US Robots and their Impacts in Developing Countries: Evidence from Colombian Workers

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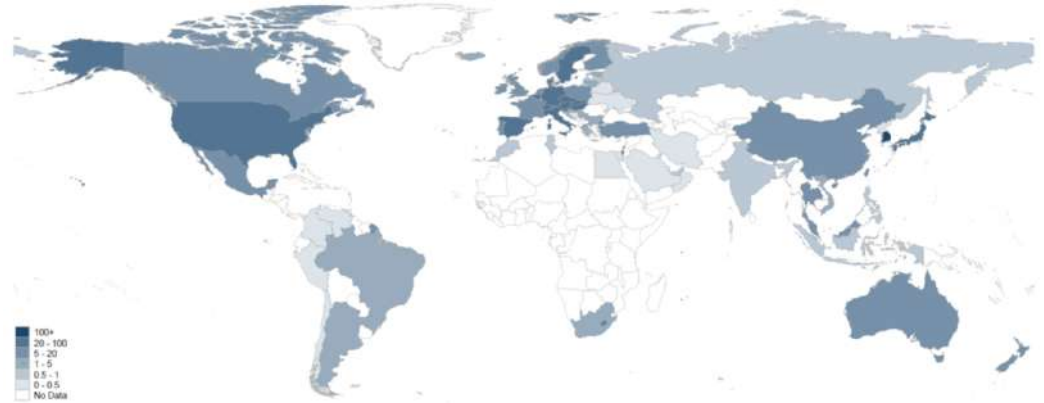
Can U.S. robot adoption affect workers in Colombia?

- Worker-level long-run effects:
  - Workers in industries highly exposed to U.S. robots experience lower cumulative earnings and longer tenure over 2009 - 2016
- Labor adjustment to robots:
  - Workers switching firms within the same industry avoid earnings losses
  - While those moving across industries or locations face the largest losses
- These effects are greater for older, high-earning workers and those in larger firms.
- Trade mechanism:
  - Robots reduce Colombian exports to the US, mainly in the primary sector

Are developing countries with limited automation exempt from its effects?

- With the spread of robots in the workplace there has been much interest in their displacement effects
- Since robots are overrepresented in developed countries, most analysis examines its impacts on their employment
- However, automation might also be affecting developing countries labor markets
  - Directly: Industrialized countries with relevant robot adoption, e.g. Brazil, China
  - Indirectly: Countries with low or no local adoption, affected by their trade partners, e.g. Colombia by U.S.

Missing evidence for developing countries with low-to-no local automation



Source: International Federation of Robotics and World Bank Development Indicators

- In 2016, 142 (developing) countries had a robot density < 1, 84% with no robots

Mechanism: the trade channel

- Induced reshoring:
  - Reduction in costs may change the comparative advantages of some industries
  - Corporations rather than offshoring or importing components from labor abundant countries, may opt for machine-intensive production at home
  - Reducing employment in developing countries
- Induced demand:
  - Productivity gains results in an industry expansion
  - Increasing the demand for goods in all linked industries, included imported goods
  - Increasing employment in developing countries
- Efficiency gains: reduce prices of goods, benefiting importers.

Colombia is a great case to analyze

- Widespread robot adoption in the U.S. since the 2000's, very limited in Colombia
- Extensive U.S. - Colombia trade: exports 35% go to US and 30% of the imports come from U.S.

