121210.9	0.021	-0.082	-0.025	0.094
		(0.018)	(0.064)	(0.074)	(0.108)
Log number secondary complete	51878.8	0.069	-0.067	-0.062	0.209
		(0.053)	(0.064)	(0.093)	(0.142)
Log number tertiary complete	30868.6	0.121	0.018	0.056	0.813*
		(0.076)	(0.197)	(0.218)	(0.455)
E. Other					
Log number working-age pop.	231568.3	0.020	-0.079	-0.005	0.158
		(0.017)	(0.056)	(0.065)	(0.099)
Log number pop. in LFP	149827	0.027	-0.102*	-0.026	0.128
		(0.017)	(0.055)	(0.065)	(0.095)
Log number living in urban area	134449.7	0.001	-0.002	0.011*	0.034*
		(0.002)	(0.003)	(0.006)	(0.020)

Notes: See notes in 4. Sample of not-yet-but-eventually-treated CZs for the period 2005–2019, including cohorts that started importing robots during 2007–2022. Sample is restricted to CZs available in ENOE. Clustering of standard errors is at the CZ level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. *Data sources*: Mexican customs records from Secretaría de Economía. IMMS public data. ENOE data.

TABLE 8: EFFECTS OF ROBOTS ON CHANGES IN LABOR MARKET OUTCOMES: 2SLS ESTIMATES USING THE **CHANGE IN ROBOT EXPOSURE BETWEEN 2011 AND 2015**

A: Population Censuses outcomes. Long differences 2010-2015

	All industries											
	Employment-to-pop		Wage-empl-to-pop		Self-empl-to-pop		Labor Force Particip. rate		Unemployment rate		Share Informal	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
MX exposure to robots	-0.4	-0.4	-0.5	-0.5	0.1	0.1	-0.3	-0.4	-0.7	-0.7	0.4	0.4
2011-2015	(1.6)	(2.1)	(1.4)	(1.6)	(1.1)	(1.2)	(1.4)	(1.9)	(1.1)	(1.2)	(1.7)	(1.6)
Observations	1,804	19	1,804	19	1,804	19	1,804	19	1,798	19	1,797	19
Adj. R-squared	0.154		0.0531		0.180		0.137		0.0231		0.155	
Mean dep. 2005	45.47		23.50		21.97		50.39		4.406		49.13	
Lower limit CI	-3.452	-4.502	-3.211	-3.571	-1.974	-2.156	-3.165	-4.099	-2.803	-3.056	-2.86	-2.793
Upper limit CI	2.703	3.713	2.216	2.565	2.22	2.373	2.479	3.388	1.386	1.659	3.699	3.606
First-stage coefficient	0.26		0.26		0.26		0.26		0.266		0.266	
First-stage F-statistic	4.895		4.895		4.895		4.895		5.169		5.17	

B: IMSS data - Insured workers. Long differences 2010-2015

	All industries						Manufacturing industry					
	Ln Number Workers		Ln Payroll		Ln Mean Wage		Ln Number Workers		Ln Payroll		Ln Mean Wage	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
MX exposure to robots	5.0	5.1	4.2	4.2	-0.9	-0.8	-26.3	-26.1	-19.7	-19.6	6.5	6.5
2011-2015	(10.9)	(9.7)	(12.5)	(8.6)	(4.5)	(2.6)	(28.4)	(16.1)	(27.7)	(15.5)	(10.1)	(6.9)
Observations	1,211	19	1,211	19	1,211	19	777	19	777	19	777	19
Adj. R-squared	0.010		0.014		0.008		0.067		0.037		0.031	
Mean dep. 2005	12050		3004000		158.10		3485		954484		134.20	
Lower limit CI	-16.44	-13.98	-20.29	-12.57	-9.682	-5.979	-81.98	-57.54	-74.04	-49.96	-13.22	-7.108
Upper limit CI	26.5	24.12	28.64	21.02	7.97	4.29	29.47	5.344	34.54	10.83	26.23	20.17
First-stage coefficient	0.252		0.252		0.252		0.24		0.24		0.24	
First-stage F-statistic	3.976		3.976		3.976		3.043		3.043		3.043	

Notes: This table presents 2SLS estimates of the effects of exposure to robots on changes in labor market outcomes between 2010 and 2015. Panel (a) presents outcomes based on population censuses and Panel (b) those based on the IMSS dataset. In all models, I instrument Mexican exposure to robots using exposure to robots from European countries. All IV estimates are from regressions weighted by CZ share in national working-age population in 1990. The covariates included in each model are region dummies, exposure to US robots (2011–2015), exposure to *maquiladoras* in 1990, demographic characteristics of CZs in 1990 (log population; share urban; share women; share population over 65; share population with high school complete; share population with college complete; and shares of employment in manufacturing, services and agriculture sectors). For each outcome, the first column presents standard error estimates that are robust to heteroskedasticity and correlation within CZ, and the second column presents robust standard errors computed following Borusyak et al. (2019) in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. *Data sources*: IMMS public data. Mexican 1990 and 2000 censuses. IFR data. Faber (2020).

TABLE 9: MECHANISMS

	Number of firms	Labor share	Gross value added (log)	GVA per worker (log)	Total fixed assets (log)	Capital per worker	Input cost (log)	Total payroll (log)	Number workers (log)	Workers prod. and sales (log)	Workers admin (log)	Hours worked (log)	Hours prod. and sales (log)	Hours admin (log)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Panel (a). All industries														
D_{mt}^{post}	0.012	-0.011	0.054*	0.028	0.017	-0.019	0.060**	0.025	0.018	0.009	0.000	0.020	0.011	-0.006
	(0.013)	(0.068)	(0.030)	(0.024)	(0.043)	(0.014)	(0.025)	(0.029)	(0.015)	(0.023)	(0.028)	(0.015)	(0.024)	(0.028)
Observations	93,464	32,979	32,352	32,352	32,908	43,054	32,982	30,945	43,054	40,283	27,181	42,913	40,149	27,071
Adj. R-squared	0.932	0.131	0.849	0.626	0.803	-0.0818	0.875	0.852	0.890	0.842	0.751	0.885	0.832	0.737
Mean	27.80	0.330	14.83	0.0642	19.09	0.0508	14.86	4.812	200.5	98.15	24.59	501.9	245.9	60.44
Panel (b). Manufacturing sector: Metal, machinery and equipment, power generation, transportation, plastics and rubber														
D_{mt}^{post}	0.024	-0.025	0.301*	0.169*	0.351**	0.026*	0.298**	0.304**	0.072	0.099	-0.040	0.077	0.105	-0.022
	(0.024)	(0.056)	(0.156)	(0.098)	(0.159)	(0.014)	(0.134)	(0.139)	(0.073)	(0.095)	(0.127)	(0.078)	(0.105)	(0.131)
Observations	5,509	769	761	761	765	983	769	695	983	901	586	983	901	586
Adj. R-squared	0.887	0.0558	0.794	0.608	0.751	0.190	0.797	0.782	0.802	0.755	0.669	0.786	0.738	0.662
Mean	12.50	0.400	15.78	0.0521	11.99	0.0478	21.20	8.296	164.1	98.48	19.18	359.7	224.1	42.48

Notes: Table 9 shows the results of estimating the TWFE model, equation 3, where the event is defined as a first-time industrial robot importation. Panel (a) presents results for all the industries and Panel (b) for the following manufacturing industries: basic metals, metal products, machinery, equipment, electronics, appliances, power generation, transportation, and other manufacturing not included in Table 10. The first dependent variable is the log number of firms at the CZ–five-digit sector level (column (1)). The following seven dependent variables are balance-sheet measures capturing firm productivity and size, aggregated to the CZ–five-digit sector level: labor share, calculated as the total wage bill divided by gross value added (column (2)); capital per worker, calculated as the total fixed assets divided by the number of workers (column (3)); log total gross value added (column (4)) and GVA per worker (column (5)); log input costs (column (6)); log total wage bill (column (7)); and log fixed assets (as a proxy for capital, column (8)). Column (9) presents results for the log number of workers, column (10) for the log number of workers in production and sales, and column (11) for the log number of workers in administrative jobs (including managers). Columns (12)–(14) show similar results for the log number of hours worked in a year. The sample includes not-yet-but-eventually-treated CZs for 2005–2019, including cohorts that started importing robots during 2007–2022. Means are calculated for the period before the event, in levels, and are reported in millions of Mexican pesos (CPI-adjusted to 2005), except for the number of workers, number of hours worked in a year (in thousands), and shares (ratios). Standard errors are clustered at the CZ level and are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. *Data sources*: Mexican economic censuses 2003, 2008, 2013, and 2018.

TABLE 10: MECHANISMS: OTHER INDUSTRIES

	Number of firms	Labor share	Gross value added (log)	GVA per worker (log)	Total fixed assets (log)	Capital per worker	Input cost (log)	Total payroll (log)	Number workers (log)	Workers prod. and sales (log)	Workers admin (log)	Hours worked (log)	Hours prod. and sales (log)	Hours admin (log)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Panel (a). Manufacturing: Wood and paper, chemical industries														
D_{mt}^{post}	-0.014	-0.018	0.031	0.014	0.063	0.032**	-0.013	-0.026	-0.084	-0.203**	-0.195*	-0.073	-0.203**	-0.185
	(0.023)	(0.031)	(0.111)	(0.066)	(0.116)	(0.013)	(0.100)	(0.114)	(0.066)	(0.100)	(0.111)	(0.067)	(0.101)	(0.114)
Observations	5,356	1,068	1,036	1,036	1,063	1,433	1,068	1,014	1,433	1,354	929	1,433	1,354	929
R-squared	0.923	0.393	0.799	0.612	0.790	0.581	0.819	0.754	0.843	0.753	0.649	0.842	0.755	0.632
Mean	24.10	0.346	32.84	0.0933	32.55	0.0542	74.43	6.827	285.4	140.3	30.88	731.1	382.7	77.46
Panel (b). Manufacturing: Textiles, apparel, leather goods, food, and beverage industries														
D_{mt}^{post}	-0.028	0.019	0.042	0.051	-0.009	0.005	0.030	0.144	-0.094	-0.017	-0.072	-0.070	0.003	-0.065
	(0.030)	(0.054)	(0.093)	(0.060)	(0.118)	(0.010)	(0.081)	(0.113)	(0.063)	(0.091)	(0.097)	(0.065)	(0.096)	(0.099)
Observations	7,393	1,721	1,715	1,715	1,690	2,235	1,721	1,443	2,235	1,902	969	2,235	1,902	969
R-squared	0.888	0.0699	0.751	0.516	0.729	0.521	0.787	0.739	0.783	0.739	0.727	0.773	0.726	0.715
Mean	15.32	0.388	15.30	0.0419	15.72	0.0378	27.63	7.844	227.6	177.7	33.62	496.6	393.5	75.50
Panel (c). Nonmanufacturing														
D_{mt}^{post}	0.017	-0.012	0.050*	0.025	0.009	-0.023	0.059**	0.015	0.027*	0.016	0.011	0.027*	0.017	0.003
	(0.013)	(0.075)	(0.030)	(0.024)	(0.043)	(0.016)	(0.025)	(0.027)	(0.014)	(0.022)	(0.029)	(0.015)	(0.023)	(0.029)
Observations	75,206	29,421	28,840	28,840	29,390	38,403	29,424	27,793	38,403	36,126	24,697	38,262	35,992	24,587
R-squared	0.935	-0.0462	0.856	0.629	0.807	-0.0718	0.881	0.861	0.899	0.852	0.757	0.894	0.841	0.742
Mean	30.28	0.325	14.11	0.0648	18.96	0.0514	11.72	4.495	196.5	92.28	24.11	496.7	233.2	59.58

