Robots, Tools, and Jobs:

Evidence from Brazilian Labor Markets

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Robots, Tools, and Jobs: Evidence from Brazilian Labor Markets*

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Abstract

What is the effect of robots and tools on employment and inequality? Using natural language processing and an instrumental variable approach, we discover that robots have led to a sizable decrease in the employment and wages of low-skilled workers in operational occupations. However, tools–machines that complement labor–have led to an equally large reinstatement of these workers, increasing their employment and wages. Using a quantitative model, we find that the lower prices of robots and tools over the last 20 years have reduced inequality and increased welfare without a significant effect on employment.

Key Words: robots, automation, tools, labor-saving, labor-augmenting

JEL:J23, J24

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1 Introduction

Technological progress has drastically reduced the cost of automation. Between 1995 and 2016, the price of industrial robots in Brazil has decreased by 40%, making automation increasingly affordable for firms.[1] This affordability has led to a surge in the adoption of robots in various industries, causing concern among economists and policymakers as a growing body of evidence has suggested that automation may lead to job losses.

However, technological progress has not only decreased the cost of labor-saving machines, such as robots, but has also caused a rapid decrease in the cost of labor-augmenting machines, such as tools. The price of imported power tools by Brazilian firms, for instance, decreased by 20% between 1995 and 2016.[2]

In this paper, we study how robots and tools affect employment, inequality, and welfare. We show that the drop in the price of tools has greatly mitigated the job losses from automation. Overall, the decrease in the price of robots and tools has led to a decrease in inequality and an increase in welfare without a significant effect on employment.

We expand the model of Acemoglu and Restrepo (2020) to include tools, i.e., machines that complement workers in their tasks, to study conceptually how robots and tools jointly affect the labor market. In the model, firms produce by performing tasks with robots or with workers. Workers can be low-skilled, with tools as complements, or high-skilled. Because tools are complements to low-skilled workers, a decrease in the price of tools increases employment and decreases inequality. The degree to which robots and tools affect the labor market will depend on the particular parameters of the model, which we identify from the data.

There are two challenges in bringing the model to the data. The first challenge lies in identifying machines that complement versus substitute the tasks done by workers. There are 535 different machines being imported by firms, making it difficult to identify their relationship to labor. The literature studying the effect of automation has addressed this challenge by limiting the focus to industrial robots, which minimizes misclassification errors

[1] The price of industrial robots is measured by their imports. Adachi et al. (2022) and Graetz and Michaels (2018) also show a sizable decrease in the international price of industrial robots.

[2] Power tools include chainsaws, bandsaws, and angle grinders, among many others. Power tools are hand-operated pieces of equipment.

but significantly restricts the scope of analysis.[3]

The second challenge is the need for plausible exogenous variation in the incentive to adopt these two machine types. The imports of machines, as with any other input, are affected by shocks to the local economy. If, for instance, a demand shock led firms to increase their demand for robots, as discussed by Bonfiglioli et al. (2020), we would not be able to separate the labor market effects of an increase in demand from the labor market effects of robots adoption?

To tackle the first challenge, we classify machines as robots or as tools, using natural language processing and detailed machine descriptions from administrative import data for Brazil. Inspired by Argente et al. (2020), we use the text similarity between machine descriptions and Wikipedia pages to classify machines.[4][5] A machine is labeled a robot if it is more similar to Wikipedia articles that describe different automation technologies than to Wikipedia pages that describe industrial tools.

Several tests indicate that the text-driven machine classification is reasonable. First, the classification delivers intuitive results. The machines most associated with robots are "Industrial Robots" and other numerically controlled machines. The machines most associated with tools are an assortment of hand-operated pieces of equipment. Second, the words relevant to the classification algorithm are those that are directly associated with robots, such as "automatic" or "numeric," or those that are associated with the use of tools, such as "hand" and "operate." Third, when machines have words associated with robots, such as "automatic," is strongly increases the probability of them being classified as such. At the same time, when machines have words associated with tools, such as "tool" or "operate," it increases the probability of them being classified as a tool. Finally, firms adopting machines classified as robots do not significantly change employment, while those adopting tools significantly increase it, which is similar to what Koch et al. (2021) found when studying industrial robot adoption.

We address the identification challenge by using tariff changes at the machine level as

[3]Industrial robots are classification number 8479 of the Harmonized System (HS). Therefore, the literature has focused on 0.5% of machines, which corresponds to 3% of all capital imports in 2019.

[4]Wikipedia pages are useful because they cover a broad set of machines, containing their description and main uses.

[5]Argente et al. (2020) use Wikipedia pages to classify patents of different products.

instruments for their adoption. Tariffs affect the final price of foreign machines and are unrelated to labor market shocks.[6] The identifying assumption is that changes in tariffs on robots and tools are orthogonal to labor market shocks. There are several pieces of evidence supporting this assumption. First, tariffs are not correlated with past labor market trends. Second, tariff changes are not correlated with campaign contributions. Third, tariffs are not correlated with other relevant policies of the period, such as subsidized loans or federal procurement. These results support the idea that tariffs on machines are not correlated with other shocks in the period.

We find that tools increase the employment and wages of low-skilled workers who operate machinery. Increasing the imports of tools by 1% would increase the employment and wages of low-skilled workers by 0.26% and 0.06%, respectively, without any effect on high-skilled workers. The effect of tools is concentrated on operational and technical workers, i.e., workers who directly operate machinery.

Robots, meanwhile, cause large disruptions in the labor market. A 1% increase in robot adoption decreases employment by 0.35%, an effect larger than what others have previously found.[7] As is the case with tools, the effect of robots is concentrated on low-skilled workers in operational occupations. These results suggest that if the adoption of tools and adoption of robots increase by the same amount, the effect on employment would not be statistically different from zero.

The identified effect of robots on employment is larger than previously found due to endogeneity in the traditional specification. The scale effect from the adoption of robots also leads to an increase in the adoption of tools. Failing to control for tools, as in previous work, leads to omitted variable bias, in which case, the parameter identified is only the effect of robots net of the effect of tools. Because tools increase employment, the estimate is upward-biased.

To move from the relative effects identified in the data to aggregate effects, we build a

[6]Dix-Carneiro and Kovak (2017) use similar variation to study the effect of tariffs on Brazilian labor markets. As they discuss, tariffs in different products have changed at different rates. To isolate the effect of tariffs on machines, we control for tariffs on the final good and other inputs of each sector.

[7]Acemoglu and Restrepo (2020) find that a 1% increase in robot adoption would decrease employment by 0.03%. Dauth et al. (2021), Rodrigo (2022), and Graetz and Michaels (2018) do not find any effect of robots on employment.

quantitative model calibrated to reproduce the empirical findings. Firms and workers are located across regions and sectors. Firms choose between adopting robots to replace workers and using tools to complement them. They use inputs from various sectors and sell products domestically or internationally. There is a capital-producing sector that produces robots and tools using final goods and imports of capital. Workers choose their skill level, region, and sector of employment, or to be outside the labor force. We calibrate key model parameters to replicate the observed effect of robots and tools on the labor market.[8]

Decreases in the prices of robots and tools over the last 20 years have increased welfare and reduced inequality without significant consequences for employment, according to the model. Imported robot and tool prices have dropped by 38.8% and 45.9%, respectively. Employment has remained stable because increased robot adoption has been counterbalanced by cheaper tools. Lower capital costs have enabled firms to cut final goods prices, boosting production and welfare. In addition, since tools complement low-skilled workers, the skill premium has decreased by 10%.

Our main contribution is to add tools to the standard theoretical, empirical, and quantitative framework studying automation, leading to new conclusions and policy implications. Graetz and Michaels (2018) and Acemoglu and Restrepo (2020) were the first papers to study the effect of automation technologies on the labor market. They showed that the increase in automation led to a decrease in employment and wages. After their seminal work, several economists have expanded their analyses to study the effect of automation at the firm level (Koch et al. (2021), Humlum (2021), Acemoglu et al. (2020), Bonfiglioli et al. (2020), Bessen et al. (2019)), in other countries (Adachi et al. (2022), Rodrigo (2022), Kugler et al. (2020), Cheng et al. (2021), Cette et al. (2021), Dauth et al. (2021)), in different educational groups (Bonfiglioli et al. (2020)), and on inequality (Adachi (2022), Acemoglu and Restrepo (2022), Bonfiglioli et al. (2021)). Exploiting the geographical concentration of robot production in a few countries, several papers have used import data to measure the degree of automation of different sectors and firms, such as Humlum (2021), Bonfiglioli et al. (2020), and Rodrigo (2022). While the effect of automation at the firm level is up for debate, there

[8] The model builds on Artuç et al. (2010), Dix-Carneiro (2014), Caliendo et al. (2019), and Kleinman et al. (2023).

is overwhelming evidence that robots decrease employment and wages at the market level.

We make several contributions to this literature. First, we add tools and worker inequality to the canonical framework of Acemoglu and Restrepo (2020), which enables us to study how developments in machines that complement workers in their tasks affect the labor market. Second, we expand the scope of the literature studying automation beyond industrial robots by classifying machines as robots or as tools using text analysis. Third, we show that previous work has underestimated the effect of robots on the labor market by not taking into account the associated increase in the adoption of tools.

The paper is organized as follows. Section 2 discusses the simple model. Section 3 discusses the data. Section 4 discusses the machine classification. Section 5 describes the empirical specifications and Section 6 presents the empirical results. Section 7 lays out the quantitative model. Section 8 describes the parameter estimation and Section 9 presents the quantitative results. Section 10 concludes.

2 Simple Model

In this section, we study a simple model to understand how tools and robots affect the labor market. The model generates implications for the effect of cheaper robots and tools on the labor market, which are later tested in the data. We make three contributions to the canonical framework of Acemoglu and Restrepo (2020). First, we add tools, a capital type that complement workers in their tasks. Second, we add worker heterogeneity, which enables us to discuss inequality. Third, we find intuitive closed-form solutions by assuming a functional form for the relative productivity of robots.

The model provides three main takeaways. First, a decrease in the price of tools increases the employment of low-skilled workers due to, among other factors, the complementarity between low-skilled workers and tools. Second, the effect of tools on high-skilled workers is uncertain because high-skilled workers and tools are substitutes. Third, an increase in the adoption of robots increases inequality, whereas an increase in the adoption of tools decreases it. In the next section, we test these predictions on the data.

2.1 Model Setup

Environment. There are two sectors: one with tasks that can be automated, such as manufacturing, and another that cannot be easily automated, such as services. The automatable sector contains a representative firm, which performs a set of tasks to produce. Production of each task can be performed by either robots or by workers using tools. There are two types of workers. Low-skilled workers operate tools to produce, while high-skilled workers manage low-skilled workers in particular tasks. Robots and tools are imported and their prices, P_R and P_T, are exogenous.[9] Wages of high- and low-skilled workers, w_H and w_L, are determined endogenously.

Total output is an aggregate of the automatable and non-automatable sectors

$$Y = \left(Y_A^{\frac{\psi-1}{\psi}} + Y_N^{\frac{\psi-1}{\psi}} \right)^{\frac{\psi}{\psi-1}},$$

where Y_A is production in the automatable sector, Y_N is production in the non-automatable sector, and ψ is the elasticity of substitution. We assume, as usual, that $\psi > 1$.

Firms and Tasks. Output in the automatable sector is given by combining production from a continuum of tasks $\nu \in [0, 1]$.[10] The production function in the automatable sector is:

$$Y_A = \left(\int_0^1 [y(\nu)]^{\frac{\lambda-1}{\lambda}} \, d\nu \right)^{\frac{\lambda}{\lambda-1}}, \tag{1}$$

where $y(\nu)$ is the output in task ν and λ is the elasticity of substitution between tasks.

Robots or Tools. Each task ν can be performed either by robots or by workers using tools:

$$y(\nu) = y_R(\nu) + y_T(\nu), \tag{2}$$

[9] In the quantitative model (Section 7), we assume that part of the production of robots and tools is done locally. For clarity, we assume that away for now.

[10] In the simple model, we assume that there is a representative firm in the automatable sector. In the quantitative model of Section 7, we assume that there are heterogeneous firms in each sector.

where $y_R(\nu)$ and $y_T(\nu)$ are the output of task ν using robots or tools, respectively. The production function of task ν with robots is:

$$y_R(\nu) = Z_R(\nu) k_R(\nu), \tag{3}$$

where $Z_R(\nu)$ is the productivity of using robots in task ν, and $k_R(\nu)$ denotes the quantity of robots. The price of robots is given by P_R.[11] Consequently, the marginal cost of completing task ν with robots is $\frac{P_R}{Z_R(\nu)}$.

Task ν can also be completed with workers and tools. If task ν is performed by workers, output is given by:

$$y_T(\nu) = Z_T(\nu) \left[(\ell_H(\nu))^{\frac{\sigma-1}{\sigma}} + \left((\ell_L(\nu))^{\delta} (k_T(\nu))^{1-\delta} \right)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}},$$

where $Z_T(\nu)$ is the productivity of using tools for task ν, $\ell_L(\nu)$ is the number of low-skilled workers in each task, $\ell_H(\nu)$ is the number of high-skilled workers managing workers in task ν, and $k_T(\nu)$ is the quantity of tools. To facilitate exposition, and following a plethora of empirical evidence, we assume that low- and high-skilled workers are substitutes: $\sigma > 1$.[12]

We assume that low-skilled workers and tools are complements with Cobb-Douglas coefficient δ. This assumption is based on the observation that most tools, such as drill presses, mechanical lathes, welding machines, and other industrial physically intensive equipment, are operated by low-skilled workers. Moreover, as will be clear in the empirical section, this assumption rationalizes the positive effect of tool adoption on the employment of low-skilled workers.

If task ν is performed by workers and tools, the marginal cost is given by

$$\frac{\Theta_T}{Z_T(\nu)} = \frac{\left((w_H)^{1-\sigma} + \left(w_L^{\delta} P_T^{1-\delta} \right)^{1-\sigma} \right)^{\frac{1}{1-\sigma}}}{Z_T(\nu)},$$

[11] Throughout this section, we assume that both robots and tools are imported, and that the country is a small open economy. Therefore, both robot and tool prices are taken as given by domestic firms and are not affected by domestic demand. In the quantitative model that we introduce in Section 7, both types of capital are produced both abroad and domestically.

[12] See Katz and Murphy (1992), Krusell et al. (2000), and Ciccone and Peri (2005).

where w_H is the wage of high-skilled workers, w_L is the wage of low-skilled workers, and P_T is the price of tools.

The marginal cost to complete task ν is

$$c(\nu) = \min\left\{\frac{P_R}{Z_R(\nu)}, \frac{\Theta_T}{Z_T(\nu)}\right\}.$$

Task Heterogeneity. Tasks are heterogeneous in the relative productivity of robots and tools. The productivity follow an i.i.d. Fréchet distribution across tasks (ν) and technologies (l):

$$F_{Z_l(\nu)}(z) = \exp\left[-T_l \times z^{-\tilde{\theta}}\right], l \in \{R, T\}.$$

$\tilde{\theta}$, the shape parameter, serves as the elasticity of substitution between technologies.[13] T_l, the scale parameter, determines the mean relative productivity.

Expenditure Share and Production. The expenditure share on tasks performed with technology $l \in \{R, T\}$ is

$$\pi_l = \frac{T_l(\Theta_l)^{-\tilde{\theta}}}{T_R(\Theta_R)^{-\tilde{\theta}} + T_T(\Theta_T)^{-\tilde{\theta}}},$$

where p_A is the price index of the automatable sector and $\Theta_R = p_R$.[14] The economy's total expenditure on tasks performed with technology l is:

$$X_l = \frac{T_l(\Theta_l)^{-\tilde{\theta}}}{T_R(\Theta_R)^{-\tilde{\theta}} + T_T(\Theta_T)^{-\tilde{\theta}}} \frac{(p_A)^{1-\psi}}{(p_A)^{1-\psi} + (p_N)^{1-\psi}} PY, l \in \{R, T\}, \tag{4}$$

where PY denotes the value of the economy's total output and $\frac{(p_A)^{1-\psi}}{(p_A)^{1-\psi}+(p_N)^{1-\psi}}$ denotes the expenditure share on the automatable sector.

Equation (4) illustrates how the price of tools can affect the adoption of robots. If the

[13] Artuc et al. (2023), a concurrent work, considers a similar assumption for the productivity of robots.

[14] γ is the Gamma constant: $\gamma = \left(\Gamma\left(\frac{\theta+1-\sigma}{\theta}\right)\right)^{\frac{1}{1-\sigma}}$. The price index of the automatable sector is $p_A = \gamma\left(\Theta_R^{-\tilde{\theta}} + \Theta_T^{-\tilde{\theta}}\right)^{-\frac{1}{\tilde{\theta}}}$.

price of tools goes up, i.e., Θ_T increases, then firms replace workers and tools with robots, decreasing the total production done with tools. The elasticity of substitution between technologies, $\tilde{\theta}$, is the main parameter governing the magnitude of this effect.

Non-Automatable Sector. In the non-automatable sector, production is carried out one-to-one with an elastically supplied exogenous factor that has a unit price.[15] Therefore,

$$p_N = 1.$$

Workers. The labor supply of both types of workers is upward sloping and equals to:

$$\ell_H = A_H w_H^{\xi}$$
$$\ell_L = A_L w_L^{\xi},$$

where A_H and A_L are parameters that affect the levels of labor supply.[16] In Section A.1, we provide the market-clearing conditions and the equilibrium definition.

2.2 Impact of Robots and Tools on Employment

We use the model to study how changes in the prices of robots and tools affect employment and inequality.[17]

The Effect of Robots on Employment is Ambiguous. Proposition 1 summarizes the effect of an exogenous change in the price of robots on the employment of low- and high-skilled workers.

[15] A similar assumption is made by Acemoglu and Restrepo (2018), with the only difference being that their non-automatable sector produces using labor. As our model takes into account workers with different skill levels, we assume that the non-automatable sector relies on a factor other than labor. This assumption helps us to mitigate the confounding effects of sector labor composition on inequality and enables us to concentrate on the impact of robots and tools. We relax this assumption in the quantitative model in Section 7.

[16] For clarity of results, we assume that high- and low-skilled workers have the same labor supply elasticity. This assumption is relaxed in the quantitative model in Section 7.

[17] We leave the proofs to Section A.2.

Proposition 1. *The effect of an exogenous increase in the price of robots is ambiguous and given by:*

$$\frac{d\log \ell_L}{d\log P_R} = \beta_R^L \left[(1-s_A)(1-\psi) + \tilde{\theta}\right] \tag{5}$$
$$\frac{d\log \ell_H}{d\log P_R} = \beta_R^H \left[(1-s_A)(1-\psi) + \tilde{\theta}\right], \tag{6}$$

where

$$\beta_R^L = \frac{(\xi+\sigma)\,\xi}{\Delta\left[s_{T,H}(1+\xi+(\sigma-1)\delta) + (1-s_{T,H})\delta(\xi+\sigma)\right] + (\xi+\sigma)(1+\xi+(\sigma-1)\delta)} > 0,$$
$$\beta_R^H = \frac{(1+\xi+(\sigma-1)\delta)\xi}{\Delta\left[s_{T,H}(1+\xi+(\sigma-1)\delta) + (1-s_{T,H})\delta(\xi+\sigma)\right] + (\xi+\sigma)(1+\xi+(\sigma-1)\delta)} > 0,$$
$$\Delta \equiv 1-\sigma-(1-s_A)(1-\psi) + \left[(1-s_A)(1-\psi)+\tilde{\theta}\right] s_R,$$

and $s_{T,H}$ is the income share of high-skilled workers in the tool bundle, s_R is the expenditure share on robots in the automatable sector, and s_A is the economy's expenditure share on the automatable sector.

