

Stemmler, Henry

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**DOES AUTOMATION LEAD TO  
DE-INDUSTRIALIZATION IN  
EMERGING ECONOMIES? –  
EVIDENCE FROM BRAZIL**

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Henry Stemmler

GEORG-AUGUST-UNIVERSITÄT GÖTTINGEN

# Does Automation Lead to De-Industrialization in Emerging Economies? - Evidence from Brazil\*

Henry Stemmler <sup>†</sup>

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## Abstract

This paper investigates several channels through which automation affects an emerging economy. Building on a Ricardian model of trade with sectoral linkages and a two-stage production technology, in which robots replace labor in certain tasks, it is shown that domestic and foreign automation have differential effects on labor markets. Based on this model, the impact of automation on local labor markets in Brazil are estimated using a shift-share approach. Local labor market exposures to industry-level stocks of robots are derived from their initial industry-employment composition. Foreign automation is found to decrease manufacturing employment through the channel of *final goods* exports, while it increases employment in the mining sector through the channel of *input* exports. This may stimulate what has been called "premature deindustrialization" in emerging economies. To account for possible endogeneity in adopting robots domestically, robot uptake in other emerging economies is used as an instrumental variable. Domestic automation is found to directly decrease the ratio of unskilled industry workers and increase the ratio of skilled workers. Also, the wage gap between the two groups widens as a consequence of domestic automation, reinforcing income inequality.

*Keywords:* automation, trade, deindustrialization, employment, wages.

*JEL-Classification:* J23, J24, F16, O33.

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<sup>†</sup>University of Goettingen, Department of Economics, Platz der Goettinger Sieben 5, 37073 Goettingen, Germany. E-Mail: henry.stemmler@uni-goettingen.de

# 1 Introduction

Technological advances have led to robots becoming a feasible alternative to manual labor. There are growing concerns that automation and other technological disruptions such as artificial intelligence will vastly displace workers and diminish wages (Brynjolfsson & McAfee, 2014; Ford, 2015).

Recent research has investigated the impact of increased usage of robots on employment, wages, productivity and trade patterns. Graetz and Michaels (2018) illustrate that automation raised labor productivity across several industrialized economies, but at the same time reduced the employment share of low-skilled workers. Acemoglu and Restrepo (2019c) find a broad decrease in employment and wages in local labor markets in the United States attributed to robot adoption. Using firm-level data from Spain, Koch, Manuylov, and Smolka (2019) show large output gains for using robots and a net increase in employment.

With production processes becoming cheaper in industrialized economies through the advancement in robotics, there are growing concerns of automation inducing deindustrialization and a shift to light manufacturing and raw-material extraction in emerging economies (Rodrik, 2016). There is however little evidence as to whether there is such a trend in local labor markets in emerging economies caused by domestic and foreign automation is taking place. There has been some indication that advanced economies are reversing their offshoring activities on the macro level. Carbonero, Ernst, and Weber (2018) document that advanced economies decrease their offshoring activities, which has a negative employment effect for emerging economies. Krenz, Prettnner, and Strulik (2018) find that robot adoption leads to reshoring, benefiting high-skilled workers in advanced economies. Artuc, Bastos, and Rijkers (2019) find that automation in the Global North increases both exports to and imports from the Global South, with the increase in exports outweighing imports. As robots become cheaper, it furthermore may become more profitable for industrialized countries to shift production from developing countries back to the domestic economy. In a recent paper, Faber (2019) demonstrates that robot adoption in the United States leads to reshoring of production entities from Mexico. Consequently, employment in local labor markets in Mexico declines, especially of machine operators, technicians and high-skilled managers and professionals in the service industry.

This paper adds to the literature, by analyzing different channels through which automation impacts local labor markets in Brazil and more specifically whether employment is shifting from higher value-adding manufacturing industries to light-manufacturing and raw-material extraction. Brazil has had a relatively large uptake of robots over the past 2 decades as compared to other Latin American countries<sup>1</sup>, making it an interesting case to study direct effects of automation on an emerging economy. There is thus far only sparse evidence about domestic automation in emerging economies; Faber (2019) for instance finds no effects on local labor markets.

That there has been a de-industrialization trend in Brazil can be seen by and the large decline of the manufacturing share in GDP (Jenkins, 2015), as can be seen in Figure A.1, and by looking at the country's exports over the years. In the early 2000's Brazil had a relatively diverse export structure, both in terms of export destinations and sectors. It has however become increasingly reliant on primary goods. In 2000, after the trade liberalization, the largest exporting sectors were transportation and machine manufacturing; mineral products for instance made up only 8% of exports (Simoes & Hidalgo, 2011). In 2014, exports of mineral products rose to 22%, while transportation and machine manufacturing together made up less

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<sup>1</sup>Only Mexico employed a larger number of robots (International Federation of Robotics, 2016).

than 15%. Figure A.2 displays how exports from the manufacturing sector and the mining sector have converged between 2000 and 2015. The recession that hit Brazil in 2014 as a consequence of the collapse of international commodity prices can at least to some part be attributed to the concentration on mineral extraction as compared to other industries (Spilimbergo & Srinivasan, 2019) and revealed the dangers of such a development.

In this paper, I shed light on how foreign automation contributed to this trend, inducing employment to shift to raw material extraction and reducing employment in final goods exporting sectors<sup>2</sup>. To do so, I differentiate between exposure to foreign automation through exports of *intermediate goods* and exposure to foreign automation through exports of *final goods*. The empirical analysis is based on a Ricardian model with production of intermediate and final goods, building on Caliendo and Parro (2015), Eaton and Kortum, 2002, Artuc et al. (2019) and Acemoglu and Restrepo (2019c), in which domestic robots replace labor in certain industry specific tasks. Foreign automation on the other hand affects local labor markets through changing trade expenditures. More specifically, foreign automation changes demand of final goods and demand for intermediate goods needed for production in the respective country. This leads to heterogeneous effects for local labor markets. To empirically test these different mechanisms, local labor market exposures to domestic and foreign automation are constructed using the initial industry-employment distribution within local labor markets in Brazil. Domestic robots are instrumented by using the average stock of robots in other developing countries, which are unlikely to be affected by local labor markets in Brazil.

Domestic automation is found to lead to a higher employment ratio of high-skilled workers and a smaller employment ratio of industry workers, similar to findings in industrialized countries (Acemoglu & Restrepo, 2019c). Specifically, an increase of one robot per thousand workers in one region in Brazil increases the employment ratio of Managers & Professionals by 0.07 percentage points and decreases the employment ratio of Plant & Machine Operators by 0.03 percentage points, relative to other regions. The increased employment of the high-skilled group is especially driven by non-routine tasks, and the declining employment of the lower-skilled group by routine tasks.

Regarding foreign automation, exposure through the channel of input exports leads to the employment ratio of the raw materials sector to increase. Conversely, foreign automation causes a declining share of employment in manufacturing industries via final goods exports. These findings are in line with the notion of automation inducing deindustrialization and a focus on raw-material extraction in emerging economies (Rodrik, 2016). Regions with an average exposure to foreign robots experience a 0.1 percentage point decline in their manufacturing employment ratio and an increase of 0.04 percentage points of the raw materials sector (mining) employment ratio by an increase of one additional weighted robot per 1000 workers<sup>3</sup>. To test whether foreign automation truly change exporting patterns, a regional input-output matrix is constructed. Indeed, foreign automation decreases the exports of final goods and increases exports of the Raw Materials sector.

Building on the recent literature that examines validity and inference in shift-share designs (for instance by Adão, Kolesár, and Morales (2018), Borusyak, Hull, and Jaravel (2018) and Goldsmith-Pinkham, Sorkin, and Swift (2018)) I use a number of robustness tests to verify the results.

The rest of the paper is structured as follows. In section section 2, the theoretical model and empirical

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<sup>2</sup>There are of course other trends that have led to a decline in manufacturing employment, most notably increasing import competition from other countries such as China (Benguria & Ederington, 2017), which will be addressed later in the paper.

<sup>3</sup>Foreign robots are weighted by export shares, which is explained in more detail below.

strategy is developed. Section 3 gives a short overview of the different data sets used in the analysis. Thereafter, in section 4 the effects of domestic and foreign automation on local labor markets in Brazil are estimated. Section 5 concludes.

## 2 Theory and Empirical Strategy

### 2.1 Automation, Trade in Intermediates and Final Goods, and Labor Markets

This section develops a model which identifies different channels through which automation may affect local labor markets of an emerging economy. The model is closely related to Artuc et al. (2019) and further builds on Caliendo and Parro (2015) and Acemoglu and Restrepo (2019c). Local labor markets in Brazil are denoted by  $r$ , foreign economies by  $j$ , with there being  $J$  regions/countries overall. There are  $K$  industries, represented by  $i$  and  $k$  and production stages by  $s$ . The production stage of intermediate goods is defined as  $s = 1$  and of final goods as  $s = 2$ . As in Autor, Dorn, and Hanson (2013) and Acemoglu and Restrepo (2019c) workers are immobile between regions and countries, but can move between industries.

#### Households

Households in region  $r$  maximize utility by consuming final goods, given by a Cobb-Douglas utility function

$$U_r = \prod_i^K (Q_{ri}^2)^{\gamma_{ri}}, \quad (1)$$

where  $\sum_i \gamma_{ri} = 1$  and  $Q_{ri}^2$  is the demand of final goods in region  $r$  from industry  $i$ . Households receive income  $I_r = w_r^L L_r + k_r$  by supplying labor  $L_r$  at wage  $w_r^L$  and receiving  $k_r$  as capital income.

#### Production

Firms in region  $r$  produce varieties  $\omega \in [0, 1]$  as intermediate goods or final goods. Firms use three inputs for production: Capital  $F$ , a task input  $T$  and intermediate inputs  $Q^1$ . As in Artuc et al. (2019), the intermediate good  $Q^1$  is used only as a production input, while  $Q^2$  is consumed by households.

The Cobb-Douglas production function of variety  $\omega$  is

$$q_{ri}(\omega_i) = z_{ri}(\omega_i) F_{ri}(\omega_i)^{\alpha_{ri}^F} \prod_k^K Q_{rik}^1(\omega_i)^{\alpha_{rik}^M} T_{ri}(\omega_i)^{\alpha_{ri}^T}. \quad (2)$$

The parameter  $\alpha_{rik}^M$  denotes the share of inputs used from industry  $k$  for the production of variety  $\omega_i$ , where  $\sum_k \alpha_{rik}^M = 1 - \alpha_{ri}^F - \alpha_{ri}^T$  (Caliendo & Parro, 2015). Allowing intermediates from other industries to be used for the production in  $i$  permits to examine important Input-Output (I-O) patterns. The efficiency of production in region  $r$  industry  $i$  is drawn from the *Fréchet* distribution as in Eaton and Kortum (2002) and given by  $z_{ri}$ , through which regions have different industry compositions.

The cost of producing  $\omega_i$  is given by

$$c_{ri} = \psi_{ri} f_{ri}^{\alpha_{ri}^F} \prod_k^K P_{rik}^1{}^{\alpha_{rik}^M} w_{ri}^{\alpha_{ri}^T}, \quad (3)$$

with  $f_{ri}$  as the rental rate for capital,  $P_{rik}^1$  the price of intermediate goods and  $w_r$  the task input price<sup>4</sup>.

Producers of the composite good of stage  $s$  supply  $Q_{ri}^s$  by minimizing the costs of the intermediate variety  $\omega_i$  from international suppliers. The production technology is an aggregator as in Caliendo and Parro (2015), given by

$$Q_{ri}^s = \left[ \int (m_{ri}(\omega_i))^{\sigma_i - \frac{1}{\sigma_i}} \right]^{\frac{\sigma_i}{\sigma_i - 1}}, \quad (4)$$

where  $\sigma_i$  is the elasticity of substitution across intermediate goods. Region  $r$  and industry  $i$ 's demand of intermediate good  $\omega_i$  from the lowest cost supplier across all countries is denoted as  $m_{ri}(\omega_i)$  and is given by

$$m_{ri}^s(\omega_i) = \left( \frac{p_{ri}(\omega_i)}{P_{ri}} \right)^{-\sigma_i} Q_{ri}^s, \quad (5)$$

where  $P_{ri}$  is the unit price of the composite good.

## Prices and Trade

Intermediate inputs and final goods can be sourced internationally. Trade is costly, with  $\tau_{rji}$  defining iceberg-type costs per unit shipped between region  $r$  and country  $j$ . The price of an intermediate or final good for region  $r$  and sector  $i$  is then

$$p_{ri}(\omega_i) = \min_j \left[ \frac{c_{ji}\tau_{rji}}{z_{ji}(\omega_i)} \right], \quad (6)$$

where  $c_{ji}$  is defined as in equation 3.

The price of the composite good can be expressed with the properties of the *Fréchet* distribution (Eaton & Kortum, 2002). Due to the probabilistic distribution of technology, countries and sectors have different levels of productivity. As in Caliendo and Parro (2015),  $\lambda_{ri}$  denotes the location parameter varying by country and sector, representing absolute advantage of a region in industry  $i$ . The shape parameter  $\theta_i$  is the industry specific variation of efficiency in production, thereby representing comparative advantage. The price of the composite good is then<sup>5</sup>

$$P_{ri} = A_i \left[ \sum_j \lambda_{ji} (c_{ji}\tau_{rji})^{-\theta_i} \right]^{-\frac{1}{\theta_i}}, \quad (7)$$

where  $A_i$  is a constant.

The expenditure share of country  $j$  on goods from region  $r$  and industry  $i$  can be written as

$$\pi_{jri} = \frac{\lambda_{ri} [(c_{ri}\tau_{rji})]^{-\theta_i}}{\sum_h \lambda_{hi} [(c_{hi}\tau_{hji})]^{-\theta_i}}. \quad (8)$$

<sup>4</sup> $\psi_{ri}$  is a placeholder for the expression  $A_{ri}(\alpha_{ri}^F)^{-\alpha_{ri}^F}(\alpha_{ri}^M)^{-\alpha_{ri}^M}(\alpha_{ri}^T)^{-\alpha_{ri}^T}$ .

<sup>5</sup>See Appendix A.1 for further derivations.

## Robots and Tasks

Tasks  $T_{ri}$  in production are allocated between human labor and robot capital in the continuum  $b \in [0, 1]$ . There is an automation frontier, which is given by  $C_i$ . This cut-off defines the advancement in robot technology in industry  $i$ , which, due to technological diffusion, is the same across the world. Let labor be defined as  $L$  and robots as  $R$  with the productivity of labor being  $\gamma_L(b)$  and of robots  $\gamma_R(b)$ . With  $\gamma_L(b)/\gamma_R(b)$  increasing, labor has a comparative advantage in tasks which are closer to 1 (Acemoglu & Restrepo, 2019a). Tasks are then allocated as

$$T_{ri}(b) = \begin{cases} \gamma_L(b)L_{ri}(b) + \gamma_R(b)R_{ri} & \text{if } b \leq C_i \\ \gamma_L(b)L_{ri}(b) & \text{if } b > C_i. \end{cases} \quad (9)$$

Tasks from 0 to  $C_i$  can theoretically be performed by robots or human workers, where producers will choose the, productivity-adjusted, cheaper input. Unit labor costs are given by  $w_{ri}^L$  and robot rental price per unit by  $w^R$ . If  $\gamma_R(b)w_{ri}^L/\gamma_L(b)w^R > 1$ , a robot will be used to complete task  $b$  (Artuc et al., 2019). Therefore, tasks for which robots are used differ among regions and countries, depending on the given wage rate. This implies that less developed economies are less likely to employ robots than industrialized countries, as wages are much lower.

