

# Does Automation in High-Income Countries Hurt Developing Ones? Evidence from the United States and Mexico

The World Bank

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March 5, 2019

# Overview

- 1 Main questions
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# Main Questions

- How does automation (both in Mexico and the US) affect Mexico's labor markets?
- Does automation in the US lower exports from Mexico to the US?
- Does automation in Mexico destroy local jobs?

- Research on the impacts of automation is focused on rich countries
- Importance of considering exposure to automation both at home and abroad (through trade)
- Concerns about reshoring (the destruction of jobs in developing countries that were originally offshored from high-income economies) are rising, but evidence is scarce.
- Limited understanding about the impacts of local adoption of robots in developing countries

# Reshoring: lots of anecdotal evidence

Opinion US trade

## Reshoring makes Michigan great again, one rung at a time

Selling all-American ladders from an apple-pie-and-oupsids town in the Rust Belt

PATTI WALDMEIR

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Reshoring

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## Reshoring and FDI boost US manufacturing jobs

Report finds posts created in America outstrip factory roles moving offshore



## 'Reshoring' could create 200,000 jobs over next decade

Tanya Poolley, Manufacturing Correspondent MARCH 10, 2014

[n](#) [e](#)

Companies bringing production back to the UK from overseas could create up to 200,000 jobs in Britain over the next decade, as a small but growing trend gains strength.

Manufacturing stands to benefit most from "reshoring", particularly sectors such as textiles, electrical equipment and machinery.

Advanced manufacturing

## Adidas's high-tech factory brings production back to Germany

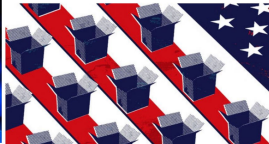
Making trainers with robots and 3D printers



Reshoring manufacturing

## Coming home

A growing number of American companies are moving their manufacturing back to the United States



## US manufacturers 'reshoring' from China

Ed Crooks in New York SEPTEMBER 25, 2013

[n](#) [e](#)

American companies are increasingly "reshoring" manufacturing operations from China to the US, according to a survey of executives.

The shift reflects China's ebbing competitive advantage as a low-cost manufacturing centre after years of rapid wage inflation and points to rising employment in US manufacturing, even though official data have shown little growth over the past year.

## Reshoring: What's the empirical evidence?

- Around 4 percent of companies in selected European economies have moved part of their activities back home between 2010 and 2012 (Dachs and Zanker, 2014).
- However, the extent of new offshoring processes continues to be substantially more important than that of reshoring
- De Backer et al. (2016): Evidence is inconclusive
  - The share of imports from lower-income countries in total domestic demand of high-income OECD countries is increasing over time.
  - In Europe, employment of MNEs has not been shifting back home, although more recent data suggest the opposite (De Backer, 2018).
  - MNE affiliates at the home location grow faster than other MNE affiliates. However, this could reflect other phenomena such as unobserved firm or country shocks.



# Reshoring and Automation: What's the evidence?

- Artuc et al. (2018) find that greater robot intensity in own production leads to: (i) a rise in imports sourced from less developed countries in the same industry; and (ii) an even stronger increase in exports to those countries.
- De Backer et al. (2018) : Evidence is inconclusive
  - Companies purchases of intermediate goods and services from foreign providers in developing countries a proxy variable for offshoring are not related to robot adoption between 2000 and 2014.
  - MNE are no more likely to bring jobs and fixed assets back home in developed countries that are automating more rapidly.
- In contrast, Dachs et al. (2017) find that European firms adopting digital manufacturing technologies (known as Industry 4.0) are significantly more likely to reshore activities.

# Our findings: a preview

- Negative (but small) impacts of robot adoption in the US on exports per worker from Mexico to the US
  - An increase in one robot per thousand workers in the US - about twice the increase observed between 2004-2014 - lowers exports per worker growth from Mexico to the US by 6.7 percent.
- Higher exposure to US automation did not affect wage employment, nor manufacturing wage employment overall.
  - However, exposure to US automation reduced manufacturing wage employment in areas where occupations were initially more susceptible of being automated;
  - But it increased manufacturing wage employment in others.
- We also find negative impacts of exposure to local automation on local labor market outcomes.

# Our contribution

- We investigate the impacts of domestic and foreign automation simultaneously
- Previous estimates may suffer from the typical omitted variable biases that affect cross-country studies.
  - Our study overcomes this limitation by exploiting variation in exports and exposure to automation across local labor markets, and using instrumental variables to address the endogeneity of automation.
- We provide new evidence on the impacts of reshoring and local automation on developing economies
  - And the heterogeneous impacts across types of local labor markets and workers

## Econometric Model and Data

# What's an industrial robot?

Automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which may be either fixed in place or mobile for use in industrial automation applications.