The effect of robots on employment depends on two counteracting forces: the productivity effect and the displacement effect. The productivity effect is captured by the first term in Equations (5) and (6): $(1-s_A)(1-\psi)$. When the price of robots falls, firms in the automatable sector become more productive and expand, increasing the demand for all workers. The displacement effect, given by $\tilde{\theta}$, comes from an increase in the measure of tasks performed by robots, which pushes down the demand for workers when the price of robots decreases. Therefore, the final effect of robots on employment will depend on these two counteracting forces.

Tools Increase Wages and Employment of Low-Skilled Workers. When the price of tools decreases, the demand for low-skilled workers increases, according to Proposition 2 below.

Proposition 2. *The effect of an increase in the price of tools on low-skilled workers is given* *by*

$$\frac{d\log \ell_L}{d\log P_T} = \beta_T^L \left[(1-s_A)(1-\psi)(1-s_R) - \tilde{\theta} s_R + \frac{s_{T,H}(1-\sigma)(\xi+1)}{s_{T,H}(\sigma-1)+(1-s_{T,H})(\xi+\sigma)}\right] < 0, \tag{7}$$

where

$$\beta_T^L = \frac{(1-\delta)\xi\left[s_{T,H}(\sigma-1)+(1-s_{T,H})(\xi+\sigma)\right]}{\Delta\left[s_{T,H}(1+\xi+(\sigma-1)\delta)+(1-s_{T,H})\delta(\xi+\sigma)\right]+(1+\xi+(\sigma-1)\delta)(\xi+\sigma)} > 0,$$

and Δ is defined in Proposition 1.

When the price of tools falls, there are three forces affecting the demand for low-skilled workers: the productivity effect, the reinstatement effect, and the complementarity effect. All of these forces lead to an increase in the demand for low-skilled workers. The first term in Equation (7), $(1-s_A)(1-\psi)(1-s_R)$, captures the productivity effect. A decrease in the price of tools increases the productivity of the automatable sector, leading to an increase in the demand for workers. The second term in Equation (7), $\tilde{\theta} s_R$, is the reinstatement effect. If tools become cheaper, firms will perform more tasks with workers and tools, increasing the demand for low-skilled workers. The third term in Equation (7), $\frac{s_{T,H}(1-\sigma)(\xi+1)}{s_{T,H}(\sigma-1)+(1-s_{T,H})(\xi+\sigma)}$, comes from the complementarity between tools and low-skilled workers. If tools become cheaper, for the tasks already performed with tools, firms will use more low-skilled workers with tools instead of high-skilled workers, which once again increases the demand for low-skilled workers. Therefore, a decrease in the price of tools increases the employment of low-skilled workers.

The Effect of Tools on High-Skilled Workers is Ambiguous. The effect of an exogenous increase in the price of tools on high-skilled employment is uncertain because it depends on a third force: the substitution effect. When the price of tools goes down, firms have the incentive to shift their production toward tools and low-skilled workers, thereby reducing the demand for high-skilled workers. This intuition is formalized in Proposition 3 below.

Proposition 3. *The effect of an increase in the price of tools on high-skilled workers is* *given by*

$$\frac{d\log \ell_H}{d\log P_T} = \beta_T^H \left[(1-s_A)(1-\psi)(1-s_R) - \tilde{\theta}s_R + (\sigma-1)\right], \tag{8}$$

where

$$\beta_T^H = \frac{(1-s_{T,H})(1+\xi)(1-\delta)\xi}{\Delta\left[s_{T,H}(1+\xi+(\sigma-1)\delta)+(1-s_{T,H})\delta(\xi+\sigma)\right]+(\xi+\sigma)(1+\xi+(\sigma-1)\delta)} > 0,$$

and Δ is defined in Proposition 1.

The terms in Equation (8) capture the productivity, reinstatement, and substitution effects, respectively. The first term, $(1-s_A)(1-\psi)(1-s_R)$, captures the productivity effect: If tools become cheaper, the automatable sector expands, driving up the demand for high-skilled workers. The second term, $\tilde{\theta}s_R$, is the reinstatement effect, i.e., if tools become cheaper, firms are going to reinstate workers in tasks previously done by robots. Finally, the last term is the substitution effect, $(\sigma-1)$. If the price of tools decrease, firms will use more low-skilled workers with tools for each task done by labor. This last force reduces the demand for high-skilled workers. Therefore, the final effect of a reduction in the price of tools on labor is ambiguous.

Robots Increase Inequality and Tools Decrease it. A change in the price of machines affects inequality because high- and low-skilled workers have different relationships to tools. When the price of robots goes down, the demand for both worker types changes. If the replacement effect dominates the productivity effect, the demand for both worker types will go down. As an exercise, suppose that the wages of low- and high-skilled workers fell by the same amount. In that case, the low-skilled worker and tool bundle would be relatively more expensive because low-skilled workers are complements to tools, whose price is fixed. Because of the complementarity with tools, the wages of low-skilled workers have to fall by more than the wages of high-skilled workers, which increases inequality. This intuition is summarized in Proposition 4 below.

Proposition 4. *Suppose $(1-s_A)(1-\psi)+\tilde{\theta} > 0$, a reduction (increase) in the price of robots* *increases (decreases) the skill premium, w_H/w_L:*

$$\frac{dw_H/w_L}{dP_R} < 0.$$

Tools have the opposite effect on inequality. When the price of tools goes down, the relative demand for low-skilled workers increases because they are complements to tools. As a consequence, the skill premium goes down.

Proposition 5. *A reduction (increase) in the price of tools decreases (increases) the skill premium, w_H/w_L:*

$$\frac{dw_H/w_L}{dP_T} > 0.$$

Discussion. The model shows that robots and tools have different implications for employment and inequality. While robots might decrease employment and increase inequality, tools increase employment and decrease inequality. In the following sections, we test these predictions on the data. We identify the particular machines that are the most similar to the model's definition of robots and tools. Then, using data for Brazil, we study their effect on the labor market.

3 Data

In this section, we describe the steps to create a dataset with machine imports by sector, region, and year in Brazil. For each sector in a given region, we observe its imports of machinery at the 4-digit HS code level.[18] On the next session, following the insights of the model, we classify these machines as robots or as tools.

RAIS. The main source of labor force information is the administrative dataset RAIS - *Relação Anual de Informações Sociais.* RAIS is a matched employer–employee dataset

[18]These data were also used by de Souza (2020). Rodrigo (2022) uses robot imports at the regional level from the same source.

collected by the Brazilian Ministry of Labor. It covers the universe of formal firms. Its use has been widespread in different areas of economics in recent years.[19]

RAIS contains data on employment, worker demographics, and firm characteristics. For employment, we observe wages, hours of work, date of hiring/firing, the establishment of work, and occupation. We also observe workers' demographics: age, gender, education, and race. Firms' sector and establishment locations are also observed.

Imports. We observe monthly imports at the municipality level with data from the Secretary of International Trade. The data contain all imports between 1997 and 2019, with information on year, HS code of the imported product, product name with a detailed description of its characteristics, city of the importing establishment, quantity, and value.

We limit the sample of HS products to capital goods that have been imported at least once by firms producing tradable goods.[20] The final list contains several industrial machines, such as industrial robots or hydraulic presses, and does not contain office equipment, such as computers or printers.

The Secretary of International Trade also records the sector of the importing firm.[21] This administrative dataset records imports by product and sector of the importing firm. This enables us to identify the sector in which each machine is used in without having to rely on input–output tables. [22]

Tariff We use changes in tariffs as exogenous variation to the price of machines. Tariff data come from the World Bank Trade Analysis Information System.

4 Machine Classification

In the data, there are 535 different capital goods imported by manufacturing firms. However, the literature studying automation typically narrows the sample to a specific capital good:

[19] de Souza (2020), Dix-Carneiro and Kovak (2019), Dix-Carneiro and Kovak (2017), Colonnelli and Prem (2019) and Colonnelli et al. (2020) are just some examples.

[20] The list of HS products classified as capital goods is from the Secretary of International Trade.

[21] To guarantee the anonymity of the firms involved, this dataset is not public.

[22] Products in this dataset are at the 8-digit Brazilian classification. They have the first 6 digits of the international HS plus 2 extra digits, which are specific to Mercorsur.

industrial robots. This choice reduces the error of misclassifying machine types but greatly limits the scope of the analysis: Industrial robots corresponded to only 3% of all capital imports in Brazil in 2019 and 0.5% of machines.

To solve this issue, we propose a text-based method to identify the relationship of machines to labor. We classify machines according to their text similarity to the description of robots and tools, inspired by Argente et al. (2020). The procedure has three steps. First, we select a set of texts that describe robots or tools. Second, we calculate the texts similarity between these texts and the machines being imported. Third, we classify each machine as a robot or as a tool, depending on which text the machine is most similar to. We describe the procedure in detail below.

Reference Text. We select a set of reference text that describe different robots and tools. Following Argente et al. (2020), as a robot description, we use all Wikipedia articles linked to industrial robots, while for tools, we use Wikipedia articles connected to power tools, hand tools, and cutting tools, which describe machines that complement workers in their tasks. Each Wikipedia article contains a description of the machine and its main application. In Appendix B.1.1, we provide a complete list of Wikipedia articles used.

Text Similarity. After removing stop-words and lemmatizing the documents, we calculate the cosine text similarity between each machine description and the Wikipedia articles. The algorithm transforms each document into a vector. Each entry in the vector represents a word. If the document contains that word, the entry in the vector is equal to 1 and zero otherwise. The similarity between two documents is given by the cosine distance between the two vectors. A formal description of the method and weights used is given in Appendix B.1.2, which follows Argente et al. (2020) closely.

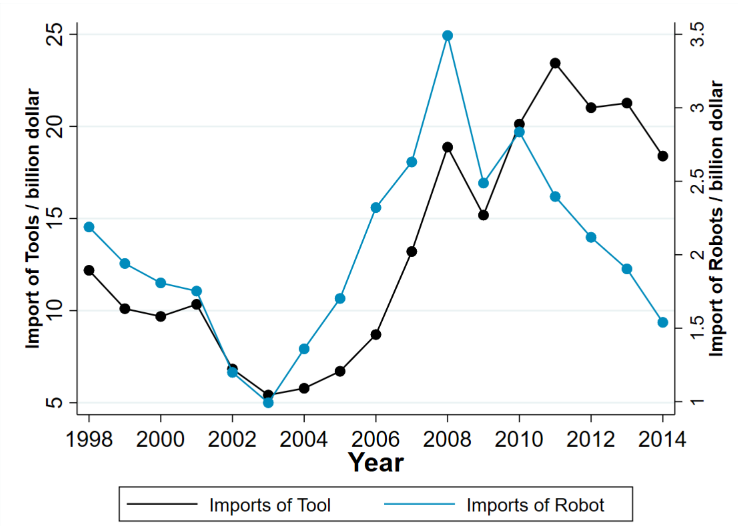
Classification. We classify machines as robots or as tools according to its closest Wikipedia article. Let s_{jw} be the text similarity between machine j and Wikipedia article w. The closest Wikipedia article to j is $w_j^* = \arg\max_w s_{jw}$. We call j a robot if w_j^* is a Wikipedia article associated with automation. We call it a tool otherwise.

4.1 Summary Statistics of Robot and Tool Imports

There are three relevant facts that, together, highlight the importance of tools among firms in Brazil.

Imports of tools are 10 times larger than imports of robots. Figure 1 shows the statistics for robot and tool imports in Brazil. Figure 1 shows that imports of tools are 10 times larger than those of robots, with both being strongly correlated over time. The high degree of correlation between these two capital types shows the necessity of two instruments to separate the effect of one from that of the other.

Figure 1: Robot and Tool Adoption over Time

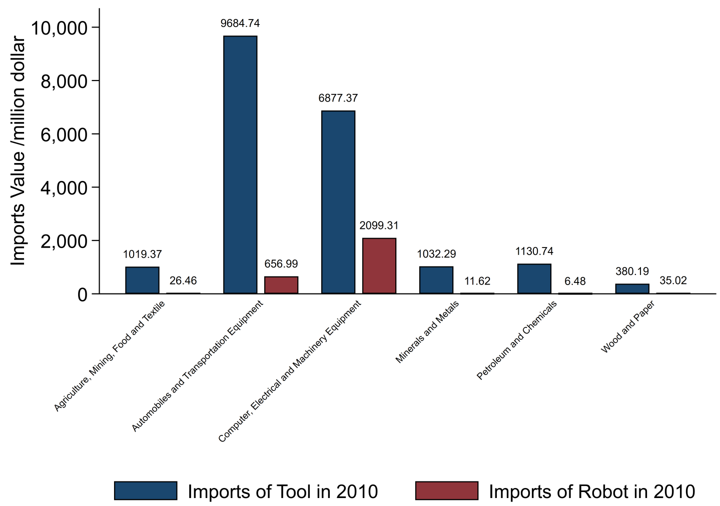


Description: This figure shows the statistics for robot and tool imports. Figure 1 shows the total imports of HS capital classified as robots or tools in real 2010 dollars.

Robot adoption is concentrated in a few sectors, whereas tools are common in all sectors. Figure 2 shows the distribution of robot and tool imports across sectors. Tools are common in most sectors, whereas robots are concentrated in the production of transportation and electrical equipment.

Robots and tools have become cheaper over time. Figure 3 shows the average price of robots and tools over time. Since 1998, their prices have decreased by 71% and 53%, respectively, which explains the large increase in the adoption of robots and tools.

Figure 2: Robot and Tool Adoption by Sector



Description: This figure shows the statistics for robot and tool imports. Figure 2 shows the imports of robots and tools in 2010 by large sector.

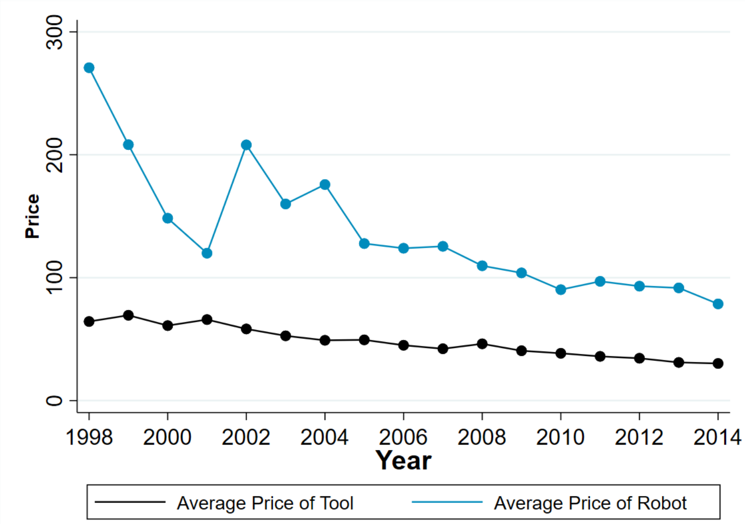
4.2 Validation of Machine Classification

We validate the text-driven machine classification through an extensive number of exercises. First, the classification delivers intuitive results. The machines most associated with robots are "Industrial Robots" and other numerically controlled machines. The ones most associated with tools are an assortment of hand-operated pieces of equipment. Second, the words relevant to the classification algorithm are those directly associated with robots, such as "automatic," "robotic," "control," and "numerical," or those associated with the use of tools, such as "tool," "operate," "handle," and "hand." Third, when machines have words associated with robots, such as "automatic," it strongly increases the probability of them being classified as such. When machines have words associated with tools, such as "tool" or "operate," it increases the probability of them being classified as a tool. Finally, firms adopting machines classified as robots do not change employment, which is similar to what Koch et al. (2021) found when studying industrial robot adoption.

Relevant Machines. If a machine is highly associated with the description of robots or tools, it should be easy for the human eye to make this inference. This is why in Table 1 we show the top 5 machines with the highest similarity to tools or robots.

The machines most associated with robots are "Industrial robots", numerically controlled

Figure 3: Robot and Tool Adoption by Sector



Description: This figure shows the statistics for robot and tool imports. Figure 3 shows the price of robots and tools. The price is calculated by dividing total imports by total weight.

Table 1: Machines with Highest Association with Robots and Tools

Rank	Product Code	Description
Panel A. Robots		
1	847950	Industrial robots
2	842611	Overhead travelling cranes on fixed support
3	846021	Grinding machines, for working metal, in which the positioning in any one axis can be set up to an accuracy of at least 0.01 mm, numerically controlled
4	845811	Horizontal lathes, incl. turning centres, for removing metal, numerically controlled
5	842890	Machinery for lifting, handling, loading or unloading
Panel B. Tools		
1	846320	Thread rolling machines, for working metal
2	820530	Planes, chisels, gouges and similar cutting tools for working wood
3	820510	Hand-operated drilling, threading or tapping hand tools
4	820411	Hand-operated spanners and wrenches, incl. torque meter wrenches, of base metal, non-adjustable
5	820412	Hand-operated spanners and wrenches, incl. torque meter wrenches, of base metal, adjustable

Description: Panel A shows the top 5 HS product codes with highest similarity to robots. Panel B shows the top 5 HS product codes with highest similarity to tools. Column 1 shows their ranking, column 2 their HS product code and column 3 their shortened description.

machines, and those that lift or move objects, such as traveling cranes. This result aligns with previous literature studying automation. Boustan et al. (2022) found that numerically controlled machines replace less educated workers performing routine tasks, just as industrial robots do. Acemoglu and Restrepo (2019) argue that numerically controlled machines, as much as industrial robots, are part of the automation process replacing tasks done by workers. As for machines that lift and move objects, Adachi (2022) notes that some industrial robots specialize in tasks such as "picking alignment, packaging, and material handling," which are also carried out by overhead cranes and other lifting machinery.

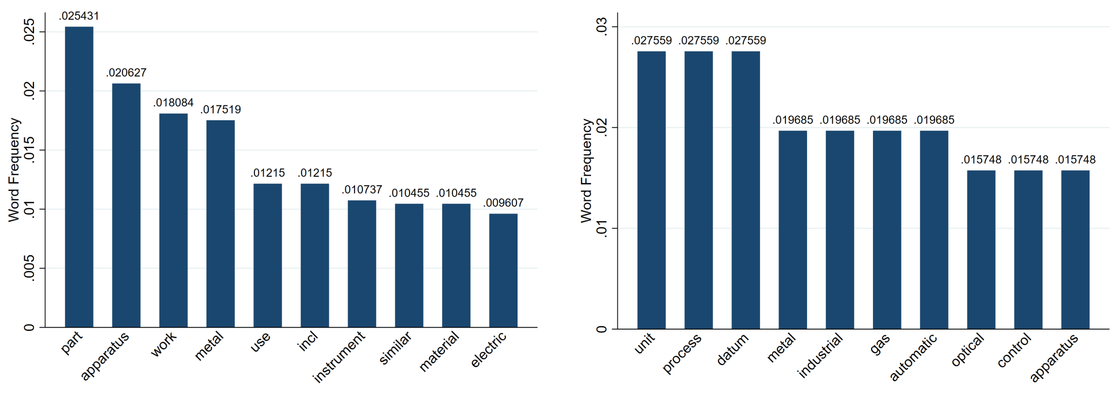
Panel B of Table 1 shows the top 5 machines with the highest similarity to tools. Most of these are hand-operated and used to work with wood or metal.[23]

[23] A thread rolling machine is a machine tool that performs threading in metal. It is commonly used in the production of bolts, nuts, and screws. It usually requires at least one operator per machine.

