The Political Economy of Automation and Fragmented Production: Evidence from Mexico*

Carles Boix† Valentina González-Rostani‡ Erica Owen§

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Abstract

How does automation in advanced economies reshape politics and violence in developing countries? We develop a political economy theory in which technology adoption in the Global North reduces demand for export-oriented labor in the Global South, depressing wages and employment and triggering social and political responses. We test this argument in Mexico, a major trade partner of the United States. Using commuting-zone data, we construct measures of exposure to foreign robot adoption and offshoring, while accounting for domestic automation and other local shocks. To address endogeneity, we instrument foreign exposure with robot diffusion in Europe. We show that regions more exposed to foreign automation experience higher levels of violent organized crime—including homicides and narcotics-related violence—and increased electoral support for left-populist candidates. These results demonstrate that automation shocks propagate through global value chains with profound consequences for violence and democratic politics in developing countries.

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†Princeton University, cboix@princeton.edu.

‡University of Southern California, gonzalez.rostani@usc.edu.

§University of Pittsburgh/Princeton University, ericaowen@pitt.edu.

1 Introduction

The acceleration of automation has reshaped employment, wages, and international production, with ramifications for political attitudes and party alignments. Economic research shows that new technologies raise firm competitiveness and labor productivity (e.g., Koch et al., 2021; Bonfiglioli et al., 2024). At the same time, automation has reduced labor's share of income, contributed to unemployment and wage stagnation among low-skilled workers, and polarized labor markets by shrinking middle-wage jobs in developed countries (e.g., Autor et al., 2003; Goos et al., 2009), accounting for a significant share of recent shifts in the U.S. wage distribution (Acemoglu and Restrepo, 2022).

Current research, primarily from advanced economies, finds that these disruptions also correlate with changes in political behavior, including higher disengagement (Boix, 2019; Gonzalez-Rostani, 2024a), greater support for populist and radical-right parties (Owen, 2019; Kurer, 2020; Anelli et al., 2021; Gonzalez-Rostani, 2025), and stronger demands for redistribution and protection (Busemeyer et al., 2023; Kurer and Häusermann, 2022; Chaudoin and Mangini, 2025; Gonzalez-Rostani, 2024b). However, we know far less about the social and political consequences of automation in the Global South. Accordingly, this paper examines how technological change–specifically foreign automation–reshapes political outcomes in the Global South, through its effects on labor market outcomes.

In a world of dense global value chains (GVCs), technological change in one region can reshape production and employment elsewhere. Emerging markets benefited from offshoring during the 1990s and 2000s. In Mexico, for instance, the expansion of maquiladoras (foreign-owned export-oriented manufacturing plants) generated manufacturing employment and export growth.[1] However, recent technological changes now threaten those gains. Input sourcing from developing countries tripled in the early 2000s but then slowed down after 2011

[1]However, even though such jobs are linked to a wage premium (Hanson, 2003), maquiladoras often created limited linkages to the domestic economy, and real wage growth for workers was modest, particularly once inflation and local cost-of-living increases are taken into account. While (Feenstra and Hanson, 1997) find evidence of a positive impact on demand for skilled labor, Atkin (2016) suggests that expansion of maquiladoras increased high school dropout rates, increasing the opportunity cost of staying in school.

as automation started to erode the advantage of low-wage labor (e.g., Faber et al., 2023). Robots can now perform tasks once offshored, spurring reshoring and altering GVC structures (De Backer et al., 2016; Rodrik, 2018a; Lund et al., 2019). By way of example, consider two cases that showcase how automation in labor-intensive, offshorable, economic activities can displace developing-country workers and weaken the employment gains once associated with globalization. In 2016, Ford relocated 3,250 jobs from Mexico to Michigan and Ohio. During the same period, United Technologies (Carrier) received a stream of federal subsidies to keep production facilities in the U.S. Carrier then invested those subsidies in automation, reducing labor demand for production workers on both sides of the border. As the CEO explained, "We're going to automate to drive the cost down so that we can continue to be competitive" (Isidore, 2016).

Indeed, emerging research in economics finds that the adoption of labor-saving technologies in advanced economies (hereafter "foreign robots" from the perspective of developing countries) lowers the relative cost of domestic production, slows offshoring, and encourages reshoring to the Global North, thereby reducing demand for Southern export-oriented manufactures. Although these shifts may increase the demand for imports of products tied to non-automated tasks in the Global South, the net effect is manufacturing displacement, heightened economic insecurity, and movement into lower-quality jobs or unemployment. A growing body of evidence links foreign automation with lower labor demand, wage stagnation, and job losses in the Global South (e.g., Artuc et al., 2019; Faber, 2020), with labor-intensive economies such as Mexico, India, Bangladesh, and Vietnam particularly exposed. Trade patterns also shift: demand for manufactured imports from developing countries falls (Hidalgo and Micco, 2024), while demand for complementary inputs such as minerals and agricultural goods rises (Stemmler, 2023). In some settings, these forces offset each other, leaving net trade balances largely unchanged (e.g., Artuc et al., 2023).

Where labor markets are slack and safety nets are thin, these shocks have important social and political consequences. First, they may affect public safety and the state's provision of order. More precisely, as local labor markets deteriorate, some may engage in informal or illicit activities, increasing crime and violence where there are criminal organizations and weak police enforcement. Second, these shocks can also reshape electoral politics. Voters in exposed communities may shift away from establishment parties associated with pro-market, globalization agendas and become more supportive of candidates who promise redistribution, social protection, and state-led industrial policies.

Empirically, we examine the effects of foreign robot adoption on violence in Mexico (1999–2018) and on presidential vote shares (2006–2024) at the commuting-zone level. Following the approaches of Acemoglu and Restrepo (2020) and Faber (2020), we construct measures of local exposure to both domestic and foreign automation. Our measure of exposure to foreign robot adoption combines the initial distribution of export-oriented employment across Mexican industries with (1) industry-level trends in U.S. robot adoption and (2) the initial U.S. reliance on imports from Mexico. We then estimate the impact of these exposure measures on wages, violent organized crime, and presidential election outcomes, with particular attention to support for left-wing populism.

Consistent with our theoretical expectations, we find that regions more exposed to foreign robot adoption experience higher levels of homicides, organized crime, and other indicators, as well as greater support for populist-left presidential candidates. These effects are not driven by domestic robot adoption. As evidence of our mechanism, we also provide evidence that exposure to foreign robots leads to worse labor market outcomes, including lower wages and employment.[2] Taken together, the findings show how technological change in advanced economies is transmitted across borders, impacting economic and political outcomes.

This paper makes three contributions. First, we provide, to our knowledge, the first systematic evidence that automation in the Global North generates social and political spillovers in the Global South, where access to comparable technology and social protection is lim-

[2] In the appendix, we also document patterns of reshoring, showing that events are concentrated in highly automated sectors and that technology adoption frequently appears as a stated motivation.

ited.[3] In doing so, we extend research on the labor-market effects of foreign automation (Artuc et al., 2019; Kugler et al., 2020; Faber, 2020), connect work on automation in advanced economies (e.g., Kurer, 2020; Gallego and Kurer, 2022) with evidence from emerging markets (Giuntella et al., 2024; Hidalgo and Micco, 2024), and engage the political economy of development (Dube and Vargas, 2013; Dube et al., 2016). Importantly, the social and political outcomes we document do not mirror those found in the North (e.g., right-wing populism). Second, we jointly study globalization and automation, showing how foreign technological change is transmitted through trade linkages to reallocate employment and reorient political outcomes (e.g., Rodrik, 2018b; Colantone et al., 2021). Finally, our results inform debates on populism and demands for compensatory policies (Stokes, 2025; Rettl, 2025) by extending theories of globalization-driven electoral backlash beyond advanced economies and by shedding new light on the transformation of electoral competition and political behavior in Latin America.

2 The Political Economy of Foreign Automation Shocks

In this section, we first detail why the adoption of foreign robots negatively affects labor market outcomes in the Global South. We then discuss the social and political consequences of exposure to foreign robot adoption. First, citizens may respond to the resulting labor market decline by exiting the legal labor market, leading to an increase in illegal activities and the criminality associated with them. Second, voters may be more likely to support left-populist candidates who promise pro-redistribution platforms and the redeployment of state-led industrial policies.

[3] For discussion of welfare states in emerging markets, see Holland (2018); Nooruddin and Rudra (2014); Rudra (2002).

2.1 Foreign Automation and Labor Market Disruption

Among other production technologies, industrial robotics have become a particularly important channel in replacing and augmenting labor, especially for emerging markets embedded in global supply chains.[4] Unlike fixed-purpose machines such as conveyor belts or bottling equipment, industrial robots are programmable, capable of executing a variety of tasks across multiple dimensions, and able to operate with minimal human control. Empirical studies of the impact of domestic automation in advanced economies find that industrial robots, often associated with higher productivity, also generate lower employment and wages (Acemoglu and Restrepo, 2020).[5] The evidence from emerging economies is more limited and mixed.

However, domestic robot adoption is not the only, or even the primary, source of automation exposure for the Global South; instead, foreign robot adoption may be. For example, according to the 2024 World Robotics Report, Mexico and Brazil operate 55,849 and 20,491 robots, respectively, compared to 381,964 in the United States. Put differently, Mexico has about 59 robots per 10,000 workers, while the U.S. has 295. These disparities mean that workers in emerging economies, part of global production chains, are competing not only with Northern workers, but also with Northern robots for offshorable tasks.

In the tasks framework (e.g. Acemoglu and Autor, 2011; Grossman and Rossi-Hansberg, 2008), the production of a good or service is broken into tasks that can be performed by different inputs: domestic labor, foreign labor, or capital. Firms allocate tasks across inputs according to comparative advantage, balancing relative costs and technological capabilities. Offshoring allows firms in the Global North to assign labor-intensive tasks to cheaper foreign workers, though doing so entails additional transaction and coordination costs.In equilibrium,

[4]For a discussion of labor substitution and augmentation, see, for instance, Acemoglu and Restrepo (2019); Acemoglu et al. (2024).

[5]Domestic robot adoption in advanced economies is also linked to a smaller share of work by unskilled labor (Graetz and Michaels, 2018), reductions in manufacturing employment (Dauth et al., 2021), declines in local employment (Chiacchio et al., 2018), and greater wage disparity between high- and low-skilled workers (Humlum, 2019).

inputs are allocated to tasks according to their comparative advantage. When the cost of automation falls, firms shift some tasks away from both domestic and foreign labor and toward capital. Data from the IFR indicate that these costs have fallen sharply, with average robot prices declining by roughly 80 percent between 1995 and 2017—from above $130,000 to under $27,000—making this form of capital far more accessible as a substitute for labor.[6] An increase in trade barriers or the wages of foreign workers can also lead to a decrease in the cost of automation relative to foreign labor.

Although the tasks framework is typically applied to the distributional consequences of automation for labor within advanced economies, it also has important implications for the division of work between North and South. Offshoring generates employment opportunities when Northern firms shift tasks abroad, but these opportunities are vulnerable to automation shocks in the North. As Northern robot adoption reduces the attractiveness of offshore production, emerging economies face potential "reshoring" and weaker trade linkages (Feenstra and Hanson, 1999a; De Backer et al., 2016). A reduction in firms' demand for labor from the Global South can arise through multiple channels, including explicit reshoring of production facilities, a slowdown in offshoring via reduced demand for Southern inputs previously supplied to the Global North through trade, and a decline in new foreign investment. We therefore use "reshoring" broadly to denote a reduction in demand for tasks performed in emerging markets. Together, these constitute a negative labor market shock, though we are not able to distinguish between them empirically.[7]

The effects of the foreign robot shock on emerging markets reflect the net balance between displacement forces that reduce demand for tasks performed by Southern labor, and productivity gains that can increase demand, especially for non-automated tasks. Existing empirical work suggests that displacement effects tend to dominate in labor-intensive export sectors. Studies of U.S. robot adoption show negative effects on both exports from and employment in Mexico (Artuc et al., 2019; Faber, 2020), consistent with automation in

[6] Construction Physics, January 2024. See also IFR, World Robotics Report.

[7] One could imagine that a factory closure or major layoffs are more salient than a gradual decline.

the Global North reducing demand for Southern manufacturing tasks. More broadly, cross-national and sectoral evidence indicates that automation facilitates reshoring (Pinheiro et al., 2023) and reallocates trade away from routine-intensive activities (Hidalgo and Micco, 2024). While some firm-level evidence points to offsetting productivity effects—where automation enables some firms to expand production and maintain imports from lower-wage countries (Stapleton and Webb, 2020), aggregate patterns suggest a rebalancing of trade flows in favor of advanced economies.[8] Taken together, the literature implies that foreign automation reshapes trade and production in ways that, on balance, reduce demand for labor-intensive tasks in developing countries.

In the short- to medium-term, we expect labor demand in exposed economies to fall because labor markets in the Global South often operate with surplus labor. This not only limits the ability of low-skilled workers to benefit from globalization (Rudra, 2005), but it also makes negative shocks harder to absorb. Displaced workers are unlikely to move into comparable industries. Instead, they tend to shift into agriculture, services, or extractive activities, which generally offer lower earnings and weaker protections than manufacturing employment. Recent evidence highlights such compositional changes, showing that foreign automation raises demand for raw materials like mining outputs (Stemmler, 2023), and decreases demand for manufactured goods. We therefore expect negative labor market effects–including reduced employment, lower wages, and greater reliance on the informal sector–to be most pronounced in communities more exposed to foreign robot adoption through global production linkages.

Importantly, the above highlights the necessity of distinguishing between domestic and foreign robot adoption when evaluating labor market outcomes. In emerging markets, the distributional effects of domestic robot adoption may diverge from exposure to foreign robot adoption because the balance of the labor-replacing and productivity-enhancing effects differs.

[8] For instance, see Artuc et al. (2023), who find that an increase in robot density in Northern countries is associated with an overall decline in net sectoral imports from the Global South.

2.2 From Labor Market Shock to Organized Crime

We argue that such economic shocks can trigger violent organized crime. A large literature links adverse labor market shocks to increases in violence and illicit activity, particularly in countries with weak institutions. The intuition follows a classic opportunity-cost logic: as legitimate employment opportunities shrink and incomes fall, criminal activities become relatively more attractive (Becker, 1968). Empirical evidence supports this mechanism. In Colombia, the collapse of coffee prices in the late 1990s depressed farm incomes and fueled civil violence in coffee-growing regions (Dube and Vargas, 2013). In rural Mexico, falling maize prices pushed farmers toward drug cultivation, enabling cartel expansion and increased violence (Dube et al., 2016). Environmental shocks had similar effects: droughts and crop failures increased homicide rates in Mexican municipalities as residents turned to the narcotics trade (Cavazos Hernandez and Sivakumar, 2022).

This logic also applies to negative labor market shocks from globalization. Exposure to trade liberalization and import competition can devastate local industries and spark social instability.[9] In Brazil, regions more exposed to steep tariff cuts in the 1990s saw sharp increases in crime, with 75–93% of the rise attributed to worsening employment prospects and weakened public services (Dix-Carneiro et al., 2018). Similar patterns emerge in Mexico, where China's entry into global manufacturing led to factory closures, layoffs, and a surge in drug trafficking and violent crime (Dell et al., 2019). According to Dell et al. (2019), organized criminal networks reduced the "entry costs" for negatively impacted workers to shift into illicit activities, increasing drug-related homicide in areas with drug trafficking organizations. These cartels may also respond by shifting activity to labor markets with more slack and lower wages because labor costs are the most significant component of their costs. In short, global market shocks are able to fuel crime by eroding the economic foundations

[9] Of course, positive shocks, like the expansion of markets through exports, can have the opposite effect. For instance, Erickson and Owen (2025) find that export opportunities benefiting avocados was associated with a decline in cartel violence in Mexico.

of legitimate work.[10]

A negative shock to labor demand, foreign robot adoption in advanced economies, has downstream implications for organized crime. As the United States and other high-income countries automate production, demand for manufactured imports from countries like Mexico declines, producing job losses, plant closures, and wage pressure in exposed local industries. Workers in these areas faced worse labor market outcomes and limited adjustment options. Unlike in wealthier countries—where workers affected by automation may relocate (Faber et al., 2022)—mobility is more constrained, particularly when traditional destination countries are also automating or tightening immigration controls. Many workers, therefore, remained in deteriorating local economies, increasing the relative appeal of informal and illicit activities.

In areas where criminal networks operated, this pool of surplus labor facilitated recruitment by lowering the opportunity cost of participation and increasing risk tolerance. Although much drug-related labor does not involve direct violence, greater labor availability allows criminal organizations to expand, compete for territory, and confront the state, raising the likelihood of violence (Dell et al., 2019; Herrera, 2019). Accordingly, we hypothesize that:

Hypothesis 1 (Organized crime) *Communities with greater exposure to foreign-robot adoption experienced increased levels of violence and organized crime.*

Finally, we note that we posit that the link between economic dislocation and violent crime operates through economic incentives—displaced workers reallocating into the underground economy—rather than through psychological distress or social breakdown (e.g., Liang et al., 2025). Accordingly, we do not expect a general increase in crime, but a selective rise in offenses tied to organized crime, where illicit activities may function as an alternative source of employment.