Plugging cost reductions through automation  $\Omega_{ri}$ <sup>6</sup> into equation 3 gives a new cost function, that incorporates cost reductions through automation:

$$c_{ri} = \psi_{ri} f_{ri}^{\alpha_{ri}^F} \prod_k^K P_{rik}^1 \alpha_{rik}^M (\Omega_{ri} w_{ri})^{\alpha_{ri}^T} \quad (10)$$

## Labor Market Effects

The above definitions allow to define different channels through which automation affects emerging economies. Labor market clearing implies that labor income equals the labor's share of region  $r$ 's and industry  $i$ 's share of exports and domestic sales (Eaton & Kortum, 2002), such that

$$w_{ri}^L L_{ri} = \alpha_{ri}^T (1 - C'_{ri}) Y_{ri}, \quad (11)$$

where  $Y_{ri}$  are total sales of industry  $i$  in region  $r$ . Using total expenditure on the intermediate good  $X^1$  and consumer demand for the final good  $X^2$ , with expenditure shares from equation 8, equation 11 can be rewritten as:

$$L_{ri} = \alpha_{ri}^T \frac{(1 - C'_{ri})}{w_{ri}^L} \sum_j \left( (\alpha_{ji}^F + \alpha_{ji}^T) \pi_{jri} X_{ji}^2 + \sum_k \alpha_{jki}^M \pi_{jkri}^1 X_{jki}^1 \right). \quad (12)$$

Totally differentiating equation 12 and using  $\hat{x} = dx/x$ , changes in labor can be rewritten as

$$\hat{L}_{ri} = -\hat{C}'_{ri} \frac{C'_{ri}}{1 - C'_{ri}} + \sum_j \left( (\alpha_{ji}^F + \alpha_{ji}^T) \frac{X_{ji}^2}{X_{ji}^2} (\hat{\pi}_{jir} + \hat{X}_{ji}^2) \right) + \sum_j \sum_k \left( \alpha_{jki}^M \frac{X_{jki}^1}{X_{jki}^1} (\hat{\pi}_{jkri} + \hat{X}_{jki}^1) \right) - \hat{w}_{ri}. \quad (13)$$

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<sup>6</sup>See Appendix A.1 for derivations.



Equation 13 shows the differential effects of automation on changes in employment in region  $r$  and industry  $i$ . The first term,  $-\hat{C}'_{ri}C'_{ri}/(1 - C'_{ri})$  captures how changes in domestic automation increase the threshold  $C'$  and thereby decrease labor in some tasks<sup>7</sup>. The next two terms distinguish how foreign automation affects labor markets through trade in intermediate and final goods<sup>8</sup>.

Firstly,  $(\alpha_{ji}^F + \alpha_{ji}^T)X_{ji}^2/X_{ji}$  denotes the share of expenditure on final goods of country  $j$  and  $\hat{\pi}_{jir} + \hat{X}_{ji}^2$  are the changes in expenditure shares on goods from region  $r$  and expenditure on final goods. A decrease in the robot rental rate  $w^R$  decreases production costs especially in developed countries, where wages are higher a priori. This changes the distribution of countries that source certain goods at the lowest price, reflected by  $\hat{\pi}_{jir}$ . Some products that were imported before are now cheaper to produce domestically.

Secondly, the expression  $\alpha_{jki}^M X_{jki}^1/X_{jki}$  denotes the share of expenditure of country  $j$  and industry  $k$  on intermediate goods from industry  $i$  and  $\hat{\pi}_{jkr} + \hat{X}_{jki}^1$  are the changes in the expenditure shares on goods from region  $r$  and expenditures on intermediate goods. Since automation increases production (especially in developed economies), also more intermediates are demanded and thus imported.

This changes the pattern of international trade; on the one hand, goods with relatively high production costs, that before automation were imported from less developed economies though, are now produced in industrialized countries (Artuc et al., 2019). At the same time, due to the rise in productivity, also more intermediates are demanded, which are less complex and still cheaper to produce in developing and emerging economies.

The last term,  $\hat{w}_{ri}$ , reflects changes in labor demand. I assume here that automation affects employment and wages simultaneously and add several controls to capture other variables that might affect labor demand. Similar to Autor et al. (2013), I firstly focus on one way that foreign automation affects Brazilian labor markets, that is through export channels. Automation could of course also have an impact through imports, which I will test for in a later stage.

## 2.2 Empirical Specification

Building on equation 13, the empirical specifications capturing the channels through which automation affects employment in Brazil are presented in this section. It has been well established in the literature that workers are imperfectly mobile across space, but move between industries (Autor et al., 2013; Dix-Carneiro & Kovak, 2015; Kovak, 2013). Therefore, local labor markets are used as the unit of analysis, instead of industries. In order to estimate the effects of robot adoption on labor markets, the industry-level shocks of an increase in robots have to be translated to the microregions in Brazil. To do this, the shift-share approach is used, which in similar contexts has been implemented by Acemoglu and Restrepo (2019c) and Faber (2019). I therefore define  $\hat{x}_r = \hat{x}_i \sum_i L_{ri}/L_r$ , hence weighting industry level shocks with the share of regional employment in this industry. Equation 13 then can be rewritten as:

<sup>7</sup>I here abstain from the possibility that automation may create new tasks, which is described in Acemoglu and Restrepo (2019b).

<sup>8</sup>For brevity, domestic expenditure on intermediate and final goods are kept within these terms, instead of including them separately.

$$\hat{L}_r = \sum_i \frac{L_{ri}}{L_r} \left[ -\hat{C}'_i \frac{C'_i}{1-C'_i} + \sum_j \left( (\alpha_{ji}^F + \alpha_{ji}^T) \frac{X_{ji}^2}{X_{ji}} (\hat{\pi}_{ji} + \hat{X}_{ji}^2) \right) + \sum_j \sum_k \left( \alpha_{jko}^M \frac{X_{jki}^1}{X_{jki}} (\hat{\pi}_{jki} + \hat{X}_{jki}^1) \right) - \hat{w}_i \right] \quad (14)$$

## Automation Measures

### Domestic Automation

The first term in square brackets in equation 14 describes how domestic automation takes over certain tasks and thereby affects labor demand. To capture the increased use of robots for tasks in production, the stock of domestic robots is used in the empirical analysis. For brevity, a time index has thus far been omitted. To link the theory with the empirics a year index  $t$  is now added. Exposure to domestic automation is defined as

$$RE_{rt}^{dom} = \sum_i \frac{L_{rit_0}}{L_{rt_0}} \frac{R_{it}}{L_{it_0}}, \quad (15)$$

where the left ratio denotes the "share" of the shift-share operator, namely the initial share<sup>9</sup> of employment in industry  $i$  in microregion  $r$  and  $R_{it}$  denotes the yearly stock of robots in that industry<sup>10</sup>.

Borusyak et al. (2018) discuss the shift-share design using panel data, specifically whether to use yearly industry shares or an initial share. In the case of serial correlation in the data, which in the automation data is present, the authors advocate using initial shares. As a robustness test, I later also account for this serial correlation in the empirical analysis by including lagged variables. The "shift" is the the yearly sectoral stock of robots in Brazil per 1000 workers, as defined in the right fraction of equation 15.

As employment of robots is likely to be endogenous to local labor market employment though, an instrumental variable (IV) approach is employed. I use the average number of robots in other emerging economies in the data set as an exogenous source for robot adoption<sup>11</sup>, as it is very unlikely that robot adoption in these countries is driven by changes in the Brazilian labor market. Figure A.4 displays the average robot stock in these countries, as well as the Brazilian robot stock.

The robot exposure IV takes the following form:

$$RE_{rt}^{dom,iv} = \sum_i \frac{L_{rit_0}}{L_{rt_0}} \frac{\bar{R}_{dev,it}}{\bar{L}_{jdev,it_0}}. \quad (16)$$

### Foreign Automation

As outlined above, automation abroad has differential effects on employment in Brazil, through changing expenditures on intermediate goods and final goods. To investigate these differential effects, two different variables are constructed.

<sup>9</sup>1995 is the first available year in the data that I can use, due to different region and industry classifications before.

<sup>10</sup>Note that for brevity the time index  $t$  was omitted above.

<sup>11</sup>These are India, Indonesia, Turkey, China and Mexico.

Equation 10 shows that automation in country  $j$  and industry  $i$  reduces its production costs. A decrease in  $c_{ji}$  in turn leads to fewer imports of the same industry from region  $r$ <sup>12</sup>, which can be seen in equation 8. Finally, labor demand in region  $r$  will decline through foreign automation if  $\hat{\pi}_{ji} + \hat{X}_{ji}^2$  is negative (see equation 14)<sup>13</sup>.

Exposure to foreign automation through trade in final goods in regions in Brazil is

$$RE_{rt}^{final} = \sum_i \frac{L_{rit_0}}{L_{rt_0}} \sum_j \frac{X_{jit_0}^2}{X_{t_0}^2} \frac{R_{jit}}{L_{jit_0}}, \quad (17)$$

where  $\sum_j X_{jit_0}^2 / X_{t_0}^2$  is the initial share of final goods exports of industry  $i$  to country  $j$ , the term  $(\alpha_{ji}^F + \alpha_{ji}^T) \frac{X_{ji}^2}{X_{ji}}$  in equation 14. The increase in foreign automation is captured by the stock of robots in country  $j$ , again given in terms of 1000 workers. The variable thus reflects how regions, that before automation had a relatively large amount of final goods exports to an industry in country  $j$  are affected a higher adoption of robots in this country's industry.

Higher production abroad through automation however increases the demand for first-stage production goods, which are likely to mostly be simple manufactured inputs and raw materials that are still cheaper produced in less developed countries.

Exposure to foreign robots through inputs thus is

$$RE_{rt}^{inp} = \sum_i \frac{L_{rit_0}}{L_{rt_0}} \sum_j \sum_k \frac{X_{jikt_0}^1}{X_{t_0}^1} \frac{R_{jkt}}{L_{jkt_0}}, \quad (18)$$

where, similar to the above, the share of expenditure on intermediate goods of region  $r$ ,  $\sum_j \sum_k \alpha_{jk}^M X_{ijk}^1 / X_{ijk}$ , is captured by  $\sum_j \sum_k X_{jikt_0}^1 / X_{t_0}^1$ , the initial share of intermediate goods exports of industry  $i$  to industry  $k$  in the partner country  $j$ . The variable accordingly reflects how regions are affected by foreign automation through input trade.

## 2.3 Estimation Equation

The above definitions in mind, the estimation equation is defined as

$$Y_{rt} = \beta_0 + \beta_1 RE_{rt}^{dom,iv} + \beta_2 RE_{rt}^{final} + \beta_3 RE_{rt}^{inp} + \chi_{rt} + \gamma_r + v_{st} + \varepsilon_{rt}$$

which is estimated via a two-stage least squares procedure, with  $RE^{dom,iv}$  being estimated in the first-stage.  $Y_{rt}$  denotes the outcome variable of interest. These are mainly employment ratios at the microregion level. Several different dimensions of employment are investigated, namely employment by skill level and by industry. In the same manner, wage rates are explored. The vector  $\chi_{rt}$  includes a set of microregion level controls which could also affect labor demand and will be described in more detail in the next section. Moreover, microregion fixed effects  $\gamma_r$  are used to control for any regional specific time-invariant characteristics. Lastly, state-year fixed effects  $v_{st}$  control for any time-varying unobserved confounders on the state level.

<sup>12</sup>Theoretically, imports could also increase if the productivity gain exceeds the trade diversion effect.

<sup>13</sup>Since automation abroad leads to an overall higher productivity,  $\hat{X}_{ji}^2$  may well be positive. The theoretical predictions are thus unclear a priori, depending on how strong automation leads to a trade diversion or productivity gain.

Standard errors are clustered on the mesoregion level, which is one geographic region above the microregion. In section 4.7 I also account for residuals possibly being correlated between regions with similar industry shares, that are not in close geographic proximity, following Adão et al. (2018).

### 3 Data

Different datasets are combined for the analysis, which are described in more detail in the following. Table A.1 in the Appendix displays how industries are matched across the different datasets. Additional datasets and notes are presented in the Appendix.

#### Robot Data

Data on the stock of country, industry and year specific robots are obtained from the International Federation of Robotics (IFR). The IFR provides the number of yearly “multipurpose industrial robot”<sup>14</sup> installations on a country, industry and application level (International Federation of Robotics, 2016). Industries are defined on the three- or two-digit level, according to ISIC classifications.

Two measures for robots are provided in the data, annual shipments (sales) and a yearly robot stock. The IFR acknowledges annual shipments to be more accurate. I therefore follow Graetz and Michaels (2018) and construct a robot stock based on annual deliveries and a depreciation rate of ten percent.

For some countries, robot data is missing for the year 2014. For these countries, I calculate their share of robots in the smallest region they belong to for 2013<sup>15</sup>. Robot data for 2014 is then constructed by multiplying these shares with the regional stock of 2014<sup>16</sup>. As the number of unclassified robots is high for certain countries and years, these are proportionally distributed to those that are classified into industries, following (Acemoglu & Restrepo, 2019c)<sup>17</sup>.

Panel A of Figure A.3 in the Appendix shows the evolution of the robot stock in the 6 industries with the most robots in Brazil. The automotive industry (right axis) has by far largest amount and largest growth rate of robots, followed by the rubber and plastic industry. Panel B displays the 6 industries that were mostly exposed to foreign robots. Foreign robot stocks are weighted by the share of exports to the specific country and sector. While the industry with the most robots is, not surprisingly, the automotive industry again (right axis), the industry with the second largest exposure is electrical equipment, followed by food, beverages and tobacco. One can furthermore see from the graph that there is variation both within and between the sectors and their growth in the stock of robots and as well as exposure to foreign robots.

<sup>14</sup>A Robot is defined by ISO 8373:2012 as an automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications (International Federation of Robotics, 2016).

<sup>15</sup>The respective country-region combinations are as follows, as defined by the IFR as: Greece and Ireland into Other Europe; Bulgaria, Estonia, Latvia and Lithuania into Eastern/Central Europe; Croatia and Slovenia into Balkan ; Romania into Other Eastern Europe.

<sup>16</sup>Also, before 2011, robots for Mexico, Canada and the United States are reported collectively as North America. To obtain country and industry-specific data for the whole period, I follow Acemoglu and Restrepo (2019c) and construct the country-specific industry shares before 2011 based on the yearly sectoral share of each country relative to North America as a whole. The resulting country-specific sector shares are then multiplied by the robots in North America in each industry.

<sup>17</sup>For a number of countries, all robots are unclassified before a certain year. Since especially for the instrumental variable yearly robot data is vital, these robots are distributed according to the share in which robots are allocated in the first year in which not all robots are unclassified.

## Trade Data

In order to construct regional exposures to foreign robots I use country and industry level trade flows from the World Input Output Database (WIOD) (Timmer, Dietzenbacher, Los, Stehrer, & de Vries, 2015). WIOD provides world input-output tables for 43 countries between 2000 and 2014. One important advantage for the analysis is that trade flows are disaggregated on the exporter sector and importer sector level, allowing to investigate input-trade between all sector combinations and to correctly assign robot exposure to an exporting industry.

To distinguish between exports of intermediate and final goods, I follow Antràs and Chor (2018)<sup>18</sup>. Final products are distinguished in the data as direct consumption by households, NGOs or governments, and capital formation by firms. Finally, yearly sector level employment data are taken from the WIOD Socio-Economic Accounts, with which are necessary to construct the stock of robots per 1000 workers in other countries.

Additionally, I use the Comtrade database to construct a measure of yearly import competition on the industry level. Comtrade includes more countries than WIOD, which contains no Latin American countries besides Brazil and Mexico. Other countries in the region are however of great importance for Brazilian imports. Imports are on the industry level and matched to this paper’s classification through the available ISIC codes. Regional import exposure is constructed in a Bartik-style, using the regional industry-employment shares as in section 2.2.

## Local Labor Market Data

Local labor market data from Brazil comes from the Relação Anual de Informações Sociais (RAIS) database of the Brazilian Ministry of Labor<sup>19</sup>. The RAIS is an annual administrative census, covering 99% of the formal enterprises, which report employee-specific data on a yearly basis. Firms are classified into sectors on a five-digit or six-digit level according to the CNAE code by the Instituto Brasileiro de Geografia e Estatística (IBGE), which is similar to ISIC, and jobs are classified into the CBO code by the Ministry of Labor, similar to ILO’s ISCO codes, also on a five-digit level.

Among others, data in the RAIS includes the employees’ age, gender, educational attainment, wage and social benefits. As microregions in Brazil are similar to commuting zones in the United States, I define them as local labor markets. I hereby follow a strand of literature that investigates local labor market outcomes in Brazil, majorly of trade liberalization, using microregions (Kovak, 2013; Costa, Garred, & Pessoa, 2016; Dix-Carneiro & Kovak, 2015; Hirata & Soares, 2016). In total, there are 558 microregions, 137 meso-regions and 27 states in Brazil.