Words Driving Classification. What words distinguish robots from tools? Are they associated with the nature of automation and equipment handling? Perhaps the algorithm uses counterintuitive words to classify machines.[24] In this subsection, we show that the key words used to classify machines are related to automation or the handling of equipment.

Figure 4: Distribution of Words Among Machines Classified as Robots or Tools

(a) Common Words Among Tools (b) Common Words Among Robots



Description: These figures display the distribution of the most common words among HS 6-digit products classified as tools or as robots.

Figure 4a shows the distribution of words among machines classified as tools. The most common words are either an action performed by a human, i.e., "use," "cut," "handle," or "make"; a tool itself, i.e., "hammer," "wrench," or "blade"; or the word "hand." Figure 4b shows the most common words among robots. Some of these words, such as "process," "automatic," and "control," are directly associated with automation. Other words, such as "unit," "datum," "metal," and "gas," appear often among robot machines because they are always followed by "automatic" or "numerical control."[25]

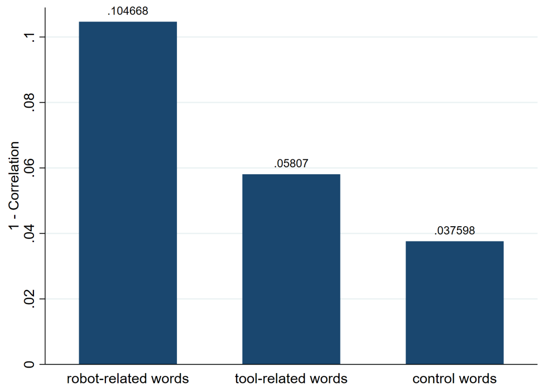
Figure 5 shows the importance of words associated with robots or tools to the classification algorithm. We calculate this in two steps. First, we select a set of words associated with tools and a set of words associated with robots. For robots, we pick the words "automatic,"

[24] For instance, if some Wikipedia articles describe an industrial robot as being "electric machines made of steel", the algorithm could use "electric" or "steel" to distinguish robots from tools. If that is the case, we should consider the method a failure because these words do not seem to be associated with the nature of automation.

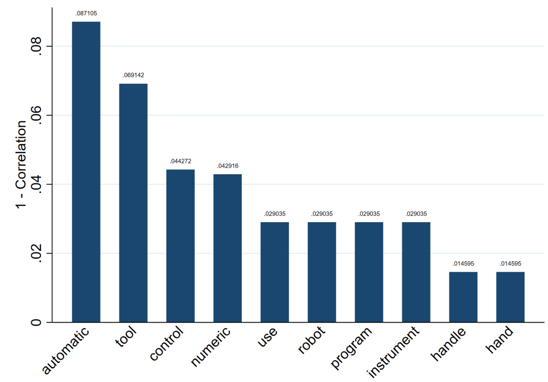
[25] For instance, HS code 844331 "Machines which perform two or more of the functions of printing, copying or facsimile transmission, capable of connecting to an automatic data processing machine or to a network" and HS code 847149 "Data-processing machines, automatic, presented in the form of systems comprising at least a central processing unit, one input unit and one output unit (excl. portable weighing <= 10 kg and excl. peripheral units)".

Figure 5: Importance of Different Words to the Machine Classification

(a) Importance of Group of Words



(b) Importance of Selected Words



Description: These figures show the importance of different words to the classification algorithm. To calculate this, we first select a set of words related to robots and a set of words related to tools. Robot words are "automatic," "numeric," "control," "robot," and "program". Tool words are "tool," "hand," "use," "handle," and "instrument". Then, we remove words associated with robot or tools from the vocabulary and run the classification algorithm. The figures plot 1 minus the correlation between the classification without a selection of words and the baseline classification. The larger the value of 1 minus the correlation, the more important that group of words is to the final classification. As a comparison group, we randomly select 5 words from the vocabulary 30 times and plot their correlation under "control words". Figure 5b repeats this exercise for each robot- and tool-related word.

"numeric," "control," "robot" and "program". For tools, we use "tool", "hand", "use", "handle", and "instrument". Then, we remove each set of words from the vocabulary, run the algorithm to classify machines, and calculate the correlation between the classification with the full vocabulary and the one without the selected words. In Figure 5, we plot 1 minus the correlation. If this number is high, it means that removing that word generates a very different classification, which has a weak correlation with the previous one. If it is small, the word removed from the vocabulary does not play an important role. As a reference point, we randomly draw 5 words from the vocabulary 30 times and average the final correlation.

According to Figure 5, words intuitively associated with automation or the handling of equipment are key for the classification algorithm. Figure 5a shows that, as expected, words associated with robots and tools are relevant to the machine classification. Figure 5b shows that the words "automatic" and "tool" are the most important for the machine classification.

Table B.1 in the Appendix shows the effect of different words on the probability that a machine is classified as a robot. Words associated with automation have a strong effect on the probability of a machine being classified as a robot. Words associated with tools, such as "hand" and "instrument," have a negative but non-significant effect on the probability of a machine being classified as a robot.

Firm-Level Event Studies. In Section B.1.4, following Koch et al. (2021), we implement a matched difference-in-differences to understand the correlation of machine adoption with employment at the firm level. We find that the adoption of robots does not correlate with firm-level employment, as Koch et al. (2021) found when studying industrial robots. This result suggests that the machines classified as robots affect employment similarly to the industrial robots.

5 Empirics

5.1 Second Stage

Our main specification is

$$\Delta \log(y_{r,s,t}) = \theta^R \Delta \log\left(robots_{r,s,t}\right) + \theta^T \Delta \log\left(tools_{r,s,t}\right) + X'_{r,s,t}\Theta + \mu_r + \mu_s + \mu_t + \epsilon_{r,s,t}. \quad (9)$$

The left-hand side, $\Delta \log(y_{r,s,t}) = \log(y_{r,s,t}) - \log(y_{r,s,t-5})$, is the 5-year difference in the log of labor market outcome $y_{r,s,t}$ of region r, sector s at year t. $robots_{r,s,t}$ is 1 plus the imports in dollars of robots in the past 5 years. Therefore, $\Delta \log\left(robots_{r,s,t}\right)$ is the growth rate in the imports of robots by region r, sector s at year t. Equivalently, $\log\left(tools_{r,s,t}\right)$ is approximately the growth rate in the imports of tools. $X_{r,s,t}$ is a set of controls.[26] μ_r and μ_s are region and sector fixed effects, respectively. Because the model is already in difference, these fixed effects capture potential differential trends between regions and sectors. μ_t is a time fixed effect.

We use a long-difference model because machine investments are lumpy and labor takes time to adjust. Capital goods are durable; firms do not purchase them repeatedly. Therefore, the estimates in a year-by-year regression would have large variance due to spikes in capital investments. In addition, machine investments should slowly affect the labor market. To account for these two facts, we use a long-difference model.

[26] The controls are the growth rate of variable $y_{r,s,t}$ in the pre-period, which captures potential labor market trends, the tariff change on sectoral output, and the tariff change on inputs excluding capital.

5.2 First Stage

Identifying the causal effect of robots and tools requires an instrument. In the absence of exogenous variation, we would not be able to separate the effect of local labor market shocks from the effect of each machine type. For instance, if a sectoral preference shock increased the demand for a sector, it would increase capital investments and labor demand. Without an instrument, we would not be able to distinguish the effect of tools, for example, from the demand shock. Local labor market shocks could generate the same problem. If firms decided to use robots because labor had become more expensive in that region, we would not be able to distinguish the effect of the labor market shock from that of the robots. Therefore, we need two instruments to identify the causal effect of each machine type.

We use tariff changes in machines as an instrument for their adoption. Tariffs satisfy the two requirements for instrumental variables: 1) They affect the incentives to purchase each of the machines and 2) They do not affect local labor markets directly, only through cheaper machines. As discussed by Dix-Carneiro and Kovak (2017) and Dix-Carneiro and Kovak (2019), Brazil has experienced to open its economy since the late 1980s. Tariff changes in this period have been driven by differences in tariffs' starting point, rather than by current shocks to the Brazilian economy. Tariffs affect the after-tax price of machines, generating incentives for their purchase, but they do not correlate with other changes in the economy. We show below that tariffs are not correlated with political connections to the government, with other policies implemented during the period, with pre-period labor market trends, or with other labor market shocks.

Following previous work, we also explore heterogeneity in the market response to changes in the prices of tools and robots to construct the instrument. According to Acemoglu and Restrepo (2020) and Graetz and Michaels (2018), robots are more likely to replace workers doing routine intensive tasks. Therefore, markets with more workers in routine-intensive jobs should respond more to changes in robot tariffs. Following this principle, we use as the instrument:[27]

$$IV^{robots}_{r,s,t} = Shr.\ Replaceable_{r,s,0} \times \tau^{R}_{s,t}, \tag{10}$$

where $Shr.\ Replaceable_{r,s,0}$ is the share of workers in occupations in the highest quartile of routine task content and $\tau^{R}_{s,t}$ is the tariff on imports of robots of sector s at time t weighted by pre-period trade flows. Similarly, we construct the instrument for tools:

$$IV^{tools}_{r,s,t} = \left(1 - Shr.\ Replaceable_{r,s,0}\right) \times \tau^{T}_{s,t}, \tag{11}$$

where $\tau^{T}_{s,t}$ is the tariff on tools. The first stage is

$$\Delta log(robots_{r,s,t}) = \pi_{1,1}\Delta IV^{robots}_{r,s,t} + \pi_{1,2}\Delta IV^{tools}_{r,s,t} + X'_{r,s,t}\Pi_1 + \mu_r + \mu_s + \mu_t + \epsilon_{r,s,t} \tag{12}$$

$$\Delta log(tools_{r,s,t}) = \pi_{2,1}\Delta IV^{robots}_{r,s,t} + \pi_{2,2}\Delta IV^{tools}_{r,s,t} + X'_{r,s,t}\Pi_2 + \mu_r + \mu_s + \mu_t + \epsilon_{r,s,t}, \tag{13}$$

where $\Delta log(robots_{r,s,t})$ and $\Delta log(tools_{r,s,t})$ are the 5-year difference in robot and tool imports, respectively, as discussed before. $IV^{robots}_{r,s,t}$ and $IV^{tools}_{r,s,t}$ are the instruments for tools and robots. $X_{r,s,t}$ is the same set of controls as before.

5.3 Validation

To validate the identification strategy, we show that the adoption of machines generated by tariff changes is not correlated with political connections to the government, with other policies implemented during the period, with pre-period trends, or with other shocks hitting the Brazilian economy.

Political Connections and Other Policies. If the effect of tariffs on machine adoption were correlated with other policies, we would not be able to separate the effect of machine adoption from the effect of these other policies. Table B.2 in the appendix shows estimates of equation (9) on the major policies implemented during the period of analysis. It shows that

[27] A similar approach was used by Graetz and Michaels (2018), Bonfiglioli et al. (2020), and Acemoglu and Restrepo (2022), to name a few.

machine adoption is not correlated with subsidized loans, public procurements, or campaign contributions.

Pre-period Trends. If changes in tariffs were correlated with pre-period trends in the labor market, we would not be able to distinguish the effect of tariffs from existing trends in the labor market. Table B.3 shows that tariff changes are not correlated with pre-period trends in the labor market.

Other Shocks. The commodity boom happened during our period of analysis. To make sure that our results are not driven by this event, Table B.2 shows that the instrument and tariff changes are not correlated with changes in export prices, import prices, or competition with Chinese exports.

6 Empirical Results

In this section, we discuss the effect of robots and tools on the labor market. We first show that our instrument is strongly associated with the adoption of robots and tools. Moreover, while robots have a strong negative effect on employment, tools have an impact with a similar magnitude but in the opposite direction. Therefore, if the adoption of these machines increases by the same amount, the effect on employment will be null. Finally, we show that the effect of robots and tools is concentrated among low-education production workers in occupations directly associated with machine operation.

Significant First Stage with Large Cross-Elasticities. Table 2 displays the instrument's impact on robot and tool adoption. In the baseline specification, an increase in the robot or tool instrument by 1 standard deviation reduces their imports by 14.2% and 8.8%, respectively. The F-statistics for all specifications are well above 10, alleviating any concern about weak instruments.[28]

[28]Tables B.4 and B.5 show that the instrument is associated with fewer imports in different functional forms. Table B.5 shows that it leads to a decrease in the probability of importing at least one tool or robot. Table B.4 uses the inverse hyperbolic sine to show that an increase in the instrument causes a decrease in the import of robots or tools.

Table 2 also reveals strong cross-elasticities, showing the necessity of considering robots and tools jointly. Raising tariffs on robots reduces the adoption of both robots and tools. Therefore, omitting tools from the main specification, as commonly done in the literature, would not provide the causal effect of robots. Instead, it would identify the effect of robots net of changes in tools.

Table 2: First Stage: Effect of Instrument on the Adoption of Robots and Tools

	(1)	(2)	(3)	(4)	(5)	(6)
	$\Delta log(robots)$	$\Delta log(robots)$	$\Delta log(robots)$	$\Delta log(tools)$	$\Delta log(tools)$	$\Delta log(tools)$
ΔIV^{tools}	0.0160***	0.0101**	0.0156***	-0.0225***	-0.0342***	-0.0261***
	(0.00406)	(0.00403)	(0.00418)	(0.00729)	(0.00716)	(0.00749)
ΔIV^{robots}	-0.195***	-0.191***	-0.211***	-0.291***	-0.284***	-0.308***
	(0.0161)	(0.0151)	(0.0167)	(0.0162)	(0.0152)	(0.0174)
Specification	Sector FE	Baseline	Market FE	Sector FE	Baseline	Market FE
N	201064	201063	201043	201064	201063	201043
R^2	0.312	0.334	0.384	0.509	0.534	0.560
F	136.8	140.7	172.1	116.8	126.7	144.8

Description: This table shows the coefficients of the first stage, i.e., regressions (12) and (13). IV^{tools} is the interaction between the share of non-replaceable occupations and tariffs on tools in each sector. IV^{robots} is the interaction between the share of replaceable occupations and tariffs on robots in each sector. $robots$ and $tools$ denote the imports in dollars of robots and tools, respectively, in the past 5-years. The difference is taken over the past 5 years. All specifications have as controls the growth rate of employment between 1993 and 1997, the tariff change on sectoral output, the tariff change on inputs excluding capital, and year fixed effects. Columns 1 and 4 add a sector fixed effect, columns 2 and 5 have sector and region fixed effects, and columns 3 and 6 have sector–region fixed effects. Standard errors are clustered at the region–sector level.

Robots decrease employment. Table3 shows the effect of robots and tools on employment. Regardless of the set of controls used, robots cause a strong decline in employment, which is a result that diverges from previous literature. In the main specification in column 5, a 1% increase in the adoption of robots drives a 0.35% decrease in employment.

Controlling for tools is paramount to identifying the effect of robots. Because changes in the price of robots also lead to an increase in the adoption of tools, not controlling for tools would lead to an omitted variable bias and mask the true effect of robots. Tables B.6 and B.7 in the appendix show the estimated effect of robots without controlling for tools, instrumenting robots only with the main instrument in (10). The effect of robots in Table B.7 is non-significant and similar in magnitude to other estimates in the literature, such as the ones found by Acemoglu and Restrepo (2020), Dauth et al. (2021), Rodrigo (2022), and Graetz and Michaels (2018), among others. As seen in Table 2, increases in the price of robots are negatively associated with the adoption of tools. Therefore, not controlling for tools results in an upward-biased estimate.

Table 3: Effect of Tools and Robots on Employment

	(1) $\Delta\log(Employment)$	(2) $\Delta\log(Employment)$	(3) $\Delta\log(Employment)$	(4) $\Delta\log(Employment)$	(5) $\Delta\log(Employment)$	(6) $\Delta\log(Employment)$
$\Delta log(tools)$	0.638**	0.510**	0.366***	0.230***	0.220***	0.229***
	(0.264)	(0.242)	(0.133)	(0.0615)	(0.0557)	(0.0560)
$\Delta log(robots)$	-0.526**	-0.413**	-0.269***	-0.368***	-0.351***	-0.306***
	(0.216)	(0.196)	(0.0992)	(0.0910)	(0.0860)	(0.0826)
Specification	No Controls	Controls	Region FE	Sector FE	Baseline	Market FE
N	236697	201064	201063	201064	201063	201043

Description: FE = fixed effects. This table shows the coefficients of regression (9) on employment. $\Delta log(tools)$ and $\Delta log(robots)$ are instrumented by the interaction of tariff changes with the share of replaceable occupations, as defined in (10) and (11). *robots* and *tools* denote the imports in dollars of robots and tools, respectively, in the past 5 years. The difference is taken over the past 5 years. All specifications have year fixed effects. In column 1, there are no controls other than year fixed effects. Column 2 adds the baseline controls, i.e., growth rate of employment between 1993 and 1997, the tariff change on sectoral output, and the tariff change on inputs excluding capital. Column 3 adds region FE to the baseline controls. Column 4 adds sector FE to the baseline controls. Column 5 includes as controls the baseline controls, region FE, and sector FE. Column 6 includes sector–region FEs and the baseline controls. Standard errors are clustered at the region–sector level.

Instrumenting robot adoption with robot imports from other countries while ignoring tools, a prevalent method, once again biases the estimates. Robot imports by other countries correlate with local tool adoption, according to Section B.3.1 of the appendix. Therefore, when tools are not controlled for, one only identifies the effect of robots net of tools. Because we control for the confounding effect of tools, we identify a stronger effect of robot adoption on employment than previously found.

Tools increase employment by as much as robots decrease it. Table 3 also shows that tools affect employment: A 1% increase in the adoption of tools leads to a 0.2% increase in employment. Columns 1 to 6 show that the estimate is robust to different specifications, with the elasticity ranging from 0.6 to 0.2.

Tools increase employment at the same rate at which robots decrease it. Therefore, if the adoption of these two machines increases by the same amount, the net effect on employment will not be statistically different from zero.

Robots and tools only affect low-skilled workers who are directly using tools. According to Table 4, robots and tools primarily affect low-skilled workers. A 1% increase in robot adoption decreases the employment and wages of workers with less than a high-school education by 0.4% and 0.1%, respectively, with no significant effect on other educational groups. As before, tools increase the employment of low-skilled workers by as much as robots decrease it.

