PLATFORM ECONOMY AND AUTOMATION SERIES

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WORKING PAPER
OCTOBER 2021

FUTURE OF WORK
IN THE GLOBAL SOUTH

The impact of robots in Latin America: Evidence from local labor markets[1]

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Abstract

We study the effects of robot penetration on labor markets for the three largest economies in Latin America: Argentina, Brazil, and Mexico, during the period 2004-2016. We exploit the significant variability in robot exposure across districts and across time to estimate its impacts on several relevant outcomes. We find that districts more exposed to robotics adoption had a worse performance relative to less exposed ones in terms of unemployment, informality, earnings, inequality, and poverty. Our results also support the idea that the unemployment costs generated by the new technologies are relatively concentrated in the middle of the skill distribution. Finally, we also show that these costs were more intense for men relative to women.

[1]This paper is part of the project "New technologies and the future of jobs in Latin America" carried out at CEDLAS–UNLP in collaboration with FOWIGS.
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1 Introduction

The debate about the impact of robots on the future of work is often polarized between those who foresee limitless opportunities and those who predict massive job destruction. Although this is not the first time that automation and new technologies have threatened a large number of jobs, the development of fully autonomous, flexible, and versatile robots is part of a remarkable progress only achieved in recent years. Modern robots can now perform activities such as welding, painting, assembling, packaging and labeling with speed and precision, differentiating them from previous advances in information and communication technologies. Even more, thanks to modern Artificial Intelligence machines can now complete cognitive tasks, a very distinctive feature of this new industrial revolution.

The increase in public interest in robotics and automation has led economists to examine the impact of industrial robots and automation on labor market outcomes such as employment and wage inequality. Graetz and Michaels (2018) study the effect of industrial robots across 17 developed countries from 1993 to 2007, and find that robots increased labor productivity, and also reduced the employment share of low-skilled workers. Acemoglu and Restrepo (2020) analyze the effects of the increase in industrial robot adoption between 1990 and 2007 on US labor markets. The exposure to robots is constructed using a combination of information on industry-level advances in acquisition of robots and the employment shares of each industry at the district level. Their results suggest that robots had a robust negative impact on employment and wages across commuting zones. Yet despite the widespread interest and concern of the impact of robots in developed countries, little is known about the impact of automation and new technologies in developing countries. Perhaps the most important reason is that developed countries are ahead of developing countries in the adoption of cutting edge technology. The acquisition of robots in developing countries, however, has sped up during the last decade.

In this paper we study the effects of robot penetration in local labor markets for the three largest economies of Latin America: Argentina, Brazil, and Mexico. Using data from the International Federation of Robotics (IFR), Figure 1 shows that although the stock of robots in these countries is far behind the stock in United States, the dynamics in terms of growth of the stock is larger for Latin American countries.[2]

For identification we exploit the fact that different labor markets experienced heterogeneous exposure to industrial robots according to their initial distribution of employment across industries. Industries like automotive, metal products, rubber and plastic products, and industrial machinery adopted industrial robots at a rate well above the average, making local labor markets specialized in these industries to be highly exposed to automation. On the other hand, local labor markets with a large share of industries like textiles, wood and furniture, or paper products remain much less exposed to the penetration of robots.

We combine two sources of data. First, household surveys from Argentina, Brazil, and Mexico from 2004 to 2016. The household surveys come from SEDLAC and have information on individuals such as age, gender and education, labor and non-labor income, employment characteristics and industry affiliation, which we standardize across countries. These data allow us to study the evolution of relevant outcomes at the local labor market level such as the employment and unemployment rate, average labor income, inequality and poverty, among others. Second, we use data from the International Federation of Robotics (IFR), which are based on yearly information on the number of industrial robots shipped to firms by the producers of robots in a given year.[3] By combining these two data sets we are able to construct a measure of robot penetration that varies at the district-year level. The construction of this variable has two stages. First, we calculate the stock of robots per thousand of workers at the industry-year level, where the number of robots comes from IFR data, and the number of workers in a given industry comes from the household surveys. Then, the exposure of districts to robotics adoption is constructed as the weighted average

[2]For instance, between 2004 and 2016 the stock of robots grew by 399% in Brazil and by 102% in the United States.

[3]An industrial robot is defined by IFR according to the International Standard Organization (ISO 8373:2012) as an 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.

of robots per thousand of workers at the industry level, with the initial share of each industry in district employment as weights. We keep the industry employment shares in each district constant at the initial year value in order to avoid endogenous changes in the exposure variable not coming from exogenous technological change.

Figure 2 shows a scatter plot of the long term change in the robot penetration rate and in the poverty rate, both computed at the district level and for the period 2004–2016 [4] The figure shows that there was a reduction in poverty in all districts in the three countries; a fact that has been widely documented (see for example Alvaredo and Gasparini, 2015). It also shows that poverty was reduced at a slower rate in districts that experienced a faster growth in the adoption of robotics (i.e. districts more exposed to robot penetration). A similar pattern is observed between the change in robot penetration and measures of inequality (not shown). Although this figure is merely descriptive, it provides us a strong motivation to further investigate the existence of a causal effect of robotization in local labor markets.

In our empirical analysis we perform district-level regressions between labor market outcomes and robot penetration. We also search for the presence of heterogeneous effects of robotization according to the gender and skill-level of individuals. Robot penetration is potentially an endogenous variable since labor markets conditions may influence firm decisions on investment in robotics. To account for this possibility, we follow an instrumental variable approach that aims to isolate the part of the growth in robot usage due to exogenous technological change as in Acemoglu and Restrepo, 2020. We instrument exposure to robots using information on industry-level adoption of robots in the United States. The idea is that the U.S. is ahead of Latin America in terms of robot adoption and that robot adoption at the industry level captures supply shifters such as advances in technology, availability and prices. The main identifying assumptions in this empirical approach are: (i) that the evolution of the industry-level stock or robots in the U.S is not correlated with shocks in Latin America; and (ii) that districts with a higher initial share of labor allocated in industries with greater

[4]Throughout the paper we use the 5.5USD PPP international poverty line to define individuals as poor or not poor.

advances in robotics technology are not being differentially affected by other labor market shocks or trends.