[10] But see Hidalgo et al. (2026), who find that NAFTA trade liberalization increased violence by reducing transportation costs, leading DTOs to engage in violent competition over transit routes.

2.3 Political response: Left populism

Adverse labor market shocks also have significant consequences at the ballot box. In much of the Global North, economic shocks from automation and globalization have reshaped politics by fueling support for right-wing populism. The displacement of middle-income, middle-skill workers and the limited response of mainstream left parties created space for populist entrepreneurs who capitalized on anti-globalization and especially anti-immigration sentiment. Studies of the United States and Europe show that exposure to robots (Anelli et al., 2019, 2021; Caselli et al., 2021; Frey et al., 2018; Gonzalez-Rostani, 2025; Milner, 2021) and imports (e.g Margalit, 2011; Jensen et al., 2017; Autor et al., 2020; Che et al., 2022; Colantone and Stanig, 2018; Milner, 2021) shifted many working-class voters to the right. Riding on the support of anti-globalization and anti-immigration voters, populist parties succeeded in reshaping an electoral map that had been frozen since the Cold War (Boix, 2019).

In contrast to advanced economies, workers in labor-abundant countries (like Mexico) were expected to benefit from trade, and thus, to support free trade (e.g. Rogowski, 1989).[11] At the mass politics level, regions of Mexico that benefited from NAFTA-related exports (in terms of employment growth), exhibited lower levels of support for AMLO during the close 2006 election. Bustos and Morales-Arilla (2024) argue that this is because there was less support in those regions for the nationalist and protectionist agenda advanced by AMLO, who, in the 2006 campaign, proposed not fully implementing Mexico's liberalization commitments under NAFTA. Yet individuals' support for openness can weaken when the expected gains from liberalization fail to materialize (Rudra et al., 2021).

Our argument has a different focus: negative shocks to locations and workers that had previously benefited from integration, driven by reshoring toward advanced economies. In these settings, workers may not reject globalization per se but instead increasingly favor state

[11] Research on individual-level preferences largely supports this with some nuance. Menéndez González et al. (2023) find that relatively skilled workers support free trade, while Dolan and Milner (2023) find that less skilled workers support free trade in Africa.

intervention and redistribution to manage the consequences of foreign automation. That attitudinal shift was likely to entail a fall in the electoral strength of any parties that had implemented an economic liberalization agenda since the 1980s. As in the North, disaffected voters warmed up to populist-nationalist solutions that rejected the so-called Washington consensus and an international order favoring macroeconomic stability and globalization. Still, whereas northern electorates supported right-wing populist parties, Global South voters often leaned toward left-wing populist forces.[12] In contrast to right-wing populist parties, left-populist politicians in the Global South, criticized markets, favored the expansion of the regulatory state, committed to a more assertive industrial policy centered on state-owned enterprises, and promised higher mandated minimum wages (Edwards, 2019).

The left-populist turn emerged for three reasons: the supply of political ideas, the dynamics of migration, and the structure of the welfare state. First, in the Global North, where mainstream center-left and center-right parties agreed on the benefits of globalization and the market economy, populist candidates often grew after grafting themselves to (small) far-right parties and focusing on an anti-immigration platform. By contrast, Latin American politics had been traditionally organized around an economically liberal (and, in electoral size, modest) right and a left-leaning, broad populist movement (Dornbusch and Edwards, 1990). The collapse of import-substituting industrialization (ISI) policies and the introduction of structural adjustment programs weakened the latter, temporarily leading an important part of the Latin American Left to embrace the pro-market and moderate pro-redistribution stances of European social democracy (Cleary, 2006; Baker and Greene, 2011; Roberts, 2015). A spike in income inequality, increased unemployment, and the spread of informal jobs resulted in growing voter disillusionment with market reforms driven by the Washington Consensus regime (Roberts, 2007; Garay, 2023). Riding on growing popular malaise about "neoliberalism" and globalization, the old Left made a political comeback in

[12] Some European voters have also switched to left-wing populist parties, mainly in more "peripheral" regions, that is, those regions that, from an economic point of view, are somewhat closer to middle-income economies: Greece, parts of Spain, and eastern Germany.

several countries (Baker and Greene, 2011; Feierherd et al., 2023; Aksoy et al., 2024), offering what Sebastian Edwards has referred to as a "new populist" program (Edwards, 2019).

Second, as net exporters of labor, the restrictive immigration policies espoused by Global North populists made little sense to Global South voters in most places. Instead, protectionist politics turned around the terms of foreign investment and the potential relocation of multinationals, and, therefore, raised the need for industrial statism. The return to state intervention was complemented with a renewed commitment to more redistribution and greater social protection (Murillo et al., 2010; Wiesehomeier and Doyle, 2013).

Finally, operating within weak-capacity states yet concerned about income distribution and poverty alleviation, populist politicians pushed for an expansion of targeted, needs-based programs, legally enforced wage increases, and sector-specific price controls. These policies emerged as traditional labor-based party systems weakened due to declining union membership and widening divisions between formal-sector insiders and precarious informal workers (Garay, 2023).

Overall, our expectation is that a decline in labor market conditions led to a leftward shift in citizens' political preferences, as voters increasingly demand pro-worker policies such as social protection, job guarantees, and redistribution. In the particular political context we examine, given the supply of parties, this shift should strengthen left populist candidates. In short:

Hypothesis 2 (Left populism) *Communities with greater exposure to foreign-robot adoption are more likely to support left-populist political parties.*

3 Background: The Mexican Context

Mexico provides a compelling case to analyze how automation in advanced economies impacts developing countries. Its deep economic integration with the United States, long-standing migration connections, and entrenched organized crime networks uniquely position

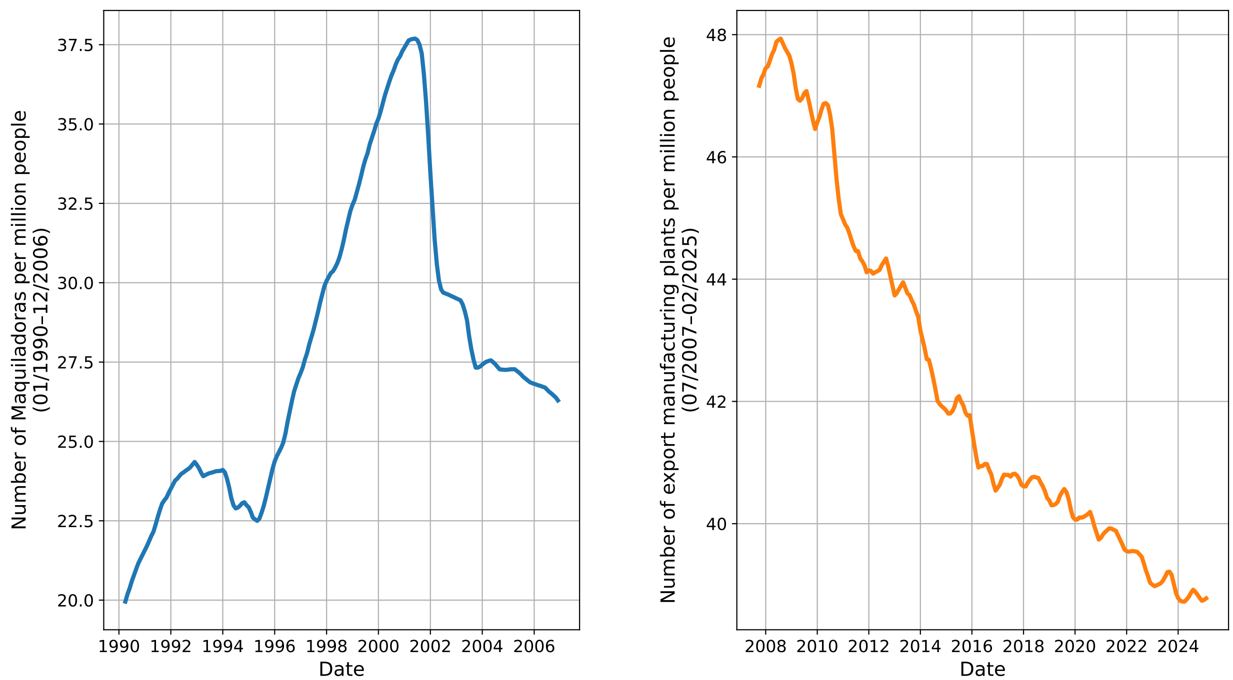
Mexico to illustrate the broader implications of automation-induced labor market shifts. The economic interdependence is particularly pronounced: in 2024, 83% of Mexico's exports went to the U.S. (López and Vázquez, 2025), constituting approximately 15% of total U.S. imports (Mann, 2024). Key sectors such as automotive manufacturing, which have rapidly embraced automation in the U.S., represent significant sources of employment in numerous Mexican regions, rendering them especially susceptible to structural changes abroad.

3.1 Economic context

The acceleration of automation in advanced economies has reduced the demand for low-skilled labor, curtailed offshoring activities (Artuc et al., 2019; Acemoglu and Restrepo, 2020; Faber, 2020), and thus exposed Mexico to substantial economic vulnerabilities. Crucially, the prevalent influence of criminal organizations within Mexico exacerbates the political and social consequences of economic shocks. Cartels have historically exploited economic downturns and institutional weaknesses, intensifying violence, especially during electoral periods, to assert territorial dominance (Dube et al., 2013; Trejo and Ley, 2021). In short, Mexico's integration into global trade, combined with volatile security dynamics, offers a particularly insightful context for studying the transnational impact of technological disruptions.

Figure 1 illustrates the evolving landscape of export-oriented manufacturing plants in Mexico from 1990 to 2025. Because of the decision in 2007 by Mexico's National Institute of Statistics to include non-Maquiladora export facilities, the left plot reports 4-month moving averages of maquiladoras from 1990 to 2006, and the right graph displays export manufacturing plants per million inhabitants from 2007 to 2025. Following the enactment of NAFTA in 1994, there was a substantial rise in export manufacturing establishments. However, since the mid-2000s, coinciding with the rapid adoption of robotics in the U.S., a marked decline in the number of these plants per capita has occurred, potentially reflecting the displacement of human labor by automation technologies.

Complementing this, Figure 2a and Figure 2b document the parallel rise of industrial



(a) Maquiladoras per million people (Jan 1990–Dec 2006).

(b) Export manufacturing plants per million people (Jul 2007–Feb 2025).

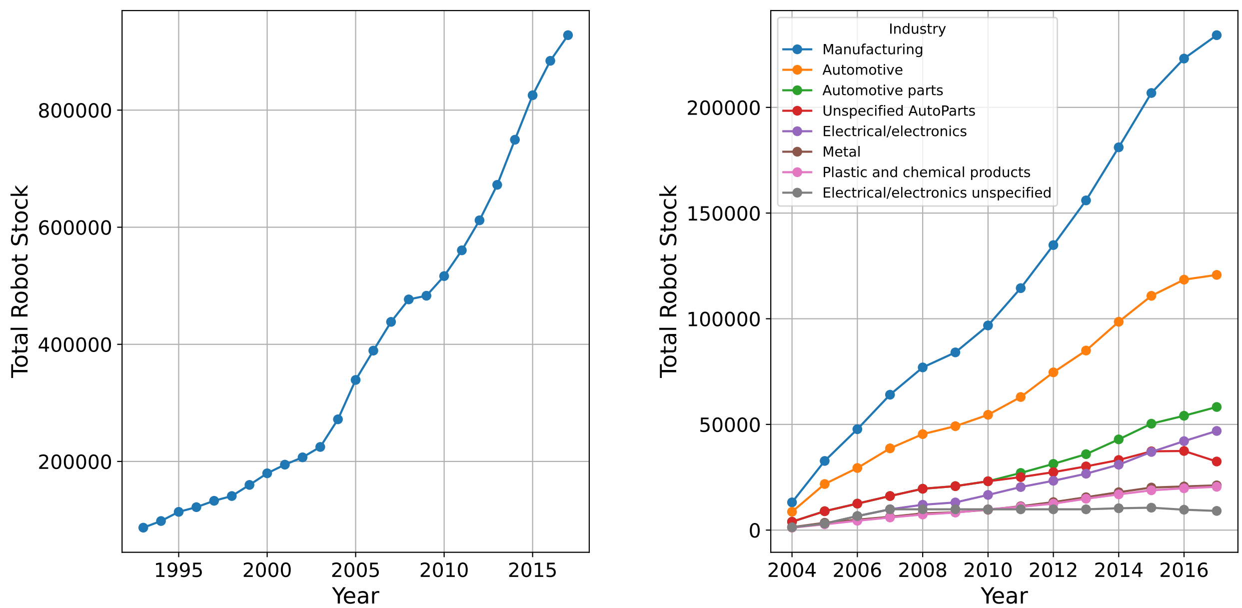
Figure 1: 4-month moving average number of maquiladoras and number of export manufacturing plants.

Note: This figure plots the 4-month moving averages of maquiladoras (Jan 1990–Dec 2006) and export manufacturing plants (Jul 2007–Feb 2025) per million inhabitants in Mexico. The break around early 2007 arises from a methodological update in INEGI's EMIME and IMMEX series when non-Maquiladora export facilities were first included. Authors' own elaboration based on data from INEGI.

robots in the United States—both in aggregate and within key sectors such as automotive, machinery, and electronics, which mirror Mexico's export structure. The timing coincides with a broader reorganization of production: since the mid-2010s, more than 200 reshoring cases from Mexico to the United States have been recorded (discussed in Appendix A.1). **??** presents illustrative examples of these relocations.

3.2 Political context

Mexico's contemporary political landscape is shaped by a long period of elite convergence around market-oriented reforms. After governing uninterruptedly for more than seven decades, the Institutional Revolutionary Party (PRI) implemented sweeping pro-market



(a) Industrial Robots (1993–2017). (b) Industrial Robots by industry (2004–2017).

Figure 2: Stock of Industrial Robots in the United States.

Note: This figure plots robot stock trends by industry in the United States, focusing on the eight industries with the highest total robot stocks from 2004 onwards. Industry-level disaggregated data is available starting from 2004. Authors' own elaboration based on data from the International Federation of Robotics (IFR), 1993–2017.

changes in the late twentieth century. Over the following two decades, the center-right National Action Party (PAN), which first took office in 2000, and the PRI, which returned to the presidency in 2012, largely converged on a technocratic consensus. This period coincided with worsening security conditions due to the expansion of organized crime and its penetration of local institutions, alongside sluggish real economic growth and rising concerns about inequality. Together, these trends eroded public trust in the political establishment and generated widespread disaffection with both major parties (Trejo and Ley, 2021; Gutiérrez-Romero and Iturbe, 2024; Gutiérrez-Romero and UNU-WIDER, 2025). Disillusionment with this status quo culminated in the decisive 2018 electoral victory of Andrés Manuel López Obrador (AMLO) and his National Regeneration Movement (MORENA), which promised a sharp break with neoliberal governance and a return to the faster growth associated with the 1960s and 1970s (Castro Cornejo, 2023).

Within this context, MORENA articulated an explicitly pro-worker political project.

AMLO often embraced technological progress while cautioning against "jobless growth." After inaugurating a highly automated distribution center in 2020—famously describing it as *"puro robot"*—he argued that, in a labor-abundant economy, public spending and private investment should prioritize employment creation.[13] This emphasis was reinforced through repeated contrasts between capital-intensive production and labor-intensive public works, including roads, railways, and energy infrastructure, as well as through critiques of offshoring and abusive outsourcing framed in terms of economic sovereignty. These themes were reflected in policy initiatives such as the 2021 restrictions on subcontracting,[14] increases in the minimum wage, the creation of the northern border *Zona Libre*, and large-scale projects including the Tren Maya and the Dos Bocas refinery. In his Sixth Government Report, AMLO characterized his administration as an effort to dismantle "antipopular, entreguista y corrupta" policies—using *entreguista* to denote the transfer of national resources to foreign interests and domestic elites.[15] Social programs such as *Jóvenes Construyendo el Futuro* and *Sembrando Vida* complemented this agenda by targeting populations displaced by economic restructuring. The electoral appeal of this approach was particularly evident in industrial regions. In Coahuila, a northern state heavily dependent on steel and automobile manufacturing, large-scale layoffs during 2019–2020 were followed by MORENA's electoral gains in 2021 and 2024. Federal promises of state intervention—including Claudia Sheinbaum's pledge to revive the steel industry—resonated with displaced workers. As one steelworker explained, government involvement "calms the situation and lifts the spirits of the more than 8,000 former workers."[16]

Taken together, support for AMLO and MORENA reflects a distinctive form of left-wing populism rather than conventional left ideology or populism alone. The party combined redistributive economic policies—such as higher minimum wages, trade protections, and

[13] Inauguración del Camino Rural a Santiago Nejapilla. Gobierno de México. December 11, 2020.
[14] "Mexican Lawmakers Approve Contentious Outsourcing Law." Reuters. April 20, 2021.
[15] "Promover leyes para frenar la política antipopular, entreguista y corrupta que se había impuesto y legalizado por el predominio de un poder oligárquico con apariencia de democracia," Discurso del presidente Andrés Manuel López Obrador en su Sexto Informe de Gobierno. September 2024.
[16] La Jornada. April 12, 2025.

public employment—with a direct anti-elite narrative that blamed a political and economic "mafia of power" for failing to protect domestic employment. This configuration places MORENA firmly within the populist tradition. At the same time, unlike many progressive left movements, MORENA emphasized law and order; for example, AMLO created the National Guard in 2019 and rapidly militarized public security while expanding military control over civilian infrastructure (e.g., Sanchez, 2024). Its populism also diverged sharply from right-wing variants in Latin America, such as Jair Bolsonaro's in Brazil, which paired nationalism and social conservatism with pro-business, market-oriented economic policies.