Table 5 shows that the effect of robots and tools is concentrated among the workers who are directly operating them, i.e., operational or technical workers. The first column shows the effect on science professionals, which include engineers, chemists, and other STEM college

Table 4: Effect of Tools and Robots on Different Educational Groups

	(1)	(2)	(3)	(4)	(5)	(6)
	$\Delta log(H.S.\ Drop.)$	$\Delta log(Earnings\ H.S.\ Drop.)$	$\Delta log(H.S.\ Complete)$	$\Delta log(Earnings\ H.S.\ Complete)$	$\Delta log(College\ or\ More)$	$\Delta log(Earnings\ College\ or\ More)$
$\Delta log(tools)$	0.262***	0.0670***	0.0334	-0.0111	0.0203	0.00479
	(0.0609)	(0.0173)	(0.0498)	(0.0204)	(0.0490)	(0.0262)
$\Delta log(robots)$	-0.422***	-0.100***	0.00477	-0.0141	-0.0296	0.00185
	(0.0902)	(0.0253)	(0.0614)	(0.0244)	(0.0483)	(0.0252)
N	191637	191637	114198	114198	74891	74891

Description: This table shows the coefficients of regression (9) on employment and earnings of different educational groups. $\Delta log(tools)$ and $\Delta log(robots)$ are instrumented by the interaction of tariff changes with the share of replaceable occupations, as defined in (10) and (11). *robots* and *tools* denote the imports in dollars of robots and tools, respectively, in the past 5 years. The difference is taken over the past 5 years. The controls are the growth rate of the left-hand-side variable between 1993 and 1997, tariff change on sectoral output, the tariff change on inputs excluding capital, year fixed effect, region fixed effects, and sector fixed effects. Columns 1 and 2 show the effect of robots and tools on employment and earnings of workers that have less education than a high-school diploma. Columns 3 and 4 show the effects on workers with high-school diploma. Columns 5 and 6 show the effect on workers with at least some college education. Standard errors are clustered at the region–sector level.

Table 5: Effect of Tools and Robots on Different Occupations

	(1)	(2)	(3)	(5)	(6)
	$\Delta log(Managers)$	$\Delta log(HS\ Professionals)$	$\Delta log(Technical\ Workers)$	$\Delta log(Adm\ Workers)$	$\Delta log(Operational\ Workers)$
$\Delta log(tools)$	-0.0626	-0.0152	0.254***	0.0230	0.336***
	(0.0632)	(0.0648)	(0.0610)	(0.0514)	(0.0808)
$\Delta log(robots)$	0.0851	0.0316	-0.166***	0.0162	-0.281***
	(0.0562)	(0.0459)	(0.0557)	(0.0642)	(0.0987)
N	46058	20096	71850	132271	146862

Description: This table shows the coefficients of regression (9) on employment of different occupations. $\Delta log(tools)$ and $\Delta log(robots)$ are instrumented by the interaction of tariff changes with the share of replaceable occupations, as defined in (10) and (11). *robots* and *tools* denote the imports in dollars of robots and tools, respectively, in the past 5 years. The controls are the growth rate of the left-hand-side variable between 1993 and 1997, tariff change on sectoral output, the tariff change on inputs excluding capital, year fixed effects, region fixed effects, and sector fixed effects. Standard errors are clustered at the region–sector level.

graduates. Column 2 shows the effect of machines on technical workers, i.e., workers in areas associated with STEM but who do not have a college degree. These include those working in mechatronics and chemistry, and electronic technicians, among many others. Despite having technical skills, 62.8% of these workers have not finished high school. Column 3 shows the effect on administrative and office workers. The last column shows the effect of machines on operational workers.

6.1 Robustness

The main empirical results show that robots decrease the employment of low-skilled operational workers, but tools increase it by a similar magnitude. In this section, we show that this conclusion is robust to alternative identification strategies, to the removal of outliers, to the addition of controls, and to limiting the sample to machines with higher text similarity to robots or tools.

Tariff as Instruments. In Section B.3.2, we reproduce the main regressions but using only using tariff variation as the instrument. We still reach the same conclusion: Robots decrease the employment of low-skilled operational workers, but tools increase it by equal magnitude.

Import by Other Countries as Instruments. In Section B.3.1, inspired by Acemoglu and Restrepo (2020) and Dauth et al. (2021), among others, we use as the instruments the imports of robots and tools by the US and Europe. We still find that tools increase the employment of low-skilled workers, whereas robots decrease it.

Outliers. It could be the case that our results are driven by specific outliers in the sample. To assess whether this is the case, in Section B.3.3 of the appendix, we repeat the main regressions but remove the markets in the top and bottom 0.1% and 0.5% change in tariffs. We still reach the same conclusion that robots decrease the employment of low-skilled operational workers, whereas tools increase it.

Controls. In Tables B.20 to B.25, we show that the results are robust to adding or removing controls. We try three different specifications. First, we remove region and sector fixed effects, which capture regional and sectoral trends. Second, we add only a sector fixed effects. Third, we control for joint sector–region fixed effects, which controls for market-specific trends. We still find that low-skilled workers who directly operate machines are more affected by both robots and tools.

Higher Degree of Text Similarity. The text similarity to the description of robots or tools is, most likely, a noise measure of the true nature of the machine. Moreover, it is possible that not all machines fall into these two classifications. To deal with this, Section B.3.5 shows the main results restricting the sample to the set of machines that have cosine text similarity above the median. We still find that robots decrease employment while labor-augmenting tools increase it.

7 Quantitative Model

In the empirical section, we have learned that tools increase employment and decrease inequality. Robots, meanwhile, increase inequality and decrease employment. These results reveal a trade-off between inequality and productivity. Increased robot adoption increases productivity but also leads to higher inequality. A government concerned with redistribution might be interested in either taxing robots, as in Beraja and Zorzi (2022), or subsidizing the adoption of tools. In this section, we develop a quantitative model of robots and tools with capital accumulation, input-output, international trade, and regions to derive counterfactuals on the aggregate effect of robots and tools.

The main channel in the quantitative model is the choice that firms make between robots, which replace workers, and tools, which complement them. To interpret the empirical elasticity and capture important elements of the economy, we add other features to the model. There are multiple regions and sectors, enabling us to reproduce the empirical strategy in the model. Firms are heterogeneous in their productivity to use different technologies and in the productivity of high-skill workers, which leads to selection into technology types. Firms use inputs from other sectors and export their output to other countries; this has been added to the model to better capture the scale effect.[29] The economy has local production and imports of robots and tools. Households choose their sector and region of employment, accumulate capital that is rented to firms, and make educational choices.

7.1 Demographics

There are $n \in \{1, ..., N\}$ regions and $s \in \{1, ..., S\}$ sectors. We denote workers in sector $S+1$ as out of the labor force. There are 6 agents in the economy: intermediate goods producers, composite goods producers, capital producers, capitalists, workers, and the government. Intermediate goods producers produce using high-skilled workers, low-skilled workers, tools, robots, and inputs from other sectors. Composite goods producers create final goods by aggregating local production with imports from all other countries. Capital producers produce tools and robots using final goods and imported capital. Capitalists accumulate capital from capital producers and rents it to firms to maximize their lifetime utility. Workers choose their region and sector of employment. At the beginning of their life, they choose whether to become high-skilled or low-skilled. The government taxes labor, rents, profits, and imports.

[29] Input-output connections are a key feature in understanding the effect of robots and tools for two reasons. First, as Figure C.1 in the appendix shows, robot adoption is more common among downstream sectors, while tools are scattered over sectors. Therefore, changes in the price of robots and tools will have different propagation through the economy. Second, input-output connections and international trade are important for understanding the productivity effect, which measures how the adoption of robots and tools affects the market size of firms and sectors.

It also provides social security to workers outside of the labor force.

7.2 Intermediate Goods Producers

Production Function with Input-Output Connections. Firms perform a set of tasks and use inputs from other sectors to produce. Output of firm i in region n and sector s is:

$$y_n^s(i) = \left[\frac{1}{\gamma^s}\left(\int_0^1 [y_n^s(i,\nu)]^{\frac{\lambda-1}{\lambda}}\, d\nu\right)^{\frac{\lambda}{\lambda-1}}\right]^{\gamma^s} \prod_{s'=1}^{S}\left[\frac{1}{\gamma^{ss'}} M_n^{ss'}(i)\right]^{\gamma^{ss'}}, \tag{14}$$

where, similar to the simple model, $y_n^s(i,\nu)$ denotes the firm's output of task ν. λ is the elasticity of substitution between tasks. $M_n^{ss'}(i)$ denotes the quantity of sector s' composite goods used by the firm. γ^s denotes the value-added share of the firm's gross output and $\gamma^{ss'}$ denotes the input-output shares. Firm production is a constant return to scale: $\gamma^s + \sum_{s'=1}^{S}\gamma^{ss'} = 1$.

Robots or Tools. Task ν can be performed with robots or tools and workers:

$$y_n^s(i,\nu) = y_n^{s,R}(i,\nu) + y_n^{s,T}(i,\nu).$$

If firm i performs task ν with robots, the production function is:

$$y_n^{s,R}(i,\nu) = Z_n^{s,R}(i,\nu) K_n^{s,R}(i,\nu),$$

where $K_n^{s,R}(i,\nu)$ is robot capital and $Z_n^{s,R}(i,\nu)$ is the productivity of firm i in completing task ν with robots.

If firm i performs task ν with tools, the task production function is:

$$y_n^{s,T}(i,\nu) = Z_n^{s,T}(i,\nu)\left[A_n^{s,H}(i)\left(\ell_n^{s,H}(i,\nu)\right)^{\frac{\sigma-1}{\sigma}} + \left(\ell_n^{s,L}(i,\nu)^{\delta} K_n^{s,T}(i,\nu)^{1-\delta}\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}},$$

where $\ell_n^{s,H}(i,\nu)$ is the number of high-skilled workers, $\ell_n^{s,L}(i,\nu)$ is the number of low-skilled workers, and $K_n^{s,T}(i,\nu)$ is the amount of tool capital. $Z_n^{s,T}(i,\nu)$ is the productivity of tools for firm i in sector s and region n in task ν. $A_n^{s,H}(i)$ is the high-skilled biased productivity of firm i, which captures that some firms are more productive with high-skilled workers.

Firm Heterogeneity. Firms are heterogeneous in the productivity of using robots, $Z_n^{s,R}(i,\nu)$, tools, $Z_n^{s,T}(i,\nu)$, and high-skilled workers, $A_n^{s,H}(i)$. We assume that $Z_n^{s,l}(i,\nu), l \in \{R, T\}$ follows a Fréchet distribution i.i.d. across regions (n), sectors (s), firms (i), tasks (ν), and technologies (l):

$$F_{Z_n^{s,l}(i,\nu)}(z) = \exp\left[-T_n^{s,l}(i) \times z^{-\tilde{\theta}}\right].$$

We normalize $T_n^{s,T}(i) \equiv 1$ and assume that $A_n^{s,H}(i)$ and $T_n^{s,R}(i)$ follow a joint log-normal distribution (see Section C.2).

7.3 Sectoral Production and Goods Trade

Sectoral Aggregates. Output at the region–sector level combines the output of firms with elasticity of substitution θ:

$$y_n^s = A_n^s \left(\int_0^1 \left[y_n^s(i)\right]^{\frac{\theta-1}{\theta}} di\right)^{\frac{\theta}{\theta-1}},$$

where A_n^s denotes region–sector level productivity.

Imports, Regional Trade, and Composite Goods. Region–sector composite goods combine the same sector's output from all domestic regions and abroad with elasticity of substitution ϵ^s, which is also the trade elasticity:[30]

$$Q_n^s = \left[\sum_{n'=1}^{N+1} (y_{nn'}^s)^{\frac{\epsilon^s-1}{\epsilon^s}}\right]^{\frac{\epsilon^s}{\epsilon^s-1}},$$

where $n' = N+1$ indicates the international market. Inter-region trade and importing incur a trade cost, $h_{nn'}^s$, and importers pay tariffs to the Brazilian government at rate τ^s. Denote $t^s = 1 + \tau^s$, including the foreign price p_{N+1}^s in the importing cost h_{nN+1}^s. Consequently, the

[30] These assumptions for sectoral production and trade are standard in the international trade literature. See Caliendo et al. (2019), among others.

composite goods price is:

$$(P_n^s)^{1-\epsilon^s} = \sum_{n'=1}^{N} (p_{n'}^s h_{nn'}^s)^{1-\epsilon^s} + (h_{nN+1}^s t^s)^{1-\epsilon^s},$$

where p_n^s is the price of sector s region n sectoral output.

7.4 Capital Goods Sector

In the capital goods sector, there are two types of agents: capital producers and capitalists. Capital goods are produced by the capital producer using domestic final goods and imported capital. Capitalists are responsible for making inter-temporal investment decisions. Capitalists own capital producers and capital. Capital is then rented to firms.[31]

Capital Producers. Every region–sector has a robot and tool producer. Production of these goods combines domestic final goods with imported capital. The production of investment goods has decreasing returns to scale.[32] The problem of a capital producer of good $l \in \{R, T\}$ is:

$$\begin{aligned} \max_{M_n^{s,l}} \Pi_n^{s,l,P} &= P_n^{s,l} I_n^{s,l} - \Sigma_n^{s,l} M_n^{s,l}, \\ \text{s.t. } I_n^{s,l} &= (M_n^{s,l})^{1-\xi^l}, \ \xi^l \in (0,1) \\ \Sigma_n^l &= \left([P_n]^{1-\epsilon^l} + \left[h_{nN+1}^{s,l} (1+\tau^{s,l}) \right]^{1-\epsilon^l} \right)^{\frac{1}{1-\epsilon^l}}, \end{aligned} \tag{15}$$

where $M_n^{s,l}$ is a composite good combining domestic final goods and import of capital l, $\xi^l \in (0,1)$ is the degree of decreasing return to scale, $P_n^{s,l}$ is the price of capital good l, and Σ_n^l is the cost index. Denote $t^{s,l} = 1 + \tau^{s,l}$. ϵ^l denotes the elasticity of substitution between domestic final goods and imported capital goods, which is also the trade elasticity for capital goods.

[31] This setup follows the literature that studies the adjustment cost of capital, for example, Cooper and Haltiwanger (2006).

[32] We add decreasing returns to scale in capital production to ensure that an equilibrium always exists.

Capitalists and Dynamic Problem. Capitalists accumulate capital from capital producers to maximize their lifetime utility. Each region–sector has a capitalist that invests in robot and tool capital. Their problem is given by:

$$\max_{I^{s,l}_{n,t}} \sum_{t=0}^{\infty} \beta^t \log(C^{s,l}_{n,t}), \; l \in \{R, T\} \tag{16}$$
$$\text{s.t. } K^{s,l}_{n,t+1} = (1-\delta)K^{s,l}_{n,t} + I^{s,l}_{n,t}$$
$$P_{n,t}C^{s,l}_{n,t} = (1-B)(R^{s,l}_{n,t}K^{s,l}_{n,t} - P^{s,l}_{n,t}I^{s,l}_{n,t} + \Pi^{s,l,P}_{n}).$$

$R^{s,l}_{n,t}K_t$ indicates the capitalist's rental income and $\Pi^{s,l}_n$ the profit of capital producers, which is owned by capitalists. Capitalists spend on investment, $P^{s,l}_{n,t}I_t$, and on the consumption of local final goods after paying. They also pay taxes at a rate of B.

7.5 Workers

Demographics, Sectoral, and Regional Choice. There are two types of workers: high-skilled and low-skilled. In each period, workers select their next period's region and sector. Workers can also choose to stay outside the labor market and receive social insurance.

To accommodate adjustments in the supply of skills, we assume that with probability ζ^H, a high-skilled worker dies, which is similar for low-skilled workers with probability ζ^L. The dead worker is replaced by an entrant in the same region–sector who decides whether to become a high- or low-skilled worker.

Worker's Dynamic Problem. Building on Artuç et al. (2010), Caliendo et al. (2019), and Kleinman et al. (2023), among others, we assume that a worker of type e has the following recursive utility:

$$\mathbb{V}^{s,e}_{n,t} = \log(u^{s,e}_{n,t}) + \max_{n' \in \{1,2,\ldots,N\}, s' \in \{1,\ldots,S,S+1\}} \left\{ \zeta^e \beta \mathbb{E}_t \left(\mathbb{V}^{s',e}_{n',t+1} \right) - \kappa^{s's}_{n'n,t} + \rho^e \epsilon^{s',e}_{n',t} \right\}, e \in \{H, L\},$$

$$\text{where } u^{s,e}_{n,t} = \max_{\left\{C^{ss',e}_{n,t}\right\}} a^{s,e}_{n,t} \prod_{s'=1}^{S} \left(\frac{C^{ss',e}_{n,t}}{\alpha^{s'}} \right)^{\alpha^{s'}} \quad \text{s.t.} \quad \sum_{s'=1}^{S} P^{s'}_{n,t} C^{ss',e}_{n,t} = (1-B) w^{s,e}_{n,t}, \tag{17}$$

where $\mathbb{V}^{s,e}_{n,t}$ is the value function of a worker in region n, sector s, and education e at time t. Workers choose their location next period, n', sector, s', and consumption of sectoral goods, $\left\{C^{ss',e}_{n,t}\right\}$. α^d and $a^{s,e}_{n,t}$ are parameters of the utility function representing the sectoral consumption shares and consumption shifters. $\kappa^{s's}_{n'n,t}$ is the mobility cost from region n, sector s to region n', sector s'. $\epsilon^{s',e}_{n',t}$ is a preference shock for regions and sectors following a Type-I extreme value distribution i.i.d. across regions, sectors, and time.[33] The income of a worker in the outside sector is equal to the social insurance payment: $w^{S+1,e}_{n,t} = b$.

Define $v^{s,e}_{n,t} \equiv E_{\left\{\epsilon^{s',e}_{n',t}\right\}} \mathbb{V}^{s,e}_{n,t}$. Using the extreme value distribution's property, the expected region–sector–type value function equals:

$$v^{s,e}_{n,t} = \log(a^{s,e}_{n,t}) + \log(1-B) + \log(\frac{w^{s,e}_{n,t}}{P_{n,t}}) + \rho^e \log \sum_{n'=1}^{N} \sum_{s'=1}^{S+1} \exp(\lambda^e \beta v^{s',e}_{n',t+1} - \kappa^{s's,e}_{n'n,t})^{1/\rho^e}. \tag{18}$$

Human Capital Choice. To account for changes in the supply of workers as a consequence of changes in the price of tools and robots, we assume that exits are replaced by entrants who choose their skill type. At the end of period t, ζ^e workers die and are replaced with entrants. These entrants are in the same sector and region as the ones exiting and choose their skill level for the next period. Their problem is given by:

$$\max \left\{ \beta v^{s,H}_{n,t} - f^H + \tilde{\rho} \tilde{\epsilon}^{s,H}_{n,t}, \beta v^{s,L}_{n,t} + \tilde{\rho} \tilde{\epsilon}^{s,L}_{n,t} \right\}, \tag{19}$$

where f^H denotes the fixed cost of becoming high-skilled and $\tilde{\epsilon}^{s,e}_{n,t}$ is a preference shock that is i.i.d. across regions, sectors, time, and skill types.

[33] $F(\epsilon) = \exp(\exp(-\epsilon - \bar{\gamma}))$, where $\bar{\gamma}$ is the Euler constant.