The sample of workers is limited to individuals aged 16–65, to only observe the working-age population. Furthermore, following Dix-Carneiro and Kovak (2017), individuals working in public administration are excluded, as the public sector operates differently than other sectors. One caveat of the data is that it does not observe informal firms. As it is unlikely that informal firms use robots in production, this is not deemed to be a huge problem in this case. However, individuals that move from formal to informal employment as a consequence of robot competition cannot be observed. Furthermore, as formalization of firms has increased

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<sup>18</sup>Furthermore, the “net inventory” correction method from Antràs, Chor, Fally, and Hillberry (2012) is also used here.

<sup>19</sup>For further information on the dataset, see also Helpman, Itskhoki, Muendler, and Redding (2017), Dix-Carneiro and Kovak (2015), Dix-Carneiro and Kovak (2017) or Alvarez, Benguria, Engbom, and Moser (2018).

sharply between 2000 and 2014, the number of observations in the dataset approximately doubled from 37 mio. observations in 2000 to 76 mio. observations in 2014. To not obtain biased results, instead of using total employment numbers, employment ratios are calculated by dividing working-age employment by all observations in the database, which include unemployed individuals at the end of a given year. These ratios can then be consistently compared over time. Furthermore, different ratios are used, based on different criteria, e.g. industry worker ratios or occupation ratios.

Complementing the data, I add microregion population and GDP, which is obtained from the IBGE data portal<sup>20</sup>.

## 4 Estimation Results

In this section, the results of estimating the exposure to domestic robots, exposure to foreign robots through the input channel and exposure to foreign robots through the final goods channel on labor market outcomes, as well as alternative specifications and several robustness tests are presented.

### 4.1 The Effect of Automation on Local Labor Market Employment

The first-stage of estimation equation 2.3, regressing regional exposure to Brazilian robots per 1000 workers on regional exposure to the average of other developing countries' robots per 1000 workers, is reported in Panel A of Table A.3. There is a strong and positive relationship between the variables in all specifications, with the coefficient being statistically significant at the 1% level. The table also provides OLS results, which are similar to the IV results discussed below.

Table 1 shows the the second stage results, where in Panel A the outcome variable is the overall employment ratio, that is the ratio of employed workers to the sum of employed and unemployed individuals. The Kleibergen-Paap F-Statistic (which is presented in the bottom of the table) is well above the usual thresholds in all specifications. Column 1 only includes the domestic robot exposure measure together with microregion dummies and state-level trends. The coefficient of domestic robot exposure is negative, but not statistically significant. Column 2 adds the foreign exposure variables, which both are negative and statistically significant. This indicates that regions which are more strongly exposed to foreign automation through trade see stronger overall employment declines.

Column 3 adds regional characteristics, which are the logs of total microregion population and GDP, the routine task intensity index, the average highschool graduate rate and the share of foreign owned enterprises. The routine task intensity index is included to capture the regional exposure to general technological advancements, such as computerization (Faber, 2019). Changes in offshoring behavior of foreign companies are controlled for by the share of foreign owned enterprises. Furthermore, including the regional import exposure measure (column 4) or lagged industry shares (column 5) does not change the results. Included industry shares are of service employment, which here can be seen as the non-tradables sector (see Borusyak et al. (2018)), as well as the lagged share of employment in the automotive industry, since this is the industry with by far the most robots and the lagged share of agriculture employment, as regions with a large share of agricultural employment are likely to evolve differently than other regions, and the lagged share of light

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<sup>20</sup><ftp://ftp.ibge.gov.br/>, last accessed 04.06.2019.

manufacturing industries<sup>21</sup>.

Table 1: Employment Ratios, Overall and by Sector

	Employment Ratios (2SLS Estimation)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<b>Panel A: Total Employment Ratio</b>							
Dom. Robot Exposure	-0.0883 (0.160)	0.299 (0.226)	0.262 (0.232)	0.263 (0.232)	0.303 (0.220)	0.304 (0.222)	0.210 (0.166)
For. Robot Exposure - Input		-0.133** (0.0517)	-0.116** (0.0538)	-0.116** (0.0532)	-0.130** (0.0528)	-0.130** (0.0530)	-0.110** (0.0543)
For. Robot Exposure - Final		-0.0904* (0.0512)	-0.0842* (0.0489)	-0.0843* (0.0490)	-0.0873* (0.0488)	-0.0873* (0.0489)	-0.102** (0.0488)
<b>Panel B: Manufacturing Employment Ratio</b>							
Dom. Robot Exposure	-0.531** (0.236)	-0.193 (0.241)	-0.189 (0.234)	-0.157 (0.233)	0.0441 (0.182)	0.211 (0.174)	-0.261* (0.147)
For. Robot Exposure - Input		0.0556 (0.0606)	0.0675 (0.0604)	0.0778 (0.0577)	-0.00726 (0.0378)	0.00339 (0.0375)	0.0403 (0.0272)
For. Robot Exposure - Final		-0.127** (0.0541)	-0.118** (0.0514)	-0.121** (0.0510)	-0.115*** (0.0433)	-0.104** (0.0463)	-0.111*** (0.0301)
<b>Panel C: Raw Materials Employment Ratio</b>							
Dom. Robot Exposure	-0.0184 (0.0221)	-0.00398 (0.0231)	-0.00251 (0.0231)	0.0131 (0.0274)	0.00748 (0.0316)	-0.0371 (0.0381)	0.0132 (0.0223)
For. Robot Exposure - Input		0.0399** (0.0192)	0.0416** (0.0189)	0.0465*** (0.0161)	0.0462** (0.0177)	0.0384** (0.0184)	0.0185** (0.00876)
For. Robot Exposure - Final		-0.0161 (0.0114)	-0.0165 (0.0117)	-0.0178* (0.0107)	-0.0159 (0.00983)	-0.0161 (0.0119)	-0.00548 (0.00447)
<b>Panel D: Service Employment Ratio</b>							
Dom. Robot Exposure	0.251 (0.177)	0.0109 (0.178)	-0.0277 (0.163)	-0.0659 (0.162)	0.0300 (0.146)	-0.0725 (0.142)	0.134 (0.169)
For. Robot Exposure - Input		-0.0175 (0.0659)	-0.0332 (0.0678)	-0.0452 (0.0666)	-0.0645 (0.0479)	-0.0654 (0.0487)	-0.0573 (0.0443)
For. Robot Exposure - Final		0.0844* (0.0429)	0.0759** (0.0380)	0.0789** (0.0377)	0.0516* (0.0270)	0.0417 (0.0261)	0.0392 (0.0281)
Observations	8355	8355	8355	8355	8355	8355	8355
Microregion FE	✓	✓	✓	✓	✓	✓	✓
State x Year FE	✓	✓	✓	✓	✓	✓	✓
Regional Char.			✓	✓	✓	✓	✓
Import Exposure				✓	✓		✓
Industry Controls					✓	✓	✓
China Import Exp.						✓	
Population Weighted							✓
KP F-Statistic	9170.9	5734.5	5692.1	5973.6	5998.1	6016.3	5400.6

**Note:** Standard errors, in parentheses, are clustered on the mesoregion level. In column 7 microregion population is used as weights. All specifications include microregion and state interacted with year fixed effects. Regional Characteristic controls are the logs of total microregion population and GDP, the share of female workers, the routine task intensity index, the average highschool graduate rate and the share of foreign owned enterprises. Industry controls are the lagged share of service workers, agricultural workers, light manufacturing and automotive workers. Employment outcomes are given by the ratio of employment to population ratios (of the RAIS data).  
\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Column 6 uses exposure to Chinese imports, as it has been shown that Chinese imports have had a strong impact on local labor market outcomes in Brazil (Benguria & Ederington, 2017; Jenkins, 2015). The results however remain robust. In the last column, regressions are weighted by regional population. While

<sup>21</sup>These are the Textile and the Paper, Publishing industries, following Acemoglu and Restrepo (2019b).

the data used covers almost all employed workers, the weights adjust for differences in the overall size of regions. Again the results stay almost the same. Taking the results of column 6 as the main specification, regions with an average exposure to foreign robots through input trade see a 0.130 percentage point decline in their employment ratio if its weighted exposure increases by one foreign robot per 1000 workers<sup>22</sup>. The corresponding decline in the employment ratio through exposure to foreign robots through final goods trade lies by 0.0873 percentage points.

In Panel B, the outcome changes to the ratio of employment in manufacturing. The negative effect of foreign automation through final goods trade on the overall employment ratio appears to be driven by declines in manufacturing employment, as the coefficient is negative and significant in all specifications. Manufacturing employment decreases in regions with an average exposure to foreign robots through final goods trade by 0.104 percentage point if its weighted exposure increases by one foreign robot per 1000 workers. Weighting the regression by regional population turns the exposure to domestic automation significant.

Whether foreign automation may lead to a shift from certain industries to raw materials extraction is examined in Panel C. The coefficient of foreign automation through the input channel is indeed statistically significant and positive in all specifications. This points towards the notion of automation inducing a "deindustrialization" and a focus on raw material extraction. The effect size is however smaller than the negative effect found for overall employment and manufacturing employment, lying by an increase of 0.0384 percentage points.

The last Panel shows no robust effects of exposure to automation on service employment. The coefficient of exposure to foreign robots through final goods is positive and statistically significant in the first 4 columns, which could indicate that workers move from manufacturing to service sector jobs, but turns insignificant when controlling for Chinese import exposure. Thus, workers do not appear to be moving to the service sector as a consequence of automation to substitute for the decline in manufacturing employment.

In Table A.4 in the Appendix, instead of yearly variation, three-year intervals are used to allow for some time adjustment to yearly shocks. The results are almost identical. In section 4.6 long and stacked differences are used to examine any longer term trends.

Overall, the evidence is in line with the main hypotheses of the paper. Foreign automation decreases manufacturing employment, as it becomes cheaper in industrialized economies to produce themselves, but increases employment in the raw materials sector increases, as more raw material inputs are demanded abroad.

## 4.2 Employment by Occupation and Routine Tasks

As a next step, the employment ratio is disaggregated by occupation group, according to the standard ISCO classification. Furthermore, workers are divided into routine tasks and non-routine tasks. How the workers are allocated into the tasks is explained in section A.2 in the Appendix.

Panel A of Table 2 reports the effects of the different exposure measures on the employment ratio of the different occupation groups. As could be expected, plant & machine operators are the ones that lose through automation. The employment ratio of this group declines both through domestic and through foreign automation through final goods, which is in line with the theoretical predictions made in section 2. Their tasks are the ones that are mostly likely to be overtaken directly by domestic robots. At the same

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<sup>22</sup>This large decline is almost exclusively driven by the Agriculture sector, as shown in Figure 1.



time, foreign automation leads to reshoring and less exports to industrialized economies (see Krenz et al. (2018) and Faber (2019)). At the same time, the employment ratio of managers and professionals increases

Table 2: Employment by Occupation

	Employment Ratio (2SLS Estimation)						
	Managers & Professionals	Technicians & Assoc. Professionals	Service Workers	Skilled Agr. Workers	Craft Workers	Plant & Machine Operators	Elementary Occupations
<b>Panel A: All Tasks</b>							
Dom. Robot Exposure	0.0756*** (0.0241)	0.00835 (0.0245)	0.0848 (0.0938)	0.458*** (0.128)	0.0340 (0.110)	-0.238** (0.104)	-0.114 (0.0914)
For. Robot Exposure - Input	-0.0303*** (0.00855)	-0.00203 (0.00983)	-0.0838*** (0.0277)	-0.126*** (0.0308)	0.0274 (0.0275)	-0.00681 (0.0148)	0.0943*** (0.0343)
For. Robot Exposure - Final	0.00556 (0.00575)	0.00267 (0.00757)	-0.00178 (0.0215)	-0.0765** (0.0373)	0.0544* (0.0302)	-0.0331** (0.0149)	-0.0338 (0.0225)
<b>Panel B: Routine Tasks</b>							
Dom. Robot Exposure	0.000974 (0.00106)	-0.0202 (0.0155)	-0.0836 (0.0728)	-0.0552 (0.103)	0.112 (0.100)	-0.236** (0.0961)	-0.0322 (0.0220)
For. Robot Exposure - Input	-0.0000999 (0.000229)	0.00895* (0.00482)	-0.0369** (0.0164)	-0.0208 (0.0261)	0.0151 (0.0225)	-0.0205 (0.0135)	0.0199 (0.0174)
For. Robot Exposure - Final	0.000312* (0.000176)	-0.00254 (0.00252)	-0.00539 (0.00737)	0.00365 (0.0210)	0.00500 (0.0264)	-0.0271** (0.0128)	0.00469 (0.00669)
<b>Panel C: Non-Routine Tasks</b>							
Dom. Robot Exposure	0.0401* (0.0213)	-0.0320 (0.0205)	0.0964* (0.0541)	0.519*** (0.155)	0.0173 (0.0451)	-0.0268 (0.0394)	-0.0483* (0.0255)
For. Robot Exposure - Input	-0.0193*** (0.00725)	-0.00101 (0.00549)	-0.0188 (0.0206)	-0.0833*** (0.0247)	0.00656 (0.00969)	0.00852 (0.00834)	0.0664*** (0.0134)
For. Robot Exposure - Final	0.00334 (0.00474)	0.00274 (0.00537)	0.00586 (0.0143)	-0.0933** (0.0434)	-0.00832 (0.0108)	-0.00702 (0.0135)	0.00750 (0.00566)
Observations	8355	8355	8355	8355	8355	8355	8355
Microregion FE	✓	✓	✓	✓	✓	✓	✓
State x Year FE	✓	✓	✓	✓	✓	✓	✓
Regional Char.	✓	✓	✓	✓	✓	✓	✓
Import Exposure	✓	✓	✓	✓	✓	✓	✓
Industry Controls	✓	✓	✓	✓	✓	✓	✓
KP F-Statistic	5998.1	5998.1	5998.1	5998.1	5998.1	5998.1	5998.1

**Note:** Standard errors, in parentheses, are clustered on the mesoregion level. In Panel A, the outcomes are the employment ratios of different occupations according to the standard ISCO classification. Panel B and C subdivide these ratios into routine and non-routine task workers (See Appendix A for further details). Regional Characteristic controls are the logs of total microregion population and GDP, the share of female workers, the share of female workers, the routine task intensity index, the average highschool graduate rate and the share of foreign owned enterprises. Industry controls are the lagged share of service workers, agricultural workers, light manufacturing and automotive workers. All controls are included in all specifications.

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

through domestic automation. This could be driven by the creation of new tasks, which demand a higher skill set of workers (Acemoglu & Restrepo, 2019a) and an incentive to invest more into skill formation. Foreign automation through input exports however has a negative effect on the employment ratio of this occupation group. This reflects that goods that have an increased demand through foreign automation, which will be investigated in more detail in section 4.5, require lesser skills. Accordingly, foreign automation through input trade has a positive effect on the employment ratio of elementary occupations, i.e. the least skilled workers. Service workers also have a decline in employment through the input channel. Lastly, skilled agricultural workers have large and statistically significant coefficients for all exposure variables. Workers of this occupation group are, besides the agricultural sector, employed mostly in the food and beverages industry. The next section will show that this latter industry, which is one of the most important industries in Brazil, drives the final goods trade effect. The positive effect for domestic automation may just reflect a displacement effect. As the coefficient for agricultural workers is extremely large, as a robustness test, the

main analysis will be done without this group in section 4.7.

Subdividing the occupation groups into routine and non-routine task workers, yields the expected results. The employment decline of plant & machine operators is driven by routine-task workers, since robots replace mostly routine tasks. The employment increase of managers and professionals on the other hand is attributed to non-routine workers. It has to be noted, that not all occupations in the RAIS dataset can be matched with the routine-task data from O\*Net, which results in a loss of observations.

Table A.5 in the Appendix displays the same estimations weighted by regional population, through which regions with higher population are treated as more important than others. The results are mostly the same to the findings here, except that the domestic robot exposure coefficient for non-routine tasks of managers & professionals is no longer statistically significant.

### 4.3 Employment by Industry

In this section, the employment effects are disaggregated by industry. Table 1 showed a decline in manufacturing employment through foreign automation but no clear effect for domestic automation. In Figure 1 the different manufacturing industries are disentangled in order to obtain a more fine-grained understanding of which differential industry-specific effects. The light-blue colored bars display exposure to domestic robots, the light-red bars show exposure to foreign robots via the final goods channel and the green bars in turn show the intermediate goods channel. The same specification as in column 6 of Table 1 is used.

