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cege Discussion Paper

No. 423

June 2021

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ISSN: 1439-2305

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

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June 25, 2021

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 has 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 variable approach and using a shift-share index of exposure to foreign robots. When all sectors are considered, the main results 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' effect on employment has mainly occurred in the agricultural and industrial machinery sectors, the former being driven by a reduction of offshoring and affecting nearly 60% of jobs in emerging countries.

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

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1 Introduction

Automation has gained significant attention from scholars and policymakers alike, not only in rich countries but also in emerging countries, especially with its strong acceleration after the financial crisis in 2008, intensified with the COVID-19 pandemic in 2020. 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 tremendous wealth it might generate, is also linked to undesired disruptions and drastic changes in the distribution of gains.

The fundamental question that emerges in this context 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; Hardy et al., 2018). 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, they are less skill intensive, they have a large agricultural sector, and they have lower employment and value-added shares in industry and manufacturing. All of these factors could aggravate any distributional impact of automation.

Despite the relevance of the question 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 a 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. 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 driven by complementarity effects.

The main empirical findings for developed countries point towards 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 have been emerging in agriculture, construction, and services. The only paper focusing partially on emerging countries is, to our knowledge, Carbonero et al. (2020), which focuses on the influence of foreign automation –in developed countries– on employment in emerging countries and investigates the abovementioned reshoring channel but disregarding the effects on the labor share.

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 emerging countries on employment, wages, labor share and capital equipment. 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 and capital equipment. 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 by 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- for the period 2008-2014, differentiating between the effects of local and foreign robots. We use an instrumental variable method with sectoral-country fixed effects (IV-FE) to address reverse causality while controlling for unobserved heterogeneity at the sector-country level. We use the number of robots from the two countries with the most similar output share as an instrument for local robots, and an exogenous shift-share index serves to identify the effect of being exposed to foreign robots.

The main results indicate that whereas on average local robots have not affected employment and the labor share in emerging countries, foreign robots have harmed employment. By exploring the channels, we show that foreign robots' effect on employment has occurred mainly in the agricultural and industrial machinery sectors, the former being driven by a reduction of offshoring and affecting nearly 60% of jobs in 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 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 several policy implications and avenues for further research.

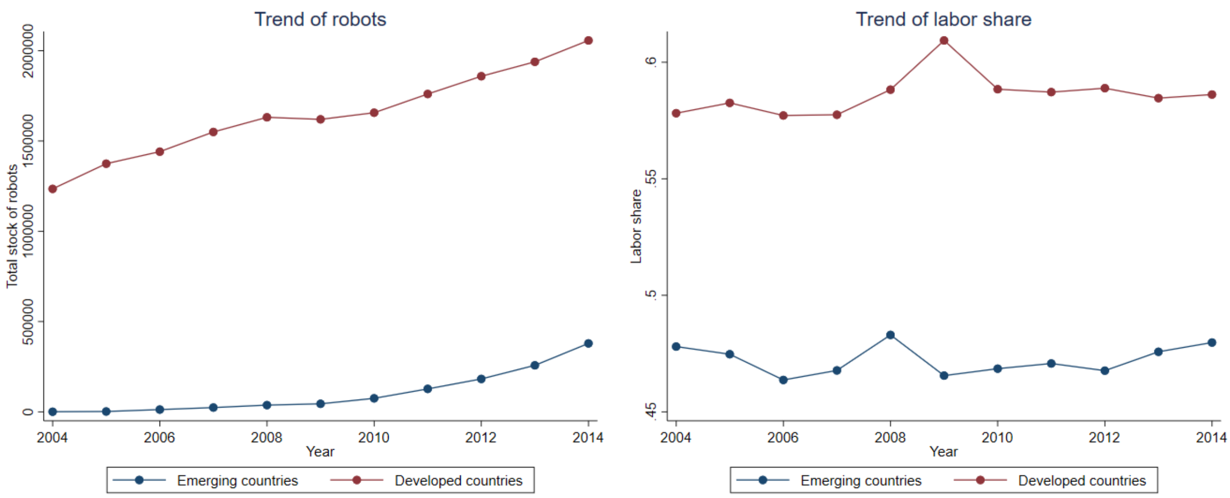
[1] as in Carbonero et al., 2020

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 total stock of robots and the labor share. 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

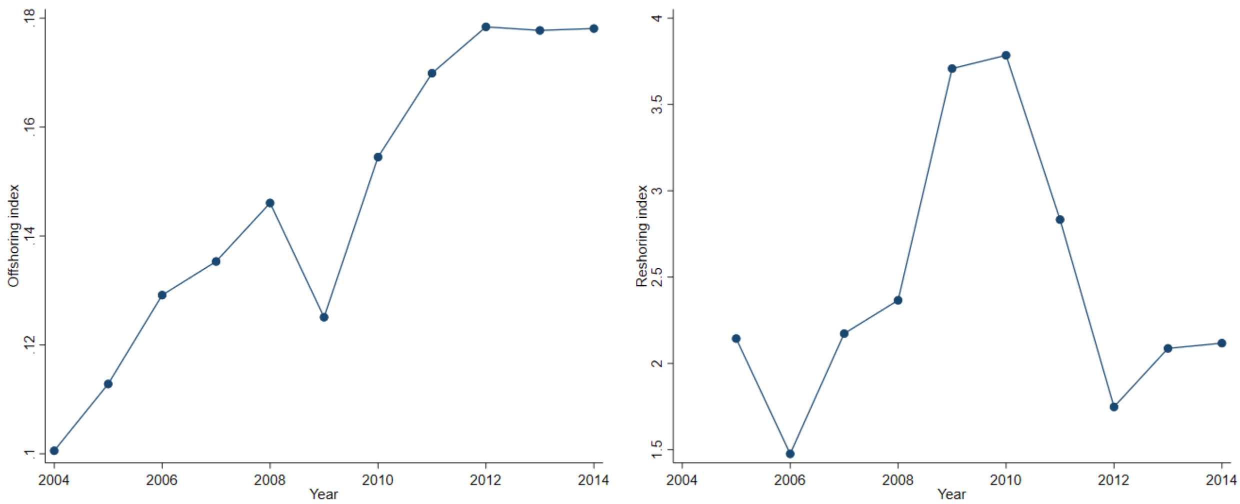


Note: Authors' elaboration using the Socioeconomic Accounts (SEA) of the World Input-Output Database (WIOD).