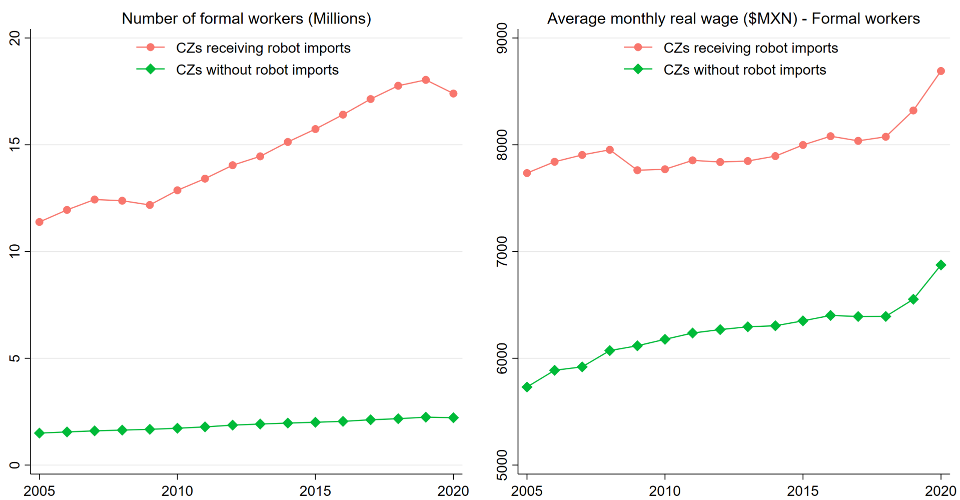
Notes: Table 10 shows the results of estimating the TWFE model, equation 3, where the event is defined as a first-time industrial robot importation. Panel (a) presents results for the following manufacturing industries: food, drinks, tobacco, energy, fossil fuels, chemicals, plastics, and rubber. Panel (b) presents results for the following manufacturing industries: textile, clothing, leather, wood, paper, printing, and nonmetallic mineral products. Panel (c) includes results for all nonmanufacturing industries. The first dependent variable is the log number of firms at the CZ–five-digit sector level (column (1)). The following seven dependent variables are balance-sheet measures capturing firm productivity and size, aggregated to the CZ–five-digit sector level: labor share, calculated as the total wage bill divided by gross value added (column (2)); capital per worker, calculated as the total fixed assets divided by the number of workers (column (3)); log total gross value added (column (4)) and GVA per worker (column (5)); log input costs (column (6)); log total wage bill (column (7)); and log fixed assets (as a proxy for capital, column (8)). Column (9) presents results for the log number of workers, column (10) for the log number of workers in production and sales, and column (11) for the log number of workers in administrative jobs (including managers). Columns (12)–(14) show similar results for the log number of hours worked in a year. The sample includes not-yet-but-eventually-treated CZs for 2005–2019, including cohorts that started importing robots during 2007–2022. Means are calculated for the period before the event, in levels, and are reported in millions of Mexican pesos (CPI-adjusted to 2005), except for the number of workers, number of hours worked in a year (in thousands), and shares (ratios). Standard errors are clustered at the CZ level and are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. *Data sources*: Mexican economic censuses 2003, 2008, 2013, and 2018.

Appendices

Appendix A Additional Figures

FIGURE A1: TRENDS IN THE MEXICAN FORMAL SECTOR

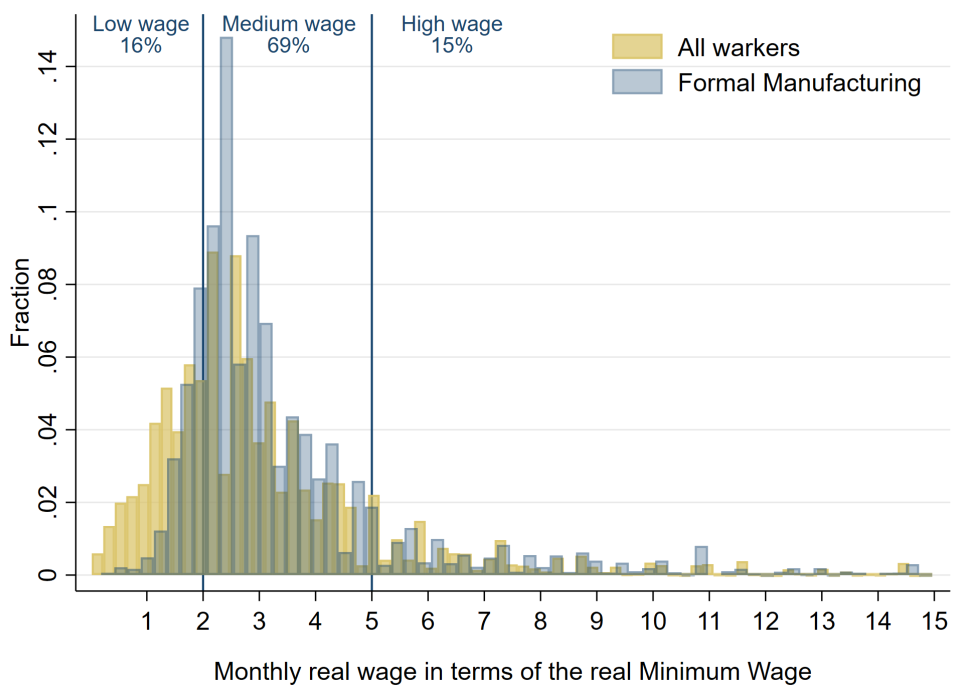
(a) Labor outcomes by wage group



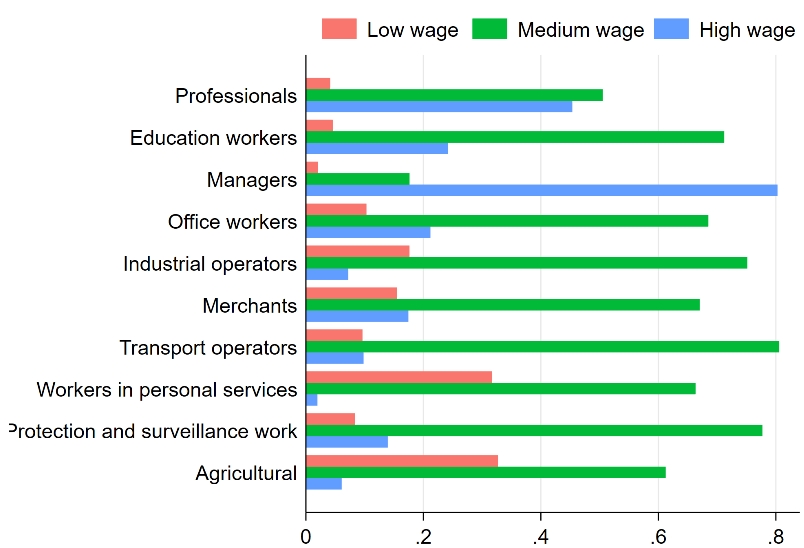
(b) Labor outcomes by treatment status

Notes: Figure A1 illustrates the trends in the number of formal workers (measured in millions) and average monthly real wages (adjusted to 2010 Mexican pesos) over time. In Panel (a), the sample of formal workers is divided into three distinct wage categories: those earning two minimum wages or less (low wage), those earning between two and five minimum wages (medium wage), and those earning more than five minimum wages (high wage). In Panel (b), the sample is divided into two groups: CZs receiving industrial robot imports at any point during the analysis period and CZs not receiving such imports. *Data sources*: IMMS public data, Mexican customs records from Secretaría de Economía.

FIGURE A2: CHARACTERIZATION OF MEXICAN MANUFACTURING SECTOR



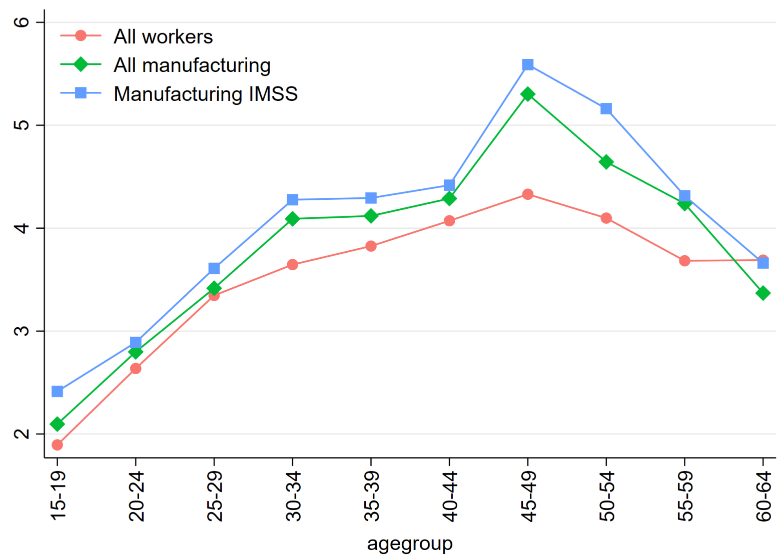
(a) Fraction of workers for each wage bin



(b) Fraction of wage group for each occupation

Notes: Panel (a) of Figure A2 shows the histogram of the log average monthly real wages (adjusted to 2005 Mexican pesos) in terms of the monthly minimum wage for either all workers or formal workers. The vertical lines divide formal workers into three distinct wage categories: those earning two minimum wages or less (low wage), those earning between two and five minimum wages (medium wage), and those earning more than five minimum wages (high wage). Panel (b) shows for each occupation the fraction of formal workers in each wage group. For example, 73% of industrial operators fall into the medium-wage group. *Data sources*: Own elaboration based on ENOE 2005, 4th quarter.

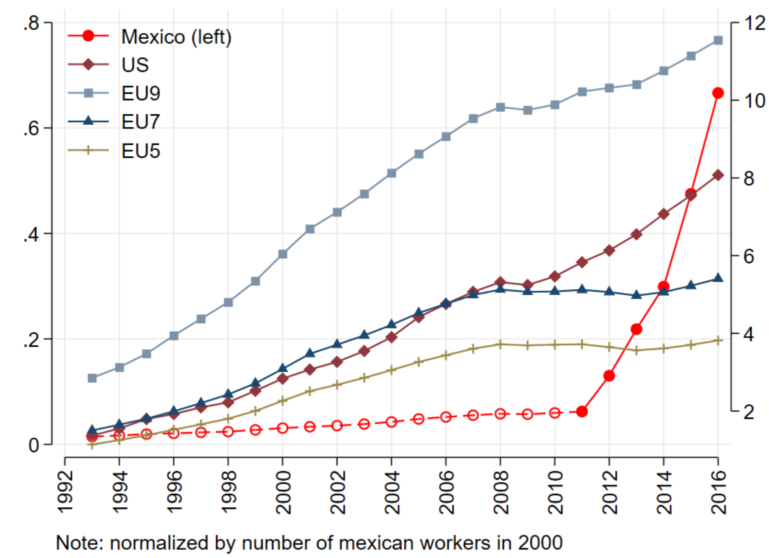
FIGURE A3: CHARACTERIZATION OF MEXICAN MANUFACTURING SECTOR



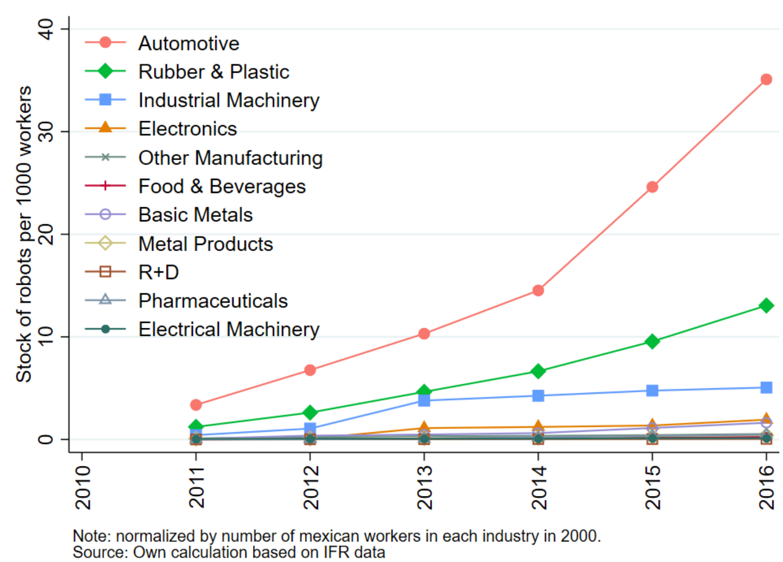
(c) Average monthly wage by age

Notes: Figure A3 illustrates the average wage trends for different groups of workers across various age brackets. The vertical axis of the figure represents the average monthly wages, measured in terms of the monthly minimum wage, for three distinct groups: all workers (across all industries), all manufacturing workers, and all formal manufacturing workers (those registered in IMSS). *Data sources*: Own elaboration based on ENOE 2005, 4th quarter.