4 Empirical Strategy

Our empirical strategy builds on the methodologies proposed by Acemoglu and Restrepo (2020) and Faber (2020), distinguishing between domestic and foreign exposure to robot adoption. The standard approach to measuring exposure to domestic robot adoption, following Acemoglu and Restrepo (2020), is defined as:

$$\text{Exposure to domestic robots}_{c(t_0,t_1)} = \sum_{i \in I} \ell_{ci,1990} \left(\frac{R^{MX}_{i,t_1} - R^{MX}_{i,t_0}}{L_{i,1990}} \right)$$

Here, R^{MX}_{i,t_1} and R^{MX}_{i,t_0} represent the number of robots in industry i in Mexico at times t_1 and t_0, respectively. $\ell_{ci,1990}$ is the share of employment in industry i relative to total employment in region c in 1990, while $L_{i,1990}$ denotes the industry's total employment at that time. Using employment shares from 1990 minimizes endogeneity concerns related to recent economic conditions or policy decisions. Our main variable of interest is foreign robot exposure, which extends the domestic measure by shifting attention to automation in trading partners, particularly the United States, following Faber (2020). To better capture external shocks, this measure also incorporates industry-level offshorability.

$$\text{Exposure to foreign robots}_{c(t_0,t_1)} = \sum_{i \in I} \ell^f_{ci,1990} \left(\frac{(R^{US}_{i,t_1} - R^{US}_{i,t_0}) \cdot O_{i,1992}}{L^f_{i,1990}} \right)$$

Here, R^{US}_{i,t_1} and R^{US}_{i,t_0} indicate the estimated number of robots in industry i in the U.S. at times t_1 and t_0, respectively. $\ell^f_{ci,1990}$ represents the share of export-producing employment in industry i relative to total employment in commuting zone c in 1990, and $L^f_{i,1990}$ is total employment in foreign industry i. The offshorability factor $O_{i,1992}$ captures the initial reliance of U.S. industries on Mexican imports as inputs, calculated as:

$O_{i,1992} = \frac{I^{MXUS}_{i,1992}}{Y^{US}_{i,1992}}$

In this formula, $I^{MXUS}_{i,1992}$ is the proportion of U.S. industry i's inputs imported from Mexico, while $Y^{US}_{i,1992}$ is the total output of U.S. industry i. This measure thus quantifies each industry's vulnerability to automation shocks based on its dependence on Mexican-produced inputs.

Finally, we address potential endogeneity arising from the correlation between robot adoption and unobserved factors affecting local labor markets by employing an instrumental variable approach, using the increase in robots in the rest of the world as an instrument for foreign exposure (and we do the same for domestic exposure). External exposure to foreign robots is thus measured as:

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

The superscript WLD denotes the sum over European countries that are also incorporating technology (i.e, excluding the US and Mexico) for which industry-level data are available from 1993 onward.[17] To address potential endogeneity in our initial offshoring to Mexico proxy, we follow Feenstra and Hanson (1999b) and Faber (2020) in defining it as the share

[17]These countries include Denmark, Finland, France, Germany, Italy, Norway, Spain, Sweden, and the United Kingdom.

of imported intermediate inputs from the same industry over total non-energy intermediates in U.S. industry i in 1990 (across all source countries).

We estimate the following equations:

$$y_{POST} = \alpha + \beta^f \text{Exp. to foreign robots}_{c(t_0,t_1)} + \beta^d \text{Exp. to domestic robots}_{c(t_0,t_1)} \\ + \ \mathbf{X}_{c,t_0}\gamma + \varepsilon_{c(t_0,t_1)}$$

$$\Delta Y_{c(t_0,t_1)} = \alpha + \beta^f \text{Exp. to foreign robots}_{c(t_0,t_1)} + \beta^d \text{Exp. to domestic robots}_{c(t_0,t_1)} \\ + \ \mathbf{X}_{c,t_0}\gamma + \varepsilon_{c(t_0,t_1)}$$

where the dependent variable is one of our main outcomes (i.e. incidence of violent crime or left party vote share). We present results using the post-shock level of the dependent variable (measured in the most recent available period t_1) as well as a first-difference specification capturing the change in the outcome over the period $(t_1 - t_0)$. The main independent variable is foreign robot exposure. Since domestic adoption may also have significant social and political effects, we include it as well. The equation controls for the influence of other relevant covariates discussed further below ($\mathbf{X}_{c,t_0}$).

The unit of analysis is Mexican local labor markets (i.e., commuting zones, CZs). CZs are clusters of municipalities that feature strong commuting ties within, and weak commuting ties across CZs. We use Faber's crosswalk from municipalities to CZs. There are 1806 CZs.

5 Data

In this section, we describe our main data sources. Our independent and several control variables are drawn from Faber (2020)'s replication data. We combine the latter with data on our outcome variables.

Independent Variable: Exposure to Robots. The independent variable in our analysis is exposure to foreign robots, which is sourced from Faber (2020). This measure comes from combining Census data, trade data, and robot data from the International Federation of Robotics (IFR). The IFR has collected data on the shipments and operational stocks of industrial robots by country and industry since 1993. These robots are defined as reprogrammable, multipurpose manipulators used in various industrial automation tasks, including manufacturing, agriculture, and utilities (IFR, 2015). Because the IFR data are available only at the country–industry–year level, it is not possible to identify which U.S. robots directly affected which Mexican regions. Instead, prior research allocates exposure across commuting zones (CZs) based on their pre-shock industry employment structure, updated with subsequent adoption either abroad or at home (Faber, 2020; Acemoglu and Restrepo, 2020). Both foreign and domestic exposure are thus measured using a Bartik-style approach, which leverages the initial industrial composition of each CZ and the number of robots adopted by industry. This captures how employment concentration shapes local exposure rather than relying on direct robot installations within each CZ.[18]

Exposure to foreign robots is not only linked to technology adoption in trade partners but also incorporates offshorability. This is captured by dividing the value of Mexican imports to the US in each industry (sourced from the UN Comtrade database) by the total output of the corresponding US industry (from the US Bureau of Labor Statistics) in 1992. In this external exposure measure, the offshoring indicator for US industries, $O_{i,1990}$, represents the share of imported intermediate goods in each industry relative to total non-energy intermediates within the US industry in 1990. This measure, inspired by the outsourcing index of Feenstra and Hanson (1999b), typically used for the 4-digit SIC72 classification, is adjusted to the broader IFR industry classification. Faber (2020) mapped each SIC72 industry to an IFR industry and calculated the employment-weighted average for each IFR industry, using

[18]Since most firms produce for both domestic and foreign markets, isolating export-related employment is challenging. However, Maquiladoras are primarily export-oriented; for example, they accounted for nearly half of Mexico's exports in 2005, making them a reliable proxy. Thus, export-producing employment ($\ell^{f}_{ci,1990}$) is measured using Maquiladora employment data from the non-digitized CEPAL (1994) report.

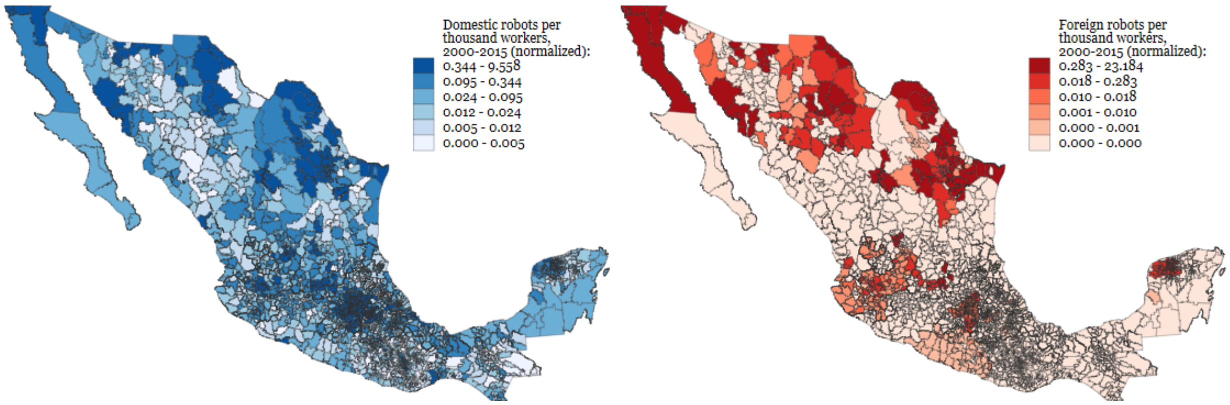


Figure 3: Commuting zone-level variation in exposure to domestic and foreign robots, 2000–2015.

employment data from the County Business Patterns (CBP) dataset.

In Figure 3, we show commuting-zone-level exposure to domestic (blue) and foreign (red) robots across Mexico between 2000 and 2015. Exposure to foreign robots, highlighted in red, is largely concentrated in the northern region, reflecting nearshoring dynamics and proximity to U.S. manufacturing centers. Cities with high foreign robot exposure include Ciudad Juárez, Tijuana, Monterrey, and Reynosa. In contrast, exposure to domestic robots, depicted in blue, shows a more balanced distribution across the country, with substantial robotization observed in central areas including Mexico City, Guadalajara, León, and other industrial hubs. This pattern underscores a broader integration of domestic automation compared to the geographically concentrated foreign robot exposure in northern industrial zones.

Dependent Variables. For the dependent variables in this analysis—crime and vote share—we use data from various sources. The data were initially collected at the municipality level and subsequently aggregated at the commuting zones (CZ) level using a crosswalk between municipalities and CZs.

Violent Organized Crime. Data on organized crime and homicides come from multiple sources. From CONAPO and the Mexican National Institute of Statistics and Geography

(INEGI), we use the 2018 homicide rate, defined as the number of homicides per 10,000 inhabitants at the municipal level, normalized by the 2018 population. To estimate changes between 1999 and 2018, we use data on the number of homicides in 1999 from the replication files of Hidalgo et al. (2026). Following Hidalgo et al. (2026), we construct the change in the homicide rate by scaling both 1999 and 2018 homicides by the 1990 population, ensuring a consistent baseline denominator over time.[19] Since official statistics do not consistently distinguish drug-related killings, overall homicide rates are often used as a proxy for narcocrime, following prior work (BenYishay and Pearlman, 2013; Dell, 2015; Cavazos Hernandez and Sivakumar, 2022). See Figure 4a for variation in homicide incidence.

As a complementary measure, we employ the organized-crime index developed by Osorio and Beltran (2020), which uses natural language processing techniques to detect references to organized crime in news reports. This proxy is available annually for 2000–2018, providing a time series to validate our findings.[20] We again estimate both the post-shock level (in 2018) and the change in the amount of organized crime.[21]

Electoral outcomes. To study the political effects of foreign robot adoption, we focus on support for left-wing parties, measured by the vote share of MORENA. Our primary analysis focuses on the post-shock elections of 2024. We also explore trends across the full period from 2006 to 2024, as well as outcomes for the right.[22] Electoral data are drawn from the Instituto Nacional Electoral (INE) database.[23] See Figure 4b for variation in Left support.

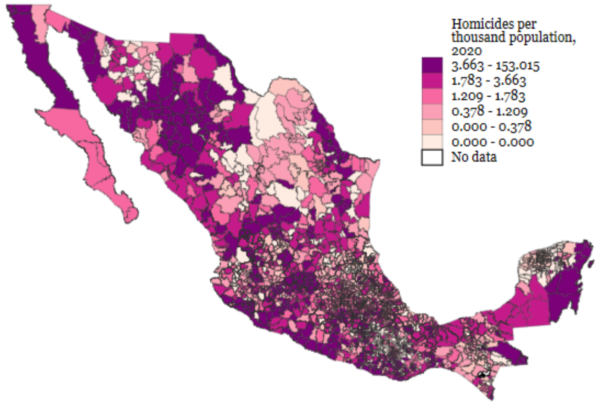
[19] Thus changes in the homicide rate reflect changes in violence rather than shifts in municipal population over time.

[20] The measure is available only for municipalities that had any instance of organized crime reported during the period. Thus, for the approximately 700 commuting zones with no reported episode of organized crime, we replace missing values with zero.

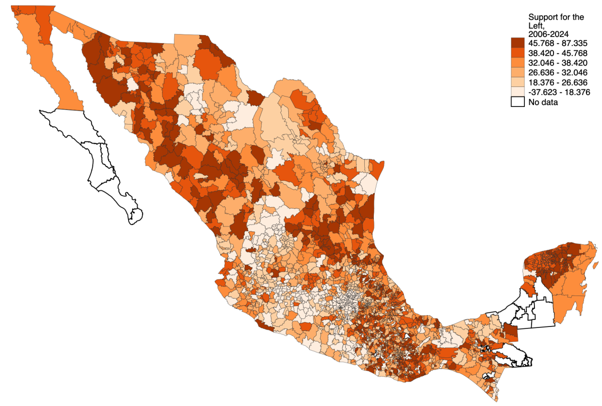
[21] In robustness analysis, we also use detailed municipal-level data from the Center for Research and National Security (CISEN) in 2016. These data allow us to isolate narcocrime and human trafficking and compute the incidence of organized crime per 10,000 inhabitants in each CZ. From CISEN, we also obtain other crime indicators, such as property crime. See Appendix Table A.10.

[22] MORENA was officially registered in 2014. For the first difference analysis, we treat AMLO's earlier vote share from 2006 as a representative of PRD as a proxy for MORENA.

[23] `https://prep2024.ine.mx/publicacion/nacional/base-datos`



(a) Homicides per thousand people in 2018.



(b) Left support 2006 to 2024

Figure 4: Commuting zone-level variation in key dependent variables.
Notes: The maps represent the variation in homicides per thousand people in 2018, and the variation in support for the Left from 2006 to 2024. Refer to Figure A.6 for a map illustrating the variation in organized crime between 2000 and 2018.

Control Variables. We control for additional factors that may shape our outcomes of interest. Our controls come from Faber (2020) unless otherwise specified. The first is the share of workers in routine task-intensive occupations. This measure is derived from occupation-level data and a crosswalk with the US case (Autor, 2013). We control for this in 1990 as a measure of vulnerability to automation prior to the shock.

We include two additional variables related to the economic context. First, we control for NAFTA exposure to capture the effects of the North American Free Trade Agreement, which came into effect in 1994, and altered industry-level tariffs for many sectors. The measure reflects each commuting zone's exposure to NAFTA, interacting its initial employment shares with the NAFTA-induced tariff change in industry. Second, we include exposure to Chinese import competition to account for the impact of increased Chinese imports to both Mexico and the US. This control, which accounts for changes in Mexican imports from China as well as the indirect competition in foreign markets, uses a Bartik-style measure that incorporates industry-specific changes in Chinese imports to both countries.[24]

Additionally, we control for pre-shock demographic characteristics of each CZ: the share of men and the share of people with primary education as their highest level of education

[24] For more details, see Faber (2020).

in 1990. We also include industry employment shares in manufacturing and the share of employment relative to the population in 1990.[25] In robustness checks, we control for distance to the U.S., the presence of drug trafficking routes (Hidalgo et al., 2026), and state fixed effects.

See Table A.2 for summary statistics.

6 Results

Before turning to the main results on crime and presidential vote share, we document how exposure to foreign automation transmitted through global value chains, generates sizable economic shocks in Mexican export-oriented regions that are consistent with the mechanisms in our argument. For each set of findings, we present both OLS results as well as the results of the instrumental variables regression.[26]

6.1 The Effect of Foreign Robots on the Labor Market

In this section, we highlight several key findings about the effects of foreign automation on local labor market outcomes. To examine foreign automation's effects on local labor markets, Table 1 reports results from specifications that parallel our main models but use economic outcomes as dependent variables. Column 1 presents our original analysis of wages, drawing on newly assembled Census microdata from IPUMS. The dependent variable is the residualized change in the average manufacturing wage between 2000 and 2015. The coefficient on foreign robot exposure is negative and statistically significant, indicating that commuting zones more tied to highly automated U.S. industries experienced weaker wage growth in manufacturing.

A natural concern is that these regions may have already been on a downward path

[25] Our results are robust when we incorporate dynamic variables, such as the changes in the employment-to-population ratio between 2000 and 2015, though this variable suffers from post-treatment bias.

[26] See Table A.3 for results of the first stage of the instrumental variables regression.