One of the hypotheses tested on this paper is that automation in developed countries may pose risks to employment in emerging countries through the disintegration of global value chains due to reduced offshoring[2] or reshoring[3]. Therefore, it is helpful to look at the recent development of these measures, as done in Figure 2. On the one hand, the left graph in Figure 2 shows that offshoring from developed countries in 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, the right part of Figure 2 shows that reshoring from emerging to developed countries has substantially increased during the period 2008-2010, which might be attributed to the financial crisis. 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).

[2] Measured in line with Feenstra and Hanson (1995): Ratio of sectoral imports of non-energy inputs of developed countries coming from emerging countries over the total usage of non-energy inputs.

[3] Measured as the Reshoring index of Krenz et al. (2021): $R_{sjt} = \frac{D_{sjt}}{F_{sjt}} - \frac{D_{sjt-1}}{F_{sjt-1}}$. Where D_{sjt} and F_{sjt} represents domestic and foreign inputs respectively, and the index is restricted to be positive ($R_{sjt} > 0$).

3 Literature review

3.1 Theoretical framework

The main theoretical framework used in the literature to explain the labor market's effects of 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 framework, the production of a pair of shoes, for example, considers different production tasks like design, extraction of weather, 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, which fosters labor demand.

It is worth noting that the overall effect of local robots on labor demand depends on the magnitude of both the displacement and productivity effects. If the former is larger than the latter, 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 that it considers the firms' strategy in developed countries of reducing local production costs by adopting industrial robots, decreasing 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 locations with low wages. The main implication is that firms with sufficiently high automation productivity will have lower costs producing at home, and hence, will prefer this option against offshoring. Since the authors consider exogenous technological progress, one of the implications is that if technological progress is sufficiently strong to produce high differences between 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 useful model. Based on the task-based framework of Acemoglu and Restrepo (2019) and on the induced effect of automation in the US on Mexican labor markets explained by Artuc et al. (2019) and Caliendo and Parro (2015), the author tries to identify the channel 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 tasks would be performed by robots if they are routinary and if automation has a comparative advantage in the performance of that task with respect 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 a negative effect of both measures on employment. Although most studies have focused on developed countries, a few studies have analyzed the effect of foreign robots on developing countries' labor markets. Concerning the methodologies, these have been varied, ranging from local labor market studies to cross-country panels. All these studies try to address the endogeneity problem of local robots in different ways, like instrumental variable strategies, the use of shift-share[4] explanatory variables or other quasi-experimental techniques like propensity score matching. As documented by several authors, the stock of robots may be 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. For the time-varying omitted variable bias, according to Carbonero et al. (2020) this can come from financial frictions that might 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 for the period 1990-2007, found that

[4] Also known as Bartik measures.

local automation in the US has harmed employment, wages, and labor share. To address the endogeneity issues, they constructed a shift-share explanatory variable that consists of a weighted average of the time-variant industry stock of robots in the US weighted by the employment share of that industry in a specific commuting zone in a base year. Furthermore, they instrumented this variable using a similar measure constructed with industrial robots' time-variant stock in the European Union (EU). Another interesting 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 about the reshoring phenomenon by Krenz et al. (2021) analyzed the effect of automation in developed countries on a sector-country panel setting using the novel measure of reshoring that is also adopted in this paper. They addressed endogeneity by using an instrumental variable approach consisting of instrumenting the sectoral stock of robots by 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 of emerging countries is still scarce and is mainly focused on single-country studies. The existent studies analyze both the impact of local and foreign automation. Among the latter, some of them show evidence that the channel of this effect is through a reduction of offshoring, while for others, this happens through reshoring. An empirical study for emerging countries by Carbonero et al. (2020) analyzed the effect of both local and foreign automation on employment of emerging countries in a sector-country panel of 14 sectors from 7 emerging countries. The exposure to foreign robots from developed countries is proxied with a variable constructed as a trade-weighted average of robots in developed countries, which weights are based on the total trade between developed and emerging countries. Subsequently, they found a negative effect of the use of robots in developed countries on general offshoring [5], concluding that the effect of the exposure to foreign robots on employment in emerging countries was explained by a reduction in offshoring from developed countries.

Several empirical papers have analyzed both local and foreign robots' effects using a local labor market approach for specific emerging countries. 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 from the US based on robot adoption in a specific industry in the US 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

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

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 United States (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 model created in the same paper empirically. He constructed the exposure to local robots in line with Acemoglu and Restrepo (2020) and the exposure to foreign robots in line with Faber (2020). To address endogeneity, the author used an Instrumental Variable (IV) approach consisting of the same index of exposure to local robots but using the average number of robots in other emerging countries from the WIOD as an exogenous source for robot adoption, finding that automation in export destination countries decreased employment in the manufacturing sector in Brazil. As was mentioned in the theoretical section, this channel could be driven by a reduction in employment in operations at the top part of the GVCs (e.g., assembled cars or shoes); thus, a reshoring process could be operating.

Finally, regarding the specific type of tasks that are at risk of being automated, Weller et al. (2019) created a modified index of the risk of automation for 12 Latin American countries based on the original index of Frey and Osborne (2017) but applying an adjustment that considers the segmentation of labor markets in the region, under the assumption that occupations in the low productivity segments would not be affected by automation[6]. The authors found that the share of jobs under risk of automation decrease from 62% with the original method of Frey and Osborne (2017) to less than 24%. One of the implications 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 World Input-Output Database (WIOD) from the University of Groningen and the International Federation of Robotics (IFR) database. Specifically, labor market outcomes (employment and real wages per worker), capital outcomes (stock of capital and return to capital), and 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. The period starts

[6]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

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 are used to construct the offshoring weights, the offshoring index, and the reshoring index.