FIGURE A4: INDUSTRIAL ROBOTS IN MEXICO: LARGE INCREASE BUT EARLY STAGE



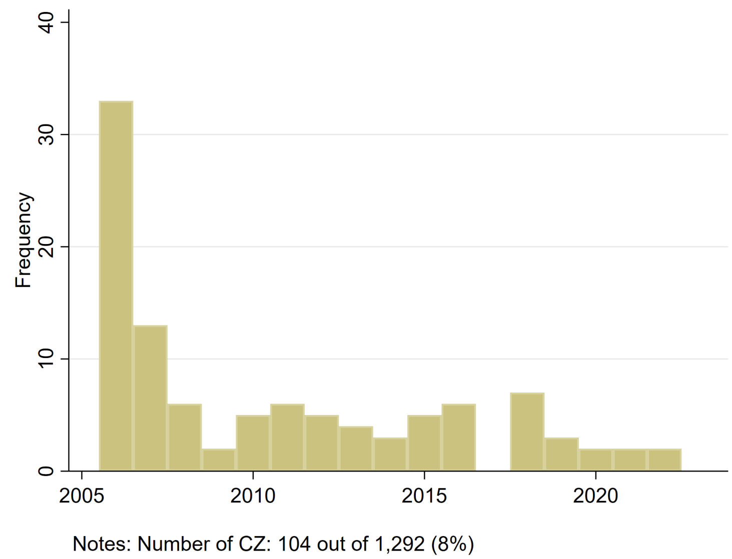
(A) Automation by country



(B) Automation by industry

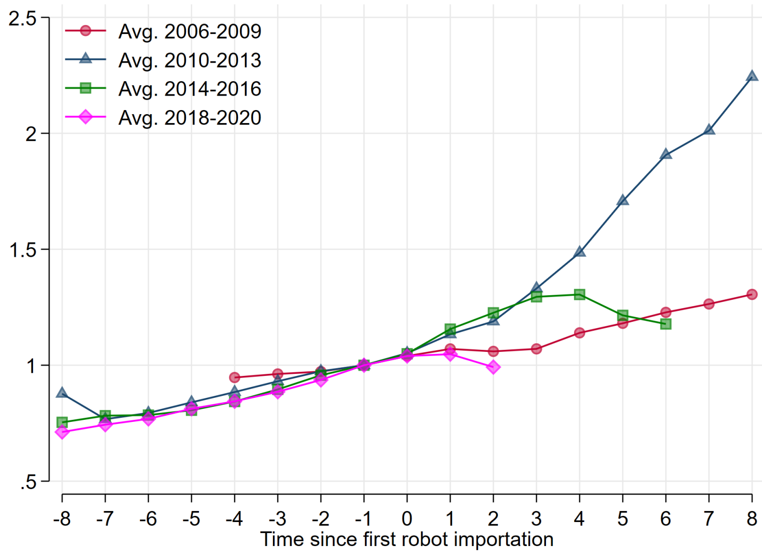
Notes: Panel (a) of Figure **??** presents a comparison of the cumulative stock of industrial robots in Mexico with that in other developed countries, specifically the United States (US) and European Union (EU) countries. It is important to note that IFR data for Mexico and the US are available only for years from 2011. To create the trend data before 2011, I impute values using the aggregate stock for North America and distributed among Mexico and the US based on their relative sizes in 2011. Panel (b) of the figure depicts the same cumulative robot stock for Mexico, but it further breaks down this stock for different 3-digit industries within the manufacturing sector. *Data source*: IFR.

FIGURE A5: NUMBER OF CZS THAT STARTED RECEIVING ROBOT IMPORTS BY YEAR

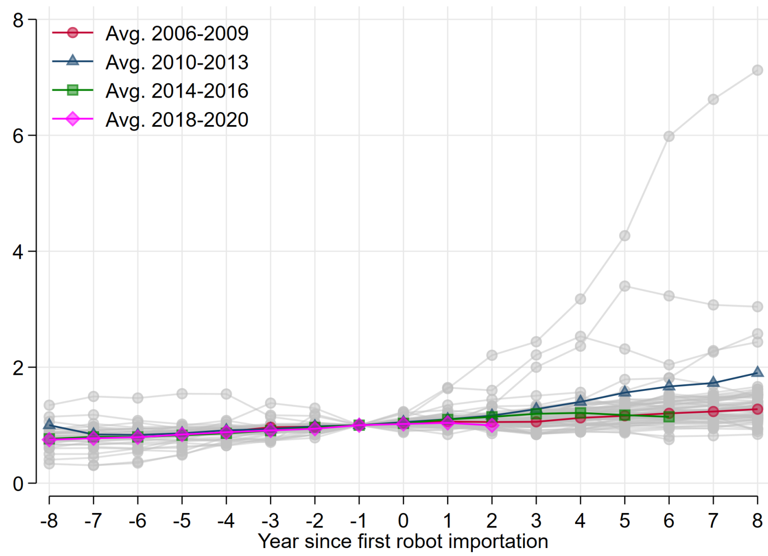


Notes: Figure A5 shows the count of CZs that started receiving industrial robot imports between 2006 and 2022. *Data sources*: Mexican customs records from Secretaría de Economía.

FIGURE A6: EVOLUTION OF NUMBER OF FORMAL WORKERS BY TREATMENT COHORT



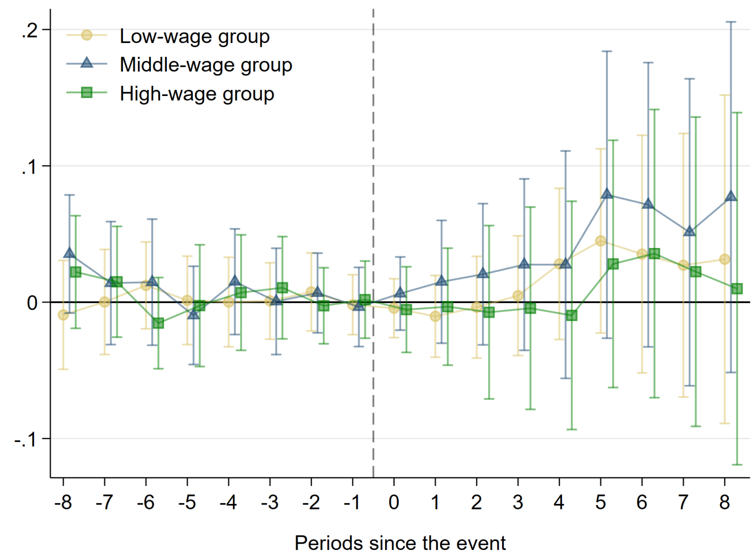
(a) CZ cohort average



(b) Including every CZ (in gray)

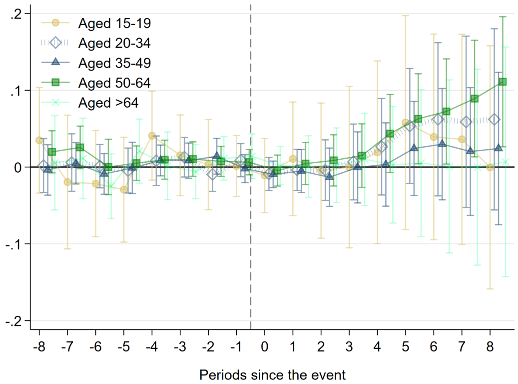
Notes: Figure A6 shows the raw means for the number of formal workers by treatment cohort over event-time. Estimates are relative to the outcomes one year before the event (period -1). Panel (a) shows cohort averages across CZs. Panel (b) shows the same figures as in Panel (a) and overlaps the raw means for each CZ separately in gray. *Data sources*: Mexican customs records from Secretaría de Economía. IMMS public data.

FIGURE A7: HETEROGENEITY BY WAGE GROUP

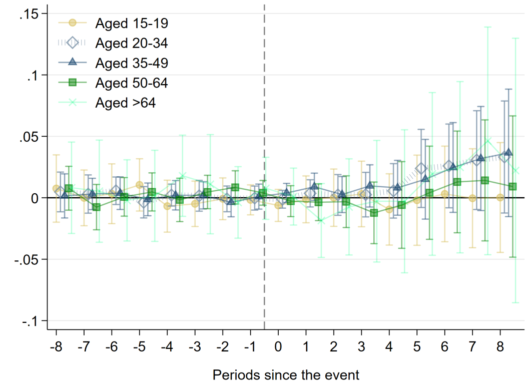


Notes: Figure A7 plots the estimated $\theta(e)$ event-study coefficients using equation 2 for three wage categories of formal workers: those earning two minimum wages or less (low wage), those earning between two and five minimum wages (medium wage), and those earning more than five minimum wages (high wage). The outcome variable is log number of formal workers. The event is defined as a first-time industrial robot importation. The vertical lines reflect the 95% uniform confidence intervals, which are robust to multiple hypothesis testing. Sample of not-yet-but-eventually-treated CZs for the period 2005–2019, including cohorts that started importing robots during 2007–2022. *Data sources*: Mexican customs records from Secretaría de Economía. IMMS public data.

