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The Impact of Automation in Developed Countries

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The impact of automation in developed countries[1]

Abstract

The digital era is reshaping labor markets. Until now, this has been a developed country type of development. Developing countries, and in particular, Latin American economies are behind in terms of the adoption of labor-replacing technologies. But this delay does not mean these technologies are not having an impact on LAC. New technologies are reshaping trade, and therefore are already affecting developing countries through this channel. We study the impact of automation process in 19 lead countries on Latin American Exports to these nations. We find that imports of lead countries in sectors prone to adopt labor-replacing technologies grew around 40% less than others sectoral imports from LAC in the last 14 years.

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1) Introduction

The digital era is reshaping labor markets.[2] Access to new labor-replacing technologies, access to financial capital and higher labor costs have put developed countries at the frontier of automation. Although countries in the south have less of an incentive to automate their production processes, automation will affect them through the trade channel in the short run. Automation reduces demand for tasks previously performed by humans in certain industries, increasing efficiency and reducing production costs in these sectors. In high-wage countries, automation reduces costs in sectors where more human tasks are susceptible to automation. This is changing or will change comparative advantages between countries and industries, and therefore, trade patterns.

Since technology adoption is faster in developed countries, the empirical literature has focused mainly on the direct effect of automation on labor and product markets in developed economies. Exceptions are Artuc et al. (2018a) and Artuc et al. (2018b). The former paper studies the impact of robot adoption across different regions of Mexico. The

[1] We thank Carmen Pages for her ideas and suggestions, and Francisca Perez for thoughtful comments. Alejandro Micco thank the IADB for financial support.

[2] See OECD (2015), Acemoglu and Restrepo (2017) and Acemoglu and Restrepo (2018).

latter, closer to our study, develops a trade model and tests it using 12 sectors bilateral trade to study the impact of robot adoption on trade.

In this paper, we study the incipient impact of robot adoption in developed countries on the demand for imports from Latin American countries (developing countries). Using Frey and Osborne (2017) classification of occupations at risk of automation, and following Micco and Pages (2018), we construct a sector index that captures the risk of work automation for each industry in the U.S. We estimate sector imports (ln) from LAC as a function of this sector index of automation risk and robots per worker. We select 19 developed economies with the highest level of robot adoption per worker. From Comtrade, we collect their imports from 15 Latin American countries for the period 2002 and 2016. Imports are aggregated into 90 sectors defined at 3-4 digit NAICS version 2007.

There is plenty of anecdotal evidence about how low-wage routine labor-intensive tasks have been replaced by a new generation of robots. A modern food processing and packaging plant, in a developed country, has a variety of different machinery including automated ovens, cutting and forming machines, sortation equipment, mixers, and blending machines, filling equipment, wrapping equipment and as many robots as a highly automated automotive assembly line. Automation allows high-quality control, production speed, and flexibility to adapt products to an increasing customized demand.[3] For example, in the beverage industry, Campari upgraded and automated its processing and bottling facility. With the new system, this company can control blending and filtering to proof cutting and bottling. They were able to increase their Overall Equipment Effectiveness (OEE) and decreased time to reach the market.[4]

In agriculture, a low-wage industry, new technological developments have allowed a company, based in the United Kingdom, to develop a farm-prototype completely automate. Autonomous vehicles and drones can handle the farming process, from planting and monitoring to maintenance and harvesting, without a single person stepping out onto the field.[5]

We use robot adoption as a proxy for labor-replacing technologies. In particular, we use the stock of robots at the country level from International Federation of Robotics (IFR) dataset and the number of workers in each country from the World Bank, to construct our measure of robot adoption. Robot is defined as actuated mechanism programmable in two or

[3] https://www.foodprocessing.com/articles/2018/automation-in-the-food-industry/

[4] https://www.rockwellautomation.com/global/industries/food-beverage/overview.page?pagetitle=Beverage-Manufacturing-Automation-and-Control-Systems&docid=3ea71180f10ff90e1543ebf8d67b2034

[5] http://www.handsfreehectare.com/

more axes with a degree of autonomy, moving within its environment, to perform intended tasks. In particular, industrial robots are defined as "automatically controlled, reprogrammable, multipurpose, manipulator, programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications".[6] For robustness, we use broadband adoption as an alternative proxy for the level of digital technologies adoption at the country level. Several studies define broadband access as an important feature to quantify the rapid digital transformations countries are undergoing.[7]

Robot figures show that automation is an ever-expanding process in developed countries. From 2010 to 2016, nearly 137,000 robots were shipped to US customers, the largest number in any seven-year period in the US robotics industry. Figure 1 presents the evolution of robots per worker in the largest robot adopter countries ('lead countries') (19), Latin American countries (7) and the rest of the world in IFRs dataset (47). For each group, we compute the simple average of robots per worker.