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 real 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 with the exchange rate data from the International Monetary Fund (IMF).

Regarding the emerging countries analyzed in this paper, 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 used to compute the bilateral input flows are the remaining 30 countries of the WIOD [7].

The sectoral classification is based on the International Standard Industrial Classification Revision 4 (ISIC Rev. 4). The classification was made to harmonize the sectors of both the WIOD and the IFR to a common level of aggregation in the line of Acemoglu and Restrepo (2020). The sectors used to construct the sector-country panel are listed in Table A.1.

As a measure of foreign robot adoption, we construct a modified form of the index of exposure to foreign robots of 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 in our variable concerning the mentioned studies is that the bilateral weights used to construct the index are offshoring weights and not final goods' trade weights. The weights we use would more accurately represent the structural

[7]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.

characteristics of the transactions in intermediate inputs involved, which according to our 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 [8] that takes the following form:

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

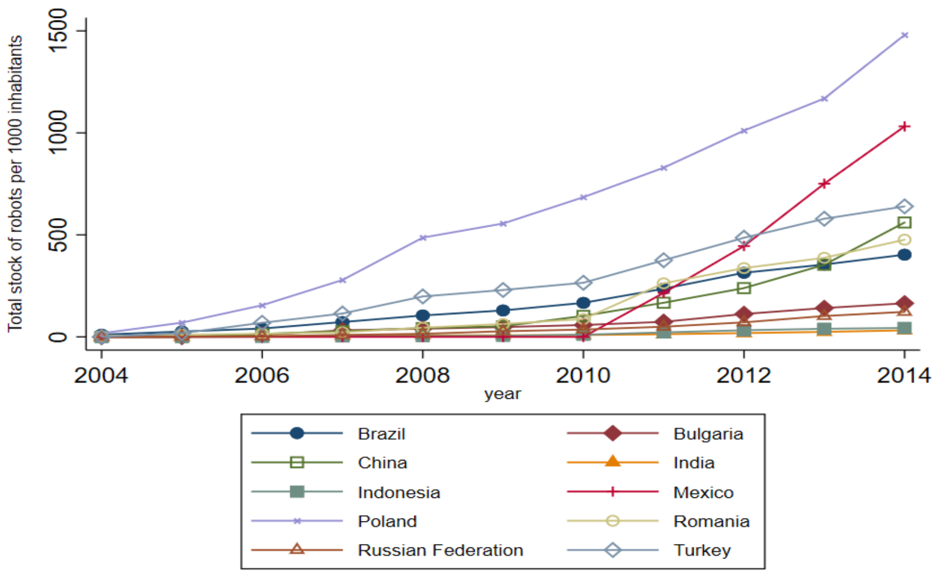
Where $w_{sji2004}$ are weights representing the participation of sector s of emerging country i in the production process of developed country j in the base year 2004. These weights can be summarized as $w_{sji2004} = \frac{X_{sij2004}}{X_{si2004}}$. Specifically, they represent the ratio of exports of non-energy inputs from sector s of emerging country i toward all the 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 inhabitants 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 25 robots per 1000 inhabitants. The two following countries until 2010 were Turkey and Brazil, respectively, which were surpassed by the spectacular increase of robot adoption of Mexico since 2010, positioning 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 are the countries with the lowest robot intensity.

[8] Also called Bartik measure.