Our main results suggest that districts with a higher share of workers allocated in industries more exposed to robotics adoption had a worse performance in relevant economic outcomes such as unemployment, informality, earnings, poverty, and inequality. Specifically, an increase in 0.1 robots per thousand of workers is associated with an increase of 0.29 p.p in the unemployment rate and 1.14 p.p in the informality rate.[5] Also, for this same increase in the penetration of robots, the headcount poverty rate increases by 3.03 p.p, and the gini coefficient increases by 0.56 p.p., while average labor income reduces by 2.3%. Given that during the studied period most districts reduced poverty and inequality, our estimates suggest that districts that experienced a faster growth in the adoption of robotics reduced poverty and inequality at a slower rate than less exposed districts. The increases in poverty and inequality are linked to the increases in unemployment and labor informality. When looking at heterogeneous effects of robot penetration among skill groups or gender, we find that the unemployment costs generated by the new technologies are relatively concentrated in the middle of the skill distribution, and more intense for men relative to women.

The rest of the paper is organized as follows. In section 2 we describe the data and the construction of the robot penetration index. Section 3 describes our empirical strategy, presenting the instrumental variable identification assumptions. Section 4 presents the main results of the paper. Section 5 concludes.

2 Data

We combine two sources of data. The first source are household surveys from Argentina, Brazil, and Mexico from 2004 to 2016. The household surveys are from SEDLAC and have information on individuals such as age, gender and education, labor and non-labor income,

[5]The average change in the robots to workers ratio was 0.12.

employment characteristics and industry affiliation, which we standardize across countries.[6] These data allow us to study the evolution of relevant outcomes at the local labor market level such as the employment and unemployment rate, average labor income, inequality, and poverty. The household surveys we use are: for Argentina the *Encuesta Permanente de Hogares* (EPH) for the years 2004 to 2016; for Brazil the *Pesquisa Nacional por Amostra de Domicílios* (PNAD) for the years 2004 to 2015 (excluding 2010); and for Mexico the *Encuesta Nacional de Ingresos y Gastos de los Hogares* (ENIGH) for the years 2004, 2005, 2006, 2008, 2010, 2012, 2014, and 2016.[7]

Table 1 shows descriptive statistics from the first and final years of each survey. We report averages and the standard deviation in parenthesis. Statistics are calculated at the district level, and then averaged at the country level. We work with 32 districts in Argentina, 27 in Brazil, and 32 in Mexico.[8] The table shows that, as mentioned before, poverty was reduced in all countries during this period. The table further shows that the average income rose and that inequality was reduced. The change in the other variables is, instead, heterogeneous across countries. The employment rate fell in Brazil and increased in Mexico, whereas the informality rate decreased in Argentina and Brazil. Standard deviations show that the evolution of all outcomes is not homogeneous across districts, a fact that is crucial for our identification strategy as it exploits variation across districts with different exposure to robotization.

Our second source of data is the International Federation of Robotics (IFR). IFR conducts yearly surveys of the number of industrial robots shipped to firms by the producers of robots in a given year. An industrial robot is defined by IFR according to the International Standard Organization (ISO 8373:2012) as an 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. The IFR uses its own indus-

[6]More details at http://www.cedlas.econo.unlp.edu.ar/wp/en/estadisticas/sedlac/.

[7]The gap in the Brazilian data occurs because the PNAD was suspended in 2010 due to the national census.

[8]The units of analysis are urban metropolitan areas for Argentina and federal states for Brazil and Mexico.

try classification, which closely follows the International Standard Industrial Classification (ISIC) revision 4. There are six non-manufacturing sectors: agriculture, forestry and fishing; mining; electricity, gas, and water supply; construction; education, research and development; and all other non-manufacturing; and there are thirteen manufacturing sectors: food and beverages; textiles and apparel; wood and furniture; paper and printing; pharmaceutical and cosmetics; chemical products; rubber and plastic; minerals; basic metals; metal products; electronics; industrial machinery; automotive; shipbuilding and aerospace industries; and miscellaneous manufacturing. We refer to this classification as IFR industries.

Figure 3 shows the stock of robots at the industry level for the year 2016 for IFR industries. In Panel A we show the aggregated stock for Argentina, Brazil, and Mexico, and in Panel B we show the stock for the United States. Although the U.S is far ahead in robotic adoption with respect to Latin American countries, the cross-industry pattern is similar across countries. Automotive is the industry with the highest adoption of robots in both the U.S. and Latin America. Other industries such as rubber and plastics, electronics, metal products, and food and beverages also show a large number of robots. On the other hand, industries such as agriculture, textiles, paper and printing, and construction are not intensive in the use of robots.

We match the household surveys and the data from IFR at the industry level. With the combination of both data sources we construct a measure of robot penetration at the industry level, defined as the of stock of robots per thousand workers. We further exploit the fact that industry composition varies across districts to construct a measure of exposure to robots at the district level. We define robot penetration at the district level as the weighted average of robots per thousand of workers across industries, where the shares of each industry in total district employment are used as weights.

Formally robot penetration is defined as

$$RP_{it} = \sum_{j} \frac{L_{ji,t=0}}{L_{i,t=0}} \frac{Robot\ Stock_{jt}}{L_{jt}/1000}, \tag{1}$$

where i indexes districts, j indexes industries, and t indexes time, *Robot Stock* is the stock of robots in the industry, L_j is the number of workers in the industry, and L_{ji} is the number of workers in the industry–district. The weights are computed as the *initial* share of industry in total employment, so that the measure of robot penetration does not reflect changes in employment composition across time. These weights are kept constant for all time periods.