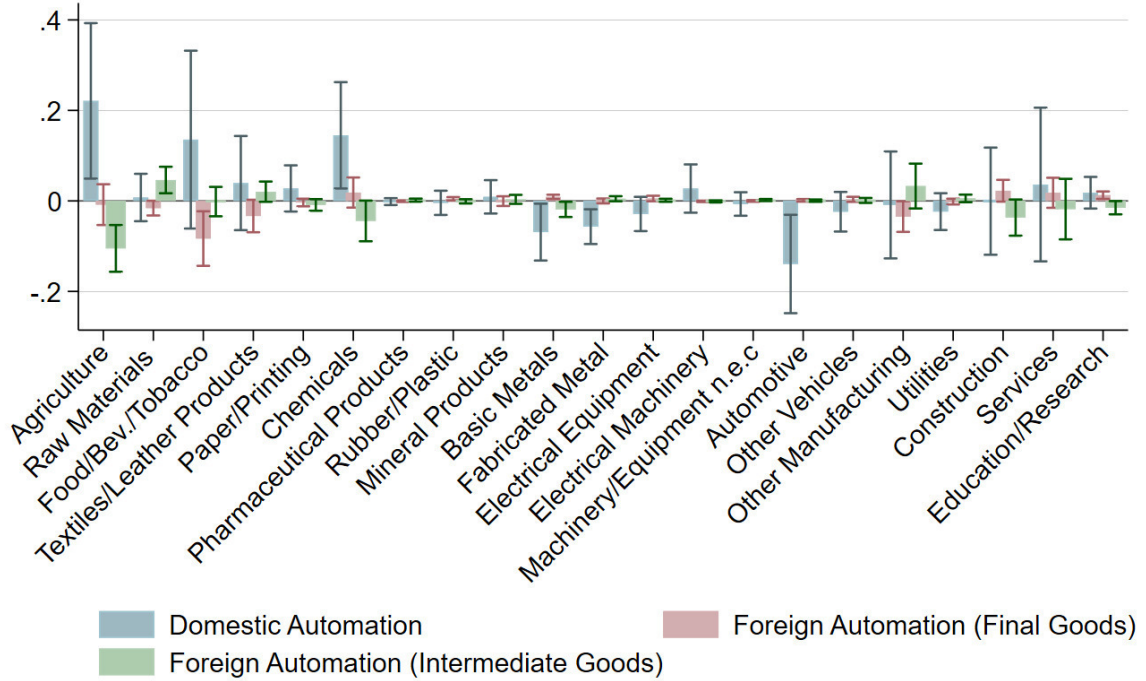
Disaggregating industries shows that some industries are positively and some negatively affected by exposure to domestic automation. It has a statistically significant and negative effect on the employment in the automotive, basic and fabricated metals industries. The automotive industry is clearly the one most susceptible to automation and reshoring, which also has the largest coefficient. A positive effect can be seen for the chemicals industry, indicating that here the increase of the ratio of managers and professionals stems from. Furthermore, the positive coefficient likely leads to there being no overall effect on manufacturing employment. Lastly, as in section 4.2, a large and positive effect on employment in agriculture can be seen, most likely reflecting a displacement effect.

Foreign automation through input trade has only positive effect on the raw materials sector and a negative effect on employment in Agriculture and the Chemicals sector, as noted above. The negative coefficient of foreign automation is largely driven by the industry Food, Beverages and Tobacco.

In the Appendix, industry employment is further disaggregated into routine and non-routine workers, as well as skilled and unskilled workers. Looking at routine-task workers in Figure A.5, employment decreases especially through exposure to domestic automation in the industries rubber & plastic, fabricated metal, electrical equipment and automotive. Non-routine worker employment ratios in turn increase in agriculture, as well as the food, beverages & tobacco and chemicals industries, as can be seen in Figure A.6.

With respect to domestic automation, the negative industry-specific employment effects can also be seen for unskilled workers (Figure A.7). The negative overall employment effects thus seems to be driven largely by unskilled, routine-task workers. In section 4.2 the employment ratio of managers & professionals was found to decrease by foreign automation through inputs. Figure A.8 shows that this decrease stems mainly from the Services sector. The positive coefficient for domestic in turn comes also from the service sector, education & research, and the chemicals and paper & printing industries.

Figure 1: Robot Exposure and Industry Employment Ratio



**Note:** The figure displays the coefficients of estimating industry level employment ratios on domestic robot exposure (blue) and foreign robot exposure through final goods (red) and through inputs (green). The same specification as in column 6 of table 1 is used. Standard errors are clustered on the mesoregion level. Controls included are microregion dummies, state trends, the logs of total microregion population and GDP, the routine task intensity index, the average highschool graduate rate, the share of foreign owned enterprises, and the lagged shares of service workers, agricultural workers and automotive workers.

#### 4.4 Wages

Not only employment levels but also wages of workers may be affected by automation. Low-skilled workers who face increased competition by robots lose bargaining power and thus might be willing to work at a lower wage rate. Conversely, as automation increases the demand for high-skilled workers, higher wages might be necessary to attract workers of higher skill levels. In Table 3 the effect of automation on the logarithm of the wage rate<sup>23</sup> of different groups of workers are presented. There is no effect of automation on the overall wage rate, as can be seen in the first column. Manufacturing workers' wages decline through higher exposure to foreign robots through final goods. This is the same pattern as was observed for employment changes. For workers in the raw materials or service sector there are no changes in wages. Looking at occupations, also for skilled workers, i.e. managers & professionals no effects emerge, though the coefficient of domestic automation is positive. Unskilled workers, which are comprised of craft workers, plant & machine operators and elementary Occupations, see declining wages with higher exposure to domestic robots, but

<sup>23</sup>The wage rate of a worker in December is used to define the microregion level wages of the specific groups, to ensure that seasonal variation or monthly inflation are not driving the results Kovak, 2013.

slightly increasing wages with high exposure to foreign robots through inputs. Domestic automation thus increases wage inequality between high - and low-skilled workers in regions in Brazil.

Table 3: Wage Effects

	Outcome: (log) Wages (2SLS Estimation)					
	All	Manufacturing	Raw Materials	Services	Skilled	Unskilled
Dom. Robot Exposure	-3.146 (3.235)	-1.605 (1.178)	-0.698 (1.415)	0.189 (0.747)	0.654 (0.731)	-0.978** (0.464)
For. Robot Exposure - Input	0.204 (0.389)	0.577* (0.348)	-0.219 (0.428)	-0.0445 (0.206)	0.271 (0.200)	0.233** (0.111)
For. Robot Exposure - Final	0.0369 (0.415)	-0.428** (0.200)	-0.342 (0.433)	0.0188 (0.227)	-0.212 (0.186)	0.0978 (0.106)
Observations	8355	8355	7087	8355	8348	8352
Microregion FE	✓	✓	✓	✓	✓	✓
State Year FE	✓	✓	✓	✓	✓	✓
Regional Characteristics	✓	✓	✓	✓	✓	✓
Import Exposure	✓	✓	✓	✓	✓	✓
Industry Controls	✓	✓	✓	✓	✓	✓
KP F-Statistic	5998.1	5998.1	4050.1	5998.1	6005.2	6000.6

**Note:** Standard errors, in parentheses, are clustered on the mesoregion level. Outcomes are the log wages of the different worker groups. The skilled group are Managers & Professionals. Unskilled are Craft Workers, Plant & Machine Operators and Elementary Occupations. All specifications include microregion and state interacted with year fixed effects. Regional Characteristic controls are the logs of total microregion population and GDP, the routine task intensity index, the share of female workers, the average highschool graduate rate and the share of foreign owned enterprises. Industry controls are the lagged share of service workers, agricultural workers, light manufacturing and automotive workers.

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

## 4.5 Exports

The main hypothesis of the paper is that foreign automation affects regional employment through changes in export demand. On the one hand, automation decreases the cost of production and thus decreases demand for final goods, but at the same time increases the demand for raw materials and inputs needed for production.

So far, the analysis has run under the assumption that regional exports flows adjust to foreign automation, which was captured by using initial input and final goods export shares to weight foreign robots, leading to regional employment ratio changes. In order to test whether regional exports really change, data on regional exports of inputs and final goods would be required. As this data is not available, I combine regional export data from the Brazilian Secretariat of Foreign Trade with the WIOD data to construct a regional I-O table, the process of which is described in further detail in section A.2.

The regional export data allows to estimate the effect of foreign automation on (log) regional input exports and (log) regional final goods exports. The estimation equations are given by:

$$X_{rijk}^1 = \alpha_0 + \alpha_1 R_{jk} + \chi + \epsilon \quad (19)$$

and

$$X_{rij}^2 = \gamma_0 + \gamma_1 R_{jk} + \phi + \epsilon, \quad (20)$$

where  $X_{rijk}^1$  are (log) input exports from region  $r$  industry  $i$  to country  $j$  industry  $k$ ,  $X_{rij}^2$  are (log) final good exports from region  $r$  industry  $i$  to country  $j$ ,  $R_{jk}$  is the stock of robots in country  $j$  industry  $k$  and  $\chi$  and  $\phi$  are different sets of control variables.

The results of estimating equations 19 and 20 are reported in Table 4<sup>24</sup>.

Table 4: Foreign Automation and Microregion Exports

	(1)	(2)	(3)	(4)	(5)	(6)
<b>Panel A: (Log) Final Goods Exports</b>						
Stock of Robots per 1000 Workers	-0.000372 (0.00140)	-0.00126 (0.00145)	-0.0149*** (0.000851)	-0.0153*** (0.000862)	-0.0160*** (0.000902)	-0.0149*** (0.00115)
Observations	257887	256716	256716	244247	204930	256716
R <sup>2</sup>	0.773	0.775	0.924	0.924	0.928	0.924
<b>Panel B: (Log) Intermediate Goods Exports</b>						
Stock of Robots per 1000 Workers	0.0100*** (0.00123)	0.00924*** (0.00131)	0.000445 (0.000428)	0.000445 (0.000341)	0.000412 (0.000405)	0.000747 (0.000394)
Observations	4541573	4520763	4520763	4520763	4309589	3647922
R <sup>2</sup>	0.429	0.434	0.505	0.505	0.507	0.519
<b>Panel C: (Log) Raw Materials Exports</b>						
Stock of Robots per 1000 Workers	0.00746*** (0.000764)	0.00693*** (0.000861)	0.00157*** (0.000448)	0.00231*** (0.000443)	0.00270*** (0.000457)	0.00157*** (0.000569)
Observations	169715	169096	169096	154000	129766	169096
R <sup>2</sup>	0.722	0.723	0.783	0.778	0.790	0.783
Microregion x Sector x Year	✓	✓	✓	✓	✓	✓
Tariff		✓	✓	✓	✓	✓
Importer Dummy	✓	✓				
Importing Sector Dummy	✓	✓				
Importer x Year			✓	✓	✓	✓
Importer x Sector			✓	✓	✓	✓
Excluding China				✓		
Only Developed Countries					✓	
Mesoregion Clustering	✓	✓	✓	✓	✓	
Region x Importer Clustering						✓

**Note:** Standard errors, in parentheses, are clustered on the mesoregion level in columns 1-5, and on region importing country pair in column 6. Column 4 excludes China as an importing country and column 5 only uses developed countries as importers.

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

In Panel A, the effect of the stock of robots per 1000 workers in the destination country and sector on the log of final goods exports are displayed. All columns include microregion sector year fixed effects, which capture all time varying effects on the exporter side<sup>25</sup>. Columns 1 and 2 include importing country and sector dummies, while in columns 3-6 importer trends and time invariant importer sector characteristics are controlled for. A negative and statistically significant effect of foreign automation on microregion exports of final goods is found, which is robust to excluding China as a destination country, using only industrialized countries as destination countries and clustering standard errors on the region and importer pair level, when using the more demanding set of fixed effects. Panel B turns to the exports of input goods. Here, no robust association to foreign automation is found. Lastly, in Panel C, only exports of raw materials are used as the outcome variable. There is a strong and robust effect of foreign automation microregion level exports.

Taken together, the results strengthen the findings of the rest of the paper. In line with the employment level outcomes, foreign automation indeed appears to decrease final goods exports but increases raw material exports.

<sup>24</sup>Export destination countries include all countries in the WIOD data.

<sup>25</sup>In the structural gravity literature this interaction is denoted as the outward multilateral resistance term (Yotov, Piermartini, Monteiro, & Larch, 2016).

## 4.6 Pre - and Long Differences

In this section, it is checked whether microregions that were more exposed to domestic or foreign automation had similar employment trends before the rate of automation took off. Should similar employment trends be found, it is likely that these are driven by other trends than exposure to domestic or foreign automation. Pre-trends are analyzed for the period between 1985, the first year for which RAIS data is available, and 1995, where the usage of robots was not yet spread<sup>26</sup>. Due to a change in the regional classification in the late 80's<sup>27</sup>, there are fewer regions available for the analysis. With the previously found patterns in mind, finding a negative effect of foreign automation on overall employment, a positive effect of foreign automation through inputs on Raw Materials employment or a negative effect of foreign automation through final goods on manufacturing employment would counteract the robustness of the results.

The first three columns of Table 5 present the results of this pre-trend analysis, where in Panel A the outcome is the overall employment ratio, in Panel B the raw materials sector employment ratio and in Panel C the manufacturing sector employment ratio. Changes in automation are measured between 1995 and 2014<sup>28</sup>. 1995 is used as the baseline year, because it is the first year which the industry and occupation classifications of this paper are available and foreign countries were at an early stage of automation. Column 1 controls only for state dummies and baseline regional characteristics, while column 2 adds baseline industry controls. In column 3, mesoregions within which there were microregions with changing classification between 1985 and 1995 are excluded.

The results do not suggest the presence of confounding pre-trends. While some of the coefficients are statistically significant, they are of opposite sign to the coefficients found in Table 1. For manufacturing employment for instance, there is a strong and positive coefficient for exposure to foreign automation through final goods for the difference in employment between 1985 and 1995, while for the period of robot exposure, a negative relationship is found. For raw materials employment, exposure foreign automation through input goods in the later period has no effect. The coefficients for domestic automation and foreign automation through final goods in turn are significant, which they aren't for the later period. No pre-trend is found for the total employment ratio. Thus, microregions which experienced larger exposure to domestic or foreign automation had either no or opposite employment developments before the automation period.

Furthermore, instead of using yearly variation in automation, the presence of long term trends are explored, by using long - and stacked differences. As outlined above, 1995 is used as a baseline for this analysis, as it is the first year with comparable data to the later years and automation had not yet been common in production. Using long-differences has the advantage that changes in the stocks of robots are larger over time and effects might need time to fully develop. On the other hand, important yearly variation is lost and the results are more prone to single year-specific effects.

Columns 4-6 display the results of the long-differences estimation. In column 6, the change in the outcome variable in the pre-trend period is controlled for. The results are similar to the results in the main specification of Table 1. The employment ratio of workers in the raw materials sector increases through foreign automation through input trade (Panel B), and manufacturing employment decreases through domestic and foreign automation through the channel of final goods (Panel C). No effects are here found regarding overall

<sup>26</sup>Brazil for instance had the first recorded robots in 1999.

<sup>27</sup>The state of Tocantins was not formed before 1988 for instance.

<sup>28</sup>For the foreign automation exposure measures, trade values from the year 2000 are taken, as this is the first available year in WIOD.

employment. Using Stacked-Differences between 1995 - 2005 and 2005 - 2014 in columns 7 to 8 does not change the results, however the coefficient for domestic automation on Manufacturing employment is no longer statistically significant, as it is in the main analysis.

