INFER WORKING PAPER SERIES

INTERNATIONAL NETWORK FOR ECONOMIC RESEARCH

No. 1 | 2023

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The Impact of Local and Foreign Automation on Labor Market Outcomes in Emerging Countries

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Abstract

In the XXI century, the labor market effects of automation have gained significant attention from scholars and policymakers alike. Concerns about potential negative effects are particularly relevant in emerging countries, where a rapid acceleration of robot adoption and an increasing involvement in global value chains have been observed in recent years, with the subsequent increase in exposure to foreign competition. This paper estimates the effect of local and foreign robots on labor market outcomes and labor shares using a panel dataset composed of 16 sectors and ten emerging countries from 2008 to 2014. The endogeneity of robots' adoption is addressed with an instrumental variables approach and using a shift-share index of exposure to foreign robots. The main results for all sectors show that only foreign robot adoption, but not local, has affected employment, whereas no effects on the labor share are found. When exploring sectoral heterogeneity, we find that the foreign robots' negative effect on employment has occurred in many sectors, being more prominent in those with higher exposure to foreign robots. Moreover, we found small and negative spillover effects of robots in other sectors on employment and wages in the newly industrialized countries examined. Finally, the results obtained when examining the sectoral heterogeneity of the effects show that the labor share is also affected in some sectors by both the use of robots in developed and emerging countries.

Keywords: Automation, Robots, Labor markets, Inequality, Emerging countries
JEL Codes: J23, O33, F16

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†Corresponding author: University of Goettingen, Germany and Universidad Jaume I, Spain. Email: imartin@gwdg.de. I would like to thank the participants in the INFER AC celebrated in Lisbon as well as two anonymous referees for their useful comments and suggestions. I also acknowledge the financial support received from Project PID2020-114646RB-C42 funded by MCIN-AEI/ 10.13039 / 501100011033 (Ministerio de Ciencia e Innovación) and Project UJI-B2020-57 (Universitat Jaume I).

1 Introduction

Automation has gained significant attention from scholars and policymakers alike, not only in rich countries but also in emerging countries. This has been especially the case with its strong acceleration after the financial crisis in 2008, intensified with the COVID-19 pandemic in 2020. In this context, some classical concerns about substantial job losses have risen again. Already in the 1930s, John Maynard Keynes made the famous prediction of large technological unemployment (Keynes, 1933) following the adoption of advanced automation technologies. Similarly, Schumpeter (1942) referred to the process of creative destruction associated with technological innovations, which despite the wealth it generates, is often linked to undesired disruptions and changes in the distribution of gains.

In this setting, a fundamental question is what are the consequences of the ongoing automation process for workers in emerging countries, where robots could replace a considerable number of routinary tasks (Schlogl and Sumner, 2020; Lewandowski et al., 2020). For instance, the rapid acceleration of robot adoption could decrease employment and trigger great political instability. These countries substantially differ from OECD countries in terms of the labor market, demographics, and industrial characteristics (Cazes and Verick, 2013). Specifically, occupations of their workers are less skill-intensive, have a large agricultural sector, and lower employment and value-added shares in manufacturing industries. All of these factors could aggravate any distributional impact of automation.

Despite the question's relevance for emerging countries, most of the existing literature investigating the labor market effects of robotization has focused on developed countries. The main theoretical predictions obtained by Acemoglu and Restrepo (2019), in a task-based framework, are that technological progress in automation could have a displacement and productivity effect. The former will mostly affect repetitive tasks, whereas the latter is generated by the increased value-added of workers performing tasks that robots cannot do. If the displacement effect is larger than the productivity effect, labor demand, employment, and wages are expected to decrease. Moreover, an aggregate effect could also emerge through final demand and inter-industry linkages. Concerning foreign robots, Krenz et al. (2021) find that automation in developed countries would reduce offshoring and produce reshoring from emerging countries if the productivity effect is strong enough to reduce the production cost below the wage bill paid in emerging countries. However, Stemmler (2019) documented a potential positive effect of robot adoption in developed countries on employment in emerging countries through the channel of complementarity in the production process between the main plants and the offshored plants.

According to the existent empirical literature, the main findings for developed countries point toward a decline in employment in routine intensive occupations, which sophisticated algorithms and robots can perform (Frey and Osborne, 2017; David and Dorn, 2013). Furthermore, according to Brynjolfsson and McAfee (2011), automation and its effects are no longer restricted to routine manufacturing tasks since even more complex artificial intelligence systems and industrial robots are now used in agriculture, construction, and services.

The only paper focusing partially on the group of emerging countries is, to our knowledge, Carbonero et al. (2020), which addresses the influence of foreign automation –in developed countries– on employment in emerging countries. Although the paper investigates the above-mentioned reshoring channel, it disregards the effects of robot usage on the labor share. A few papers have focused on specific countries (Faber, 2020; Kugler et al., 2020; Stemmler, 2019).

In this paper, we contribute to the existent literature with four novelties. We are the first to study the effects of 'local' robot adoption in a group of emerging countries on employment, wages, and the labor share of income. Second, we also evaluate the effect of foreign robotization -use of robots in the main trade partners of emerging countries- not only on employment and wages [1] but also on the labor share. Third, we present sectoral results to disentangle what are the activities most affected by robot adoption. Finally, the main methodological contribution is that we tackle endogeneity issues using an instrumental variables approach in which our proposed instrument has sectoral variation. More specifically, the empirical application uses a sector-country panel dataset that includes 16 sectors in ten emerging countries -Brazil, Bulgaria, China, India, Indonesia, Mexico, Poland, Romania, Russia, and Turkey- covering the period from 2008 to 2014, and differentiating between the effects of local and foreign robots. We use an instrumental variables method with sectoral-country fixed effects (IV-FE) to address reverse causality while controlling for unobserved heterogeneity at the sector-country level. The stock of robots per 1000 workers from the two countries with the most similar output share are used as instruments for local robots, and an exogenous shift-share index serves to identify the effect of being exposed to foreign robots. The availability of suitable instrumental variables that fulfill the criteria for being valid instruments in the statistical sense leads us to prefer this method over other competing approaches, such as propensity score matching [2].

The main results indicate that, on average, local robots have not negatively affected employment and the labor share in emerging countries, whereas foreign robots have harmed employment. By exploring sectoral heterogeneity, we show that foreign robots' effect on employment has occurred mainly in sectors with higher exposure to foreign robots. Moreover, we find small spillover effects showing that using robots in other sectors reduces employment and wages in the newly industrialized countries examined. Finally, when examining the sectoral heterogeneity of the effects, the results show that the labor share of income is also affected in some sectors by both the use of robots in developed and emerging countries.

Our results have implications for the development policy agenda, given that the effects of automation on employment, wages, and the labor share could hinder the achievement of some of the targets included in the Sustainable Development Goals (SDGs). In particular, governments and international organizations should take the necessary complementary measures to avoid putting at risk the targets of SDG 8 (Decent Work and Economic Growth) and SDG 9 (Reduced Inequality). This paper uses the labor share as a distributive measure

[1] As in Carbonero et al., (2020).

[2] We thank an anonymous referee for pointing this out.

since it represents a good proxy for inequality at the sectoral level, given its high correlation with income inequality at the national level (Jacobson and Occhino, 2012).

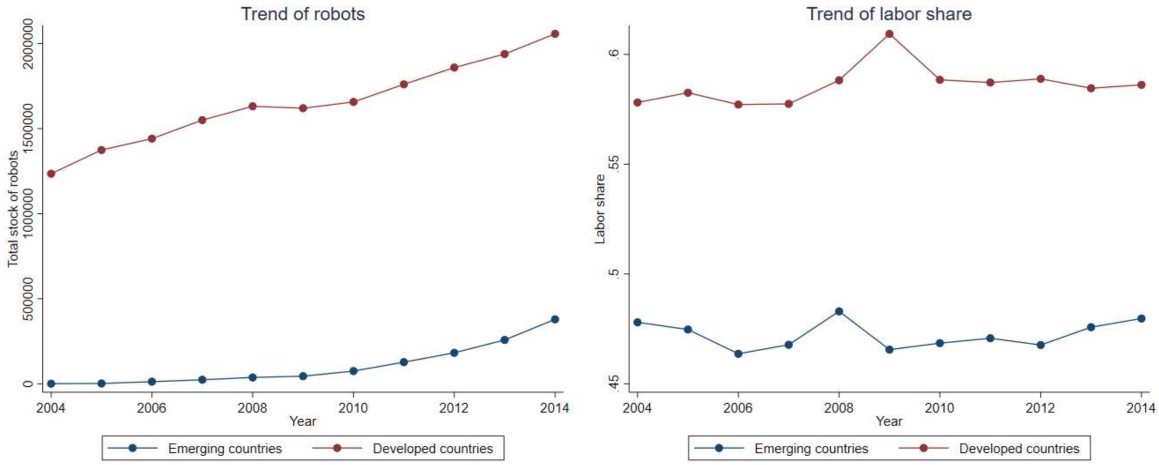
The remainder of the paper is organized as follows. Section 2 presents the aggregate world patterns of automation and the main stylized facts concerning labor market outcomes. Section 3 summarizes the closely related theories and the empirical literature on the labor market effects of automation. Section 4 presents the data and variables, and section 5 outlines the empirical strategy and presents the results and the transmission channels. Finally, Section 6 concludes and outlines some policy implications and avenues for further research.

2 Aggregated trends

This section shows the main aggregate trends of robot adoption, labor share, offshoring, and reshoring for emerging and developed countries. Figure 1 shows the evolution over time of the total stock of robots (left graph) and the labor share (right graph). Regarding robot adoption, the difference between both types of countries is enormous and reflects the fact that automation in emerging countries is a relatively new phenomenon, evolving from no robots in 2004 to nearly 500,000 in 2014, while developed countries had more than one million robots in 2004 and reached nearly two million in 2014. One of the main explanations for the late adoption of robots in emerging countries is that wages in these countries are much lower than in the developed world, implying that automation might be a financially non-viable method in many cases (Mattos et al., 2020).

The labor share has been historically lower in emerging countries. More specifically, it can be observed that in 2004 the sample average of the labor share was around 0.47 in emerging countries and 0.57 in developed countries, while the gap has not been reduced over the years. This high concentration of national value added by capital owners in emerging countries could imply that any potential adverse effect of automation on the labor share might trigger social unrest and political instability in these countries.