Government. The government taxes workers, capital producers, capitalists, and imports to subsidize social security for workers outside of the labor force. The social insurance payment to a worker not in the labor force is endogenously determined by the government's budget constraint, written as the following:

$$
\begin{aligned}
&(1-B)b\sum_{n=1}^{N}(\ell_n^{S+1,H}+\ell_n^{S+1,L}) = \\
&B\sum_{s=1}^{S}\sum_{n=1}^{N}\left(w_n^{s,H}\ell_n^{s,H}+w_n^{s,L}\ell_n^{s,L}+R_n^R K_n^R-\Sigma_n^R M_n^R+R_n^T K_n^T-\Sigma_n^T M_n^T\right)+TD_n.
\end{aligned}
\tag{20}
$$

The left-hand side refers to the net social security payment to those who do not work (in sector $S+1$). On the right-hand side, tax revenues include social insurance taxes and foreign transfers, TD_n, which are equal to the trade deficit due to trade in composite goods and imported capital goods.[34]

8 Model Estimation

The model is estimated by targeting key moments of the Brazilian economy and the elasticities that we identified in Section 6. In this section, we briefly discuss the estimation strategy. We leave the details to Section C.

Calibration. Sectoral trade elasticities, input-output coefficients, final consumption shares, and the social insurance tax rate are set to the numbers estimated by De Souza and Li (2022). We estimate the migration elasticities for both skill types and the skill choice elasticity exploiting variation in migration shares across regions and sectors, the region-sector specific share of new workers that are high skilled, and cross region–sector differences in real wages, following the method by Artuç et al. (2010), Dix-Carneiro (2014), and Caliendo et al. (2019).[35] Exit rates by skill group are calibrated to match movements out of the labor force from RAIS. We present the details of calibrating these parameters in Section C.3.

[34] See Equation (C.19).

[35] We follow the literature to instrument current wages with past wages, which are unlikely to correlate with current amenity shocks.

Estimation. We estimate the parameters related to production and technology choice to reproduce the identified effect of robots and tools on the labor market. We generate in the model the tariff changes observed between 1997 and 2010 and, employing the same identification strategy, we choose $\tilde{\theta}$, the elasticity of substitution between robots and tools; θ, the elasticity of substitution between firms; σ, the elasticity of substitution between high-skilled and low-skilled workers; and δ, the share of low-skilled workers in output produced with tools, to reproduce the identified effect of robots and tools on the employment of high- and low-skilled workers. As shown in propositions 1 and 2, these parameters play a critical role in the effect of robots and tools on the employment of different skill groups. We present the details of the estimation procedure in Section C.4. Table 6 shows the main parameters; the remaining ones are presented in Section C.4.

Table 6: Parameters Estimated in the Model: Robot and Tool Technologies

Parameter	**Name**	**Value**
θ	Elasticity of substitution between robots and tools	11.5510
ψ	Elasticity of substitution between firms	6.3254
σ	Elasticity of substitution between high-skilled and low-skilled workers	3.2981
δ	Share of low-skilled workers in output produced with tools	0.5477

Description: This table presents the model parameters that are estimated with the SMM method in the model and focuses on the important parameters related to robot and tool technologies. We present the other estimated parameters in Table C.5.

9 Quantitative Results

Figure 6 shows the aggregate effect of changes in the prices of robots and tools. Each plot contains changes in the prices of robots and tools on the x-axis. On the y-axis, the figures display aggregate employment, GDP, welfare, and skill premium across all sectors and regions. Unlike the empirics, which only identify relative effects, the model uncovers the aggregate consequences of changes in the prices of robots and tools.

Figure 6 shows that a decrease in the price of robots would decrease employment and welfare while increasing GDP and skill premium. A 80% drop in the price of robots would decrease employment by 2%. Because workers are being replaced by robots, their welfare decreases. GDP increases from lower robot prices because firms become more productive with cheaper inputs. Skill premium increases because robots lead to more layoffs of low-skilled workers.

According to the results in Figure 6, if the prices of robots and tools fell by the same amount, welfare would increase and inequality would decrease without any effect on employment. The red line in Figure 6 plots changes in employment, GDP, workers' welfare, and skill premium from changes in the price of both machines. Tools and robots have an opposite effect on the labor market. Robots replace workers in their tasks, whereas tools reinstate them. Because these effects are of comparable magnitude, aggregate employment barely changes if the prices of these two machines fall by the same amount. GDP and welfare, meanwhile, increase significantly from the reduced machine cost. If the price of machines decreases, firms reduce their marginal cost, which benefits consumers. Inequality decreases because tools are complements to low-skilled workers.

Between 1997 and 2014, the after-tariff import price of robots and tools fell by 38.8% and 45.9%, respectively. How has that affected the Brazilian economy? Table 7 answers this question. It presents the aggregate effects of cheaper robots and tools. The first line shows the counterfactual with both capital prices changing. On the second line, only the tool price changes, and on the third line, only the robot price changes.

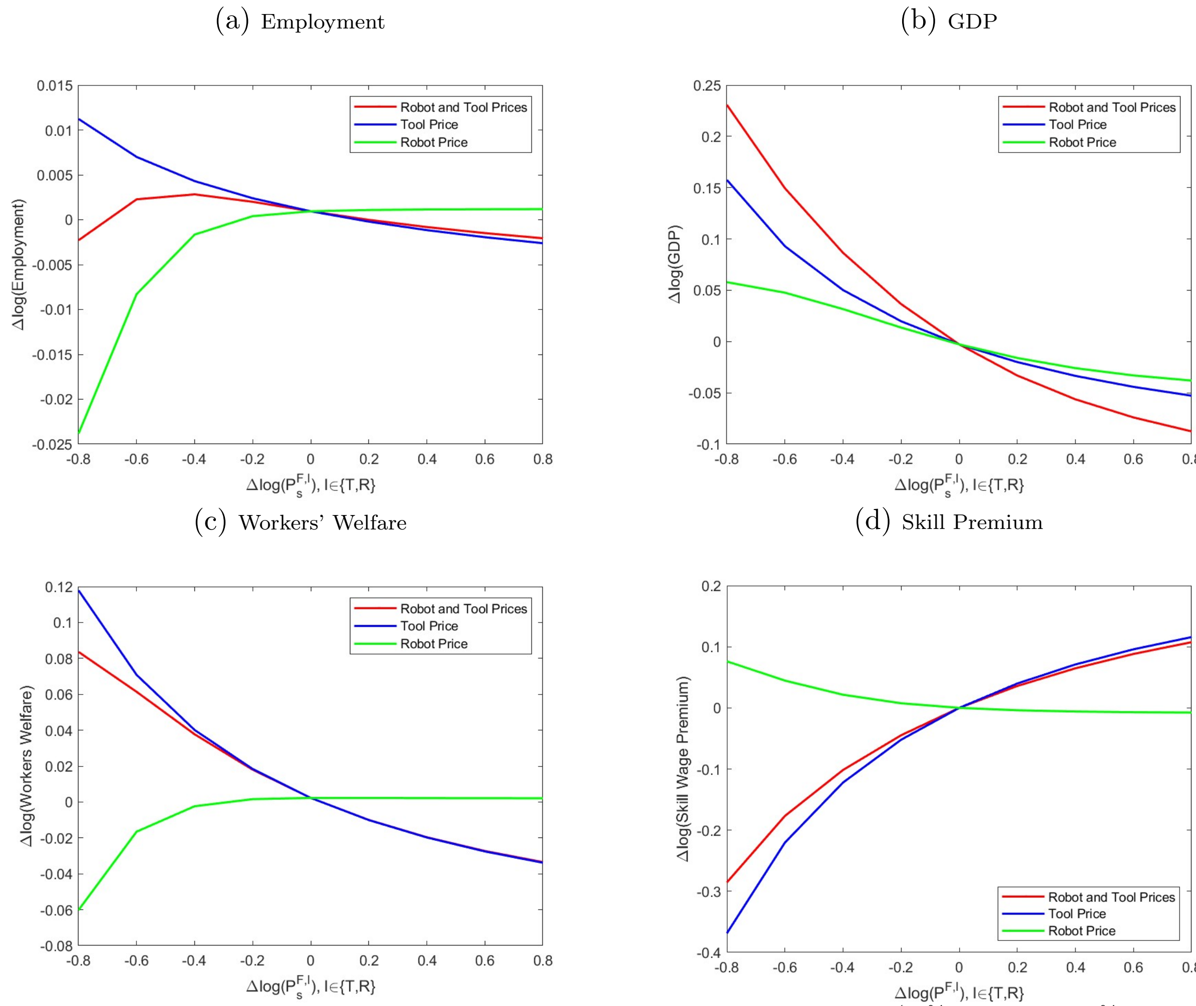
Cheaper robots and tools, due to advances in the production of these technologies, has led to large GDP gains in Brazil with small changes in employment and lower inequality. Due to cheaper tools, employment has increased. Because both machines have led to higher productivity, GDP and welfare has increased. Moreover, because tools are compliments to low-skilled workers, inequality in the labor market has decreased.

Table 7: **Aggregate Effects of Reduced International Capital Goods Prices**

	Avg. Robot Price Chg.	Avg. Tool Price Chg.	Employment	GDP	Workers' Welfare	Skill Premium
Both Robots and Tools	-38.8%	-45.9%	0.3%	9.4%	5.1%	-10.3%
Tools	0	-45.9%	0.5%	6.8%	5.0%	-12.6%
Robots	-38.8%	0	-0.2%	2.4%	-0.01%	3.0%

Description: This table presents the initial trade flow weighted average of international robot and tool price changes, and the effects of lower international capital goods prices on employment, GDP, workers' welfare, and skill premium. The skill premium is defined as the average wage of a high-skilled worker relative to the average wage of a low-skilled worker.

Figure 6: **Aggregate Effects of Robot and Tool Capital Import Price Changes**



Description: The figure illustrates the effects of varying robot and tool import prices (80% decrease to 80% increase) on aggregate employment, GDP, workers' welfare, and skill premium, relative to the initial steady state. Red lines represent simultaneous robot and tool price changes, blue lines represents tool-only changes, and green lines represents robot-only changes. Uniform price changes across all sectors are considered.

10 Conclusion

Technological progress over the past few decades has led to cheaper robots and tools. In this paper, we shed light on how this phenomenon has affected the labor market in Brazil. We find that while the adoption of robots has led to substantial declines in the employment and wages of low-skilled workers in operational occupations, the simultaneous decrease in the cost of tools has played a vital role in mitigating these job losses.

We used natural language processing and an instrumental variable approach to overcome the challenges associated with classifying machines and finding their causal effect. With natural language processing, we identified machines related to automation and those that complement workers in their tasks. We used import tariff variation as an instrument for the adoption of robots and tools.

Our research makes significant contributions to the existing literature on the effect of automation on the labor market. Notably, we expand the analytical framework by adding tools. Additionally, our findings challenge previous estimations of the impact of robots on employment, emphasizing the importance of accounting for the simultaneous adoption of tools, which has often been overlooked in previous analyses.

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A Appendix for Simple Model

In this section, we derive the proofs for Section 2.

A.1 Equilibrium of Simple Model

The market-clearing condition for high-skilled workers is the following:

$$l_H = \frac{1}{w_H}\frac{(w_H)^{1-\sigma}}{(\Theta_T)^{1-\sigma}}\frac{(\Theta_T)^{-\tilde{\theta}}}{(\Theta_R)^{-\tilde{\theta}}+(\Theta_T)^{-\tilde{\theta}}}\frac{p_A^{1-\psi}}{p_A^{1-\psi}+p_N^{1-\psi}}PY = A_H(w_H)^{\xi}. \tag{A.1}$$

The market-clearing condition for low-skilled workers implies that:

$$l_L = \frac{1}{w_L}\delta\frac{\left(\left([w_L]^{\delta}\left[P_T\right]^{1-\delta}\right)\right)^{1-\sigma}}{(\Theta_T)^{1-\sigma}}\frac{(\Theta_T)^{-\tilde{\theta}}}{(\Theta_R)^{-\tilde{\theta}}+(\Theta_T)^{-\tilde{\theta}}}\frac{p_A^{1-\psi}}{p_A^{1-\psi}+p_N^{1-\psi}}PY = A_L(w_L)^{\xi}. \tag{A.2}$$

Without loss of generality, we normalize the economy's total output, PY, to 1. Therefore, the equilibrium is defined with wages $\{w_H, w_L\}$, such that Equations (A.1) and (A.2) hold.

A.2 Proofs of Simple Model

To derive proofs for the propositions in Section 2.2, we begin with the following two lemmas:

Lemma 1. The impact of tool and robot price shocks on the employment of high-skilled and low-skilled workers can be summarized as follows:

$$\begin{aligned}\operatorname{dlog}\ell_H = &-\frac{\Delta(1-s_{T,H})(1+\xi)(1-\delta)\xi}{\Delta\left[s_{T,H}(1+\xi+(\sigma-1)\delta)+(1-s_{T,H})\delta(\xi+\sigma)\right]+(\xi+\sigma)(1+\xi+(\sigma-1)\delta)}\operatorname{dlog}P_T\\ &+\frac{(\Delta+\sigma-1+(1-s_A)(1-\psi))(1+\xi+(\sigma-1)\delta)\xi}{\Delta\left[s_{T,H}(1+\xi+(\sigma-1)\delta)+(1-s_{T,H})\delta(\xi+\sigma)\right]+(\xi+\sigma)(1+\xi+(\sigma-1)\delta)}\operatorname{dlog}P_R,\end{aligned} \tag{A.3}$$

and

$$\mathrm{dlog}\,\ell_L = -\frac{\left(\Delta\left[(1-s_{T,H})(\xi+\sigma)+s_{T,H}(\sigma-1)\right]+(\sigma-1)(\xi+\sigma)\right)(1-\delta)\xi}{\Delta\left[s_{T,H}(1+\xi+(\sigma-1)\delta)+(1-s_{T,H})\delta(\xi+\sigma)\right]+(\xi+\sigma)(1+\xi+(\sigma-1)\delta)}\,\mathrm{dlog}\,P_T$$
$$+\frac{(\Delta+\sigma-1+(1-s_A)(1-\psi))(\xi+\sigma)\xi}{\Delta\left[s_{T,H}(1+\xi+(\sigma-1)\delta)+(1-s_{T,H})\delta(\xi+\sigma)\right]+(\xi+\sigma)(1+\xi+(\sigma-1)\delta)}\,\mathrm{dlog}\,P_R, \tag{A.4}$$

in which $\Delta = 1-\sigma-(1-s_A)(1-\psi)+\left[(1-s_A)(1-\psi)+\tilde{\theta}\right]s_R$ summarizes the impact of tool price shocks on high-skilled workers. $s_{T,H}$ represents the share of tool technology expenditures devoted to high-skilled workers. s_A denotes the economy's expenditure share on automatable sectors. s_R denotes the expenditure share on robots for automatable tasks.

Proof of Lemma 1 Based on the definition of the input cost of the tools bundle, Θ_T, its log linearization is equal to the following:

$$\mathrm{dlog}(\Theta_T) = s_{T,H}\,\mathrm{dlog}(w_H)+(1-s_{T,H})\delta\,\mathrm{dlog}(w_L)+(1-s_{T,H})(1-\delta)\,\mathrm{dlog}(P_T).$$

Log linearize Equation (A.1):[36]

$$\begin{aligned}(1+\xi)\,\mathrm{dlog}(w_H) = {} & (1-\sigma)\,\mathrm{dlog}(w_H)-(1-\sigma)\,\mathrm{dlog}(\Theta_T)-\tilde{\theta}\,\mathrm{dlog}(\Theta_T)\\ & +\tilde{\theta}s_R\,\mathrm{dlog}(P_R)+\tilde{\theta}(1-s_R)\,\mathrm{dlog}(\Theta_T)\\ & +(1-\psi)s_R\,\mathrm{dlog}(P_R)+(1-\psi)(1-s_R)\,\mathrm{dlog}(\Theta_T)\\ & -s_A\left((1-\psi)s_R\,\mathrm{dlog}(P_R)+(1-\psi)(1-s_R)\,\mathrm{dlog}(\Theta_T)\right).\end{aligned} \tag{A.5}$$

Plug in $\mathrm{dlog}(\Theta_T)$ and collect terms:

$$\begin{aligned}&(\xi+\sigma+\Delta s_{T,H})\,\mathrm{dlog}\,w_H+(\Delta(1-s_{T,H})\delta)\,\mathrm{dlog}\,w_L\\ &= -\Delta(1-s_{T,H})(1-\delta)\,\mathrm{dlog}\,P_T-(1-\sigma-(1-s_A)(1-\psi)-\Delta)\,\mathrm{dlog}\,P_R,\end{aligned} \tag{A.6}$$

[36] In these derivations, we normalize GDP, PY, to 1.

where $\Delta = 1 - \sigma - (1-s_A)(1-\psi) + \left[(1-s_A)(1-\psi) + \tilde{\theta}\right] s_R$.

Log linearize Equation (A.2):

$$\begin{aligned}(1+\xi)\,\mathrm{dlog}(w_L) &= (1-\sigma)\delta\,\mathrm{dlog}(w_L) + (1-\sigma)(1-\delta)\,\mathrm{dlog}\,P_T - (1-\sigma)\,\mathrm{dlog}\,\Theta_T - \tilde{\theta}\,\mathrm{dlog}(\Theta_T) \\ &\quad + \tilde{\theta} s_R\,\mathrm{dlog}(P_R) + \tilde{\theta}(1-s_R)\,\mathrm{dlog}(\Theta_T) \\ &\quad + (1-\psi)s_R\,\mathrm{dlog}(P_R) + (1-\psi)(1-s_R)\,\mathrm{dlog}(\Theta_T) \\ &\quad - s_A\left((1-\psi)s_R\,\mathrm{dlog}(P_R) + (1-\psi)(1-s_R)\,\mathrm{dlog}(\Theta_T)\right). \qquad \text{(A.7)}\end{aligned}$$

Plug in $\mathrm{dlog}(\Theta_T)$ and collect terms:

$$\begin{aligned}&(\Delta s_{T,H})\,\mathrm{dlog}\,w_H + (1+\xi+[\Delta(1-s_{T,H})-1+\sigma]\,\delta)\,\mathrm{dlog}\,w_L \\ &= -(\Delta(1-s_{T,H})-1+\sigma)(1-\delta)\,\mathrm{dlog}\,P_T - (1-\sigma-(1-s_A)(1-\psi)-\Delta)\,\mathrm{dlog}\,P_R. \qquad \text{(A.8)}\end{aligned}$$

Combine Equations (A.6) and (A.8), eliminate $\mathrm{dlog}\,w_L$, and solve for $\mathrm{dlog}\,w_H$:

$$\begin{aligned}\mathrm{dlog}\,w_H &= -\frac{\Delta(1-s_{T,H})(1+\xi)(1-\delta)}{\Delta\left[s_{T,H}(1+\xi+(\sigma-1)\delta) + (1-s_{T,H})\delta(\xi+\sigma)\right] + (\xi+\sigma)(1+\xi+(\sigma-1)\delta)}\,\mathrm{dlog}\,P_T \\ &+ \frac{(\Delta+\sigma-1+(1-s_A)(1-\psi))(1+\xi+(\sigma-1)\delta)}{\Delta\left[s_{T,H}(1+\xi+(\sigma-1)\delta) + (1-s_{T,H})\delta(\xi+\sigma)\right] + (\xi+\sigma)(1+\xi+(\sigma-1)\delta)}\,\mathrm{dlog}\,P_R. \qquad \text{(A.9)}\end{aligned}$$

Eliminate $\mathrm{dlog}\,w_H$, and solve for $\mathrm{dlog}\,w_L$:

$$\begin{aligned}\mathrm{dlog}\,w_L &= -\frac{\Delta\left[(1-s_{T,H})(\xi+\sigma) + s_{T,H}(\sigma-1)\right] + (\sigma-1)(\xi+\sigma)}{\Delta\left[(1-s_{T,H})\delta(\xi+\sigma) + s_{T,H}(1+\xi+(\sigma-1)\delta)\right] + (1+\xi+(\sigma-1)\delta)(\xi+\sigma)}(1-\delta)\,\mathrm{dlog}\,P_T \\ &+ \frac{(\Delta+\sigma-1+(1-s_A)(1-\psi))(\xi+\sigma)}{\Delta\left[(1-s_{T,H})\delta(\xi+\sigma) + s_{T,H}(1+\xi+(\sigma-1)\delta)\right] + (1+\xi+(\sigma-1)\delta)(\xi+\sigma)}\,\mathrm{dlog}\,P_R. \qquad \text{(A.10)}\end{aligned}$$

These elasticities lead to the price shocks on the employment of high- and low-skilled workers presented in the text.