Figure 3: Evolution of the stock of industrial robots per 1000 inhabitants

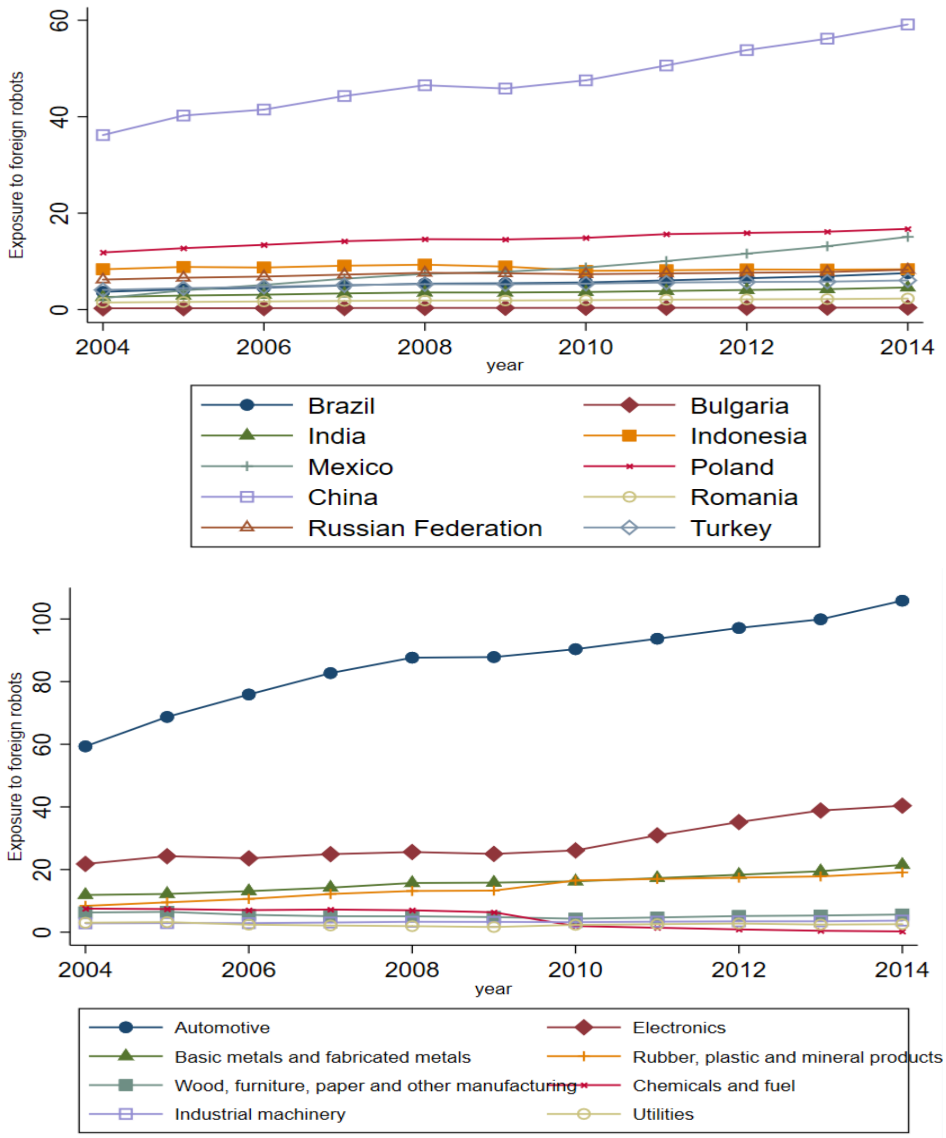


Note: Authors' elaboration using the International Federation of Robotics database.

The other side of the coin is exposure to foreign robots. For this case, Figure 4 shows the evolution of our index of exposure to foreign robots over time by country and sector (the top 8 sectors). A striking feature is that China 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 Japan, the US, and the Republic of Korea. Besides, China shows a stable increase in exposure to foreign robots over time, which can be explained by the fast robot adoption of the US and the Republic of Korea. In descending order of exposure to foreign robots, the other emerging countries are Poland, Mexico, Indonesia, Russia, Brazil, Turkey, India, Romania, and Bulgaria. It is worth noting that Poland is the European country with the highest exposure to foreign robots, which can be explained by its high participation in offshoring activities from Germany, a country with a high stock of robots. On the other hand, Mexico has presented a continuous increase in the index from 2010, which results from the high robot adoption of the US, Mexico's main trade partner.

Regarding the average sectoral exposure to foreign robots, it can be seen that the "Automotive" sector is the more exposed, followed by "Electronics," "Basic metals and fabricated metals," and "Rubber, plastic, and mineral products;" it is evident that in those cases the index is driven by the high stock of robots in those sectors of developed countries.

Figure 4: Evolution of the exposure to foreign robots



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).

Table 1 shows the descriptive statistics of the main variables used in the empirical model. Almost all the variables belong to our sample of emerging countries, except the Offshoring and Reshoring indices, which are calculated for developed countries and are used to disentangle the transmission channels in Subsection 5.4. The definitions, measurement units, and sources of the variables can be found in Table A.2.

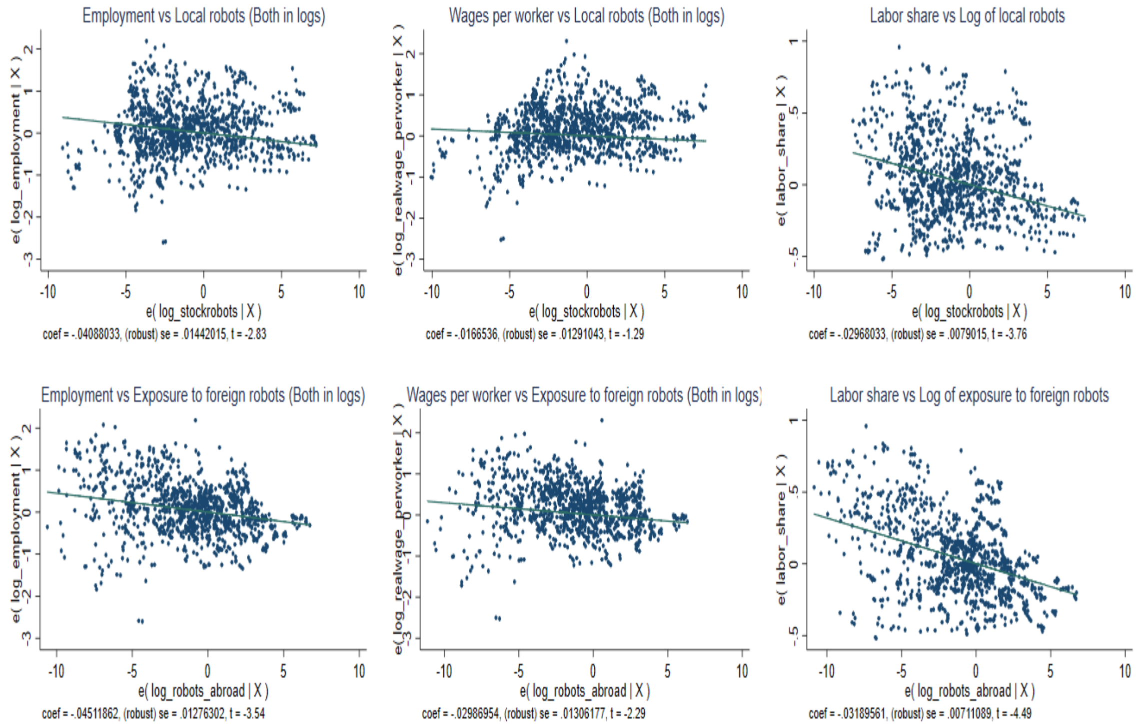
Table 1: Descriptive statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max	Sample
Employment	1,105	7,122	28,605	6.69	295,008	Emerging countries
Local robots	1,105	998	6,521	0	138,444	Emerging countries
Exposure to foreign robots	1,105	11,328	42,447	0	389,452	Emerging countries
Value-added	1,105	85,474	196,746	84	1,916,260	Emerging countries
Real wage per worker	1,105	17,718	35,684	372	264,744	Emerging countries
Inshoring	1,105	0.206	0.237	0	1	Emerging countries
Labor share	1,087	0.473	0.192	0.063	0.995	Emerging countries
Stock of capital	1,087	235,156	613,922	162	6,515,089	Emerging countries
Return of capital	1,087	0.484	1.43	0.001	17.83	Emerging countries
Capital/output	1,087	1.004	0.951	0.015	8.36	Emerging countries
Relative price of capital	1,087	0.119	0.229	0	2.6	Emerging countries
Offshoring	3,693	0.156	0.160	0.004	0.901	Developed countries
Reshoring	3,229	0.311	0.623	0	4.32	Developed countries

Notes: In the sample of emerging countries: Observations are lower for Labor share, Stock of capital, Return of capital, and Capital/output because some aberrant observations of negative compensation of capital were dropped in the labor share and capital regressions. In the sample of developed countries: Observations of Reshoring are lower than Offshoring since it is a dynamic measure, which means that one year is lost during the estimation.