Table 1: Effect of Robot Exposure on Economic Outcomes

OLS	(1) Δ Wages	(2) Δ Employment	(3) Δ Working Age Pop.
External exposure to foreign robots	-0.0270*	-1.084**	-0.799**
	(0.0152)	(0.446)	(0.365)
External exposure to domestic robots	-0.116*	-1.825	0.435
	(0.0603)	(3.372)	(2.314)
Demographics	✓	✓	✓
Industry	✓	✓	✓
Observations	1610	1800	1800
R^2	0.014	0.082	0.217

IV	(1) Δ Wages	(2) Δ Employment	(3) Δ Working Age Pop.
Exposure to foreign robots	-0.0289*	-1.186**	-0.879**
	(0.0152)	(0.504)	(0.418)
Exposure to domestic robots	-0.112*	-1.741	0.400
	(0.0582)	(3.136)	(2.150)
Demographics	✓	✓	✓
Industry	✓	✓	✓
Observations	1610	1800	1800
R^2	0.014	0.081	0.215
F	8.198	4.486	11.28
Kleibergen-Paap Wald F-stat	100.2	175.5	175.5

Notes: All dependent variables refer to changes between 2000 and 2015, with column 1 referring to changes in manufacturing wages (residualized), column 2 the log of employment, and column 3 to the log number of the working-age population. All specifications include the following control variables: 1) Demographics: 1990 CZ demographics, including the share of men and the share of people with primary education as their highest level; 2) Industry: shares of employment in manufacturing in 1990 and the 1990 level of employment-to-population ratio. Regressions in columns 2 and 3 are weighted by a CZ's share of the national working-age population in 1990. Standard errors are robust to heteroskedasticity and clustered by state. The coefficients marked with $***$, $**$, and $*$ are significant at the 1%, 5%, and 10% confidence levels, respectively. Refer to Table A.4 for the full table.

before the 2000–2015 period. Appendix Table A.5 addresses this by relating our measures of foreign robot exposure to wage changes between 1990 and 2000, as well as to robot exposure computed for 1993–2000. In both cases, foreign robot exposure is positively rather than negatively associated with earlier wage growth. We therefore find no evidence of adverse pre-trends, which supports the interpretation that the 2000–2015 decline in wages reflects the foreign automation shock rather than long-run divergence.

Column 2, which relies on data from Faber (2020), shows that greater exposure to foreign robots is associated with a decline in employment between 2000 and 2015. Finally, column 3 of Table 1 shows that commuting zones more exposed to foreign robots experience a decline in the size of the working-age population. This pattern is consistent with out-migration or reduced in-migration into areas hit by employment and wage losses. Taken together, the evidence on exports, employment, wages, and population points to a sizeable negative labor market shock in regions tied to offshorable, robot-intensive production in the United States.

In the Appendix, we document further economic mechanisms related to reshoring. We analyze patterns of reshoring events from the Reshoring Initiative (Reshoring-Initiative, 2025). These events are concentrated in automotive, machinery, and electronics-—highly automated U.S. industries where foreign automation most strongly depresses Mexican exports (see Appendix Figure A.5). Indeed, topic analysis of announcements also identifies technology and automation as a distinct motive alongside supply-chain and policy considerations (see Table A.1).

6.2 The Effect of Foreign Robots on Violent Organized Crime

We now present results related to organized crime. Table 2 shows that coefficient on foreign robot exposure is positive and statistically significant, suggesting that greater foreign automation exposure is associated with more organized crime, consistent with Hypothesis 1. Looking at the IV regressions, in Column 1, a one standard deviation increase in foreign robot exposure results in an increase of 0.28 homicides per 10,000 population, equating to a 4.84 percentage point increase relative to the standard deviation of the homicide rate. In Column 2, where the dependent variable is the index of organized crime, the coefficient on foreign robot exposure is positive and statistically significant. A one standard deviation increase in foreign robot exposure is associated with a 3.01 unit increase in the organized crime index, equal to a 42.4 percent increase relative to the standard deviation of the index.

When we examine changes in the homicide rate (Column 3) and changes in organized crime (Column 4), the coefficients on foreign robot exposure remain positive and statistically significant. The advantage of the first-difference specification is that it accounts for time-invariant commuting-zone characteristics over the period. Although the magnitudes are

Table 2: Effect of Robot Exposure on Violence

OLS	(1) Homicides	(2) Org. Crime	(3) Δ Homicides	(4) Δ Org. Crime
External exposure to foreign robots	0.253*	2.736***	18.95*	2.465***
	(0.142)	(0.841)	(10.04)	(0.770)
External exposure to domestic robots	-1.116***	-3.708**	-17.51	-3.456**
	(0.360)	(1.754)	(11.83)	(1.689)
Demographics	✓	✓	✓	✓
Industry	✓	✓	✓	✓
Observations	1797	1800	1796	1800
R^2	0.126	0.421	0.493	0.392
IV	(1) Homicides	(2) Org. Crime	(3) Δ Homicides	(4) Δ Org. Crime
Exposure to foreign robots	0.280*	3.014***	20.85*	2.715***
	(0.162)	(1.041)	(11.76)	(0.949)
Exposure to domestic robots	-1.053***	-3.474**	-16.33	-3.239*
	(0.336)	(1.742)	(12.11)	(1.667)
Demographics	✓	✓	✓	✓
Industry	✓	✓	✓	✓
Observations	1797	1800	1796	1800
R^2	0.133	0.376	0.403	0.352
F	2.687	6.098	1.182	6.733
Kleibergen-Paap Wald F-stat	178.1	178.0	178.1	178.0

Notes: The dependent variable in column 1 refers to the homicide rate, sourced from CONAPO. Column 2 is the organized crime index with data from Osorio and Beltran (2020). Columns 3 and 4 refer to the change for variables in 1 and 2. All specifications include the following control variables: 1) Demographics: 1990 CZ demographics, including the share of men and the share of people with primary education as their highest level; 2) Industry: shares of employment in manufacturing in 1990 and the 1990 level of employment-to-population ratio. All regressions are weighted by a CZ's share of the national working-age population in 1990. Standard errors are robust to heteroskedasticity and clustered by state. The coefficients marked with $***$, $**$, and $*$ are significant at the 1%, 5%, and 10% confidence levels, respectively. Refer to the full Table in Appendix Table A.6.

not directly comparable to those in the levels specification, it is important to note that the change in the homicide rate (per 10,000 population) is calculated relative to the 1990 population baseline to ensure consistency with the Hidalgo data, whereas the level specification in Model 1 is scaled relative to the 2018 population. Importantly, homicide rates increased dramatically over this period—from a mean of 26.56 in 1999 to 608 in 2018 (per 10,000)—reflecting the broader surge in violence in Mexico. The larger coefficient in the first-difference specification should therefore be interpreted against this substantial nationwide increase in violent crime.

Substantively, the positive relationship between foreign robot exposure and measures of violent organized crime suggests that technological advancements abroad, particularly in countries like the US, can undermine offshoring and reduce economic opportunities in developing countries. As foreign firms adopt automation and reorganize supply chains, the resulting decline in demand for exports disrupts local industries, deepens local poverty, and leaves some individuals with fewer alternatives beyond participation in illegal activities or organized crime.

Our findings are robust across a wide range of alternative specifications and sample restrictions. We control for distance to the United States and state fixed effects (Table A.7), as well as for the presence of at least one drug trafficking route (Table A.8). Restricting the sample to commuting zones exposed to the foreign robot shock—defined as those with any maquiladora employment in 1990—yields similar results (Table A.9). The results are substantively unchanged when we instrument only for foreign robot exposure, indicating that our findings are not driven by the joint IV structure (Table A.11). Finally, Table A.10 shows that the findings hold when organized crime is measured as narcocrime (2018) or human trafficking (2018). However, looking at property crime, which we view as a placebo not directly related to organized crime or labor market motivations, we find no effect of foreign robot exposure.

6.3 The Effect of Foreign Robots on Populist Backlash

Table 3 presents OLS and IV estimates of the impact of foreign robot exposure on vote shares in the presidential elections of 2024 across commuting zones. Column 1 shows a positive and statistically significant relationship between foreign robot exposure and support for left-wing populism, indicating that regions more exposed to automation abroad systematically exhibited greater backing for MORENA in 2024. Our preferred IV specification, which addresses potential endogeneity by isolating plausibly exogenous variation in foreign robot exposure, similarly reveals a significant increase in MORENA's vote share. In contrast, column 2 shows a decline in support for right- and center-right parties (PAN and PRI), which are traditionally associated with the political establishment (Castro Cornejo, 2023).

Table 3: Effect of Robot Exposure on Electoral Outcomes

OLS	(1) Sheinbaum (Left)	(2) Galvez (Right)	(3) Δ Left	(4) Δ Right
External exposure to foreign robots	1.069**	-0.642*	0.889***	-0.549*
	(0.447)	(0.367)	(0.248)	(0.283)
External exposure to domestic robots	4.101*	-3.223	-1.702	2.879
	(2.337)	(1.951)	(2.360)	(2.512)
Demographics	✓	✓	✓	✓
Industry	✓	✓	✓	✓
Observations	1795	1795	1787	1787
R^2	0.261	0.199	0.309	0.315
IV	(1) Sheinbaum (Left)	(2) Galvez (Right)	(3) Δ Left	(4) Δ Right
Exposure to foreign robots	1.163**	-0.696*	0.981***	-0.610**
	(0.472)	(0.390)	(0.281)	(0.309)
Exposure to domestic robots	3.893*	-3.057*	-1.600	2.718
	(2.101)	(1.765)	(2.193)	(2.343)
Demographics	✓	✓	✓	✓
Industry	✓	✓	✓	✓
Observations	1795	1795	1787	1787
R^2	0.281	0.214	0.310	0.316
F	10.62	6.505	5.274	4.601
Kleibergen-Paap Wald F-stat	178.1	178.1	178.5	178.5

Notes: The dependent variables in columns 1–2 represent each candidate's share of valid votes for the 2024 elections. Columns 3–4 capture the change in support between 2006 and 2024. For the left-bloc comparison, we contrast support for AMLO in the 2006 presidential election—when he ran under the left coalition *Coalición por el Bien de Todos* (PRD–PT–Convergencia)—with support for Sheinbaum in 2024, who ran under *MORENA* in alliance with *Sigamos Haciendo Historia*. For the right-bloc comparison, we contrast support for Gálvez Ruiz in 2024 with the main right-of-center candidates in 2006: Felipe Calderón, who ran under the *PAN*, and Roberto Madrazo, who ran under the *Alianza por México* (PRI–PVEM). We also include Roberto Campa of *Nueva Alianza*, whose platform in 2006 leaned toward the center-right. All specifications include the following control variables: 1) Demographics: 1990 CZ demographics, including the share of men and the share of people with primary education as their highest level; 2) Industry: shares of employment in manufacturing in 1990 and the 1990 level of employment-to-population ratio. All regressions are weighted by a CZ's share of the national working-age population in 1990. Standard errors are robust to heteroskedasticity and clustered by state. The coefficients marked with $***$, $**$, and $*$ are significant at the 1%, 5%, and 10% confidence levels, respectively. Refer to the full Table in Appendix A.12.

When we examine the change in vote share between 2006 and 2024, we find consistent effects for both left- and right-wing parties. Greater exposure to foreign robots is associated with increased support for the Left (Column 3) and decreased support for the Right (Column 4). In our preferred IV regression, a one standard deviation increase in foreign robot exposure leads to a 0.981 increase in Left vote share, corresponding to approximately a 6.3 percentage point shift relative to the standard deviation of change in Left support.

These results indicate greater support for left-wing populist, anti-establishment candidates in communities highly exposed to foreign automation, consistent with Hypothesis 2.

Economic disruptions stemming from foreign automation appear to heighten demand for redistributive and economically statist policies.

In Mexico, this backlash coalesced around MORENA, which appealed to affected voters through commitments to cash transfers, expanded social programs, higher minimum wages, improved pensions, and domestic infrastructure investment. Economic nationalism also featured prominently: MORENA criticized prior administrations and international economic pressures, emphasized energy sovereignty, and sought to reclaim strategic sectors—positions that resonated in communities exposed to international competition.

We focus on the 2024 election in our primary analysis because AMLO's 2018 victory may partly reflect anti-incumbent economic voting. However, we obtain similar though less precisely estimated results when examining the change in support for AMLO between 2006 and 2018 (Column 3, Table A.16); notably, the effect of foreign robot exposure on Left vote share remains positive and statistically significant in our preferred first-difference IV regression.

Finally, the 2024 electoral results are robust across alternative specifications. The estimates remain stable when controlling for distance to the United States and including state fixed effects (Table A.13), accounting for the presence of drug trafficking routes (Table A.14), restricting the sample to commuting zones with maquiladora employment in 1990 (Table A.15), and instrumenting solely for foreign robot exposure.

7 Conclusions

This study shows that the political economy of automation cannot be understood within national borders. In a world of global production networks, technological change in one location is transmitted across borders through shifts in firm-sourcing and production decisions. As U.S. firms adopt robots, they reorganize their demand for tasks, reducing demand for labor in regions specialized in labor-intensive manufacturing. Mexico, which is deeply integrated into U.S. production networks, thus experiences local labor market shocks as a result of automation abroad. Our results demonstrate that this exposure to foreign automation reduces wages and employment in exposed regions, which has significant social and political consequences, including increased organized violence and shifts in electoral support. Taken together, the findings highlight global production networks as a central channel through which technological change in advanced economies reshapes economic, social, and political outcomes in developing countries.

Using regional exposure measures and an instrumental variable strategy, we find that areas more exposed to foreign automation experience higher levels of violent organized crime and greater electoral support for left-wing populist candidates. These effects are robust to accounting for domestic automation and other shocks. In short, when firms in the North automate, communities in the South absorb the costs—through job loss, heightened insecurity, and political realignment.

Our findings have important implications for several key political economy debates. First, our work speaks to the literature on automation and political behavior in the Global South. Studies of automation's domestic impact in advanced democracies have linked worker displacement to voter discontent, often manifested in the rise of radical-right or anti-establishment movements. Our findings extend this line of inquiry to the developing world, showing that automation-driven job loss can generate a populist backlash in emerging democracies as well, albeit with contextually specific outcomes. In Mexico's case, communities hard-hit by foreign robot adoption gravitated toward left-wing populism, rallying behind candidates who promised redistribution, economic nationalism, and an expanded role for the state.

Second, our results have implications for the study of violence and governance in developing contexts. We show that foreign automation shocks destabilize local security: in Mexican regions facing falling labor demand, organized violent crime rose. The pattern aligns with theories that criminal organizations exploit economic stress and institutional weakness to consolidate power (Trejo and Ley, 2021; Dube et al., 2013; Hernández Huerta, 2020).

Third, our findings also have important implications for the globalization and development literature, including the political economy of inequality. Although trade and offshoring brought more employment and growth to developing economies, recent technological advances abroad are eroding those gains by undercutting low-wage comparative advantage. This has important consequences for developing and emerging markets that are seeking pathways to development.

Finally, the mechanism linking foreign automation to adverse political and social outcomes is broadly applicable to situations where technological change in advanced economies reduces offshoring, demand for imports, or investment in labor-intensive activities abroad. While Mexico exemplifies exposure to U.S. automation through North American production networks, analogous dynamics may occur elsewhere. In such cases, in manufacturing, or for instance, business-processing, emerging-market regions integrated into those value chains experience negative employment shocks (e.g, Colombia or Brazil). These shocks depress local incomes, weaken social stability, and alter political preferences. The exact consequences, however, depend on national context, including the nature of economic integration, state and institutional capacity, and the channels through which discontent is mobilized (such as the supply of parties). Other cases that merit attention could include the potential impacts of AI-automation on India and the Philippines, automation in the EU impacting Poland (though Poland also adopts), or other emerging markets in Southeast Asia.

In conclusion, this study underscores that the political economy of automation is fundamentally global. For policymakers, the clear message is that technological change must be understood as a shared challenge and opportunity. Developing robust strategies to manage automation's ripple effects will be essential to sustaining economic development, social stability, and democratic health in an increasingly interconnected age.

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A Online Appendix

Contents

A.1 Reshoring from Mexico

This section examines cases of reshoring from Mexico to the United States since the mid-2000s, with a particular focus on automation-driven relocations.

The dataset was manually compiled from the *Reshore Now* library.[27] All cases available with associated news articles and basic project descriptions were included (a total of 184 cases of restoring from Mexico to the US). For each reshoring event, we collected information on the company involved, the year of reshoring announcement, the industry sector affected, the stated motivations for reshoring, and additional project details when available. Importantly, we focused exclusively on cases where production was previously located in Mexico and subsequently relocated to the United States.

Figure A.1 presents the number of reshoring cases by year. The data show a notable concentration of reshoring announcements between 2012 and 2014. Figure A.5 depicts the distribution of reshoring cases across industries, with automotive and transportation sectors accounting for the largest share, followed by miscellaneous manufacturing and machinery industries.