Lemma 2. In the denominators, $\Delta\left[s_{T,H}(1+\xi+(\sigma-1)\delta) + (1-s_{T,H})\delta(\xi+\sigma)\right] + (\xi+\sigma)(1+\xi+(\sigma-1)\delta) > 0$.

Based on Lemma 2, we can determine whether robot and tool price shocks increase the employment of high-skilled and low-skilled workers by looking at the signs of the numerators in Lemma 1.

Proof of Lemma 2 Plug in $\Delta = 1 - \sigma - (1 - s_A)(1 - \psi) + \left[(1 - s_A)(1 - \psi) + \tilde{\theta}\right] s_R$ and collect terms:

$$
\begin{aligned}
&\Delta \left[s_{T,H}(1 + \xi + (\sigma - 1)\delta) + (1 - s_{T,H})\delta(\xi + \sigma)\right] + (\xi + \sigma)(1 + \xi + (\sigma - 1)\delta) \\
&= (1 - s_A)(\psi - 1)(1 - s_R) \left[s_{T,H}(1 + \xi + (\sigma - 1)\delta) + (1 - s_{T,H})\delta(\xi + \sigma)\right] \\
&+ \tilde{\theta} s_R \left[s_{T,H}(1 + \xi + (\sigma - 1)\delta) + (1 - s_{T,H})\delta(\xi + \sigma)\right] \\
&- (\sigma - 1) \left[s_{T,H}(1 + \xi + (\sigma - 1)\delta) + (1 - s_{T,H})\delta(\xi + \sigma)\right] \\
&+ (\xi + \sigma)(1 + \xi + (\sigma - 1)\delta) \\
&= (1 - s_A)(\psi - 1)(1 - s_R) \left[s_{T,H}(1 + \xi + (\sigma - 1)\delta) + (1 - s_{T,H})\delta(\xi + \sigma)\right] \\
&+ \tilde{\theta} s_R \left[s_{T,H}(1 + \xi + (\sigma - 1)\delta) + (1 - s_{T,H})\delta(\xi + \sigma)\right] \\
&- (\sigma - 1) \left[s_{T,H}(1 + \xi + (\sigma - 1)\delta)\right] \\
&+ (\xi + \sigma)(1 + \xi + s_{T,H}(\sigma - 1)\delta) \\
&= (1 - s_A)(\psi - 1)(1 - s_R) \left[s_{T,H}(1 + \xi + (\sigma - 1)\delta) + (1 - s_{T,H})\delta(\xi + \sigma)\right] \\
&+ \tilde{\theta} s_R \left[s_{T,H}(1 + \xi + (\sigma - 1)\delta) + (1 - s_{T,H})\delta(\xi + \sigma)\right] \\
&+ (\xi + 1)s_{T,H}(1 + \xi + s_{T,H}(\sigma - 1)\delta) + (\xi + \sigma)(1 - s_{T,H})(1 + \xi) > 0.
\end{aligned}
\tag{A.11}
$$

Equation (A.11) is positive because all terms in the equation are positive.

Proof of Proposition 1 Based on Lemma 2, in Equations (A.3) and (A.4), the sign of the impact of robot price changes on employment of both types depends on the sign of $(\Delta + \sigma - 1 + (1 - s_A)(1 - \psi))$. Plugging in $\Delta = 1 - \sigma - (1 - s_A)(1 - \psi) + \left[(1 - s_A)(1 - \psi) + \tilde{\theta}\right] s_R$, we show that $\Delta + (1 - s_A)(1 - \psi) + \sigma - 1 = \left[\underbrace{(1 - s_A)(1 - \psi)}_{\text{Productivity Effect},<0} + \underbrace{\tilde{\theta}}_{\text{Substitution Effect},>0}\right] s_R$.

Proof of Proposition 2 The sign of $\frac{\text{dlog}\, l_L}{\text{dlog}\, P_T}$ is determined by the sign of $-\left(\Delta\left[(1-s_{T,H})(\xi+\sigma)+s_{T,H}(\sigma-1)\right]+(\sigma-1)(\xi+\sigma)\right)$. Plug in $\Delta = 1-\sigma-(1-s_A)(1-\psi)+\left[(1-s_A)(1-\psi)+\tilde{\theta}\right]s_R$ and collect terms:

$$\begin{aligned}
&-\left(\Delta\left[(1-s_{T,H})(\xi+\sigma)+s_{T,H}(\sigma-1)\right]+(\sigma-1)(\xi+\sigma)\right)\\
=&\left((1-s_{T,H})(\xi+\sigma)+s_{T,H}(\sigma-1)\right)\left((1-\psi)(1-s_A)(1-s_R)-\tilde{\theta}s_R+\frac{(1-\sigma)s_{T,H}(\xi+1)}{(1-s_{T,H})(\xi+\sigma)+s_{T,H}(\sigma-1)}\right).
\end{aligned} \tag{A.12}$$

Equation (A.12) is negative because all terms in the equation are negative.

Proof of Proposition 3 The sign of $\frac{\text{dlog}\, l_H}{\text{dlog}\, P_T}$ is determined by the sign of $-\Delta$, which can be further decomposed into the productivity effect, the reinstatement effect, and the substitution effect:

$$-\Delta = \underbrace{(1-s_A)(1-\psi)(1-s_R)}_{\text{Productivity Effect},<0} + \underbrace{-\tilde{\theta}s_R}_{\text{Reinstatement Effect},<0} + \underbrace{\sigma-1}_{\text{Substitution Effect},>0}.$$

Proof of Proposition 4 Equivalently, we demonstrate that

$$\frac{\text{dlog}\, w_H}{\text{dlog}\, P_R} < \frac{\text{dlog}\, w_L}{\text{dlog}\, P_R}, \frac{\text{dlog}\, \ell_H}{\text{dlog}\, P_R} < \frac{\text{dlog}\, \ell_L}{\text{dlog}\, P_R}.$$

Assume that robots are substitutes for both low-skilled and high-skilled workers: $\Delta+\sigma-1+(1-s_A)(1-\psi)>0$. Plugging in Equations (A.9) and (A.10), low-skilled wages respond more to robot price shocks if and only if $0=\xi-\xi<(\sigma-1)(1-\delta)$, which is always true.

Furthermore, low-skilled employment responds more to robot price shocks if and only if $1=\frac{\xi}{\xi}<\frac{\sigma}{1-\delta+\sigma\delta}$, which is always true.

Proof of Proposition 5 Equivalently, we demonstrate that

$$\frac{\text{dlog}\, w_H}{\text{dlog}\, P_T} > \frac{\text{dlog}\, w_L}{\text{dlog}\, P_T}, \frac{\text{dlog}\, \ell_H}{\text{dlog}\, P_T} > \frac{\text{dlog}\, \ell_L}{\text{dlog}\, P_T}.$$

$\frac{\text{dlog}\, w_H}{\text{dlog}\, P_T} > \frac{\text{dlog}\, w_L}{\text{dlog}\, P_T}$ holds true if and only if $0=\xi-\xi<\frac{1}{1-s_{T,H}}\left[\frac{(\sigma-1)(\xi_1+\sigma)}{\Delta}+\sigma-1\right]$, which is always true. Additionally, $\frac{\text{dlog}\, \ell_H}{\text{dlog}\, P_T} > \frac{\text{dlog}\, \ell_H}{\text{dlog}\, P_T}$ holds true if and only if $1=\frac{\xi}{\xi}<\frac{1}{1-s_{T,H}}\left[\frac{(\sigma-1)(\xi+\sigma)}{\Delta}+\sigma-s_{T,H}\right]$, which is always true.

Corollary 1. The impact of tool and robot price shocks on (real) GDP can be summarized as follows:

$$
\begin{aligned}
\mathrm{dlog}(Y) = & -\frac{s_A(1-s_R)(1-s_{T,H})(1-\delta)(\xi+\sigma)(\xi_2+1)}{\Delta\left[(1-s_{T,H})\delta(\xi+\sigma)+s_{T,H}(1+\xi+(\sigma-1)\delta)\right]+(1+\xi+(\sigma-1)\delta)(\xi+\sigma)}\,\mathrm{dlog}\, P_T \\
& -\frac{s_A s_R\left[(\xi+1)(\xi+1)+(\xi+1)(\sigma-1)s_{T,H}\delta+(\xi+1)(\sigma-1)(1-s_{T,H})\right]}{\Delta\left[(1-s_{T,H})\delta(\xi+\sigma)+s_{T,H}(1+\xi+(\sigma-1)\delta)\right]+(1+\xi+(\sigma-1)\delta)(\xi+\sigma)}\,\mathrm{dlog}\, P_R.
\end{aligned}
\tag{A.13}
$$

Equation (A.13) shows that a country's GDP can be increased by lowering the cost of either tools or robots.

Proof of Corollary 1 Since we normalize nominal GDP, $PY = 1$, the change in real GDP $\mathrm{dlog}\, Y = -\,\mathrm{dlog}\, P$. Note that:

$$
\begin{aligned}
\mathrm{dlog}\, P = & \; s_A s_R\,\mathrm{dlog}\, P_R + s_A(1-s_R)s_{T,H}\,\mathrm{dlog}\, w_H + s_A(1-s_R)(1-s_{T,H})\delta\,\mathrm{dlog}\, w_L \\
& + s_A(1-s_R)(1-s_{T,H})(1-\delta)\,\mathrm{dlog}\, P_T.
\end{aligned}
$$

Plugging in $\mathrm{dlog}\, w_H$ and $\mathrm{dlog}\, w_L$ according to Equations (A.9) and (A.10) and collecting terms, we get Equation (A.13).

B Appendix for Empirical Analysis

B.1 Data

B.1.1 List of Wikipedia Articles

Robots. numerical control, industrial robot, cartesian coordinate robot, robotic arm, SCARA, articulated robot, parallel manipulator.

Tools. air hammer, angle grinder, metalworking hand tool, axe, mortiser, ball peen hammer, multiple lining tool, multi tool, beam compass, nail gun, belt sander, biscuit joiner, paniki, block plane, pickaxe, candle snuffer, piercing saw, card scraper, pliers, C-clamp, pneumatic torque wrench, ceramic tile cutter, podger spanner, porter cable, circular saw, pritchel, clamp, profile gauge, claw tool, corner chisel, random orbital sander, crowbar, reciprocating saw, die grinder, rivet gun, disc cutter, rotary hammer, domino joiner, drift pin, sabre saw, electric torque wrench, sally saw, F-clamp, sander, Fein multimaster RS, fuller, scissors, hacking knife, screw extractor, hackle, hacksaw, scriber, halligan bar, set square, hammer drill, set tool, hammer, shear, hand saw, shove knife, hand scraper, shovel, handspike, slide hammer, hand steel, snips, hand truck, spike maul, hardy tool, spline roller, hawk, stanley odd jobs, heat gun, stone and muller, honing steel, hook, tap wrench, hydraulic torque wrench, ice scraper, thread restorer, impact wrench, tongs, jackhammer, track saw, jigsaw, trash hook, knockout punch, upholstery hammer, laminate trimmer, vise, machete, wall chaser, machinist square, wire brush, magnetic switchable device, workbench, measuring rod, wrench.

B.1.2 Text Similarity

In this section, we describe in detail how we calculate the text similarity between Wikipedia articles and machines. Most of the steps follow Argente et al. (2020).

Parsing. To transform documents in vectors, we first need to determine what corresponds to each element of the vector. In our baseline application, we use words as tokens, i.e., 1-gram.

Lemmatization. To avoid counting conjugations of the same word as different words, we use the WordNet lexical database (wordnet.princeton.edu) to reduce words to their root forms by removing conjugations such as plural suffixes.

Selection. To avoid counting frequent and uninformative words, such as "the" and "and", we drop terms that appear in more than 80% of documents.

Vectorization. Following the previous steps, we can characterize each document with a vector of dummies for words it contains. Let $m \in \{1, ..., M\} = \mathcal{M}$ be the set for words in the document. Let c_{km} be a dummy variable taking 1 if document k contains word m. Therefore, document k can be represented by vector c_m with entries c_{km}.

Normalization. Rare words are more important for characterizing differences across documents than common words. To take that into account, we weight each word using total-frequency-inverse-document-frequency (tf-idf). Each term m of the dataset is weighted by

$$\omega_m = \log\left(\frac{K+1}{d_m+1}\right) + 1 \text{ where } d_m = \sum_k \mathbb{I}\left\{c_{km} > 0\right\}.$$

After weighting, each document is weighted by word frequency vector f_k with entries

$$f_{km} = \frac{\omega_m c_{km}}{\sqrt{\sum_{m'} (\omega_m c_{km})^2}}.$$

Similarity Scores. Using the normalized word vector for each document, f_k, we can calculate the similarity scores. The similarity between machine j and Wikipedia article w is given by

$$s_{jw} = \sum_{m \in \mathbb{M}} f_{jm} \times f_{pm}. \tag{B.1}$$

Final Classification. For machine j, the closest Wikipedia article is $w*_j = \arg\max_w s_{jw}$. We call j a robot if $w*_j$ is a Wikipedia article associated with automation and a tool otherwise.

B.1.3 Identifying Firms Importing Machines

Importers List. A final dataset enables us to identify the importing firm: the registry of importing firms. Every year, the Secretary of International Trade provides a list of all establishments that have imported any product that year. The list contains the name of the firm and its tax identifier. It does not contain any information on the product imported or its value.

Using the four datasets presented, we can identify a set of firms importing capital goods. We can identify a firm that is importing a capital good if this firm is the only importing firm in its sector and city in the year that the capital good is purchased. There are four steps to construct this dataset: 1) identify capital goods, 2) classify the sector of each capital good, 3) identify the city and sector of importers, and 4) identify unique firms in each sector, city and year pair.[37]

First, we classify capital goods according to a classification provided by the Secretary of International Trade. This list classifies each HS4 product as capital, intermediate, or consumer goods.

Second, we assign a sector to each good based on the sectoral imports dataset. We say that capital good i can be used in sector j if that sector has ever imported capital good i. Therefore, this list links every product to a set of sectors that accept that product in their production process.

In the third step, we link each importing establishment from the importers list database to a sector and city using RAIS. Because both datasets are at the establishment level, we can link each importing establishment to a sector and city.

In the fourth and final step, we identify a set of firms importing capital goods. With importing data, the sector–product list, and the information on importing firms, we can identify some of the firms importing machines. From the import dataset together with the sector–product list, we know the location and sector of the firm making the purchase. Using the data created in step 3, we can identify a set of possible importers. In about 0.3% of these transactions, the exact importer is identified, Which gives us a set of 9.939 establishments engaging in 57.447 machine transactions.

B.1.4 Event-Study

Empirical Specification and Identification. To identify the effect of robots and tools at the firm level, we use a matched difference-in-differences.[38] For each firm that imports a

[37] This procedure was first used by de Souza (2020).

[38] To match firms, we follow Iacus et al. (2012). A similar strategy has been used by Bessen et al. (2019), Calel (2020), and Furman et al. (2021), among many others.

robot or a tool, we find a set of control firms that match in terms of employment, number of high-school dropouts, age, and sector in the three years before the adoption of the machine.[39] With the matched group of firms at hand, We implement the following specification for firms adopting tools

$$y_{i,g(i),t} = \sum_{j=-5}^{5} \beta_j \times \log\left(\text{Tools Import}_{i,g(i)}\right) + \mu_{g(i),t} + \mu_i + \epsilon_{i,g(i),t}, \quad \text{(B.2)}$$

where $\log\left(\text{Tools Import}_{i,g(i)}\right)$ is the log of tool imports first made by firm i, j is the distance in years to the first tool purchase, β_j is the correlation of firm-level outcomes j years to the machine import, and $y_{i,g(i),t}$ is an outcome of firm i, matched to group $g(i)$, in year t. If the firm is in the control group, i.e., it has not imported a labor-augmenting machine, β_j is always zero. $\mu_{g(i),t}$ is a year–group fixed effect that captures common shocks to firms in the same sector and with similar labor market outcomes. μ_i is a firm fixed effect. We can write the model for labor-saving machines in an equivalent way. We limit the sample to the set of firms that we observe importing labor-augmenting or labor-saving machines with a probability of 1.

We interpret β_j as the correlation between labor-augmenting machine adoption and labor outcome y. It is worth mentioning that the assumptions for a causal statement in this specification are very strong. The identifying assumption in difference-in-differences is of parallel trends. In other words, if it were not for the adoption of imported machines, the control and treatment groups would follow parallel paths. This assumption seems unreasonable in this scenario for two reasons: anticipation and shocks leading to the adoption of machines. First, the adoption of a new set of machines is not a surprise to the firm. Therefore, it is likely that firms adjust their size or employment composition before importing the machine. Second, the adoption of tools could itself be a response to labor market shocks affecting firms with particular characteristics. For instance, as shown by Bonfiglioli et al. (2020), demand shocks could induce firms to adopt robots. Therefore, we would not be able to separate the effect of a demand shock from the effect of the adoption of tools. Therefore, for these reasons, we

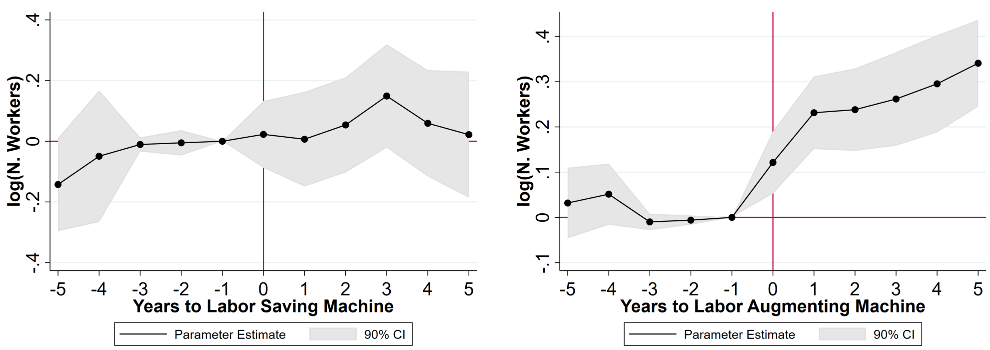
[39] Due to sample size limitations, we are unable to constrain the sample to machine importers only.

do not expect the parallel trends assumption to hold in this case, despite parallel pre-period trends, and we interpret these results as correlations and not causal effects.

Results. Figure B.1 shows the correlation of robot and tool adoption with employment. Robot adoption is not significantly correlated with employment. At the same time, the import of tools is significantly correlated with increased employment at the firm level.