Common applications include:

- Welding
- Assembling
- Dispensing
- Handling
- Processing

# Measuring exposure to US automation at the local level

Based on a Revealed Comparative Advantage (RCA) approach, we construct the export-weighted average of the increase in the number of robots per thousand workers by sector in the US over time:

$$robots\_RCA_{m,2004,2014}^{US} = \sum_i^I \omega_{m,i,2004} \left[ \left( \frac{robots_{2014,i}^{US}}{emp_{2000,i}^{US}} \right) - \left( \frac{robots_{2004,i}^{US}}{emp_{2000,i}^{US}} \right) \right]$$

Where  $robots_{2014,i}^{US}$  stands for the number of robots in industry  $i$  in the year 2014 in the US and  $emp_{2000,i}^{US}$  denote the number of workers in industry  $i$  in the year 2014 in the US.

Each weight  $\omega_{m,i,2004}$  is the share of exports to the US from region  $m$  and industry  $i$  in Mexico in 2004, on the total exports from region  $m$  to the US in 2004.

This would give more weight to the automation of sectors where the region has a revealed comparative advantage (RCA).

# Measuring exposure to local automation at the local level

1) Revealed Comparative Advantage (RCA) approach:

$$robots\_RCA_{m,2011,2014}^{MX} = \sum_i^I \omega_{m,i,2004} \left[ \left( \frac{robots_{2014,i}^{MX}}{emp_{2000,i}^{MX}} \right) - \left( \frac{robots_{2011,i}^{MX}}{emp_{2000,i}^{MX}} \right) \right]$$

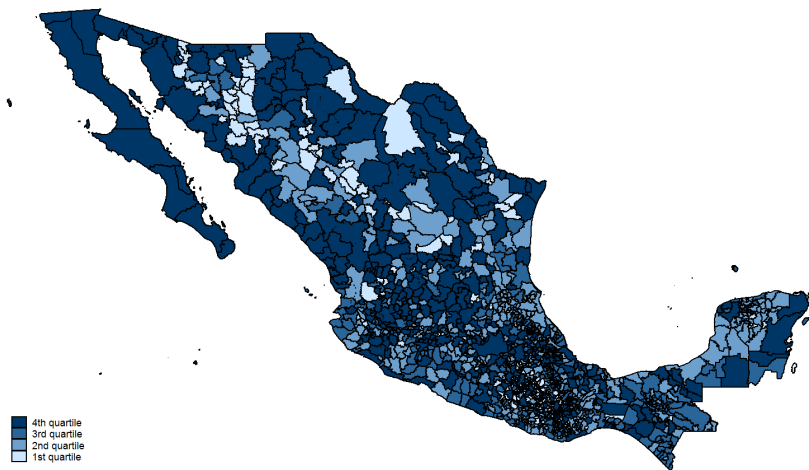
2) Employment-weighted (as in Acemoglu and Restrepo (2017))

$$robots\_emp_{m,2011,2014}^{MX} = \sum_i^I \mu_{m,i,2004} \left[ \left( \frac{robots_{2014,i}^{MX}}{emp_{2000,i}^{MX}} \right) - \left( \frac{robots_{2011,i}^{MX}}{emp_{2000,i}^{MX}} \right) \right]$$

3) Employment and RCA-weighted

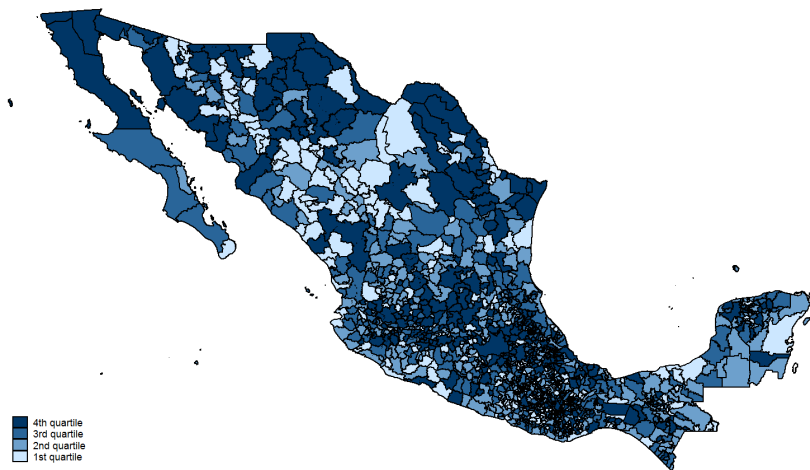
$$robots\_RCA\_emp_{m,2011,2014}^{MX} = \sum_i^I \mu_{m,i,2004} \frac{exports_{m,i,2004}}{exports_{2000,i,m}} \left[ \left( \frac{robots_{2014,i}^{MX}}{emp_{2000,i}^{MX}} \right) - \left( \frac{robots_{2011,i}^{MX}}{emp_{2000,i}^{MX}} \right) \right]$$