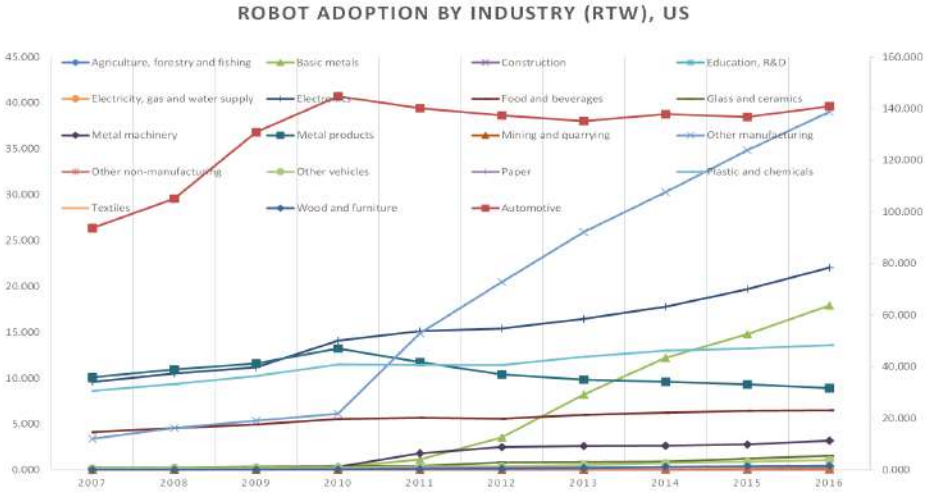
Contribution to the literature

- *Impacts of robots on labor markets*, mainly for developed countries –Acemoglu and Restrepo (2020), Graetz and Michaels (2018), Guiuntella et al. (2022), Rodrigo (2022)
- *Impacts of robots on reshoring* –Krenz et al. (2018), Kinkel et al. (2016), Artuc et al. (2019), Faber (2020), Stapleton & Webb (2023)
- *Closest*: –Faber (2020) negative impacts of U.S. robots on formal employment and reduces exports growth in Mexico's local labor markets.
- **Our paper has two main advantages:**
  - **Identification:** Low robot adoption in Colombia compared to Mexico or Brazil.
  - **Worker level-long term effects:** Examine employer-employee data, and look at wages and labor mobility in addition to employment, controlling for firm and worker characteristics.

Colombian data

- Formal employment:
  - *Planilla Integrada de Liquidación de Aportes*, PILA (2011-2016), Ministry of Health and Social Protection
  - Workers' age, gender
  - Firms' location, industry, size
- Trade data:
  - Exports and Imports by industry and LLM $\sim$ commuting zone (2008-2013), Ministry of Industry, Trade and Services
- U.S. robots:
  - U.S. stock of robots by industry-year (1997-2017), IFR
  - Value of industrial machinery, included robots, at the municipality level (1997-2017)

U.S robot adoption by sector



Source: Robots per thousand workers (RPTW) computed with data from IFR and US Census Bureau. On the right axis is the scale for Automotive industry in red.

What is the effect of U.S. robots in Colombian LLMs?

$$\hat{E}_{ij\tau} = \alpha_0 + \alpha_1 Exposure\,to\,US\,Robots_{j\tau} + X'_{ij,t_0}\alpha_2 + Z'_{i,t_0}\alpha_3 + \epsilon_{ij\tau} \quad (1)$$

$$\hat{E}_{ij\tau} = \sum_{t=2009}^{t=2016} E_{ijt}/\ddot{E}_{it_0}$$

- is the cumulative earnings from 2009 to 2016, normalized by the average earnings over 2008 and 2009, $\ddot{E}_{it_0}$, for worker i in industry j in 2009
- X'_{ij,t_0} worker characteristics Z'_{i,t_0} economic conditions in industry j
- The exposure to U.S. robots is defined as:

$$Exposure\,to\,Robots_{j\tau} = \frac{\Delta Robots^{US}_{j\tau}}{Labor^{US}_{jt_0}/1000}$$

Impacts on worker cumulative earnings, 2009-2016

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Exposure to US robots	-2.099***	-2.229***	-2.084***	-2.714**	-2.697**	-2.763**	-1.897**
	(0.673)	(0.693)	(0.695)	(1.028)	(1.008)	(1.044)	(0.894)
Age cohort dummies	✓	✓	✓	✓	✓	✓	✓
Gender		✓	✓	✓	✓	✓	✓
Employment history			✓	✓	✓	✓	✓
Earning history				✓	✓	✓	✓
Colombian robots					✓	✓	✓
Local internet access						✓	✓
China imports							✓
Observations	2,947,682	2,947,682	2,947,682	2,947,682	2,947,682	2,947,682	2,947,682