Figure 1: Robot adoption and labor shares in emerging and developed countries

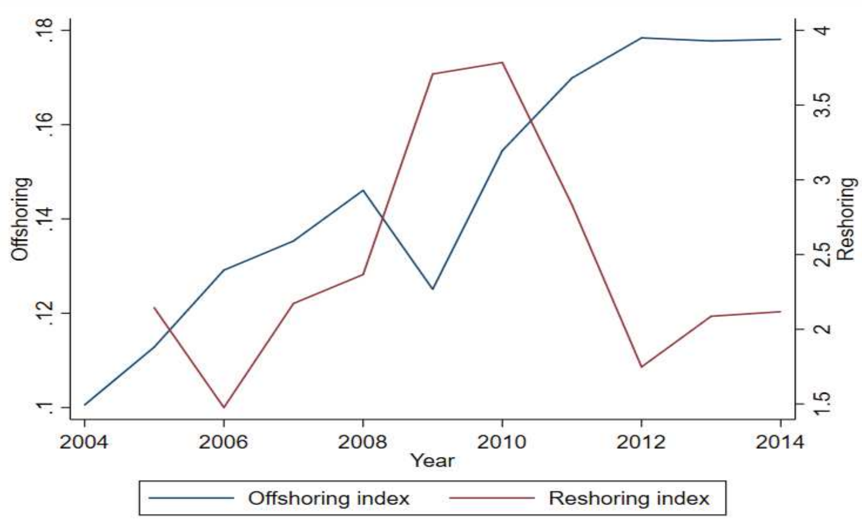


Note: Authors' elaboration using the Socioeconomic Accounts (SEA) of the World Input-Output Database (WIOD).

A channel through which automation in developed countries may pose risks to employment in emerging countries is the disintegration of global value chains due to reduced offshoring or increased reshoring. The former is measured, in line with Feenstra and Hanson (1995), as the ratio of sectoral imports of non-energy inputs of developed countries coming from emerging countries over the total usage of non-energy inputs. The latter is measured as the reshoring index used by Krenz et al. (2021): $R_{sjt} = \frac{D_{sjt}}{F_{sjt}} - \frac{D_{sjt-1}}{F_{sjt-1}}$. D_{sjt} and F_{sjt} represents domestic and foreign inputs, respectively, and the index is restricted to be positive ($R_{sjt} > 0$). The recent development of these measures over time is shown in Figure 2. On the one hand, offshoring from developed countries to emerging countries increased steadily until 2008, decreased abruptly after the financial crisis, and then increased steadily again until 2012. After this year, the index has stayed constant. In the framework of this paper, one of the reasons for the stagnation of the positive trend of offshoring could have been the automation process in developed countries, which might have reduced the incentives to offshore new units of production.

On the other hand, Figure 2 also shows that reshoring from emerging to developed countries has substantially increased during the period 2006-2010, which might be attributed to the financial crisis, but also to other factors in pre-crisis years. After that, the index steadily decreased until 2012 and then slightly increased until 2014. It is interesting to note that the increase of reshoring in 2012-2014 occurred while offshoring was maintained constant, which might represent repatriation of existing production processes and stagnation in the offshore of new processes due to automation in developed countries.

Figure 2: Trends of offshoring and reshoring in developed countries with respect to emerging countries



Note: Offshoring index of Feenstra and Hanson (1995) (left) and reshoring index of Krenz et al. (2021) (right). Authors' elaboration using the World Input-Output Tables (WIOT) of the World Input-Output Database (WIOD).

3 Literature review

3.1 Theoretical framework

The main theoretical basis used in the literature to explain the labor market's effects on local robots is the task-based framework proposed by Acemoglu and Autor (2011). This framework's main innovation is to consider tasks instead of factors of production as the direct component of the production function, while factors of production such as labor and capital are the elements that perform those tasks. In this setting, the production of a pair of shoes, for example, considers different tasks like design, extraction of leather, weaving, and processing, and different non-production tasks like accounting, marketing, transportation, and sales. Each of these tasks can be performed by labor or capital (e.g., industrial robots and software), and automation can displace labor in the performance of certain tasks.

In addition to the seminal paper by Acemoglu and Autor, Acemoglu and Restrepo (2019, 2018) developed a model of automation in the form of industrial robots according to which some tasks are not automated and can only be produced by labor while other tasks are automated and can be produced by capital or labor. A central assumption of the model is that firms' optimal decision is to use capital in all the automated tasks. To analyze the effect of automation, the authors derived the task-content production function as a function of the factors of production involved and the range of tasks. Here, there are two main effects of automation. First, automation shifts the task content of production against labor because it allows capital to perform tasks previously performed by labor; this is known as the "Displacement Effect." Second, automation induces a "Productivity Effect" by increasing the value-added produced by non-displaced labor, fostering labor demand. It is important to notice that additional impacts on the labor market might emerge through final demand for sectoral output and inter-industry linkages. This third positive general equilibrium effect materializes when other industries expand or contract, and aggregated demand varies as a consequence.

It is worth noting that the overall effect of local robots on labor demand depends on the magnitude of the above-mentioned effects. If the displacement effect is larger than the productivity effect and the aggregate net effects are negative, then the net effect on employment and wages could be negative, which is the hypothesis tested in this paper. In this context, it is relevant to test the expected effect of automation on wages and employment of emerging countries, considering some relevant factors such as their low robot adoption and the structural characteristics of their labor markets.

The potential negative effect of developed countries' robots on offshoring toward emerging countries and its adverse effect on employment was theoretically addressed by Krenz et al. (2021), who constructed a model explaining the firms' decision between producing at home or in offshored destinations. This model's main innovation is the consideration that, in developed countries, the firms' strategy of reducing local production costs by adopting industrial robots decreases their incentives to offshore in a global value chain setting. In the model, intermediate inputs can be produced at home by local low-skilled workers and industrial robots or abroad by foreign low-skilled workers in low-wage locations. The main implication is that firms with sufficiently high automation productivity would have lower costs producing at home and hence, prefer this option against offshoring. Since the authors consider exogenous technological progress, another implication is that if technological progress is sufficiently strong to produce high differences between the productivity of automation and the rental rate of robots, then the decrease of offshoring and the reshoring process would increase over time.

Regarding the potential negative effect of automation on emerging countries' labor market outcomes through GVCs, Stemmler (2019) developed a theoretical model based on the model of Acemoglu and Restrepo (2019) and on the induced effect of automation in the United States (US) on Mexican labor markets explained by Artuc et al. (2019) and Caliendo and Parro (2015). The author identifies the channels through which foreign automation would affect Brazil's labor market. For this purpose, he set up a general equilibrium model where local labor markets are defined as Brazilian regions. According to the model, households in a specific region maximize utility by consuming final goods given by a Cobb-Douglas utility function, while firms produce different varieties of intermediate inputs or final goods, which can be sourced internationally subject to trade costs. In developed countries, the main implication is that robots would perform tasks if they are routinary and if automation has a comparative advantage in performing that task relative to labor from emerging countries. It is straightforward to see that sectors and countries with higher wages would be more likely to automate production in such a model since their unit cost of labor is higher.

3.2 Empirical evidence

The empirical evidence of the effects of both local robots' adoption and exposure to foreign robots on labor market outcomes is mixed, with the predominant findings of negative employment effects. A summary of the main outcomes of the existent studies can be found in Table A.1. Although most studies have focused on developed countries, a few studies have analyzed the effect of foreign robots on developing countries' labor markets (Carbonero et al., 2020; Faber, 2020; Kugler et al., 2020; Stemmler, 2019). The methodologies range from local labor market studies to cross-country panel analyses. All these studies address the potential endogeneity of local robots in different ways, such as using instrumental variable strategies, shift-share[3] explanatory variables, or quasi-experimental techniques like propensity score matching. As documented by several authors, the stock of robots is potentially endogenous to local labor market conditions due to reverse causality and time-varying omitted variable bias. Regarding the former, the abundance of workers may decrease the incentive to install robots (Carbonero et al., 2020), but also positive shifts in employment could increase robot adoption due to complementarity effects. Concerning the time-varying omitted variable bias, according to Carbonero et al. (2020) this can come from financial frictions that might

[3] Also known as Bartik measures.

limit both the usage of labor and robots.

Regarding developed countries, Acemoglu and Restrepo (2020), using a local labor market approach for 722 American commuting zones in the US for the period 1990-2007, found that local automation in the US has harmed employment, wages, and labor shares. To address the endogeneity issue, they constructed a shift-share variable consisting of a weighted average of the time-variant industry stock of robots in the US, using the employment share of that industry in a specific commuting zone in a base year as weights. This variable was instrumented using a similar measure constructed with time-variant industrial robots' stocks in the European Union (EU). Another seminal study for developed countries by Acemoglu et al. (2020) analyzed the effect of local automation on labor market outcomes in France. The authors analyze this phenomenon using firm-level data with a sample of 55,390 firms for the period 2010 to 2015 using a similar shift-share approach as in Acemoglu and Restrepo (2020). Moreover, a recent study by Alguacil et al. (2020) shows that robot adoption has had a positive effect on the extensive and intensive margin of exports in Spain due to its positive effect on firm TFP. In the context of our research question, this result indicates that the productivity effect of local robots could be high enough to counteract the displacement effect. Another empirical study focused on the reshoring phenomenon by Krenz et al. (2021) analyzed the effect of automation in developed countries on a sector-country panel setting using a novel measure of reshoring. They addressed endogeneity by instrumenting the sectoral stock of robots with the sum of the sectoral stock of robots of the two countries with the most similar output share, finding a positive and significant effect of automation on reshoring.

The empirical evidence of the impact of automation on labor market outcomes in emerging countries is still scarce and is mainly focused on single-country studies that analyze both the impact of local and foreign automation (Faber, 2020; Kugler et al., 2020; Stemmler, 2019). Some of the studies focusing on the latter impact show evidence indicating that the channel of this effect is through a reduction of offshoring, while other studies find that this happens through reshoring. An exception to the single-country focus is Carbonero et al. (2020), who analyzed the effect of both local and foreign automation on employment in 7 emerging countries in a sector-country panel framework. In their study, the exposure to foreign robots from developed countries is constructed as a trade-weighted average of robots in developed countries. The main findings point towards a negative effect of the use of robots in developed countries on general offshoring [4], concluding that the effect of the exposure to foreign robots on employment in emerging countries is explained by a reduction in offshoring from developed countries.

