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The impact of robots in Latin America: Evidence from local labor markets*

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Abstract

We study the effect of robots on labor markets in Argentina, Brazil, and Mexico, the major robot users in Latin America, during the period 2004–2016. We exploit spatial and time variations in exposure to robots arising from initial differences in industry specialization across geographic locations and the evolution of robot adoption across industries, to estimate a causal effect of robots on local labor market outcomes. We find that district's exposure to robots causes a relative deterioration in labor market indicators such us unemployment and labor informality. We document that robots mainly replace formal salaried jobs, affecting young and semi-skilled workers to a greater extent, and that informal employment acts as a buffer that prevents a larger increase in unemployment.

JEL Classification: J23, J24, J31, J46, O14, O17, R10.
Keywords: Robot Adoption, Local Labor Markets, Latin America, Unemployment, Informality.

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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 a wide range of activities such as welding, painting, assembling, packaging, labeling and transporting with high speed and precision, differing from previous advances in technology.

The theoretical impact of robots on the demand for labor, wages and employment is ambiguous. The task framework of Acemoglu and Restrepo (2019) describes two main countervailing mechanisms: (i) a displacement effect tends to reduce demand for labor and wages because robots perform tasks previously done by workers; while (ii) a reinstatement effect arising from productivity gains increases demand for labor both in automating and non-automating sectors.[1] These effects crucially depend on the degree of labor mobility and, also, on the distribution of gains from automation technologies (Gregory, Salomons, and Zierahn, 2021). There are indirect effects as well because firms adopting robots may expand at the expense of their competitors, altering market structure. Also, if automation changes relative prices, there might be shifts in consumption patterns.

In this paper we study the effect of robots on local labor market outcomes in the three largest economies of Latin America: Argentina, Brazil, and Mexico. During the last fifteen years, robot adoption has made a big jump in these countries. The stock of robots rose from virtually zero in 2004 to 2,000 in 2016 in Argentina, from 200 to more than 10,000 in Brazil, and from 2,500 to a whopping 20,000 in Mexico (International Federation of Robotics, IFR). We focus on the impact of robotization on local unemployment, employment levels, wages, and labor informality, the latter being a relevant margin of adjustment for labor markets in Latin America.

Labor informality is a distinctive feature of labor markets in developing countries. Relevant for our study, Gasparini and Tornarolli (2009) report labor informality rates of 43

[1] Autor and Salomons (2018) break down this effect into four components: own-industry output effects, cross-industry input–output effects, between-industry shifts, and final demand effects.

percent in Argentina, 35 percent in Brazil, and 59 percent in Mexico, for the years 2005, 2003 and 2002.[2] The greater flexibility brought in by informal work arrangements has the potential to act as a buffer for negative impacts of exogenous shocks on labor demand. This idea is supported by empirical evidence on cases of trade liberalization in Latin America (Cruces, Porto and Viollaz, 2018; Dix-Carneiro and Kovak, 2019; César, Falcone, and Gasparini, 2021; Ponczek and Ulyssea, 2022), where increases in labor informality mitigate displacement of workers into unemployment.[3]

Firms that hire informal workers save in tax costs but face an expected cost of being caught. Due to larger visibility and probability of being audited, the expected cost of being caught is increasing in firm size (Ulyssea, 2018; Cruces et al., 2018). There is a negative correlation between size and informality, with large firms hiring a larger share of formal workers than small firms. Large firms are also more productive and able to benefit from and finance the costs of investing in robotization. Investment in robotics is therefore more likely to replace formal workers in large firms and to displace them into unemployment and informality.

Our empirical approach is based on district-level regressions of labor market outcomes on exposure to robots. It allows us to estimate the general equilibrium effect of robots operating at the local labor market level, considering that workers might move across firms, occupations, industries and formal-informal jobs in response to robot adoption, while assuming that there are no spillovers across geographic units.

We construct district-level labor market outcomes by aggregating individual-level infor-

[2]The labor informality rate is computed as the share of employed individuals without contributions to social security. For a review of the relationship between informality and development see La Porta and Shleifer (2014) and Ulyssea (2020).

[3]Several papers study trade liberalization episodes that occurred in Latin America during the early 1990s. Dix-Carneiro and Kovak (2019) estimate a model of mobility across sectors and find that following the Brazilian trade liberalization, regions facing larger tariff reductions exhibited larger increases in informality. Ponczek and Ulyssea (2022) find larger losses in employment in Brazilian regions where labor market regulations were more strictly enforced. Cruces, Porto and Viollaz (2018) document short–run increases in informality in liberalized tradable sectors and long–run increases in informality in non-tradables via general equilibrium effects after trade liberalization in Argentina. Arias et al. (2018) and Dix-Carneiro et al. (2021) build general equilibrium frameworks that take spillovers across sectors into consideration and estimate transitions in and out of informality for the cases of Brazil and Mexico, and for the case of Brazil, respectively. For the case of Chile, César, Falcone and Gasparini (2021) find that increased import competition following China's accession to the WTO led to a deterioration of employment and wages of unskilled workers and to an increase in labor informality.

mation from household surveys. Regarding robots, no direct measure of robot adoption at the district-level is available. We thus define a Bartik-type exposure based on information on industry-level purchases of robots and the initial share of each industry in total district employment. This definition exploits the fact that different geographic locations experienced heterogeneous exposure to industrial robots depending on their initial industrial composition. Industries such as automotive, rubber and plastics, industrial machinery, metal products, and food and beverages adopted industrial robots at a rate well above the average, making local labor markets specialized in these industries to be highly exposed to automation. By comparison, locations with a large fraction of employment in agriculture, textiles, wood and furniture, paper and printing, construction or services remained barely exposed to robot adoption.

Exposure to robots is potentially endogenous because labor markets conditions may influence firm decisions to invest in robotics. To account for this issue, we adopt the instrumental variable approach of Acemoglu and Restrepo (2020) based on industry-level robot adoption across European countries as an exogenous source of variation in robot exposure. Robot adoption in European countries, which are technologically ahead of Latin America, capture industry supply shifters such as advances in technology, availability and prices. The instrument isolates the growth in robot use that is due to exogenous technological change.

Our findings are that districts more exposed to robots had a worse relative performance in terms of unemployment and labor informality. Specifically, an increase of 0.027 robots per thousand workers, which is the average annual change in exposure to robots during 2004–2016, leads to a relative rise in the unemployment rate of 0.10 percentage points and to an increment in the labor informality rate of 0.23 percentage points. Wage losses concentrate on middle-age workers (36–49) in formal salaried jobs and on senior workers (50–65) in informal salaried jobs. Given that during the period under study most districts experienced an improvement in labor market indicators, our estimates suggest that locations undergoing a more rapid growth in exposure to robots accomplished smaller gains than less exposed areas. Notice that our estimation strategy delivers relative effects across districts but cannot identify level effects.

We find that robots mainly replace formal jobs, in line with the idea that these machines accomplish risky and unhealthy production tasks that were previously performed by formal workers. The impacts of robots on unemployment and informality are decreasing on age and education, and virtually non-significant for senior and highly skilled workers. We highlight that the informal sector acts as a buffer for unemployment, especially for young and semi-skilled individuals, who find fewer formal salaried job opportunities and end up in informal jobs or working as self-employed.

Our estimates are robust to the exclusion of the automotive industry (which features the largest robot adoption), alternative computation of standard errors, different definitions of the outcome and instrumental variables, the elimination of outliers, the exclusion of the years of the global financial crisis (2008–2010), the non-use of population weights and the exclusion of capital districts.

Our paper relates to a prolific literature that studies the effects of industrial robots on labor markets. Most papers document a negative impact of robots on the employment and wages of unskilled workers, while the effect on total employment is context-specific. The pioneer work of Graetz and Michaels (2018) studies the effect of robots across 17 developed countries from 1993 to 2007, and finds that robots increased labor productivity, lowered output prices and reduced the employment share of low-skilled workers. Acemoglu and Restrepo (2020) document that robot use has had a robust negative impact on employment and wages across US commuting zones. Other papers that argue that there are negative effects from robot adoption on groups of workers are Webb (2020), Dauth et al. (2021) and Humlum (2021). Acemoglu, Lelarge, and Restrepo (2020) show that French firms adopting robots between 2010 and 2015 reduce their costs and expand at the expense of competitors. Koch, Manuylov, and Smolka (2021) report a similar finding for Spanish manufacturing firms, and emphasize the complementarity between robots and exporting in boosting productivity. Moll, Rachel, and Restrepo (2021) argue that the benefits of automation accrue to high-skilled workers and also to the owners of capital, which increases inequality by rising returns to wealth and leading to stagnant wages at the bottom of the income distribution. On the side of determinants, Acemoglu and Restrepo (2021) uncover that aging leads to greater industrial automation because it creates a shortage of young workers specialized in manual production tasks.

The main contribution of our paper is to extend the analysis of the impact of the robotization process to the developing world. While most of the evidence on the impact of robots focuses on developed economies, or its effects on third countries through reshoring and trade (Faber, 2020, Artuc et al., 2020, Kugler et al., 2020), robot adoption has sped up during the last decades in developing countries as well, and this trend may continue in the near future. By extending the analysis to developing countries, we are able to highlight a different margin of adjustment to the technological shock generated by the incorporation of robots to the production process: labor informality. We show that robots mostly replace formal salaried jobs and that some workers find shelter in the informal sector, cushioning the impact of the technological shock on employment.

The rest of the paper is organized as follows. Section 2 describes the data and the measure of exposure to robots. Section 3 discusses the empirical strategy and the identifying assumptions. Section 4 presents the empirical results, tests of pre-trends and robustness exercises. Section 5 concludes. Additional tables and figures are reported in the appendix.

2 Data

Labor market outcomes are constructed from household surveys from 2004 to 2016. Available years are 2004–2016 for Argentina (*Encuesta Permanente de Hogares*, EPH); 2004–2009 and 2011–2015 for Brazil (*Pesquisa Nacional por Amostra de Domicílios*, PNAD); 2004, 2005, 2006, 2008, 2010, 2012, 2014, and 2016 for Mexico (*Encuesta Nacional de Ingresos y Gastos de los Hogares*, ENIGH). Household surveys are processed following the protocol of the Socioeconomic Database for Latin America and the Caribbean (SEDLAC), a joint project of CEDLAS-UNLP and the World Bank. The standardized surveys have information at the individual level on demographic characteristics, employment characteristics, income, industry of affiliation, and occupation, all homogenized and comparable across countries and years of data.

We aggregate individual data to construct the unemployment rate, the informality rate, the number of informal salaried jobs, the number of formal salaried jobs, the number of self-employment jobs, the average wage of informal salaried workers, the average wage of formal salaried workers and the average self-employment income, at the district-level. The unemployment rate is the share of adults in the labor force that have been actively looking for a job in the last month. The labor informality rate is the fraction of salaried workers that do not contribute to any pension fund and do not have rights to receive a contributory pension when retired. Labor incomes are expressed in constant USD PPP 2011. Individual weights are used to compute all district-level variables and are representative at the district levels.