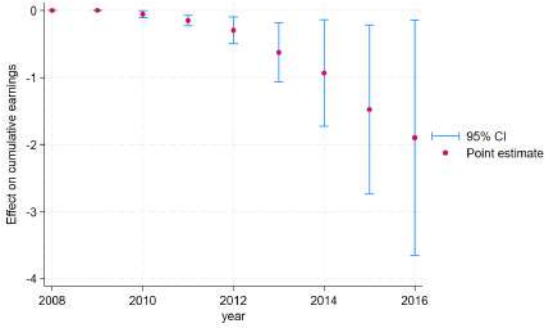
- $\Delta Robots_{p85-15} \Rightarrow$ a reduction of 1.4% of cumulative relative earnings over 7-year window

Impacts on worker earnings and employment, 2009-2016

	(1) Cumulative wage earnings	(2) Years with earnings > 0	(3) Earnings / Year
Exposure to US robots	-1.897**	0.214	-0.308***
	(0.894)	(0.202)	(0.104)
Observations	2,947,682	2,947,682	2,947,682

▸ Alternative robot exposure measures ▸ Alternative employment measures

Dynamic effects of US robots on Colombian workers



Cumulative earnings

Workers adjustments to US robots: across firms, industries, sectors

	(1) All firms	(2)	(3) Same Sector	(4)	(5) Other Sector
Same Industry		Yes	Yes	No	No
Same Firm		Yes	No	No	No
Panel A: Cumulative earnings					
Exposure to US robots	-1.897**	-0.843	2.910	-2.730*	-1.567
	(0.894)	(1.206)	(1.906)	(1.461)	(1.064)
Panel B: Years with earnings					
Exposure to US robots	0.214	0.527	1.395***	-0.110	-0.203
	(0.202)	(0.412)	(0.321)	(0.134)	(0.140)
Panel C: Earnings/year					
Exposure to US robots	-0.308***	-0.168	0.256	-0.402*	-0.217
	(0.104)	(0.123)	(0.247)	(0.205)	(0.143)
Observations	2,947,682	1,111,292	902,506	289,942	643,942

Workers adjustments to US robots: across locations

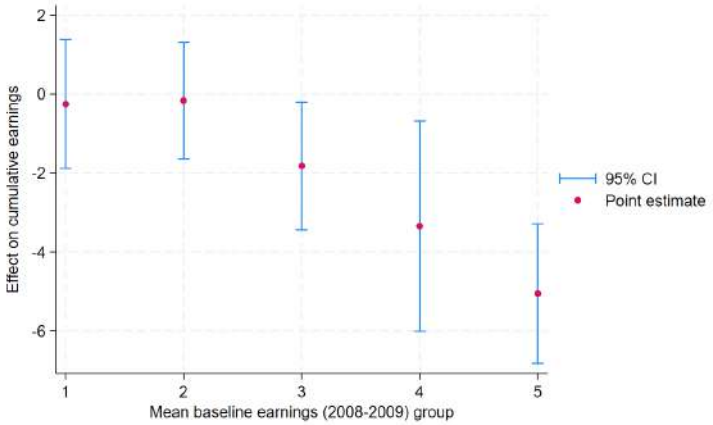
	(1) All CZ	(2) Initial CZ	(3) Changed CZ
Panel A: Cumulative earnings			
Exposure to US robots	-1.897**	-1.748*	-2.663**
	(0.894)	(0.919)	(1.144)
Panel B: Years with earnings			
Exposure to US robots	0.214	0.241	0.136
	(0.202)	(0.237)	(0.078)
Panel C: Earnings/year			
Exposure to US robots	-0.308***	-0.287**	-0.423**
	(0.121)	(0.147)	(0.208)
Observations	2,947,682	2,342,288	605,394