The conditional correlations between the variables of interest are computed after estimating three models by Pooled Ordinary Least Squared regression (OLS) with employment, real wage per worker, and the labor share as dependent variables and local robots and exposure to foreign robots as explanatory variables. Sectoral value-added and the offshoring 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. These regressions report the conditional correlations between the variables keeping constant all the control variables. The corresponding scatter plots and the predicted lines can be observed in Figure 5. Regarding employment, it can be observed that it is negatively correlated at 1% of significance level (t-statistics larger than 2.57) with both local robots and exposure to foreign robots, with the latter being slightly stronger (-0.045 vs. -0.040). Furthermore, the real wage per worker is only negatively correlated at 5% of significance level with exposure to foreign robots, with a coefficient of -0.029. Finally, the correlation between the labor share and both automation measures is strong, being -0.029 for the log of local robots and -0.031 for the log of exposure to foreign robots.

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



Notes: 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 between employment and local automation might indicate that the displacement effect is larger than the productivity effect on average. In addition, the negative correlation between wages, employment, and the labor share with the exposure to foreign robots 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 where sectors maximize their profits, in the same vein as in Carbonero et al. (2020). Log-linearizing the production function, maximizing profits with respect to labor, and including the log of local robots and the log of the exposure to foreign robots results in Equation 2.

$$\begin{aligned} ln(Y_{sit}) &= \beta_1 ln(Local.robots)_{sit} + \beta_2 ln(Exposure.foreign.robots)_{sit} + \beta_1 ln(X_{sit}) \\ &\quad + \beta_2 ln(VA_{sit}) + \beta_2 ln(Inshoring_{sit}) + \gamma_{si} + \gamma_t + \epsilon_{sit} \end{aligned} \tag{2}$$

Here, Y_{sit} refers to two different dependent variables: employment and real annual wage per worker. Local robots are the stock of robots in each sector s in country i measured at year t. Similarly, and for the same units of analysis, exposure to foreign robots is proxied by the above-mentioned index, while the control variables are sectoral value-added (VA), which works as a demand shifter; the inshoring index of Andersson et al. (2017) to control for the direct effect of inshoring [9] flows on labor demand, and X_{sit}, which includes real 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 γ_t measures year fixed effects that accounts for any yearly shocks common to every sector and country.

The next specification assesses industrial robots' impact on the labor share, which is our distributive measure. It is taken from Karabarbounis and Neiman (2014) and have the following form:

$$\begin{aligned} L.share_{sit} = {} & \beta_1 ln(Local.robots)_{sit} + \beta_2 ln(Exposure.foreign.robots)_{sit} + \beta_3 ln(\frac{K}{Y})_{sit} \\ & + \beta_3 ln(\frac{r}{w})_{sit} + \beta_3 ln(VA)_{sit} + \gamma_{si} + \gamma_t + \epsilon_{sit} \end{aligned} \tag{3}$$

where $L.share$ is the labor share for sector s of country i measured in year t and is 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) proxy for capital intensity; the ratio of the return of capital over the real 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.

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 complementary equations are estimated to account for the effect of automation on the stock and return of capital. The functional form of these equations is similar to Equation 2 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 stock of capital equation and the stock of capital for the return of capital equation.

5.2 Instrumental Variable 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 its production process (e.g., low value-added and extractive activities).

[9] 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.

Second, there could be specific sector-country shocks that 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 problems are addressed by using the approach of Krenz et al. (2021), based on instrumenting the local sectoral stock of robots with the sum of the stock of robots 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.1 shows the average sectoral output structure of Mexico and the two most similar countries: Canada and the US. In this illustration, the log of the sum of the US and Canada's sectoral stock of robots is used as an instrument for sectoral robots in Mexico.

Formally, for each sector s in a specific emerging country i, the instrumental variable takes the following form:

$$log(Robots.IV_{sit}) = log(Robots.stock_{srt} + Robots.stock_{slt}) \tag{4}$$

where r and l represent the countries with the closest output share to emerging country i. Afterward, the model is estimated by Two-Stage Least Squared (2SLS). Given that this strategy is applied to the demeaned form of the equation of interest, this estimator is an IV-FE.

This strategy would successfully account for endogeneity and produce consistent estimators if the instrument is relevant and exogenous (Greene, 2008). Regarding the former condition, and as can be seen in Table 2, the first stage regressions for the specifications of employment, real wage per worker, and labor share show a strong positive relationship between the instrument and the log of local robots. In particular, the instrument's coefficient is equal to 0.497, 0.499, and 0.392, respectively, being statistically significant at 5% of significance level for the employment and labor share specifications, and at 1% for the real wage per worker specification.

The F-test for each specification reported in Table 2 indicates that the instrument is relevant in all three estimations [10].

[10] One standard criterion to decide if an instrument is relevant is to look at the F-test of the first stage regression (Schmidheiny, 2015). According to this criterion, if the F-test is higher than 10, the instrument can be considered relevant

Table 2: First stage results

	Employment specification	Wage specification	Labor share specification
	Ln(Local robots)	Ln(Local robots)	Ln(Local robots)
ln(Robots_IV)	0.497**	0.499***	0.392**
	(0.207)	(0.187)	(0.170)
ln(Value-added)	1.082**	2.000***	0.947
	(0.466)	(0.438)	(0.652)
ln(annual real wage per worker)	0.828***		
	(0.273)		
ln(Exposure to foreign robots)	-0.837***	-0.942***	-0.869***
	(0.193)	(0.163)	(0.184)
Inshoring index	-0.439	-1.086	-0.123
	(2.307)	(2.324)	(2.139)
ln(employment)		-1.083*	
		(0.554)	
ln(capital/output)			-0.264
			(0.739)
ln(r/w)			-0.967***
			(0.294)
Sector-country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	1105	1105	1087
R-squared	0.786	0.788	0.805
F-test	82.03	95.79	151.24

Notes: FE regression of local robots on the instrument. Control variables and year dummies are included.
*** stands for significant at the 0.01 level, ** at the 0.05 level and * at the 0.1 level. Cluster SE at the sector-country level in parenthesis.