Table A1 in the appendix shows descriptive statistics from the first and final years of each survey. We report the average and standard deviation (in parenthesis) across districts. There are 32 districts in Argentina, 27 in Brazil, and 32 in Mexico. The units of analysis are urban metropolitan areas in Argentina and federal states in Brazil and Mexico. We restrict the sample to urban areas, where the concentration of robot adoption has occurred. In the cases of Argentina and Brazil there have been decreases in labor informality, declines in the number of informal salaried jobs, and significant increases in average wages. In Mexico there have been increases in the employment rate and also in the informality rate. Wages have increased moderately and self-employment incomes decreased markedly. In the three countries there has been increments in both the number of formal salaried jobs and the number of self-employment jobs. At the beginning of the sample the unemployment rates are 12.3, 9.8 and 3.8 percent in Argentina, Brazil and Mexico. Informality is a prevalent phenomenon in Latin America with rates of 47.3, 30.6 and 53.7 percent at the beginning of the sample. The average monthly formal wage is 941, 651 and 871 constant USD of 2011 corrected by PPP. The average monthly self-employment income is 669, 573 and 581 USD, and informal wages are even lower (482, 322 and 516 USD).

A second source of data is a dataset compiled by the International Federation of Robotics (IFR). IFR conducts annual surveys of the number of industrial robots shipped to firms worldwide by robot manufacturers. An industrial robot is defined by IFR according to the International Standard Organization (ISO 8373:2012) as an *automatically controlled, multipurpose manipulator, (re)programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications.* These devices are able to perform a wide range of tasks, such as welding, painting, packaging and transporting, with very little human involvement. The IFR uses its own industry classification, which closely follows the International Standard Industrial Classification (ISIC) revision 4. There are six non-manufacturing sectors: agriculture, forestry and fishing; mining and quarrying; electricity, gas and water supply; construction; education, research and development; and other non-manufacturing; and there are fifteen manufacturing sectors: food and beverages; textiles and apparel; wood and furniture; paper and printing; pharmaceutical and cosmetics; chemical products; rubber and plastics; glass, stone, and minerals; basic metals; metal products; electronics; industrial machinery; automotive; shipbuilding and aerospace industries; and miscellaneous manufacturing.

Figure A1 in the appendix depicts the stock of robots at the industry level for the year 2016 in each country. Automotive is the industry with the highest adoption of robots in all countries, a fact that is taken into consideration in the robustness exploration of our empirical analysis. Other industries such as rubber and plastics, industrial machinery, metal products, and food and beverages also employ a large number of robots. On the other hand, sectors such as agriculture, mining, textiles, wood and furniture, paper and printing, construction, and services are not intensive in the use of robots.

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

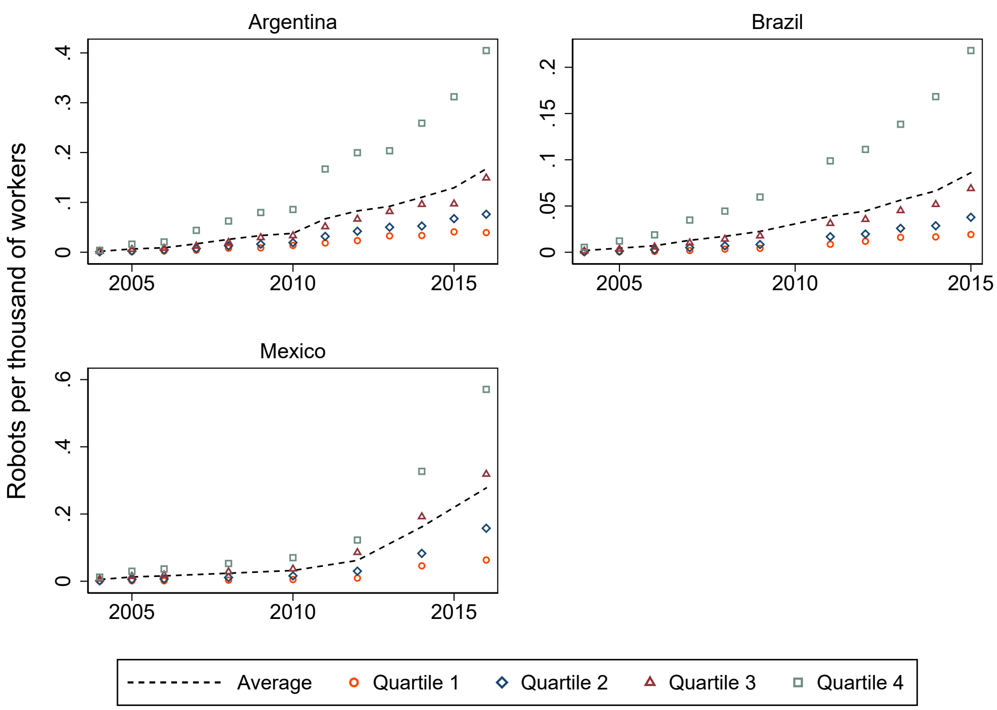
Formally, exposure to robots in district i of country c at time t is defined as:

$$ER_{ict} = \sum_{j} \left(\frac{L_{jic,t=0}}{L_{ic,t=0}} \right) \left(\frac{Robot\ Stock_{jct}}{L_{jct}/1000} \right) \tag{1}$$

where j indexes industries. *Robot Stock*$_{jct}$ is the industry stock of robots at the country-year level, L_{jic} is the number of industry workers in district i of country c, and L_{ic} is the number of workers at the district level in each country. The weights are computed as the *initial* industry share in district employment, and do not vary over time so that the measure of exposure to robots does not reflect temporary changes in employment composition.[4]

Figure 1 presents the evolution of exposure to robots in each country. It plots the average exposure to robots across all districts and separately by quartiles of exposure. Exposure to robots grew significantly between 2004 and 2016, from values close to zero to 0.17, 0.09, and 0.28 robots per thousand workers in Argentina, Brazil and Mexico, respectively. While some districts experienced a sharp increase in exposure to robots, others remained barely exposed. Differences in average exposure to robots between districts in the first and fourth quartiles in 2016 range from 0.04 to 0.40 in Argentina, 0.02 to 0.22 in Brazil, and 0.06 to 0.57 in Mexico.

Figure 1: Average exposure to robots by country and quartiles of exposure



Notes. Exposure to robots computed from equation (1) and averaged across all districts in each country and separately by country-quartile of exposure. District exposure to robots is weighted by district's share of country's population of working age in 2004. Own calculations using data from the IFR and household surveys.

[4]Industry employment shares are constructed with pre-sample data from 1992–1994. Results are robust to using different years of data or only one year of data.

3 Empirical strategy

We estimate district-level regressions that exploit the variability in labor market outcomes and exposure to robots over time and across districts within each country. The baseline regression equation is:

$$Y_{ict} = \beta_0 + \beta_1 ER_{ict} + x'_{ict}\beta_2 + \alpha_i + \delta_{ct} + \varepsilon_{ict} \tag{2}$$

where i, c and t index districts, countries and time, respectively. The outcome variables, represented by Y, are the unemployment rate, the labor informality rate, the (log) number of formal salaried jobs, the (log) number of informal salaried jobs, the (log) number of self-employment jobs, the (log) average formal wage, the (log) average informal wage and the (log) average self-employment income. The explanatory variable ER is exposure to robots per thousand workers at the district level; x are control variables, α_i are district fixed effects, δ_{ct} are time×country fixed effects, and ε_{it} is a mean-zero disturbance. District-level fixed effects capture time-invariant unobserved heterogeneity across districts. Country×year fixed effects control for time-varying shocks across countries. Results are identified by exploiting the within-district variation in exposure to robots and outcomes in each country over time.

While the impact of robot exposure on labor market outcomes could vary by country, the number of districts in each country is not large enough to estimate heterogeneous effects across countries. We therefore pool together districts from Argentina, Brazil and Mexico and estimate average effects across the three countries.

Exposure to robots is potentially endogenous. Labor market conditions may have an impact on firm's decisions to invest in robotics and unobserved local shocks may affect both robot adoption and the labor market outcomes in our analysis. Moreover, there could be reverse causality from labor market conditions to robot adoption or measurement error in robot adoption. To account for this issue we adopt an instrumental variable design similar to Acemoglu and Restrepo (2020). To identify the component of exposure to robots driven by exogenous changes in technology, we instrument the independent variable with the average industry exposure to robots across 22 European countries, which are all the countries with complete and comparable information in the IFR and EU KLEMS datasets.[5] This measure is constructed as:

$$ER_{ict}^{IV} = \sum_{j} \left(\frac{L_{jic,t=0}}{L_{ic,t=0}} \right) \left(\frac{1}{22} \sum_{k \in Europe} \frac{Robot\ Stock_{kjt}}{L_{kjt}/1000} \right), \tag{3}$$

where j and k index industries and European countries, respectively; $\frac{Robot\ Stock_{kjt}}{L_{kjt}/1000}$ is the stock of robots per thousand workers in each industry-country pair. We construct the district-level instrumental variable as the average industry exposure to robots across the 22 European countries weighted by the initial industry share in district i employment. Employment data at the industry-level for European countries was obtained from the EU KLEMS database (Release 2019). The first-stage unconditional correlation between ER_{it} and ER_{it}^{IV} is strong, with a linear coefficient of 0.174, a standard error of 0.022 and an R-squared of 0.773 (Figure A2 in the appendix).

The idea of the identification strategy is to exploit the fact that European countries are ahead of Latin America in terms of robotization. Variation in robot adoption in Europe across industries and over time captures advances in technology, availability and prices that are exogenous supply shifters for robot adoption in Latin America. The identifying assumptions are: (i) that the evolution of the average industry exposure to robots across European countries is not correlated with shocks in Latin America; and (ii) that districts with a higher initial share of labor allocated to industries with greater advances in robotics technology are not differentially affected by other labor market shocks or trends.

As robustness exercises, we construct two alternative IVs. First, we calculate a weighted measure of exposure to robots in Europe with weights given by the inverse export share of each European country to each Latin American country, to partially address the concern that robot adoption in Europe may affect Latin America through trade competition and reduced offshoring. Second, we calculate the average industry exposure to robots across the five European countries used by Acemoglu and Restrepo (2020): Denmark, Finland, France, Italy, and Sweden. The authors document that these countries are technologically more

[5]The countries are Austria, Belgium, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Lithuania, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, and United Kingdom.

advanced than the U.S. in robotics and experience rapid population aging, which is a major determinant of robot adoption.[6]

We include several specifications that control for a large set of preexisting trends related to demographic composition, economic conditions, the relevance of the automotive industry for local employment, the importance of industries exposed to increasing bilateral trade with China, the prominence of industries exposed to offshoring, and the exposure to task routinization of occupations. These controls allow us to address the concern that results might represent the continuation of local trends starting before the period under study. We further run a validity pre-trend analysis exercise that tests for pre-sample changes in observable district-level variables.

We weight each observation by the district share of country's population of working age in 2004. This estimation strategy provides average treatment effects that are weighted by workers instead of local labor markets. We present and discuss the results of unweighted regressions in the section of robustness exercises.