# Exposure to US automation (2004-2014)





# Exposure to local automation (2011-2014)



# Impact of US automation on Mexican exports

We estimate the following equation using OLS:

$$\begin{aligned}\Delta \ln \left( \frac{exports_{m,t}}{Emp_{m,2000}} \right) = \\ = \alpha + \beta^{US} robots\_RCA_{m,t,t-\tau}^{US} + \beta^{MX} robots_{m,t,t-\tau}^{MX} + \Phi X + \epsilon_{i,t}\end{aligned}$$

The sign of  $\beta^{US}$  is not clear ex-ante:

More likely to be negative if robots in the US improve the competitiveness of the US relative to Mexico's

More likely to be positive if automation enhances US productivity and consequently the demand for Mexican products

# Instrumental variables

We instrument exposure to US automation using exposure to European automation:

$$robots\_RCA_{m,2004,2014}^{EU} = \sum_i^I \omega_{m,i,2004} \left[ \left( \frac{robots_{2014,i}^{EU}}{emp_{2000,i}^{EU}} \right) - \left( \frac{robots_{2004,i}^{EU}}{emp_{2000,i}^{EU}} \right) \right]$$

And we instrument exposure to local automation using exposure to South American automation:

$$robots\_RCA_{m,2004,2014}^{SA} = \sum_i^I \omega_{m,i,2004} \left[ \left( \frac{robots_{2014,i}^{SA}}{emp_{2000,i}^{SA}} \right) - \left( \frac{robots_{2004,i}^{SA}}{emp_{2000,i}^{SA}} \right) \right]$$

# Impact of US automation on Mexico's local labor markets

Reduced-form specification:

$$\Delta (Empl_{m,t}) = \pi + \pi^{US} robots\_RCA_{m,t,t-\tau}^{US} + \pi^{MX} robots_{m,t,t-\tau}^{MX} + \Pi X + u_{i,t}$$

Impact of US automation through exports:

$$\Delta (Empl_{m,t}) = \theta + \theta^{US} \Delta \ln \left( \widehat{\frac{exports_{m,t}}{Emp_{m,2000}}} \right) + \theta^{MX} robots_{m,t,t-\tau}^{MX} + \Theta X + v_{i,t}$$

Where  $\Delta \ln \left( \widehat{\frac{exports_{m,t}}{Emp_{m,2000}}} \right)$  is the predicted value from the first-stage equation:

$$\Delta \ln \left( \frac{exports_{m,t}}{Emp_{m,2000}} \right) = \alpha + \beta^{US} robots\_RCA_{m,t,t-\tau}^{US} + \beta^{MX} robots_{m,t,t-\tau}^{MX} + \Phi X + \epsilon_{i,t}$$

- **Trade data:** data on exports and imports by municipality, year, destination and product come from the tax authority of Mexico, and covers each municipality over the 2004-2014 period.
- **Automation data:** Data on the stock of robots by country, year and sector of economic activity comes from the International Federation of Robotics (IFR).
- **Labor market indicators:** tabulations from the 2000 and 2010 Census of Population and Housing and the 2015 Population Count to obtain labor market indicators, as well as demographic characteristics of the population at the municipal level. We use data on the number of employees by sector of economic activity and municipality from the 1999 Economic Census to estimate the employment weights used to construct the measure of exposure to local automation.