Figure 1: Technology Adoption

Figure 1a: Robots per workers

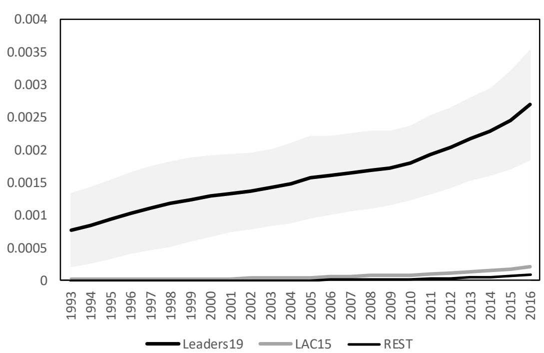
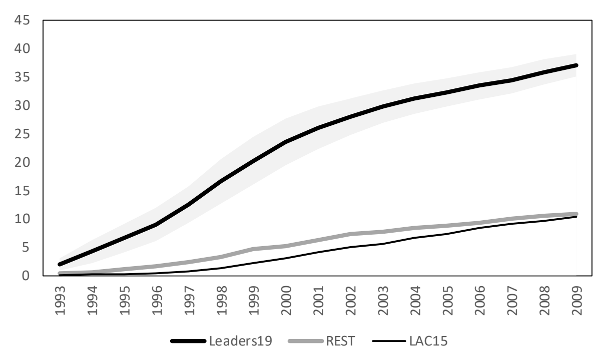


Figure 1b: Broadband per capita



Note: Leaders19 reports the simple average of the stock of robots per worker in the 19 lead countries in terms of automation. LAC reports the simple average of 7 Latin American Countries reporting to the IFR and Rest shows the simple average of the remaining 47 countries in the IFR dataset. If countries are not present in the previous year we assume that the stock of robots is 0. Idem for Figure 1b but using Broad Band per capita from the World Bank instead of robots.
Source: World Bank for population and employment rate, and IFR for the stock of robots.

There is an important difference in terms of robot adoption across countries. Lead countries have 0.003 robots per worker in 2016. This is 29 times more robots per worker than in LAC and 13 times more than in the rest of the sample. However, the data shows that there is convergence; robots per worker increased at an average annual rate of 23% in LAC since the year 2000, while for the group of lead countries, the average annual rate was 5%. In the

[6] ISO definition.
[7] See IMD (2018) and World Bank (2016).

last 6 years, these rates increased, reaching 34 and 7% for LAC and the lead countries, respectively. With these differences in terms of growth rates, LAC will catch up the lead countries in 21 years.[8]

Figure 1b presents the evolution of broadband per capita for the same three groups. We also see a large difference in broadband adoption between lead countries and LAC. Although broadband is a more mature technology and therefore the difference between lead countries and LAC is smaller.

Frey and Osborne (2017) and following studies claim that as a result of recent developments, 47 percent of US jobs and 57 percent of jobs across the OECD are susceptible to automation.[9] Brynjolfsson and McAfee (2014) argue that recent technological innovations will increase productivity in a wide range of industries, but that new technologies also have adverse effects, particularly on low- and middle-skilled workers. Most of these studies stem from an assessment by experts of the risk of automation for a subset of occupational titles, based on the tasks these occupations involved. There are few facts about the actual impact of automation. The exceptions are Acemoglu and Restrepo (2018) and Graetz and Michael (2017). The latter find that robot adoption increases productivity in the economy.

Using Frey and Osborne (2017) classification of occupations by the risk of automation, Figure 2a plots the average annual wage for occupations with different levels of risk in 2010. We divide occupations by risk of automation into ten equal groups. There is a negative correlation between risk of automation and wages (-0.55); low-wages occupations are more susceptible to automation.