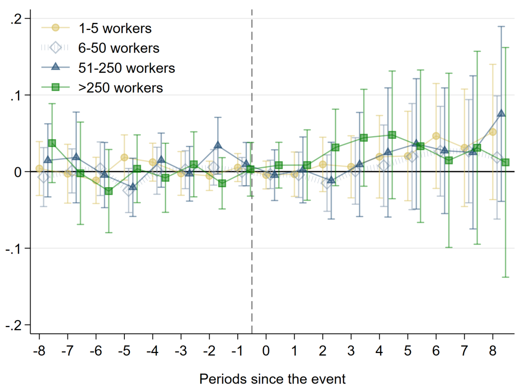
FIGURE A8: HETEROGENEITY IN DYNAMIC EFFECTS ON FORMAL EMPLOYMENT AND WAGES



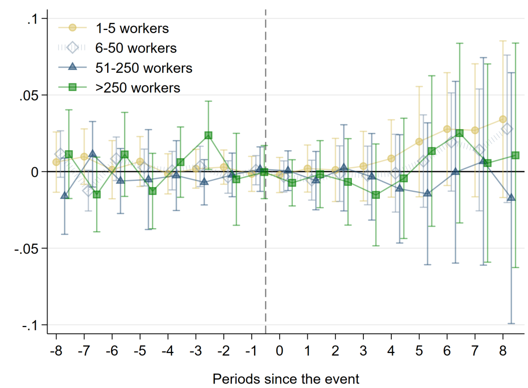
(a) Ln formal workers by **age group**



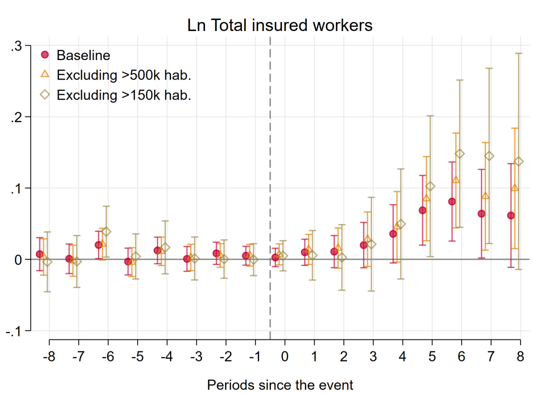
(b) Ln formal wage by **age group**



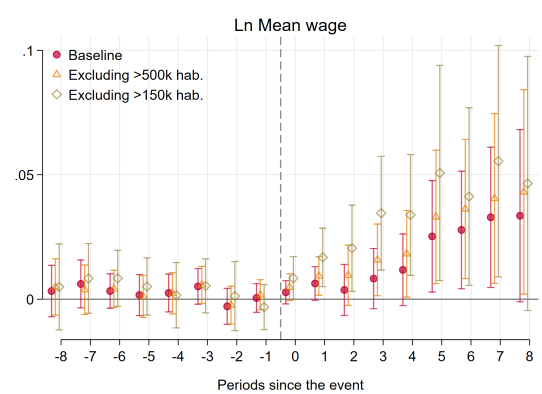
(c) Ln formal workers by **firm size**



(d) Ln formal wage by **firm size**



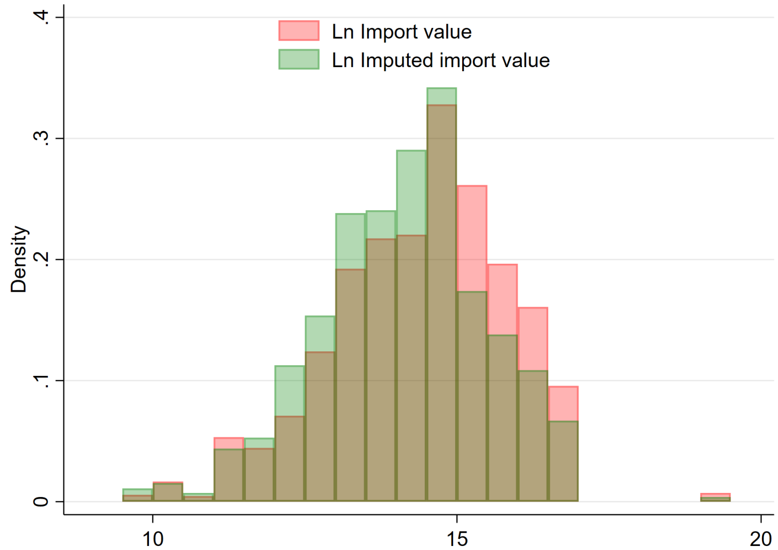
(e) Ln formal workers by **CZ size**



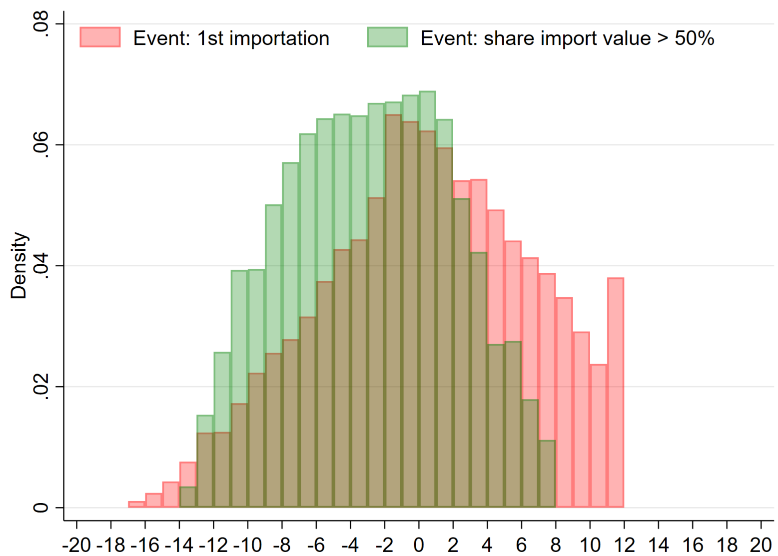
(f) Ln formal wage by **CZ size**

Notes: Figure A8 plots the estimated $\theta(e)$ event-study coefficients using equation 2. The outcome variable is, in turn, the log number of formal workers (Panels (a), (c), and (e)) and the log average real monthly wage for formal workers, deflated to constant pesos using Mexican CPI (Panels (b), (d), and (f)). The event is defined as a first-time industrial robot importation. The vertical lines reflect the 95% uniform confidence intervals, which are robust to multiple hypothesis testing. Sample of not-yet-but-eventually-treated CZs for the period 2005–2019, including cohorts that started importing robots during 2007–2022. *Data sources*: Mexican customs records from Secretaría de Economía. IMMS public data.

FIGURE A9: ALTERNATIVE MEASURES OF ROBOT ADOPTION EVENT



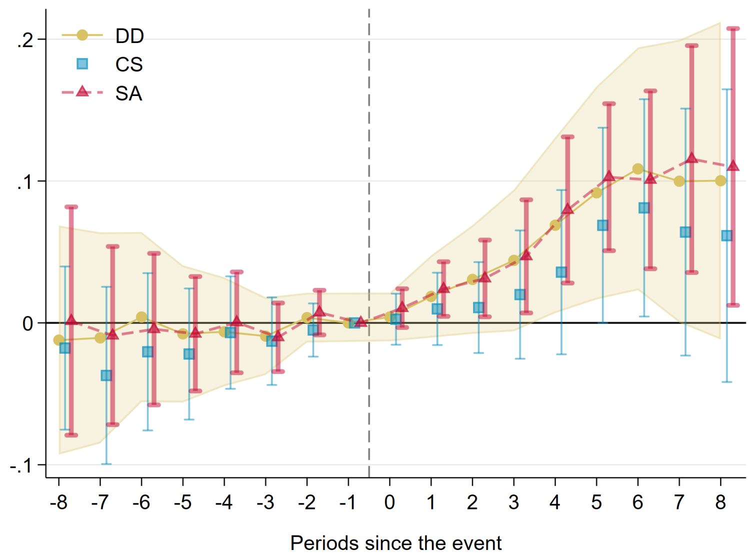
(a) Histogram of imputed and not-imputed values of robot imports



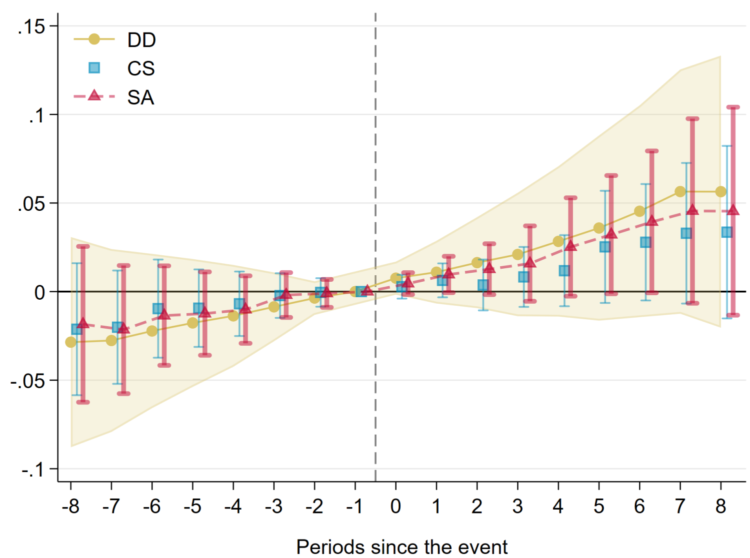
(b) Histogram of original event and alternative events based on import value

Notes: See main text for further explanation. *Data sources*: Mexican customs records from Secretaría de Economía. IMMS public data.

Figure A10: Event-study methods



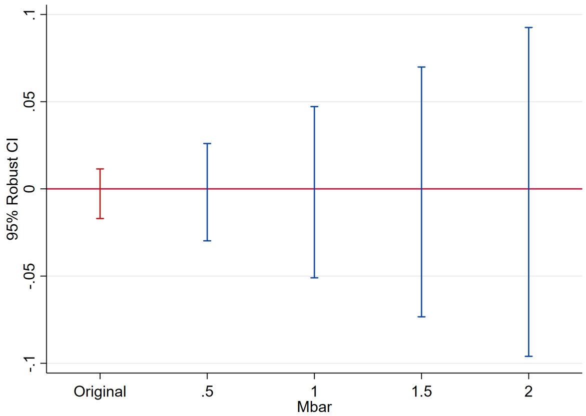
(a) Ln Number of formal workers



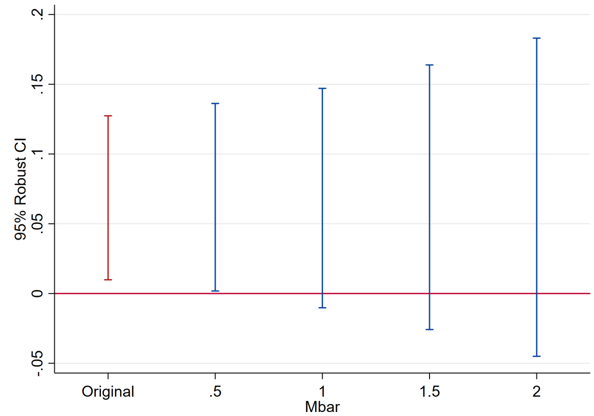
(b) Ln Average monthly wage – formal workers

Notes: Figure A10 overlaps the estimated event-study coefficients using three different methods: CS (Callaway and Sant'Anna (2021)), SA (Sun and Abraham (2021)), and DD (two-way fixed effect model). Estimates are relative to the outcomes one year before the event (period -1). The outcome variable is, in turn, the log number of formal workers (Panel (a)) and log average real monthly wage for formal workers, deflated to constant 2010 pesos using Mexican CPI (Panel (b)). The event is defined as a first-time industrial robot importation. The shaded area and vertical lines reflect the 95% pointwise confidence intervals for DD and SA and uniform confidence intervals for CS. The clustering of standard errors is at the CZ level. Sample of not-yet-but-eventually-treated CZs for 2005–2019, including cohorts that started importing robots during 2007–2022. The unit of observation is the CZ–4-digit industry (N=100,619; 71 CZs). *Data sources*: Mexican customs records from Secretaría de Economía. IMMS public data.