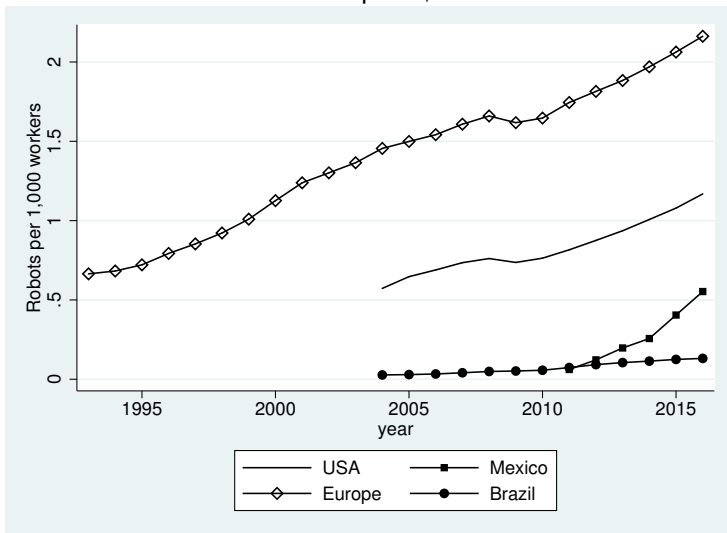
# Local labor market definition

- The number of official metropolitan areas (around 60) in Mexico is too low to obtain precise estimates of the impacts of automation.
- We group municipalities into functional territories following Berdegue et al. (2017)
  - This methodology allows to increase the sample of areas significantly
  - Using a combination of commuting flows and satellite night light data, the authors group 2,446 municipalities into 1,534 functional territories.
  - These functional territories include large metropolitan areas such as Mexico City, which contains 88 municipalities, but also small and remote municipalities with no connections.
  - These functional territories seem to be consistent with the local labor market assumption that local trade and technological shocks do not spill-over to other areas through labor migration.

- We use data from EUKLEMS on adoption of Information Technology (IT) and Communication Technology (CT) by sector and time for the US to estimate a measure of exposure of Mexican LLMs to such technologies in the US, for a robustness test.
- We use data on the degree of offshorability and routine task intensity of Mexican occupations from Mahutga et al. (2018).
- We use data the susceptibility of automation of occupations from Artuc et al (2018), which we convert to the Mexican classification of occupations using correspondence tables.
- Data on fixed assets, machinery and value added per worker by LLM come from the publicly available tabulates of the Mexican Economic Censuses for 2003 and 2013.

# Descriptive statistics (1)

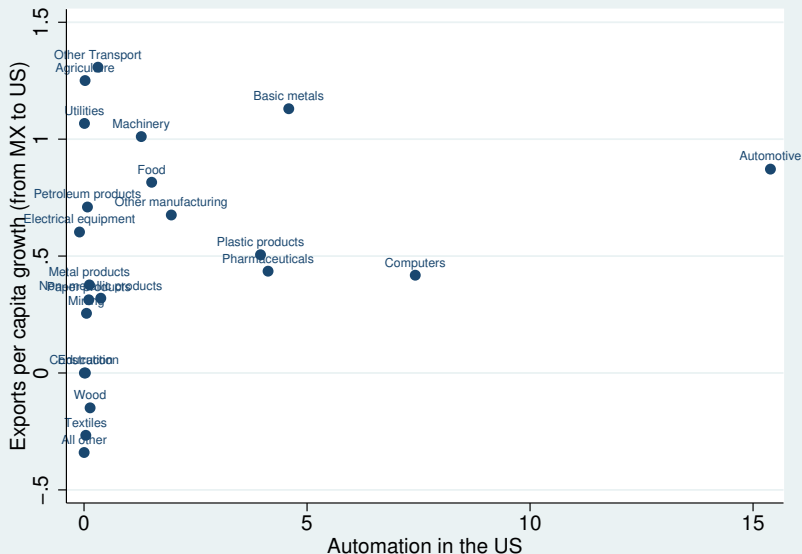
Stock of robots per 1,000 workers





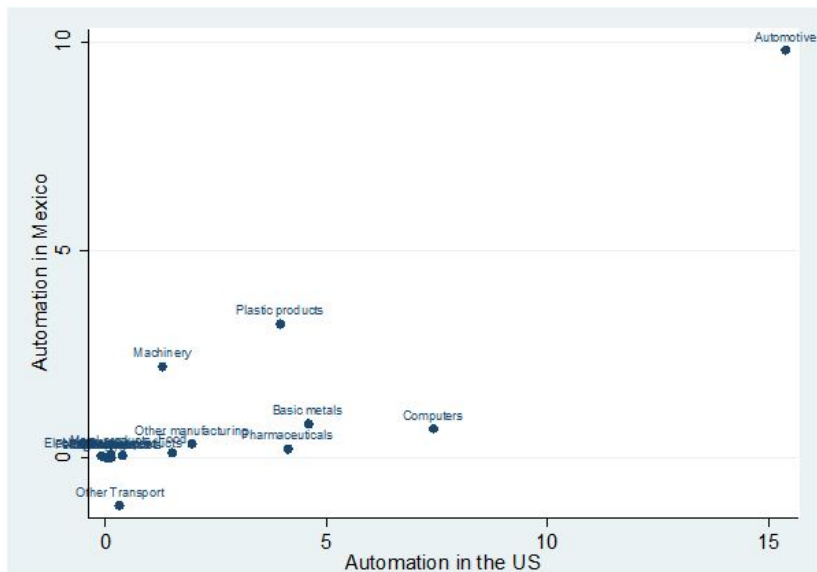
# Descriptive statistics (2)