4 Results

4.1 Main estimates

This section discusses the main findings of the paper. We are interested in labor market outcomes at the district-level: the unemployment rate, labor informality rate, number of formal salaried jobs, number of informal salaried jobs, number of self-employment jobs, average formal wage, average informal wage and average self-employment income.

Baseline estimates of equation (1) are reported in Table 1. All columns display fixed effect-two-stage least squares estimates in which exposure to robots is instrumented using robot penetration in European countries as an exogenous shifter. Different columns subsequently account for several preexisting trends, computed as the value of a given variable in 2004 interacted with year dummies. The variables used to compute preexisting trends are

[6] Aging creates a shortage of young and middle-age workers specialized in manual production tasks that fosters the development and adoption of robotics technology, which is then exported to other countries experiencing less rapid demographic change (Acemoglu and Restrepo, 2021).

the following. From column (1) onward we include demographic variables: log population in age groups 0–17, 18–35, 36–49, 50–65, and more than 65; and the shares of population of working age with no high-school, high school degree and college degree. Column (2) adds economic variables: the log average per capita income, employment rate, female labor force participation, share of salaried workers, employment shares in the primary and manufacturing sectors and public transfers as a percentage of district total income. Column (3) adds the district employment share of the automotive industry (the largest robot adopter). Columns (4) and (5) add district exposure to imports and exports to China (column 4), and offshoring (column 5). The exposures in columns 4 and 5 are computed as shift-share variables as a weighted average of the initial industry-level imports, exports and offshoring index of Feenstra and Hanson (1999), using the initial industry shares in district employment as weights. Column (6) adds a district-level index of job routinization. Routinization is defined as a quantification of district jobs that are repetitive, codifiable, and therefore susceptible to be replaced by automation technology such as robots.[7] All regressions include district and country–year fixed effects and therefore exploit within district variation over time in each country. Standard errors are robust against heteroskedasticity and clustered at the district level.

Panel A shows that the instrument has a strong predictive power and it is statistically significant at the 1 percent level in all specifications; the hypothesis of weak instrument is rejected. In Panel B the dependent variable is the unemployment rate. Results suggest that there is a positive and significant effect of exposure to robots on unemployment. An increase in the robot to worker ratio of 0.027 (i.e., the average annual growth of exposure to robots) results in a rise in the local unemployment rate of around 0.10 percentage points (column 6); compared to a district with no exposure to robots, *ceteris paribus*.[8]

In Panel C we report the estimates for labor informality, defined as the fraction of unregistered salaried workers. 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

[7] We use the district-level routinization index of Brambilla et al. (2022). The index is defined at the occupation level using information from the Survey for Adult Skills from the OECD and aggregated to the district level as a weighted average where occupation shares in district employment are used as weights.

[8] The median annual change in exposure to robots at the district level between 2004 and 2016 was 0.011; the mean and standard deviation were 0.027 and 0.042.

loss in job quality. An increase in the robot to worker ratio of 0.027 leads to a relative increment in the share of salaried individuals working under informal labor arrangements of 0.23 percentage points. Notice that the unemployment and informality rates are computed over different populations (individuals in the labor force vs. employed salaried workers) and, thus, coefficients in Panels B and C are not directly comparable.

The economic magnitudes of estimated coefficients are large and need to be interpreted with caution. A possible explanation is that the measure of exposure to robots picks up not only the effect of robot adoption, but also other complementary automation efforts (e.g. software adoption, outsourcing).[9]

Panels D, E and F display the estimates for district employment levels: number of formal salaried jobs, number of informal salaried jobs and number of self-employment jobs, respectively. The three variables are expressed in logarithms so point estimates can be interpreted as semi-elasticities.[10] In panel D we find that robots have a strong displacement effect on formal salaried jobs. Presumably, robots accomplish risky and unhealthy production tasks that were previously performed by formal workers covered by health insurance and social protection. Furthermore, robot adopters are likely to be large companies that exhibit higher rates of labor formalization than non-adopters. The point estimates for log number of informal salaried workers and log number of self-employed workers (Panels E and F) are positive and not close to zero, however, the number of observations is not high enough to have precision in the estimation. We interpret these results with caution, as not incompatible with the idea that informality acts as a buffer.

Table 2 reports the baseline estimates for the impact of robots on labor income. Point estimates for the log average monthly wage of formal workers (Panel A) and informal workers (Panel B) are negative and somewhat large but imprecisely estimated (not statistically significant).[11] The magnitude of the point estimates in Panel A (formal wages) are about

[9]The seminal paper of Milgrom, Qian, and Roberts (1991) theoretically proves that the firm's problem (whether to adopt any or all of the technological advances) exhibits important non-convexities and there are strong complementarities among firm decisions that extend beyond manufacturing production towards organization, engineering and distribution.

[10]As a robustness exercise we compute these three employment outcomes as a fraction of population of working age (Table A3).

[11]Estimates become statistically significant under more liberal construction of confidence intervals such as using non-clustered standard errors or standard-errors clustered at the regional level instead of the district

one or two times larger than point estimates in Panel B (informal wages) across the different column specifications (except for column 1), in line with the idea that the negative impact of robots is larger for formal jobs than for informal jobs. Results in Panels C suggest that robots have no significant effect on the average income of self-employed individuals.

For completeness, we report fixed effects–ordinary least squares estimates in Table A2 of the appendix, which closely follows the format in Tables 1 and 2. FE–OLS estimates for unemployment, labor informality and the number of formal salaried jobs are robust and statistically significant. The comparison of the economic magnitudes of FE–OLS and FE–2SLS estimates suggests that there are unobserved shocks at the district level that have positively affected both formal employment and robot adoption. For instance, firms might be more likely to invest in robotics in years of sound economic growth in the local economy that translates into increasing formal labor demand.

The main contributions of this paper are the ideas that industrial robots replace mostly formal jobs and that the greater flexibility introduced by informal work arrangements and self-employment jobs cushions the automation-driven effect on unemployment. The last finding is in line with recent evidence for developing countries pointing out that the informal sector acts as a buffer in the context of weaker labor markets. Similar arguments have been made for the effects of trade and globalization (Cruces, Porto and Viollaz, 2018; Dix-Carneiro and Kovak, 2019; César, Falcone, and Gasparini, 2021; Dix-Carneiro, Goldberg, Meghir, and Ulyssea, 2021; Ponczek and Ulyssea, 2022).

4.2 Heterogeneous effects by age and skill

In this section we explore the heterogeneous effects of robot penetration by age and worker skill level. Figure 2 plots the estimated coefficients and confidence intervals from running regression (1) separately for different age groups: young (18 to 35), middle-aged (36–49) and workers with seniority (50–65).

We find that the effects of robots on unemployment and informality are decreasing in age and virtually non-significant for workers over 50. Senior workers have longer tenure

level. Our preferred specification, however, is the more conservative approach of building confidence intervals based on standard errors clustered at the district level, as displayed in the table.

on their jobs, a sunk investment in specific skills and are more costly for firms to replace; they are also more likely to be in supervising positions. In contrast, young workers are the most affected by robotization. In a context of labor automation, young workers find less job opportunities in the formal sector and remain unemployed, end up accepting an informal labor arrangement or working as self-employed. It is likely that the increasing availability of digital work platforms allows the young to work in flexible jobs at relatively low entry costs but presumably lower wages.

Wage losses in formal salaried jobs concentrate in the middle-age group, which suggests that most of these workers maintain their formal jobs despite losing some salary. Young workers experience relative wage losses in the three types of labor forms, but estimated coefficients are non-significant. The point estimate for formal wages of workers over 50 is positive but non-significant. Senior workers in informal salaried jobs exhibit strong wage losses probably because this group has low labor mobility and little flexibility to adapt to the rapid ongoing changes in the working environment. This is not the case for self-employed workers over 50 (the point estimate is positive but non-significant), who are likely to have a trade and enough work experience to protect themselves from a weakening in local labor market conditions.

Figure 3 plots the estimated coefficients and confidence intervals from running regression (1) separately for different skill groups: low-skilled (primary education or below), semi-skilled (secondary education) and highly skilled (tertiary education).

The impact of robots on unemployment is decreasing on education and negative for highly skilled individuals. This is expected since highly skilled workers do not tend to be employed in manual production jobs that can be performed by robots. Instead, they are likely to work together with robots in a complementary manner. Only low-skilled individuals experience a relative increase in unemployment as a result of robot adoption. The effect on informality concentrates in the group of semi-skilled workers, which suggests that informality is a more effective buffer for the semi-skilled than for the low-skilled. The difference across groups plausible arises from their different average informality rates, of 28 and 48 percent respectively. The lower rate for the semi-skilled implies that there is more scope for informality to work as a margin of adjustment for this group than for low-skilled workers

In this line, we find that semi-skilled individuals are the most affected by the robotization-induced job losses in the formal sector, and that some of these workers find shelter in the informal salaried sector. It seems that highly skilled workers are moving towards self-employment jobs as a result of robotization, but the point estimate is non-significant.

Relative wage changes induced by robotization are non-significant, but we can infer some ideas by analyzing the direction of estimated coefficients. Wage declines in the formal sector are largest for the low-skilled and semi-skilled workers. These groups also suffer earning losses in informal salaried jobs and self-employment jobs. We find a positive impact of robots on the wages of highly skilled workers in informal salaried jobs. However, these gains do not extend to highly skilled individuals employed in the formal sector, which is presumably related to income under-reporting. In fact, Latin American household surveys have many limitations to survey the richest workers and capturing top incomes.