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.

The second stage regression takes the following form:

$$ln(Y_{sit}) = \beta_1 ln(\widehat{Local.robots})_{sit} + \beta_2 ln(Exposure.foreign.robots)_{sit} + \beta_1 ln(X_{sit}) + \gamma_{si} + \gamma_t + \epsilon_{sit} \quad (5)$$

where $ln(Y_{sit})$ is the natural log of employment and real wages per worker, and the labor share (in three different models). While $ln(\widehat{Local.robots})$ represents the predicted values estimated in each specification's first stage, and X_{sit} refers to the control variables.

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. Finally, every observation is weighted by the average number of workers in each sector-country over the whole period to account for differences in scale (e.g., the quantity of workers in sectors of China vs. in Romania).

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 imprecise coefficient of -0.96 in the FE estimation (significant at 10%), while the magnitude of the coefficient is higher (more negative) and significant at 5% in the IV-FE, 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 1.37% 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 real annual wage per worker and the labor share.

Table 3: Effect of automation on labor market outcomes

	ln(Employment)		ln(Real wage per worker)		Labor share	
	(1)	(2)	(3)	(4)	(5)	(6)
	FE	IV-FE	FE	IV-FE	FE	IV-FE
ln(Local robots)	-0.019	-0.077	0.023	0.059	-0.003	0.001
	(0.020)	(0.057)	(0.020)	(0.042)	(0.002)	(0.007)
ln(Exposure to foreign robots)	-0.096*	-0.137**	-0.094	-0.161	-0.005	-0.002
	(0.053)	(0.062)	(0.071)	(0.108)	(0.007)	(0.009)
ln(Value-added)	0.699***	0.748***	1.041***	0.497**	0.009	0.006
	(0.110)	(0.134)	(0.092)	(0.195)	(0.021)	(0.020)
ln(Annual real wage per worker)	-0.580***	-0.496***				
	(0.089)	(0.122)				
Inshoring index	-0.501	-0.545	-0.727	-1.629**	0.023	0.025
	(0.462)	(0.468)	(0.633)	(0.826)	(0.072)	(0.072)
ln(Employment)			-0.903***	-0.908***		
			(0.065)	(0.098)		
ln(capital/output)					0.062**	0.065**
					(0.025)	(0.026)
ln(Relative price of capital)					-0.054***	-0.050**
					(0.015)	(0.021)
Sector-country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1105	1105	1105	1105	1087	1086
R-squared	0.655	0.591	0.783	0.698	0.611	0.605

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

One can think that the lack of statistical significance of the effect of foreign robots on the labor share is counterintuitive given the negative effect of the exposure to foreign robots on employment reported in columns (1) and (2) of Table 3. However, this is not the case if there is a reduction of capital equipment following automation by reducing foreign direct investment or capital outflows, 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 4, 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 confirm the intuition behind the lack of effect of exposure to foreign robots on the labor share: there is a negative and significant effect of the exposure to foreign robots on both the stock and the return of capital. In particular, the IV-FE results show that increasing the exposure to foreign robots by 10% leads ceteris paribus to a decrease of 1.24% on capital stock and a decrease of 1.6% on its return. Both results could be driven by reshoring or by a reduction in offshoring.

Table 4: Effect of automation on the stock and return of capital

	ln(Stock of capital)		ln(Return of capital)	
	(1)	(2)	(3)	(4)
	FE	IV-FE	FE	IV-FE
ln(Local robots)	-0.021**	-0.092**	-0.089**	-0.183***
	(0.010)	(0.045)	(0.038)	(0.061)
ln(Exposure to foreign robots)	-0.073***	-0.124***	-0.086	-0.161**
	(0.024)	(0.041)	(0.060)	(0.075)
ln(Value-added)	0.735***	0.898***	0.809***	1.016***
	(0.054)	(0.109)	(0.159)	(0.143)
ln(Return of capital)	-0.260***	-0.407***		
	(0.084)	(0.112)		
Inshoring index	-0.306	-0.286	0.331	0.184
	(0.241)	(0.301)	(0.350)	(0.439)
ln(Stock of capital)			-0.937***	-0.911***
			(0.145)	(0.114)
Sector-country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	1087	1086	1087	1086
R-squared	0.959	0.937	0.636	0.520

Note: *** 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 Transmission channels

Our hypothesis is that the effects of the exposure to foreign robots on labor market outcomes would concentrate in sectors with a high reduction of offshoring or high reshoring. In order to explore the validity of this explanation, Table 5 reports the results of evaluating sectoral heterogeneity using two different sub-samples: First, in our subsample of emerging countries, we reestimate the models of employment, capital stock, and the labor share (Equations 2 and 3) interacting the exposure to foreign robots with sectoral dummies. Second, in a subsample of 30 developed countries[11], we regress offshoring[2] -toward- and reshoring[3] from emerging countries on robot stock interacted with sectoral dummies, controlling for value-added, sector-country FE, and year dummies.

Columns 1, 2, and 3 report the sectoral effects of the exposure to foreign robots index in emerging countries on employment, capital stock, and labor share, respectively. Columns 4 and 5 report the sectoral effects of developed countries' robots on offshoring -toward- and reshoring from emerging countries. We observe heterogeneous effects of exposure to foreign robots on employment, capital stock, and labor share of emerging countries depending on the sector, which would reflect the fact that some robots in developed countries might be complementary to workers and capital equipment of some sectors of emerging countries. Also, 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 agriculture, which is by far the sector with more workers employed in emerging countries (around 60%) as can be seen in Figure A.2. Hence, for agriculture, an increase in the index by 10% would decrease employment by 2.59% on average, which might be triggered by a decrease in offshoring, as column (4) suggests. In addition, a negative effect of foreign robots on employment in the

[11] 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.