Concerning the empirical papers that have analyzed both local and foreign robots' effects on specific emerging countries, it is worth focusing on the studies dedicated to the Brazilian, Colombian and Mexican cases. For the case of Mexico, Faber (2020) constructed a measure of exposure to local robots in line with Acemoglu and Restrepo (2020). He also used a novel index of exposure to foreign robots based on robot adoption in a specific industry

[4] Offshoring toward all the countries, not just toward emerging ones.

in the US and interacted with the offshoring participation of Mexico in that industry in a base year. Furthermore, they instrumented changes in the sector-specific stock of robots in Mexico and the US with changes in the number of robots in the rest of the world, finding no effect of local robots on employment in Mexico and a large negative effect of US robots on Mexican employment attributed to reshoring. For the Colombian case, Kugler et al. (2020) found a negative effect of the exposure to robots from the US on local employment by using a shift-share approach. Stemmler (2019) analyzed the effect of both local and foreign automation on labor market outcomes in Brazil for the period 2000-2014 using a local labor market approach to estimate the theoretical model built in the same paper. He constructed the exposure to local robots in line with Acemoglu and Restrepo (2020) and the exposure to foreign robots as in Faber (2020). The author used an Instrumental Variable (IV) approach using the average number of robots in other emerging countries as an exogenous source for robot adoption to address endogeneity. He finds that automation in export destination countries decreased employment in the manufacturing sector in Brazil. As already mentioned in the theoretical section, this channel could be driven by a reduction in employment in operations at the final stages of the GVCs (e.g., assembled cars or shoes), thus indicating that a reshoring process could be operating.

Finally, regarding the specific type of tasks that are at risk of being automated, Weller et al. (2019) used a modified index of the risk of automation for 12 Latin American countries based on the original index of Frey and Osborne (2017) adjusted by the segmentation of labor markets in the region, under the assumption that occupations in the low productivity segments would not be affected by automation[5]. The authors found that the share of jobs at risk of automation decreases from 62% with the original index of Frey and Osborne (2017) to less than 24% with his proposed adjustment. One implication is that, although representing a low share of total employment, sectors that adopt industrial robots in emerging countries have relatively high structural productivity levels. Thus, automation in those sectors has the potential to generate large productivity effects that can counteract the displacement effect.

4 Data and stylized facts

4.1 Data

The data comes from two main sources. The first is The World Input-Output Database (WIOD) [6] from the University of Groningen. The second source is the International Federation of Robotics (IFR) database. More specifically, labor market outcomes (employment and nominal wages per worker), capital outcomes (stock of capital and return to capital), and

[5]The authors show that on average, almost a half of these countries' workers are employed in low productivity sectors, with great differences between countries. For example, the share of workers in low productivity sectors is around 30% in Chile, almost 40% in Uruguay and Argentina, and more than 70% in Bolivia, El Salvador, and Honduras

[6]Although the World Input–Output Database (WIOD) provides annual time-series of world input–output tables available only until 2014, it provides data on factor inputs enlarging the scope of potential applications (Woltjer et al., 2021).

the labor share come from the Socioeconomic Accounts (SEA) of the WIOD at the sector-country level. The stock of industrial robots comes from the IFR database. The SEA and IFR databases are harmonized and merged to obtain a sector-country panel dataset of 16 sectors from 10 emerging countries for 2008-2014, resulting in 160 cross-sectional units and 960 observations. Our sample starts in 2008 because before that year, the stock of robots in emerging countries was almost negligible. Furthermore, the bilateral sector-country trade of intermediate inputs from the World Input-Output Tables (WIOT) of the WIOD is used to construct the offshoring weights and the inshoring index [7].

The automation measure selected is the stock of industrial robots according to the definition of the International Federation of Robotics: "automatically controlled, reprogrammable multipurpose manipulator programmable in three or more axes" (IFR, 2018), and this can be either fixed in place or mobile for use in industrial automation applications. Moreover, industrial robots are "reprogrammable" if they can be designed so that the programmed motions or auxiliary functions can be changed without physical alteration; "multipurpose" if they are capable of being adapted to a different application with physical alteration; while the "axis" characteristic refers to the direction used to specify the robot motion in a linear or rotary mode. Unfortunately, the IFR considers the stock of robots by industry and country without considering their specific quality. Regarding the dependent variables, the employment variable is defined as the total number of employees (in thousands) in each sector; the nominal wage per worker is constructed by dividing the total compensation to workers by the number of workers, and the capital stock is defined in nominal values. Originally expressed in local currency, all the monetary values were converted into international dollars using nominal exchange rates from the International Monetary Fund (IMF).

Regarding the selection of emerging countries, following the World Bank definition, these are defined as countries with a Gross National Income (GNI) per capita lower than 12,536 current international US dollars in 2008, derived by the Atlas method. These countries are Brazil, Bulgaria, China, India, Indonesia, Mexico, Poland, Romania, Russia, and Turkey. While the developed countries considered to compute the bilateral input flows used to construct our indicators are the remaining 30 countries in the WIOD database [8].

The sectoral classification is based on the International Standard Industrial Classification Revision 4 (ISIC-Rev4). We harmonized the WIOD and the IFR sectors to a common level of aggregation in line with Acemoglu and Restrepo (2020). The sectoral categories used to construct the sector-country panel and their ISIC-rev4 code are listed in Table A.2.

As a measure of foreign robot adoption, we construct a modified form of the index of

[7] This inshoring index is in line with Andersson et al. (2017) and controls for the direct effect of inshoring. It is measured as $Inshoring_{sit}=\frac{X_{sit}}{Q_{sit}}$, where X_{sit} represents sectoral exports from sector s of emerging country i to developed countries and Q_{sit} is the total production in this sector.

[8] These countries are Australia, Austria, Belgium, Canada, Switzerland, Cyprus, Czech Republic, Germany, Denmark, Spain, Estonia, Finland, France, Great Britain, Croatia, Hungary, Ireland, Italy, Japan, Korea, Lithuania, Luxembourg, Latvia, Malta, Netherlands, Norway, Portugal, Slovakia, Slovenia, Sweden, and the US.

exposure to foreign robots used in Carbonero et al. (2020), which is a generalization for the cross country case of the index used by Faber (2020) for the offshoring flows from the US to Mexico. The main difference between our index and the one in these studies is that the bilateral weights we apply are offshoring weights and not final goods' trade weights. Hence, these weights accurately represent the structural characteristics of the transactions in intermediate inputs used in production, which according to the literature review, is the channel by which automation in developed countries might affect labor market outcomes and the labor share in emerging countries.

The exposure to foreign robots index is a shift-share measure [9] that takes the following form:

$$ExposureForeignRobots_{sit} = \sum_{i=1}^{I} w_{sij2004} * Robots_{sjt} \tag{1}$$

where $w_{sji2004}$ are weights representing the participation of sector s of emerging country i in the production process of developed country j in the base year 2004. These weights are calculated as $w_{sji2004} = \frac{X_{sij2004}}{X_{si2004}}$. Specifically, they represent the ratio of exports of non-energy inputs from sector s of emerging country i used in the production of all sectors of developed country j over the total exports of non-energy inputs of sector s of emerging country i. The base year of 2004 is used to avoid a potential endogeneity problem generated by reverse causality (e.g., an increase in employment in emerging countries might increase offshored firms' production, thus increasing intermediate inputs exported to developed countries). Since the sample period began in 2008, it is reasonable to think that any persistence in the effect of employment on offshored production in 2004 vanishes over time.

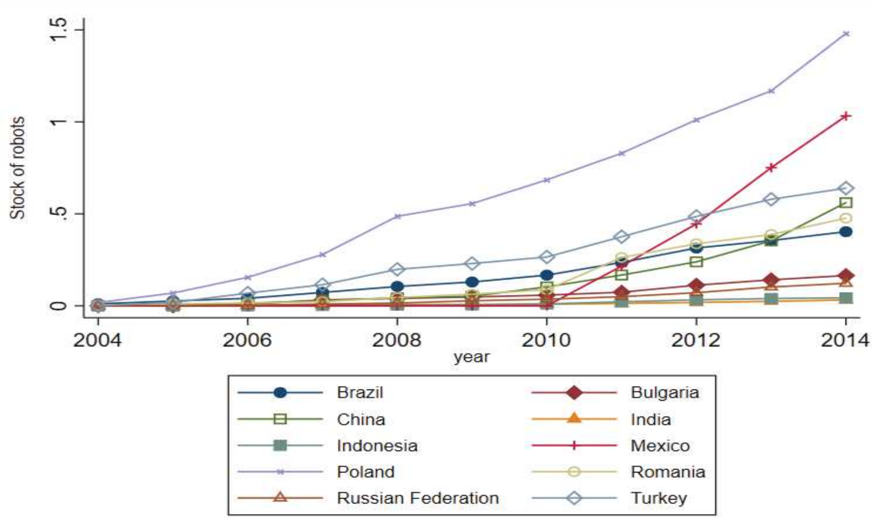
4.2 Stylized facts

Figure 3 shows the evolution of the stock of robots per 1000 workers for the selected emerging countries. The figure shows that Poland has been by far the country with the highest robot-use intensity during the whole period reaching a maximum of nearly 1.5 robots per 1000 inhabitants. The next two countries in the ranking until 2010 were Turkey and Brazil, respectively, which were surpassed by Mexico in 2012-2013 [10], which positioned itself as the second in the ranking. Another striking feature is China's quick catch-up from 2008, positioning itself as the fourth country with the highest robot intensity in 2014. Another country with relatively high robot intensity is Romania, the top fifth in terms of robot intensity in 2014, surpassing Brazil. Meanwhile, India and Indonesia have the lowest robot intensity in our sample. To better observe the dynamics of the countries with lower robot adoption, Figure A.1 depicts the same trend, excluding Poland (the country with the highest robot adoption per 1000 workers).

[9] Also called Bartik measure.

[10] In the IFR database, information for Mexico and Canada is lumped together under "North America" before 2011. Therefore, our panel is unbalanced since does not have observations for Mexico before 2011.