4.3 Pre-trend analysis

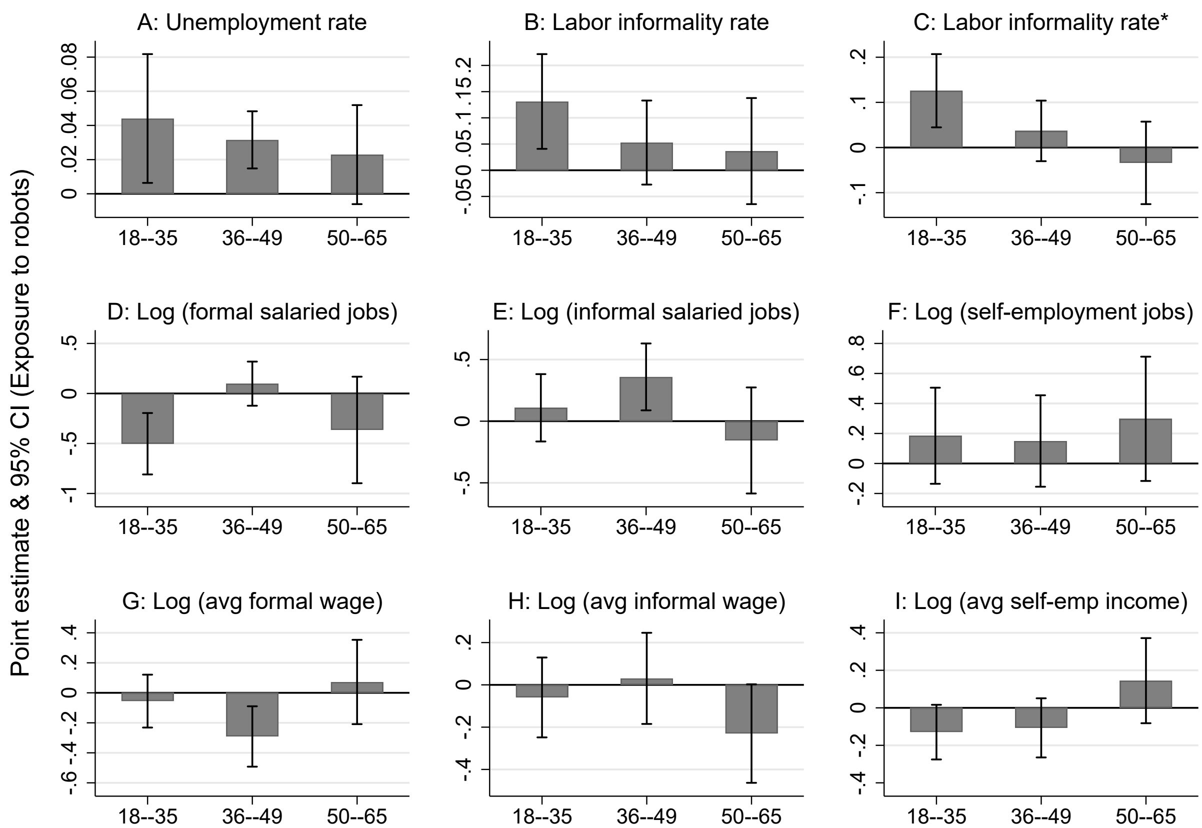
A concern of our empirical strategy, shared with most exercises of estimation of treatment effects, is whether district-level exposure to robots correlates with preexisting district-level trends. If that were the case our estimates could be biased by preexisting trends that persisted during the exposure period. Our empirical strategy controls for a large set of trends based on observed variables in the initial year of data, which substantially ameliorates this concern. As a validity test, we further look at observed variables in a pre-sample period to rule out that their past changes are correlated with later exposure to robots.

We define a pre-sample period from 1998 to 2004. We run the following OLS regression:

$$\Delta x_{ic0} = \gamma_0 + \gamma_1 \Delta ER_{ict} + \delta_c + \Delta\varepsilon_{ic0} \tag{4}$$

For each variable x we regress the change between 1998 and 2004 (Δx_{i0}) on the change in exposure to robotization during 2004-2016 (ΔER_{it}); where x are district-level observables during the pre-sample period. We consider the following district-level observables: unemployment rate, informality rate, average wage, share of non-primary workers in total district employment, exposure to task routinization (defined as in Table 1), share of salaried

Figure 2: Heterogeneous effects of robots by age

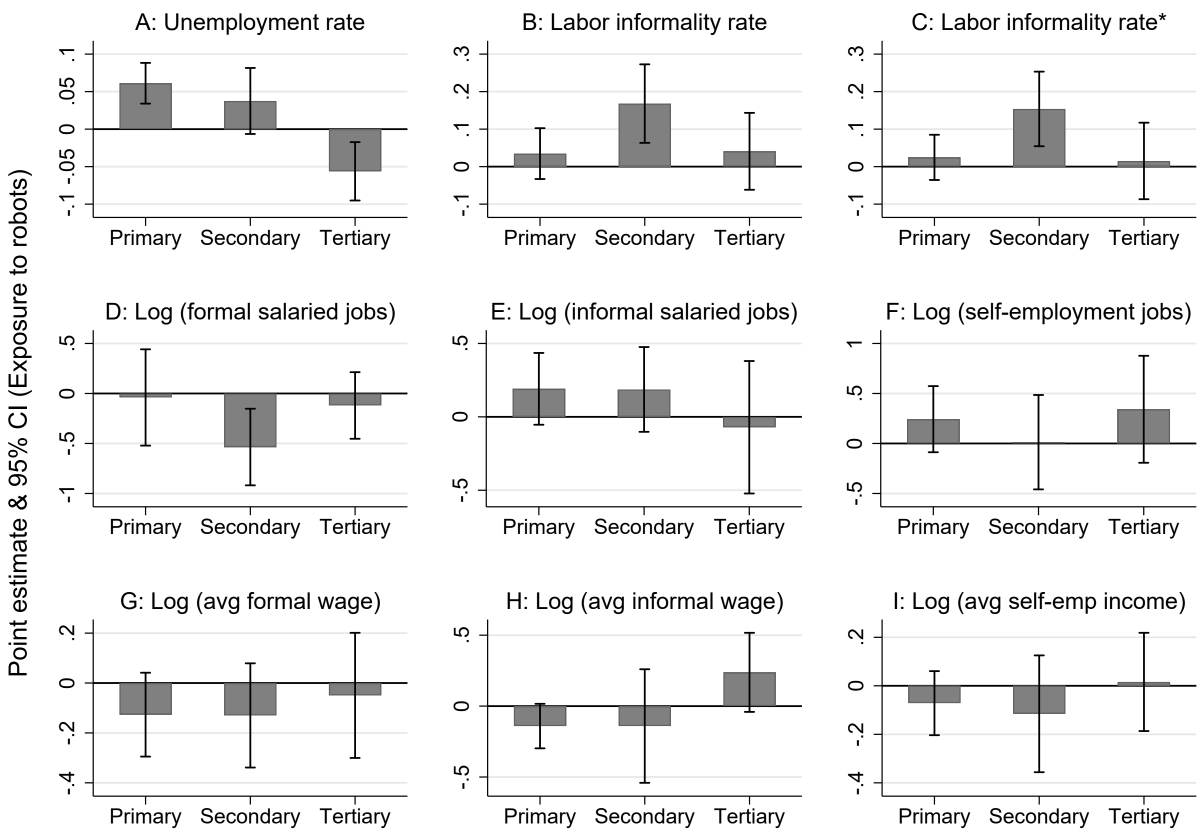


Notes. Observations = 963. Regressions are analogous to Tables 1 and 2, Column (6). Point estimates correspond to separate regressions for three mutually exclusive samples based on age: 18–35, 36–49, 50–65. Labor informality rate is the fraction of unregistered salaried workers. The second definition (*) includes self-employed workers without a tertiary degree as informal. The capped lines provide 95 percent confidence intervals.

workers in total district employment, share of semi-skilled workers (high-school diploma), share of highly skilled workers (tertiary education diploma) and district's share of country's population of working age.

Results are reported in Table 3, column (1). All estimates are non-significant, which shows that there is no correlation between past trends in district observables and the later change in exposure to robots. The first three lines in Table 3 refer to the three main outcomes in our empirical analysis–unemployment, informality and wages–albeit computed for a pre-sample period. The point estimate of the effect on unemployment, in addition to being non-significant, is considerably lower than the coefficient for our in-sample analysis of Table 1. Moreover, the point estimates for informality are of opposite sign when compared to Table

Figure 3: Heterogeneous effects of robots by education



Notes. Observations = 963. Regressions are analogous to Table 1 and 2, Column (6). Point estimates correspond to separate regressions for three mutually exclusive samples based on education: primary is less than high-school (unskilled), secondary is high-school completed (semi-skilled), and tertiary is college complete (highly skilled). The second definition (*) includes self-employed workers without a tertiary degree as informal. The capped lines provide 95 percent confidence intervals.

1.

For completeness we run additional exercises in columns (2) to (4). In column (2), we replace ΔER with the instrument ΔER^{IV}. In column (3), we replace ΔER with a dummy variable that indicates whether ΔER is above the median across districts. Column (4) is analogous to column (3) with the difference that the dummy variable is computed based on ΔER^{IV}. All results remain non-significant.

4.4 Robustness exercises

In this section we perform a series of robustness exercises. We estimate several alternatives to our baseline regression to check the robustness of results to: different employment outcomes, alternative definitions of the instrumental variable, rule out the influence of outliers, omit the years of the global financial crisis, exclude capital districts, not use weights in the regression, leave aside districts with greatest importance of the automotive industry (which exhibits the largest adoption of robotics) and estimate conservative confidence intervals with clustering at the industry level. We describe these tests below. All results, unless noted otherwise, are quantitatively very similar to our baseline estimates in Tables 1 and 2. They are reported in the appendix.

Robustness to alternative employment outcomes. Table A3 presents the estimates for the impact of robots on the employment rate (Panel A), the shares (on the population of working age) of formal salaried jobs (Panel B), informal salaried jobs (Panel C) and self-employment jobs (Panel D), and the inactivity rate (Panel E). Our main estimates for unemployment are computed for individuals that are economically active (i.e. either employed or unemployed), while the estimates in Table A3 include also inactive individuals. In line with our main estimates, we find that districts more exposed to robots exhibit a relative decline in the participation of formal salaried jobs and a relative increase in the fraction of informal salaried jobs. Point estimates for the employment rate are negative but statistically indistinguishable from zero. The impact of robots on inactivity is negative but non-significant, which suggests that some inactive individuals enter the labor force in response to robot adoption.

Robustness to alternative definitions of the instrument. The baseline instrument is computed using information from 22 European countries, which are all the countries with complete information available in the EU KLEMS and IFR datasets. We explore the robustness of our results to computing two alternative instruments. (1) A weighted measure of exposure to robots with weights given by the inverse export share of each European country to each Latin American country. The goal is to partially address the concern that robot adoption in Europe may affect Latin America through trade competition and reduced offshoring. Results are in Table A4. (2) Average industry exposure to robots in Europe across the same five countries used by Acemoglu and Restrepo (2020), which are Denmark, Finland, France, Italy, and Sweden. The authors argue that these economies are the most technologically advanced and experience rapid population aging, a major determinant of robot adoption (Acemoglu and Restrepo, 2021). Results are in Table A5. Point estimates for the number of self-employment jobs and formal wages become statistically significant, which suggests that the choice of countries included in the instrument is not a trivial decision.

Robustness to outliers in exposure to robots. Because robot adoption is strongly uneven across industries, there are outliers in the district exposure to robot adoption. To rule out that results are driven by outliers, we perform a robustness exercise in which we exclude extreme values defined as the top and bottom 1 percent of the distribution of exposure to robots. Results are in Table A6.

Robustness to excluding the global financial crisis, 2008–2010. The effect of the global financial crisis could be correlated with the robotic intensity of industries. To take this potential bias into account, we estimate our baseline regression excluding the years 2008-2010. Results are in Table A7.

Robustness to excluding largest districts. The largest districts may me subject to differential labor market dynamics than the rest of the country. To take this potential bias into account, we estimate our baseline regression excluding the largest district in each country (Buenos Aires, Sao Paulo and Mexico city). Results are in Table A8. The impact of robots on formal wages become statistically significant in the preferred specification, which suggests that formal wage losses are lower in largest districts than in the rest of the country. Point estimates for the number of self-employment jobs also become significant.