Micco and Pages (2018) study the evolution of employment at the occupation and industry level in the US as a function of their employment risk of automation. They use Frey and Osborne (2017) sorting to classify 288 US industries as a function of the share of workers at risk of automation.[10] They find evidence in favor of the idea that new technologies have substituted more jobs in occupations and sectors classified as risky by Frey and Osborne (2017). They find similar results when they use routine cognitive and manual tasks from Autor, Levy, and Murnane (2003) . Figure 2b presents average annual wages for sectors as a function of the share of jobs at risk of automation. As in the case of occupations, there is

[8] We use 23% and 5% rate of growth for LAC and the lead countries, respectively.

[9] The digital era and automation will affect the whole economy not only manufacturing. See the Boston Consulting Group (2015), McKinsey (2017) and The World Development Bank (2015).

[10] Defined at 3-4 digit NAICS version 2007.

a strong negative correlation between risk of automation and the average annual wages at the industry level. The simple pairwise correlation is -0.61.

Figure 2: Wages and risk of automation

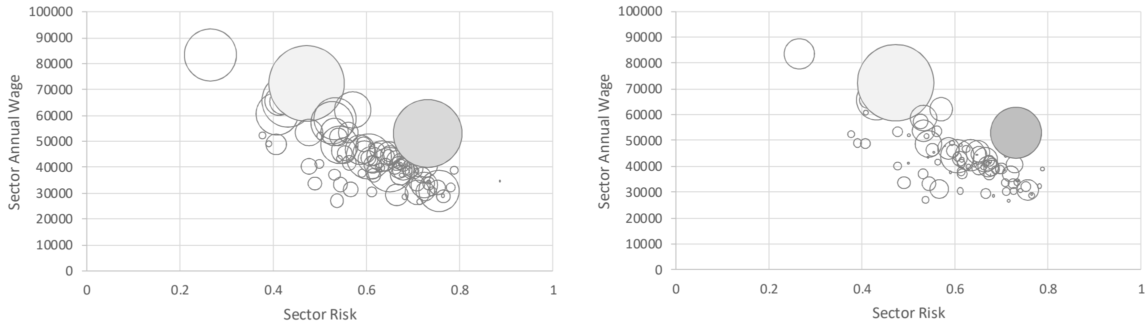
Note: Occupation Risk of Automation from Frey and Osborne (2017), wages from the BLS (different years) and Share of workers at Risk of Automation is sum of job at Risk of Automation (Probability>70%) divided by total employment in the industry. Data are for all sectors in the US economy.
Source: Frey and Osborne (2017) and BLS.

New labor-replacing technologies affect mainly low-wages occupations which are concentrated in specific sectors. This evidence suggests that automation in general, and robot adoption in particular, should benefit sectors that demand low skill/wage occupations. Hence, global automation, which is mainly concentrated in developed countries, should change the comparative advantage between sectors-countries in global trade. Countries that specialize in these sectors more susceptible to automation will lose some of their comparative advantages vis-à-vis lead countries in automation.

Figure 3a and 3b show US imports from the World and Latin America as a function of sector nominal annual wage and risk of automation in the US. The size of the bubble is proportional to the relative importance of this sector in the US import basket. For the World as well as for Latin America, the largest export sectors to the US are Oil and Gas Extraction (NAICS 211), and Motor Vehicle Manufacturing (NAICS 3363). Also, an important share of US imports from Latin American countries that concentrate in sectors with a relatively high risk of automation, suggesting that the effects for these countries might be significant. Using US sectors average wage, we compute the weighted average wage of US imports from the World and from LAC. We find that the average wage of imports from the World is only 4% lower than the weighted average wage of imports from LAC. Weighted sector risk of automation is almost identical for LAC and the for the World. It is important to note that this result is mainly driven by the oil and gas sector.

Figure 3: The US imports by sector average wage and sector risk of automation

3a: US imports from the World　　3b: US imports from Latin America



Note: The light gray bubble is the Oil and Gas Extraction sector. The grey bubble is the car industry.
Source: Authors´ calculations using data from...

To anticipate our results we find that lead countries´ imports from LAC have a lower rate of growth in sectors with a higher risk of automation. Lead countries' imports from LAC in an industry in the 90th percentile of the share of employment at risk of automation relative to an industry in the 10th percentile is 29 percentage points lower when we move from the 10th percentile of robot penetration to the 90th percentile.

The rest of the paper is organized as follow. Section 2 presents the methodology and data we use to estimate the impact of automation on Latin American countries exports to developed countries. Section 3 presents our main results. Section 4 concludes. Appendix A presents a complete description of data used and robustness results.