Figure 3: Evolution of the stock of industrial robots per 1000 workers in emerging countries

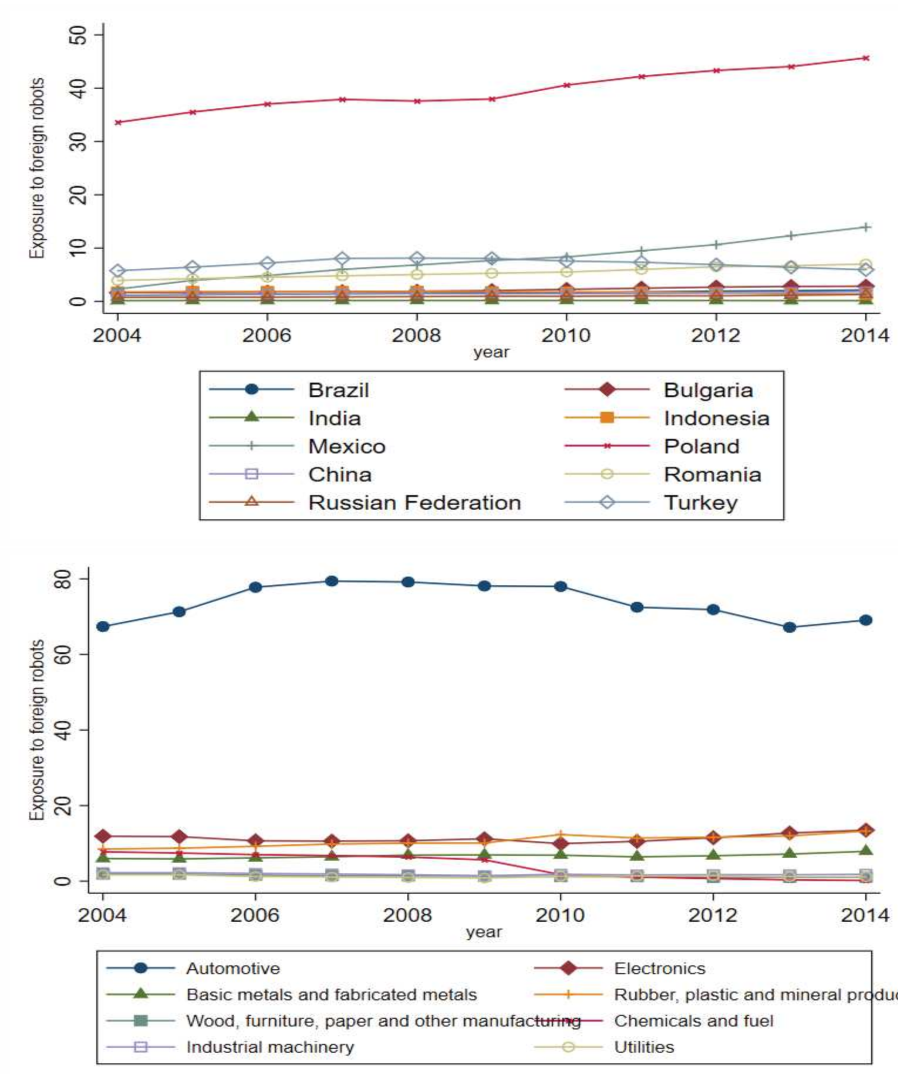


Note: Authors' elaboration using the International Federation of Robotics database. Stock of robots per 1000 workers.

The other side of the coin is exposure to foreign robots. Figure 4 shows the evolution of the aggregated exposure to foreign robots by country and sector for the top 8 sectors. A striking feature is that Poland is by far the country with the highest exposure to foreign robots, which can be explained by its vast participation in offshoring activities from countries with a high stock of robots like Germany. In descending order, other emerging countries with high levels of exposure to foreign robots are Mexico, Romania, and Turkey.

Regarding the sectoral exposure to foreign robots, it can be seen that the "Automotive" sector is the more exposed, followed by "Electronics," "Rubber, plastic and mineral products," and "Basic metals and fabricated metals." In those cases, the value of the overall index is driven by the high stock of robots in those sectors used in developed countries. To better observe the dynamics of the countries with lower exposure to foreign robots, Figure A.2 depicts the same trend, excluding Poland.

Figure 4: Evolution of the exposure to foreign robots per 1000 workers in emerging countries



Notes: Authors' elaboration using the International Federation of Robotics (IFR) database and the World Input-Output Database (WIOD). Upper graph: By emerging country. Lower graph: By sector (Considering the eight sectors with higher exposure to foreign robots). Exposure to foreign robots is calculated according to Eq. (1) and corresponds to the total stock of exposure per 1000 workers.

Table 1 shows the descriptive statistics of the main variables used in the empirical model. The definitions, measurement units, and sources of the variables can be found in Table A.3.

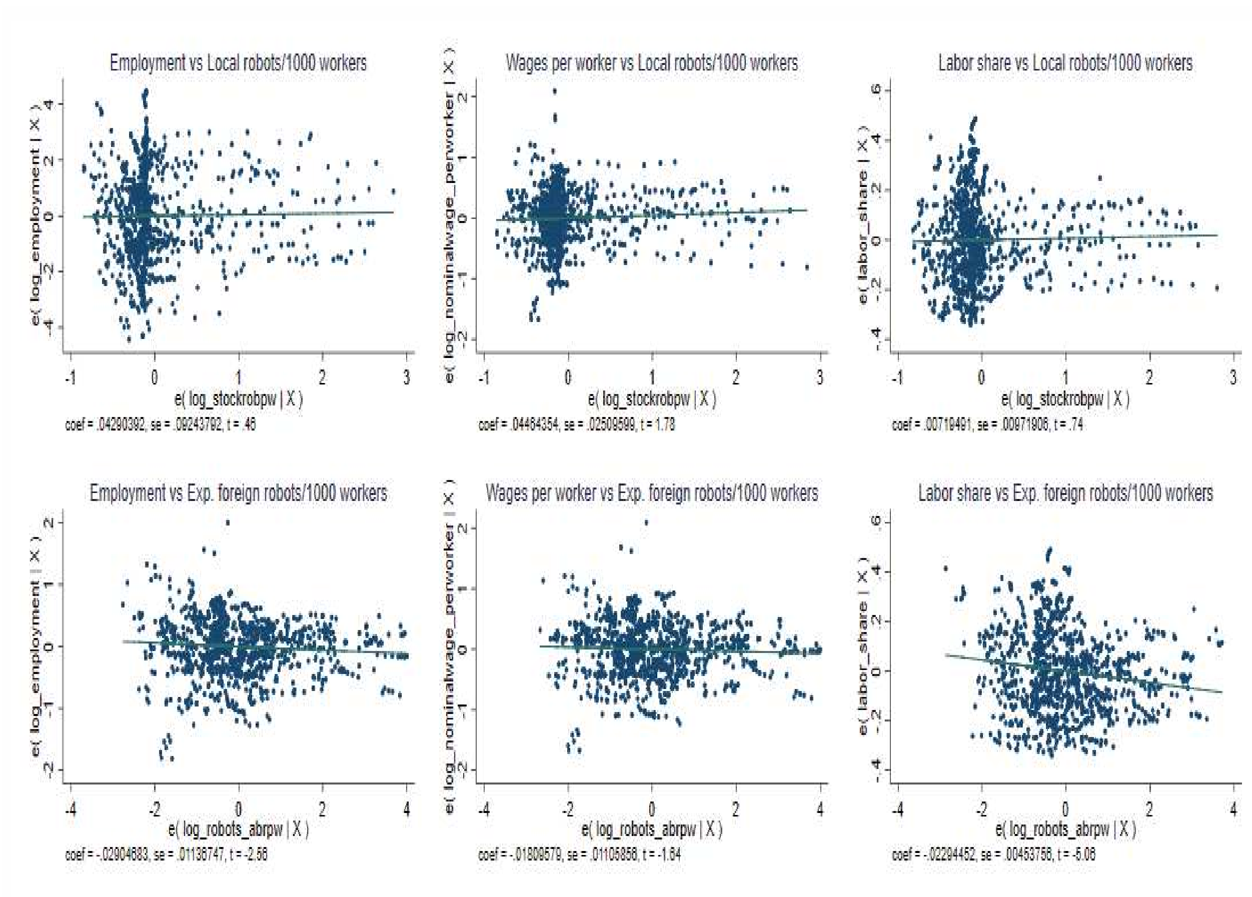
Table 1: Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Employment	1,105	7122	28605	6.69	295008
Local robots per thousand workers	1,105	0.7	2.37	0	26.3
Exposure to foreign robots per thousand workers	1,105	18	76.53	0	924
Value added	1,105	85474	196746	84	1916260
Nominal wage per worker	1,105	19145	39850	397	326655
Inshoring	1,105	0.2	0.24	0	1
Labor share	1,087	0.47	0.19	0.064	0.99
Capital/output	1,087	1	0.95	0.0152	8.35
Relative price of capital	1,087	0.00012	0.00023	0	0.003

Notes: The number of observations is lower for Labor share, Stock of capital, Return of capital, and Capital/output because some inconsistent observations showing negative compensation of capital were dropped in the estimations.

The conditional correlations between the variables of interest are computed after estimating three models by Pooled Ordinary Least Squared regression (OLS). Employment, nominal wage per worker, and the labor share are used as dependent variables, and local robots and exposure to foreign robots are the targeted explanatory variables (both per thousand workers). Sectoral value-added and the inshoring index are included as control variables in the employment and wage regressions, while the ratio capital/output and the relative price of capital are included in the labor share regressions. The corresponding scatter plots, and the predicted fits are shown in Figure 5. Regarding employment, it can be observed that it is negatively correlated almost at 1% of significance level (t-statistics of 2.56) with exposure to foreign robots, while there is no evident correlation with local robots. Furthermore, the nominal wage per worker is negatively correlated almost at 10% of significance level with exposure to foreign robots, with a coefficient of -0.018; and positively correlated with local robots at a 5% level, with a coefficient of 0.04. Finally, the correlation between the labor share and exposure to foreign robots is negative and significant at a 1% level, with a coefficient of -0.022.

Figure 5: Conditional correlations between labor market outcomes and industrial robots



Notes: All variables in logs except the labor share. Scatter plot and predicted fit resulting from an OLS regression of labor market outcomes on both local robots and exposure to foreign robots, including sectoral value-added and the inshoring index as control variables in the employment and wage regressions, and the ratio capital/output and the relative price of capital in the labor share regression.

The negative correlation of the exposure to foreign robots with wages, employment, and the labor share might be a sign of automation inducing a reduction in offshoring. The empirical section will disentangle whether these correlations indicate the presence of a causal effect.