Figures 4 and 5 show the variability of the robot penetration measure. Figure 4 shows the average robot penetration at the district level. Robot penetration grew significantly between 2004 and 2016, from values close to zero to 0.16, 0.8, and 1.2 robots per thousand workers in Argentina, Brazil and Mexico. Figure 5 computes the average robot penetration by quartiles across districts. The decomposition in quartiles shows that while some districts experienced sharp increases in exposure to robots, other districts remained barely exposed. Differences in averages range from 0.03 to 0.4 in Argentina, 0.15 to 0.195 in Brazil, and 0.02 to 0.3 in Mexico.

3 Empirical strategy

We perform district-level regressions in which we exploit variability to robot exposure across time and across districts. The baseline estimation equation is

$$Y_{it} = \beta_0 + \beta_1 RP_{it} + \alpha_i + \delta_t + \varepsilon_{it}, \tag{2}$$

where i and t index districts and time. The outcome variables, represented by Y, are unemployment, employment, poverty, informality of employment, average labor income, inequality, and poverty. The dependent variable is robot penetration by thousands of workers defined at the district level, α_i are district-level fixed effects; δ_t are time effects, and ε_{it} is a mean-zero disturbance. District-level fixed effects capture time-invariant unobserved heterogeneity across districts, so that results are identified from within-district changes in robot exposure and outcome variables across time.

Robot penetration is potentially an endogeneous variable as labor market conditions may have an impact on firms' decisions to invest in robotics. To account for this issue we follow an instrumental variable approach similar to Acemoglu and Restrepo (2020). To identify the component of robot penetration driven by changes in technology, we instrument exposure to robots using an analogous measure constructed from the penetration of robots in U.S industries. The measure is constructed as

$$IVRP_{it} = \sum_{j} \frac{L_{ji,t=0}}{L_{i,t=0}} \frac{Robot\ Stock_{jt}^{U.S}}{L_{jt}^{U.S}/1000}, \tag{3}$$

where $Robot\ Stock^{U.S}/L^{U.S.}$ is the stock of robots per thousand workers in each US industry. We construct the district-level instrument as the average robot penetration in the US weighted by the industry share in total district employment.

The idea of the identification strategy is that United States is a country that is ahead of Latin America in terms of robot adoption. The idea is that the U.S. is ahead of Latin America in terms of robot adoption and that robot adoption at the industry level captures supply shifters such as advances in technology, availability and prices. The main identifying assumptions in this empirical approach are: (i) that the evolution of the industry-level stock or robots in the U.S is not correlated with shocks in Latin America; and (ii) that districts with a higher initial share of labor allocated in industries with greater advances in robotics technology are not being differentially affected by other labor market shocks or trends.

Figure 6 shows the correlation between the regressioin variable RP and the instrument $IVRP$. There is a strong positive correlation. Table 2 shows the first stage results. The four columns correspond to different specifications. All specifications include year and district fixed effects. The four specifications sequentially include initial district characteristics (unemployment rate, employment rate, and an index of average routinization of occupations) interacted with year effects in order to capture differential trends. In all specifications the instrument is statistically significant at the 1 percent level, showing strong predictive power, and the hypothesis of weak instrument is rejected.

4 Results

This section describes the main findings of our paper. We are interested in several outcomes at the district level such as employment, unemployment, informality, wages, poverty, and inequality. We are also interested in looking at possible heterogeneous effects of robotization on different groups of individuals, in particular according to their skill level and gender.

We present the baseline district-level estimates of equation (1) in Tables 3 to 6. All tables are structured in a similar manner and all specifications include year and district fixed effects. We start with the employment rate, in Table 3 Panel A. The employment rate is the share of employed individuals in the total working age population. It is defined between 0 and 1. Columns (1) and (2) show FE-OLS and FE-2SLS estimators including district and year fixed effects. Column (3) adds an unemployment pre-existing trend, that is constructed as the interaction between the district unemployment rate in the initial period and year dummies. Column (4) includes a pre-existing trend to account for the initial level of employment in the district. Given that robotization is not the only technological change that took place during the last years, in column (5) we include a control for the initial exposure of the district to task routinization, interacted with year dummies. This variable aims to take into account the fact that different districts are more or less exposed to the adoption of new technologies according to the share of occupations that are susceptible to being automated within each district.[9] In all columns coefficients are positive but not statistically significant, indicating that exposure to robots has not had an effect on district level employment.

In Panel B we report results on the unemployment rate. The unemployment rate is

[9]See Autor, Levy and Murnane (2003) and Acemoglu and Autor (2011). We construct the index of task routinization exposure at the district level combining the SEDLAC household surveys with data from the Programme for the International Assessment of Adult Competencies (PIAAC) conducted by the OECD. We first construct indexes of routinization at the occupation level from the PIACC surveys. We then calculate district level indexes as the weighted average of the occupational level indexes, using the share of each occupation in total district employment as weights.

the share of individuals in the labor force that have been actively looking for a job in the last month and have not found one. It is important to mention that employment and unemployment are rates defined over different baseline populations (working age population in the case of employment, and labor force in the case of unemployment) are therefore they are not complements. Thus, it is worth looking at unemployment separately from employment. Results show that indeed there is a positive an significant effect on unemployment (columns 3 to 5, which control for differential trends). An increase in the ratio of robots to workers of 0.10 results in an increase in district-level unemployment that ranges from 0.29 to 0.31 percentage points.[10]

In Panel C we report results for labor informality. The informality rate is the share of employed individuals that are not contributing to a pension fund. The informality rate goes up as a result of exposure to robots, which implies that among individuals that do not lose their jobs due to robots, there is a loss in job quality. The estimated coefficient for informality is approximately two times larger in magnitude than the coefficient for unemployment, which is in line with recent evidence for developing countries pointing out that the informal sector can work as a buffer for displaced workers. In the absence of a large informal sector that is able to absorb part of the displaced labor force, the effect of robots and technological change on unemployment would be much larger. Similar arguments have been made for the effects of trade and globalization (Dix-Carneiro, Goldberg, Meghir, and Ulyssea (2021); Cesar, Falcone, and Gasparini (2020)).