Table 5: Automation and Employment - Pre- and Long-Term Effects

	Pre - Trend (1985-1995)			Long Differences (1995-2014)			Stacked Differences (1995-2005, 2005-2014)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
<b>Panel A: Total Employment Ratio</b>									
Dom. Robot Exposure (Diff)	0.0143 (0.0358)	0.0289 (0.0377)	0.0590* (0.0300)	0.00673 (0.0252)	0.0435 (0.0751)	0.0480 (0.0777)	0.0155 (0.0126)	-0.0171 (0.0298)	-0.00769 (0.0263)
For. Robot Exposure - Input (Diff)	-0.0961 (0.0980)	-0.150* (0.0839)	-0.171** (0.0852)	-0.00535 (0.0840)	0.00701 (0.101)	0.0409 (0.101)	-0.0143 (0.0867)	-0.0299 (0.0741)	0.0280 (0.0750)
For. Robot Exposure - Final (Diff)	0.172 (0.104)	0.122 (0.115)	0.0321 (0.0851)	-0.0589 (0.0612)	-0.0457 (0.120)	0.0140 (0.0999)	0.129*** (0.0485)	-0.0548 (0.0557)	-0.0163 (0.0547)
Observations	544	544	518	557	557	544	1116	1116	1090
<b>Panel B: Raw Materials Employment Ratio</b>									
Dom. Robot Exposure (Diff)	-0.00995* (0.00543)	-0.0140* (0.00779)	-0.0166** (0.00817)	0.000563 (0.00455)	0.0356 (0.0240)	0.0281* (0.0161)	0.000213 (0.00258)	0.00254 (0.00512)	0.000855 (0.00454)
For. Robot Exposure - Input (Diff)	0.0347 (0.0312)	0.0293 (0.0283)	0.0307 (0.0294)	0.0841*** (0.0194)	0.162*** (0.0458)	0.130*** (0.0377)	0.0632*** (0.0167)	0.0678*** (0.0216)	0.0577*** (0.0173)
For. Robot Exposure - Final (Diff)	0.0200 (0.0166)	0.0546** (0.0212)	0.0634*** (0.0230)	0.00120 (0.0141)	0.00225 (0.0187)	0.00956 (0.0160)	-0.00224 (0.00622)	0.0109 (0.0101)	0.00996 (0.00925)
Observations	544	544	518	557	557	544	1116	1116	1090
<b>Panel C: Manufacturing Employment Ratio</b>									
Dom. Robot Exposure (Diff)	-0.0911*** (0.0289)	-0.0357 (0.0262)	-0.0166 (0.0236)	0.0494* (0.0250)	-0.200** (0.0812)	-0.187** (0.0777)	-0.00313 (0.0117)	-0.00518 (0.0201)	-0.00389 (0.0196)
For. Robot Exposure - Input (Diff)	-0.0662 (0.0497)	-0.141*** (0.0502)	-0.166*** (0.0496)	0.0403 (0.0634)	-0.123 (0.0788)	-0.0962 (0.0755)	0.0133 (0.0439)	-0.0533 (0.0481)	-0.0349 (0.0529)
For. Robot Exposure - Final (Diff)	0.257*** (0.0804)	0.271*** (0.0773)	0.217*** (0.0721)	-0.324*** (0.0487)	-0.239*** (0.0546)	-0.225*** (0.0532)	-0.157*** (0.0434)	-0.0779** (0.0343)	-0.0709* (0.0359)
Observations	544	544	518	557	557	544	1116	1116	1090
State FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Initial Regional Characteristics	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE							✓	✓	✓
Initial Industry Shares		✓	✓		✓	✓		✓	✓
Excl. States with Changing Regions			✓						
Controlling for Pre-Trend						✓			✓
KP F-Statistic	14721.8	16354.4	17058.2	12756.6	172.0	176.8	2966.7	1130.7	1153.5

**Note:** Standard errors, in parentheses, are clustered on the mesoregion level. In column 3, mesoregions are excluded that had changing regional classifications. Population weights, used in columns 3, 6 and 9, are based on microregion population in 1997 (first available year). Regional Characteristics are the baseline share of highschool graduates, baseline share of foreign owned firms, baseline share of female workers, baseline routine task intensity index, baseline population and baseline GDP. In columns 1-3, the share of foreign owned firms is taken from 1995, due to data unavailability in 1985. Also, employment cannot be restricted by age in the pre-trends analysis in columns 1-3. The employment to population ratio is thus calculated with the unemployment share.

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

## 4.7 Robustness Tests

Table 6 presents a number of robustness tests, which are based on the current shift-share literature and other literature about Brazil. Panel A shows the total employment ratio, Panel B the raw materials employment ratio and Panel C the manufacturing employment ratio. The first two columns use different sets of fixed effects as compared to the main analysis. In column 1 only year dummies are included instead of state-trends, while in column 2 mesoregion trends are used. Both of these do not change the results.

Since residuals might not be only correlated between regions of close vicinity but also between regions with a similar industry structure, in column 3, shift-share adjusted standard errors are used, following Adão



et al. (2018)<sup>29</sup>. The size of the standard errors actually decreases, as compared to the original results. This may be due to a small sample bias of having relatively few industries. The authors point out though, that overrejection is more severe in the case of a small number of sectors and clustering on the regional level. Since the shift-share standard errors yield tighter confidence intervals as regional clustering, there seems to be little cross-regional correlation in the residuals driven by the shift-share structure.

Table 6: Robustness Tests

	Employment Ratio (2SLS Estimation)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<b>Panel A: Total Employment Ratio</b>								
Dom. Robot Exposure	0.333 (0.274)	0.382 (0.234)	0.303** (0.105)	0.311 (0.221)	0.914 (1.522)	-0.913 (1.901)	-1.210 (1.671)	0.360 (0.233)
For. Robot Exposure - Input	0.0283 (0.0793)	-0.0829 (0.0611)	-0.130** (0.0189)	-0.130** (0.0526)	0.0703 (0.154)	-0.126*** (0.0573)	-0.0108 (0.0509)	-0.0976* (0.0541)
For. Robot Exposure - Final	-0.0119 (0.0681)	-0.0657 (0.0469)	-0.0873** (0.0211)	-0.0889* (0.0490)	-0.180** (0.0810)	-0.0686 (0.0528)	-0.0528 (0.0404)	-0.0999* (0.0565)
<b>Panel B: Raw Materials Employment Ratio</b>								
Dom. Robot Exposure	-0.0167 (0.0400)	0.000458 (0.0453)	0.00748 (0.0197)	0.00864 (0.0325)	0.0520 (0.169)	0.253 (0.398)	0.271 (0.399)	-0.00198 (0.0273)
For. Robot Exposure - Input	0.0459*** (0.0170)	0.0445** (0.0196)	0.0462*** (0.007)	0.0440** (0.0174)	0.0223 (0.0221)	0.0372** (0.0161)	0.0376** (0.0160)	0.0379** (0.0164)
For. Robot Exposure - Final	-0.00940 (0.00690)	-0.0156 (0.0114)	-0.0159 (0.0034)	-0.0143* (0.00974)	-0.0262** (0.0115)	-0.0161** (0.00800)	-0.0165** (0.00801)	-0.0128 (0.00843)
<b>Panel C: Manufacturing Employment Ratio</b>								
Dom. Robot Exposure	0.132 (0.204)	0.0291 (0.167)	0.0441 (0.085)	0.0236 (0.159)	3.858** (1.754)	-2.627** (1.246)	-2.533** (1.246)	0.138 (0.164)
For. Robot Exposure - Input	0.000935 (0.0304)	0.0194 (0.0437)	-0.00726 (0.020)	-0.0270 (0.0320)	0.385*** (0.0749)	-0.0206 (0.0347)	-0.0210 (0.0353)	0.0437 (0.0322)
For. Robot Exposure - Final	-0.117** (0.0466)	-0.126*** (0.0476)	-0.115*** (0.0219)	-0.0988** (0.0410)	-0.194*** (0.0677)	-0.0652* (0.0393)	-0.0621 (0.0383)	-0.120** (0.0514)
Observations	8370	8355	8355	8355	8355	8355	8355	8355
Microregion FE	✓	✓	✓	✓	✓	✓	✓	✓
Regional Char.	✓	✓	✓	✓	✓	✓	✓	✓
Industry Controls	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓							
Mesoregion Year FE		✓						
State Year FE			✓	✓	✓	✓	✓	✓
Shift-Share S.E.			✓					
Additional Industry Controls				✓	✓	✓	✓	✓
Lagged Shocks					✓			
Excl. Outlier Exposure						✓		
Excl. Agr. Employment							✓	
Foreign Exposure through Imports								✓
KP F-Statistic	5273.8	5210.6	5998.1	6697.2	33.24	8.948	9.006	7040.7

**Note:** This Table reports additional robustness tests. All columns use regional characteristic controls, which are the logs of total microregion population and GDP, the share of female workers, the routine task intensity index, the average highschool graduate rate and the share of foreign owned enterprises. Industry controls are the lagged share of service workers, agricultural workers, light manufacturing and automotive workers. Column 1 uses only year fixed effects, instead of state trends, and column 2 uses mesoregion trends. In column 3, shift share clustered standard errors from Adão, Kolesár, and Morales (2018) are used. In all other columns standard errors are clustered on the mesoregion level. In column 4, the lagged share of workers in the industries Rubber & Plastic and Electrical Equipment, as well as the Construction sector are included. Column 5 adds lagged values of the automation exposure variables and the respective outcome variable. Exposure to the automotive industry is excluded in column 6 and agricultural employment in column 7. In column 8, the analysis is run without regions with a higher than 90% share of service workers in the year 2000. Exposure to foreign automation through imports is added in column 8.

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

<sup>29</sup>For the calculations, the authors' provided R package was used. I thank the authors for making the code publicly available and their helpful comments.



In column 4 additional lagged industry shares are included. These industries are the rubber and plastic and the electrical equipment, as these, besides the automotive industry, have the highest exposure rates regarding domestic and foreign automation, respectively (see Figure 1). Furthermore, the lagged share of employment in the construction sector is added, as it grew substantially through fiscal spending in Brazil and played a large role in the corruption scandal around 2014 (Spilimbergo & Srinivasan, 2019). The inclusion of these does not change the results.

As increased exposure to automation, measured by yearly increases in the sector level stock of robots, is serially correlated, I include lags of the shock exposures and the respective outcome variables in column 5 to isolate the yearly variation of the shocks (Borusyak et al., 2018). The inclusion of these indeed affects the results, with the coefficient of foreign exposure through inputs on raw materials sector employment turning insignificant. Furthermore, the coefficients increase in magnitude.

In column 6, as suggested by Borusyak et al. (2018), I exclude exposure to the Automotive sector, as it has by far the highest numbers of robots both domestically and foreign weighted, to see whether it drives the results. The estimation without the outlier industry turns the coefficient of foreign exposure through final goods in the regression with the overall employment ratio as an outcome insignificant.

As was found in Figure 1, agriculture has one of the largest employment changes through exposure to automation. To test whether this may be a driver behind the overall employment results, workers in the agriculture sector are excluded from the analysis in column 7. The results are similar to the baseline results, with the difference that the input channel for overall employment is not significant (the respective coefficient was strongly negative in Figure 1).

Lastly, in column 8 exposure to foreign automation through imports (through both channels) is added. This measure controls for the possibility that foreign automation does not affect local labor markets through exports, but through changes in imports. The exposures are constructed as in equations 17 and 18, just using import shares instead of export shares. The results are robust even with the inclusion of these terms.

Given the scope of the tests, the results appear largely robust, as the coefficients of interest remain significant in almost all specifications. The Kleibergen-Paap F-statistic drops when becoming more demanding, remains above the usual thresholds though.

## 5 Conclusion

In this paper, I investigate how domestic and foreign automation affect local labor markets in Brazil. By distinguishing exposure to foreign automation through the channel of input exports and through the channel exports of final goods, the notion of automation in industrialized countries inducing "premature deindustrialization" in emerging economies is examined. A shift-share approach is used to translate industry-level shocks to regional employment ratios. To account for endogeneity in domestic robot adoption, an instrumental variable approach is used, exploiting exogenous variation in the average stock of robots in other emerging economies.

A Ricardian model with production of intermediate and final goods is developed building on Artuc et al. (2019), Caliendo and Parro (2015) and Acemoglu and Restrepo (2019c), in which domestic robots replace labor in certain industry specific tasks. Foreign automation on the other hand affects local labor markets through changes in demand for intermediate and final goods.

Building on this model, a novel approach is used to study the effects that automation has on an emerging economy. Through the channel of final goods exports, automation in export destination countries is found to decrease employment in the manufacturing sector in Brazil. The negative effect is particularly strong for plant & machine operators. Conversely, through the channel of input trade, I find that foreign automation leads to an increase in employment in the raw materials sector. Here workers in elementary occupations see an employment gain, mostly in non-routine tasks.

To test whether foreign automation truly affects employment through changes in export demand, a regional input-output matrix is constructed. An increase in regional exports of raw materials and a decline in final goods exports confirm the main results.

Furthermore, I find that employment is adversely affected in regions which are more exposed to domestic automation. plant & machine operators lose both in terms of employment and wages. Higher skilled workers, namely managers & professionals, in turn see rising employment ratios. Workers employed in routine-tasks are furthermore more likely to be replaced by robots than workers in non-routine tasks. Looking at industry specific effects, declining employment is especially evident in the automotive industry, but also in Metal industries.

A number of robustness tests are undergone to verify the results. These include testing for shift-share related misspecifications Adão et al. (2018), Borusyak et al. (2018), pre-trends, long- and stacked-differences and other changes to the empirical specifications. Most of the estimates remain unchanged to the tests.

The paper provides evidence as to how the industry structure of an emerging economy may vastly be changed through automation, both domestically and in foreign economies. The findings may cause further worries in the notion of premature deindustrialization in emerging economies through technological change in developed economies (Rodrik, 2016, 2018). Less skilled industry workers in particular lose through domestic automation but also through foreign automation through final goods, while the least-skilled group, which is Elementary Occupations, and the skilled group have employment gains. Furthermore, increasing wage-differences may exacerbate income inequality between high- and low-skilled workers.

## References

- Acemoglu, D. & Restrepo, P. (2018). Low-skill and high-skill automation. *Journal of Human Capital*, 12(2), 204–232.
- Acemoglu, D. & Restrepo, P. (2019a). Artificial intelligence, automation and work. *The Economics of Artificial Intelligence: An Agenda*.
- Acemoglu, D. & Restrepo, P. (2019b). Automation and new tasks: How technology displaces and reinstates labor. *Journal of Economic Perspectives*, Spring 2019 (Volume 33, Number 2), 3–30.
- Acemoglu, D. & Restrepo, P. (2019c). Robots and jobs: Evidence from us labor markets. *Journal of Political Economy*, forthcoming.
- Adão, R., Kolesár, M., & Morales, E. (2018). Shift-share designs: Theory and inference.
- Almeida, R. K., Corseuil, C. H. L., & Poole, J. P. (2017). *The impact of digital technologies on routine tasks: Do labor policies matter?* The World Bank.
- Alvarez, J., Benguria, F., Engbom, N., & Moser, C. (2018). Firms and the decline in earnings inequality in brazil. *American Economic Journal: Macroeconomics*, 10(1), 149–189.
- Antràs, P. & Chor, D. (2018). On the measurement of upstreamness and downstreamness in global value chains.
- Antràs, P., Chor, D., Fally, T., & Hillberry, R. (2012). Measuring the upstreamness of production and trade flows. *American Economic Review*, 102(3), 412–416.
- Artuc, E., Bastos, P., & Rijkers, B. (2019). Robots, tasks and trade. The World Bank.
- Autor, D. H., Dorn, D., & Hanson, G. H. (2013). The china syndrome: Local labor market effects of import competition in the united states. *American Economic Review*, 103(6), 2121–2168.
- Benguria, F. & Ederington, J. (2017). Decomposing the effect of trade on the gender wage gap.
- Borusyak, K., Hull, P., & Jaravel, X. (2018). Quasi-experimental shift-share research designs.
- Brynjolfsson, E. & McAfee, A. (2014). *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*. WW Norton & Company.
- Caliendo, L., Dvorkin, M., & Parro, F. (2015). The impact of trade on labor market dynamics.
- Caliendo, L. & Parro, F. (2015). Estimates of the trade and welfare effects of nafta. *The Review of Economic Studies*, 82(1), 1–44.
- Carbonero, F., Ernst, E., & Weber, E. (2018). Robots worldwide: The impact of automation on employment and trade. *ILO Research Department Working Paper*, (36).
- Costa, F., Garred, J., & Pessoa, J. P. (2016). Winners and losers from a commodities-for-manufactures trade boom. *Journal of International Economics*, 102, 50–69.
- Dix-Carneiro, R. & Kovak, B. K. (2015). Trade liberalization and the skill premium: A local labor markets approach. *American Economic Review*, 105(5), 551–557.
- Dix-Carneiro, R. & Kovak, B. K. (2017). Trade liberalization and regional dynamics. *American Economic Review*, 107(10), 2908–2946.
- Eaton, J. & Kortum, S. (2002). Technology, geography, and trade. *Econometrica*, 70(5), 1741–1779.
- Faber, M. (2019). Robots and reshoring: Evidence from mexican labor markets.
- Flach, L. (2016). Quality upgrading and price heterogeneity: Evidence from brazilian exporters. *Journal of International Economics*, 102, 282–290.