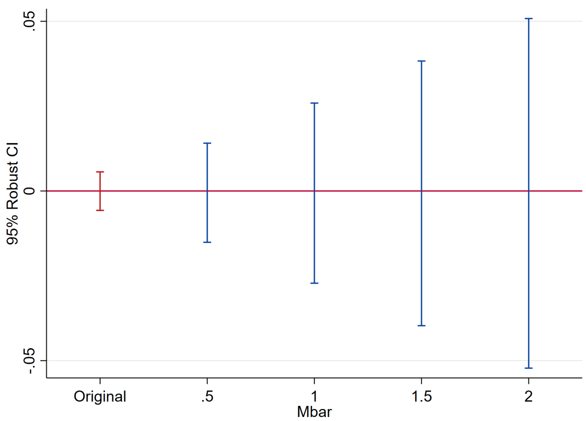
Figure A11: Pretrends sensitivity analysis



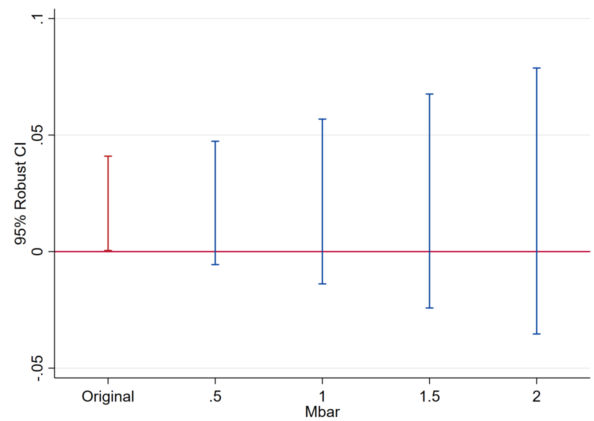
(a) Ln Num. formal workers: Short run



(b) Ln Num. formal workers: Long run



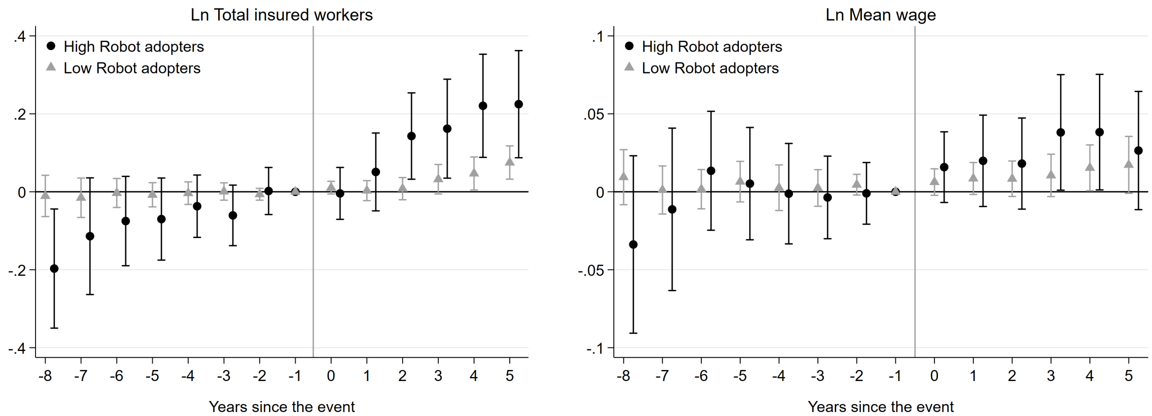
(c) Ln Avg. real formal wages: Short run



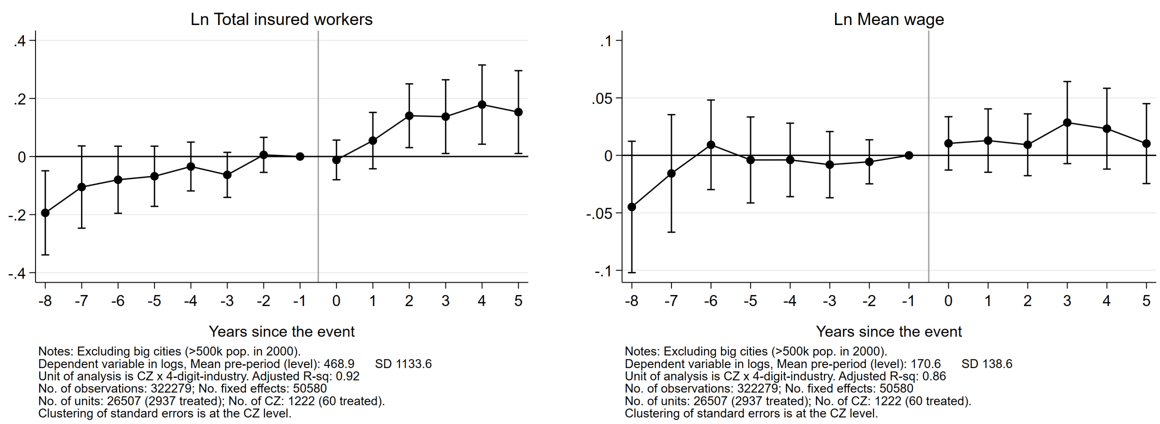
(d) Ln Avg. real formal wages: Long run

Notes: Figure A11 shows the result of a sensitivity analysis proposed by Rambachan and Roth (2023) over the coefficients estimated under the CS method. This analysis estimates the post-treatment effect under different assumptions about parallel trend violations, demonstrating the extent to which the postevent trend differences would need to deviate from pretrends to render the estimates negative or statistically insignificant. It provides confidence intervals that enable the post-treatment departure from parallel trends to reach a magnitude of up to $Mbar$ times the maximum pretreatment deviation, with M being a variable that can take different values. The outcome variable is, in turn, the log number of formal workers (Panels (a) and (b)) and log average real monthly wage for formal workers, deflated to constant 2010 pesos using Mexican CPI (Panels (c) and (d)). The event is defined as a first-time industrial robot importation. Short term refers to the year of the event, and long term refers to six years after the event occurs. The clustering of standard errors is at the CZ level. Sample of not-yet-but-eventually-treated CZs for 2005–2019, including cohorts that started importing robots during 2007–2022. The unit of observation is the CZ–4-digit industry. *Data sources*: Mexican customs records from Secretaría de Economía. IMMS public data.

Figure A12: TWFE models: DD & DDD



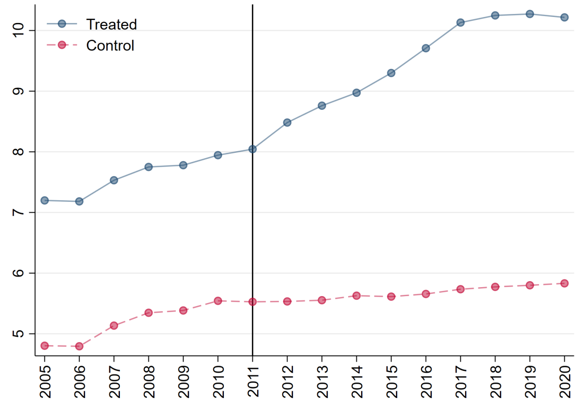
(a) DD estimates: CZ–3-dig. industry level



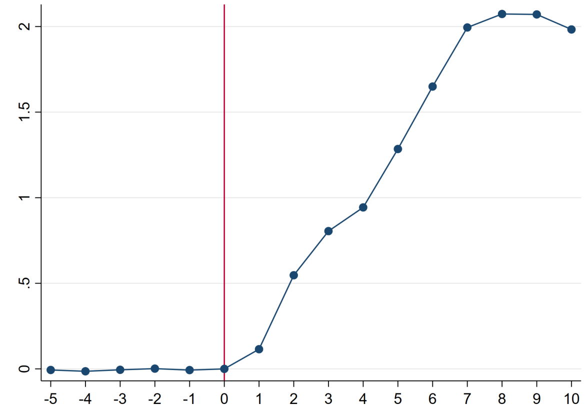
(b) DDD estimates: CZ–3-dig. industry level

Notes: Figure 5 displays the estimated event-study coefficients obtained using equation 2, a TWFE model. The unit of observation is the CZ–3-digit industry. In Panel (a), the results of the difference-in-differences specification are presented, showing overlapping estimates from two different subsamples: "high robot adopters", comprising manufacturing industries with higher rates of robot adoption observed in the IFR data, and "low robot adopters", which include the remaining nonmanufacturing industries. Panel (b) shows estimates from the triple difference-in-differences specification, where the third difference is introduced by contrasting high and low robot adopters. The outcome variable is, in turn, the log number of formal workers and log average real monthly wage for formal workers, deflated to constant 2010 pesos using Mexican CPI. The event is defined as a first-time industrial robot importation. The clustering of standard errors is at the CZ level. Sample of CZs with population smaller than 500 thousands inhabitants for the period 2005–2019, including cohorts that started importing robots during 2007–2022. *Data sources*: Mexican customs records from Secretaría de Economía. IMMS public data.

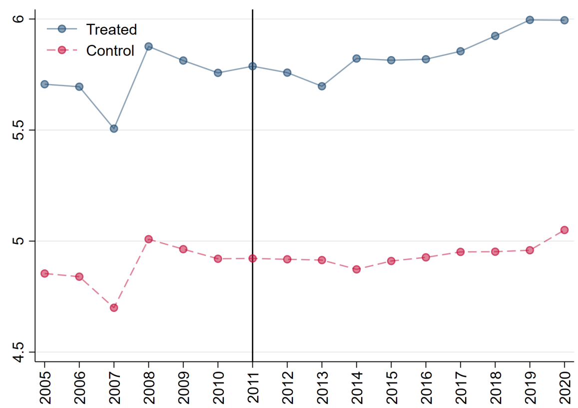
Figure A13: SDD estimates for CZ #24050 (2011 cohort)



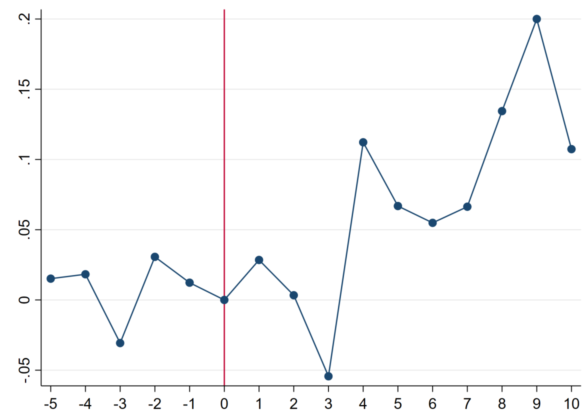
(a) Ln Num. formal workers: Trends



(b) Ln Num. formal workers: DD



(c) Ln Avg. real formal wage: Trends



(d) Ln Avg. real formal wage: DD

Notes: Figure A13 exhibits the estimated treatment effects using the synthetic difference-in-difference model as outlined by Arkhangelsky et al. (2021) for a specific CZ (belonging to 2011 cohort) that experiences a statistically significant positive formal employment and wage effect. The comparison group for these estimates is derived from the pool of all CZs that have never been treated, and it employs optimal weighting of units and pre-event periods in its construction. The dataset comprises a panel of CZs, balanced in calendar time, spanning from 2005 to 2019. The outcome variables are the logarithm of the number of formal workers and the logarithm of the average real monthly wage for formal workers, adjusted to constant 2010 pesos using Mexican CP. The event is defined as a first-time industrial robot importation. Panels (a) and (c) present the raw means of the treated CZ and the synthetic control. Panels (b) and (d) show the corresponding difference between treatment and control over event-time. *Data sources*: Mexican customs records from Secretaría de Economía. IMMS public data.