Table 4 reports the effect on income, wage and working hours. Panel A studies the average labor income. It is important to mention that the expected direction of this effect is not straightforward. On the one hand, robots can displace workers from their original jobs to lower-productivity lower-paying jobs. This idea is in line with our previous results for informality, where robot-displaced workers reallocate to informal jobs. On the other hand, as possibly robots tend to displace unskilled workers, which on average have lower earnings,

[10]The average change in the robots to workers ratio was 0.12.

the average labor income of the district could go up. Our results show that estimated coefficients are negative and statistically significant in all 2SLS specifications, implying that robot-displaced workers reallocate to lower paying jobs. Similar results are shown in Panel B for the average wage, although coefficients are lower in magnitude and imprecisely estimated. Given that our identification strategy works with average outcome variables at the district level, we cannot follow the career path of individuals to actually confirm this hypothesis. However, we can follow outcome variables for specific groups of individuals and test this idea. We come back to this in the next subsection.

In Panel C we report results for average working hours. In line with our results for employment, coefficients are positive and not statistically significant, confirming that there are no clear effects on employment either as a dichotomous variable (Table 3) or as hours of work.

Tables 5 and 6 report results for poverty and inequality. In Table 5 we report the effects on three Foster-Greer-Thorbecke indexes: The headcount ratio ($FGT0$, in Panel A), defined as the share of individuals with income below the poverty line of 5.5USD per day; the poverty gap index ($FGT1$, in Panel B), defined as the average deviation with respect to the poverty line; and the poverty severity index ($FGT2$, in Panel C), defined as the average squared deviation from the poverty line. For the three indexes coefficients are positive and statistically significant in all specifications, implying that the adoption of robots has had a pervasive effect on poverty at the local level. The impact on the headcount ratio ranges from 3 to 3.5 percentage points for an increase of 0.10 in the robot to workers ratio in the 2SLS specifications (columns 2 to 5).

We find similar results for income inequality. They are displayed in Table 6. We compute three measures of inequality: the gini coefficient, the ratio of percentiles 75th to 25th, and the ratio of percentiles 90th to 10th. Inequality increases as a result of exposure to robots. Given that during the studied period most districts reduced poverty and inequality, our estimates suggest that districts that experienced a faster growth in the adoption of robotics reduced poverty and inequality at a slower rate than less exposed districts. The increases in poverty and inequality are linked to the increases in unemployment and labor informality.

4.1 Heterogeneous effects

In this section we study whether the impact of robot exposure is different across groups of worker characteristics. We split the working age population by skill level and by gender and run regression (1) separately for each group. Results are in Tables 7 and 8. For the sake of brevity we report results based on the last specification (column 5), estimated with 2SLS and including trends according to initial district characteristics.

Table 7 splits workers in three skill groups: low skilled (no high school degree), medium skill level (high school degree), and highly skilled (additional education after high school). Employment rates increase for low and highly skilled workers, whereas unemployment rates increase only for medium skilled workers. These results are in line with the task-based approach literature, which finds that new technologies have a larger impact on employment in the middle of the skill distribution (Autor, Levy and Murnane, 2003; Spitz-Oener, 2006; Goos and Manning, 2007; Goos, Manning, and Salomons, 2014; and Michaels, Natraj, and Van Reenen, 2014).

The informality rate increases for all groups but it is imprecisely estimated. The point estimate is largest for the low-skilled group. Labor income also decreases for the low skilled group. Both results suggest a decrease in job quality at the lower end of the skill distribution.

Table 8 splits workers by gender. Estimated coefficients show that male workers are negatively affected by district exposure to robots relative to women. The unemployment and informality rates increase for male workers, and their average labor income decreases. On the other hand, point estimates are positive for women for employment rates. These results are in line with the "the added worker effect", where new family members (potentially women) start looking for a job when the main family worker faces a job loss or labor income reduction.

5 Concluding Remarks

In this paper we presented evidence on the effects of robot penetration in local labor markets for the three largest economies of Latin America: Argentina, Brazil, and Mexico.

Using data from the International Federation of Robotics (IFR) and from household surveys, we found that districts with a higher share of workers allocated in industries more exposed to robotics adoption had a worse performance in relevant economic outcomes such as unemployment, informality, earnings, poverty, and inequality. In particular, given that during the studied period most districts reduced poverty and inequality, our estimates suggest that districts that experienced a faster growth in the adoption of robotics reduced poverty and inequality at a slower rate than less exposed districts. The increases in poverty and inequality are linked to the increases in unemployment and labor informality.

Our results are consistent with related literature finding higher adjustment costs to the incorporation of new technologies for individuals in the middle of the skill distribution.

Overall, we believe that our findings are of key relevance for developing countries, where automation and robotization are still phenomena with a long way to go, and where a significant share of workers may see their jobs threatened in the near future.