"Industrial Machinery" sector is found, but the mechanism of such effect is unclear since developed countries' robots in this sector do not have an effect neither on offshoring nor reshoring.

Some interesting findings are the positive effects of foreign robots on employment in "Rubber, plastic and mineral products," "Electronics," and "Pharmaceutical products" shown in column (1), which seems to be related to the positive effect of developed countries' robots on offshoring toward emerging countries as shown by column (4). However, since these sectors represent only a small share of total employment in emerging countries [12], these effects do not influence the total average effect of foreign robots. In addition, in almost all cases, the direction of the effect of foreign robots on capital stock is the same as for employment, and the overall effect on the labor share depends on which of the two effects –positive or negative– dominates. For example, exposure to foreign robots has a negative effect on the labor share for agriculture (negative effect on employment is higher than for capital stock) and a positive one for electronics (positive effect on employment is higher than for capital stock). Finally, the direction of the effect of the use of foreign robots on the reshoring index (column 5) is not matched with significant effects of foreign robots on the main outcomes of emerging countries, which could indicate that the reduction of offshoring-and not reshoring- is the main transmission channel behind the results.

[12] None of these sectors represents more than 3% of total employment share

Table 5: Sectoral effects of robotization

	(1) Employment b/se	(2) Capital stock b/se	(3) Labor share b/se	(4) Offshoring b/se	(5) Reshoring b/se
Mining and quarrying	0.112	0.104	-0.009	-0.002	0.099
	(0.119)	(0.096)	(0.008)	(0.003)	(0.076)
Agriculture, hunting, forestry, and fishing	-0.259***	-0.137***	-0.030***	-0.007***	-0.054
	(0.036)	(0.042)	(0.009)	(0.001)	(0.059)
Wood, furniture, paper, and other manufactures	0.242	0.124**	0.003	0.003**	-0.033
	(0.221)	(0.049)	(0.029)	(0.001)	(0.034)
Education/research	-0.016	-0.140*	0.005	0.003	-0.164***
	(0.114)	(0.084)	(0.016)	(0.003)	(0.054)
Rubber, plastic, and mineral products	0.378***	0.191**	0.036	0.015***	-0.070*
	(0.122)	(0.078)	(0.032)	(0.004)	(0.038)
Basic metals and fabricated metals	0.136	0.227	-0.034	-0.002*	-0.021
	(0.366)	(0.365)	(0.043)	(0.001)	(0.025)
Utilities	0.176	0.170**	0.006	0.001*	-0.015
	(0.146)	(0.067)	(0.023)	(0.001)	(0.021)
Manufacture of other non-metallic minerals	0.349	0.327	-0.007	0.002	0.067
	(0.246)	(0.214)	(0.016)	(0.002)	(0.064)
Automotive	0.344	0.469	0.016	0.001	-0.055***
	(0.426)	(0.395)	(0.050)	(0.004)	(0.019)
Electronics	0.561***	0.342***	0.082***	0.022**	0.028
	(0.122)	(0.084)	(0.027)	(0.010)	(0.036)
Food and beverages	-0.007	0.054	-0.068***	-0.005*	0.077*
	(0.165)	(0.107)	(0.019)	(0.003)	(0.045)
Textiles	-0.143	0.102*	-0.058**	0.008	0.113**
	(0.115)	(0.061)	(0.028)	(0.010)	(0.051)
Industrial machinery	-0.383***	-0.296	-0.032*	0.004*	-0.001
	(0.141)	(0.218)	(0.019)	(0.002)	(0.036)
Construction	-0.044	-0.010	0.014	0.002	-0.021
	(0.058)	(0.042)	(0.032)	(0.002)	(0.095)
Pharmaceutical products	0.229***	0.041	0.022*	0.001	-0.043
	(0.069)	(0.035)	(0.011)	(0.002)	(0.028)
Chemical and fuel	-0.000	-0.044***	0.009***	0.000	0.069
	(0.017)	(0.016)	(0.002)	(0.001)	(0.049)
Sector-country FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	1105	1087	1087	3693	3229
R-squared	0.777	0.969	0.670	0.290	0.375

Notes: Columns 4 and 5 are calculated for a sample of developed countries: Sectoral effects of developed countries' robots on offshoring -toward- and reshoring from emerging countries. Control variables are not shown. They are the same as those used in Equations (2) and (3) for Employment, Capital stock, and the Labor share, while only value-added is used as a control for Offshoring and Reshoring. *** stands for significant at the 0.01 level, ** at the 0.05 level, and * at the 0.1 level. Cluster SE in parenthesis.

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 from 10 emerging from 2008-2014.

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 important effect on employment, which is not leading to an average decrease in the labor share, being instead compensated by an equivalent negative effect on the stock and the return of capital. Simultaneously, the effect of foreign robots is heterogeneous by sector, with negative effects in some sectors and positive in others. It is important to remark that the extrapolation of these results to any particular country of the sample should be made with caution since the results represent average effects for all the sectors of the considered countries.

When allowing for heterogeneous sectoral effects in our model, on the one hand, we find adverse effects of the exposure to foreign robots on employment and the labor share in agriculture and industrial machinery. The former seems to be driven by a reduction in offshoring in agriculture; while it is not clear for the case of industrial machinery, a potential unexplored channel could be through trade in final goods belonging to the last stage of the value chain. The rationale behind such results is that robot adoption in those sectors in developed countries can generate a high-cost saving by replacing a large number of workers in emerging countries. Furthermore, the fact that agriculture is the sector with the highest employment share in the emerging countries in the sample (near 60%) implies that this sector mainly drives the overall negative effect of the exposure to foreign robots on employment shown in Table 3. On the other hand, we find positive effects of foreign robots on employment in "Rubber, plastic and mineral products," "Electronics," and "Pharmaceutical products." These might be driven by the complementarity effects outlined in the theoretical models.