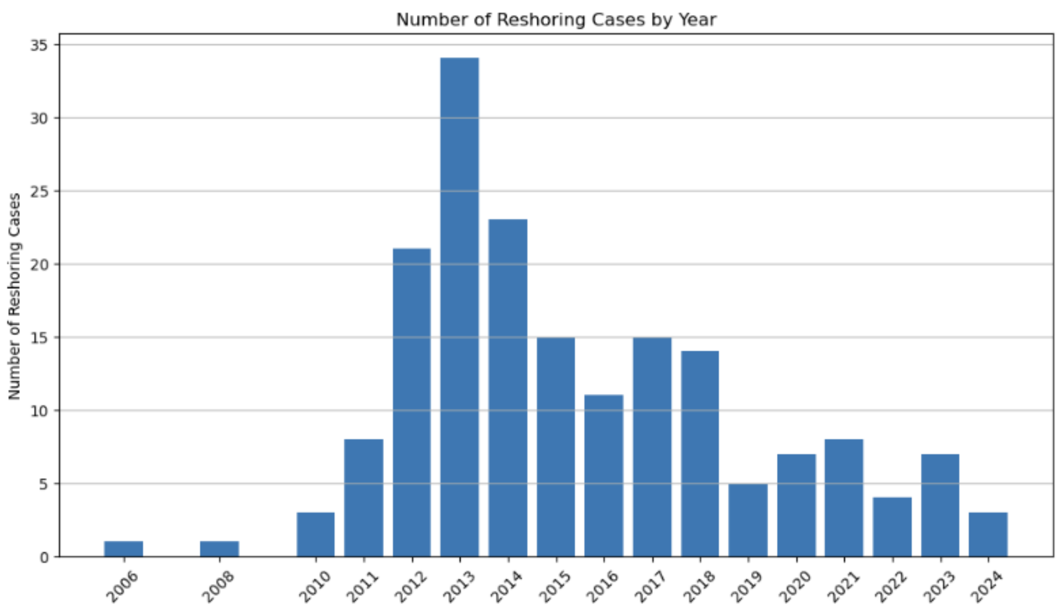

Figure A.1: Number of Reshoring Cases by Year

To better understand the motivations behind reshoring, we conducted a textual analysis of project descriptions. Figure A.3 shows a word cloud summarizing the most frequently cited terms, highlighting incentives, proximity to customers, supply chain improvements, and automation as prominent themes.

Building on this, we employed an unsupervised topic modeling approach (Latent Dirichlet Allocation, LDA) to classify the main reasons for reshoring. Figure A.4 displays the share of each topic identified through this analysis. The LDA model identified four dominant reshoring rationales, with one of the topics being automation:

[27] https://www.reshorenow.org/main-reshoring-library/

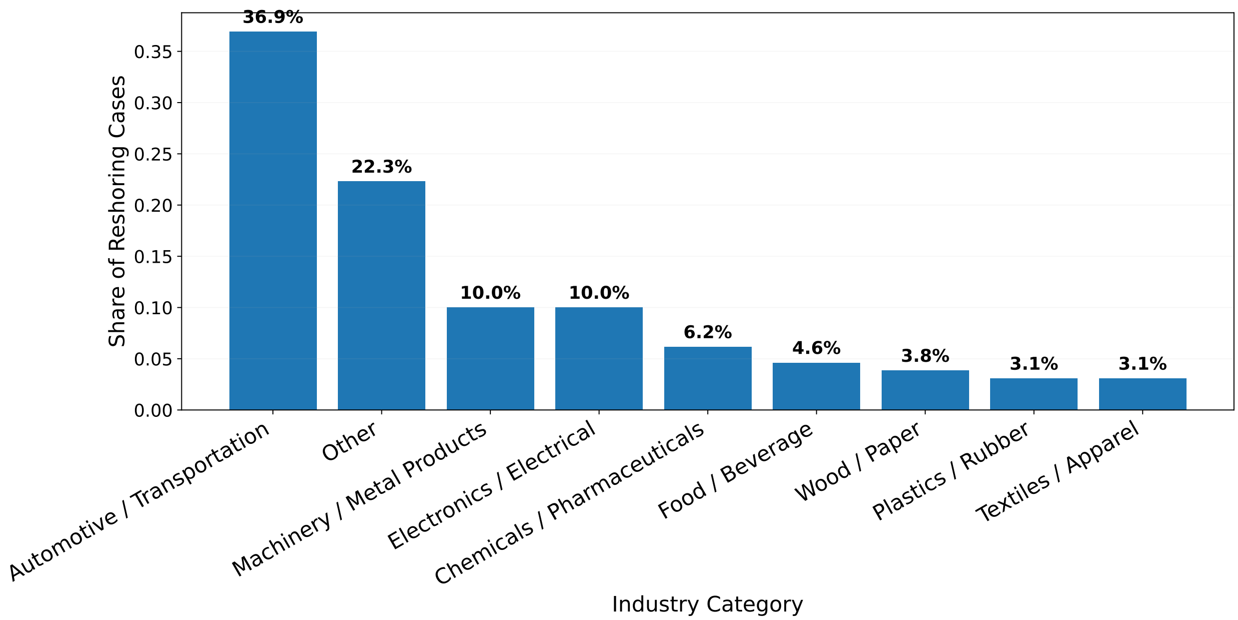

Figure A.2: Share of Reshoring Cases by Industry Category

- **Brand Image and Wages:** Several companies emphasized concerns related to brand reputation, customer responsiveness, and the control of labor costs. Commonly cited terms include *image*, *brand*, *wages*, and *responsiveness*.
- **Supply Chain and Quality:** Many cases referenced efforts to strengthen logistics, reduce lead times, improve product quality, and enhance supply chain resilience. Keywords associated with this topic include *cost*, *lead*, *market*, *quality*, and *supply chain*.
- **Proximity and Incentives:** Proximity to the U.S. customer base and access to government incentives emerged as crucial drivers in a significant number of cases. Terms such as *proximity*, *incentives*, *government*, and *tax* are central to this topic.
- **Technology and Automation:** A growing share of reshoring is associated with investments in technological capabilities, automation, and manufacturing process innovations. Relevant terms include *technology*, *automation*, *workforce*, and *innovation*.

A.2 Reshoring Industries and Underlying Motivations

Firm-level evidence on reshoring is consistent with this aggregate pattern. To illustrate these dynamics, we collected a novel dataset of reshoring events from the Reshoring Initiative (Reshoring-Initiative, 2025). Two patterns stand out. First, the industries with the greatest number of reshoring cases are the same sectors in which foreign automation has the strongest negative effect on Mexican exports. As shown in Figure A.5, automotive production is the activity most frequently brought back to the United States, followed by machinery and electronics—industries that are also among the most automated in the U.S. market. Second, a topic analysis of reshoring announcements reveals that "Technology and Automation"

Figure A.3: Word Cloud of Main Reshoring Reasons

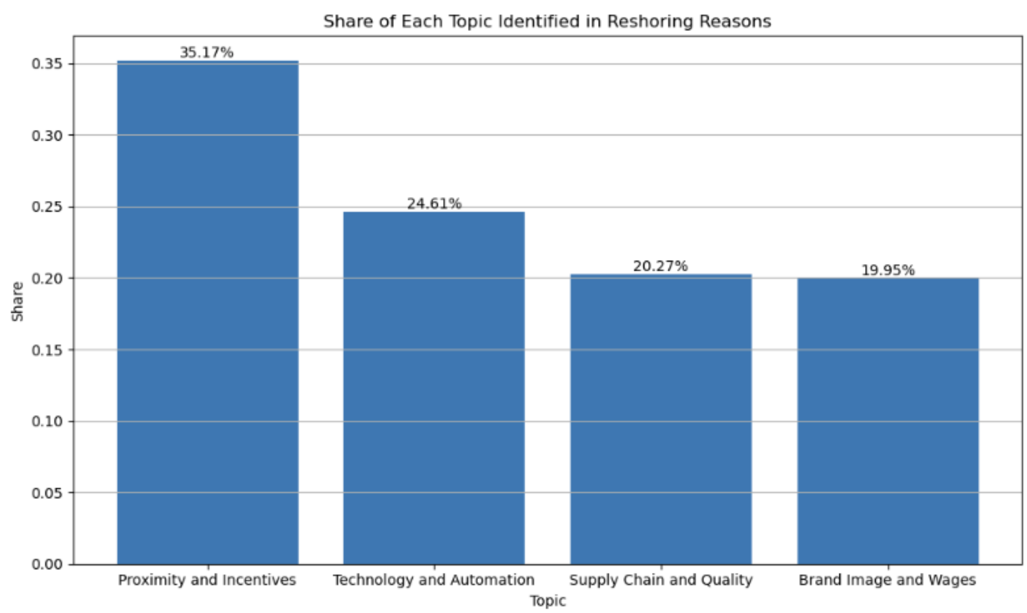

Figure A.4: Share of Each Topic Identified in Reshoring Reasons (LDA Topic Analysis) emerges as a distinct rationale, alongside themes related to proximity to customers, government incentives, and supply-chain reliability (see Table A.1). While these cases highlight the most visible instances of firms relocating entire plants, they almost certainly understate the scale of adjustment: smaller, less publicized responses—such as reducing imports of intermediate goods from Mexico rather than fully reshoring—are likely far more prevalent.

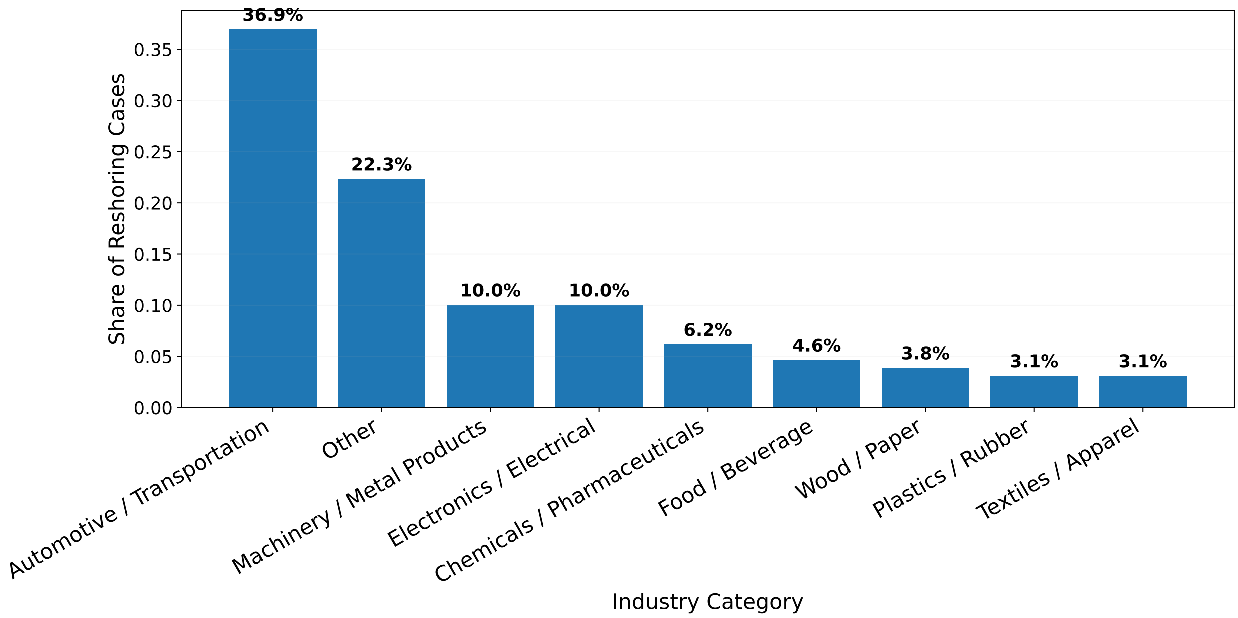

Figure A.5: Share of Reshoring Cases by Industry

Label	Representative Words	Share
Proximity and Incentives	specified, proximity, incentives, customers, market, government, labor, concessions, tax, infrastructure	0.3517
Technology and Automation	workforce, eco, synergies, availability, training, skilled, technology, automation, innovation, manufacturing	0.2461
Supply Chain and Quality	time, cost, lead, market, quality, rework, warranty, total, supply, chain	0.2027
Brand Image and Wages	image, brand, customer, wages, rising, capacity, utilized, risk, responsiveness, improvement	0.1995

Table A.1: Topics Identified in Reshoring Reasons

Notes: Representative words correspond to the highest-probability terms from the LDA model. Shares reflect the mean posterior distribution across documents.

A.3 Descriptive Statistics

Figure A.6 displays commuting zone-level variation in organized crime between 2000 and 2018.

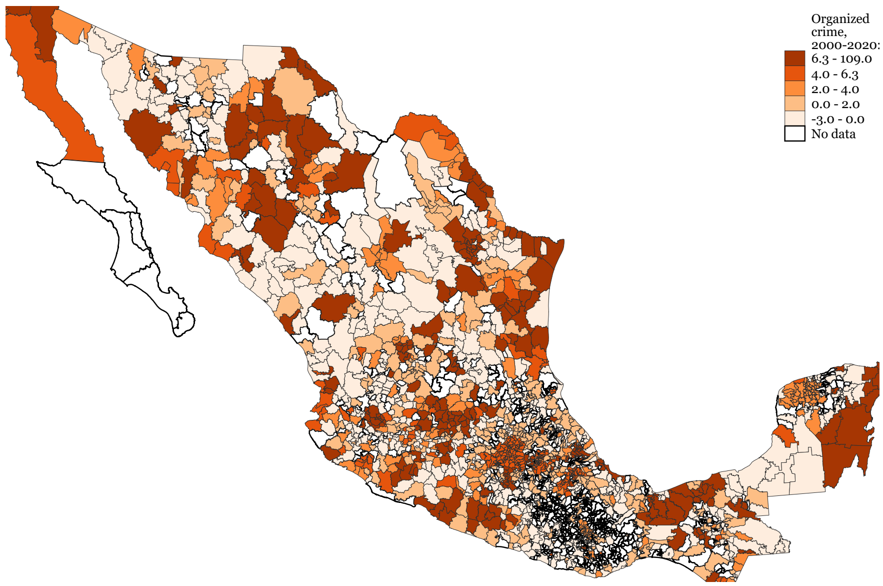

Figure A.6: Commuting zone-level variation in organized crime, 2000-2018.

Table A.2: Summary statistics

	Obs	Mean	SD	Min	Max
Panel A: Robot Exposure Variables					
	n	mean	sd	min	max
Exposure to foreign robots		0.120	1.162	0.000	23.184
Exposure to domestic robots		0.102	0.378	0.000	9.558
External exposure to foreign robots		0.120	1.165	-0.058	20.967
External exposure to domestic robots		0.102	0.377	-0.393	9.364
Observations	1801				
Panel B: Crime Outcomes					
	n	mean	sd	min	max
Homicides		2.282	5.783	0.000	153.015
Org. Crime		1.945	7.106	0.000	111.000
Δ Homicides		3.216	21.415	-26.560	605.052
Δ Org. Crime		1.862	6.921	-3.000	109.000
Narco		0.708	2.468	0.000	66.701
Human Traffic		0.010	0.101	0.000	3.678
Crimes		22.770	57.827	0.000	1530.200
Observations	1801				
Panel C: Voting Outcomes					
	n	mean	sd	min	max
Sheinbaum (Left)		69.107	15.247	6.047	99.812
Galvez (Right)		21.851	12.526	0.000	93.363
Δ Left		34.191	15.551	-37.623	87.335
Δ Right		-41.267	14.923	-88.034	34.759
AMLO (Left)		52.267	17.408	7.654	96.894
Anaya (Right)		19.026	11.857	1.290	77.412
Δ Left		15.943	13.125	-34.833	63.613
Δ Right		-44.050	14.523	-96.224	25.684
Observations	1798				
Panel D: Economic Outcomes					
	n	mean	sd	min	max
Δ Wages		-3.632	1.567	-16.495	4.816
Δ Employment		32.835	42.907	-197.716	233.044
Δ Working Age Pop.		15.924	20.191	-69.124	233.877
Observations	1800				
Panel E: Control Variables					
	n	mean	sd	min	max
Share of routine workers in 1990		0.097	0.073	0.000	0.591
Exposure to Chinese import competition		0.625	1.289	0.000	20.598
Exposure to tariff changes from NAFTA		-0.032	0.014	-0.120	0.001
Change in employment-to-population ratio 00-15		3.136	5.752	-27.285	28.333
Share of men in 1990		0.494	0.025	0.381	0.645
Share of people with primary education in 1990		0.370	0.125	0.000	0.850
Share of manufacturer workers in 1990		0.095	0.105	0.000	1.000
Employment to population 1990		17.665	10.080	0.000	46.667
Drugs Route		0.267	0.443	0.000	1.000
Distance to US		801.911	254.501	11.879	1350.600
Observations	1801				

A.4 Results First stage

Table A.3: First stage IV results

	First Stage Regressions	
	(1) Domestic Robots	(2) Foreign Robots
External exposure to domestic robots	1.057***	-0.0118
	(0.0116)	(0.0882)
External exposure to foreign robots	0.00246	0.911***
	(0.00203)	(0.0483)
Share of routine workers in 1990	0.467***	0.732
	(0.112)	(1.041)
Exposure to Chinese import competition	-0.0105***	0.147**
	(0.00362)	(0.0660)
Exposure to tariff changes from NAFTA	-2.172***	1.235
	(0.545)	(3.974)
Change in employment-to-population ratio 00-15	-0.000496	0.00185
	(0.000531)	(0.00389)
Share of men in 1990	0.500**	-0.00745
	(0.201)	(2.138)
Share of people with primary education in 1990	0.0367	-0.717*
	(0.0331)	(0.395)
Share of manufacturer workers in 1990	-0.288***	-1.395**
	(0.0700)	(0.568)
Employment to population 1990	-0.00332***	-0.00445
	(0.000692)	(0.00437)
Observations	1795	1795

Dependent variables: Exposure to domestic robots (column 1) and foreign robots (column 2).