5 Empirical strategy

5.1 Model specification

The employment and wage equations are derived assuming a standard Cobb-Douglas specification in the same vein as in Carbonero et al. (2020). This specification is also a sectoral adaptation of the labor demand function estimated in Gregory et al. (2016)[11]. Specifically, a representative sector s in country i maximize the following profit function in year t:

[11] Gregory et al. (2016) used tasks instead of sectors.

$$\phi_{sit} = pQ_{sit} - w_{sit} * Emp_{sit} - r_{sit} * K_{sit}, \quad with \;\; Q_{sit} = AEmp_{sit}^{\alpha} * K_{sit}^{1-\alpha} \tag{2}$$

Where p, Q, w, Emp, r and K represent output price, output, nominal wage per worker, employment, return of capital and stock of capital respectively. Optimizing this profit function with respect to employment, log-linearizing and expressing the equation in regression format gives[12]:

$$ln(Emp_{sit}) = \beta_3 ln(Q)_{sit} + \beta_5 ln(w)_{sit} + \epsilon_{sit} \tag{3}$$

Following the theoretical framework of section 3, we include two key variables that affect labour demand: the log of local robots per thousand workers and the log of the exposure to foreign robots per thousand workers. The first representing a local technological factor and the second an external factor. In addition, value added is included instead of output, as it can more accurately measure the economic performance of sectors. This new equation takes the following form:

$$\begin{aligned} ln(Emp_{sit}) = {} & \beta_1 ln(LocalRobotspw)_{sit} + \beta_2 ln(ExposureForeignRobots)_{sit} + \beta_3 ln(VA)_{sit} \\ & + \beta_4 ln(Inshoring)_{sit} + \beta_5 ln(X)_{sit} + \gamma_{si} + \lambda_t + \epsilon_{sit} \end{aligned} \tag{4}$$

where Emp_{sit} refers to employment in sector s, country i and year t. Alternatively, nominal annual wage per worker is also used as a dependent variable. $LocalRobotspw_{sit}$ denotes the stock of local robots per thousand workers in sector s and country i at year t. Similarly, and for the same units of analysis, $ExposureForeignRobots_{sit}$ denotes the exposure to foreign robots proxied by the index given by Equation 1, while the explanatory variables are sectoral value-added (VA), which control for output supply factors; the inshoring index of Andersson et al. (2017) that controls for the direct effect of inshoring [13] flows on labor demand, and X_{sit}, which includes nominal annual wage per worker for the employment equation and total employment for the wage equation. Finally, γ_{si} measures sector-country fixed effects and controls for any sectoral heterogeneity specific to each country that is constant over time; while λ_t measures year fixed effects that account for any yearly shocks common to every sector and country. The inclusion of sector-country FE could be considered a proxy for labor market conditions and quality of institutions (these proxied variables have country or sectoral-country variation and do not vary much over short periods). In this equation, we expect a negative sign of both β_1 and β_2 due to the displacement effect of local robots for the former and the reshoring effect of foreign robots for the latter. However, we also expect β_1 to be low or negligible given the low robot adoption in emerging countries and the counteracting productivity effect of robots that might cancel out the displacement effect.

[12] Output prices are normalized to 1

[13] Measured as $Inshoring_{sit}=\frac{X_{sit}}{Q_{sit}}$, where X_{sit} represents sectoral exports from sector s of emerging country i toward developed countries and Q_{sit} is the total production of this sector.

Ideally, we would like to account for human capital in the production function, but this is not possible due to a lack of data[14]. We abstract from product demand dynamics since the paper's focus is to compare the effects of local and foreign automation through their specific impacts on the labor market. By assuming market equilibrium in the product market, the inclusion of value-added in equation 7 helps us to control for any demand factor related to both robots and employment (like the increase in output demand following automation (Bessen, 2019)).

The next specification assesses industrial robots' impact on the labor share, which is our distributive measure. Whereas Autor and Salomons (2018) estimated the effect of industrial robots on the labor share using derivations from aggregated production functions, we used the approach of Karabarbounis and Neiman (2014), which derives the determinants of the labor share from a general equilibrium model considering a CES production function. In the model, the labor share depends on the mark-up charged by firms, capital intensity, and the relative price of capital. Therefore, our labor share equation takes the following form:

$$\begin{aligned} LaborShare_{sit} = {} & \delta_1 ln(LocalRobotspw)_{sit} + \delta_2 ln(ExposureForeignRobots)_{sit} + \delta_3 ln(\frac{K}{Y})_{sit} \\ & + \delta_4 ln(\frac{r}{w})_{sit} + \delta_5 ln(VA)_{sit} + \phi_{si} + \theta_t + \nu_{sit} \end{aligned} \tag{5}$$

where $LaborShare$ is the labor share in sector s and country i at year t, defined as the share of total value added that goes to workers. The control variables, all in natural logarithms, are the ratio capital/output (K/Y), which is a proxy for capital intensity; the ratio of the return of capital over the nominal wage per worker (r/w), indicating the relative price of capital, and total value-added (VA) as a proxy for the mark-up charged by firms. As before, sector-country, ϕ_{si}, and year FE, θ_t, are included as co-variates to proxy for unobserved heterogeneity. It is worth noting that the potential reduction of offshoring or reshoring associated with the exposure to foreign robots could trigger a reduction of both labor and capital, maintaining the labor share constant. Therefore, two additional models are estimated to account for the effect of automation on the stock and return of capital. The functional form of these models is similar to Equation 7 but with the stock of capital and return of capital as dependent variables and with the control variable X_{sit}, representing the return of capital for the former and the stock of capital for the latter equation.

5.2 Instrumental variables approach

The stock of local robots could be endogenous for several reasons. First, there could be a reverse causality issue. Notably, an increase in employment could generate an increase in robot adoption because some workers and robots might complement each other; also, labor-intensive sectors may have fewer incentives to adopt robots because of the innate characteristics of their production process (e.g., low value-added and extractive activities).

[14]The latest version of the WIOD database (2016) does not have measures of sectoral human capital.

Second, there specific sector-country shocks could affect both robot adoption and labor market outcomes, such as technological shocks (e.g., the invention of a new and more efficient engineering process in the Mexican electronic sector).

These endogeneity issues are addressed by using an instrumental variables approach. Specifically, we instrument local sectoral robots per 1000 workers with the sectoral robots per 1000 workers from the two countries with the most similar output share. The main idea is that these countries would benefit to similar degrees from sector-specific technological progress in automation, which is the exogenous innate determinant of automation (Zeira, 1998; Acemoglu and Restrepo, 2018). As a mode of illustration, Figure A.3 shows the sectoral output structure of Mexico and the two most similar countries: Canada and the US. In this illustration, the log of the sectoral robots per thousand workers of the US and Canada are used as instruments for the same variable in Mexico. Formally, for each sector s, emerging country i and year t, we have two instrumental variables:

$$ln(RobotsIV_1 srt) = ln(\frac{RobotsStock_{srt}}{EMP_{srt}}) \tag{6}$$

$$ln(RobotsIV_2 slt) = ln(\frac{RobotsStock_{slt}}{EMP_{slt}}) \tag{7}$$

where r and l represent the countries with the closest output share to emerging country i. The empirical models outlined in the previous sub-section are estimated by Two-Stage Least Squares (2SLS). Given that this strategy is applied to the demeaned form of the equations of interest, the corresponding estimator is an IV-FE.

This strategy would successfully account for endogeneity and produce consistent estimators if the instruments are relevant and exogenous (Greene, 2008). Regarding the former condition, as shown in Table 2, the first stage regressions for the specifications of employment, nominal wage per worker, and labor share report a strong positive correlation between the instruments and the log of local robots per worker. In particular, the two instruments' coefficients are positive and statistically significant at the 5% and 1% significance levels. Moreover, the F-test values reported in the last row of Table 2 indicate that the instruments are relevant in all three estimations [15].

[15] A standard criterion to decide if an instrument is not weak is to look at the F-test of the first stage regression (Schmidheiny, 2015). As a rule of thumb, if the F-test is higher than 10, the instrument is considered relevant. The Kleibergen-Paap rk Wald F statistic is reported.

Table 2: First stage results of the Intstrumental Variables estimation

	(1) Employment specification b/se	(2) Wage specification b/se	(3) Labor share specification b/se
ln(Robots IV 1)	0.146**	0.146**	0.140**
	(0.060)	(0.061)	(0.060)
ln(Robots IV 2)	0.403***	0.401***	0.404***
	(0.153)	(0.153)	(0.150)
ln(Exposure to foreign robots per worker)	-0.151*	-0.139	-0.162*
	(0.090)	(0.091)	(0.096)
ln(Value added)	0.150*	0.125*	0.121
	(0.076)	(0.073)	(0.104)
ln(Nominal wage per worker)	-0.016		
	(0.062)		
Inshoring index	0.320	0.328	0.298
	(0.297)	(0.295)	(0.303)
ln(Employment)		0.087	
		(0.069)	
ln(Capital/output)			-0.164
			(0.110)
ln(Relative price of capital)			-0.031
			(0.028)
Year FE	Yes	Yes	Yes
Observations	1105	1105	1087
R-squared	0.462	0.464	0.470
F test	23.12	22.60	21.43

Notes: ***, **, * denote statistical significance at the 0.01, 0.05 and 0.10 level, respectively. Clustered standard errors (SE) in parenthesis. The dependent variable is the stock of robots per thousand workers in all models.

Regarding the exclusion restriction, it is reasonable to think that robot adoption in other countries with similar output structures is not correlated with local labor market outcomes of emerging countries other than through the common exogenous technological progress in automation that also affects local robots in emerging countries. In fact, many related papers have used the stock of robots of other countries as instruments; for example, Acemoglu and Restrepo (2020) and Micco et al. (2019) used the sectoral penetration of robots in European countries that are ahead of the US in robotics as an instrument for the exposure to robots in the US. To provide further evidence of the exogeneity of the instruments, we performed the Hansen test of overidentifying restrictions, in which the null hypothesis of exogeneous instruments was not rejected (p-value of 0.69 for the employment specification and 0.31 for the labor share specification), hence, supporting our identification strategy.