2) Data and Empirical Strategy

a. Data

To construct the share of workers at risk of automation at the sector level we follow Micco and Pages (2018). Employment and wage data at sector and occupation level come from the Bureau of Labor Statistic (BLS). Occupations are defined using the Standard Occupational Sector (SOC) system at 6 digits of aggregation. The BLS uses the North American Industry Classification Standard (NAICS) to define industries/sectors at 4-digit level of aggregation.

We merge Frey and Osborne (2017) probability of automation at the occupation level with the BLS's employment and wages at the occupation level by sector. Then we compute two measures of risk of automation at the sector level in 2004: i) the share of occupations that have a probability of automation higher to 70% by at the sector level; ii) the employment-weighted average of the occupation probability of automation at the sector level. We end up with 285 sectors.

For imports, we use Comtrade data for the period 2002 and 2016. To focus on the impact of robot adoption on imports from Latin America, we restrict our sample to exports from 15 Latin American nations to 19 lead countries in robot adoption. We aggregate imports data from HS at 6 digits into 106 sectors defined at 2-3 digit NAICS version 2007. We have 106 sectors with positive imports, for 90 of which we can compute the risk of automation.[11]

The 15 Latin American countries considered are: Argentina, Brazil, Bolivia, Chile, Colombia, Costa Rica, Ecuador, Mexico, Nicaragua, Honduras, Peru, Panama, Paraguay, Venezuela, and Uruguay.

To define lead countries in automation we use robot data from IFR and total employment from the World Bank. We compute robots per worker in each country. The IFR reports information for 76 countries, and we assume that the lead countries are those in the top 25% of robots per worker in 2016. Using this definition, we select the following 19 countries: Austria, Belgium, Switzerland, Czech Republic, Germany, Denmark, Spain, Finland, France, Hungary, Italy, Japan, South Korea, Netherlands, Singapore, Slovak Republic, Slovenia, Sweden and USA.

We use the CEPPI gravity[12] dataset and World Bank data for standard gravity variables: Distance, GDP, contiguity, Free Trade Agreement and time zone.

Table 1 presents summary statistics for risk of automation for each Latin American country in the sample using the two mentioned measures. For each country, we compute the risk of automation as the average of the risk of automation at the sector level (computed for the US) weighted by the corresponding share of exports of these sectors for each country. We assume that the risk of automation in the US is similar to that of the other lead countries. Table 1 also shows GDP per worker and per capita (in log), and Robots per worker at the country-year level. Finally, presents imports (in log) by lead countries from LAC for the whole economy and the manufacturing sector.

[11] We do not have risk of automation for NAICS 2007 sectors 111-114, 1119, 1121-1125, 1129, 1132, 1141, 9100, 9200 and 9900.

[12] See http://www.cepii.fr/CEPII/en/bdd_modele/bdd.asp

Table 1: Summary Statistics

	Automation Risk	Automation Probability	GDP/Worker ln	GDP/pc ln	Robots/Work 2016 [1/10^6]
ARG	0.57	0.68	10.18	9.84	116
BOL	0.48	0.60	8.55	8.66	-
BRA	0.52	0.65	10.01	9.58	129
CHL	0.54	0.66	10.31	9.93	18
COL	0.50	0.60	9.52	9.36	5
CRI	0.48	0.55	9.94	9.52	-
ECU	0.49	0.59	9.36	9.20	-
HND	0.68	0.72	8.54	8.32	-
MEX	0.56	0.63	10.03	9.70	377
NIC	0.66	0.72	8.32	8.39	-
PAN	0.55	0.63	10.00	9.77	-
PER	0.52	0.64	9.21	9.26	2
PRY	0.56	0.70	8.96	8.93	-
URY	0.56	0.69	10.20	9.78	-
VEN	0.47	0.55	10.24	9.75	2
Avg.LAC	0.54	0.64	9.56	9.33	43
Std.Dev.	0.06	0.05	0.67	0.51	98
Aut. Leaders	0.57	0.64	11.29	10.57	2,695
Std.Dev	0.03	0.03	0.41	0.27	1,813
World	0.57	0.65	9.43	9.18	876
Std.Dev	0.07	0.05	1.42	1.22	1,473

Note: Automation Risk and Automation Probability are calculated as the average of each measure of risk of automation at the sector level (computed for the US) weighted by the corresponding share of exports of these sectors in each country.
Source: Authors´ calculations.

b. Empirical Strategy

To study the impact of robot adoption in lead countries on LAC exports we use the standard trade gravity model:[13]

$$\begin{aligned} imports_{mxjt} &= \alpha_t + \alpha_{mj} + \alpha_{xj} + \beta_m gdp_{mt} + \beta_x gdp_{xt} + \beta_m pop_{mt} + \beta_x pop_{xt} + dist_{mx} \\ &\quad + \lambda RiskA_j Rob\_pw_{mt} + \gamma Rob\_pw_{mt} + \theta X_{mxjt} + \varepsilon_{mxjt} \end{aligned} \qquad [1]$$

[13] For examples of gravity models see Rose (2000).