- Ford, M. (2015). *The rise of the robots: Technology and the threat of mass unemployment*. Oneworld Publications.
- Frey, C. B. & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change*, 114, 254–280.
- Goldsmith-Pinkham, P., Sorkin, I., & Swift, H. (2018). Bartik instruments: What, when, why, and how.
- Graetz, G. & Michaels, G. (2018). Robots at work. *Review of Economics and Statistics*, 100(5), 753–768.
- Hardy, W., Keister, R., & Lewandowski, P. (2018). Educational upgrading, structural change and the task composition of jobs in europe. *Economics of Transition*, 26(2), 201–231.
- Helpman, E., Itskhoki, O., Muendler, M.-A., & Redding, S. J. (2017). Trade and inequality: From theory to estimation. *The Review of Economic Studies*, 84(1), 357–405.
- Hirata, G. & Soares, R. R. (2016). Competition and the racial wage gap: Testing becker’s model of employer discrimination.
- International Federation of Robotics. (2016). World robotics: industrial robots.
- Jenkins, R. (2015). Is chinese competition causing deindustrialization in brazil? *Latin American Perspectives*, 42(6), 42–63.
- Koch, M., Manuylov, I., & Smolka, M. (2019). Robots and firms. *Working Paper*.
- Kovak, B. K. (2013). Regional effects of trade reform: What is the correct measure of liberalization? *American Economic Review*, 103(5), 1960–1976.
- Krenz, A., Prettnner, K., & Strulik, H. (2018). Robots, reshoring, and the lot of low-skilled workers.
- Muendler, M.-A., Poole, J., Ramey, G., & Wajenberg, T. (2004). Job concordances for brazil: Mapping the classificaçao brasileira de ocupaçoes (cbo) to the international standard classification of occupations (isco-88).
- Rodrik, D. (2016). Premature deindustrialization. *Journal of Economic Growth*, 21(1), 1–33.
- Rodrik, D. (2018). New technologies, global value chains, and developing economies.
- Simoes, A. & Hidalgo, C. A. (2011). The economic complexity observatory: An analytical tool for understanding the dynamics of economic development.
- Spilimbergo, A. & Srinivasan, K. (Eds.). (2019). *Brazil: boom, bust, and road to recovery*.
- Timmer, M. P., Dietzenbacher, E., Los, B., Stehrer, R., & de Vries, G. J. (2015). An illustrated user guide to the world input–output database: The case of global automotive production. *Review of International Economics*, 23(3), 575–605.
- Yotov, Y. V., Piermartini, R., Monteiro, J.-A., & Larch, M. (2016). *An advanced guide to trade policy analysis: The structural gravity model*. World Trade Organization Geneva, Switzerland.

# A Appendix

## A.1 Theory Appendix

### Prices and Expenditures

The efficiency of production of each country/region in industry  $i$  is the realization of the random variable  $z_{ri}$  from the probability distribution  $F_{ri} = Pr [Z_i \leq z]$ , which with the properties from the Fréchet distribution becomes

$$F_{ri} = e^{-T_{rji}^{-\theta_i}}, \quad (\text{A.1})$$

with  $T_{rji} = \lambda_{ri}(c_{ri}\tau_{rji})^{-\theta_i}$ . Caliendo, Dvorkin, and Parro (2015) show that the lowest price of a good  $\omega_i$  in region  $r$  also has a Fréchet distribution

$$Pr [p_{ri} \leq p] = 1 - e^{-\psi_{ri}p^{-\theta_i}}, \quad (\text{A.2})$$

where  $\psi_{ri} = \lambda_{ri}(c_{ri}\tau_{rji})^{-\theta_i}$ , which is a statistic of technologies, input costs, geographic barriers and tariff policies (Eaton & Kortum, 2002; Caliendo & Parro, 2015). The authors further show that due to the properties of probability density functions the price index is

$$P_{ri} = A_i \psi_{ri}^{\frac{-1}{\theta_i}}$$

, which is equivalent to equation 7.

The expenditure of country  $j$  on goods from region  $r$  and industry  $i$  can also be denoted in probability terms as

$$X_{jri} = Pr \left[ \frac{c_{ri}\tau_{rji}}{z_{ri}(\omega_i)} \leq \min_{h \neq r} \frac{c_{hi}\tau_{hji}}{z_{hi}(\omega_i)} \right] X_{ji}, \quad (\text{A.3})$$

where overall expenditure of country  $j$  industry  $i$  is multiplied by the probability of region  $r$  having the lowest price. To derive equation 8, equations A.1 and A.2 are plugged into A.3.

### Costs and Labor

Following Acemoglu and Restrepo (2018), a region-specific threshold  $C'_r$  is defined, below which producers in region  $r$  use robots instead of human capital. The threshold  $C'_{ri}$  is given by  $w_{ri}^L/\gamma_L(C'_{ri}) = w^R/\gamma_R(C'_{ri})$ . The threshold implies a reduction in task related costs, according to

$$\omega_{ri} = \frac{(1 - C'_{ri})w_{ri}^L + C'_{ri}w^R}{w_{ri}}.$$

Equation 11 can be rewritten as

$$w_{ri}^L L_{ri} = \alpha_{ri}^T (1 - C'_{ri}) \sum_j \pi_{jri} X_{ji},$$

since expenditure on goods of region  $r$  and industry  $i$  is  $Y_{ri} = \sum_j \pi_{jri} X_{ji}$ .

Further disaggregating expenditures, using the fact that  $Y_{ri} = \sum_j \sum_k X_{jkr}$  and that  $X_{jkr} = \pi_{jkr} X_{jki}$ , yields equation 12.

## A.2 Additional Datasets

### Microregion Exports

To differentiate between final goods exports and intermediate goods exports, a microregion level Input-Output table is constructed. Regional export data comes from the SECEX database (Secretaria de Comércio Exterior—Foreign Trade Secretariat), which contains information about export quantities and values, product classification and destination country (see Flach (2016) for further information). Exports (measured in values) are aggregated by sector on the microregion level and classified by the international Harmonized System, which allows me to translate them to the industry codes used in the analysis.

To construct the I-O matrix, data from SECEC and WIOD are combined. From the WIOD, the shares of yearly intermediate exports and final goods exports from sector  $i$  in Brazil to sector  $k$  in partner country  $j$  from all exports of sector  $i$  to this partner country are taken:

$$S_{ijk}^1 = \frac{X_{ijk}^1}{X_{ij}}, \quad S_{ij}^2 = \frac{X_{ij}^2}{X_{ij}},$$

where  $S_{ijk}^1$  is the share of input exports and  $S_{ij}^2$  is the share of final goods exports.

These shares are multiplied with the microregion level exports from the SECEX data. This yields microregion level exports of intermediates from sector  $i$  in Brazil to sector  $k$  in country  $j$ , and final goods exports from sector  $i$  in Brazil to country  $j$ :

$$X_{rijk}^1 = S_{ijk}^1 X_{rij}, \quad X_{rij}^2 = S_{ij}^2 X_{rij}.$$

To control for changes in trade barriers, tariff data is taken from the WTO Integrated Data Base (IDB). MFN Tariffs are on the level of partner country  $j$  and sector  $k$ .

### Routine Task Intensity

In order to control for other technological progresses affecting employment of certain workers, most importantly computerization Frey and Osborne (2017), a measure of routine task intensity of each microregion is included.

Data of routine task intensity comes from the O\*NET 2000 release, which associates the importance of certain tasks to 800 occupations in the United States. Following Almeida, Corseuil, and Poole (2017), and assuming that occupations in Brazil entail similar tasks as the U.S., occupations are assigned a routine intensity. These are matched with the Brazilian occupation system CBO<sup>30</sup>. Thereafter, an average regional routine intensity index is constructed.

To classify workers into routine and non-routine task workers, for each occupation from O\*NET the most important task is extracted. If this task is classified as being routine, the worker is then assigned to be a routine worker.

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<sup>30</sup>I use the crosswalks developed by Hardy, Keister, and Lewandowski (2018) and Muendler, Poole, Ramey, and Wajnberg (2004) to match O\*NET SOC occupations to CBO Brazil occupations.

### A.3 Tables

Table A.1: Industry Codes and Aggregation

Our code	Description	IFR	WIOD (2016)	RAIS (before 2006)	RAIS (after 2006)	Code (ISIC Rev. 4)
1	Agriculture, forestry and fishing	A-B	A01, A02, A03	0-9999	0-4999	01-03
2	Mining and quarrying	C	B	10000-14999	5000-9999	05-09
3	Food, Beverages, Tobacco	10-12	10-12	15000-16999	10000-12999	10-12
4	Textiles and Leather Products	13-15	13-15	17000-19999	13000-15999	13-15
5	Paper and Printing	17-18	17, 18	21000-22999	17000-18999	17-18
6	Chemicals	20-21	19, 20	23000-24499, 24600-24999	19000-20999	19-20
7	Pharmaceuticals	19	21	24500-24599	21000-21999	21
8	Rubber and Plastic	22	22	25000-25999	22000-22999	22
9	Other non-metallic mineral products	23	23	26000-26999	23000-23999	23
10	Basic Metals	24	24	27000-27999	24000-24999	24
11	Fabricated metal products, except machinery and equipment	25	25	28000-28999	25000-25999	25
12	Computer, electronic and optical products	260, 261, 262, 263, 264	26	29000-29999	26000-26999	26
13	Manufacture of electrical equipment	271, 275, 279	27	30000-30999, 32000-33999	27000-27999	27
14	Manufacture of machinery and equipment n.e.c.	28	28	31000-31999	28000-28999	28
15	Manufacture of motor vehicles, trailers and semi-trailers	29	29	34000-34999	29000-29999	29
16	Manufacture of other transport equipment	30	30	35000-35999	30000-30999	30
17	Other manufacturing*	91, 16	31-32, 16	20000-20999, 36000-37999	16000-16999, 31000-33999	31, 32, 16
18	Utilities	E	36, 37-39	40000-41999	35000-39999	D, E
19	Construction	F	F	45000-45999	41000-43999	F
20	Education, Research & Development	P	M72, P85	73000- 73999,80000- 80999	72000-72999, 85000-85999	72, P
21	Services	90	G, H, I, J, K, L, M (excluding 72), N, Q, R, S,	50000-72999, 74000-79999, 81000-99999	45000-71999, 73000-84999, 86000-99999	G, H, I, J, K, L, M (excluding 72), N, Q, R, S, T, U

\* includes "Wood and Furniture", since Wood and Furniture is aggregated in the IFR data, and Furniture and Other Manufacturing in the WIOD data

Table A.2: Descriptive Statistics

Variables - Values in Changes	All Regions	Exposure to Domestic Robots		Exposure to Foreign Robots - Input		Exposure to Foreign Robots - Final	
		<Median	>Median	<Median	>Median	<Median	>Median
Panel A: Outcomes							
Employment Ratio	-0.12 [10.81]	-0.97 [13.49]	0.74 [7.11]	-0.20 [12.59]	-0.04 [8.68]	-1.24 [13.22]	1.01 [7.53]
Skilled Empl. Ratio	0.84 [1.91]	0.37 [2.41]	1.31 [1.05]	0.77 [1.87]	0.92 [1.96]	0.46 [2.44]	1.22 [1.05]
Machine Op. Empl. Ratio	-4.86 [3.96]	-3.44 [3.61]	-6.30 [3.77]	-4.46 [3.98]	-5.28 [3.89]	-3.85 [3.58]	-5.88 [4.05]
Raw Materials Empl. Ratio	-2.33 [5.45]	-2.24 [5.81]	-2.42 [5.08]	-0.50 [3.48]	-4.17 [6.39]	-1.79 [5.13]	-2.87 [5.72]
Manufacturing Empl. Ratio	-1.26 [7.15]	0.18 [6.29]	-2.71 [7.67]	-1.69 [6.88]	-0.84 [7.41]	-0.65 [6.10]	-1.88 [8.04]
Service Empl. Ratio	3.47 [9.91]	1.09 [12.57]	5.87 [5.26]	1.99 [12.06]	4.97 [6.86]	1.21 [12.52]	5.76 [5.46]
(log) Wages	-21.85 [90.68]	-17.60 [95.59]	-26.10 [85.45]	-31.48 [105.96]	-12.21 [71.14]	-19.54 [94.17]	-24.16 [87.15]
Skilled-Unskilled Wage Diff.	-89.77 [69.70]	-95.50 [89.12]	-84.14 [42.24]	-91.54 [85.28]	-88.02 [49.99]	-93.98 [85.98]	-85.63 [48.52]
Panel B: Covariates							
Dom. Robot Exposure	0.67 [1.25]	0.17 [0.09]	1.17 [1.62]	0.49 [0.60]	0.85 [1.65]	0.25 [0.29]	1.09 [1.65]
For. Robot Exposure - Input	10.40 [7.58]	9.37 [8.18]	11.48 [6.77]	4.44 [2.42]	16.40 [6.11]	8.89 [8.36]	11.95 [6.35]
For. Robot Exposure - Final	7.18 [8.24]	3.41 [3.90]	10.96 [9.62]	4.79 [4.60]	9.59 [10.18]	2.07 [1.36]	12.31 [9.04]
HS Graduate Rate	41.53 [42.20]	37.61 [47.70]	45.44 [35.53]	30.14 [48.84]	52.91 [30.37]	35.38 [48.13]	47.68 [34.30]
Share of For. owned Firms	-0.02 [0.19]	-0.02 [0.07]	-0.03 [0.26]	-0.03 [0.26]	-0.01 [0.06]	-0.02 [0.06]	-0.03 [0.27]
(log) Population	15.50 [11.95]	15.10 [12.89]	15.90 [10.95]	16.46 [12.61]	14.53 [11.20]	16.08 [13.18]	14.92 [10.58]
(log) GDP	171.48 [29.06]	173.23 [27.64]	169.73 [30.36]	173.09 [24.93]	169.87 [32.63]	173.84 [28.89]	169.12 [29.08]
Avg. Routine Task Intensity	-1.48 [7.35]	-1.20 [9.27]	-1.76 [4.70]	-0.80 [8.25]	-2.17 [6.26]	-1.22 [8.75]	-1.75 [5.61]
Service Employment Share	4.67 [11.71]	3.49 [14.47]	5.85 [7.91]	3.52 [13.01]	5.82 [10.14]	3.40 [13.59]	5.94 [9.32]
Automotive Employment Share	0.07 [1.12]	0.01 [1.00]	0.14 [1.23]	0.03 [0.82]	0.12 [1.36]	0.01 [0.94]	0.14 [1.28]
Light Manuf. Empl. Share	-0.44 [6.63]	0.15 [7.98]	-1.03 [4.87]	-0.83 [8.01]	-0.05 [4.86]	-0.06 [7.97]	-0.81 [4.93]
World Import Exposure	4418.05 [7021.24]	4443.62 [9162.04]	4392.47 [3850.79]	3299.42 [7195.49]	5536.67 [6669.80]	4690.65 [8968.78]	4145.44 [4264.34]
Chinese Import Exposure	532.83 [610.53]	331.49 [659.15]	734.17 [480.61]	424.92 [432.15]	640.74 [732.61]	357.86 [499.11]	707.80 [660.51]

*Notes:* This table provides descriptive statistics according to exposure to the three automation measures. All values are given as differences between 2000 and 2014 and multiplied by 100. The import exposure values are divided by 10000. Sample means and standard deviation (in brackets) are shown. Light Manufacturing is composed of workers in the Textile and the Paper & Printing industries. Skilled employed workers stands for Managers and Professionals.