Figure B.1: Robots, Tools, and Employment

(a) Robots and Employment (b) Tools and Employment



Description: This figure shows the estimated coefficients of model B.2 on employment and average wage of firms adopting labor-augmenting machines. For each firm importing a labor-augmenting machine, we create a control firm that matches in terms of employment, share of high-school dropouts, age, and sector in the three years before the adoption of the machine. The sample is from 1997 to 2015. Standard errors are clustered at the firm level.

B.1.5 Other Tables and Figures

Table B.1: **Correlation between Words and Classification**

Dependent Variable: $\mathbb{I}(Robot)$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\mathbb{I}(contain\ \text{“}automatic\text{”})$	0.251***									
	(0.0636)									
$\mathbb{I}(contain\ \text{“}numeric\text{”})$		0.536***								
		(0.112)								
$\mathbb{I}(contain\ \text{“}control\text{”})$			0.203***							
			(0.0660)							
$\mathbb{I}(contain\ \text{“}robot\text{”})$				0.933***						
				(0.251)						
$\mathbb{I}(contain\ \text{“}tool\text{”})$						-0.0731				
						(0.0484)				
$\mathbb{I}(contain\ \text{“}hand\text{”})$							-0.0492			
							(0.0408)			
$\mathbb{I}(contain\ \text{“}use\text{”})$								-0.0548		
								(0.0373)		
$\mathbb{I}(contain\ \text{“}handle\text{”})$									0.0222	
									(0.0774)	
$\mathbb{I}(contain\ \text{“}instrument\text{”})$										-0.0178
										(0.0428)
N	535	535	535	535	535	535	535	535	535	535
R^2	0.028	0.041	0.017	0.025	0.000	0.004	0.003	0.004	0.000	0.000

Description: This table shows the estimates of model: $\mathbb{I}_m\{Robot\} = \beta_x \mathbb{I}_m\,(contain\ \text{"}x\text{"}) + \epsilon_m$, where $\mathbb{I}_m\{Robot\}$ is a dummy if machine m is a robot, $\mathbb{I}_m\,(contain\ \text{"}x\text{"})$ is a dummy if machine m has the word x, and β_x is the correlation between having a particular word and the probability of being classified as a robot.

B.2 Empirics

Table B.2: **Validation: Political Connections and Other Policies**

\textbf{}	(1)	(2)	(3)	(4)	(5)	(6)
	$\Delta log\,(SubsidizedLoan)$	$\Delta log\,(Vl.FederalProcurement)$	$\Delta log\,(NumberFederalProcurement)$	$\Delta log\,(CampaignContribution)$	$\Delta International\ Import\ Price$	$\Delta International\ Export\ Price$
$\Delta log(tools)$	-0.0134	1.479	0.489	1.263	-0.0266	-0.217
	(1.511)	(2.482)	(0.792)	(1.872)	(0.0667)	(0.181)
$\Delta log(robots)$	0.295	-0.646	-0.142	-0.420	-0.0860	0.189
	(1.122)	(2.284)	(0.735)	(1.727)	(0.0994)	(0.269)
N	45065	45065	45065	45065	144553	49733

Description: This table shows the coefficients of regression (9) on outcomes related to prominent policies of the period. $\Delta log(tools)$ and $\Delta log(robots)$ are instrumented by the interaction of tariff changes with the share of replaceable occupations, as defined in (10) and (11). *robots* and *tools* denote the imports in dollars of robots and tools, respectively, in the past 5 years. The difference is taken over the past 5 years. The controls are the growth rate of the left-hand-side variable between 1993 and 1997, tariff change on sectoral output, the tariff change on inputs excluding capital, year fixed effects, region fixed effects, and sector fixed effects. In the first column, the left-hand side is the total loans made by the BNDES, the second and third columns show the value and number of federal procurement, the fourth column shows the total campaign contributions made by firms, the fifth column shows the price of imports, and the last column shows the average price of exports. Standard errors are clustered at the region–sector level.

Table B.3: **Validation: Pre-Period Labor Market Outcomes**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$\Delta\log(Employment)$	$\Delta wage$	$\Delta Wage\ Bill$	$\Delta Avg.\ Yrs.\ Educ.$	$\Delta H.S.\ Drop.\ or\ Less$	$\Delta H.S.\ Complete$	$\Delta Some\ College\ or\ More$
$\Delta log(tools)$	-0.155***	-0.0113	-0.166***	0.00319	-0.116**	-0.144	-0.0291
	(0.0562)	(0.0230)	(0.0619)	(0.0161)	(0.0502)	(0.0918)	(0.0305)
$\Delta log(robots)$	0.284**	0.0573	0.341***	0.00698	0.193*	0.200*	-0.0166
	(0.110)	(0.0454)	(0.125)	(0.0289)	(0.0998)	(0.121)	(0.0592)
N	11820	11820	11820	11703	11505	6698	4671

Description: This table shows the coefficients of regression (9) on outcomes related to prominent policies of the period. $\Delta log(tools)$ and $\Delta log(robots)$ are instrumented by the interaction of tariff changes with the share of replaceable occupations, as defined in (10) and (11). *robots* and *tools* denote the imports in dollars of robots and tools, respectively, in the past 5 years. The difference is taken over the past 5 years. The controls are tariff change on sectoral output, the tariff change on inputs excluding capital, year fixed effects, region fixed effects, and sector fixed effects. In the first column, the left-hand side is the total loans made by the BNDES, the second and third columns show the value and number of federal procurement, the fourth column shows the total campaign contributions made by firms, the fifth column shows the price of imports, and the last column shows the average price of exports. Standard errors are clustered at the region-sector level.

B.3 Empirical Results

Table B.4: First Stage with Inverse Hyperbolic Sine

	(1)	(2)	(3)	(4)	(5)	(6)
	$\Delta IHS(Robots_{r,s,t})$	$\Delta IHS(Robots_{r,s,t})$	$\Delta IHS(Robots_{r,s,t})$	$\Delta IHS(tools_{r,s,t})$	$\Delta IHS(tools_{r,s,t})$	$\Delta IHS(tools_{r,s,t})$
IV^{tools}	0.0157***	0.00954**	0.0157***	-0.0250***	-0.0369***	-0.0281***
	(0.00436)	(0.00433)	(0.00449)	(0.00769)	(0.00756)	(0.00790)
IV^{robots}	-0.212***	-0.208***	-0.230***	-0.304***	-0.296***	-0.321***
	(0.0171)	(0.0160)	(0.0177)	(0.0167)	(0.0157)	(0.0180)
Specification	Sector FE	Baseline	Market FE	Sector FE	Baseline	Market FE
N	201064	201063	201043	201064	201063	201043
R^2	0.315	0.336	0.385	0.517	0.541	0.566
F	140.9	145.0	177.2	117.3	127.0	144.9

Description: FE = fixed effects. This table shows the coefficients of the first stage, i.e., regressions (12) and (13), but instead of using log, it uses the inverse hyperbolic sine. IV^{tools} is the interaction between the share of non-replaceable occupations and tariffs on tools of each sector. IV^{robots} is the interaction between the share of replaceable occupations and tariffs on robots of each sector. *robots* and *tools* denote the imports in dollars of robots and tools, respectively, in the past 5 years. The difference is taken over the past 5 years. All specifications have as controls the growth rate of employment between 1993 and 1997, the tariff change on sectoral output, the tariff change on inputs excluding capital, and year fixed effects. Columns 1 and 4 add a sector fixed effect, columns 2 and 5 have sector and region fixed effects, and columns 3 and 6 have sector–region fixed effects. Standard errors are clustered at the region–sector level.

Table B.5: **First Stage with Dummy**

	(1)	(2)	(3)	(4)	(5)	(6)
	$\Delta\mathbb{I}\{robots_{r,s,t}\}$	$\Delta\mathbb{I}\{robots_{r,s,t}\}$	$\Delta\mathbb{I}\{robots_{r,s,t}\}$	$\Delta\mathbb{I}\{tools_{r,s,t}\}$	$\Delta\mathbb{I}\{tools_{r,s,t}\}$	$\Delta\mathbb{I}\{tools_{r,s,t}\}$
IV^{tools}	0.000300	0.00189	0.00467***	-0.0373***	-0.0329***	-0.0245***
	(0.00180)	(0.00180)	(0.00166)	(0.00655)	(0.00644)	(0.00645)
IV^{robots}	0.122***	0.115***	0.136***	-0.0487***	-0.0463***	-0.0361**
	(0.0170)	(0.0163)	(0.0181)	(0.0164)	(0.0159)	(0.0177)
Specification	Sector FE	Baseline	Market FE	Sector FE	Baseline	Market FE
N	168500	168500	168369	128428	128423	128206
R^2	0.132	0.168	0.344	0.071	0.135	0.283
F	16.73	16.17	25.25	8.815	6.989	4.702

Description: FE = fixed effects. This table shows the coefficients of the first stage, i.e., regressions (12) and (13), but instead of using log, it uses a dummy if that region or sector has imported at least one robot or tool in the past 5 years. IV^{tools} is the interaction between the share of non-replaceable occupations and tariffs on tools of each sector. IV^{robots} is the interaction between the share of replaceable occupations and tariffs on robots of each sector. *robots* and *tools* denote the imports in dollars of robots and tools, respectively, in the past 5 years. The difference is taken over the past 5 years. All specifications have as controls the growth rate of employment between 1993 and 1997, the tariff change on sectoral output, the tariff change on inputs excluding capital, and year fixed effects. Columns 1 and 4 add a sector fixed effect, columns 2 and 5 have sector and region fixed effects, and columns 3 and 6 have sector–region fixed effects. Standard errors are clustered at the region–sector level.

Table B.6: First Stage without Tools Instrument

	(1) $\Delta log(robots)$	(2) $\Delta log(robots)$	(3) $\Delta log(robots)$	(4) $\Delta log(tools)$	(5) $\Delta log(tools)$	(6) $\Delta log(tools)$
IV^{robots}	-0.199***	-0.193***	-0.213***	-0.287***	-0.277***	-0.305***
	(0.0161)	(0.0151)	(0.0167)	(0.0161)	(0.0150)	(0.0173)
Specification	Sector FE	Baseline	Market FE	Sector FE	Baseline	Market FE
N	201064	201063	201043	201064	201063	201043
R^2	0.312	0.334	0.384	0.509	0.534	0.560
F	171.2	175.9	229.7	137.3	145.7	180.9

Description: FE = fixed effects. This table shows the coefficients of a first stage without controlling for the tools instrument. IV^{robots} is the interaction between the share of replaceable occupations and tariffs on robots of each sector. *robots* and *tools* denote the imports in dollars of robots and tools, respectively, in the past 5 years. The difference is taken over the past 5 years. All specifications have as controls the growth rate of employment between 1993 and 1997, the tariff change on sectoral output, the tariff change on inputs excluding capital, and year fixed effects. Columns 1 and 4 add a sector fixed effect, columns 2 and 5 have sector and region fixed effects, and columns 3 and 6 have sector–region fixed effects. Standard errors are clustered at the region–sector level.

Table B.7: Employment and Robots without Controlling for Tools

	(1) $\Delta\log(Employment)$	(2) $\Delta\log(Employment)$	(3) $\Delta\log(Employment)$	(4) $\Delta\log(Employment)$	(5) $\Delta\log(Employment)$	(6) $\Delta\log(Employment)$
$\Delta log(robots_{r,s,t})$	-0.00881	-0.00360	-0.00241	-0.0362	-0.0351	0.0221
	(0.00870)	(0.00862)	(0.00944)	(0.0309)	(0.0316)	(0.0287)
N	236697	201064	201063	201064	201063	201043
R^2	-0.000	0.011	0.010	0.004	0.004	-0.004

Description: This table shows the coefficients of regression (9) on employment but without tools and its instrument. $\Delta log(robots)$ is instrumented by the interaction of tariff changes with the share of replaceable occupations, as defined in (10). *robots* denote the imports in dollars of robots in the past 5 years. The difference is taken over the past 5 years. In column 1, there are no controls. Column 2 adds the baseline controls, i.e., growth rate of employment between 1993 and 1997, the tariff change on sectoral output, the tariff change on inputs excluding capital, and year fixed effects. Column 3 adds region FE to the baseline controls. Column 4 adds sector FE to the baseline controls. Column 5 includes as controls the baseline controls, region FE, and sector FE. Column 6 includes sector-region FEs and the baseline controls. Standard errors are clustered at the region–sector level.

B.3.1 Robot and Tool Imports as Instrument and Comparison to the Literature

In this section, we follow the procedure adopted by Acemoglu and Restrepo (2020) and Dauth et al. (2021), among others, and instrument robot and tool adoption with their import by other countries. We find that the main results remain the same. Moreover, if tools are removed from the specification, the estimated effect of robots is upward-biased and closer to zero, which is similar to what has been found in the literature.

First Stage. The instrument is given by the imports of robots and tools by the US or Europe. The first stage is:

$$\Delta log(robots_{r,s,t}) = \pi^W_{1,1}\Delta IMP^{robots}_{s,t} + \pi^W_{1,2}\Delta IMP^{tools}_{s,t} + \epsilon_{r,s,t} \tag{B.3}$$

$$\Delta log(tools_{r,s,t}) = \pi^W_{2,1}\Delta IMP^{robots}_{s,t} + \pi^W_{2,2}\Delta IMP^{tools}_{s,t} + \epsilon_{r,s,t}, \tag{B.4}$$

where $IMP^{robots}_{s,t}$ are the imports of robots by the US and Europe assigned to sector s in the past 5 years. Similarly, $IMP^{tools}_{s,t}$ is the imports of tools by the US and Europe. The identifying assumption is that the increased adoption of machines by these countries is driven by supply side factors, such as a decrease in the machines' price or increase in their quality.

Results. Table B.8 shows that the imports of robots and tools in Brazil are associated with their imports in the US and Europe. In most specifications, the cross-elasticities are also large and significant, implying that increased imports of robots (tools) in developed countries leads to higher adoption of tools (robots) in Brazil. As before, this implies that removing tools from specification (9) will lead to a downward bias in the estimated effect of robots.

Table B.8: First Stage with Imports by Other Countries as Instrument

	(1)	(2)	(3)	(4)	(5)	(6)
	$\Delta log(robots)$	$\Delta log(robots)$	$\Delta log(robots)$	$\Delta log(tools)$	$\Delta log(tools)$	$\Delta log(tools)$
ΔIMP^{tools}	0.0594**	0.0669**	0.0639**	0.215***	0.193***	0.162**
	(0.0262)	(0.0322)	(0.0301)	(0.0602)	(0.0701)	(0.0664)
ΔIMP^{robots}	1.002***	1.033***	1.034***	0.150***	-0.0271	0.0660
	(0.0333)	(0.0369)	(0.0341)	(0.0458)	(0.0533)	(0.0473)
N	187658	130537	130536	187658	130537	130536
R^2	0.037	0.045	0.096	0.050	0.058	0.122
F	454.8	177.0	203.7	11.99	6.579	6.660
Specification	No Controls	Controls	Region FE	No Controls	Controls	Region FE

Description: FE = fixed effects. This table shows the coefficients of the first stage, i.e., regressions (B.3) and (B.4). IMP^{tools} and $IMP^{robots}_{s,t}$ are the imports of tools and robots by the US and Europe assigned to each sector in the past 5 years. *robots* and *tools* denote the imports in dollars of robots and tools, respectively, in the past 5 years. The difference is taken over the past 5 years. Columns 1 and 4 do not have any controls. Columns 2 and 5 have as controls the growth rate of employment between 1993 and 1997, the tariff change on sectoral output, the tariff change on inputs excluding capital, and year fixed effects. Columns 3 and 6 add region fixed effects to the baseline controls. Standard errors are clustered at the region–sector level.

Table B.9 shows the effect of robots and tools on the labor market when using imports by other countries as instruments. It is still true that tools increase employment and earnings, whereas robots decrease them. Compared to the elasticities identified in 6, the effect of tools is larger and the effect of robots smaller. Moreover, tools also positively affect the employment of workers with college or more education. Still, the estimated effect of robots is larger than previously found on the literature.

Table B.9: Effect of Robots and Tools with Imports by Other Countries as Instrument

	(1) $\Delta\log(Employment)$	(2) $\Delta log(Earnings)$	(3) $\Delta log(Wage\ Bill)$	(4) $\Delta log(H.S.\ Drop.)$	(5) $\Delta log(H.S.\ Complete)$	(6) $\Delta log(College\ or\ More)$
$\Delta log(tools)$	0.762***	0.209***	0.971***	0.541***	0.0856	0.446***
	(0.241)	(0.0679)	(0.300)	(0.193)	(0.129)	(0.155)
$\Delta log(robots)$	-0.163***	-0.0332**	-0.196***	-0.221***	-0.0723***	0.0407
	(0.0547)	(0.0151)	(0.0677)	(0.0417)	(0.0231)	(0.0306)
N	187658	187658	187658	176644	159812	100575

Description: This table shows the coefficients of regression (9) on the labor market using as the instrument the imports of robots and tools by the US and Europe. $\Delta log(tools)$ and $\Delta log(robots)$ are instrumented by imports of robots and tools by other countries, as defined in (B.3) and (B.4). *robots* and *tools* denote the imports in dollars of robots and tools, respectively, in the past 5 years. The difference is taken over the past 5 years. The controls are the growth rate of the left-hand-side variable between 1993 and 1997, tariff change on sectoral output, the tariff change on inputs excluding capital, year fixed effects, region fixed effects, and sector fixed effects. Standard errors are clustered at the region–sector level.

Table B.10 shows the bias arising from removing tools from the main empirical model. Instrumenting robots with their imports by other countries only identifies the net effect of robots. This happens because, according to the results in Table B.8, the adoption of robots by other countries also increases the adoption of tools in Brazil. When tools are removed from the main empirical model, only the net effect is identified. The estimates found are much smaller and closer in magnitude to what Acemoglu and Restrepo (2020) found.

Table B.10: Effect of Robots with Imports by Other Countries as Instrument and Without Controlling for Tools

	(1) $\Delta\log(Employment)$	(2) $\Delta log(Earnings)$	(3) $\Delta log(Wage\ Bill)$	(4) $\Delta log(H.S.\ Drop.)$	(5) $\Delta log(H.S.\ Complete)$	(6) $\Delta log(College\ or\ More)$
$\Delta log(robots)$	-0.0627***	-0.00568	-0.0684***	-0.160***	-0.0680***	0.0135
	(0.0214)	(0.00564)	(0.0234)	(0.0215)	(0.0217)	(0.0218)
N	187658	187658	187658	176644	159812	100575

Description: This table shows the coefficients of regression (9) without controlling for the adoption of tools. $\Delta log(tools)$ is instrumented by imports of robots by other countries. *robots* and *tools* denote the imports in dollars of robots and tools, respectively, in the past 5 years. The difference is taken over the past 5 years. The controls are the growth rate of the left-hand-side variable between 1993 and 1997, tariff change on sectoral output, the tariff change on inputs excluding capital, year fixed effects, region fixed effects, and sector fixed effects. Standard errors are clustered at the region–sector level.