Where m is the importer country (one of the 19 lead countries), x the exporter country (one of the 15 LAC), j the sector defined at 2-3 digit NAICS classification, and t the year. Imports stands for ln imports,[14] gdp for countries´ output (ln), pop for population, dist for distance, $RiskA_j$ for sector risk of automation, Rob_pw_{mt} for robots per worker (ln) in the importer country and X_{mxjt} other country-specific characteristics and bilateral controls.

Our main coefficient of interest is λ, which captures the difference in level of (ln) imports across sectors with different levels of risk of automation combined with the degree of adoption of labor-replacing technologies for the importing lead country. Under our null hypothesis imports from sectors with a high risk of automation should present lower import growth from LAC.

For robustness we use broadband per capita instead of robots per worker, we study heterogeneous effects between large and small Latin American countries, and finally we estimate the main model leaving out one country and sector at each time.

3) Results

In this section, we study the evolution of (ln) imports for 90 subsectors as a function of their risk of automation. Our sample covers all exports of the 15 Latin American countries to the 19 lead countries in terms of robot adoption for the period 2002 and 2016. We should expect that *ceteris paribus* imports in sectors of lead countries with a higher risk of automation should present a lower import rate of growth.

We find that lead countries´ imports from LAC have a lower rate of growth in sectors with a higher risk of automation. After controlling for country-year and country-pair-industry fixed effects, we find that industries with a higher share of employees at risk of automation present lower export growth rates. Lead countries' imports from LAC in an industry in the 90th percentile of the share of employment at risk of automation relative to an industry in the 10th percentile is 29 percentage points lower when we move from the 10th percentile of robot penetration to the 90th percentile.[15]

First, we present our main results using country-pair-industry fixed effect regressions. Then we present a set of robustness tests.

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[14] Following the trade gravity literature, to avoid extreme negative values for small imports, we use ln of imports plus 1: ln(imp+1).

[15] For the distribution of robot penetration, we consider every country-year observation.

a. Main results

Table 2 shows the results of estimating empirical specification [1] for (ln) imports in country m, from country x in sector j as a dependent variable. The main result for imports is presented in column (1) of Table 2. After controlling for distance (ln), importer and exporter country GDP (ln), time zone difference, to have a FTA, contiguity, (ln) robots per worker in m, importer and exporter country-sector fixed effect and year fixed effects, we find that sectors with higher share of workers in occupation at risk of automation present a reduction in their imports relative to sectors with a lower share of employees at risk. The sign of the coefficient for the interaction term is negative and statistically significant at 1 percent.

The row labeled Diff-Diff at the bottom of table 2 shows the magnitude of the impact of robots per worker on import differentials across sectors and countries, according to our estimation. For example, in column (1), this differential is -29 percentage points. This number is interpreted as follows: Imports in an industry in the 90th percentile of the share of employment at risk of automation (Risk 0.74) relative to an industry in the 10th percentile (Risk 0.46) is 29 percentage points higher in a country-year with low robot adoption (that is, in the 10th percentile of robot adoption in our sample of lead country-year) than in a country-year with high robot adoption (in the 90th percentile). If we use differences between the 75th and 25th percentile in sectors and robot adoption the difference is 6.5 percentage points.

The other control variables have the expected sign except for exporter GDP (ln). Ten percent increase in distance reduces by five percent trade. Countries in different time zone have lower trade, even after controlling for distance. To have free trade agreement increase trade by 17 percent. Contiguity, in our sample only Mexico and the USA, increases trade. An increase in demand, represented by an increase in the importer country (ln) nominal GDP increases trade. We find an unexpected negative sign for exporter (ln) nominal GDP. This may come from the fact that (ln) nominal GDP that uses to account for size is mainly captured by the exporter-country fixed effect.