A number of policy implications emerge from the results in this paper for emerging countries, having in mind the potential effects of the exposure to foreign robots from developed countries on their labor market outcomes. First, policymakers can identify destabilizing factors from automation in "Agriculture" and "Industrial machinery" of 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 offshore production incentives.

Finally, we leave for further research 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 level. This will allow us to know how specific workers are affected by robot adoption.

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A Appendix

Table A.1: Classification of sectors

Number	Sector
1	Agriculture, hunting, forestry, and
2	Automotive
3	Basic metals and fabricated metals
4	Chemicals and fuel
5	Construction
6	Education/research & development
7	Electronics
8	Food and beverages
9	Industrial machinery
10	Manufacture of other non-metallic minerals
11	Mining and quarrying
12	Pharmaceutical products
13	Rubber, plastic, and mineral products
14	Textiles
15	Utilities
16	Wood, furniture, paper, and other manufactures

Table A.2: Characteristics of variables

Variable	Definition
Employment	Workers engaged
Annual real wage per worker	Compensation of workers/Employment
Labor share	Share of value-added allocated to workers
Local robots	Robot stock of emerging countries
Exposure to foreign robots	Offshoring-weighted Robot stock of developed countries
Stock of capital	Nominal capital stock
Return of capital	Capital compensation divided by stock of capital
Value-added	Gross value added at current basic prices
Output	Gross output at current basic prices
Capital/output	Nominal capital stock/Gross output at current basic prices
Relative price of capital	Return of capital/Annual real wage per worker
Inshoring	Exports of non-energy inputs/Total production of non-energy inputs
Offshoring	Imports of non-energy inputs/Total usage of non-energy inputs
Reshoring	Yearly difference of ratio Domestic inputs/Foreign inputs

Variable	Measurement unit	Source
Employment	Thousand units	SEA
Annual real wage per worker	Thousands of int. USD	SEA
Labor share	Percentage	SEA
Local robots	Individual units	SEA
Exposure to foreign robots	Index	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
Ratio capital/output	Mill. of int.USD	SEA
Relative price of capital	Mill. of int.USD	SEA
Inshoring	Index	WIOT
Offshoring	Index	WIOT
Reshoring	Index	WIOT

Note: "/" indicates division.

Figure A.1: Average output shares over time in Mexico, Canada and the United States

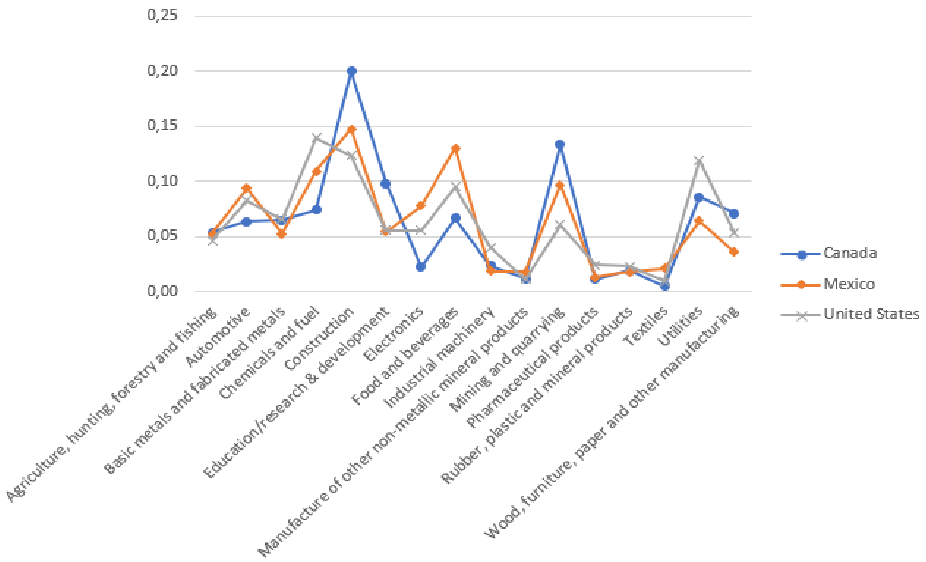
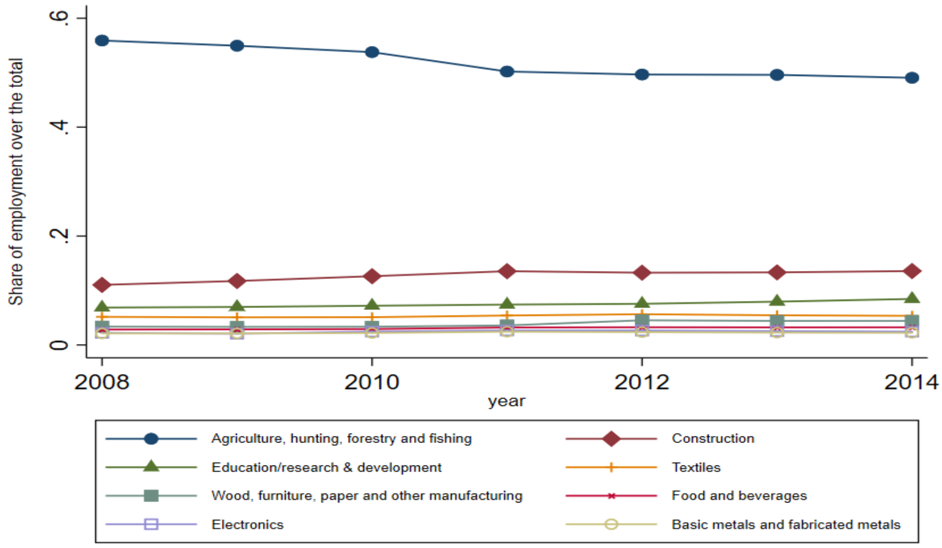


Figure A.2: Evolution of the sectoral employment share in emerging countries



Note: The figure shows the eight sectors of emerging countries with higher employment share.