Robustness to not using district importance weights. The baseline specification is a weighted regression with weights given by district share in total country population of working age in 2004. We explore an unweighted alternative specification in which all districts are given the same importance in the regression irrespective of their size. Results are in Table A9. Under this specification estimated coefficients for the number of self-employment jobs become significant, which suggests that reallocation towards self-employment is more common in less densely populated areas.

Robustness to excluding districts with greatest importance of the automotive industry. In their discussion of Bartik instruments, Goldsmith-Pinkham, Sorkin, and Swift (2020) recommend to report the industries with the highest Rotemberg weights (i.e. those that explain a greater fraction of the variation in the instrument). We report these statistics in Table A10. The first column in Panel A shows that the automotive industry has the highest Rotemberg weight (86.5 percent), which indicates that reduced-form estimates may be sensitive to unobserved shocks affecting local labor markets specialized in this industry. This is the main reason behind the inclusion of a preexisting trend for the employment share in the automotive industry in our main regression analysis. We conduct a robustness exercise excluding districts with the greatest participation of the automotive industry in local employment.[12] Results are in Table A11 and show that estimates do not change substantially when these districts are excluded.

Robustness to clustering errors at the industry level. In Bartik (shift-share) regression models such as ours, errors could share common shocks across districts with similar industrial compositions. Adao, Kolesar and Morales (2019) and Borusyak, Hull and Jaravel (2021) discuss settings of shift-share designs in which confidence intervals obtained following the usual methods tend to be too liberal. We conduct a robustness exercise in which we apply the method of Adao et al. (2019) to correct standard errors for clustering at the original level of the shock variable, that is, the industry level. Under this methodology, the point-estimates of the coefficients are by construction the same, while the confidence intervals are estimated more conservatively. We report results in Table A12. Results on unemployment and informality remain strongly robust while those on the number of formal salaried jobs are no longer statistically significant. A potential explanation is that increasing bilateral trade between districts with a similar industry structure may lead to higher industry productivity and employment (and presumably wages), which generates a positive correlation in the errors of districts with the highest exposure to robotization.[13]

Robustness to population shifts. Cross-district migration represents a potential threat to our empirical strategy. Our estimates may be biased if workers migrate across geographic locations in response to robot adoption and changes in local economic conditions. To address this potential concern we estimate regressions using the logarithm of population

[12]The excluded districts are Gran Cordoba (Argentina), San Nicolas (Argentina), Sao Paulo (Brazil), Amazonas (Brazil), Chihuahua (Mexico) and Cohauila (Mexico).

[13]Related contributions have documented that robot adoption encourages the growth of international trade (Artuc et al., 2020; Koch et al, 2021). Bilateral trade is pervasive in our sample, especially between Brazil and Argentina, and also presumably high across different districts within each country.

counts as dependent variables. Panel A corresponds to total population and Panel B to population of working age (15–65). Point estimates are positive but not-statistically significant, which is reassuring as it indicates that population shifts across districts do not drive our results.

5 Concluding Remarks

In this paper we present evidence on the effects of robot adoption on local labor markets in the three largest economies of Latin America: Argentina, Brazil, and Mexico; the major robot users in the region. Using data from national household surveys and the International Federation of Robotics, we show that districts with a higher share of workers allocated to industries more exposed to robot adoption exhibited a worse relative performance in terms of labor market indicators such as unemployment and labor informality, than less exposed locations.

We document that robots mainly replace formal jobs. The informal sector acts as a buffer for unemployment, especially for young and semi-skilled individuals, who end up in informal salaried jobs or working as self-employed. Relative wage losses concentrate on middle-age workers in formal salaried jobs and on senior workers in informal salaried jobs. Highly skilled individuals are the least affected by robotization.

Finally, and importantly, our estimates deliver relative effects across districts but cannot account for the aggregate impact of robot adoption, which depend on spillovers across industries in different geographic locations and other general equilibrium effects (e.g. changes in input and output prices, firms productivity, and aggregate demand multiplier effects).

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Table 1: The effects of robots on employment outcomes

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: First-stage regression						
Exposure to robots (IV)	0.269***	0.267***	0.253***	0.251***	0.249***	0.251***
	(0.037)	(0.039)	(0.033)	(0.031)	(0.031)	(0.031)
KP F-stat	49.6	39.7	48.0	52.6	49.7	50.9
R-squared	0.938	0.958	0.963	0.965	0.965	0.967
Panel B: Unemployment rate						
Exposure to robots	0.013	0.031***	0.035***	0.036***	0.036***	0.038***
	(0.016)	(0.012)	(0.012)	(0.011)	(0.012)	(0.012)
Panel C: Labor informality rate						
Exposure to robots	0.054	0.062**	0.078**	0.080**	0.084***	0.087***
	(0.033)	(0.032)	(0.033)	(0.031)	(0.030)	(0.031)
Panel D: Log (number of formal salaried jobs)						
Exposure to robots	−0.219**	−0.179	−0.236*	−0.246**	−0.260**	−0.265**
	(0.112)	(0.125)	(0.129)	(0.118)	(0.119)	(0.113)
Panel E: Log (number of informal salaried jobs)						
Exposure to robots	0.006	0.104	0.117	0.114	0.119	0.132
	(0.121)	(0.115)	(0.123)	(0.124)	(0.122)	(0.108)
Panel F: Log (number of self-employment jobs)						
Exposure to robots	0.070	0.163	0.218	0.201	0.180	0.194
	(0.120)	(0.143)	(0.152)	(0.155)	(0.144)	(0.147)
Observations	963	963	963	963	963	963
Preexisting trends						
Demographics	Yes	Yes	Yes	Yes	Yes	Yes
Economic conditions	-	Yes	Yes	Yes	Yes	Yes
Automotive industry	-	-	Yes	Yes	Yes	Yes
Trade with China	-	-	-	Yes	Yes	Yes
Offshoring	-	-	-	-	Yes	Yes
Routinization	-	-	-	-	-	Yes

Notes. All regressions include district and country-year fixed effects, and run by 2SLS using industry exposure to robots in 22 European countries weighted by industrial composition at the district level as instrument. Preexisting trends are: logarithm of populations under ages 0–17, 18–35, 36–49, 50–65, and older than 65, and the shares of population of working age with no high-school, high-school complete and college complete (Column 1 and onwards); log average per capita income, employment rate, female labor force participation, share of salaried workers, employment shares in the primary and manufacturing sectors and public transfers as a percentage of district's total income (Column 2 and onwards); employment share in the automotive industry (Column 3 and onwards); exposure to China's imports and exports (Column 4 and onwards); exposure to offshoring (Column 5); and exposure to routine task content of jobs (Column 6). Robust standard errors clustered at the district level are in parentheses. Regressions weighted by district's share of country's population of working age in 2004. Significance at the 1, 5 and 10 percent levels denoted with ***, ** and *.

Table 2: The effects of robots on labor incomes

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Log (average formal wage)						
Exposure to robots	−0.050	−0.129	−0.115	−0.106	−0.096	−0.097
	(0.082)	(0.086)	(0.088)	(0.088)	(0.083)	(0.083)
Panel B: Log (average informal wage)						
Exposure to robots	−0.084	−0.046	−0.047	−0.037	−0.041	−0.045
	(0.065)	(0.079)	(0.087)	(0.090)	(0.094)	(0.085)
Panel C: Log (average self-employment income)						
Exposure to robots	−0.178	−0.163	−0.063	−0.032	−0.023	−0.007
	(0.134)	(0.134)	(0.143)	(0.129)	(0.128)	(0.117)
Observations	963	963	963	963	963	963
Preexisting trends						
Demographics	Yes	Yes	Yes	Yes	Yes	Yes
Economic conditions	-	Yes	Yes	Yes	Yes	Yes
Automotive industry	-	-	Yes	Yes	Yes	Yes
Trade with China	-	-	-	Yes	Yes	Yes
Offshoring	-	-	-	-	Yes	Yes
Routinization	-	-	-	-	-	Yes

Notes. All regressions include district and country-year fixed effects, and run by 2SLS using industry exposure to robots in 22 European countries weighted by industrial composition at the district level as instrument. Preexisting trends are: logarithm of populations under ages 0–17, 18–35, 36–49, 50–65, and older than 65, and the shares of population of working age with no high-school, high-school complete and college complete (Column 1 and onwards); log average per capita income, employment rate, female labor force participation, share of salaried workers, employment shares in the primary and manufacturing sectors and public transfers as a percentage of district's total income (Column 2 and onwards); employment share in the automotive industry (Column 3 and onwards); exposure to China's imports and exports (Column 4 and onwards); exposure to offshoring (Column 5); and exposure to routine task content of jobs (Column 6). Robust standard errors clustered at the district level. Regressions weighted by district's share of country's population of working age in 2004. Significance at the 1, 5 and 10 percent levels denoted with ***, ** and *.

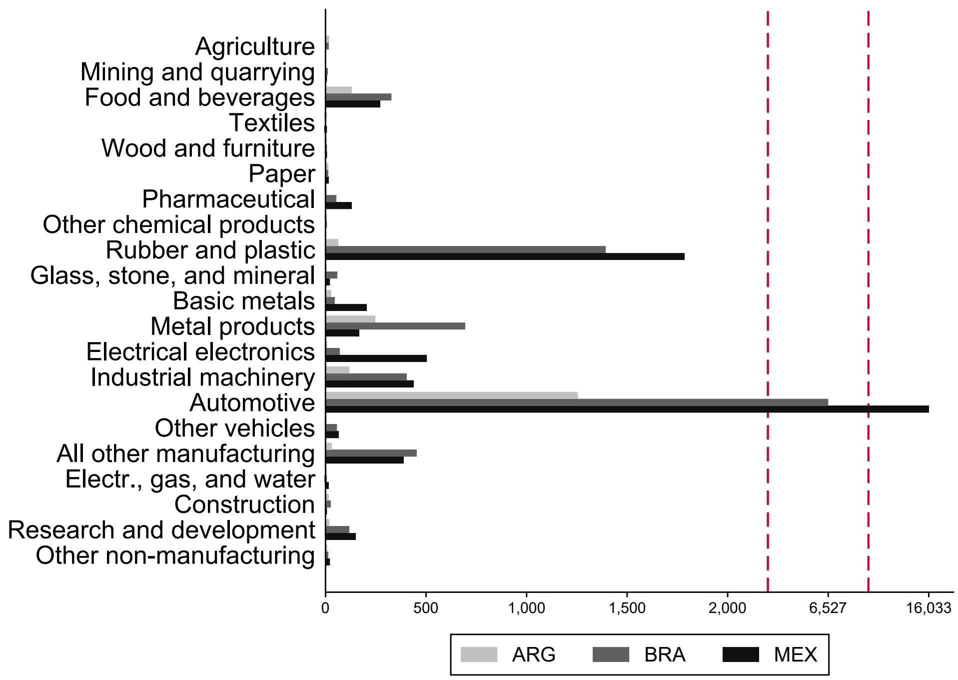
Table 3: Pre-trend tests

	Change in exposure to robots	Change in exposure to robots (IV)	High exposure to robots	High exposure to robots (IV)
Unemployment rate	−0.015	−0.006	−0.003	−0.006
	(0.012)	(0.005)	(0.006)	(0.007)
Labor informality rate	−0.050	−0.010	0.001	−0.002
	(0.098)	(0.025)	(0.019)	(0.018)
Log average wage	−0.056	−0.026	−0.055	−0.046
	(0.178)	(0.068)	(0.036)	(0.042)
Share of non-primary workers	−0.021	−0.004	0.002	0.008
	(0.044)	(0.014)	(0.012)	(0.010)
Exposure to task routinization	−0.002	−0.000	0.004	−0.001
	(0.005)	(0.002)	(0.003)	(0.002)
Share of salaried workers	−0.018	−0.001	0.003	0.011
	(0.038)	(0.013)	(0.013)	(0.007)
Share of semi-skilled workers	0.029	0.011	0.003	0.001
	(0.029)	(0.011)	(0.012)	(0.015)
Share of highly-skilled workers	−0.017	−0.004*	0.000	0.010
	(0.019)	(0.002)	(0.002)	(0.009)
Share of population of working age	0.010	−0.000	−0.003	−0.003
	(0.022)	(0.007)	(0.007)	(0.007)
Observations	88	88	88	88