Exports from Mexico to the US, vs. Automation in the US, 2004-2014



# Descriptive statistics (3)

Automation in Mexico (2011-2014) vs. Automation in the US (2004-2014)



Results: Impacts on Exports to the US

# OLS results: The impact of exposure to US robots on exports to US

## Controlling for exposure to domestic automation

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A						
Exposure to US Robots	-16.65** (6.953)	-12.03* (7.077)	-11.15 (6.995)	-12.37* (7.122)	-11.91* (7.074)	-4.760 (7.302)
Exposure to Domestic Robots (export-weighted)	3.820 (3.598)	3.167 (3.676)	-2.250 (4.691)	3.165 (3.682)	3.157 (3.682)	-39.71 (26.65)
Observations	1,446	1,443	1,429	1,443	1,440	1,440
Panel B						
Exposure to US Robots	-9.083*** (2.457)	-5.880** (2.584)	-14.36*** (4.522)	-6.207** (2.554)	-5.774** (2.587)	-11.08* (5.912)
Exposure to Domestic Robots (employment-weighted)	-1.530 (1.661)	-0.846 (1.763)	-1.594 (1.634)	-0.908 (1.730)	-0.880 (1.774)	-4.397 (7.385)
Observations	1,446	1,443	1,429	1,443	1,440	1,440
Panel C						
Exposure to US Robots	-11.27*** (2.740)	-8.728*** (2.759)	-19.45*** (4.796)	-8.829*** (2.725)	-8.614*** (2.770)	-16.71*** (5.920)
Exposure to Domestic Robots (export- and employment-weighted)	0.822* (0.462)	1.450** (0.637)	4.635*** (0.995)	1.337** (0.623)	1.439** (0.636)	24.67*** (7.930)
Observations	1,446	1,443	1,429	1,443	1,440	1,440
State Fixed Effects	YES	YES	YES	YES	YES	YES
Local labor market initial characteristics	NO	YES	YES	YES	YES	YES
Excludes highly exposed areas	NO	NO	YES	NO	NO	NO
Initial share of manufacturing employment	NO	NO	NO	YES	NO	NO
Initial share of routine and non-routine manual employment	NO	NO	NO	NO	YES	NO
Excludes auto industry	NO	NO	NO	NO	NO	YES

The coefficient associated with the exposure to robots should be interpreted as the percent change in exports per worker growth

# IV results: First-stage equations

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Dependent Variable: Exposure to US Automation (export-weighted)						
Exposure to EU Robots (export-weighted)	-0.00446 (0.00909)	0.955*** (0.00863)	0.980*** (0.0222)	0.953*** (0.00862)	0.956*** (0.00861)	1.384*** (0.0921)
Exposure to Automation in South America (employment-weighted)	0.0534* (0.0301)	0.0450* (0.0273)	0.0583* (0.0337)	0.0357 (0.0251)	0.0442 (0.0271)	0.0587 (0.0445)
Observations	1,446	1,443	1,429	1,443	1,440	1,440
Panel B: Dependent Variable: Exposure to Domestic Automation (employment-weighted)						
Exposure to EU Robots (export-weighted)	-0.340*** (0.109)	-0.333*** (0.108)	-0.614*** (0.185)	-0.330*** (0.107)	-0.333*** (0.108)	0.0715*** (0.0264)
Exposure to Automation in South America (employment-weighted)	3.505*** (0.492)	3.497*** (0.495)	3.697*** (0.559)	3.512*** (0.496)	3.495*** (0.496)	1.374*** (0.0217)
Observations	1,446	1,443	1,429	1,443	1,440	1,440
State Fixed Effects	YES	YES	YES	YES	YES	YES
Local labor market initial characteristics	NO	YES	YES	YES	YES	YES
Excludes highly exposed areas	NO	NO	YES	NO	NO	NO
Initial share of manufacturing employment	NO	NO	NO	YES	NO	NO
Initial share of routine and non-routine manual employment	NO	NO	NO	NO	YES	NO
Excludes auto industry	NO	NO	NO	NO	NO	YES