The second stage regression for the employment equation takes the following form:

$$
\begin{aligned}
ln(Emp_{sit}) = {} & \beta_1 ln(\widehat{LocalRobots})_{sit} + \beta_2 ln(ExposureForeignRobots)_{sit} + \beta_3 ln(VA)_{sit} \\
& + \beta_4 ln(Inshoring)_{sit} + \beta_5 ln(X)_{sit} + \gamma_{si} + \lambda_t + \epsilon_{sit}
\end{aligned}
\tag{8}
$$

where $ln(Emp_{sit})$ is the natural log of employment (alternatively nominal wages per worker). While $ln(\widehat{LocalRobots})$ represents the predicted values estimated in the first stage, and X_{sit} refers to the control variables. While for the labor share (equation 5), the second stage regression takes the following form:

$$
\begin{aligned}
LaborShare_{sit} = {} & \delta_1 ln(\widehat{LocalRobots})_{sit} + \delta_2 ln(ExposureForeignRobots)_{sit} + \delta_3 ln(\frac{K}{Y})_{sit} \\
& + \delta_4 ln(\frac{r}{w})_{sit} + \delta_5 ln(VA)_{sit} + \phi_{si} + \theta_t + \nu_{sit}
\end{aligned}
\tag{9}
$$

where $ln(\widehat{LocalRobots})$ represents the predicted values estimated in the first stage, and the other variables have been defined above.

5.3 Main results

This section presents and discusses the main results obtained by estimating each model with the corresponding dependent variable. Table 3 reports the FE and IV-FE results for the employment variable in columns (1) and (2), the wage variable in columns (3) and (4), and the labor share in columns (5) and (6). Each estimation includes sector-country FE and year dummies, while the standard errors are clustered at the sector-country level to address autocorrelation and heteroskedasticity.

Regarding the employment specification, it can be observed that local robots do not affect employment, with all the control variables having the expected sign. On the other hand, exposure to foreign robots has a negative and significant impact, with a coefficient of -0.10 in the FE estimation (significant at the 5% level). The magnitude and significance of the effect remain almost unchanged in the IV-FE estimation (column (2)), indicating that an increase of 10% in the index of exposure to foreign robots in a specific sector leads ceteris paribus (c.p.) to a decrease of 1.03% on employment in that sector. This result could be driven by the reshoring effect (Krenz et al., 2021) or by a reduction in offshoring (Carbonero et al., 2020). In contrast, neither local nor foreign robots affect the nominal annual wage per worker and the labor share. As a robustness check and to address the potential non-stationarity of the explanatory variables, we replicated the estimations using a first difference method, obtaining qualitatively similar results, as shown in Table A.4. The results for employment are qualitatively similar (negative and statistically significant effect of exposure to foreign robots on employment, columns (1) and (2)). A positive and significant effect of local robots is observed (column (3)), which vanishes in the IV specification (column

(4)). The only noticeable difference is that there is a negative and significant effect of the exposure to foreign robots on the labor share in both the FD and IV-FD specifications (columns (5) and (6)). These are in line with results shown in the next sub-section (Table 5, column (3)), which reports the negative effects of the exposure to foreign robots on the labor share in some sectors.

Table 3: Effect of automation on labor market outcomes in emerging countries

	ln(Employment)		ln(nominal wage per worker)		Labor share	
	(1)	(2)	(3)	(4)	(5)	(6)
	FE	IV-FE	FE	IV-FE	FE	IV-FE
ln(Local robots per worker)	0.037	0.040	0.006	-0.020	0.007	0.010
	(0.024)	(0.047)	(0.033)	(0.053)	(0.005)	(0.011)
ln(Exposure to foreign robots per worker)	-0.102**	-0.103**	-0.010	-0.005	-0.013	-0.014
	(0.040)	(0.044)	(0.042)	(0.046)	(0.009)	(0.010)
ln(Value added)	0.368***	0.368***	0.404***	0.407***	-0.091***	-0.092***
	(0.078)	(0.076)	(0.096)	(0.097)	(0.012)	(0.012)
ln(Nominal wage per worker)	-0.512***	-0.512***				
	(0.076)	(0.074)				
Inshoring index	-0.146	-0.148	-0.186	-0.175	-0.014	-0.015
	(0.111)	(0.112)	(0.129)	(0.128)	(0.033)	(0.032)
ln(Employment)			-0.629***	-0.625***		
			(0.101)	(0.102)		
ln(Capital/output)					-0.103***	-0.102***
					(0.015)	(0.015)
ln(Relative price of capital)					-0.138***	-0.138***
					(0.012)	(0.012)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1105	1105	1105	1105	1087	1086
R-squared	0.490	0.490	0.611	0.610	0.747	0.747

Notes: ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 level, respectively. Clustered SE in parenthesis. Local robots and exposure to foreign robots are expressed per thousand workers.

As shown in Figure 4, Poland is an outlier regarding the exposure to foreign robots indicator, with a value that is almost double that in the other emerging countries. Therefore, as a robustness check, we re-estimated the equations of Table 3 excluding Poland. The results of these regressions are shown in Table A.5 and indicate that the effect of the exposure to foreign robots remains almost unchanged. This outcome indicates that the effect on employment is not driven by Poland and its high exposure to foreign robotization. When excluding Poland, the magnitude of the negative coefficient of the exposure to foreign robots slightly increases in magnitude (-0.111 vs. -0.103), being statistically significant at the 5% level, as in the main results. The effects on nominal wages and labor shares remain non-statistically significant.

The lack of statistical significance of the effect of foreign robots on the labor share could be seen as counterintuitive, given the negative effect of the exposure to foreign robots on employment reported in columns (1) and (2) of Table 3. Indeed, it could be that there is a simultaneous reduction of capital equipment following automation, which could increase the labor share. Hence, it is relevant to see the potential effect of the exposure to foreign robots on capital stock and return of capital. This is shown in Table A.6, which reports the results of regressing both the log of capital stock and the log of return to capital on the log of the exposure to foreign robots. The results discard any potential effect of the exposure to foreign robots on capital outcomes.

Next, Table 4 shows the results of the potential spillover effects derived from the use of local robots in other sectors[16]. The estimated coefficients for the newly added variable are negative, small and statistically significant in both models, FE and IV-FE for the employment and wage specifications in columns (1)-(4), respectively. On the other hand, the coefficient of the spillover indicator is not statistically significant in the labor share specification. In summary, we observe a small negative spillover effects of robot adoption on employment and wages. We argue that these effects might be due to either competition in the labor market or the product market. In the labor market, higher robot adoption could increase the demand for complementary workers (high skilled workers), hence, attracting workers from other sectors. In the product market, robot adoption could make some sectors more productive and hence more competitive, affecting the output and employment of other sectors (in line with Acemoglu et al. (2020)). However, and regarding the spillover effects of robot adoption on employment, its magnitude is considerably low relative to the effect of the exposure to foreign robots (representing just an 8% of this effect), and hence, does not deserve particular attention.

Table 4: Effect of automation on labor market outcomes in emerging countries

	ln(Employment)		ln(nominal wage per worker)		Labor share	
	(1)	(2)	(3)	(4)	(5)	(6)
	FE	IV-FE	FE	IV-FE	FE	IV-FE
ln(Local robots per worker)	0.042*	0.048	0.015	-0.007	0.008*	0.012
	(0.023)	(0.048)	(0.032)	(0.054)	(0.005)	(0.011)
ln(Exposure to foreign robots per worker)	-0.099**	-0.100**	-0.005	-0.002	-0.012	-0.013
	(0.040)	(0.043)	(0.042)	(0.046)	(0.009)	(0.010)
ln(Spillover indicator)	-0.008*	-0.009**	-0.014***	-0.013***	-0.002	-0.002
	(0.004)	(0.004)	(0.004)	(0.005)	(0.001)	(0.001)
ln(Value added)	0.370***	0.369***	0.406***	0.408***	-0.091***	-0.092***
	(0.078)	(0.077)	(0.096)	(0.097)	(0.012)	(0.012)
ln(Nominal wage per worker)	-0.515***	-0.515***				
	(0.076)	(0.074)				
Inshoring index	-0.158	-0.161	-0.205	-0.194	-0.016	-0.018
	(0.111)	(0.112)	(0.127)	(0.128)	(0.033)	(0.032)
ln(Employment)			-0.630***	-0.626***		
			(0.101)	(0.102)		
ln(Capital/output)					-0.104***	-0.103***
					(0.015)	(0.015)
ln(Relative price of capital)					-0.138***	-0.138***
					(0.012)	(0.012)
Year FE	Yes	No	Yes	No	Yes	No
Observations	1105	1105	1105	1105	1087	1086
R-squared	0.492	0.492	0.614	0.613	0.747	0.747

*** stands for significant at the 0.01 level, ** at the 0.05 level and * at the 0.1 level. Cluster SE in parenthesis.

5.4 Sectoral heterogeneity

In this sub-section, we explore the potential existence of a certain aggregation bias by allowing for sectoral heterogeneity of the effects of automation on the labor market. Our hypothesis is that the aggregate effects of the use of local robots and the exposure to foreign robots on labor market outcomes could be driven by sectors with a high reduction of offshoring or high reshoring. In order to explore the validity of this hypothesis, Table 5 reports

[16]As a measure of spillover effects, we used a weighted average of the stock of robots per 1000 workers of all the other sectors different than sector s, with the weights being the employment share of each of those sectors with respect to national employment.

the results of evaluating sectoral heterogeneity by estimating the models for employment and the labor share (equations 7 and 5) with interaction terms between the two robotization target variables and sectoral dummies, controlling for value-added and all the other control variables included in equations 7 and 5.

Columns (1) and (2) report the sectoral effects of exposure to foreign robots and the use of local robots on employment, respectively. In particular, the results in column (1) indicate that the average negative effect of exposure to foreign robots on employment found in the last section is driven by sectors with higher exposure per worker, whereas for the rest of the sectors, there are no significant effects. Concerning the use of local robots, the effect on employment appears to be significant only for two sectors. Whereas a positive and significant effect of robotization on employment is found for utilities, which is one of the sectors with higher skill intensity -ranked third, with a high-skilled intensity of 18% according to a taxonomy of sectors based on their skill level composition (Table A.7)-[17], a negative and significant effect of robots on employment is shown for chemicals and fuel, which is one of the sectors with lower-skilled intensity according to the same taxonomy of sectors. Columns (3) and (4) report the sectoral effects of the exposure to foreign robots and the use of local robots on the labor share. It can be observed that, although the average effect was not found to be significant, results in column (3) report negative and significant effects in 9 sectors, all of which are matched with negative employment effects. Differently, column (4) shows that the effects of local robot usage are positive and significant for the automotive sector, negative and significant for chemicals and fuel, and no significant effects are found for the rest of the sectors.