Table A.3: First Stage and OLS Results

	Employment Ratios - OLS Estimation						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<b>Panel A: First Stage</b>							
Dom. Robot Exposure	0.0559*** (0.000583)	0.0563*** (0.000744)	0.0564*** (0.000747)	0.0565*** (0.000731)	0.0565*** (0.000729)	0.0566*** (0.000729)	0.0555*** (0.000755)
For. Robot Exposure - Input		-0.00375*** (0.00141)	-0.00395*** (0.00143)	-0.00331** (0.00154)	-0.00309** (0.00145)	-0.00341** (0.00152)	-0.00153 (0.00135)
For. Robot Exposure - Final		-0.00162 (0.00221)	-0.00176 (0.00219)	-0.00193 (0.00216)	-0.00209 (0.00215)	-0.00175 (0.00193)	-0.00152 (0.00211)
<b>Panel B: Employment Ratio</b>							
Dom. Robot Exposure	-0.147 (0.188)	0.175 (0.237)	0.158 (0.236)	0.157 (0.237)	0.183 (0.222)	0.180 (0.214)	0.112 (0.165)
For. Robot Exposure - Input		-0.133** (0.0518)	-0.116** (0.0539)	-0.116** (0.0534)	-0.130** (0.0529)	-0.131** (0.0531)	-0.113** (0.0543)
For. Robot Exposure - Final		-0.0818 (0.0505)	-0.0770 (0.0483)	-0.0770 (0.0484)	-0.0790 (0.0484)	-0.0793 (0.0487)	-0.0928* (0.0495)
<b>Panel C: Manufacturing Employment Ratio</b>							
Dom. Robot Exposure	-0.720** (0.317)	-0.453 (0.313)	-0.436 (0.305)	-0.414 (0.307)	-0.174 (0.236)	-0.0345 (0.216)	-0.361** (0.154)
For. Robot Exposure - Input		0.0557 (0.0605)	0.0676 (0.0604)	0.0772 (0.0576)	-0.00724 (0.0378)	0.00306 (0.0375)	0.0379 (0.0276)
For. Robot Exposure - Final		-0.109** (0.0530)	-0.101** (0.0505)	-0.103** (0.0503)	-0.0997** (0.0436)	-0.0879* (0.0472)	-0.101*** (0.0303)
<b>Panel D: Raw Materials Employment Ratio</b>							
Dom. Robot Exposure	-0.0174 (0.0255)	0.000627 (0.0252)	0.00289 (0.0241)	0.0145 (0.0271)	0.0139 (0.0319)	-0.0220 (0.0394)	0.0151 (0.0223)
For. Robot Exposure - Input		0.0399** (0.0192)	0.0416** (0.0189)	0.0465*** (0.0161)	0.0462** (0.0177)	0.0384** (0.0184)	0.0185** (0.00875)
For. Robot Exposure - Final		-0.0164 (0.0112)	-0.0169 (0.0116)	-0.0179* (0.0107)	-0.0164 (0.00996)	-0.0171 (0.0120)	-0.00567 (0.00440)
<b>Panel E: Service Employment Ratio</b>							
Dom. Robot Exposure	0.360* (0.212)	0.165 (0.209)	0.114 (0.184)	0.0862 (0.180)	0.136 (0.156)	0.0458 (0.147)	0.152 (0.170)
For. Robot Exposure - Input		-0.0176 (0.0655)	-0.0332 (0.0675)	-0.0449 (0.0663)	-0.0645 (0.0477)	-0.0653 (0.0485)	-0.0568 (0.0443)
For. Robot Exposure - Final		0.0736* (0.0419)	0.0662* (0.0373)	0.0684* (0.0368)	0.0443* (0.0265)	0.0341 (0.0264)	0.0374 (0.0278)
Observations	8355	8355	8355	8355	8355	8355	8355
Microregion FE	✓	✓	✓	✓	✓	✓	✓
State x Year FE	✓	✓	✓	✓	✓	✓	✓
Regional Char.			✓	✓	✓	✓	✓
Import Exposure				✓	✓		✓
Industry Controls					✓	✓	✓
China Import Exp.						✓	
Population Weighted							✓

**Note:** Standard errors, in parentheses, are clustered on the mesoregion level. Panel A reports the first-stage results of the estimation equation. Panels B-E display the corresponding OLS results to Table 1. In column 7 microregion population is used as weights. All specifications include microregion and state interacted with year fixed effects. Regional Characteristic controls are the logs of total microregion population and GDP, the share of female workers, the routine task intensity index, the average highschool graduate rate and the share of foreign owned enterprises. Industry controls are the lagged share of service workers, agricultural workers, light manufacturing and automotive workers. Employment outcomes are given by the ratio of employment to population ratios (of the RAIS data).

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Table A.4: Employment Ratios, Overall and by Sector - Three Year Intervals

	Employment Ratios - 2SLS Estimation						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<b>Panel A: Total Employment Ratio</b>							
Dom. Robot Exposure	-0.132 (0.168)	0.201 (0.246)	0.162 (0.251)	0.153 (0.254)	0.212 (0.242)	0.251 (0.240)	0.186 (0.192)
For. Robot Exposure - Input		-0.163*** (0.0540)	-0.144** (0.0576)	-0.147** (0.0570)	-0.164*** (0.0556)	-0.158*** (0.0555)	-0.117* (0.0654)
For. Robot Exposure - Final		-0.0577 (0.0550)	-0.0463 (0.0524)	-0.0455 (0.0525)	-0.0470 (0.0528)	-0.0470 (0.0536)	-0.101* (0.0553)
<b>Panel B: Manufacturing Employment Ratio</b>							
Dom. Robot Exposure	-0.594*** (0.224)	-0.237 (0.226)	-0.229 (0.214)	-0.203 (0.216)	-0.00149 (0.167)	0.173 (0.165)	-0.224 (0.145)
For. Robot Exposure - Input		0.0511 (0.0580)	0.0655 (0.0574)	0.0723 (0.0556)	-0.0146 (0.0383)	0.00289 (0.0375)	0.0235 (0.0257)
For. Robot Exposure - Final		-0.126*** (0.0481)	-0.114** (0.0444)	-0.116*** (0.0438)	-0.109*** (0.0370)	-0.102** (0.0404)	-0.112*** (0.0282)
<b>Panel C: Raw Materials Employment Ratio</b>							
Dom. Robot Exposure	-0.0136 (0.0218)	-0.0102 (0.0220)	-0.00896 (0.0226)	0.0337 (0.0363)	0.0281 (0.0416)	-0.0386 (0.0312)	0.0308 (0.0284)
For. Robot Exposure - Input		0.0352** (0.0161)	0.0376** (0.0158)	0.0492*** (0.0152)	0.0479*** (0.0161)	0.0333** (0.0157)	0.0212** (0.00836)
For. Robot Exposure - Final		-0.0110 (0.00995)	-0.0107 (0.0103)	-0.0141 (0.00960)	-0.0115 (0.00913)	-0.00912 (0.0100)	-0.00388 (0.00470)
<b>Panel D: Service Employment Ratio</b>							
Dom. Robot Exposure	0.258 (0.165)	-0.0598 (0.169)	-0.0908 (0.156)	-0.152 (0.163)	-0.0517 (0.151)	-0.112 (0.139)	0.0969 (0.172)
For. Robot Exposure - Input		-0.0280 (0.0620)	-0.0476 (0.0651)	-0.0642 (0.0642)	-0.0918* (0.0506)	-0.0854* (0.0513)	-0.0605 (0.0536)
For. Robot Exposure - Final		0.107** (0.0415)	0.0965*** (0.0361)	0.101*** (0.0363)	0.0818*** (0.0289)	0.0714*** (0.0269)	0.0363 (0.0337)
Microregion FE	✓	✓	✓	✓	✓	✓	✓
State x Year FE	✓	✓	✓	✓	✓	✓	✓
Regional Char.			✓	✓	✓	✓	✓
Import Exposure				✓	✓		✓
Industry Controls					✓	✓	✓
China Import Exp.						✓	
Population Weighted							✓
KP F-Statistic	6892.9	5733.7	5691.4	6062.5	5459.7	5282.8	5232.0
Observations	3342	3342	3342	3342	3342	3342	3342

**Note:** In this Table, instead of yearly variation, three-year intervals are used (Due to the data availability, the last interval is from 2012-2014). Standard errors, in parentheses, are clustered on the mesoregion level. In column 7 microregion population is used as weights. All specifications include microregion and state interacted with year fixed effects. Regional Characteristic controls are the logs of total microregion population and GDP, the routine task intensity index, the share of female workers, the average highschool graduate rate and the share of foreign owned enterprises. Industry controls are the lagged share of service workers, agricultural workers, light manufacturing and automotive workers. Employment outcomes are given by the ratio of employment to population ratios (of the RAIS data).

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Table A.5: Employment by Occupation (Weighted)

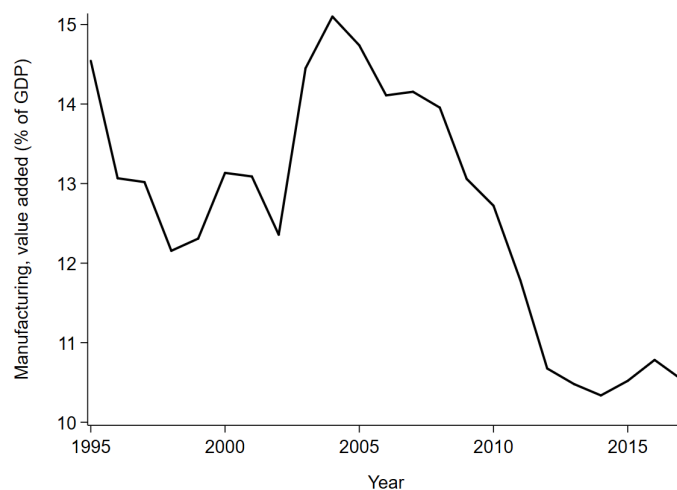
	Employment Ratio (Population Weighted)						
	Managers & Professionals	Technicians & Assoc. Professionals	Service Workers	Skilled Agr. Workers	Craft Workers	Plant & Machine Operators	Elementary Occupations
<b>Panel A: All Tasks</b>							
Dom. Robot Exposure	0.104* (0.0616)	-0.0187 (0.0258)	0.0874 (0.0985)	0.659*** (0.112)	-0.198* (0.103)	-0.253*** (0.0900)	-0.165** (0.0749)
For. Robot Exposure - Input	-0.0418*** (0.0148)	0.0321** (0.0128)	-0.161*** (0.0312)	-0.128*** (0.0259)	0.0713** (0.0290)	-0.0244 (0.0199)	0.146*** (0.0217)
For. Robot Exposure - Final	-0.00550 (0.0106)	-0.000817 (0.0104)	0.00159 (0.0282)	-0.116*** (0.0308)	0.0873*** (0.0333)	-0.0462** (0.0216)	-0.0110 (0.0307)
<b>Panel B: Routine Tasks</b>							
Dom. Robot Exposure	-0.00312* (0.00180)	-0.0482** (0.0204)	-0.150*** (0.0562)	0.0387 (0.0803)	-0.0605 (0.0839)	-0.209** (0.0817)	-0.0502** (0.0228)
For. Robot Exposure - Input	-0.00163*** (0.000496)	0.0275*** (0.00651)	0.0301** (0.0147)	-0.0420** (0.0203)	0.0206 (0.0206)	-0.0444*** (0.0163)	0.0440*** (0.00867)
For. Robot Exposure - Final	0.00124*** (0.000471)	-0.00521 (0.00473)	-0.0183* (0.0109)	0.00624 (0.0230)	0.0433* (0.0247)	-0.0510** (0.0215)	0.0107 (0.00747)
<b>Panel C: Non-Routine Tasks</b>							
Dom. Robot Exposure	0.0381 (0.0431)	-0.0491*** (0.0183)	0.110 (0.0685)	0.643*** (0.134)	-0.0648 (0.0417)	-0.0508 (0.0313)	-0.0581* (0.0350)
For. Robot Exposure - Input	-0.00902 (0.0121)	0.0219*** (0.00703)	-0.0916*** (0.0210)	-0.0747*** (0.0275)	0.0127 (0.00848)	0.0113 (0.00794)	0.0827*** (0.00893)
For. Robot Exposure - Final	-0.00707 (0.0101)	-0.000682 (0.00688)	0.0199 (0.0152)	-0.132*** (0.0430)	-0.00499 (0.00787)	0.00437 (0.00919)	0.0149 (0.0112)
Observations	8355	8355	8355	8355	8355	8355	8355
Population Weights	✓	✓	✓	✓	✓	✓	✓
Microregion FE	✓	✓	✓	✓	✓	✓	✓
State x Year FE	✓	✓	✓	✓	✓	✓	✓
Regional Char.	✓	✓	✓	✓	✓	✓	✓
Import Exposure	✓	✓	✓	✓	✓	✓	✓
Industry Controls	✓	✓	✓	✓	✓	✓	✓
KP F-Statistic	5400.6	5400.6	5400.6	5400.6	5400.6	5400.6	5400.6

**Note:** Standard errors, in parentheses, are clustered on the mesoregion level. In all specifications, total regional population is used as weight. In Panel A, the outcomes are the employment ratios of different occupations according the standard ISCO classification. Panel B and C subdivide these ratios into routine and non-routine task workers (See Appendix A for further details). Regional Characteristic controls are the logs of total microregion population and GDP, the share of female workers, the routine task intensity index, the average highschool graduate rate and the share of foreign owned enterprises. Industry controls are the lagged share of service workers, agricultural workers, light manufacturing and automotive workers. All controls are included in all specifications.

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

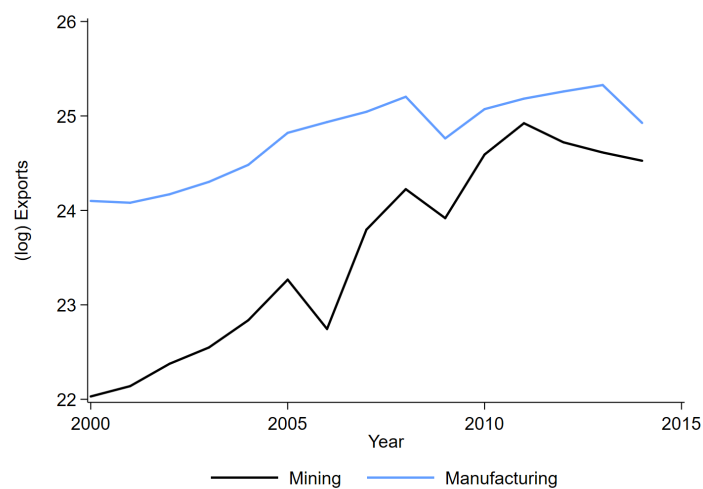
## A.4 Figures

Figure A.1: Share of Manufacturing in Value Added in Brazil



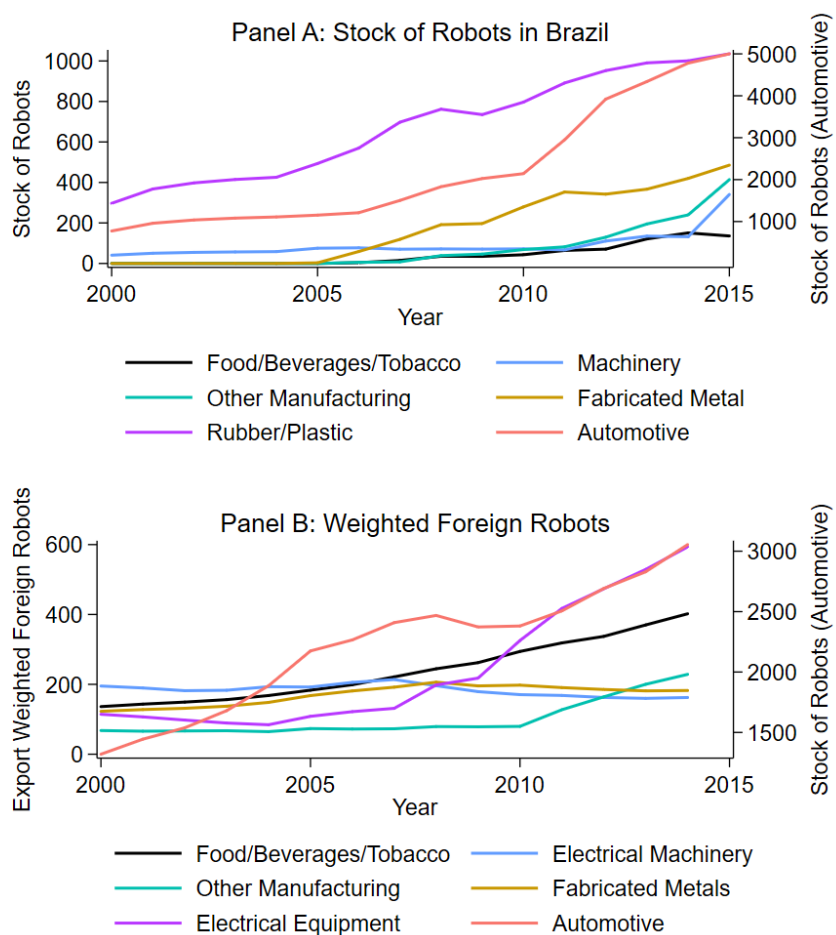
**Note:** The Figure displays the share of manufacturing in value added in Brazil between 2000 and 2017. Data comes from World Bank National Accounts data and OECD National Accounts data files.