# IV results: Impacts of automation on exports to US

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A						
Exposure to US Robots	-33.93*** (12.11)	-29.82** (12.30)	-21.65* (12.10)	-27.81** (12.20)	-29.44** (12.24)	26.44 (22.26)
Exposure to Domestic Robots (export-weighted)	12.11** (5.791)	10.95* (5.766)	1.251 (6.701)	10.11* (5.690)	10.84* (5.743)	-222.1*** (85.85)
Observations	1,446	1,443	1,429	1,443	1,440	1,440
Panel B						
Exposure to US Robots	-8.584*** (2.667)	-6.712** (2.827)	-19.17*** (5.516)	-6.454** (2.767)	-6.566** (2.828)	-30.34*** (8.522)
Exposure to Domestic Robots (employment-weighted)	-2.258 (2.275)	-1.707 (2.260)	-2.727 (1.987)	-1.514 (2.275)	-1.696 (2.245)	-8.789 (7.451)
Observations	1,446	1,443	1,429	1,443	1,440	1,440
Panel C						
Exposure to US Robots	-10.87*** (2.969)	-9.175*** (3.064)	-22.81*** (5.932)	-8.670*** (2.983)	-8.999*** (3.066)	-33.88*** (8.885)
Exposure to Domestic Robots (export- and employment-weighted)	0.815* (0.478)	1.089** (0.515)	3.765*** (0.960)	1.023* (0.524)	1.073** (0.513)	10.70 (8.661)
Observations	1,446	1,443	1,429	1,443	1,440	1,440
State Fixed Effects	YES	YES	YES	YES	YES	YES
Local labor market initial characteristics	NO	YES	YES	YES	YES	YES
Excludes highly exposed areas	NO	NO	YES	NO	NO	NO
Initial share of manufacturing employment	NO	NO	NO	YES	NO	NO
Initial share of routine and non-routine manual employment	NO	NO	NO	NO	YES	NO
Excludes auto industry	NO	NO	NO	NO	NO	YES

# IV results: Impacts of automation on exports by destination

	(1)	(2)
	<b>Exports per worker, log change</b>	
	Panel A: to US	
Exposure to US Robots	-6.712** (2.827)	-6.454** (2.767)
Exposure to Domestic Robots (employment-weighted)	-1.707 (2.260)	-1.514 (2.275)
Observations	1,419	1,419
	Panel B: to US partners	
Exposure to US Robots	-6.026** (2.739)	-6.527** (2.695)
Exposure to Domestic Robots (employment-weighted)	-1.566 (2.087)	-1.986 (2.197)
Observations	1,419	1,419
	Panel D: to Non-US partners	
Exposure to US Robots	-3.682 (3.209)	-3.916 (3.206)
Exposure to Domestic Robots (employment-weighted)	-0.959 (0.970)	-1.190 (1.043)
Observations	1,419	1,419
State Fixed Effects	YES	YES
Local labor market initial characteristics	YES	YES
Initial share of manufacturing employment	NO	YES

# IV results: Impacts of automation on exports by category

	(1)	(2)	(3)	(4)
	Total Exports, log change		Total Imports, log change	
Panel A: Raw Materials				
Exposure to US Robots	-3.402	-3.325	12.92**	12.68**
	(2.780)	(2.823)	(5.412)	(5.420)
Exposure to Domestic Robots (employment-weighted)	1.160	1.233	1.061	0.724
	(1.298)	(1.300)	(5.158)	(5.213)
Observations	1,443	1,443	1,443	1,443
Panel B: Intermediate Goods				
Exposure to US Robots	-8.614**	-8.581**	19.15**	18.91**
	(4.038)	(4.057)	(7.857)	(7.872)
Exposure to Domestic Robots (employment-weighted)	3.990	3.953	-10.75*	-10.06*
	(2.839)	(2.860)	(5.576)	(5.543)
Observations	1,443	1,443	1,443	1,443
Panel D: Capital Goods				
Exposure to US Robots	-4.159	-4.350	-18.47*	-18.65*
	(5.339)	(5.405)	(10.53)	(10.54)
Exposure to Domestic Robots (employment-weighted)	1.818	1.634	-4.553	-4.643
	(2.038)	(1.967)	(3.549)	(3.640)
Observations	1,443	1,443	1,443	1,443
Panel E: Consumption Goods				
Exposure to US Robots	-10.41**	-10.02**	9.867	9.859
	(4.366)	(4.384)	(8.197)	(8.179)
Exposure to Domestic Robots (employment-weighted)	-3.847	-3.518	1.611	1.607
	(2.805)	(2.871)	(4.027)	(4.026)
Observations	1,443	1,443	1,443	1,443
State Fixed Effects	YES	YES	YES	YES
Local labor market initial characteristics	YES	YES	NO	YES
Initial share of manufacturing employment	NO	YES	NO	YES



# IV results: Impacts of US automation on exports, robustness checks

The results are robust to controlling for:

- Imports from China
- Exposure to US ICT investments
- Domestic ICT
- Share of offshorable jobs