Instruments: External exposure to domestic robots and foreign robots.

Standard errors clustered at the state level in parentheses.

Notes: Cragg-Donald F-statistic: 16430.403. Kleibergen-Paap Wald F-statistic: 384.059

A.5 Results: Economics

Table A.4: Effect of Robot Exposure on Economic Outcomes - Full Table - refers to Table 1

OLS	(1) Δ Wages	(2) Δ Employment	(3) Δ Working Age Pop.
External exposure to foreign robots	-0.0270*	-1.084**	-0.799**
	(0.0152)	(0.446)	(0.365)
External exposure to domestic robots	-0.116*	-1.825	0.435
	(0.0603)	(3.372)	(2.314)
Share of routine workers in 1990	0.0864	79.44	115.4**
	(1.046)	(62.13)	(44.08)
Exposure to Chinese import competition	0.0403	2.104*	1.539*
	(0.0310)	(1.127)	(0.792)
Exposure to tariff changes from NAFTA	-10.28***	56.85	-127.9
	(3.390)	(169.4)	(120.2)
Share of men in 1990	1.593	33.54	69.44
	(1.406)	(99.31)	(76.89)
Share of people with primary education in 1990	0.988***	-55.58**	-66.14***
	(0.243)	(26.11)	(18.18)
Share of manufacturer workers in 1990	0.117	-30.77	-46.30***
	(0.464)	(23.41)	(14.82)
Employment to population 1990	0.0140***	-0.641	0.187
	(0.00331)	(0.420)	(0.231)
Observations	1610	1800	1800
R^2	0.014	0.082	0.217
IV	(1) Δ Wages	(2) Δ Employment	(3) Δ Working Age Pop.
Exposure to foreign robots	-0.0289*	-1.186**	-0.879**
	(0.0152)	(0.504)	(0.418)
Exposure to domestic robots	-0.112*	-1.741	0.400
	(0.0582)	(3.136)	(2.150)
Share of routine workers in 1990	0.116	81.09	115.8***
	(1.029)	(59.90)	(42.55)
Exposure to Chinese import competition	0.0424	2.260**	1.673**
	(0.0312)	(1.113)	(0.780)
Exposure to tariff changes from NAFTA	-10.43***	54.62	-125.8
	(3.316)	(168.2)	(117.9)
Share of men in 1990	1.612	34.36	69.20
	(1.368)	(97.37)	(75.74)
Share of people with primary education in 1990	0.981***	-56.36**	-66.77***
	(0.237)	(25.68)	(17.86)
Share of manufacturer workers in 1990	0.0881	-32.92	-47.40***
	(0.453)	(22.91)	(14.50)
Employment to population 1990	0.0137***	-0.652	0.184
	(0.00327)	(0.405)	(0.221)
Observations	1610	1800	1800
R^2	0.014	0.081	0.215
F	8.198	4.486	11.28
Kleibergen-Paap Wald F-stat	100.2	175.5	175.5

Notes: All dependent variables refer to changes between 2000 and 2015, with column 1 referring to changes in manufacturing wages (residualized), column 2 the log of employment, and column 3 to the log number of the working-age population. All specifications include the following control variables:1) Demographics: 1990 CZ demographics, including the share of men and the share of people with primary education as their highest level; 2) Industry: shares of employment in manufacturing in 1990 and the 1990 level of employment-to-population ratio. Regressions in columns 2 and 3 are weighted by a CZ's share of the national working-age population in 1990. Standard errors are robust to heteroskedasticity and clustered by state. The coefficients marked with $***$, $**$, and $*$ are significant at the 1%, 5%, and 10% confidence levels, respectively.

Table A.5: Effect of Robot Exposure on Economic Outcomes, pre-shock

OLS	(1) Δ Wages 90-00	(2) Δ Wages 90-00
External exposure to foreign robots 93-00	0.173***	
	(0.0281)	
External exposure to domestic robots 93-00	-2.175**	
	(0.910)	
External exposure to foreign robots		0.0510***
		(0.0127)
External exposure to domestic robots		-0.0950**
		(0.0428)
Demographics	✓	✓
Industry	✓	✓
Observations	1367	1367
R^2	0.012	0.012

IV	(1) Δ Wages 90-00	(2) Δ Wages 90-00
Exposure to foreign robots 93-00	0.179***	
	(0.0316)	
Exposure to domestic robots 93-00	-2.200**	
	(0.912)	
Exposure to foreign robots		0.0539***
		(0.0145)
Exposure to domestic robots		-0.0942**
		(0.0411)
Demographics	✓	✓
Industry	✓	✓
Observations	1367	1367
R^2	0.012	0.012
F	15.44	12.53
Kleibergen-Paap Wald F-stat	375.3	98.38

Notes: The dependent variable in columns 1 and 2 refers to the change in average manufacturing wages (residualized) between 1990 and 2000. All specifications include the following control variables: 1) Demographics: 1990 CZ demographics, including the share of men and the share of people with primary education as their highest level; 2) Industry: shares of employment in manufacturing in 1990 and the 1990 level of employment-to-population ratio. All regressions are weighted by a CZ's share of the national working-age population in 1990. Standard errors are robust to heteroskedasticity and clustered by state. The coefficients marked with $***$, $**$, and $*$ are significant at the 1%, 5%, and 10% confidence levels, respectively.

A.6 Results: Violence

Table A.6: Effect of Robot Exposure on Violence - Full table refers to Table 2

OLS	(1) Homicides	(2) Org. Crime	(3) Δ Homicides	(4) Δ Org. Crime
External exposure to foreign robots	0.253*	2.736***	18.95*	2.465***
	(0.142)	(0.841)	(10.04)	(0.770)
External exposure to domestic robots	-1.116***	-3.708**	-17.51	-3.456**
	(0.360)	(1.754)	(11.83)	(1.689)
Share of routine workers in 1990	5.996	48.19*	-18.84	46.78*
	(6.963)	(25.42)	(58.28)	(24.99)
Exposure to Chinese import competition	0.191	0.957	0.118	0.919
	(0.142)	(0.851)	(2.756)	(0.876)
Exposure to tariff changes from NAFTA	33.95	79.47	296.7	83.19
	(23.24)	(86.70)	(252.6)	(83.84)
Share of men in 1990	-7.425	-66.94	20.97	-69.48
	(24.08)	(46.37)	(229.0)	(45.82)
Share of people with primary education in 1990	-0.956	-18.43*	2.583	-18.56*
	(3.014)	(9.566)	(37.52)	(9.430)
Share of manufacturer workers in 1990	-2.197	-14.51	88.60	-12.46
	(3.831)	(13.51)	(69.27)	(13.47)
Employment to population 1990	-0.0427	0.0906	-0.274	0.0618
	(0.0417)	(0.111)	(0.266)	(0.114)
Observations	1797	1800	1796	1800
R^2	0.126	0.421	0.493	0.392
IV	(1) Homicides	(2) Org. Crime	(3) Δ Homicides	(4) Δ Org. Crime
Exposure to foreign robots	0.280*	3.014***	20.85*	2.715***
	(0.162)	(1.041)	(11.76)	(0.949)
Exposure to domestic robots	-1.053***	-3.474**	-16.33	-3.239*
	(0.336)	(1.742)	(12.11)	(1.667)
Share of routine workers in 1990	6.284	47.62*	-26.45	46.32*
	(6.861)	(25.96)	(68.94)	(25.49)
Exposure to Chinese import competition	0.138	0.477	-3.121	0.486
	(0.142)	(1.065)	(4.317)	(1.072)
Exposure to tariff changes from NAFTA	31.32	68.22	235.9	72.82
	(22.41)	(85.53)	(283.3)	(82.55)
Share of men in 1990	-6.896	-65.16	29.66	-67.82
	(23.53)	(47.25)	(247.6)	(46.34)
Share of people with primary education in 1990	-0.717	-16.15	18.10	-16.50*
	(2.999)	(9.821)	(40.12)	(9.609)
Share of manufacturer workers in 1990	-2.108	-11.31	113.0	-9.605
	(3.809)	(14.35)	(84.36)	(14.26)
Employment to population 1990	-0.0450	0.0924	-0.236	0.0631
	(0.0407)	(0.112)	(0.278)	(0.114)
Observations	1797	1800	1796	1800
R^2	0.133	0.376	0.403	0.352
F	2.687	6.098	1.182	6.733
Kleibergen-Paap Wald F-stat	178.1	178.0	178.1	178.0

Notes: The dependent variable in column 1 refers to the homicide rate, sourced from CONAPO. Column 2 is the organized crime index with data from Osorio and Beltran (2020). Columns 3 and 4 refer to the change for variables in 1 and 2. All specifications include the following control variables: 1) Demographics: 1990 CZ demographics, including the share of men and the share of people with primary education as their highest level; 2) Industry: shares of employment in manufacturing in 1990 and the 1990 level of employment-to-population ratio. All regressions are weighted by a CZ's share of the national working-age population in 1990. Standard errors are robust to heteroskedasticity and clustered by state. The coefficients marked with $***$, $**$, and $*$ are significant at the 1%, 5%, and 10% confidence levels, respectively.

Table A.7: Effect of Robot Exposure on Violence, controlling for distance to the US and State FE.

OLS	(1) Homicides	(2) Org. Crime	(3) Δ Homicides	(4) Δ Org. Crime
External exposure to foreign robots	0.0767**	1.765***	13.21***	1.542***
	(0.0362)	(0.141)	(0.651)	(0.137)
External exposure to domestic robots	-0.355***	-0.0977	-12.63***	0.00144
	(0.136)	(0.528)	(2.444)	(0.513)
Distance to US	0.00366***	0.00708**	0.0733***	0.00619**
	(0.000784)	(0.00304)	(0.0141)	(0.00296)
Share of routine workers in 1990	0.0803	60.31***	-126.7***	56.61***
	(2.380)	(9.244)	(42.83)	(8.993)
Exposure to Chinese import competition	0.202***	1.398***	6.239***	1.374***
	(0.0523)	(0.203)	(0.942)	(0.198)
Exposure to tariff changes from NAFTA	50.69***	90.01**	525.4***	96.74**
	(11.11)	(43.18)	(200.1)	(42.00)
Share of men in 1990	13.73**	4.613	136.9	7.874
	(5.965)	(23.16)	(107.5)	(22.54)
Share of people with primary education in 1990	-0.721	-6.855	-9.898	-6.419
	(1.273)	(4.944)	(22.90)	(4.810)
Share of manufacturer workers in 1990	-2.580**	-35.72***	33.35	-34.35***
	(1.258)	(4.887)	(22.64)	(4.755)
Employment to population 1990	-0.00604	-0.00758	0.983***	-0.0158
	(0.0181)	(0.0704)	(0.326)	(0.0685)
Region	✓	✓	✓	✓
Observations	1797	1800	1796	1800
R^2	0.408	0.627	0.674	0.611
IV	(1) Homicides	(2) Org. Crime	(3) Δ Homicides	(4) Δ Org. Crime
Exposure to foreign robots	0.0841**	1.936***	14.49***	1.693***
	(0.0392)	(0.155)	(0.736)	(0.150)
Exposure to domestic robots	-0.333***	0.0383	-11.06***	0.116
	(0.127)	(0.505)	(2.395)	(0.489)
Distance to US	0.00369***	0.00799***	0.0797***	0.00699**
	(0.000777)	(0.00308)	(0.0146)	(0.00298)
Share of routine workers in 1990	0.243	60.60***	-119.4***	56.83***
	(2.345)	(9.292)	(44.09)	(9.002)
Exposure to Chinese import competition	0.187***	1.107***	3.965***	1.121***
	(0.0542)	(0.215)	(1.020)	(0.208)
Exposure to tariff changes from NAFTA	49.90***	85.89**	474.2**	93.28**
	(10.93)	(43.31)	(205.5)	(41.95)
Share of men in 1990	13.94**	5.275	148.2	8.408
	(5.881)	(23.30)	(110.8)	(22.57)
Share of people with primary education in 1990	-0.698	-6.133	-4.762	-5.785
	(1.256)	(4.977)	(23.61)	(4.822)
Share of manufacturer workers in 1990	-2.658**	-35.83***	30.04	-34.43***
	(1.236)	(4.898)	(23.23)	(4.744)
Employment to population 1990	-0.00638	0.00818	1.066***	-0.00173
	(0.0179)	(0.0708)	(0.336)	(0.0686)
Region	✓	✓	✓	✓
Observations	1797	1800	1796	1800
R^2	0.410	0.614	0.645	0.600
F	29.59	69.66	81.28	65.50
Kleibergen-Paap Wald F-stat	15103.4	15129.6	15091.5	15129.6

Notes: The dependent variable in column 1 refers to the homicide rate, sourced from CONAPO. Column 2 is the organized crime index with data from Osorio and Beltran (2020). Columns 3 and 4 refer to the change for variables in 1 and 2. All specifications include the following control variables: 1) Demographics: 1990 CZ demographics, including the share of men and the share of people with primary education as their highest level; 2) Industry: shares of employment in manufacturing in 1990 and the 1990 level of employment-to-population ratio. All regressions are weighted by a CZ's share of the national working-age population in 1990. 3) Distance to the US and 4) State FE. All regressions are weighted by a CZ's share of the national working-age population in 1990. The coefficients marked with $***$, $**$, and $*$ are significant at the 1%, 5%, and 10% confidence levels, respectively.

Table A.8: Effect of Robot Exposure on Violence, controlling for drug traffic routes

OLS	(1) Homicides	(2) Org. Crime	(3) Δ Homicides	(4) Δ Org. Crime
External exposure to foreign robots	0.253*	2.749***	19.02*	2.478***
	(0.143)	(0.804)	(9.909)	(0.733)
External exposure to domestic robots	-1.116***	-3.706*	-17.50	-3.455*
	(0.359)	(1.818)	(11.97)	(1.755)
Drugs Route	-0.0197	2.156	12.03	2.209
	(0.462)	(2.588)	(8.511)	(2.580)
Share of routine workers in 1990	6.076	43.65	-43.97	42.14
	(6.616)	(25.91)	(72.23)	(25.30)
Exposure to Chinese import competition	0.191	0.985	0.275	0.948
	(0.141)	(0.806)	(2.447)	(0.828)
Exposure to tariff changes from NAFTA	33.97	64.05	210.9	67.37
	(23.97)	(75.62)	(268.2)	(73.13)
Share of men in 1990	-7.498	-67.79	17.32	-70.36
	(24.09)	(44.15)	(221.8)	(43.66)
Share of people with primary education in 1990	-0.964	-18.22*	3.808	-18.35*
	(3.026)	(9.328)	(36.79)	(9.181)
Share of manufacturer workers in 1990	-2.206	-15.11	85.30	-13.07
	(3.881)	(12.92)	(63.46)	(12.78)
Employment to population 1990	-0.0434	0.109	-0.174	0.0807
	(0.0403)	(0.101)	(0.262)	(0.102)
Observations	1793	1796	1796	1796
R^2	0.126	0.426	0.499	0.397
IV	(1) Homicides	(2) Org. Crime	(3) Δ Homicides	(4) Δ Org. Crime
Exposure to foreign robots	0.281*	3.031***	20.96*	2.733***
	(0.163)	(0.992)	(11.56)	(0.899)
Exposure to domestic robots	-1.053***	-3.472*	-16.32	-3.237*
	(0.336)	(1.806)	(12.23)	(1.731)
Drugs Route	0.0336	2.746	16.12	2.741
	(0.462)	(2.717)	(11.13)	(2.686)
Share of routine workers in 1990	6.251	41.82	-60.21	40.54
	(6.533)	(26.45)	(88.29)	(25.77)
Exposure to Chinese import competition	0.139	0.510	-2.926	0.519
	(0.141)	(0.991)	(3.801)	(0.997)
Exposure to tariff changes from NAFTA	30.97	48.61	120.7	53.22
	(23.00)	(74.42)	(308.3)	(71.73)
Share of men in 1990	-6.986	-66.16	24.77	-68.84
	(23.53)	(44.42)	(238.0)	(43.64)
Share of people with primary education in 1990	-0.718	-15.87*	19.81	-16.22*
	(2.994)	(9.508)	(38.86)	(9.290)
Share of manufacturer workers in 1990	-2.131	-12.03	108.7	-10.33
	(3.838)	(13.32)	(76.42)	(13.15)
Employment to population 1990	-0.0452	0.116	-0.100	0.0866
	(0.0390)	(0.103)	(0.311)	(0.104)
Observations	1793	1796	1796	1796
R^2	0.133	0.384	0.413	0.360
F	2.439	6.673	1.191	6.682
Kleibergen-Paap Wald F-stat	205.7	205.7	205.7	205.7

Notes: The dependent variable in column 1 refers to the homicide rate, sourced from CONAPO. Column 2 is the organized crime index with data from Osorio and Beltran (2020). Columns 3 and 4 refer to the change for variables in 1 and 2. All specifications include the following control variables: 1) Demographics: 1990 CZ demographics, including the share of men and the share of people with primary education as their highest level; 2) Industry: shares of employment in manufacturing in 1990 and the 1990 level of employment-to-population ratio. 3) Dummy indicating whether it is a drug traffic route. All regressions are weighted by a CZ's share of the national working-age population in 1990. Standard errors are robust to heteroskedasticity and clustered by state. The coefficients marked with $***$, $**$, and $*$ are significant at the 1%, 5%, and 10% confidence levels, respectively.