Notes. All variables are expressed as average annual changes. Each coefficient corresponds to a separate regression. Dependent variables in row panels. Changes in row variables refer to years 1998-2004. Explanatory variables in columns. Changes in column variables refer to years 2004-2016. Column (1): Change in ER; Column (2): Change in ER^{IV}; Column (3): Change in ER above the median; Column (4): Change in ER^{IV} above the median. Regressions control for country fixed effects. Regressions weighted by district's share of country's population of working age in 2004. Robust standard errors clustered at the district level. Significance at the 1, 5 and 10 percent levels denoted with *, ** and *.

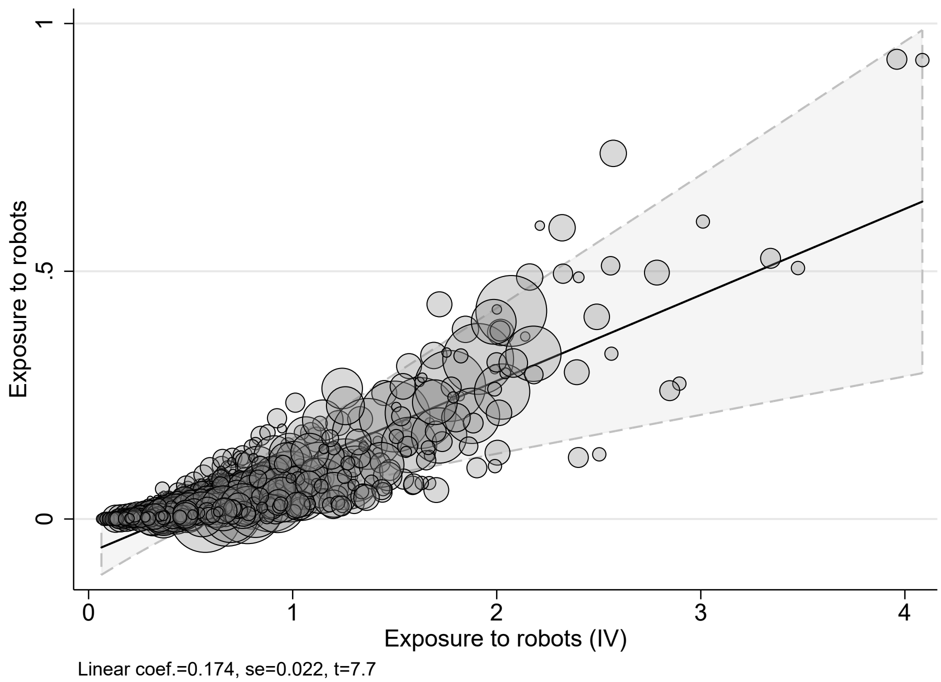
Appendix: Additional figures and tables

Figure A1: Stock of robots by industry



Notes. Own calculations using data from the International Federation of Robotics (IFR). Dotted lines correspond to changes in the axis scale.

Figure A2: First-stage unconditional correlation



Notes. Scatter plot of local exposure to robots on the instrumental variable at the district-year level. The fitted line is a linear prediction of this relation and the shaded area represents the 95% confidence interval. Marker size indicates district's share of country's labor force in 2004.

Table A1: Local labor markets statistics

	Argentina		Brazil		Mexico	
	2004	2016	2004	2015	2004	2016
Employment rate	0.648	0.662	0.673	0.668	0.664	0.703
	(0.041)	(0.050)	(0.038)	(0.035)	(0.035)	(0.027)
Unemployment rate	0.123	0.080	0.098	0.101	0.038	0.035
	(0.031)	(0.024)	(0.025)	(0.020)	(0.012)	(0.010)
Labor informality rate	0.473	0.328	0.306	0.192	0.537	0.591
	(0.074)	(0.070)	(0.081)	(0.066)	(0.093)	(0.097)
Labor informality rate*	0.548	0.428	0.444	0.345	0.602	0.624
	(0.083)	(0.076)	(0.095)	(0.086)	(0.088)	(0.094)
Number of formal salaried jobs	717.3	1140.8	3630.2	5028.2	738.1	856.3
	(615.1)	(1038.7)	(3522.1)	(4793.8)	(620.8)	(661.9)
Number of informal salaried jobs	697.9	604.0	1296.8	946.9	826.7	1189.1
	(666.9)	(602.7)	(1053.0)	(719.6)	(708.1)	(924.1)
Number of self-employment jobs	451.5	524.7	1682.8	1910.7	446.7	479.4
	(399.1)	(493.2)	(1274.1)	(1500.6)	(319.8)	(364.6)
Formal wage	940.5	1181.3	650.6	840.2	871.1	969.1
	(168.0)	(183.1)	(140.5)	(159.7)	(110.8)	(139.7)
Informal wage	481.9	612.6	322.3	478.1	515.5	534.8
	(166.1)	(121.0)	(80.0)	(120.9)	(111.0)	(111.9)
Self-employment income	668.7	760.2	573.2	771.3	580.7	440.1
	(271.8)	(214.5)	(187.7)	(209.9)	(167.8)	(116.7)
Number of districts	29	32	27	27	32	32
Number of individuals	56032	72123	204251	409775	40039	97434

Notes. Own calculations from SEDLAC database. Labor market statistics are restricted to adults under aged 18–65 and represent the country average. Standard deviation in parenthesis. Employment rate is the fraction of employed adults in the total adult population. Unemployment rate is the share of adults in the labor force that have been actively looking for a job in the last month. Labor informality rate is the fraction of unregistered salaried workers. The second definition (*) includes self-employed workers without a tertiary degree as informal. Employment levels are expressed in thousand workers. Monthly wages expressed in constant USD PPP 2011.

Table A2: FE–OLS estimates

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Unemployment rate						
Exposure to robots	0.026*	0.033***	0.041***	0.043***	0.045***	0.046***
	(0.014)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Panel B: Labor informality rate						
Exposure to robots	0.024	0.030	0.047	0.056*	0.061**	0.063**
	(0.028)	(0.030)	(0.032)	(0.031)	(0.028)	(0.028)
Panel C: Log (number of formal salaried jobs)						
Exposure to robots	−0.099	−0.065	−0.125	−0.152**	−0.173**	−0.159**
	(0.079)	(0.077)	(0.081)	(0.074)	(0.070)	(0.066)
Panel D: Log (number of informal salaried jobs)						
Exposure to robots	0.034	0.093	0.110	0.114	0.116	0.136
	(0.106)	(0.097)	(0.103)	(0.105)	(0.101)	(0.100)
Panel E: Log (number of self-employment jobs)						
Exposure to robots	−0.074	−0.004	0.024	−0.012	−0.028	−0.026
	(0.096)	(0.112)	(0.124)	(0.124)	(0.115)	(0.118)
Panel F: Log (average formal wage)						
Exposure to robots	−0.042	−0.110	−0.099	−0.092	−0.072	−0.061
	(0.064)	(0.067)	(0.070)	(0.069)	(0.061)	(0.065)
Panel G: Log (average informal wage)						
Exposure to robots	−0.026	−0.020	−0.019	−0.009	−0.012	0.005
	(0.046)	(0.053)	(0.059)	(0.060)	(0.060)	(0.060)
Panel H: Log (average self-employment income)						
Exposure to robots	−0.143**	−0.172**	−0.051	−0.033	−0.030	−0.022
	(0.072)	(0.080)	(0.082)	(0.070)	(0.066)	(0.067)
Observations	963	963	963	963	963	963
Preexisting trends						
Demographics	Yes	Yes	Yes	Yes	Yes	Yes
Economic conditions	-	Yes	Yes	Yes	Yes	Yes
Automotive industry	-	-	Yes	Yes	Yes	Yes
Trade with China	-	-	-	Yes	Yes	Yes
Offshoring	-	-	-	-	Yes	Yes
Routinization	-	-	-	-	-	Yes

Notes. Analogous to Tables 1 and 2. Regressions run by fixed effect-ordinary least squares (FE–OLS).

Table A3: The effects of robots on employment outcomes

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Employment rate						
Exposure to robots	0.025	0.005	−0.004	−0.008	−0.009	−0.007
	(0.024)	(0.027)	(0.028)	(0.026)	(0.027)	(0.026)
Panel B: Share of formal salaried jobs						
Exposure to robots	−0.043	−0.029	−0.050	−0.052*	−0.056*	−0.054**
	(0.030)	(0.031)	(0.031)	(0.029)	(0.029)	(0.027)
Panel C: Share of informal salaried jobs						
Exposure to robots	−0.004	0.049	0.056	0.056	0.058	0.061
	(0.039)	(0.038)	(0.041)	(0.041)	(0.040)	(0.037)
Panel D: Share of self-employment jobs						
Exposure to robots	0.002	0.010	0.015	0.012	0.009	0.011
	(0.019)	(0.023)	(0.025)	(0.025)	(0.024)	(0.025)
Panel E: Inactivity rate						
Exposure to robots	−0.035	−0.027	−0.020	−0.017	−0.016	−0.020
	(0.025)	(0.028)	(0.029)	(0.028)	(0.028)	(0.027)
Observations	963	963	963	963	963	963
Preexisting trends						
Demographics	Yes	Yes	Yes	Yes	Yes	Yes
Economic conditions	-	Yes	Yes	Yes	Yes	Yes
Automotive industry	-	-	Yes	Yes	Yes	Yes
Trade with China	-	-	-	Yes	Yes	Yes
Offshoring	-	-	-	-	Yes	Yes
Routinization	-	-	-	-	-	Yes

Notes. Analogous to Tables 1 and 2. The employment rate is the fraction of population of working age (18–65) that is employed. The shares of formal salaried jobs, informal salaried jobs and self-employment jobs are calculated on the population of working age. The inactivity rate is the fraction of population of working age that is economically inactive (i.e. out of the labor force).