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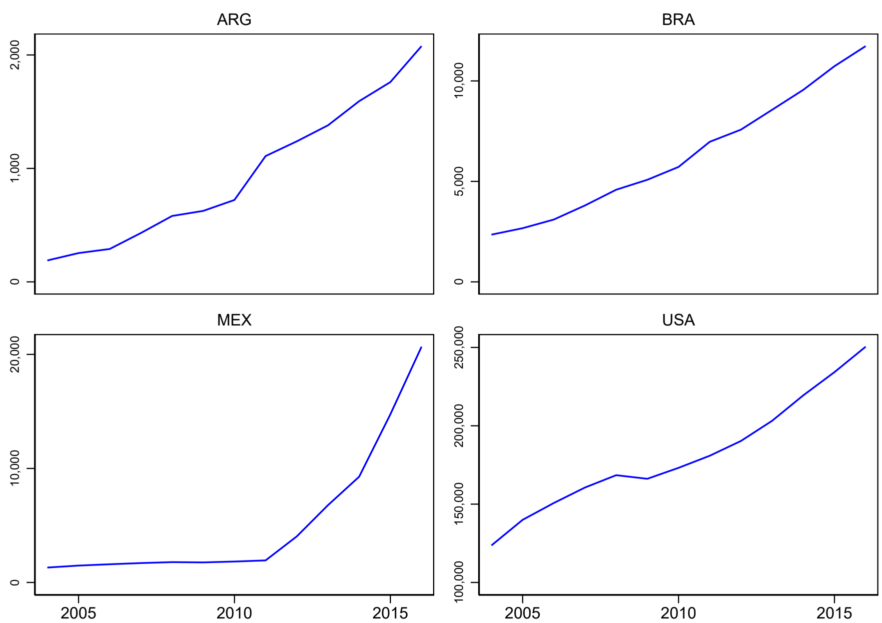
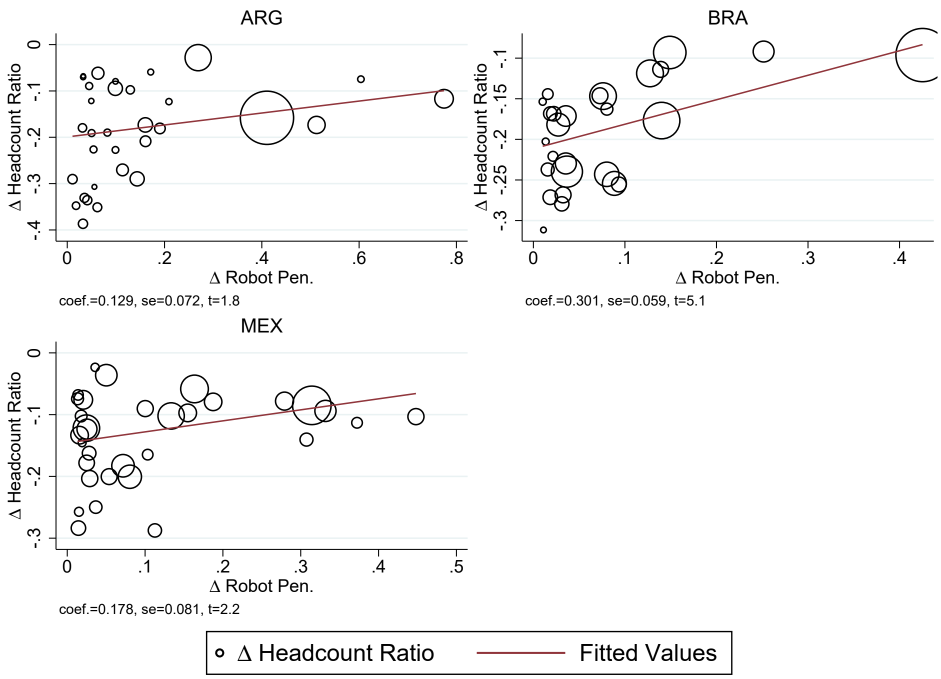
Figure 1: Evolution of the stock of robots



Source. Own calculations based on data from the International Federation of Robotics (IFR).

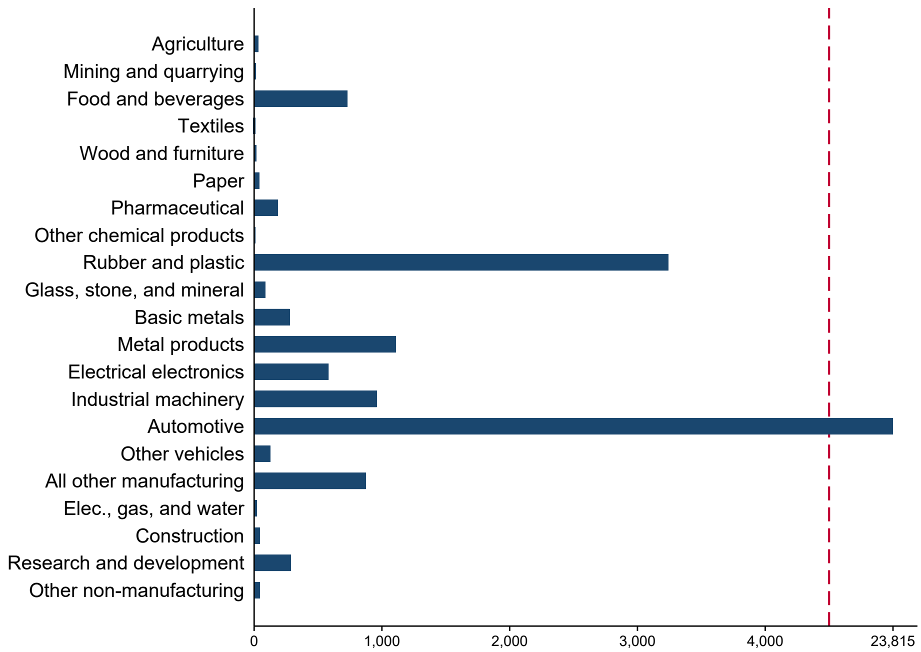
Figure 2: Long term changes in robotization and poverty