Heterogeneous effects of US robots

- By gender:
  - WAGES: negative effects larger for men –statistically equal to women–
  - EMPL: positive effects larger for women –significant only for women–
- By age group:
  - WAGES: negative effects on wages monotonic increasing with age
  - EMPL: nonsignificant positive effects on employment –negative for older group–
- By firm size:
  - WAGES: negative effects are 2x larger for workers at large companies (250+)
  - EMPL: positive effects larger for workers at a SME company

Heterogeneous effects of US robots

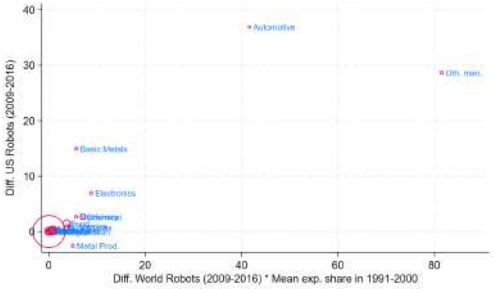
Figure: US robot impacts on Colombian earnings by income group in 2009



IV: WRLD Exposure (Acemoglu & Restrepo (2020), Faber (2020))

$$Exposure\,to\,WLD\,Robots_{j\tau} = \frac{\Delta Robots_{j\tau}^{WLD}}{Labor_{j,t_0}/1000} \times O_{j,t_0} \tag{2}$$

- Exclusion restriction: global robot adoption affects Colombia only via US robots



IV: WRLD Exposure

$$Exposure\,to\,WLD\,Robots_{j\tau} = \frac{\Delta Robots_{j\tau}^{WLD}}{Labor_{j,t_0}/1000} \times O_{j,t_0} \tag{3}$$

	(1) Cumulative wage earnings	(2) Years with earnings > 0	(3) Earnings / Year
Exposure to US robots	-1.646^{*}	0.349^{*}	-0.294^{**}
	(0.950)	(0.168)	(0.119)
		First Stage	
Exposure to World Robots	0.424^{***}	0.424^{***}	0.424^{***}
	(0.090)	(0.090)	(0.090)
Kleibergen-Paap F statistic	22.29	22.29	22.29
Observations	2,947,682	2,947,682	2,947,682

Trade channel empirical evidence

- To estimate if the impact of robots is greater in industries more exposed to US robots, we use trade data by industry j, year t, and CZ c:

$$Trade_{jct} = \alpha_0 + \alpha_1 Exposure\,to\,USRobots_{jt} + \gamma_j + \lambda_t + \xi_c + \epsilon_{ij\tau} \tag{4}$$

- $Trade_{jtc} = Exports_{jtc}, Imports_{jtc}$

Trade channel results

	Exports to the U.S. (logs)[1]		
	(1)	(2)	(3)
Exposure to US robots, t	-0.010***		-0.114***
	(0.002)		(0.013)
Exposure to US robots, t-5		-0.010***	
		(0.002)	
First-stage coefficient			0.886***
			(.0066)
First-stage F-statistic			539.57
	Imports from the U.S. (logs)		
Exposure to US robots, t	0.008***		0.005
	(0.002)		(0.009)
Exposure to US robots, t-5		0.010***	
		(0.002)	
First-stage coefficient			0.886***
			(.0066)
First-stage F-statistic			539.57
Observations	7,687	7,687	7,687

[1]Note: Include industry, CZ, year fixed effects and standard errors clustered at the CZ level.

Trade channel results: Interaction with Primary Sector

	Exports to the U.S. (logs)[2]		
	(1) All Sample	(2) Intermediate	(3) Final
Exposure to US robots	-0.004***	-0.002	-0.025***
	(0.001)	(0.001)	(0.006)
Primary	1.892***	1.983***	1.945***
	(0.187)	(0.273)	(0.379)
Primary × Exposure to US robots, t	-0.190***	-0.182***	-0.201***
	(0.021)	(0.031)	(0.041)
R2	0.257	0.293	0.290
Observations	16,591	7,415	5,608

[2]Note: Include industry, CZ, year fixed effects and standard errors clustered at the CZ level.