Figure A14: Comparison of 2SLS estimates with results from Acemoglu and Restrepo (2020)

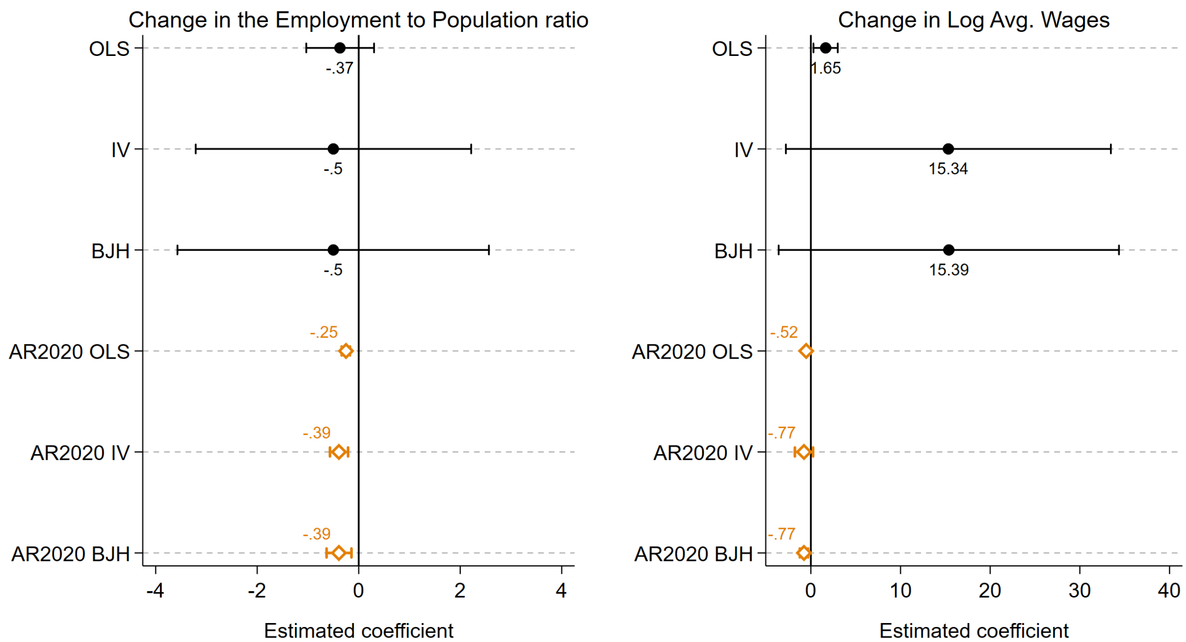
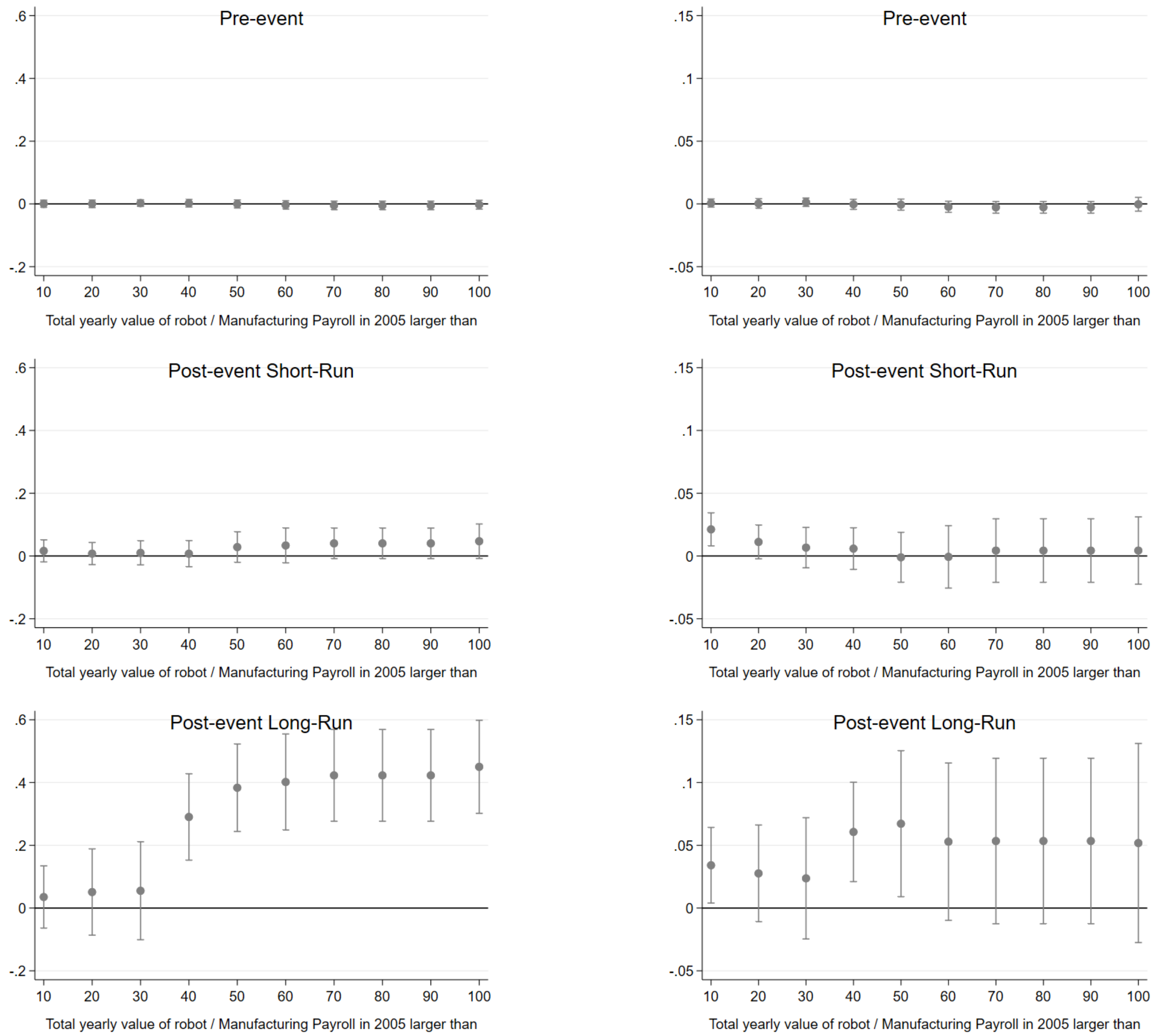


Figure A14 compares OLS and IV estimates from Acemoglu and Restrepo (2020) for the US and my own replication for Mexico. BJH refers to the standard error estimator proposed by Borusyak et al. (2021). *Data sources*: Mexican customs records from Secretaría de Economía. IMMS public data. Mexican censuses 1990 and 200. IFR data. Faber (2020).

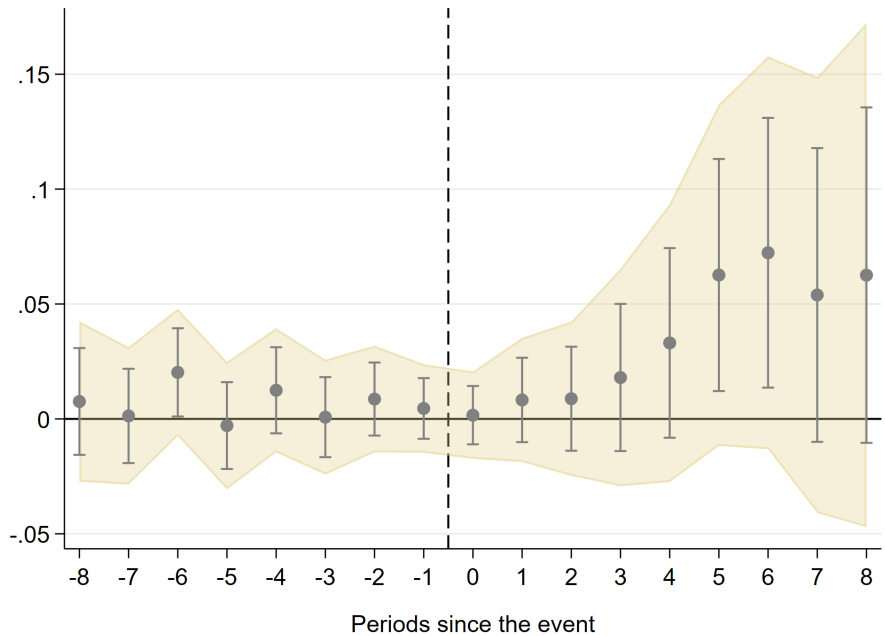
FIGURE A15: ALTERNATIVE EVENT DEFINITION USING ROBOT IMPORTS VALUE

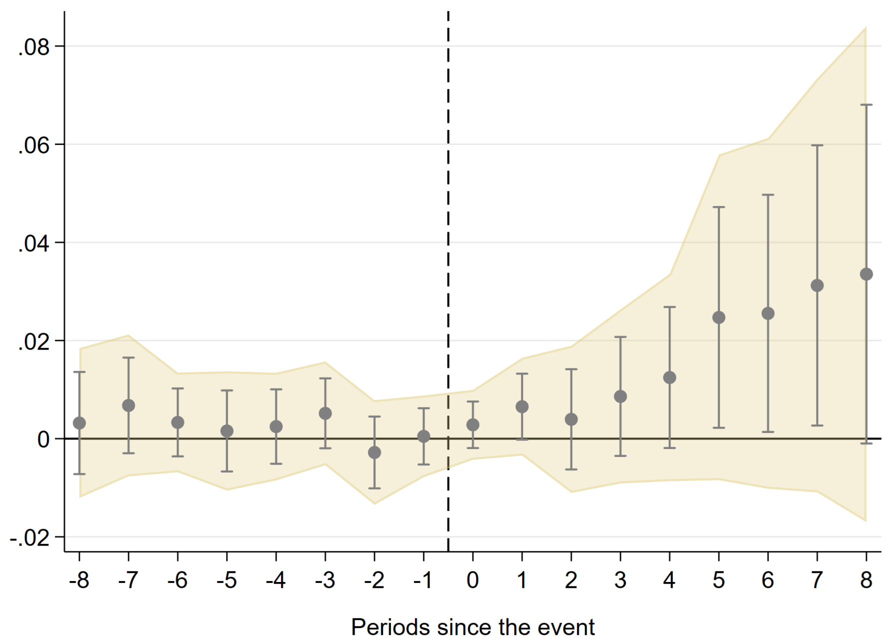
(a) Ln Number of formal workers (b) Ln Avg. monthly wage – formal workers



Notes: Figure A15 plots the simple average of estimated $\theta(e)$ event-study coefficients using equation 2 (Callaway and Sant'Anna (2021) method) for different event-periods. The event is defined as the period where the cumulative total value of robot imports is larger than X% of the CZ's 2005 total wage bill (where X% varies on the horizontal axes). Pre-event: years -5 to -1; postevent short run: years 0 to 4; long-run: years 5 to 8. The outcome variable is, in turn, log number of formal workers (Panel (a)) and log average real monthly wage for formal workers, deflated to constant 2010 pesos using Mexican CPI (Panel (b)). Clustering of standard errors is at the CZ level. Sample of not-yet-but-eventually-treated CZs for the period 2005–2019, including cohorts that started importing robots during 2007–2022. *Data sources*: Mexican customs records from Secretaría de Economía. IMMS public data.

Figure A16: CONTROLLING FOR PLANT OPENINGS BY LARGE FIRMS





Notes: Figure A16 shows the estimated event-study coefficients using a two-way fixed effect model, controlling for the opening of large (more than 250 workers) manufacturing firms (which survive up to the 2018 Mexican economic census). In the first graph, the outcome variable is the log number of formal workers, and in the second graph, it is the log average real monthly wage for formal workers, deflated to constant 2010 pesos using Mexican CPI. The clustering of standard errors is at the CZ level. The event is defined as a first-time industrial robot importation. *Data sources*: Mexican customs records from Secretaría de Economía. IMMS public data. Mexican economic census 2018.

Appendix B Additional Tables

Table B1: Characterization of Mexican manufacturing sector by wage group

	All workers			Manufacturing IMSS workers		
	Low wage	Medium wage	High wage	Low wage	Medium wage	High wage
	(1)	(2)	(3)	(4)	(5)	(6)
A. By occupation						
Professionals	3%	7%	21%	1%	4%	19%
Education workers	2%	5%	17%	0%	0%	1%
Managers	0%	1%	8%	0%	0%	10%
Office workers	7%	14%	20%	6%	8%	19%
Industrial operators	25%	35%	15%	80%	74%	37%
Merchants	15%	10%	7%	4%	5%	8%
Transport operators	3%	7%	6%	1%	4%	3%
Workers in personal services	29%	11%	2%	7%	3%	1%
Protection and surveillance work	1%	5%	3%	0%	1%	1%
Agricultural	17%	5%	1%	0%	0%	1%
Total	100%	100%	100%	100%	100%	100%
N (mill.)	7.84	13.54	3.84	0.59	2.30	0.44
B. By age group						
15–19	19%	8%	1%	13%	7%	0%
20–24	18%	17%	6%	25%	20%	7%
25–29	12%	17%	13%	15%	19%	17%
30–34	11%	15%	17%	15%	16%	20%
35–39	10%	13%	17%	11%	13%	19%
40–44	8%	11%	17%	9%	11%	16%
45–49	6%	8%	14%	5%	6%	10%
50–54	5%	5%	8%	3%	4%	6%
55–59	4%	4%	4%	2%	3%	3%
60–64	3%	1%	3%	1%	1%	1%
65+	3%	1%	1%	0%	0%	0%
Total	100%	100%	100%	100%	100%	100%
N (mill.)	7.62	13.51	3.84	0.58	2.29	0.44

Notes: Panel (a) of Table B1 shows the share of workers in each occupation within each wage group for the sample of all workers and the subsample of workers in the manufacturing sector who are registered in IMSS. Panel (b) shows similar statistics by age group. Wage categories: those earning two minimum wages or less (low wage), those earning between two and five minimum wages (medium wage), and those earning more than five minimum wages (high wage). *Data sources*: Own elaboration based on ENOE 2005, 4th quarter.