Table A4: Instrument based on (weighted) average exposure to robots

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Unemployment rate						
Exposure to robots	0.022	0.037***	0.044***	0.046***	0.045***	0.048***
	(0.018)	(0.012)	(0.013)	(0.012)	(0.013)	(0.013)
Panel B: Labor informality rate						
Exposure to robots	0.046	0.054*	0.075**	0.082***	0.081***	0.086***
	(0.030)	(0.029)	(0.031)	(0.031)	(0.030)	(0.030)
Panel C: Log (number of formal salaried jobs)						
Exposure to robots	−0.187*	−0.166	−0.238**	−0.251**	−0.250**	−0.240**
	(0.102)	(0.105)	(0.111)	(0.104)	(0.104)	(0.098)
Panel D: Log (number of informal salaried jobs)						
Exposure to robots	0.020	0.095	0.120	0.130	0.126	0.156
	(0.126)	(0.109)	(0.119)	(0.120)	(0.119)	(0.113)
Panel E: Log (number of self-employment jobs)						
Exposure to robots	0.053	0.139	0.195	0.160	0.132	0.142
	(0.113)	(0.146)	(0.158)	(0.163)	(0.149)	(0.151)
Panel F: Log (average formal wage)						
Exposure to robots	−0.039	−0.095	−0.075	−0.069	−0.068	−0.060
	(0.079)	(0.086)	(0.089)	(0.089)	(0.085)	(0.088)
Panel G: Log (average informal wage)						
Exposure to robots	−0.081	−0.046	−0.053	−0.040	−0.050	−0.037
	(0.061)	(0.066)	(0.076)	(0.080)	(0.084)	(0.076)
Panel H: Log (average self-employment income)						
Exposure to robots	−0.210*	−0.218*	−0.099	−0.077	−0.056	−0.036
	(0.113)	(0.118)	(0.131)	(0.121)	(0.120)	(0.116)
KP F-stat	190.4	191.7	186.6	219.1	187.4	202.4
Observations	963	963	963	963	963	963
Preexisting trends						
Demographics	Yes	Yes	Yes	Yes	Yes	Yes
Economic conditions	-	Yes	Yes	Yes	Yes	Yes
Automotive industry	-	-	Yes	Yes	Yes	Yes
Trade with China	-	-	-	Yes	Yes	Yes
Offshoring	-	-	-	-	Yes	Yes
Routinization	-	-	-	-	-	Yes

Notes. Analogous to Tables 1 and 2. The instrument is based on 22 European countries weighted by industrial composition at the district level as instrument; and exposure to robots at the industry-year level is weighted by the inverse export share of each European country.

Table A5: Instrument based on 5 European countries

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Unemployment rate						
Exposure to robots	-0.002	0.032^{**}	0.029^{*}	0.029^{*}	0.030^{*}	0.033^{**}
	(0.022)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Panel B: Labor informality rate						
Exposure to robots	0.103^{**}	0.090^{**}	0.093^{**}	0.089^{**}	0.090^{**}	0.094^{***}
	(0.047)	(0.041)	(0.039)	(0.036)	(0.035)	(0.036)
Panel C: Log (number of formal salaried jobs)						
Exposure to robots	-0.394^{**}	-0.309	-0.319^{*}	-0.308^{*}	-0.307^{*}	-0.323^{**}
	(0.177)	(0.195)	(0.192)	(0.176)	(0.176)	(0.162)
Panel D: Log (number of informal salaried jobs)						
Exposure to robots	0.031	0.099	0.103	0.095	0.100	0.108
	(0.161)	(0.162)	(0.165)	(0.161)	(0.157)	(0.126)
Panel E: Log (number of self-employment jobs)						
Exposure to robots	0.239	0.358^{**}	0.395^{**}	0.381^{**}	0.374^{**}	0.396^{**}
	(0.174)	(0.183)	(0.177)	(0.181)	(0.174)	(0.177)
Panel F: Log (average formal wage)						
Exposure to robots	-0.094	-0.216^{**}	-0.204^{**}	-0.194^{**}	-0.185^{**}	-0.190^{**}
	(0.090)	(0.094)	(0.094)	(0.093)	(0.094)	(0.096)
Panel G: Log (average informal wage)						
Exposure to robots	-0.182^{*}	-0.127	-0.124	-0.113	-0.113	-0.126
	(0.107)	(0.122)	(0.125)	(0.129)	(0.131)	(0.119)
Panel H: Log (average self-employment income)						
Exposure to robots	-0.152	-0.048	-0.045	-0.003	-0.006	0.015
	(0.213)	(0.201)	(0.200)	(0.176)	(0.176)	(0.155)
KP F-stat	19.7	20.1	25.3	28.3	28.9	29.1
Observations	963	963	963	963	963	963
Preexisting trends						
Demographics	Yes	Yes	Yes	Yes	Yes	Yes
Economic conditions	-	Yes	Yes	Yes	Yes	Yes
Automotive industry	-	-	Yes	Yes	Yes	Yes
Trade with China	-	-	-	Yes	Yes	Yes
Offshoring	-	-	-	-	Yes	Yes
Routinization	-	-	-	-	-	Yes

Notes. Analogous to Tables 1 and 2. The instrument is based on the 5 European countries weighted by industrial composition at the district level as instrument. These 5 countries are the same group used in Acemoglu and Restrepo (2021): Denmark, Finland, France, Italy, and Sweden.

Table A6: Exclusion of outliers in exposure to robots

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Unemployment rate						
Exposure to robots	0.016	0.043**	0.044**	0.041**	0.039**	0.042**
	(0.022)	(0.018)	(0.019)	(0.018)	(0.020)	(0.021)
Panel B: Labor informality rate						
Exposure to robots	0.056	0.080*	0.092**	0.088**	0.086**	0.098**
	(0.046)	(0.045)	(0.045)	(0.043)	(0.042)	(0.043)
Panel C: Log (number of formal salaried jobs)						
Exposure to robots	−0.325**	−0.319*	−0.350*	−0.336*	−0.319*	−0.302*
	(0.161)	(0.191)	(0.195)	(0.181)	(0.182)	(0.176)
Panel D: Log (number of informal salaried jobs)						
Exposure to robots	−0.101	0.053	0.076	0.074	0.083	0.151
	(0.155)	(0.154)	(0.164)	(0.153)	(0.147)	(0.129)
Panel E: Log (number of self-employment jobs)						
Exposure to robots	0.115	0.183	0.210	0.196	0.167	0.205
	(0.173)	(0.190)	(0.209)	(0.214)	(0.200)	(0.214)
Panel F: Log (average formal wage)						
Exposure to robots	−0.011	−0.087	−0.067	−0.058	−0.064	−0.063
	(0.089)	(0.098)	(0.098)	(0.098)	(0.098)	(0.099)
Panel G: Log (average informal wage)						
Exposure to robots	−0.156	−0.073	−0.079	−0.064	−0.061	−0.046
	(0.109)	(0.115)	(0.119)	(0.120)	(0.124)	(0.118)
Panel H: Log (average self-employment income)						
Exposure to robots	−0.192	−0.134	−0.041	−0.020	−0.010	−0.025
	(0.228)	(0.236)	(0.252)	(0.219)	(0.213)	(0.196)
KP F-stat	53.1	49.0	57.0	58.5	58.1	55.6
Observations	943	943	943	943	943	943
Preexisting trends						
Demographics	Yes	Yes	Yes	Yes	Yes	Yes
Economic conditions	-	Yes	Yes	Yes	Yes	Yes
Automotive industry	-	-	Yes	Yes	Yes	Yes
Trade with China	-	-	-	Yes	Yes	Yes
Offshoring	-	-	-	-	Yes	Yes
Routinization	-	-	-	-	-	Yes

Notes. Analogous to Tables 1 and 2. Observations in the bottom and top 1 percent of the distribution of exposure to robots are excluded from the sample.

Table A7: Exclusion of global financial crisis, 2008–2010

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Unemployment rate						
Exposure to robots	0.011	0.029**	0.031**	0.032***	0.032**	0.033***
	(0.017)	(0.012)	(0.013)	(0.012)	(0.012)	(0.013)
Panel B: Labor informality rate						
Exposure to robots	0.050	0.061*	0.081**	0.083**	0.088***	0.090***
	(0.036)	(0.036)	(0.036)	(0.033)	(0.034)	(0.034)
Panel C: Log (number of formal salaried jobs)						
Exposure to robots	−0.198	−0.167	−0.233*	−0.246*	−0.265**	−0.268**
	(0.122)	(0.138)	(0.140)	(0.128)	(0.131)	(0.124)
Panel D: Log (number of informal salaried jobs)						
Exposure to robots	0.012	0.112	0.135	0.127	0.130	0.141
	(0.116)	(0.115)	(0.122)	(0.124)	(0.124)	(0.109)
Panel E: Log (number of self-employment jobs)						
Exposure to robots	0.012	0.118	0.173	0.158	0.140	0.151
	(0.123)	(0.137)	(0.147)	(0.147)	(0.137)	(0.141)
Panel F: Log (average formal wage)						
Exposure to robots	−0.060	−0.137	−0.130	−0.121	−0.106	−0.104
	(0.086)	(0.090)	(0.092)	(0.090)	(0.086)	(0.085)
Panel G: Log (average informal wage)						
Exposure to robots	−0.100	−0.059	−0.057	−0.040	−0.038	−0.039
	(0.070)	(0.085)	(0.095)	(0.096)	(0.099)	(0.091)
Panel H: Log (average self-employment income)						
Exposure to robots	−0.153	−0.111	−0.023	0.010	0.008	0.019
	(0.136)	(0.137)	(0.142)	(0.129)	(0.129)	(0.119)
KP F-stat	51.6	42.3	50.8	56.1	52.9	54.1
Observations	749	749	749	749	749	749
Preexisting trends						
Demographics	Yes	Yes	Yes	Yes	Yes	Yes
Economic conditions	-	Yes	Yes	Yes	Yes	Yes
Automotive industry	-	-	Yes	Yes	Yes	Yes
Trade with China	-	-	-	Yes	Yes	Yes
Offshoring	-	-	-	-	Yes	Yes
Routinization	-	-	-	-	-	Yes

Notes. Analogous to Tables 1 and 2. The years 2008 to 2010 are excluded from the sample.