Table 2: Empirical estimations results

	Value of Imports (ln)			
	OLS	OLS	OLS	OLS
Distance (ln)	-0.54			
	(8.65)***			
Nominal GDP importer	1.15	1.14		
(ln)	(21.83)***	(24.38)***		
Nominal GDP exporter	-0.63	-0.63		
(ln)	(19.21)***	(23.38)***		
Risk of Automation	-311.91	-320.42	-322.07	
x Rob./Workers Imp.(ln)	(6.30)***	(6.65)***	(7.89)***	
Rob./Workers Imp.(ln)	149.35	175.99		
	(4.82)***	(5.66)***		
Time Difference	-0.15			
	(22.32)***			
Free Trade Agg.	0.17	0.24		
	(6.09)***	(0.038)***		
Contiguity	1.82			
	(25.71)***			
Risk of Automation				0.899
X dummy 2002				(3.62)***
Risk of Automation				1.076
X dummy 2003				(4.44)***
Risk of Automation				0.781
X dummy 2004				(3.41)***
Risk of Automation				0.446
X dummy 2005				(1.98)**
Risk of Automation				0.177
X dummy 2006				(0.80)
Risk of Automation				-0.012
X dummy 2007				(0.05)
Risk of Automation				-0.028
X dummy 2008				(0.13)
Risk of Automation				-0.165
X dummy 2009				(0.75)
Risk of Automation				-0.339
X dummy 2010				(1.56)
Risk of Automation				-0.772
X dummy 2011				(3.60)***
Risk of Automation				-1.105
X dummy 2012				(5.21)***
Risk of Automation				-0.803
X dummy 2013				(3.93)***
Risk of Automation				-1.06
X dummy 2014				(5.18)***
Risk of Automation				-1.14
X dummy 2015				(5.69)***
Risk of Automation				-0.994
X dummy 2016				(5.14)***
R2	0.71	0.82	0.83	0.83
Observations	183,103	181,032	182,406	182,406
Fixed Effect	Year	Year	Imp-Year	Imp-Year
			Exp-Year	Exp-Year
	Imp-Sect	Bilateral-Sect	Bilateral-Sect	Bilateral-Sect
	Exp-Sect			
Diff-Diff 90-10	-0.29	-0.29	-0.30	
Diff-Diff 75-25	-0.065	-0.067	-0.067	

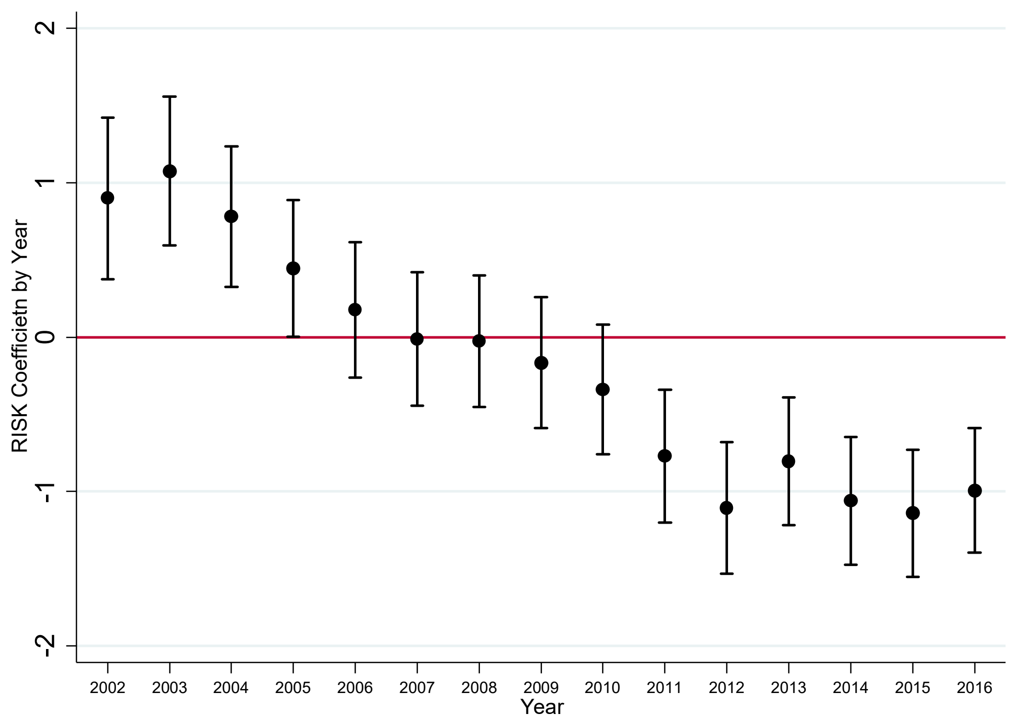
Note: Diff-Diff 90-10: We consider the difference between sectors in percentile 90 and 10 for risk of automation (0.28), and between lead country-year in percentile 90 and 10 for robots per worker (ln) (0.0033). Robust p-statistics in parentheses.