[17] Constructed with the previous version of WIOD for 2009 (last year covered).

Table 5: Sectoral effects of foreign and local automation, top 10 sectors with higher exposure to foreign robots

	ln(Employment)		Labor share	
	(1)	(2)	(3)	(4)
	Foreign robots	Local robots	Foreign robots	Local robots
Wood, furniture, paper, and other manufactures	-0.264***	0.013	-0.076***	-0.055
	(0.089)	(0.121)	(0.024)	(0.040)
Rubber, plastic, and mineral products	-0.492***	0.003	-0.129***	-0.006
	(0.118)	(0.028)	(0.028)	(0.008)
Basic metals and fabricated metals	-0.480***	0.027	-0.123***	-0.003
	(0.112)	(0.041)	(0.041)	(0.013)
Utilities	-0.403***	0.353**	-0.114***	-0.021
	(0.144)	(0.168)	(0.043)	(0.054)
Manufacture of other non-metallic mineral products	-0.660***	-0.292	-0.132*	-0.088
	(0.235)	(0.336)	(0.075)	(0.089)
Automotive	-0.463***	0.051	-0.061***	0.013**
	(0.113)	(0.033)	(0.022)	(0.006)
Electronics	-0.406***	0.143	-0.123***	0.015
	(0.113)	(0.095)	(0.046)	(0.019)
Food and beverages	-0.622***	-0.307	-0.117***	-0.132
	(0.217)	(0.530)	(0.031)	(0.099)
Industrial machinery	-0.277***	0.051	-0.038***	0.002
	(0.101)	(0.054)	(0.014)	(0.012)
Chemicals and fuel	0.004	-1.363**	0.017	-0.286**
	(0.046)	(0.585)	(0.012)	(0.142)
Other sectors	-0.112	0.092	-0.028	0.003
	(0.085)	(0.097)	(0.019)	(0.021)
Sector-Year FE	Yes	Yes	Yes	Yes
Observations	1105	1105	1087	1087
R-squared	0.576	0.500	0.784	0.751

Notes: ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 level, respectively. Local and exposure to foreign robots are expressed per thousand workers. Other sectors is an aggregated category including the seven sectors with the lowest exposure to foreign robots.

6 Conclusion and policy implications

The automation process in the form of robot adoption in production has been an increasing trend in developed countries since the beginning of the XXI century and has also gained relevance in emerging countries since 2008. This paper estimated the effects of local and foreign automation on labor market outcomes and the labor share in emerging countries using a panel dataset composed of 16 sectors in 10 emerging countries.

The empirical strategy used consists of controlling for unobserved heterogeneity and addressing endogeneity with an IV-FE approach. The results show that although we are not able to identify an average effect of local robots, the exposure to foreign robots has a negative and relevant effect on employment, which is not accompanied by a decrease in the average labor share. Moreover, the effect of the exposure to foreign robots differs by sector, with negative effects in the sectors that are highly exposed to foreign competition. It is important to remark that the extrapolation of these results to any particular sample country should be made with caution since the results represent average effects for all the considered countries.

When allowing for heterogeneous sectoral effects, on the one hand, we find adverse effects of the exposure to foreign robots on employment and the labor share in many sectors. These are sectors with higher than average exposure to foreign robots. The rationale behind such results is that robot adoption in those sectors in developed countries can generate high-cost savings by replacing a large number of workers in emerging countries. On the other hand, we find positive effects of local robots usage on employment in "Utilities" and negative effects in "Chemical and fuel." The former might be driven by the complementarity effects outlined in the theoretical models, whereas the latter may be by the preponderance of the displacement effect.

A number of policy implications arise from the results in this paper. First, policymakers can identify destabilizing factors in emerging countries from automation in the sectors highly exposed to foreign automation in developed countries. In this sense, the automation trends of these sectors in developed countries can serve as crucial information when evaluating labor, distributive, or macro policies in emerging countries. Second, countries should increase their efforts to invest in human capital and educational policies in these sectors to make their workers more complementary to foreign robots, thus protecting them from job losses and increasing their productivity. In addition, and depending on the context, emerging countries could implement more flexible tax policies toward offshored plants from sectors with high automation in developed countries to decrease their production costs and increase their incentives to offshore production.

Finally, we leave for further research the extension of the analysis to more recent years using the database Eora[18], as well as a more granular investigation of the effect of automation on the labor market, which could be done by using firm-level data for single emerging countries. Likewise, another matter that deserves further investigation is the decomposition of the employment and wage effects by workers' skill levels. This will allow us to know how specific workers are affected by robot adoption.

[18] The UNCTAD-Eora Global Value Chain (GVC) database offers global coverage and includes data over the period from 1990 to 2018 for the key GVC indicators. Available at: https://www.worldmrio.com/unctadgvc/.

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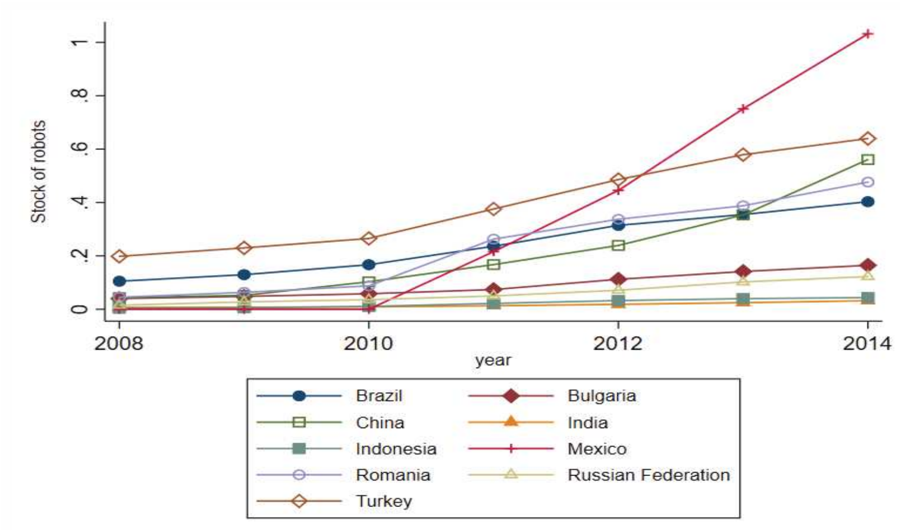
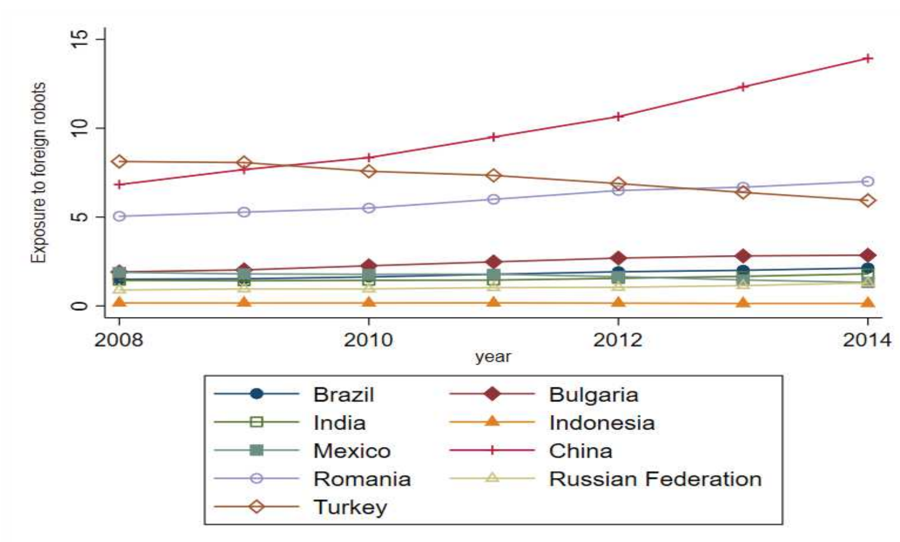
A Appendix

Figure A.1: Evolution of the stock of industrial robots per 1000 workers in emerging countries. Excluding Poland



Note: Authors' elaboration using the International Federation of Robotics database.

Figure A.2: Evolution of the exposure to foreign robots per 1000 workers in emerging countries. Excluding Poland



Notes: Authors' elaboration using the International Federation of Robotics (IFR) database and the World Input-Output Database (WIOD).Exposure to foreign robots is calculated according to Eq. (1) and corresponds to total stock of exposure per 1000 workers.