## Results: Impacts on Labor Market Outcomes

# OLS results: Impacts of US automation on employment

Dependent variable: Wage employment in tradeable sector to working age population ratio (change)					
	(1)	(2)	(3)	(4)	(5)
Panel A: Employment in Tradable Sector (Census counts)					
Exposure to US Robots	0.0473	0.0235	0.0246	0.0254	0.0216
	(0.0812)	(0.0778)	(0.0759)	(0.0764)	(0.0741)
Observations	1,446	1,443	1,429	1,443	1,440
Panel B: Employment in Manufacturing Sector (Census counts)					
Exposure to US Robots	0.0122	2.24e-05	-0.00171	0.000411	0.00508
	(0.0513)	(0.0474)	(0.0464)	(0.0475)	(0.0447)
Observations	1,446	1,443	1,429	1,443	1,440
Panel C: Employment in Tradable Sector (IPUMS)					
Exposure to US Robots	0.0638	0.0550	0.0608	0.0563	-0.0429
	(0.0954)	(0.0953)	(0.0983)	(0.1000)	(0.0928)
Observations	1,446	1,443	1,429	1,443	1,440
State Fixed Effects	YES	YES	YES	YES	YES
Exposure to local automation	YES	YES	YES	YES	YES
Initial share of exports and imports on value added	YES	YES	YES	YES	YES
Local labor market initial characteristics	NO	YES	YES	YES	YES
Excludes highly exposed areas	NO	NO	YES	NO	NO
Initial share of manufacturing employment	YES	YES	YES	YES	YES
Initial share of routine and non-routine manual employment	NO	NO	NO	YES	YES
Excludes auto industry	NO	NO	NO	NO	YES

## IV results: Impacts of US automation on employment, by level of job replaceability

- Exposure to US automation in areas with a higher share of replaceable jobs, generates a larger decline in employment in the tradeable sector
- However, there are no impacts on total employment

	(1)	(2)
	OLS	
	tradable	Manufacturing
$robots\_RCA^{US}$	0.108** (0.0528)	0.0988* (0.0507)
$robots\_RCA^{US} \times \text{Replaceability}$	-0.261 (0.159)	-0.502*** (0.184)
Replaceability	-0.642** (0.308)	-0.144 (0.112)
Domestic Robots	-0.0341*** (0.0104)	-0.0258*** (0.00742)
State Fixed Effects	YES	YES
Initial characteristics	YES	YES
Observations	1,384	1,294

# IV results: Impacts of domestic automation on employment

	(1)	(2)	(3)	(4)	(5)	(6)
<b>Panel A: Wage Employment to Population Ratio</b>						
Domestic Robots (L-weighted)	-0.0720*** (0.0268)	-0.0792*** (0.0173)	-0.0767*** (0.0195)	-0.0394*** (0.0133)	-0.0772*** (0.0163)	-0.254*** (0.0552)
<b>Panel B: Total Employment to Population Ratio</b>						
Domestic Robots (L-weighted)	0.0427 (0.0502)	0.00733 (0.0171)	0.0156 (0.0159)	-0.00911 (0.0168)	0.00545 (0.0165)	0.0639 (0.0600)
<b>Panel C: Informal Employment to Population Ratio</b>						
Domestic Robots (L-weighted)	0.157** (0.0692)	0.155*** (0.0465)	0.149*** (0.0534)	0.0783* (0.0457)	0.152*** (0.0465)	0.509*** (0.173)
<b>Panel E: Log monthly wage</b>						
Domestic Robots (L-weighted)	-0.179 (0.300)	-0.156 (0.314)	-0.181 (0.363)	-0.138 (0.303)	-0.141 (0.276)	-0.427 (1.472)
Observations	1,443	1,443	1,429	1,443	1,440	1,443
US Automation	YES	YES	YES	YES	YES	YES
State Fixed Effects	YES	YES	YES	YES	YES	YES
Exports to US per worker, log change	YES	YES	YES	YES	YES	YES
Initial characteristics	NO	YES	YES	YES	YES	YES
Excludes highly exposed areas	NO	NO	YES	NO	NO	NO
Manufacturing Employment	NO	NO	NO	YES	NO	NO
Occupational structure	NO	NO	NO	NO	YES	NO
Excludes auto industry	NO	NO	NO	NO	NO	YES