Table B2: Growth in robot adoption by industry 2015–2010 (%)

	N workers	Change in stock of robots 2010-2015 (%)					
	MEX 2000	MEX	US	EU9	EU7	EU5	LA
All industries	31049.6	694.8	38.2	12.7	2.9	-0.2	96.1
Automotive	460.6	662.3	108.2	3.2	-13.1	-21.6	216.9
Rubber & Plastic	138.5	711.2	92.3	62.8	50.8	45.9	89.5
Industrial Machinery	87.6	1077.1	1485.7	72.9	82.8	79.2	474.2
Electronics	248.1	4714.3	119.3	-6.3	-23.8	-27.4	70.7
Other Manufacturing	739.8	303.9	877.8	-23.2	15.9	45.8	393.3
Food & Beverages	1153.3	2300.0	97.9	49.3	69.3	76.8	344.7
Basic Metals	126.1	1455.6	10162.7	28.8	70.6	65.1	315.0
Metal Products	415.3	322.6	31.9	23.1	8.8	2.8	114.0
R+D	2594.1	489.5	369.9	2.1	22.4	43.6	418.5
Pharmaceuticals	284.3	4850.0	104.6	116.3	130.5	131.9	121.9
Electrical Machinery	204.4	136.4	11554.5	107.5	83.4	81.5	200.0
Other Services	16312.5		279.5	313.1	153.2	590.9	
Minerals	457.1		401.2	-3.4	1.2	2.5	475.0
Paper	236.4		2046.2	12.1	40.9	45.8	300.0
Utilities	159.3			55.6	30.2	152.0	
Wood Products	571.0		1136.4	-25.4	5.5	13.0	150.0
Construction	2767.1		173.9	36.0	32.1	108.7	1200.0
Mining	197.7		1750.0	-29.8	-33.3	-22.7	440.0
Textiles	1474.9		900.0	0.0	-12.1	-3.6	
Agriculture	5678.9		666.7	32.3	15.5	16.5	1600.0
Stock of robots							
in year 2000		963	87999	187480	95756	70249	1300
in year 2010		1855	169550	306760	157492	115105	6514
in year 2015		14743	234245	345770	162070	114883	12775

Notes: Table B2 shows the number of workers in Mexico 2000 and the change in the stock of robots between 2010 and 2015, calculated as the % change relative to the base year. EU9 includes Germany, Denmark, Spain, Finland, France, UK, Italy, Norway, and Sweden; EU7 excludes Germany and Norway; EU5 excludes the UK and Spain; LA includes Argentina, Brazil, Chile, Colombia, Peru and Venezuela. *Data sources*: IFR data. Mexican population census 2000.

TABLE B3: LABOR MARKET VARIABLES DO NOT PREDICT EVENT TIMING AFTER INCLUDING FIXED EFFECTS

	All industries				Manufacturing industries			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln Number of formal workers	0.027***	0.0904***	0.005	0.005	0.019***	0.059***	0.002	0.001
	(0.007)	(0.009)	(0.004)	(0.004)	(0.005)	(0.009)	(0.005)	(0.005)
Ln Avg. monthly formal wage	0.046***	0.098***	0.008	0.004	0.090***	0.080***	0.005	0.006
	(0.013)	(0.021)	(0.012)	(0.013)	(0.020)	(0.027)	(0.014)	(0.017)
CZ $\times$ 4-dig. sector FE		x	x	x		x	x	x
Year FE			x				x	
Year $\times$ 4-dig. sector $\times$ Region FE				x				x
Observations	100,619	100,423	100,423	98,988	23,935	23,873	23,873	23,241
Adj. R-squared	0.022	0.334	0.660	0.655	0.025	0.336	0.666	0.658
P-val F-stat	0.00	0.00	0.25	0.40	0.00	0.00	0.77	0.90

Notes: Table B3 shows the estimates of a linear probability model where the outcome is a binary variable indicating whether the CZ started receiving industrial robot imports. The model includes two explanatory variables at the CZ–4-dig. sector–year level: log number of formal workers and log average real monthly wage for formal workers, deflated to constant 2010 pesos using Mexican CPI. The last row displays the p-value of a joint significance test for the two included covariates. Clustering of standard errors is at the CZ level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Refer to notes in Table 4 for the definitions of the different samples. *Data sources*: Mexican customs records from Secretaría de Economía. IMMS public data.

TABLE B4: SUMMARY OF ESTIMATES: ANNUAL AVERAGES

	Pre-event	Postevent short run	Postevent long run
	(1)	(2)	(3)
A. Log Number formal Workers			
Baseline	0.003	0.008	0.055**
	(0.004)	(0.011)	(0.028)
Balanced sample	0.002	0.001	0.049
	(0.004)	(0.012)	(0.030)
Manufacturing	0.005	0.003	0.073
	(0.007)	(0.019)	(0.048)
Manufacturing robot adopters	0.006	0.000	0.085
	(0.008)	0.023	(0.058)
Never treated	0.011***	0.036***	0.105***
	(0.003)	(0.009)	(0.019)
B. Log Average Wage – formal workers			
Baseline	0.002	0.006	0.028**
	(0.002)	(0.004)	(0.013)
Balanced sample	0.002	0.006	0.026**
	(0.002)	(0.005)	(0.013)
Manufacturing	0.004	0.001	0.024
	(0.002)	(0.007)	(0.019)
Manufacturing robot adopters	0.002	0.004	0.036
	(0.003)	(0.009)	(0.023)
Never treated	0.002	0.006*	0.025***
	(0.001)	(0.004)	(0.008)

Notes: Table B4 shows the same results as in Table 4 but using as outcomes the average of the last month of each quarter for each year instead of the value for December. The table shows the simple average of estimated $\theta(e)$ event-study coefficients using equation 2 for different periods. Pre-event: years -5 to -1; postevent short run: years 0 to 4; long-run: years 5 to 8. The outcome variable is, in turn, log number of formal workers (Panel (a)) and log average real monthly wage for formal workers, deflated to constant 2010 pesos using Mexican CPI (Panel (b)). The event is defined as a first-time industrial robot importation. Clustering of standard errors is at the CZ level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Refer to notes in Table 4 for the definition of the different samples. *Data sources*: Mexican customs records from Secretaría de Economía. IMMS public data.

TABLE B5: EXCLUDING 2009 AND 2010 COHORTS

	Pre-event	Postevent short run	Postevent long run
	(1)	(2)	(3)
A. Log Number formal workers			
Baseline	0.004	0.011	0.051*
	(0.004)	(0.011)	(0.028)
Balanced sample	0.003	0.000	0.045*
	(0.004)	(0.010)	(0.026)
Manufacturing	0.007	0.007	0.078
	(0.009)	(0.018)	(0.049)
Manufacturing robot adopters	0.009	0.010	0.109*
	(0.010)	(0.023)	(0.059)
Never treated	0.012***	0.037***	0.091***
	(0.004)	(0.009)	(0.020)
B. Log Average Wage – formal workers			
Baseline	0.001	0.007*	0.032***
	(0.002)	(0.004)	(0.013)
Balanced sample	0.001	0.007	0.031***
	(0.002)	(0.005)	(0.013)
Manufacturing	0.002	0.000	0.028
	(0.003)	0.008	(0.019)
Manufacturing robot adopters	0.000	0.007	0.047**
	0.003	(0.010)	(0.022)
Never treated	0.001	0.006	0.027***
	(0.001)	(0.004)	(0.009)

Notes: Table B5 shows the same results as in Table 4 but excluding cohorts 2009 and 2010 from the sample. The table shows the simple average of estimated $\theta(e)$ event-study coefficients using equation 2 for different periods. Pre-event: years -5 to -1; postevent short run: years 0 to 4; long run: years 5 to 8. The outcome variable is, in turn, log number of formal workers (Panel (a)) and log average real monthly wage for formal workers, deflated to constant 2010 pesos using Mexican CPI (Panel (b)). The event is defined as a first-time industrial robot importation. Clustering of standard errors is at the CZ level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Refer to the notes of Table 4 for the definitions of the different samples. *Data sources*: Mexican customs records from Secretaría de Economía. IMMS public data.

TABLE B6: EFFECTS OF ROBOTS ON CHANGES IN LABOR MARKET OUTCOMES: 2SLS ESTIMATES USING THE **CHANGE IN ROBOT EXPOSURE BETWEEN 2010 AND 2015**

A: Population Censuses outcomes. Long differences 2010-2015

	All industries											
	Employment-to-pop		Wage-empl-to-pop		Self-empl-to-pop		Labor Force Particip. rate		Unemployment rate		Share Informal	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
MX exposure to robots	-0.2	-0.4	-0.3	-0.5	0.1	0.1	-0.2	-0.3	-0.3	-0.7	0.3	0.4
2011-2015	(0.5)	(2.1)	(0.5)	(1.6)	(0.4)	(1.6)	(0.5)	(1.9)	(0.4)	(1.2)	(0.6)	(1.6)
Observations	1,804	19	1,804	19	1,804	19	1,804	19	1,798	19	1,797	19
Adj. R-squared	0.154		0.05		0.180		0.137		0.026		0.155	
Mean dep. 2005	45.47		23.50		21.97		50.39		4.406		49.13	
Lower limit CI	-1.3	-4.5	-1.2	-3.6	-0.6	-2.1	-1.2	-4.1	-0.9	-3.1	-0.8	-2.8
Upper limit CI	0.9	3.7	0.6	2.6	0.9	2.4	0.7	3.4	0.4	1.7	1.5	3.6
First-stage coefficient	0.721		0.721		0.721		0.721		0.716		0.716	
First-stage F-statistic	39.55		39.55		39.55		39.55		38.75		38.75	

B: IMSS data - Insured workers. Long differences 2010-2015

	All industries						Manufacturing industry					
	Ln Number Workers		Ln Payroll		Ln Mean Wage		Ln Number Workers		Ln Payroll		Ln Mean Wage	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
MX exposure to robots	4.4	5.1	4.7	4.2	0.2	-0.9	-3.4	-25.7	-1.6	-19.2	1.8	6.4
2011-2015	(3.6)	(9.7)	(4.2)	(8.5)	(1.5)	(2.7)	(6.7)	(15.7)	(7.4)	(15.3)	(2.7)	(6.9)
Observations	1,211	19	1,211	19	1,211	19	777	19	777	19	777	19
Adj. R-squared	0.010		0.014		0.007		0.014		0.012		0.011	
Mean dep. 2005	12050		3.004e+06		158.1		3485		954484		134.2	
Lower limit CI	-2.7	-13.9	-3.5	-12.5	-2.7	-6.1	-16.5	-56.6	-16.0	-49.3	-3.5	-7.0
Upper limit CI	11.5	24.2	12.8	20.9	3.1	4.3	9.7	5.2	12.9	10.9	7.1	19.9
First-stage coefficient	0.74		0.74		0.74		0.76		0.76		0.76	
First-stage F-statistic	38.14		38.14		38.14		36.12		36.12		36.12	

Notes: This table presents 2SLS estimates of the effects of exposure to robots on changes in labor market outcomes between 2010 and 2015. Panel (a) presents outcomes based on population censuses and Panel (b) those based on the IMSS dataset. In all models, I instrument Mexico's exposure to robots using exposure to robots from European countries. All IV estimates are from regressions weighted by the CZ share in national working-age population in 1990. The covariates included in each model are region dummies, exposure to US robots (2011–2015), exposure to *maquiladoras* in 1990, demographic characteristics of commuting zones in 1990 (log population; share urban; share women; share population over 65; shares population with high school complete and population with college complete; shares employment in manufacturing, services and agriculture sectors). For each outcome, the first column presents standard error estimates that are robust to heteroskedasticity and correlation within CZ, and in the second column, robust standard errors computed following Borusyak et al. (2019) are given in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. *Data sources*: IMMS public data. Mexican 1990 and 2000 censuses. IFR data. Faber (2020).