Table A.9: Effect of Robot Exposure on Violence, only exposed CZs

OLS	(1) Homicides	(2) Org. Crime	(3) Δ Homicides	(4) Δ Org. Crime
External exposure to foreign robots	0.317**	2.672***	19.04*	2.418***
	(0.147)	(0.866)	(9.835)	(0.792)
External exposure to domestic robots	-1.876***	-5.774**	-28.40	-5.444**
	(0.563)	(2.244)	(19.16)	(2.156)
Share of routine workers in 1990	16.05	5.666	-75.18	5.837
	(11.74)	(62.20)	(209.6)	(62.61)
Exposure to Chinese import competition	0.240	1.151	0.116	1.081
	(0.176)	(0.954)	(3.377)	(0.978)
Exposure to tariff changes from NAFTA	154.8***	115.5	1195.9	138.3
	(47.28)	(192.8)	(769.5)	(190.0)
Share of men in 1990	34.13	-219.8	136.0	-223.7
	(45.99)	(149.7)	(965.3)	(146.7)
Share of people with primary education in 1990	-11.43	-38.91	10.76	-42.19
	(7.041)	(27.35)	(143.3)	(26.95)
Share of manufacturer workers in 1990	1.579	33.26	279.4	34.02
	(7.551)	(23.87)	(165.9)	(24.23)
Employment to population 1990	-0.204	0.266	-1.389	0.245
	(0.148)	(0.505)	(2.171)	(0.490)
Observations	249	249	249	249
R^2	0.345	0.576	0.535	0.544
IV	(1) Homicides	(2) Org. Crime	(3) Δ Homicides	(4) Δ Org. Crime
Exposure to foreign robots	0.357**	2.983***	21.22*	2.700***
	(0.169)	(1.052)	(11.32)	(0.959)
Exposure to domestic robots	-1.776***	-5.587**	-27.89	-5.260**
	(0.526)	(2.273)	(19.61)	(2.148)
Share of routine workers in 1990	15.64	-4.257	-154.1	-3.000
	(11.19)	(68.00)	(240.9)	(67.83)
Exposure to Chinese import competition	0.152	0.523	-4.210	0.512
	(0.183)	(1.186)	(4.923)	(1.187)
Exposure to tariff changes from NAFTA	150.1***	104.6	1155.3	127.8
	(42.56)	(187.8)	(789.3)	(182.5)
Share of men in 1990	35.23	-221.8	107.2	-225.3
	(43.49)	(150.2)	(1040.0)	(146.0)
Share of people with primary education in 1990	-10.86	-35.27	35.20	-38.88
	(6.860)	(27.43)	(149.4)	(26.64)
Share of manufacturer workers in 1990	1.904	39.30	326.6*	39.41
	(7.305)	(25.44)	(189.7)	(25.47)
Employment to population 1990	-0.200	0.349	-0.735	0.319
	(0.138)	(0.541)	(2.179)	(0.522)
Observations	249	249	249	249
R^2	0.348	0.510	0.440	0.484
F	4.251	22.05	3.725	34.38
Kleibergen-Paap Wald F-stat	189.9	189.9	189.9	189.9

Notes: The sample is limited to only those CZs that were exposed pre-shock (i.e, the share of maquiladoras was not 0). The dependent variable in column 1 refers to the homicide rate, sourced from CONAPO. Column 2 is the organized crime index with data from Osorio and Beltran (2020). Columns 3 and 4 refer to the change for variables in 1 and 2. All specifications include the following control variables: 1) Demographics: 1990 CZ demographics, including the share of men and the share of people with primary education as their highest level; 2) Industry: shares of employment in manufacturing in 1990 and the 1990 level of employment-to-population ratio. All regressions are weighted by a CZ's share of the national working-age population in 1990. Standard errors are robust to heteroskedasticity and clustered by state. The coefficients marked with $***$, $**$, and $*$ are significant at the 1%, 5%, and 10% confidence levels, respectively.

Table A.10: Effect of Robot Exposure on Violence: Nacro, Human Trafficking and Property Crimes

OLS	(1) Narco	(2) Human Traffic	(3) Crimes
External exposure to foreign robots	0.682**	0.00379*	1.051
	(0.280)	(0.00219)	(0.936)
External exposure to domestic robots	-1.512**	0.00682	-10.42***
	(0.715)	(0.00618)	(3.720)
Demographics	✓	✓	✓
Industry	✓	✓	✓
Observations	1797	1797	1797
R^2	0.389	0.060	0.084

IV	(1) Narco	(2) Human Traffic	(3) Crimes
Exposure to foreign robots	0.752**	0.00414	1.180
	(0.336)	(0.00253)	(1.028)
Exposure to domestic robots	-1.422**	0.00650	-9.841***
	(0.692)	(0.00577)	(3.449)
Demographics	✓	✓	✓
Industry	✓	✓	✓
Observations	1797	1797	1797
R^2	0.334	0.055	0.089
F	4.058	6.361	3.066
Kleibergen-Paap Wald F-stat	178.1	178.1	178.1

Notes: The dependent variable in column 1 is organized crime (levels), column 2 is human trafficking, and column 3 is property crimes unrelated to organized crime, all measured per 10,000 population and sourced from CISEN. In all the cases, we only have data on the levels. All specifications include the following control variables: 1) Demographics: 1990 CZ demographics, including the share of men and the share of people with primary education as their highest level; 2) Industry: shares of employment in manufacturing in 1990 and the 1990 level of employment-to-population ratio. All regressions are weighted by a CZ's share of the national working-age population in 1990. Standard errors are robust to heteroskedasticity and clustered by state. The coefficients marked with $***$, $**$, and $*$ are significant at the 1%, 5%, and 10% confidence levels, respectively.

Table A.11: Effect of Robot Exposure on Violence, only instrumenting Foreign Robots

IV	(1) Homicides	(2) Org. Crime	(3) Δ Homicides	(4) Δ Org. Crime
Exposure to foreign robots	0.281*	3.017***	20.86*	2.719***
	(0.162)	(1.040)	(11.76)	(0.948)
Exposure to domestic robots	-1.074***	-3.598**	-16.38	-3.370**
	(0.333)	(1.771)	(11.65)	(1.699)
Share of routine workers in 1990	6.268	47.53*	-26.48	46.22*
	(6.885)	(25.86)	(69.16)	(25.39)
Exposure to Chinese import competition	0.139	0.483	-3.119	0.492
	(0.141)	(1.061)	(4.299)	(1.068)
Exposure to tariff changes from NAFTA	31.47	69.07	236.2	73.72
	(22.44)	(84.36)	(285.3)	(81.39)
Share of men in 1990	-6.939	-65.40	29.56	-68.08
	(23.57)	(47.27)	(248.5)	(46.36)
Share of people with primary education in 1990	-0.684	-15.96	18.17	-16.30*
	(3.000)	(9.778)	(39.48)	(9.560)
Share of manufacturer workers in 1990	-2.051	-10.97	113.2	-9.250
	(3.848)	(14.51)	(84.57)	(14.44)
Employment to population 1990	-0.0451	0.0913	-0.236	0.0620
	(0.0406)	(0.111)	(0.275)	(0.114)
Observations	1797	1800	1796	1800
R^2	0.133	0.376	0.403	0.352
F	2.720	5.967	1.180	6.589
Kleibergen-Paap Wald F-stat	356.9	356.8	356.9	356.8

Notes: The dependent variable in column 1 refers to the homicide rate, sourced from CONAPO. Column 2 is the organized crime index with data from Osorio and Beltran (2020). Columns 3 and 4 refer to the change for variables in 1 and 2. All specifications include the following control variables: 1) Demographics: 1990 CZ demographics, including the share of men and the share of people with primary education as their highest level; 2) Industry: shares of employment in manufacturing in 1990 and the 1990 level of employment-to-population ratio. All regressions are weighted by a CZ's share of the national working-age population in 1990. Standard errors are robust to heteroskedasticity and clustered by state. The coefficients marked with $***$, $**$, and $*$ are significant at the 1%, 5%, and 10% confidence levels, respectively.

A.7 Results: Voting

Table A.12: Effect of Robot Exposure on Electoral Outcomes - Full table refers to Table 3

OLS	(1) Sheinbaum (Left)	(2) Galvez (Right)	(3) Δ Left	(4) Δ Right
External exposure to foreign robots	1.069**	-0.642*	0.889***	-0.549*
	(0.447)	(0.367)	(0.248)	(0.283)
External exposure to domestic robots	4.101*	-3.223	-1.702	2.879
	(2.337)	(1.951)	(2.360)	(2.512)
Share of routine workers in 1990	-10.03	23.32	-83.54**	100.6***
	(23.51)	(20.96)	(34.33)	(35.58)
Exposure to Chinese import competition	-1.563	0.914	1.101	-1.694**
	(0.944)	(0.768)	(0.758)	(0.823)
Exposure to tariff changes from NAFTA	72.87	-75.51	-75.99	61.34
	(104.7)	(110.4)	(128.4)	(120.9)
Share of men in 1990	104.2	-38.74	108.5	-60.92
	(79.70)	(58.83)	(70.14)	(70.12)
Share of people with primary education in 1990	-1.703	-7.457	-24.03	18.84
	(16.06)	(15.04)	(15.62)	(14.57)
Share of manufacturer workers in 1990	-29.37**	24.20**	-11.66	6.376
	(11.38)	(10.41)	(13.95)	(15.34)
Employment to population 1990	-0.218	0.152	0.833***	-0.900***
	(0.226)	(0.169)	(0.279)	(0.250)
Observations	1795	1795	1787	1787
R^2	0.261	0.199	0.309	0.315
IV	(1) Sheinbaum (Left)	(2) Galvez (Right)	(3) Δ Left	(4) Δ Right
Exposure to foreign robots	1.163**	-0.696*	0.981***	-0.610**
	(0.472)	(0.390)	(0.281)	(0.309)
Exposure to domestic robots	3.893*	-3.057*	-1.600	2.718
	(2.101)	(1.765)	(2.193)	(2.343)
Share of routine workers in 1990	-12.70	25.26	-83.53**	99.75***
	(22.69)	(20.84)	(33.34)	(34.46)
Exposure to Chinese import competition	-1.693*	0.984	0.940	-1.576*
	(0.899)	(0.754)	(0.732)	(0.812)
Exposure to tariff changes from NAFTA	79.89	-81.29	-80.66	68.00
	(100.7)	(107.8)	(123.7)	(116.5)
Share of men in 1990	102.2	-37.21	109.3	-62.29
	(76.57)	(56.91)	(68.64)	(68.77)
Share of people with primary education in 1990	-1.012	-7.844	-23.25	18.29
	(15.56)	(14.63)	(15.26)	(14.20)
Share of manufacturer workers in 1990	-26.63**	22.35**	-10.75	6.306
	(11.07)	(10.47)	(13.69)	(14.99)
Employment to population 1990	-0.200	0.138	0.833***	-0.893***
	(0.222)	(0.167)	(0.271)	(0.241)
Observations	1795	1795	1787	1787
R^2	0.281	0.214	0.310	0.316
F	10.62	6.505	5.274	4.601
Kleibergen-Paap Wald F-stat	178.1	178.1	178.5	178.5

Notes: The dependent variables in columns 1–2 represent each candidate's share of valid votes for the 2024 elections. Columns 3–4 capture the change in support between 2006 and 2024. For the left-bloc comparison, we contrast support for AMLO in the 2006 presidential election—when he ran under the left coalition *Coalición por el Bien de Todos* (PRD–PT–Convergencia)—with support for Sheinbaum in 2024, who ran under *MORENA* in alliance with *Sigamos Haciendo Historia*. For the right-bloc comparison, we contrast support for Gálvez Ruiz in 2024 with the main right-of-center candidates in 2006: Felipe Calderón, who ran under the *PAN*, and Roberto Madrazo, who ran under the *Alianza por México* (PRI–PVEM). We also include Roberto Campa of *Nueva Alianza*, whose platform in 2006 leaned toward the center-right. All specifications include the following control variables: 1) Demographics: 1990 CZ demographics, including the share of men and the share of people with primary education as their highest level; 2) Industry: shares of employment in manufacturing in 1990 and the 1990 level of employment-to-population ratio. All regressions are weighted by a CZ's share of the national working-age population in 1990. Standard errors are robust to heteroskedasticity and clustered by state. The coefficients marked with $***$, $**$, and $*$ are significant at the 1%, 5%, and 10% confidence levels, respectively.

Table A.13: Effect of Robot Exposure on Electoral Outcomes, controlling for distance to the US and State FE.

OLS	(1) Sheinbaum (Left)	(2) Galvez (Right)	(3) Δ Left	(4) Δ Right
External exposure to foreign robots	0.639***	-0.772***	0.836***	-1.003***
	(0.115)	(0.112)	(0.131)	(0.137)
External exposure to domestic robots	0.0267	-0.393	0.190	-0.467
	(0.432)	(0.421)	(0.491)	(0.513)
Distance to US	-0.000921	-0.000747	-0.00856***	0.00848***
	(0.00249)	(0.00243)	(0.00284)	(0.00297)
Share of routine workers in 1990	-61.59***	65.53***	-13.76	21.38**
	(7.575)	(7.380)	(8.616)	(9.010)
Exposure to Chinese import competition	0.0816	0.173	-0.493***	0.875***
	(0.167)	(0.162)	(0.189)	(0.198)
Exposure to tariff changes from NAFTA	139.3***	-133.7***	17.68	-15.20
	(35.36)	(34.45)	(40.22)	(42.05)
Share of men in 1990	33.04*	-0.996	18.27	6.796
	(18.98)	(18.49)	(21.58)	(22.57)
Share of people with primary education in 1990	11.88***	-15.37***	-15.45***	13.76***
	(4.052)	(3.948)	(4.618)	(4.829)
Share of manufacturer workers in 1990	10.75***	-9.720**	3.765	-5.803
	(4.003)	(3.900)	(4.549)	(4.757)
Employment to population 1990	0.141**	-0.180***	0.0476	-0.0664
	(0.0577)	(0.0562)	(0.0657)	(0.0687)
Region	✓	✓	✓	✓
Observations	1795	1795	1787	1787
R^2	0.677	0.579	0.679	0.676

IV	(1) Sheinbaum (Left)	(2) Galvez (Right)	(3) Δ Left	(4) Δ Right
Exposure to foreign robots	0.701***	-0.848***	0.918***	-1.101***
	(0.125)	(0.121)	(0.142)	(0.148)
Exposure to domestic robots	0.0730	-0.432	0.243	-0.519
	(0.405)	(0.394)	(0.462)	(0.482)
Distance to US	-0.000589	-0.00116	-0.00812***	0.00794***
	(0.00247)	(0.00240)	(0.00283)	(0.00295)
Share of routine workers in 1990	-61.51***	65.59***	-13.74	21.45**
	(7.465)	(7.250)	(8.524)	(8.891)
Exposure to Chinese import competition	-0.0230	0.296*	-0.628***	1.035***
	(0.173)	(0.168)	(0.197)	(0.205)
Exposure to tariff changes from NAFTA	137.9***	-132.6***	16.18	-13.82
	(34.77)	(33.77)	(39.70)	(41.41)
Share of men in 1990	33.25*	-1.062	18.47	6.673
	(18.72)	(18.18)	(21.37)	(22.29)
Share of people with primary education in 1990	12.15***	-15.69***	-15.10***	13.33***
	(3.999)	(3.884)	(4.576)	(4.773)
Share of manufacturer workers in 1990	10.72***	-9.762**	3.762	-5.849
	(3.933)	(3.820)	(4.486)	(4.679)
Employment to population 1990	0.147***	-0.188***	0.0559	-0.0771
	(0.0569)	(0.0552)	(0.0650)	(0.0678)
Region	✓	✓	✓	✓
Observations	1795	1795	1787	1787
R^2	0.678	0.583	0.678	0.676
F	90.04	59.32	91.97	91.08
Kleibergen-Paap Wald F-stat	15085.2	15085.2	15019.9	15019.9

Notes: The dependent variables in columns 1–2 represent each candidate's share of valid votes for the 2024 elections. Columns 3–4 capture the change in support between 2006 and 2024. For the left-bloc comparison, we contrast support for AMLO in the 2006 presidential election—when he ran under the left coalition *Coalición por el Bien de Todos* (PRD–PT–Convergencia)—with support for Sheinbaum in 2024, who ran under *MORENA* in alliance with *Sigamos Haciendo Historia*. For the right-bloc comparison, we contrast support for Gálvez Ruiz in 2024 with the main right-of-center candidates in 2006: Felipe Calderón, who ran under the *PAN*, and Roberto Madrazo, who ran under the *Alianza por México* (PRI–PVEM). We also include Roberto Campa of *Nueva Alianza*, whose platform in 2006 leaned toward the center-right. All specifications include the following control variables: 1) Demographics: 1990 CZ demographics, including the share of men and the share of people with primary education as their highest level; 2) Industry: shares of employment in manufacturing in 1990 and the 1990 level of employment-to-population ratio. 3) Distance to the US and 4) State FE. All regressions are weighted by a CZ's share of the national working-age population in 1990. The coefficients marked with $***$, $**$, and $*$ are significant at the 1%, 5%, and 10% confidence levels, respectively.