*, **, *** denote statistically significant at 10, 5 and 1 percent levels, respectively.

In Column (2) we include country-pair-sector fixed effects. The model controls for variables that remain constant over time between two countries for a given product. Our results remain almost unchanged. In column (3), beside country-pair-sector fixed effect, we include exporter and importer country year fixed effects. Our main results hold without almost any change.

Figure 3: Estimated Coefficient of Risk of Automation by year

Coefficient from Table [2] column (4)



Note: Coefficient and 95 percent confident interval from column (4) in Table 2.
Source. Authors´ calculations.

The last column in Table 2 studies the evolution of imports year by year for sectors with different levels of risk of automation. We interact our proxy for risk of automation with year dummies. In this exercise, we assume that lead countries' adoption of robots, or process of automation, is the same over time. Figure (3) presents year coefficients and their 95 percent confidence intervals. Lead countries imports from LAC have been falling monotonically in sectors with a high risk of automation.

The coefficient in Figure 3 are interpreted as follows: the difference of the risk of automation between the industry in the 90th and 10^{th} percentile is 0.28 (Risk 0.74 – Risk

0.46), therefore to see the relative evolution between these two sectors over time we have to multiply 0.28 by the Risk-Year coefficient in the figure. The coefficient difference between 2002 and 2016 is around 2, therefore the share of imports of industries in the 90th and 10th percentile fall 50%.

4) Robustness

Table 3 presents robustness tests. Table 3a redoes Column (4) in Table 2 including an interaction term for smallest countries in LAC. These countries are Bolivia, Costa Rica, Ecuador, Nicaragua, Honduras, Panama, and Paraguay. In column (1) we include all sectors, and in column (2) we only include Manufacturing sectors. Columns (3) and (4) use computer and broadband adoptions instead of robots per workers, respectively.

Column (1) shows that the coefficient for risk of automation interacted with importer countries robot adoption is negative and significant. Small countries in Latin America seem to have been more affected by robot adoption in lead countries. The econometrics exercise suggests an effect that is 33% larger for small LAC.

In column (2) we restrict the sample to the manufacturing sector. The effect is still negative and statistically significant at one percent, although the coefficient for the effect is smaller than in column (3) in Table (2). When we use and alternative proxy for new labor-replacing technologies, broadband per capita, results hold.

Figure 3a reports estimates of risk of automation interacted with robots per worker using the specification from Column (3) in Table 2 but dropping one LAC exporter country from our sample at a time. Figure 3b presents the same exercise dropping one lead robot adopter country at a time, Figure 3c presents the same exercise but dropping one sector at a time. In all cases, the estimated coefficient is negative and significant at conventional confidence intervals. However, it is also apparent in this table that excluding either Korea or NAICS 3341 (Computer and Peripheral Equipment Manufacturing) makes a substantial difference in the point estimates increasing the estimated effects.

Table 3: Robustness of main results to alternative specifications and sample.

	Value of Imports (ln)		
	OLS	OLS	OLS
Risk of Automation	-281.45	-280.22	
x Rob./Workers Imp.(ln)	(5.73)***	(5.82)***	
Risk of Automation Small-Cty	-145.57		
x Rob./Workers Imp.(ln)	(4.49)***		
Risk of Automation			-0.34
x Broad Band pc Imp.(ln)			(8.23)***
R2	0.83	0.83	0.83
Observations	182,406	177,251	170,051
Fixed Effect	Imp-Year	Imp-Year	Imp-Year
	Exp-Year	Exp-Year	Exp-Year
	Bilateral-Sect	Bilateral-Sect	Bilateral-Sect
Sectors	All	Manufacturing	All
Diff-Diff 90-10	-0.26	-0.26	-0.13
Diff-Diff 90-10 Small	-0.392		

Note: Diff-Diff 90-10: We consider the difference between sectors in percentile 90 and 10 for (ln) Risk of Automation (0.28), and between countries leaders´ countries in percentile 90 and 10 for robots per workers. Robust P values in parenthesis.