Table A8: Exclusion of largest districts

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Unemployment rate						
Exposure to robots	0.030**	0.044***	0.045***	0.044***	0.041***	0.044***
	(0.012)	(0.011)	(0.011)	(0.011)	(0.012)	(0.012)
Panel B: Labor informality rate						
Exposure to robots	0.039	0.062*	0.072**	0.072**	0.078***	0.084***
	(0.032)	(0.035)	(0.033)	(0.031)	(0.028)	(0.027)
Panel C: Log (number of formal salaried jobs)						
Exposure to robots	−0.206*	−0.251*	−0.273**	−0.275**	−0.288**	−0.320***
	(0.109)	(0.135)	(0.137)	(0.125)	(0.125)	(0.114)
Panel D: Log (number of informal salaried jobs)						
Exposure to robots	−0.033	0.016	0.038	0.037	0.049	0.046
	(0.122)	(0.120)	(0.124)	(0.127)	(0.124)	(0.109)
Panel E: Log (number of self-employment jobs)						
Exposure to robots	0.142	0.267	0.281*	0.286*	0.271*	0.300*
	(0.124)	(0.164)	(0.162)	(0.160)	(0.163)	(0.168)
Panel F: Log (average formal wage)						
Exposure to robots	−0.043	−0.132	−0.126	−0.121	−0.125	−0.138*
	(0.081)	(0.085)	(0.088)	(0.084)	(0.080)	(0.080)
Panel G: Log (average informal wage)						
Exposure to robots	−0.069	−0.073	−0.068	−0.062	−0.061	−0.067
	(0.063)	(0.096)	(0.102)	(0.104)	(0.109)	(0.103)
Panel H: Log (average self-employment income)						
Exposure to robots	−0.095	−0.073	−0.040	−0.032	−0.028	−0.030
	(0.144)	(0.155)	(0.156)	(0.141)	(0.135)	(0.116)
KP F-stat	49.0	38.3	48.1	53.0	52.4	56.4
Observations	931	931	931	931	931	931
Preexisting trends						
Demographics	Yes	Yes	Yes	Yes	Yes	Yes
Economic conditions	-	Yes	Yes	Yes	Yes	Yes
Automotive industry	-	-	Yes	Yes	Yes	Yes
Trade with China	-	-	-	Yes	Yes	Yes
Offshoring	-	-	-	-	Yes	Yes
Routinization	-	-	-	-	-	Yes

Notes. Analogous to Tables 1 and 2. The largest district of each country is excluded from the sample.

Table A9: Unweighted regressions

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Unemployment rate						
Exposure to robots	0.015	0.027***	0.029***	0.028***	0.027**	0.028**
	(0.015)	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)
Panel B: Labor informality rate						
Exposure to robots	0.045	0.067	0.076*	0.081**	0.085**	0.090***
	(0.044)	(0.044)	(0.042)	(0.037)	(0.036)	(0.031)
Panel C: Log (number of formal salaried jobs)						
Exposure to robots	−0.265***	−0.252**	−0.273**	−0.270**	−0.275**	−0.280**
	(0.093)	(0.123)	(0.119)	(0.117)	(0.118)	(0.115)
Panel D: Log (number of informal salaried jobs)						
Exposure to robots	−0.082	0.018	0.037	0.063	0.074	0.093
	(0.171)	(0.170)	(0.173)	(0.161)	(0.160)	(0.130)
Panel E: Log (number of self-employment jobs)						
Exposure to robots	0.097	0.308**	0.338**	0.319**	0.313**	0.312**
	(0.121)	(0.151)	(0.148)	(0.143)	(0.146)	(0.146)
Panel F: Log (average formal wage)						
Exposure to robots	0.013	−0.016	−0.004	−0.005	−0.000	−0.008
	(0.094)	(0.099)	(0.102)	(0.100)	(0.099)	(0.097)
Panel G: Log (average informal wage)						
Exposure to robots	−0.116	−0.047	−0.052	−0.040	−0.051	−0.045
	(0.085)	(0.109)	(0.117)	(0.112)	(0.116)	(0.108)
Panel H: Log (average self-employment income)						
Exposure to robots	−0.096	−0.019	0.009	0.002	−0.010	−0.035
	(0.134)	(0.154)	(0.151)	(0.140)	(0.133)	(0.133)
KP F-stat	86.6	57.6	75.7	75.0	76.2	73.9
Observations	963	963	963	963	963	963
Preexisting trends						
Demographics	Yes	Yes	Yes	Yes	Yes	Yes
Economic conditions	-	Yes	Yes	Yes	Yes	Yes
Automotive industry	-	-	Yes	Yes	Yes	Yes
Trade with China	-	-	-	Yes	Yes	Yes
Offshoring	-	-	-	-	Yes	Yes
Routinization	-	-	-	-	-	Yes

Notes. Analogous to Tables 1 and 2. Regressions do not include district weights.

Table A10: Summary of Rotemberg weights

Panel A: Negative and positive weights			
	Sum	Mean	Share
Negative	-0.003	-0.001	0.003
Positive	1.003	0.091	0.997

Panel B: Top 5 Rotemberg weight industries				
	$\hat{\alpha}_k$	g_k	$\hat{\beta}_k$	Ind Share
Automotive	0.864	6.462	0.007	1.098
Metal products	0.061	0.723	-0.552	2.165
Rubber and plastic	0.045	0.303	-0.463	2.090
Industrial machinery	0.011	0.418	0.015	0.872
Food and beverages	0.009	0.168	-0.209	4.275

Notes. Statistics for the Rotemberg weights. Statistics correspond to aggregated weights for a given industry across years (Panel B). Panel A reports the share and sum of negative Rotemberg weights. Panel B reports the top five industries with highest Rotemberg weights. The g_k is the national industry exposure to robots, $\hat{\beta}_k$ is the coefficient from the just-identified regression, and Ind Share is the industry share (multiplied by 100 for legibility).

Table A11: Exclusion of districts with greatest importance of automotive

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Unemployment rate						
Exposure to robots	-0.006	0.020	0.027^{*}	0.026^{**}	0.028^{**}	0.028^{**}
	(0.013)	(0.012)	(0.014)	(0.012)	(0.012)	(0.012)
Panel B: Labor informality rate						
Exposure to robots	0.064	0.066	0.080^{*}	0.071	0.078^{*}	0.083^{*}
	(0.043)	(0.046)	(0.046)	(0.045)	(0.044)	(0.044)
Panel C: Log (number of formal salaried jobs)						
Exposure to robots	-0.328^{**}	-0.298^{*}	-0.377^{**}	-0.350^{**}	-0.367^{**}	-0.359^{**}
	(0.138)	(0.174)	(0.177)	(0.169)	(0.169)	(0.155)
Panel D: Log (number of informal salaried jobs)						
Exposure to robots	-0.087	0.020	0.013	0.008	0.027	0.058
	(0.135)	(0.143)	(0.156)	(0.154)	(0.155)	(0.129)
Panel E: Log (number of self-employment jobs)						
Exposure to robots	0.118	0.254	0.148	0.146	0.139	0.160
	(0.145)	(0.156)	(0.163)	(0.162)	(0.164)	(0.163)
Panel F: Log (average formal wage)						
Exposure to robots	-0.009	-0.120	-0.117	-0.114	-0.103	-0.107
	(0.106)	(0.115)	(0.104)	(0.099)	(0.101)	(0.101)
Panel G: Log (average informal wage)						
Exposure to robots	-0.102	-0.109	-0.106	-0.101	-0.104	-0.099
	(0.079)	(0.105)	(0.124)	(0.124)	(0.128)	(0.106)
Panel H: Log (average self-employment income)						
Exposure to robots	-0.129	-0.140	-0.068	-0.037	-0.037	-0.039
	(0.164)	(0.197)	(0.216)	(0.184)	(0.177)	(0.157)
KP F-stat	56.6	47.3	71.1	72.2	77.8	78.6
Observations	901	901	901	901	901	901
Preexisting trends						
Demographics	Yes	Yes	Yes	Yes	Yes	Yes
Economic conditions	-	Yes	Yes	Yes	Yes	Yes
Automotive industry	-	-	Yes	Yes	Yes	Yes
Trade with China	-	-	-	Yes	Yes	Yes
Offshoring	-	-	-	-	Yes	Yes
Routinization	-	-	-	-	-	Yes

Notes. Analogous to Tables 1 and 2. Regressions do not include the two districts of each country with the greatest participation of the automotive industry, which exhibits the highest Rotemberg weight.

Table A12: Inference based on AKM confidence intervals

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Unemployment rate						
Exposure to robots	0.013***	0.031*	0.035	0.036**	0.036***	0.038***
	(0.001)	(0.018)	(0.026)	(0.017)	(0.013)	(0.015)
Panel B: Labor informality rate						
Exposure to robots	0.054***	0.062	0.078	0.080	0.084**	0.087**
	(0.004)	(0.088)	(0.080)	(0.052)	(0.033)	(0.039)
Panel C: Log (number of formal salaried jobs)						
Exposure to robots	−0.219**	−0.179	−0.236	−0.246	−0.260	−0.265
	(0.099)	(0.752)	(0.933)	(0.886)	(0.703)	(0.755)
Panel D: Log (number of informal salaried jobs)						
Exposure to robots	0.006	0.104	0.117	0.114	0.119	0.132
	(0.112)	(0.717)	(0.885)	(0.859)	(0.678)	(0.724)
Panel E: Log (number of self-employment jobs)						
Exposure to robots	0.070	0.163	0.218	0.201	0.180	0.194
	(0.102)	(0.714)	(0.919)	(0.851)	(0.677)	(0.717)
Panel F: Log (average formal wage)						
Exposure to robots	−0.050	−0.129	−0.115	−0.106	−0.096	−0.097
	(0.048)	(0.418)	(0.516)	(0.504)	(0.397)	(0.431)
Panel G: Log (average informal wage)						
Exposure to robots	−0.084*	−0.046	−0.047	−0.037	−0.041	−0.045
	(0.045)	(0.509)	(0.601)	(0.578)	(0.452)	(0.509)
Panel H: Log (average self-employment income)						
Exposure to robots	−0.178***	−0.163	−0.063	−0.032	−0.023	−0.007
	(0.044)	(0.469)	(0.510)	(0.477)	(0.377)	(0.414)
Observations	963	963	963	963	963	963
Preexisting trends						
Demographics	Yes	Yes	Yes	Yes	Yes	Yes
Economic conditions	-	Yes	Yes	Yes	Yes	Yes
Automotive industry	-	-	Yes	Yes	Yes	Yes
Trade with China	-	-	-	Yes	Yes	Yes
Offshoring	-	-	-	-	Yes	Yes
Routinization	-	-	-	-	-	Yes

Notes. Analogous to Tables 1 and 2. The coefficients are the same as in the baseline table. Standard errors are based on Adao, Kolesar and Morales (2019) and clustered at the industry level.

Table A13: Population dynamics

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Log (total population)						
Exposure to robots	−0.072	0.026	0.021	0.017	0.013	0.019
	(0.046)	(0.041)	(0.046)	(0.047)	(0.046)	(0.041)
Panel B: Log (population of working age)						
Exposure to robots	-0.104^{*}	0.003	0.006	0.006	0.001	0.007
	(0.053)	(0.050)	(0.055)	(0.056)	(0.055)	(0.050)
KP F-stat	49.6	39.7	48.0	52.6	49.7	50.9
Observations	963	963	963	963	963	963
Preexisting trends						
Demographics	Yes	Yes	Yes	Yes	Yes	Yes
Economic conditions	-	Yes	Yes	Yes	Yes	Yes
Automotive industry	-	-	Yes	Yes	Yes	Yes
Trade with China	-	-	-	Yes	Yes	Yes
Offshoring	-	-	-	-	Yes	Yes
Routinization	-	-	-	-	-	Yes

Notes. Analogous to Tables 1 and 2.