TABLE B7: SUMMARY OF ESTIMATES: DIFFERENT METHODS

Model	Formal Workers			Log Average Wage		
	Pre-event	Postevent short run	Postevent long run	Pre-event	Postevent short run	Postevent long run
	(1)	(2)	(3)	(4)	(5)	(6)
CA Only not-yet-treated	0.005	0.016	0.069***	0.001	0.007	0.030**
	(0.004)	(0.012)	(0.029)	(0.002)	(0.004)	(0.013)
SA Last-treated cohort	-0.003	0.038***	0.107***	-0.006	0.014*	0.041*
	(0.013)	(0.013)	(0.036)	(0.007)	(0.007)	(0.023)
CA Never-treated	0.012***	0.041***	0.108***	0.001	0.006	0.026***
	(0.004)	(0.010)	(0.021)	(0.001)	(0.004)	(0.008)
SA Never-treated	-0.027***	0.050***	0.141***	-0.000	0.004	0.022***
	(0.008)	(0.008)	(0.019)	(0.003)	(0.003)	(0.008)
DD Only not-yet-treated	-0.005	0.033*	0.100**	-0.011	0.017	0.049
	(0.015)	(0.019)	(0.046)	(0.011)	(0.013)	(0.032)
DDD Only not-yet-treated	-0.018	0.072*	0.180*	-0.013	0.007	0.020
	(0.038)	(0.039)	(0.096)	(0.014)	(0.017)	(0.041)
DD Never-treated	-0.024***	0.046***	0.134***	-0.003	0.005	0.020***
	(0.010)	(0.010)	(0.021)	(0.004)	(0.004)	(0.008)
DDD Never-treated	0.019	0.018	0.041	-0.006	0.006	0.012
	(0.023)	(0.023)	(0.047)	(0.008)	(0.008)	(0.016)
Synthetic DD		0.071			0.068	
		(0.306)			(0.302)	
Bartik IV		0.051			-0.008	
		(0.097)			(0.026)	

Notes: Table B7 presents a summary of results from different models and methods. Sample including cohorts that started importing robots during 2007–2022. Pre-event: years -5 to -1; postevent short run: years 0 to 4; long run: years 5 to 8. The outcome variables are the log number of formal workers and the log average real monthly wage for formal workers, deflated to constant 2010 pesos using Mexican CPI. The event is defined as a first-time industrial robot importation. Clustering of standard errors is at the CZ level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. *Data sources*: Mexican customs records from Secretaría de Economía. IMMS public data.

TABLE B8: MECHANISMS: BALANCED SAMPLE

	Number of firms	Labor share	Gross value added (log)	GVA per worker (log)	Total fixed assets (log)	Capital per worker	Input cost (log)	Total payroll (log)	Number workers (log)	Workers prod. and sales (log)	Workers admin (log)	Hours worked (log)	Hours prod. and sales (log)	Hours admin (log)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Panel (a). All industries														
D_{mt}^{post}	0.027*	0.019	0.042	0.018	0.001	-0.042	0.052*	0.021	0.024	0.022	0.012	0.019	0.013	-0.001
	(0.015)	(0.047)	(0.028)	(0.023)	(0.041)	(0.029)	(0.026)	(0.029)	(0.018)	(0.027)	(0.034)	(0.018)	(0.027)	(0.034)
Observations	30,397	30,397	30,397	30,397	30,397	30,397	30,397	30,397	30,397	30,185	20,039	30,308	30,099	19,963
Adj. R-squared	0.968	0.154	0.843	0.620	0.803	-0.0909	0.874	0.854	0.905	0.860	0.763	0.901	0.851	0.751
Mean	62	0.476	15.92	0.0671	20.49	0.0886	15.65	4.843	207.2	87.95	21.15	489.4	212.5	50.72
Panel (b). Manufacturing sector: Metal, machinery and equipment, power generation, transportation, plastics and rubber														
D_{mt}^{post}	0.056	-0.014	0.286*	0.119	0.324**	0.015	0.242*	0.283*	0.167*	0.225*	0.056	0.178*	0.241*	0.093
	(0.042)	(0.040)	(0.150)	(0.092)	(0.135)	(0.013)	(0.137)	(0.143)	(0.095)	(0.127)	(0.130)	(0.102)	(0.132)	(0.135)
Observations	687	687	687	687	687	687	687	687	687	687	469	687	687	469
Adj. R-squared	0.972	0.0930	0.776	0.574	0.744	0.527	0.778	0.786	0.826	0.789	0.704	0.810	0.770	0.695
Mean	62.95	0.480	18.10	0.0561	12.97	0.0795	23.99	8.328	198.9	107.6	22.65	404.1	226	47.61

Notes: Table B8 shows the results of estimating the TWFE model, equation 3, where the event is defined as a first-time industrial robot importation. Panel (a) presents results for all industries and Panel (b) for the following manufacturing industries: basic metals, metal products, machinery, equipment, electronics, appliances, power generation, transportation, and other manufacturing not included in Table B9. The first dependent variable is the log number of firms at the CZ–five-digit sector level (column (1)). The first dependent variable is the log number of firms at the CZ–five-digit sector level (column (1)). The following seven dependent variables are balance-sheet measures capturing firm productivity and size, aggregated to the CZ–five-digit sector level: labor share, calculated as the total wage bill divided by gross value added (column (2)); capital per worker, calculated as the total fixed assets divided by the number of workers (column (3)); log total gross value added (column (4)) and GVA per worker (column (5)); log input costs (column (6)); log total wage bill (column (7)); and log fixed assets (as a proxy for capital, column (8)). Column (9) presents results for the log number of workers, column (10) for the log number of workers in production and sales, and column (11) for the log number of workers in administrative jobs (including managers). Columns (12)–(14) show similar results for the log number of hours worked in a year. The sample includes not-yet-but-eventually-treated CZs for 2005–2019, including cohorts that started importing robots during 2007–2022. Means are calculated for the period before the event, in levels, and are reported in millions of Mexican pesos (CPI-adjusted to 2005), except for the number of workers, number of hours worked in a year (in thousands), and shares (ratios). Standard errors are clustered at the CZ level and are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. *Data sources*: Mexican economic censuses 2003, 2008, 2013, and 2018.

TABLE B9: MECHANISMS: OTHER INDUSTRIES, BALANCED SAMPLE

	Number of firms	Labor share	Gross Value Added	GVA per worker	Total fixed assets	Capital per worker	Input cost	Total payroll	Number workers	Workers prod. and sales	Workers admin	Hours worked	Hours prod. and sales	Hours admin
			(log)	(log)	(log)		(log)	(log)	(log)	(log)	(log)	(log)	(log)	(log)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Panel (a) Manufacturing: Wood and Paper, Chemical Industry														
D_{mt}^{post}	0.103**	-0.006	-0.022	-0.018	-0.019	0.032*	-0.074	-0.033	-0.004	-0.074	-0.020	-0.015	-0.094	-0.019
	(0.040)	(0.027)	(0.112)	(0.061)	(0.117)	(0.018)	(0.109)	(0.114)	(0.074)	(0.102)	(0.142)	(0.075)	(0.104)	(0.146)
Observations	989	989	989	989	989	989	989	989	989	987	677	989	987	677
R-squared	0.974	0.228	0.784	0.611	0.783	0.604	0.808	0.758	0.846	0.771	0.648	0.844	0.769	0.627
Mean	94.91	0.390	34.43	0.0972	34.37	0.0965	78.99	6.876	299.9	130.6	23.67	726.3	341.2	60.29
Panel (b) Manufacturing: Textiles, Apparel, Leather Goods, Food, and Beverage Industry														
D_{mt}^{post}	0.027	-0.019	0.117	0.056	0.087	-0.006	0.100	0.146	0.061	0.130	0.096	0.074	0.116	0.086
	(0.043)	(0.044)	(0.101)	(0.061)	(0.118)	(0.007)	(0.084)	(0.114)	(0.070)	(0.103)	(0.101)	(0.072)	(0.107)	(0.109)
Observations	1,436	1,436	1,436	1,436	1,436	1,436	1,436	1,436	1,436	1,420	736	1,436	1,420	736
R-squared	0.942	0.0748	0.733	0.489	0.737	0.617	0.772	0.740	0.808	0.754	0.751	0.796	0.738	0.736
Mean	43.76	0.446	17.93	0.0456	17.59	0.0649	32.34	7.873	250.3	166.7	29.38	525.6	360.9	64.90
Panel (c) Nonmanufacturing														
D_{mt}^{post}	0.024	0.022	0.035	0.015	-0.009	-0.047	0.050*	0.012	0.020	0.015	0.009	0.014	0.007	-0.006
	(0.014)	(0.052)	(0.028)	(0.023)	(0.042)	(0.032)	(0.026)	(0.027)	(0.018)	(0.025)	(0.035)	(0.018)	(0.026)	(0.035)
Observations	27,285	27,285	27,285	27,285	27,285	27,285	27,285	27,285	27,285	27,091	18,157	27,196	27,005	18,081
R-squared	0.968	0.162	0.850	0.624	0.806	-0.0817	0.881	0.864	0.913	0.869	0.768	0.909	0.860	0.756
Mean	61.72	0.480	15.05	0.0673	20.29	0.0899	12.14	4.521	201.5	81.56	20.66	480.4	199.1	49.80

Notes: Table B9 shows the results of estimating the TWFE model, equation 3, where the event is defined as a first-time industrial robot importation, and balancing the sample in calendar time. Panel (a) presents results for the following manufacturing industries: food, drinks, tobacco, energy, fossil fuels, chemicals, plastics, rubber. Panel (b) for results for the following manufacturing industries: textile, clothing, leather, wood, paper, printing, and nonmetallic mineral products. Panel (c) includes all nonmanufacturing industries. The first dependent variable is the log number of firms at the CZ–five-digit sector level (column (1)). The first dependent variable is the log number of firms at the CZ–five-digit sector level (column (1)). The following seven dependent variables are balance-sheet measures capturing firm productivity and size, aggregated to the CZ–five-digit sector level: labor share, calculated as the total wage bill divided by gross value added (column (2)); capital per worker, calculated as the total fixed assets divided by the number of workers (column (3)); log total gross value added (column (4)) and GVA per worker (column (5)); log input costs (column (6)); log total wage bill (column (7)); and log fixed assets (as a proxy for capital, column (8)). Column (9) presents results for the log number of workers, column (10) for the log number of workers in production and sales, and column (11) for the log number of workers in administrative jobs (including managers). Columns (12)–(14) show similar results for the log number of hours worked in a year. The sample includes not-yet-but-eventually-treated CZs for 2005–2019, including cohorts that started importing robots during 2007–2022. Means are calculated for the period before the event, in levels, and are reported in millions of Mexican pesos (CPI-adjusted to 2005), except for the number of workers, the number of hours worked in a year (in thousands), and shares (ratios). Standard errors are clustered at the CZ level and are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. *Data sources*: Mexican Economic Censuses (2003, 2008, 2013, 2018).