Figure A.2: Exports of the Manufacturing and Mining sectors



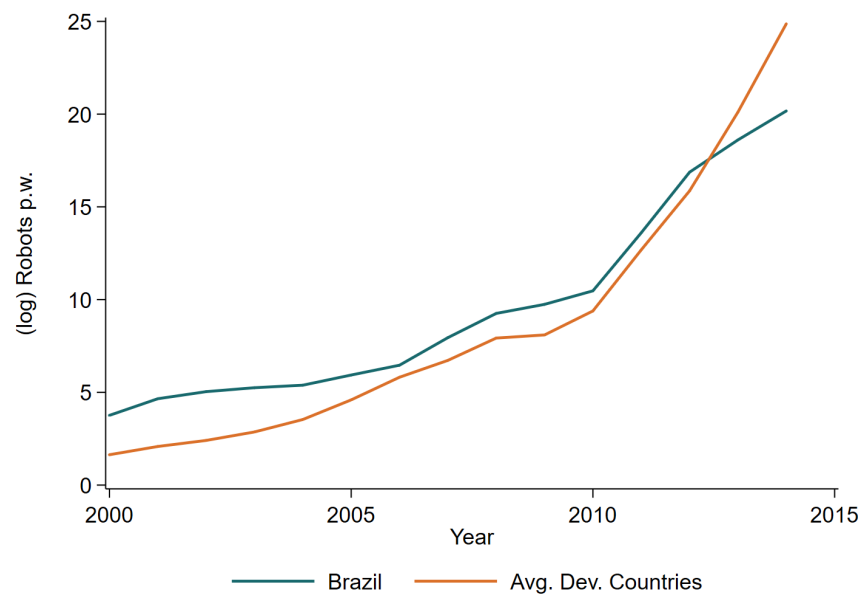
**Note:** The Figure displays the log exports of the Manufacturing sector and the Mining sector of Brazil between 2000 and 2017. Data comes from the Comtrade Database.

Figure A.3: Stock of Robots in Brazil by Industry



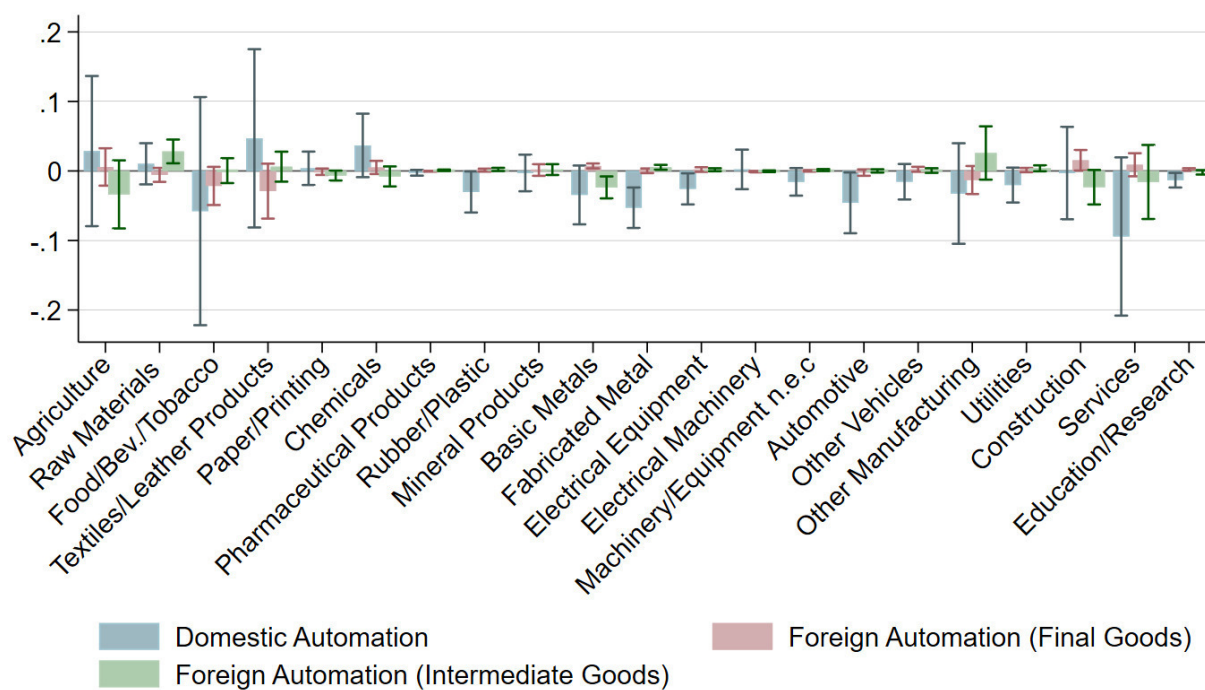
**Note:** Panel A displays the stock of robots in Brazil between 2000 and 2015 in the 6 industries with the most robots. In Panel B, the stock of robots in partner countries are weighted by the share of exports to the partner country industry. The right axis refers to the stock of robots of the Automotive industry in both panels. Data comes from the IFR.

Figure A.4: Robot Adoption in Brazil and Other Developing Economies



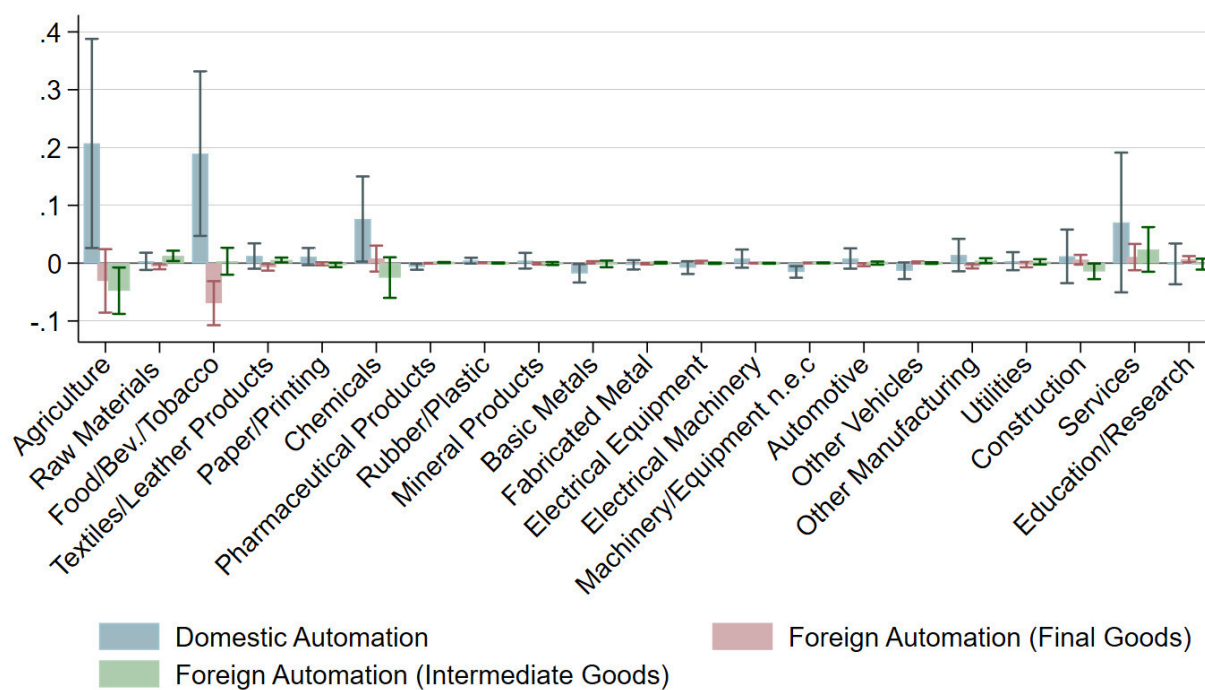
**Note:** The Figure displays the log of total robots per worker in Brazil and the log of average robots per worker in India, Indonesia, Turkey, China and Mexico. Data comes from the IFR.

Figure A.5: Robot Exposure and Industry Employment Ratio - Routine Workers



**Note:** The Figure displays the coefficients of estimating routine-task industry level employment ratios on domestic robot exposure (blue), foreign robot exposure through final goods (red) and through inputs (green). The same specification as in column 6 of table 1 is used. Standard errors are clustered on the mesoregion level. Controls included are microregion dummies, state trends, the logs of total microregion population and GDP, the routine task intensity index, the average highschool graduate rate, the share of foreign owned enterprises, and the lagged shares of service workers, agricultural workers and automotive workers.

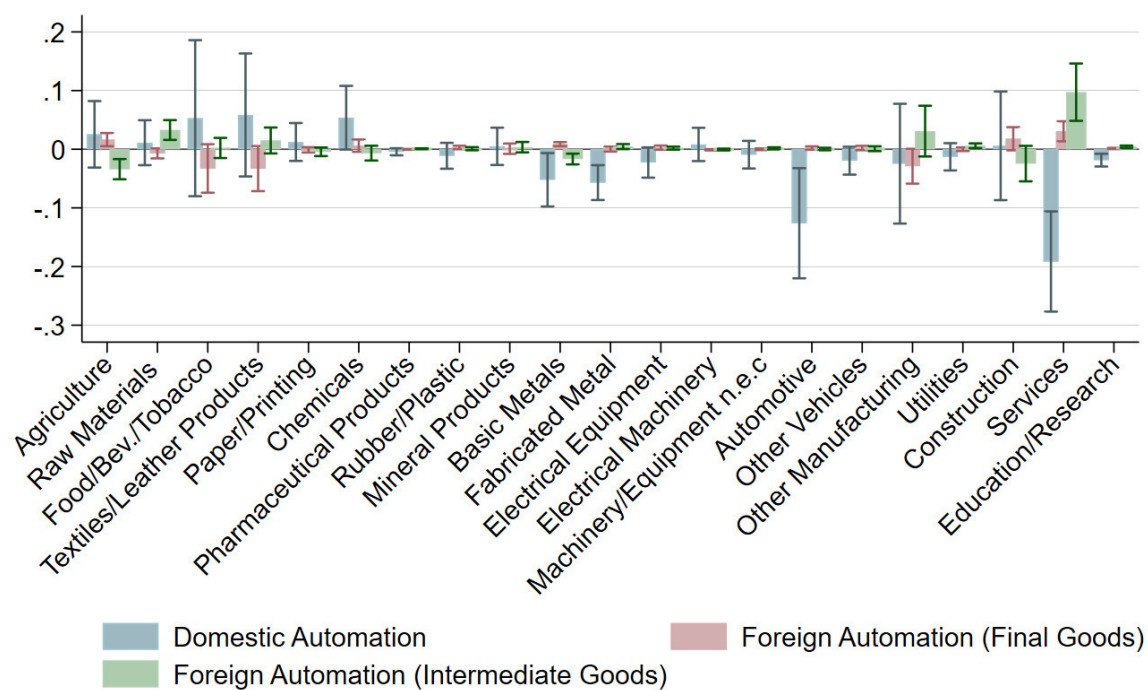
Figure A.6: Robot Exposure and Industry Employment Ratio - Non-Routine Workers



**Note:** The Figure displays the coefficients of estimating non routine-task industry level employment ratios on domestic robot exposure (blue), foreign robot exposure through final goods (red) and through inputs (green). The same specification as in column 6 of table 1 is used. Standard errors are clustered on the mesoregion level. Controls included are microregion dummies, state trends, the logs of total microregion population and GDP, the routine task intensity index, the average highschool graduate rate, the share of foreign owned enterprises, and the lagged shares of service workers, agricultural workers and automotive workers.

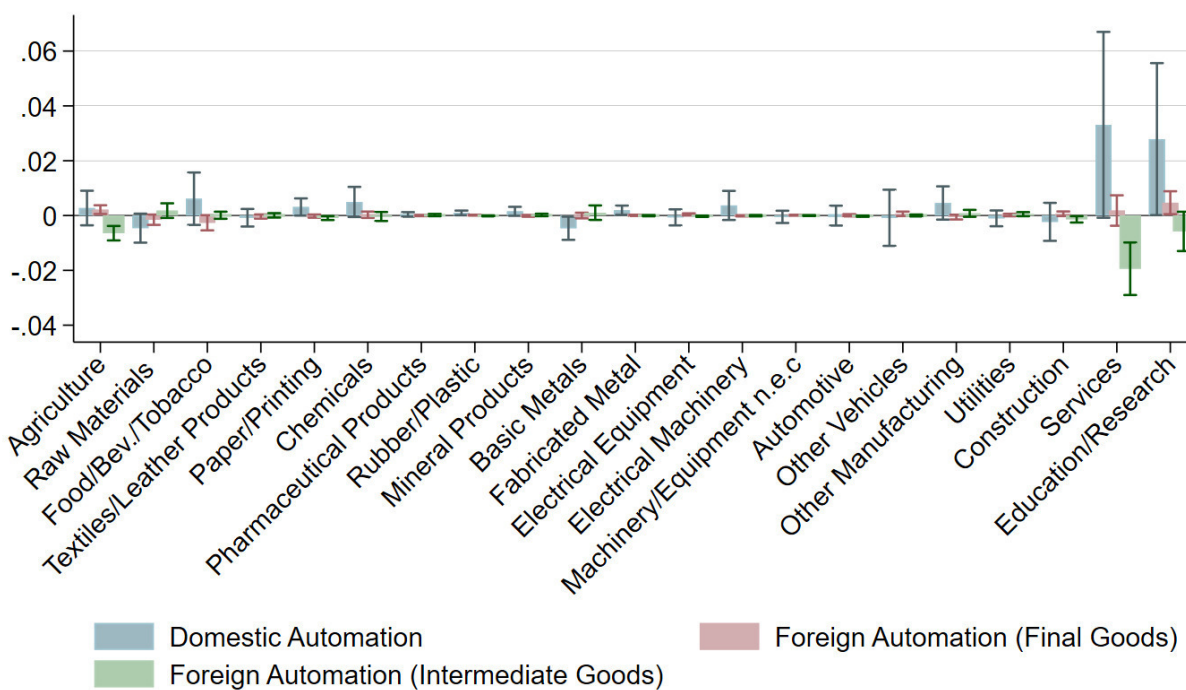


Figure A.7: Robot Exposure and Industry Employment Ratio - Unskilled Workers



**Note:** The Figure displays the coefficients of estimating skilled worker employment ratios on domestic robot exposure (blue), foreign robot exposure through final goods (red) and through inputs (green). Unskilled workers are comprised of Craft Workers, Plant & Machine Operators and Elementary Occupations. The same specification as in column 6 of table 1 is used. Standard errors are clustered on the mesoregion level. Controls included are microregion dummies, state trends, the logs of total microregion population and GDP, the routine task intensity index, the average highschool graduate rate, the share of foreign owned enterprises, and the lagged shares of service workers, agricultural workers and automotive workers.

Figure A.8: Robot Exposure and Industry Employment Ratio - Skilled Workers



**Note:** The Figure displays the coefficients of estimating unskilled worker employment ratios on domestic robot exposure (blue), foreign robot exposure through final goods (red) and through inputs (green). The same specification as in column 6 of table 1 is used. Skilled workers are Managers & Professionals. Standard errors are clustered on the mesoregion level. Controls included are microregion dummies, state trends, the logs of total microregion population and GDP, the routine task intensity index, the average highschool graduate rate, the share of foreign owned enterprises, and the lagged shares of service workers, agricultural workers and automotive workers.