Conclusions

- We document that workers in industries highly exposed to U.S. robots experience lower cumulative earnings and longer tenure over 2009 - 2016
  - Workers switching firms within the same industry avoid earnings losses
  - While those moving across industries or locations face the largest losses
- These effects are robust to local technological change and import competition
- These effects are greater for older, high-earning workers and those in larger firms.
- We provide evidence that robots reduce Colombian exports to the US, mainly in the primary sector

Appendix

Impacts on worker earnings and employment, 2009-2016

	(1) Cumulative earnings	(2) Years with earnings > 0	(3) Earnings / Year
Panel A:			
Exposure to US robots $\times$	-2.763	0.894***	-0.543*
Intermediate exports	(1.986)	(0.158)	(0.282)
Panel B:			
Exposure to US robots $\times$	-5.777***	0.173	-0.868***
Final exports	(0.895)	(0.435)	(0.127)
Observations	2,947,682	2,947,682	2,947,682

Back

Impacts on employment, 2009-2016

	(1) Years with earnings > 0	(2) Years employed 2010-2016	(3) Months employed 2010-2016	(4) Cumulative hirings	(5) Cumulative separations
Exposure to US robots	0.214	0.006*	0.072*	-0.214***	-0.347***
	(0.202)	(0.003)	(0.036)	(0.068)	(0.094)
Observations	2,947,682	2,947,682	2,947,682	2,947,682	2,947,682

Back

Impacts on Colombian workers, low and high attachment

	(1) Cumulative wage earnings	(2) Years with earnings > 0	(3) Earnings / Year
Exposure to US robots	-1.769*	0.306	-0.314**
	(0.972)	(0.209)	(0.115)
Observations	4,385,223	4,385,223	4,385,223

Back

What is the effect of U.S. robots in Colombian LLMs?

$$y_{i,j,c,t} = \alpha + \rho Exposure^{US}_{j,c,t} + \beta X_{i,j,c,t} + \theta_j + \pi_c + v_t + \epsilon_{i,j,c,t}$$

- $y_{i,j,c,t}$ is $ln(wage_{i,j,c,t}), P(employed_{i,j,c,t}), P(hired_{i,j,c,t}), P(fired_{i,j,c,t})$
- The exposure to U.S. robots is defined as:

$$ExposuretoRobots_{jct} = l^{COL}_{jc2008} \times \left(\frac{Robots^{US}_{jt}}{Labor^{US}_{j2008}/1000} \right)$$

Summary statistics

Panel A: outcome variables, 2009-2016	Mean	Std. Dev.
100×Cumulative earnings rel. to 2008-2009	953.7	651.8
100×Years with earnings > 0	615.1	159.0
100×Earnings per year rel. to 2008-2009	154.6	88.07
Cumulative change of empl.	1.512	1.438
Cumulative hirings	0.845	0.784
Cumulative separations	0.667	0.766
Years employed	4.922	2.117
Panel B: worker characteristics in 2009		
Age	37.36	9.342
Gender (female=1)	0.418	0.493
Firm size 1-50 employees	0.277	0.447
Firm size 50-250 employees	0.241	0.428
Firm size 250+ employees	0.483	0.500
Earnings (in millions)	10.655	10.037
Observations	2,947,682	

Summary statistics

Panel A: outcome variables, 2009-2016 Panel C: technological shock	Mean	Std. Dev.
Exposure to US robots$_{2009}$	0.897	6.876
Exposure to US robots$_{(2009,2016)}$	0.569	3.477
Exposure to World robots$_{(2009,2016)}$ $\times$ exports share	1.165	7.182
Observations	2,947,682	