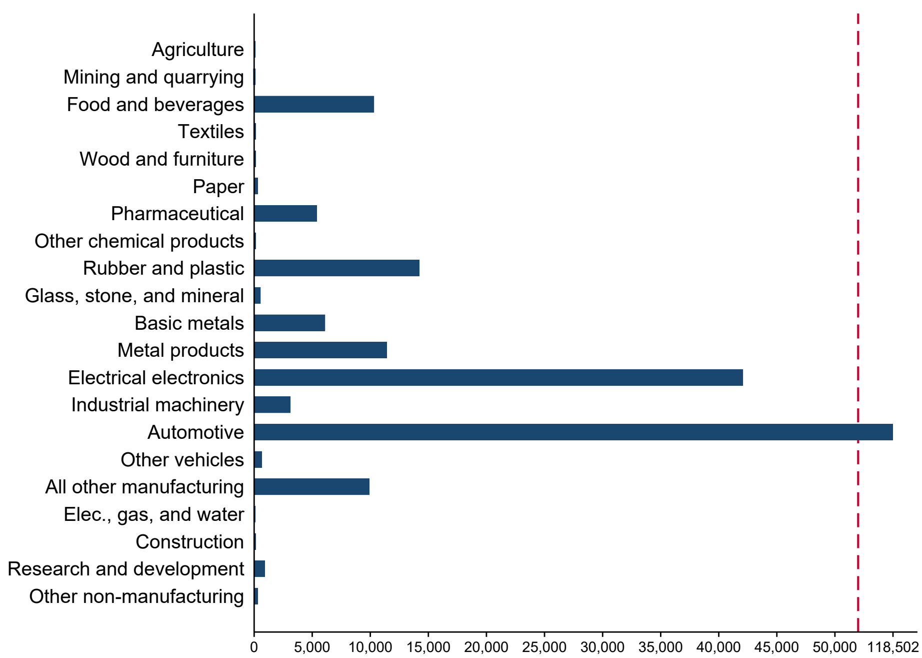
Notes. Horizontal axis: change in the robot penetration ratio at the district level between 2004 and 2016. Vertical axis: change in the head count ratio at the district level between 2004 and 2016. District level observations are plotted with circles with size proportional to the district share in total country population. Sources: own calculations from Encuesta Permanente de Hogares (EPH) for Argentina, Pesquisa Nacional por Amostra de Domicílios (PNAD) for Brazil, Encuesta Nacional de Ingresos y Gastos de los Hogares (ENIGH) for Mexico, and International Federation of Robotics (IFR).

Figure 3: Robots Stock by Industry

(a) Argentina, Brazil, and Mexico

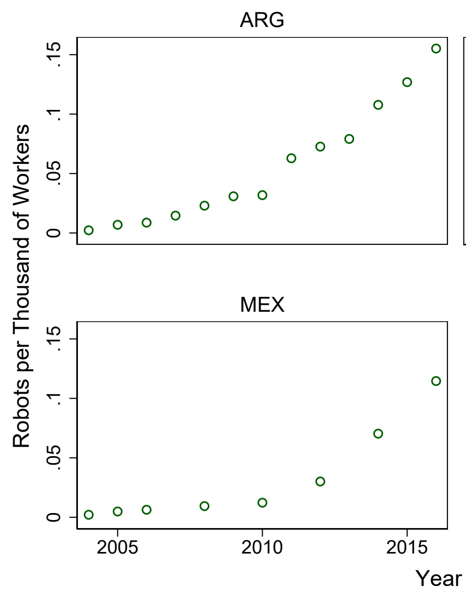


(b) United States



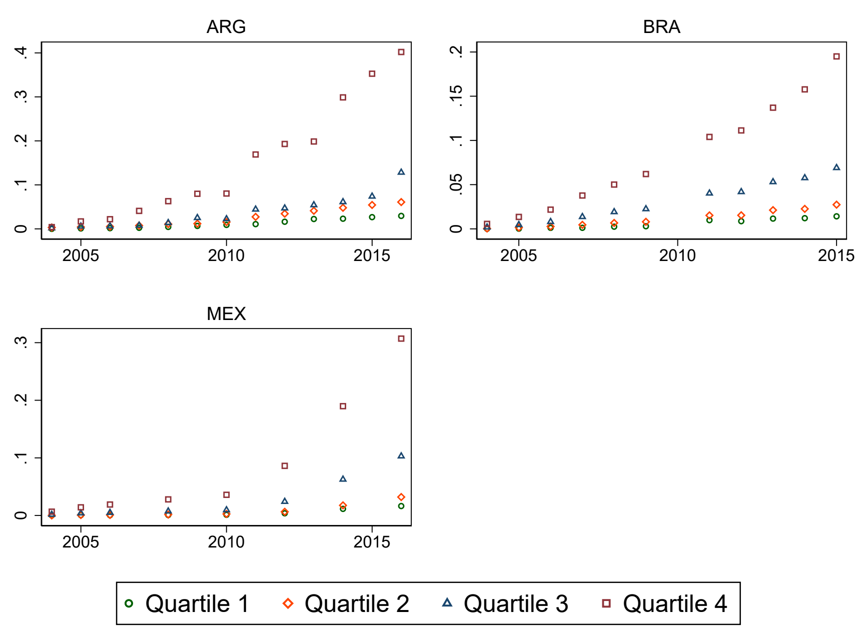
Source. Own calculations based on International Federation of Robotics (IFR).