Figure A.3: Average output shares in Mexico, Canada and the United States

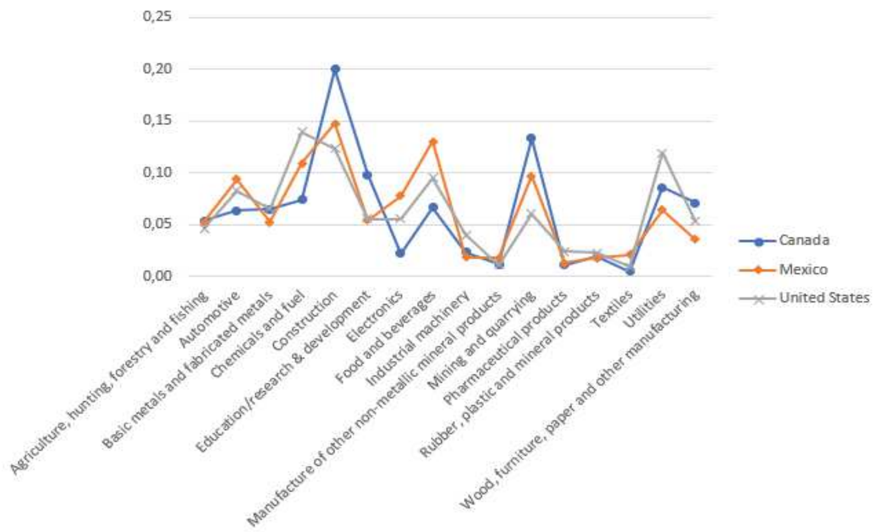


Table A.1: Approach and main findings of selected empirical studies

Author/s (year)	Scope	Empirical approach	Target variables & Effects
Acemoglu and Restrepo (2020)	United States, 772 commuting zones	IV	Employment (-) wages (-)
Acemoglu, Lelarge and Restrepo (2020)	France, firm level	Panel Data	Employment (-), productivity (+) labor share (-)
Aghion, Antonin and Buenl (2019)	France, industry level	IV	Employment (-)
Alguacil, Lo Turco and Martínez-Zarzoso (2020)	Spain, Firm level	PSM-DID	Exports (+), TFP(+)
Artuc, Bastos, and Rijkers (2018).	OECD countries, 16 industries	IV	Exports/Imports to/from LDCs (+)
Ballestar, Díaz-Chao, Sainz and Torrent-Sellens (2020)	Spain, firm level	SEM	Labour productivity SMEs/large firms (+/ns)
Bessen et al. (2019)	Netherlands, firm level	Diff-in-diff	Job stability (-) wage rates (ns)
Borjas and Freeman (2019)	US, 26 industries	IV	Employment (-) wages (-)
Carbonero, Ernst and Weber (2018)	41 countries, 20 sectors	IV	Employment (+) offshoring (-)
Chiacchio, Petropoulos and Pichler (2018)	6 EU countries, 16 regions , 15 sectors	IV	Employment (-) wages growth (ns)
Dauth, Findeisen, Suedekum and Woessner (2017)	Germany, 72 industries	IV	Employment (ns) productivity (+)
De Backer, DeStefano,Menon, Ran Suh (2018)	Developed and less developed countries	Panel Data	Offshoring in HDCs (-) reshoring (ns)
Dekle (2020)	Japan, industry level	IV	Employment (ns), productivity (+) general equilibrium macroeconomic effect (+)
DeStefano, De Backer and Ran Suh (2019)	33 developed countries, 16 industries	Panel Data	Export / Import quality (+)
Dinlersoz and Wolf (2018)	US, firm level	Semi-parametric	Labor share (-) TFP (+) Capital share (+)
Dixon, Hong and Wu (2020)	Canada, Firm level	Panel Data	Employment (+) productivity (+)
Dottori (2020)	Italy, industry level	IV	Employment (-) wages (+)
Faber (2020)	Mexico, commuting zones	IV	Employment (-) Exports to US (-)
Graetz and Michaels (2018)	17 EU countries, 14 industries	IV	Labour productivity growth (+) TFP (+) employment (ns) wages (+)
Klener, Fernández-Macías and Antón (2020)	28 EU countries, 10 industries	Panel Data	Employment (+) Low skill(?)
Koch, Manuylov and Smolka (2019)	Spain, firm level	PSM	Production (+) employment (+) robot adopters
Krenz, Pretter and Strulik (2021)	43 countries, 9 industries	IV	Reshoring (+)
Kluger, Kluger, Ripani and Rodrigo (2020)	Colombia, sectoral level	IV	Employment (-)
Stapleton and Webb (2020)	Spain, firm level	IV	Employment (+) labor share (-) productivity (+) imports from LDCs (+)
Stemmler, H. (2019)	Brazil, industry level	IV	Employment (-)

Table A.2: Classification of sectors according to ISIC-rev4 code

Sectoral classification used in the paper	ISIC rev4 2-digit code
Agriculture, hunting, forestry, and fishing	01, 02 and 03
Automotive	29 and 30
Basic metals and fabricated metals	24 and 25
Chemicals and fuel	19 and 20
Construction	41, 42 and 43
Education/research & development	85 and 72
Electronics	26 and 27
Food and beverages	56
Industrial machinery	28
Manufacture of other non-metallic mineral products	23
Mining and quarrying	05, 06, 07, 08 and 09
Pharmaceutical products	21
Rubber, plastic, and mineral products	22
Textiles	13, 14 and 15
Utilities	61, 53 and 35
Wood, furniture, paper, and other manufacturing	16, 31, 32 and 17

Table A.3: Definition and source of the variables

Variable	Measurement unit	Source
Employment	Thousand units	SEA
Annual nominal wage per worker	Thousands of int. USD	SEA
Labor share	Percentage	SEA
Local robots per thousand workers	Individual units per thousand workers	SEA
Exposure to foreign robots per thousand workers	Individual units per thousand workers	SEA AND WIOT
Stock of capital	Mill. of int.USD	SEA
Return of capital	Mill. of int.USD	SEA
Value-added	Mill. of int.USD	SEA
Output	Mill. of int.USD	SEA
Capital/output	Mill. of int.USD	SEA
Relative price of capital	Mill. of int.USD	SEA
Inshoring	Index	WIOT

Note: SEA refers to the Socioeconomic Accounts and WIOT refers to the World Input-Output Tables; both from the WIOD database.

Table A.4: Effect of automation on labor market outcomes: FD model

	ln(Employment)		ln(nominal wage per worker)		Labor share	
	(1)	(2)	(3)	(4)	(5)	(6)
	FD	IV-FD	FD	IV-FD	FD	IV-FD
dlog_stockrobpw	0.031**	0.102*	0.026	0.044	0.007*	0.026
	(0.014)	(0.055)	(0.017)	(0.041)	(0.004)	(0.016)
dlog_robots_abrpw	-0.185***	-0.283***	-0.036	-0.049	-0.035***	-0.063***
	(0.046)	(0.090)	(0.028)	(0.031)	(0.011)	(0.022)
dlog_VA	0.230***	0.182***	0.340***	0.322***	-0.135***	-0.149***
	(0.048)	(0.047)	(0.069)	(0.066)	(0.016)	(0.018)
dlog_nominalwage_perworker	-0.436***	-0.411***				
	(0.072)	(0.077)				
dInshoring	-0.059	-0.109	-0.113	-0.139	-0.006	-0.027
	(0.079)	(0.081)	(0.097)	(0.102)	(0.031)	(0.032)
dlog_employment			-0.683***	-0.700***		
			(0.073)	(0.073)		
dlog_capital_output					-0.113***	-0.119***
					(0.015)	(0.018)
dlog_relativeprice_r					-0.122***	-0.122***
					(0.016)	(0.020)
Year FE	Yes	No	Yes	Yes	Yes	Yes
Observations	1104	1104	1104	1104	1082	1080
R-squared	0.450	0.475	0.578	0.604	0.774	0.783

Notes: ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 level, respectively. FD denotes model with variables in first differences.

Table A.5: Effect of automation on labor market outcomes in emerging countries. Sample without Poland

	ln(Employment)		ln(nominal wage per worker)		Labor share	
	(1)	(2)	(3)	(4)	(5)	(6)
	FE	IV-FE	FE	IV-FE	FE	IV-FE
ln(Local robots per worker)	0.037	0.024	0.007	0.130	0.008	0.007
	(0.025)	(0.046)	(0.035)	(0.111)	(0.005)	(0.011)
ln(Exposure to foreign robots per worker)	-0.113**	-0.111**	-0.014	-0.031	-0.015	-0.015
	(0.044)	(0.048)	(0.047)	(0.062)	(0.010)	(0.011)
ln(Value added)	0.375***	0.377***	0.411***	0.583***	-0.087***	-0.087***
	(0.081)	(0.080)	(0.101)	(0.104)	(0.012)	(0.012)
ln(Nominal wage per worker)	-0.505***	-0.506***				
	(0.079)	(0.077)				
Inshoring index	-0.190	-0.184	-0.196	0.159	-0.026	-0.026
	(0.119)	(0.118)	(0.138)	(0.160)	(0.035)	(0.034)
ln(Employment)			-0.632***	-0.649***		
			(0.109)	(0.113)		
ln(Capital/output)					-0.101***	-0.102***
					(0.016)	(0.016)
ln(Relative price of capital)					-0.137***	-0.137***
					(0.012)	(0.012)
Year FE	Yes	No	Yes	No	Yes	No
Observations	993	993	993	993	980	979
R-squared	0.500	0.499	0.599	0.511	0.750	0.750

Notes: ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 level, respectively. Clustered SE in parenthesis. Local and exposure to foreign robots are expressed per 1000 workers.

Table A.6: Effect of automation on the stock and return of capital in emerging countries

	ln(Stock of capital)		ln(Return to capital)	
	(1)	(2)	(3)	(4)
	FE	IV-FE	FE	IV-FE
ln(Local robots per worker)	-0.017	-0.072	-0.043	-0.050
	(0.033)	(0.044)	(0.031)	(0.076)
ln(Exposure to foreign robots per worker)	0.003	0.012	0.030	0.031
	(0.021)	(0.023)	(0.036)	(0.040)
ln(Value added)	0.633***	0.644***	1.620***	1.621***
	(0.061)	(0.061)	(0.151)	(0.156)
log_r	-0.241***	-0.242***		
	(0.053)	(0.052)		
Inshoring index	-0.267**	-0.240**	0.086	0.090
	(0.111)	(0.108)	(0.189)	(0.192)
log_K			-1.521***	-1.521***
			(0.122)	(0.122)
Year FE	Yes	No	Yes	No
Observations	980	979	980	979
R-squared	0.858	0.855	0.530	0.530

Notes: ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 level, respectively. Clustered SE in parenthesis. Local and exposure to foreign robots are expressed per 1000 workers. Return of capital constructed as the sectoral compensation to capital divided by the sectoral stock of capital.

Table A.7: Skill intensity of sectors in emerging countries: shares of hours worked by different skill levels

Sector	Share high skilled	Share medium skilled	Share low skilled
Education/research & development	48%	12%	40%
Mining and quarrying	18%	46%	37%
Utilities	18%	36%	47%
Chemicals and fuel	16%	38%	46%
Wood, furniture, paper, and other manufacturing	13%	43%	44%
Basic metals and fabricated metals	12%	47%	41%
Manufacture of other non-metallic mineral products	12%	48%	39%
Automotive	11%	44%	45%
Other manufacturing industries	10%	43%	46%
Rubber, plastic, and mineral products	10%	43%	47%
Industrial machinery	10%	44%	46%
Electronics	9%	34%	57%
Food and beverages	7%	52%	41%
Construction	6%	57%	36%
Textiles	6%	56%	38%
Agriculture, hunting, forestry, and fishing	1%	83%	16%

Notes: Ordered from highest to lowest share of high skilled workers. Definition of skills according to the WIOD database: Workers classified as low skilled have an educational attainment of lower secondary school or less; medium skilled have completed higher of upper secondary or post-secondary non-tertiary education; and high skilled have tertiary (e.g. bachelor degree) or post-tertiary education (e.g. master or PhD).