# IV results: Labor market impacts, by skill

	(1)	(2)	(3)	(4)	(5)	(6)
<b>Panel A. Wage Employment to Population Ratio</b>						
	<b>Less than highschool</b>		<b>Highschool</b>		<b>College</b>	
<i>robots_emp<sup>MX</sup></i>	-0.0522*** (0.0141)	-0.0238** (0.0115)	-0.181*** (0.0163)	-0.127*** (0.0241)	-0.0486 (0.0508)	-0.0626 (0.0542)
<b>Panel B. Informal to Total Employment Ratio</b>						
	<b>Less than highschool</b>		<b>Highschool</b>		<b>College</b>	
<i>robots_emp<sup>MX</sup></i>	0.0869*** (0.0232)	0.0286 (0.0206)	0.150*** (0.0310)	0.0972*** (0.0251)	0.0992** (0.0396)	0.0917** (0.0388)
<b>Log Monthly Wage</b>						
	<b>Less than highschool</b>		<b>Highschool</b>		<b>College</b>	
<i>robots_emp<sup>MX</sup></i>	-0.0826 (0.278)	-0.0497 (0.253)	0.139 (0.115)	0.147 (0.107)	0.105 (0.105)	0.158 (0.135)
US Automation	YES	YES	YES	YES	YES	YES
State Fixed Effects	YES	YES	YES	YES	YES	YES
Initial characteristics	YES	YES	YES	YES	YES	YES
Manufacturing employment	NO	YES	NO	YES	NO	YES

# IV results: Labor market impacts, by gender

	(1)	(2)	(3)	(4)	(5)	(6)
<b>Panel A: Men</b>						
Domestic Robots (L-weighted)	-0.0958** (0.0437)	-0.0937*** (0.0280)	-0.0918*** (0.0310)	-0.0443** (0.0200)	-0.0914*** (0.0265)	-0.274*** (0.0917)
<b>Panel B: Women</b>						
Domestic Robots (L-weighted)	-0.0475* (0.0259)	-0.0650*** (0.0138)	-0.0624*** (0.0165)	-0.0359** (0.0147)	-0.0634*** (0.0129)	-0.234*** (0.0455)
Observations	1,443	1,443	1,429	1,443	1,440	1,443
US Automation	YES	YES	YES	YES	YES	YES
State Fixed Effects	YES	YES	YES	YES	YES	YES
Exports to US per worker, log change	YES	YES	YES	YES	YES	YES
Initial characteristics	NO	YES	YES	YES	YES	YES
Excludes highly exposed areas	NO	NO	YES	NO	NO	NO
Manufacturing Employment	NO	NO	NO	YES	NO	NO
Occupational structure	NO	NO	NO	NO	YES	NO
Excludes auto industry	NO	NO	NO	NO	NO	YES

# IV results: Labor market impacts, robustness checks

	(1)	(2)	(3)	(4)	(5)
	<b>Wage Employment to Population Ratio, Census counts</b>				
Exposure to Domestic Robots (employment-weighted)	-0.0728*** (0.0151)	-0.0728*** (0.0151)	-0.0728*** (0.0151)	-0.0722*** (0.0147)	-0.0696*** (0.0144)
Observations	1,419	1,419	1,419	1,419	1,419
State Fixed Effects	YES	YES	YES	YES	YES
Local labor market initial characteristics	NO	YES	YES	YES	YES
Total fixed assets to value added, growth	YES	NO	NO	NO	NO
Machinery assets to value added, growth	NO	YES	NO	NO	NO
ICT assets to value added, growth	NO	NO	YES	NO	NO
Exposure to Chinese imports, growth	NO	NO	NO	YES	NO
Initial share of offshoreable jobs	NO	NO	NO	NO	YES



# IV results: Wage inequality impacts

	(1)	(2)	(3)	(4)
	<b>50-10 ratio</b>			
Domestic Robots (L-weighted)	0.0214 (0.199)	0.0365 (0.217)	-0.120 (0.222)	0.495 (1.393)
Observations	1,434	1,420	1,434	1,361
	<b>90-50 ratio</b>			
Domestic Robots (L-weighted)	0.524* (0.274)	0.509* (0.300)	0.415 (0.263)	2.550 (1.797)
Observations	1,434	1,420	1,434	1,361
	<b>90-10 ratio</b>			
Domestic Robots (L-weighted)	0.546*** (0.177)	0.545*** (0.147)	0.294* (0.162)	2.904*** (0.599)
Observations	1,434	1,420	1,434	1,361
US automation	YES	YES	YES	YES
State Fixed Effects	YES	YES	YES	YES
Initial characteristics	YES	YES	YES	YES
Manufacturing employment	NO	NO	YES	NO
Excludes auto industry	NO	NO	NO	YES

# Conclusions

- Our findings are consistent with some evidence of reshoring (or lower pace of offshoring), as Mexican local labor markets more exposed to automation in the US witnessed lower export growth than less exposed areas
- However, the impacts of reshoring (or decreased offshoring) on labor market outcomes is negligible.
- We also find negative impacts of local robot adoption on the labor market outcomes of unskilled workers.

Thanks!