Figure 4
Average robot penetration at the district-level



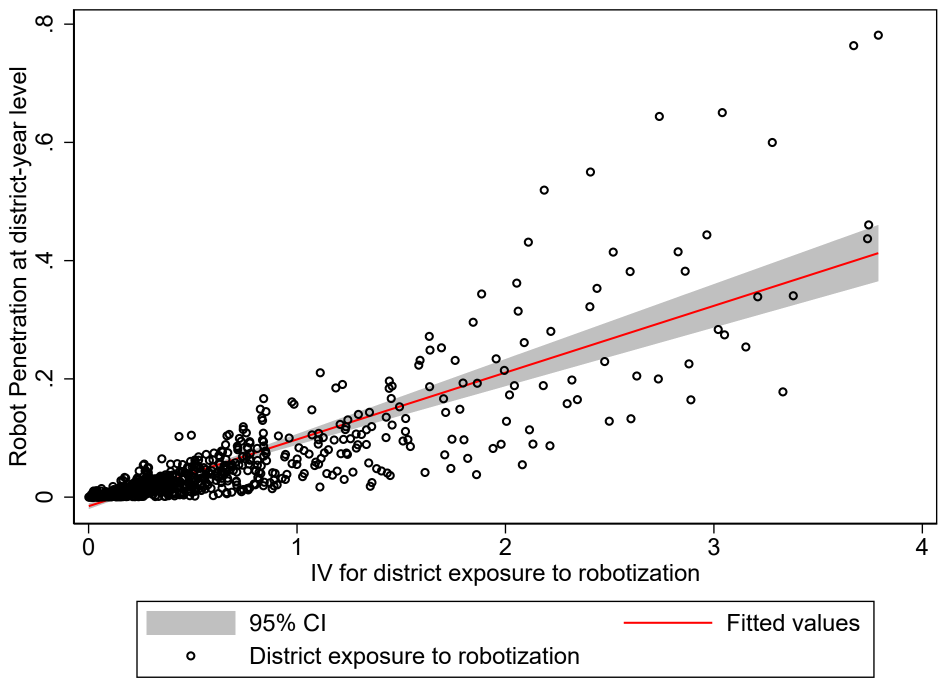
Notes: Robot penetration computed from equation (1) and averaged across districts.

Figure 5
Average robot penetration by quartiles of exposure



Notes: Robot penetration computed from equation (1) and quartiles computed across districts.

Figure 6
First-stage correlation



Notes. Scatterplot of robot penetration RP on $IVRP$.

Table 1: Local Labor Markets Statistics

	Argentina		Brazil		Mexico	
	2004	2016	2004	2015	2004	2016
Poverty rate	0.28 (0.13)	0.09 (0.04)	0.48 (0.17)	0.29 (0.13)	0.39 (0.15)	0.25 (0.13)
Gini	0.45 (0.03)	0.39 (0.02)	0.55 (0.03)	0.49 (0.03)	0.48 (0.05)	0.45 (0.04)
Employment Rate	0.59 (0.04)	0.59 (0.05)	0.67 (0.05)	0.63 (0.05)	0.63 (0.04)	0.68 (0.03)
Ununemployment Rate	0.10 (0.04)	0.06 (0.02)	0.08 (0.03)	0.09 (0.02)	0.03 (0.01)	0.03 (0.01)
Informality Rate (legal)	0.46 (0.10)	0.30 (0.09)	0.40 (0.09)	0.26 (0.08)	0.60 (0.11)	0.65 (0.11)
Informality Rate (prod.)	0.41 (0.08)	0.38 (0.07)	0.57 (0.10)	0.50 (0.10)	0.50 (0.10)	0.44 (0.09)
Log (labor income)	739.29 (228.66)	986.88 (286.09)	542.68 (183.12)	759.89 (235.46)	645.42 (160.45)	681.01 (171.71)
Log (wages)	4.69 (1.33)	6.56 (1.73)	3.41 (1.07)	6.47 (5.02)	3.46 (0.82)	3.92 (0.86)

Notes: Own calculations from SEDLAC database. Poverty rate is the percentage of population with income below the $5.5USD 2011 PPP poverty line. Labor market statistics are restricted to adults aged 18-65. Employment is the share of employed adults in the total adult population. Unemployment is the share of adults in the labor force that have been actively looking for job in the last month. Labor informality (labor definition) is the share of salaried workers that have no right to receive a pension when retired. Labor informality (productive definition) is the share of salaried workers belonging to firms with five or less employees and non-professional self-employed individuals. Labor income is the monthly value in constant USD PPP 2011. Wage is the hourly value in constant USD PPP 2011.

Table 2: First Stage

	(1)	(2)	(3)	(4)
Dep var: Robot Penetration				
Robot Penetration IV	0.136***	0.136***	0.136***	0.138***
	(0.020)	(0.019)	(0.019)	(0.019)
Weak IV F-stat	46.6	50.6	50.5	49.6
N	963	963	963	963
PT Unemployment x Year FE	No	Yes	Yes	Yes
PT Employment x Year FE	No	No	Yes	Yes
PT Task Routinization Exposure x Year FE	No	No	No	Yes

Notes: All regressions include year and district fixed effects. Robust standard errors in parenthesis. Significance at the 1, 5 and 10 percent levels denoted with *, ** and *.

Table 3: Employment, unemployment, and informality

	OLS	2SLS			
	(1)	(2)	(3)	(4)	(5)
Panel A: Employment Rate					
Robot Penetration	0.024	0.034	0.027	0.035	0.033
	(0.022)	(0.027)	(0.026)	(0.026)	(0.026)
Panel B: Unemployment Rate					
Robot Penetration	-0.004	0.026	0.031^{**}	0.029^{**}	0.029^{**}
	(0.013)	(0.021)	(0.013)	(0.013)	(0.013)
Panel C: Informality Rate					
Robot Penetration	0.007	0.104	0.101^{**}	0.103^{**}	0.114^{**}
	(0.034)	(0.075)	(0.049)	(0.026)	(0.049)
N	963	963	963	963	963
PT Unemployment x Year FE	No	No	Yes	Yes	Yes
PT Employment x Year FE	No	No	No	Yes	Yes
PT Task Routinization Exposure x Year FE	No	No	No	No	Yes

Notes: All regressions include year and district fixed effects. Robust standard errors in parenthesis. Significance at the 1, 5 and 10 percent levels denoted with *, ** and *.

Notes: All regressions include year and district fixed effects. Robust standard errors in parenthesis. Significance at the 1, 5 and 10 percent levels denoted with ***, ** and *. Unemployment rate is the share of adults in the labor force that have been actively looking for job in the last month.