5) Conclusion

The digital era is reshaping labor markets. Until now, this has been the story for developed countries. Developing countries, and in particular, Latin American economies are lagging behind in terms of the adoption of labor-replacing technologies.

This delay in the automation process in LAC does not mean that robots and/or any current labor-replacing technology it is not affecting already LAC. New technologies are reshaping trade and therefore are already affecting developing countries through this channel. We provide evidence that these labor-replacing technologies affect mainly sectors with low average wages in the US, as automation will make these low-wage sectors more competitive, and they may change comparative competitive advantages between sectors-countries.

Figure 3: Robustness of main results excluding one country and sector at a time.

Figure 3a: Excluding one exporter country

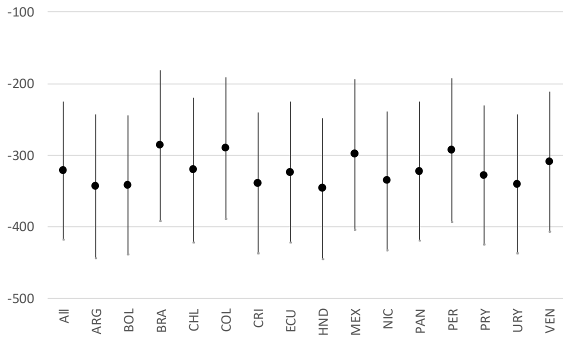


Figure 3b: Excluding one importer country

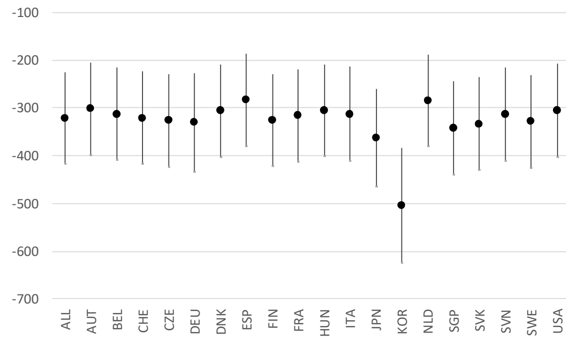
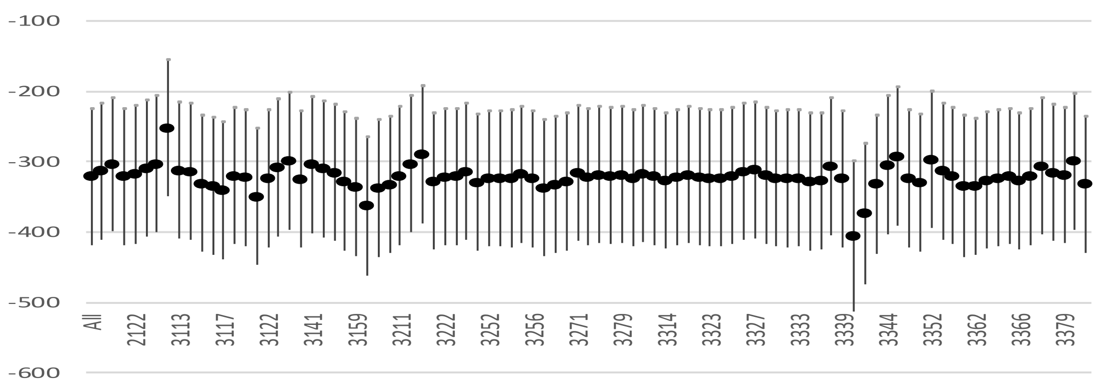


Figure 3c: Excluding one sector at a time



Note: Specification from column (3) in Table 2 dropping either one importer/exporter country or one sector at a time. In each figure, 'All' stands for the results from column (3) in Table 2 using the whole sample of countries and sectors.

Source: Author´s calculations.

In this paper, we study the impact of the automation process in 19 lead countries on Latin American countries' exports to these economies. We find there has been a change in trade patterns in the last years. Latin American countries' exports to lead countries, mainly high developed countries, have been rising at a lower growth rate in sectors with higher risk of automation in the US. This indicates that comparative advantages between sectors-countries are already changing. One standard deviation in terms of robot adoption in lead countries implies that their imports from Latin America in these sectors grew substantially less in the last 10 years.

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