Table A.14: Effect of Robot Exposure on Electoral Outcomes, controlling for drug traffic routes

OLS	(1) Sheinbaum (Left)	(2) Galvez (Right)	(3) Δ Left	(4) Δ Right
External exposure to foreign robots	1.052**	-0.629*	0.859***	-0.521
	(0.437)	(0.362)	(0.307)	(0.346)
External exposure to domestic robots	4.101*	-3.222*	-1.707	2.886
	(2.172)	(1.804)	(2.066)	(2.223)
Drugs Route	-2.893	2.156	-6.527***	6.069**
	(1.902)	(1.824)	(2.285)	(2.613)
Share of routine workers in 1990	-3.870	18.82	-69.03*	87.21**
	(24.68)	(21.12)	(34.21)	(35.57)
Exposure to Chinese import competition	-1.600*	0.943	1.007	-1.605*
	(0.856)	(0.713)	(0.679)	(0.812)
Exposure to tariff changes from NAFTA	93.32	-90.99	-30.85	18.99
	(97.22)	(105.7)	(138.0)	(130.9)
Share of men in 1990	105.6	-39.79	112.6	-64.73
	(80.81)	(60.24)	(71.11)	(71.40)
Share of people with primary education in 1990	-1.996	-7.255	-24.57*	19.32
	(15.45)	(14.69)	(14.10)	(13.55)
Share of manufacturer workers in 1990	-28.60**	23.60**	-10.37	5.135
	(10.66)	(10.37)	(14.53)	(16.54)
Employment to population 1990	-0.244	0.170	0.780***	-0.852***
	(0.226)	(0.168)	(0.243)	(0.213)
Observations	1791	1791	1783	1783
R^2	0.272	0.208	0.353	0.350
IV	(1) Sheinbaum (Left)	(2) Galvez (Right)	(3) Δ Left	(4) Δ Right
Exposure to foreign robots	1.146**	-0.684*	0.948***	-0.580
	(0.470)	(0.390)	(0.357)	(0.382)
Exposure to domestic robots	3.893**	-3.056*	-1.605	2.724
	(1.961)	(1.637)	(1.933)	(2.083)
Drugs Route	-2.660	2.016	-6.341***	5.958**
	(1.808)	(1.755)	(2.249)	(2.561)
Share of routine workers in 1990	-7.020	21.05	-69.41**	86.61**
	(23.69)	(20.85)	(33.16)	(34.34)
Exposure to Chinese import competition	-1.725**	1.009	0.853	-1.492*
	(0.821)	(0.706)	(0.685)	(0.824)
Exposure to tariff changes from NAFTA	98.72	-95.80	-36.76	26.37
	(93.68)	(103.5)	(133.0)	(126.4)
Share of men in 1990	103.6	-38.22	113.3	-66.04
	(77.55)	(58.20)	(69.51)	(69.95)
Share of people with primary education in 1990	-1.291	-7.649	-23.79*	18.78
	(14.99)	(14.29)	(13.83)	(13.22)
Share of manufacturer workers in 1990	-25.94**	21.80**	-9.542	5.131
	(10.44)	(10.43)	(14.26)	(16.12)
Employment to population 1990	-0.224	0.155	0.781***	-0.846***
	(0.222)	(0.166)	(0.237)	(0.206)
Observations	1791	1791	1783	1783
R^2	0.291	0.221	0.352	0.350
F	12.98	7.799	4.263	3.657
Kleibergen-Paap Wald F-stat	205.7	205.7	207.5	207.5

Notes: The dependent variables in columns 1–2 represent each candidate's share of valid votes for the 2024 elections. Columns 3–4 capture the change in support between 2006 and 2024. For the left-bloc comparison, we contrast support for AMLO in the 2006 presidential election—when he ran under the left coalition *Coalición por el Bien de Todos* (PRD–PT–Convergencia)—with support for Sheinbaum in 2024, who ran under *MORENA* in alliance with *Sigamos Haciendo Historia*. For the right-bloc comparison, we contrast support for Gálvez Ruiz in 2024 with the main right-of-center candidates in 2006: Felipe Calderón, who ran under the *PAN*, and Roberto Madrazo, who ran under the *Alianza por México* (PRI–PVEM). We also include Roberto Campa of *Nueva Alianza*, whose platform in 2006 leaned toward the center-right. All specifications include the following control variables: 1) Demographics: 1990 CZ demographics, including the share of men and the share of people with primary education as their highest level; 2) Industry: shares of employment in manufacturing in 1990 and the 1990 level of employment-to-population ratio. 3) Dummy indicating whether it is a drug traffic route. All regressions are weighted by a CZ's share of the national working-age population in 1990. Standard errors are robust to heteroskedasticity and clustered by state. The coefficients marked with $***$, $**$, and $*$ are significant at the 1%, 5%, and 10% confidence levels, respectively.

Table A.15: Effect of Robot Exposure on Electoral Outcomes, only exposed CZs

OLS	(1) Sheinbaum (Left)	(2) Galvez (Right)	(3) Δ Left	(4) Δ Right
External exposure to foreign robots	0.828	-0.488	0.725***	-0.453
	(0.494)	(0.411)	(0.253)	(0.284)
External exposure to domestic robots	6.440	-4.676	1.094	0.898
	(3.902)	(3.133)	(3.110)	(3.252)
Share of routine workers in 1990	39.18	-0.736	-158.3***	203.4***
	(43.06)	(44.55)	(44.79)	(47.64)
Exposure to Chinese import competition	-0.831	0.263	0.680	-1.228*
	(1.208)	(1.038)	(0.586)	(0.691)
Exposure to tariff changes from NAFTA	222.1	-227.9	-232.2	217.0
	(215.1)	(193.7)	(179.5)	(187.0)
Share of men in 1990	91.68	54.73	185.8	-53.37
	(192.3)	(160.0)	(108.7)	(142.3)
Share of people with primary education in 1990	10.68	-26.64	-74.24**	62.92**
	(27.84)	(25.49)	(27.46)	(30.03)
Share of manufacturer workers in 1990	-41.75**	37.49**	-6.800	-0.675
	(19.04)	(16.73)	(19.15)	(26.18)
Employment to population 1990	-0.864*	0.660	2.287***	-2.493***
	(0.499)	(0.465)	(0.474)	(0.404)
Observations	249	249	249	249
R^2	0.294	0.249	0.623	0.597
IV	(1) Sheinbaum (Left)	(2) Galvez (Right)	(3) Δ Left	(4) Δ Right
Exposure to foreign robots	0.901*	-0.528	0.802***	-0.505*
	(0.505)	(0.426)	(0.277)	(0.304)
Exposure to domestic robots	5.962*	-4.336	0.972	0.871
	(3.381)	(2.728)	(2.759)	(2.910)
Share of routine workers in 1990	30.83	4.747	-162.7***	205.1***
	(39.63)	(43.42)	(43.13)	(46.18)
Exposure to Chinese import competition	-0.933	0.313	0.540	-1.123
	(1.137)	(1.001)	(0.583)	(0.698)
Exposure to tariff changes from NAFTA	242.6	-242.5	-227.5	218.6
	(194.6)	(178.5)	(164.8)	(174.2)
Share of men in 1990	81.78	61.56	182.3*	-52.93
	(178.8)	(150.7)	(103.8)	(136.7)
Share of people with primary education in 1990	10.86	-26.64	-73.56***	62.31**
	(25.72)	(23.95)	(25.87)	(28.44)
Share of manufacturer workers in 1990	-37.17**	34.51**	-4.287	-1.726
	(17.92)	(16.58)	(18.15)	(24.94)
Employment to population 1990	-0.797*	0.616	2.323***	-2.507***
	(0.473)	(0.450)	(0.458)	(0.397)
Observations	249	249	249	249
R^2	0.331	0.272	0.625	0.597
F	35.81	17.08	18.23	9.288
Kleibergen-Paap Wald F-stat	189.9	189.9	189.9	189.9

Notes: The sample is limited to only those CZs that were exposed pre-shock (i.e, the share of maquiladoras was not 0). The dependent variables in columns 1–2 represent each candidate's share of valid votes for the 2024 elections. Columns 3–4 capture the change in support between 2006 and 2024. For the left-bloc comparison, we contrast support for AMLO in the 2006 presidential election—when he ran under the left coalition *Coalición por el Bien de Todos* (PRD–PT–Convergencia)—with support for Sheinbaum in 2024, who ran under *MORENA* in alliance with *Sigamos Haciendo Historia*. For the right-bloc comparison, we contrast support for Gálvez Ruiz in 2024 with the main right-of-center candidates in 2006: Felipe Calderón, who ran under the *PAN*, and Roberto Madrazo, who ran under the *Alianza por México* (PRI–PVEM). We also include Roberto Campa of *Nueva Alianza*, whose platform in 2006 leaned toward the center-right. All specifications include the following control variables: 1) Demographics: 1990 CZ demographics, including the share of men and the share of people with primary education as their highest level; 2) Industry: shares of employment in manufacturing in 1990 and the 1990 level of employment-to-population ratio. All regressions are weighted by a CZ's share of the national working-age population in 1990. Standard errors are robust to heteroskedasticity and clustered by state. The coefficients marked with $***$, $**$, and $*$ are significant at the 1%, 5%, and 10% confidence levels, respectively.

Table A.16: Effect of Robot Exposure on Electoral Outcomes - 2018 Election

OLS	(1) AMLO (Left)	(2) Anaya (Right)	(3) Δ Left 2018	(4) Δ Right 2018
External exposure to foreign robots	0.451	-0.364	0.364	-0.277
	(0.448)	(0.266)	(0.221)	(0.247)
External exposure to domestic robots	5.214**	-3.770**	-0.884	2.367
	(2.494)	(1.454)	(2.359)	(2.199)
Share of routine workers in 1990	72.50**	-36.15	-7.147	42.20
	(29.27)	(26.80)	(26.49)	(34.77)
Exposure to Chinese import competition	-1.456	0.903*	1.131	-1.687**
	(1.038)	(0.531)	(0.771)	(0.777)
Exposure to tariff changes from NAFTA	7.513	-51.21	-119.6	80.69
	(170.1)	(136.7)	(104.1)	(75.00)
Share of men in 1990	88.03	-75.01*	106.9*	-97.87
	(75.62)	(41.56)	(52.46)	(68.37)
Share of people with primary education in 1990	15.36	-10.25	-10.48	15.64
	(19.33)	(14.92)	(12.11)	(12.53)
Share of manufacturer workers in 1990	-62.88***	40.03***	-44.50***	22.02
	(19.10)	(13.29)	(14.83)	(13.65)
Employment to population 1990	-0.429	0.440*	0.636**	-0.624**
	(0.276)	(0.226)	(0.269)	(0.286)
Observations	1797	1797	1789	1789
R^2	0.172	0.171	0.206	0.241
IV	(1) AMLO (Left)	(2) Anaya (Right)	(3) Δ Left 2018	(4) Δ Right 2018
Exposure to foreign robots	0.482	-0.390	0.402*	-0.310
	(0.469)	(0.284)	(0.240)	(0.268)
Exposure to domestic robots	4.938**	-3.571***	-0.832	2.236
	(2.273)	(1.322)	(2.189)	(2.054)
Share of routine workers in 1990	69.83**	-34.19	-7.058	41.38
	(28.45)	(26.29)	(25.83)	(34.14)
Exposure to Chinese import competition	-1.475	0.923*	1.062	-1.618**
	(1.026)	(0.528)	(0.747)	(0.766)
Exposure to tariff changes from NAFTA	17.64	-58.48	-121.9	85.93
	(167.4)	(136.1)	(99.54)	(73.41)
Share of men in 1990	85.57	-73.23*	107.3**	-99.00
	(73.07)	(39.93)	(51.37)	(66.84)
Share of people with primary education in 1990	15.53	-10.40	-10.15	15.33
	(18.76)	(14.56)	(11.80)	(12.22)
Share of manufacturer workers in 1990	-60.79***	38.46***	-44.18***	22.23*
	(18.66)	(12.94)	(14.65)	(13.39)
Employment to population 1990	-0.411	0.427*	0.635**	-0.618**
	(0.271)	(0.221)	(0.263)	(0.280)
Observations	1797	1797	1789	1789
R^2	0.182	0.178	0.208	0.240
F	3.116	4.894	4.198	4.277
Kleibergen-Paap Wald F-stat	178.1	178.1	178.5	178.5

Notes: The dependent variables in columns 1–2 represent each candidate's share of valid votes for the 2018 elections. Columns 3–4 capture the change in support between 2006 and 2018. For the left-bloc comparison, we contrast support for AMLO in the 2006 presidential election—when he ran under the left coalition *Coalición por el Bien de Todos* (PRD–PT–Convergencia)—with support for AMLO in 2024, who ran under *MORENA*. For the right-bloc comparison, we contrast support for Anaya in 2018 with the main right-of-center candidates in 2006: Felipe Calderón, who ran under the *PAN*, and Roberto Madrazo, who ran under the *Alianza por México* (PRI–PVEM). We also include Roberto Campa of *Nueva Alianza*, whose platform in 2006 leaned toward the center-right. All specifications include the following control variables: 1) Demographics: 1990 CZ demographics, including the share of men and the share of people with primary education as their highest level; 2) Industry: shares of employment in manufacturing in 1990 and the 1990 level of employment-to-population ratio. All regressions are weighted by a CZ's share of the national working-age population in 1990. Standard errors are robust to heteroskedasticity and clustered by state. The coefficients marked with $***$, $**$, and $*$ are significant at the 1%, 5%, and 10% confidence levels, respectively.

Table A.17: Effect of Robot Exposure on Electoral Outcomes, only instrumenting Foreign Robots

IV	(1) Sheinbaum (Left)	(2) Galvez (Right)	(3) Δ Left	(4) Δ Right
Exposure to foreign robots	1.156**	-0.693*	0.979***	-0.612**
	(0.476)	(0.392)	(0.282)	(0.308)
Exposure to domestic robots	4.160*	-3.199*	-1.530	2.790
	(2.149)	(1.798)	(2.256)	(2.436)
Share of routine workers in 1990	-12.50	25.16	-83.48**	99.80***
	(22.59)	(20.76)	(33.37)	(34.43)
Exposure to Chinese import competition	-1.705*	0.991	0.937	-1.579*
	(0.898)	(0.753)	(0.735)	(0.814)
Exposure to tariff changes from NAFTA	78.07	-80.32	-81.14	67.50
	(100.2)	(107.5)	(124.1)	(116.6)
Share of men in 1990	102.8	-37.49	109.4	-62.15
	(76.32)	(56.87)	(68.56)	(68.64)
Share of people with primary education in 1990	-1.425	-7.625	-23.36	18.17
	(15.48)	(14.52)	(15.18)	(14.14)
Share of manufacturer workers in 1990	-27.35**	22.73**	-10.94	6.110
	(11.23)	(10.49)	(13.65)	(14.95)
Employment to population 1990	-0.198	0.137	0.833***	-0.893***
	(0.222)	(0.167)	(0.271)	(0.241)
Observations	1795	1795	1787	1787
R^2	0.281	0.214	0.310	0.316
F	11.05	6.744	5.254	4.637
Kleibergen-Paap Wald F-stat	356.8	356.8	357.6	357.6

Notes: The dependent variables in columns 1–2 represent each candidate's share of valid votes for the 2024 elections. Columns 3–4 capture the change in support between 2006 and 2024. For the left-bloc comparison, we contrast support for AMLO in the 2006 presidential election—when he ran under the left coalition *Coalición por el Bien de Todos* (PRD–PT–Convergencia)—with support for Sheinbaum in 2024, who ran under *MORENA* in alliance with *Sigamos Haciendo Historia*. For the right-bloc comparison, we contrast support for Gálvez Ruiz in 2024 with the main right-of-center candidates in 2006: Felipe Calderón, who ran under the *PAN*, and Roberto Madrazo, who ran under the *Alianza por México* (PRI–PVEM). We also include Roberto Campa of *Nueva Alianza*, whose platform in 2006 leaned toward the center-right. All specifications include the following control variables: 1) Demographics: 1990 CZ demographics, including the share of men and the share of people with primary education as their highest level; 2) Industry: shares of employment in manufacturing in 1990 and the 1990 level of employment-to-population ratio. All regressions are weighted by a CZ's share of the national working-age population in 1990. Standard errors are robust to heteroskedasticity and clustered by state. The coefficients marked with $***$, $**$, and $*$ are significant at the 1%, 5%, and 10% confidence levels, respectively.