Table 4: Labor income, wages, and hours

	OLS	2SLS			
	(1)	(2)	(3)	(4)	(5)
Panel A: Log Avg Labor Income					
Robot Penetration	-0.069	-0.268^{*}	-0.267^{***}	-0.280^{***}	-0.261^{***}
	(0.062)	(0.139)	(0.100)	(0.100)	(0.096)
Panel B: Log Avg Wage					
Robot Penetration	-0.056	-0.169	-0.168	-0.199	-0.151
	(0.096)	(0.188)	(0.155)	(0.139)	(0.136)
Panel C: Log Weekly Hours					
Robot Penetration	-0.005	0.019	0.016	0.019	0.017
	(0.026)	(0.033)	(0.029)	(0.100)	(0.027)
N	963	963	963	963	963
PT Unemployment x Year FE	No	No	Yes	Yes	Yes
PT Employment x Year FE	No	No	No	Yes	Yes
PT Task Routinization Exposure x Year FE	No	No	No	No	Yes

Notes: All regressions include year and district fixed effects. Robust standard errors in parenthesis. Significance at the 1, 5 and 10 percent levels denoted with *, ** and *.

Table 5: Poverty

	OLS	2SLS			
	(1)	(2)	(3)	(4)	(5)
Panel A: FGT 0					
Robot Penetration	0.161***	0.356***	0.360***	0.349***	0.303***
	(0.040)	(0.097)	(0.081)	(0.077)	(0.070)
Panel B: FGT 1					
Robot Penetration	0.104***	0.219***	0.222***	0.217***	0.175***
	(0.025)	(0.056)	(0.049)	(0.047)	(0.042)
Panel C: FGT 2					
Robot Penetration	0.070***	0.146***	0.147***	0.144***	0.114***
	(0.018)	(0.038)	(0.034)	(0.077)	(0.029)
N	963	963	963	963	963
PT Unemployment x Year FE	No	No	Yes	Yes	Yes
PT Employment x Year FE	No	No	No	Yes	Yes
PT Task Routinization Exposure x Year FE	No	No	No	No	Yes

Notes: All regressions include year and district fixed effects. Robust standard errors in parenthesis. Significance at the 1, 5 and 10 percent levels denoted with *, ** and *.

Table 6: Inequality

	OLS	2SLS			
	(1)	(2)	(3)	(4)	(5)
Panel A: Gini Coefficient					
Robot Penetration	0.009	0.056	0.056*	0.052*	0.056*
	(0.018)	(0.037)	(0.031)	(0.031)	(0.029)
Panel B: Ratio p75-p25					
Robot Penetration	0.217	0.465	0.505*	0.504*	0.495*
	(0.180)	(0.325)	(0.297)	(0.296)	(0.267)
Panel C: Ratio p90-p10					
Robot Penetration	0.028	3.166*	3.164**	3.451**	3.757***
	(1.118)	(1.867)	(1.585)	(0.031)	(1.438)
N	963	963	963	963	963
PT Unemployment x Year FE	No	No	Yes	Yes	Yes
PT Employment x Year FE	No	No	No	Yes	Yes
PT Task Routinization Exposure x Year FE	No	No	No	No	Yes

Notes: All regressions include year and district fixed effects. Robust standard errors in parenthesis. Significance at the 1, 5 and 10 percent levels denoted with *, ** and *.

Table 7: Results by skill level

	All	Low Skilled	Mid Skilled	High Skilled
	(1)	(2)	(3)	(4)
Panel A: Employment Rate				
Robot Penetration	0.033	0.061*	0.011	0.050*
	(0.026)	(0.032)	(0.039)	(0.029)
Panel B: Unemployment Rate				
Robot Penetration	0.029**	0.020	0.062***	−0.005
	(0.013)	(0.015)	(0.019)	(0.011)
Panel C: Informality Rate				
Robot Penetration	0.114**	0.057	0.034	0.018
	(0.049)	(0.060)	(0.052)	(0.039)
Panel D: Gini Log. Labor Income				
Robot Penetration	0.056*	0.014	0.006	0.107**
	(0.029)	(0.027)	(0.039)	(0.042)
Panel E: Log Avg Lab. Income				
Robot Penetration	−0.261***	−0.351***	−0.160	0.045
	(0.096)	(0.110)	(0.116)	(0.116)
N	963	963	963	963
PT Unemployment x Year FE	Yes	Yes	Yes	Yes
PT Employment x Year FE	Yes	Yes	Yes	Yes
PT Task Routinization Exposure x Year FE	Yes	Yes	Yes	Yes

Notes: All regressions include year and district fixed effects. Robust standard errors in parenthesis. Significance at the 1, 5 and 10 percent levels denoted with *, ** and *.

Table 8: Results by gender

	All	Female	Male
	(1)	(2)	(3)
Panel A: Employment Rate			
Robot Penetration	0.033	0.052	0.004
	(0.026)	(0.036)	(0.023)
Panel B: Unemployment Rate			
Robot Penetration	0.029**	0.017	0.037***
	(0.013)	(0.020)	(0.013)
Panel C: Informality Rate			
Robot Penetration	0.114**	0.132**	0.097**
	(0.049)	(0.062)	(0.044)
Panel D: Gini Log. Labor Income			
Robot Penetration	0.056*	0.097**	0.039
	(0.029)	(0.040)	(0.033)
Panel E: Log Avg Lab. Income			
Robot Penetration	−0.261***	−0.141	−0.327***
	(0.096)	(0.112)	(0.105)
N	963	963	963
PT Unemployment x Year FE	Yes	Yes	Yes
PT Employment x Year FE	Yes	Yes	Yes
PT Task Routinization Exposure x Year FE	Yes	Yes	Yes

Notes: All regressions include year and district fixed effects. Robust standard errors in parenthesis. Significance at the 1, 5 and 10 percent levels denoted with *, ** and *.

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The Future of Work in the Global South (FoWiGS) is an initiative supported by the International Development Research Centre (IDRC) and coordinated by the Center for the Implementation of Public Policies Promoting Equity and Growth (CIPPEC).

It aims at understanding the implications of technological change on jobs from a Global South perspective bringing data, knowledge, and policy frameworks to build evidence-based narratives on the future of work in developing countries.

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