B.3.2 Tariff Instrument

Table B.11: **Tariff IV: Employment, Labor-Saving, and Labor-Augmenting Machines**

	(1) $\Delta\log(Employment)$	(2) $\Delta\log(Employment)$	(3) $\Delta\log(Employment)$	(4) $\Delta\log(Employment)$	(5) $\Delta\log(Employment)$	(6) $\Delta\log(Employment)$
$\Delta log(tools)$	0.158***	0.155***	0.150***	0.174***	0.168***	0.189***
	(0.0299)	(0.0327)	(0.0305)	(0.0340)	(0.0314)	(0.0334)
$\Delta log(robots)$	-0.108***	-0.102***	-0.0889***	-0.278***	-0.271***	-0.271***
	(0.0210)	(0.0220)	(0.0191)	(0.0486)	(0.0472)	(0.0474)
N	263362	201730	201729	201730	201729	201709

Description: FE= fixed effects. This table shows the coefficients of regression (9) on employment. $\Delta log(tools)$ and $\Delta log(robots)$ are instrumented by the average tariffs on robots and tools. *robots* and *tools* denote the imports in dollars of robots and tools, respectively, in the past 5 years. The difference is taken over the past 5 years. All specifications have year fixed effects. In column 1, there are no controls other than year fixed effects. In column 1 there are no controls. Column 2 adds the baseline controls, i.e., growth rate of employment between 1993 and 1997, the tariff change on sectoral output, the tariff change on inputs excluding capital, and year fixed effects. Column 3 adds region FE to the baseline controls. Column 4 adds sector FE to the baseline controls. Column 5 includes as controls the baseline controls, region FE, and sector FE. Column 6 includes sector–region FEs and the baseline controls. Standard errors are clustered at the region–sector level.

Table B.12: **Tariff IV: Labor Market, Labor-Saving, and Labor-Augmenting Machines**

\textbf{}	(1)	(2)	(3)	(4)	(5)
	$\Delta wage$	Δ*Wage Bill*	Δ*H.S. Drop. or Less*	Δ*H.S. Complete*	Δ*Some College or More*
$\Delta log(tools_{r,s,t})$	0.0450***	0.213***	0.159***	0.0763**	0.0410
	(0.00952)	(0.0361)	(0.0316)	(0.0344)	(0.0341)
$\Delta log(robots_{r,s,t})$	-0.0440***	-0.315***	-0.282***	-0.00962	-0.0187
	(0.0146)	(0.0544)	(0.0475)	(0.0356)	(0.0294)
N	201729	201729	192184	114198	74891

Description: This table shows the coefficients of regression (9) on labor market outcomes using tariffs as instrument. $\Delta log(tools)$ and $\Delta log(robots)$ are instrumented by the average tariffs on robots and tools. *robots* and *tools* denote the imports in dollars of robots and tools, respectively, in the past 5 years. The difference is taken over the past 5 years. The controls are the growth rate of the left-hand-side variable between 1993 and 1997, tariff change on sectoral output, the tariff change on inputs excluding capital, year fixed effects, region fixed effects, and sector fixed effects. Standard errors are clustered at the region–sector level.

Table B.13: **Tariff IV: Occupations, Labor-Saving, and Labor-Augmenting Machines**

	(1)	(2)	(3)	(4)	(5)
	Δ*Managers*	Δ*HS Professionals*	Δ*Technical Workers*	Δ*Adm Workers*	Δ*Operational Workers*
$\Delta log(tools)$	-0.0216	0.0291	0.169***	0.123***	0.209***
	(0.0383)	(0.0487)	(0.0431)	(0.0329)	(0.0408)
$\Delta log(robots)$	0.0493	0.00797	-0.0427	-0.145***	-0.222***
	(0.0316)	(0.0349)	(0.0353)	(0.0365)	(0.0542)
N	46058	20096	71850	132271	146862

Description: This table shows the coefficients of regression (9) on the employment of different occupations using tariffs as instrument. $\Delta log(tools)$ and $\Delta log(robots)$ are instrumented by the average tariffs on robots and tools. *robots* and *tools* denote the imports in dollars of robots and tools, respectively, in the past 5 years. The difference is taken over the past 5 years. The controls are the growth rate of the left-hand-side variable between 1993 and 1997, tariff change on sectoral output, the tariff change on inputs excluding capital, year fixed effects, region fixed effects, and sector fixed effects. Standard errors are clustered at the region–sector level.

B.3.3 Outliers

Table B.14: Effect of Tools and Robots on Employment Dropping Top and Bottom 0.1% of Tariff Changes

	(1)	(2)	(3)	(4)	(5)	(6)
	$\Delta \log(Employment)$	$\Delta \log(Employment)$	$\Delta \log(Employment)$	$\Delta \log(Employment)$	$\Delta \log(Employment)$	$\Delta \log(Employment)$
$\Delta log(tools)$	0.590***	0.454**	0.343***	0.222***	0.213***	0.223***
	(0.228)	(0.198)	(0.119)	(0.0578)	(0.0527)	(0.0532)
	(0.264)	(0.242)	(0.133)	(0.0615)	(0.0557)	(0.0560)
$\Delta log(robots)$	-0.486***	-0.367**	-0.250***	-0.356***	-0.341***	-0.296***
	(0.187)	(0.161)	(0.0893)	(0.0879)	(0.0838)	(0.0809)
Specification	No Controls	Controls	Region FE	Sector FE	Baseline	Market FE
N	236283	200733	200732	200733	200732	200712

Description: FE= fixed effects. This table shows the coefficients of regression (9) on employment. Sectorswith tariff changes in the top and bottom 0.1% are dropped. $\Delta log(tools)$ and $\Delta log(robots)$ are instrumented by the interaction of tariff changes with the share of replaceable occupations, as defined in (10) and (11). *robots* and *tools* denote the imports in dollars of robots and tools, respectively, in the past 5 years. The difference is taken over the past 5 years. All specifications have year fixed effects. In column 1, there are no controls other than year fixed effects. Column 2 adds the baseline controls, i.e., growth rate of employment between 1993 and 1997, the tariff change on sectoral output, the tariff change on inputs excluding capital, and year fixed effects. Column 3 adds region FE to the baseline controls. Column 4 adds sector FE to the baseline controls. Column 5 includes as controls the baseline controls, region FE, and sector FE. Column 6 includes sector–region FEs and the baseline controls. Standard errors are clustered at the region–sector level.

Table B.15: Effect of Tools and Robots on Employment Dropping Top and Bottom 0.5% of Tariff Changes

	(1) $\Delta\log(Employment)$	(2) $\Delta\log(Employment)$	(3) $\Delta\log(Employment)$	(4) $\Delta\log(Employment)$	(5) $\Delta\log(Employment)$	(6) $\Delta\log(Employment)$
$\Delta log(tools)$	0.877**	0.722*	0.450***	0.305***	0.290***	0.291***
	(0.424)	(0.404)	(0.167)	(0.0863)	(0.0770)	(0.0769)
$\Delta log(robots)$	-0.711**	-0.577*	-0.323***	-0.512***	-0.485***	-0.416***
	(0.343)	(0.324)	(0.123)	(0.141)	(0.132)	(0.128)
Specification	No Controls	Controls	Region FE	Sector FE	Baseline	Market FE
N	233774	198502	198501	198502	198501	198479

Description: This table shows the coefficients of regression (9) on employment. Sectors with tariff changes in the top and bottom 0.5% are dropped. $\Delta log(tools)$ and $\Delta log(robots)$ are instrumented by the interaction of tariff changes with the share of replaceable occupations, as defined in (10) and (11). *robots* and *tools* denote the imports in dollars of robots and tools, respectively, in the past 5 years. The difference is taken over the past 5 years. All specifications have year fixed effects. In column 1 there are no controls other than year fixed effects. Column 2 adds the baseline controls, i.e., growth rate of employment between 1993 and 1997, the tariff change on sectoral output, the tariff change on inputs excluding capital, and year fixed effects. Column 3 adds region FE to the baseline controls. Column 4 adds sector FE to the baseline controls. Column 5 includes as controls the baseline controls, region FE, and sector FE. Column 6 includes sector–region FEs and the baseline controls. Standard errors are clustered at the region–sector level.

Table B.16: Effect of Tools and Robots on Labor Market Dropping Top and Bottom 0.1% of Tariff Changes

	(1) $\Delta wage$	(2) $\Delta Wage\ Bill$	(3) $\Delta H.S.\ Drop.\ or\ Less$	(4) $\Delta H.S.\ Complete$	(5) $\Delta Some\ College\ or\ More$
$\Delta log(tools)$	0.0537***	0.266***	0.249***	0.0314	0.0130
	(0.0159)	(0.0617)	(0.0579)	(0.0478)	(0.0469)
$\Delta log(robots)$	-0.0764***	-0.415***	-0.408***	0.0104	-0.0208
	(0.0252)	(0.0981)	(0.0881)	(0.0604)	(0.0478)
N	200732	200732	191327	114001	74749

Description: This table shows the coefficients of regression (9) on labor market outcomes. Sectors with tariff changes in the top and bottom 0.1% are dropped. $\Delta log(tools)$ and $\Delta log(robots)$ are instrumented by the interaction of tariff changes with the share of replaceable occupations, as defined in (10) and (11). *robots* and *tools* denote the imports in dollars of robots and tools, respectively, in the past 5 years. The difference is taken over the past 5 years. The controls are the growth rate of the left-hand-side variable between 1993 and 1997, tariff change on sectoral output, the tariff change on inputs excluding capital, year fixed effects, region fixed effects, and sector fixed effects. Standard errors are clustered at the region–sector level.

Table B.17: Effect of Tools and Robots on Labor Market Dropping Top and Bottom 0.5% of Tariff Changes

\textbf{}	(1) $\Delta wage$	(2) $\Delta Wage\ Bill$	(3) $\Delta H.S.\ Drop.\ or\ Less$	(4) $\Delta H.S.\ Complete$	(5) $\Delta Some\ College\ or\ More$
$\Delta log(tools)$	0.0673***	0.356***	0.344***	0.0386	0.0470
	(0.0220)	(0.0909)	(0.0886)	(0.0562)	(0.0523)
$\Delta log(robots)$	-0.108***	-0.590***	-0.590***	0.0131	-0.0490
	(0.0378)	(0.156)	(0.146)	(0.0771)	(0.0596)
N	198501	198501	189181	112782	73986

Description: This table shows the coefficients of regression (9) on labor market outcomes. Sectors with tariff changes in the top and bottom 0.5% are dropped. $\Delta log(tools)$ and $\Delta log(robots)$ are instrumented by the interaction of tariff changes with the share of replaceable occupations, as defined in (10) and (11). *robots* and *tools* denote the imports in dollars of robots and tools, respectively, in the past 5 years. The difference is taken over the past 5 years. The controls are the growth rate of the left-hand-side variable between 1993 and 1997, tariff change on sectoral output, the tariff change on inputs excluding capital, year fixed effects, region fixed effects, and sector fixed effects. Standard errors are clustered at the region–sector level.

Table B.18: Effect of Tools and Robots on Different Occupations Dropping Top and Bottom 0.1% of Tariff Changes

	(1)	(2)	(3)	(4)	(5)
	Δ*Managers*	Δ*HS Professionals*	Δ*Technical Workers*	Δ*Adm Workers*	Δ*Operational Workers*
$\Delta log(tools)$	-0.0570	-0.0127	0.233***	0.0198	0.336***
	(0.0607)	(0.0607)	(0.0572)	(0.0489)	(0.0776)
$\Delta log(robots)$	0.0812	0.0387	-0.143***	0.0287	-0.275***
	(0.0548)	(0.0434)	(0.0537)	(0.0626)	(0.0967)
N	45984	20049	71724	132043	146640

Description: This table shows the coefficients of regression (9) on employment of different occupational groups. Sectors with tariff changes in the top and bottom 0.1% are dropped. $\Delta log(tools)$ and $\Delta log(robots)$ are instrumented by the interaction of tariff changes with the share of replaceable occupations, as defined in (10) and (11). *robots* and *tools* denote the imports in dollars of robots and tools, respectively, in the past 5 years. The difference is taken over the past 5 years. The controls are the growth rate of the left-hand-side variable between 1993 and 1997, tariff change on sectoral output, the tariff change on inputs excluding capital, year fixed effects, region fixed effects, and sector fixed effects. Standard errors are clustered at the region–sector level.

Table B.19: Effect of Tools and Robots on Different Occupations Dropping Top and Bottom 0.5% of Tariff Changes

	(1)	(2)	(3)	(4)	(5)
	Δ*Managers*	Δ*HS Professionals*	Δ*Technical Workers*	Δ*Adm Workers*	Δ*Operational Workers*
$\Delta log(tools)$	-0.0307	0.0103	0.272***	0.0344	0.468***
	(0.0716)	(0.0850)	(0.0686)	(0.0633)	(0.128)
$\Delta log(robots)$	0.0582	0.0418	-0.155**	0.0322	-0.424**
	(0.0687)	(0.0618)	(0.0703)	(0.0874)	(0.167)
N	45523	19858	70938	130604	144918

Description: This table shows the coefficients of regression (9) on employment of different occupational groups. Sectors with tariff changes in the top and bottom 0.5% are dropped. $\Delta log(tools)$ and $\Delta log(robots)$ are instrumented by the interaction of tariff changes with the share of replaceable occupations, as defined in (10) and (11). *robots* and *tools* denote the imports in dollars of robots and tools, respectively, in the past 5 years. The difference is taken over the past 5 years. The controls are the growth rate of the left-hand-side variable between 1993 and 1997, tariff change on sectoral output, the tariff change on inputs excluding capital, year fixed effects, region fixed effects, and sector fixed effects. Standard errors are clustered at the region–sector level.

B.3.4 Controls

Table B.20: Effect of Tools and Robots on Different Educational Groups without Region and Sector FEs

	(1)	(2)	(3)	(4)	(5)	(6)
	Δ log(*H.S. Drop.*)	Δ log(*Earnings Drop.*)	Δ log(*H.S. Complete*)	Δ log(*Earnings Complete*)	Δ log(*College or More*)	Δ log(*Earnings College or More*)
$\Delta log(tools)$	0.819**	0.328**	0.114	0.0457	-0.0485	0.00809
	(0.366)	(0.147)	(0.0899)	(0.0395)	(0.0661)	(0.0350)
$\Delta log(robots)$	-0.691**	-0.282**	-0.0651	-0.0534**	0.0428	-0.00991
	(0.294)	(0.118)	(0.0622)	(0.0268)	(0.0413)	(0.0216)
N	191640	191640	114198	114198	74892	74892

Description: This table shows the coefficients of regression (9) on employment and earnings of different educational groups. $\Delta log(tools)$ and $\Delta log(robots)$ are instrumented by the interaction of tariff changes with the share of replaceable occupations, as defined in (10) and (11). *robots* and *tools* denote the imports in dollars of robots and tools, respectively, in the past 5 years. The difference is taken over the past 5 years. The controls are the growth rate of the left-hand-side variable between 1993 and 1997, tariff change on sectoral output, the tariff change on inputs excluding capital, and year fixed effects. Columns 1 and 2 show the effect of robots and tools on employment and earnings of workers that have less education than a high-school diploma. Columns 3 and 4 show the effect on workers with high-school diploma. Columns 5 and 6 show the effect on workers with at least some college education. Standard errors are clustered at the region–sector level.

Table B.21: Effect of Tools and Robots on Different Educational Groups without Region FE

	(1)	(2)	(3)	(4)	(5)	(6)
	Δ log(*H.S. Drop.*)	Δ log(*Earnings Drop.*)	Δ log(*H.S. Complete*)	Δ log(*Earnings Complete*)	Δ log(*College or More*)	Δ log(*Earnings College or More*)
$\Delta log(tools)$	0.284***	0.0898***	0.0414	-0.00337	0.0381	0.00177
	(0.0694)	(0.0219)	(0.0517)	(0.0214)	(0.0511)	(0.0274)
$\Delta log(robots)$	-0.452***	-0.134***	-0.0112	-0.0240	-0.0452	0.00559
	(0.0991)	(0.0311)	(0.0622)	(0.0251)	(0.0504)	(0.0265)
N	191640	191640	114198	114198	74892	74892

Description: This table shows the coefficients of regression (9) on employment and earnings of different educational groups. $\Delta log(tools)$ and $\Delta log(robots)$ are instrumented by the interaction of tariff changes with the share of replaceable occupations, as defined in (10) and (11). *robots* and *tools* denote the imports in dollars of robots and tools, respectively, in the past 5 years. The difference is taken over the past 5 years. The controls are the growth rate of the left-hand-side variable between 1993 and 1997, tariff change on sectoral output, the tariff change on inputs excluding capital, year fixed effects, and region fixed effects. Columns 1 and 2 show the effect of robots and tools on employment and earnings of workers that have less education than a high-school diploma. Columns 3 and 4 show the effect on workers with a high-school diploma. Columns 5 and 6 show the effect on workers with at least some college education. Standard errors are clustered at the region–sector level.

Table B.22: **Labor Market, Labor-Saving, and Labor-Augmenting Machines – Market Fixed Effects**

	(1) $\Delta\log(\textit{H.S. Drop.})$	(2) $\Delta\log(\textit{Earnings Drop.})$	(3) $\Delta\log(\textit{H.S. Complete})$	(4) $\Delta\log(\textit{Earnings Complete})$	(5) $\Delta\log(\textit{College or More})$	(6) $\Delta\log(\textit{Earnings College or More})$
$\Delta log(tools)$	0.262***	0.0389***	0.0110	-0.0114	0.00589	0.00973
	(0.0596)	(0.0147)	(0.0469)	(0.0190)	(0.0470)	(0.0257)
$\Delta log(robots)$	-0.370***	-0.0532**	0.0595	-0.00711	-0.00878	0.00360
	(0.0861)	(0.0211)	(0.0559)	(0.0219)	(0.0433)	(0.0232)
N	191608	191608	114181	114181	74863	74863

Description: This table shows the coefficients of regression (9) on employment and earnings of different educational groups. $\Delta log(tools)$ and $\Delta log(robots)$ are instrumented by the interaction of tariff changes with the share of replaceable occupations, as defined in (10) and (11). *robots* and *tools* denote the imports in dollars of robots and tools, respectively, in the past 5 years. The difference is taken over the past 5 years. The controls are the growth rate of the left-hand-side variable between 1993 and 1997, tariff change on sectoral output, the tariff change on inputs excluding capital, year fixed effects, and region-sector fixed effects. Columns 1 and 2 show the effect of robots and tools on employment and earnings of workers that have less education than a high-school diploma. Columns 3 and 4 show the effect on workers with a high-school diploma. Columns 5 and 6 show the effect on workers with at least some college education. Standard errors are clustered at the region–sector level.

Table B.23: Occupations, Labor-Saving, and Labor-Augmenting Machines – Year Fixed Effects

	(1) $\Delta\log(\textit{Managers})$	(2) $\Delta\log(\textit{HS Professionals})$	(3) $\Delta\log(\textit{Technical Workers})$	(4) $\Delta\log(\textit{Adm Workers})$	(5) $\Delta\log(\textit{Operational Workers})$
$\Delta log(tools)$	-0.203	-0.0981	0.120*	-0.229	0.178
	(0.151)	(0.0680)	(0.0708)	(0.153)	(0.230)
$\Delta log(robots)$	0.150*	0.103***	0.0132	0.185*	-0.0574
	(0.0854)	(0.0356)	(0.0426)	(0.107)	(0.174)
N	46062	20100	71851	132273	146863

Description: This table shows the coefficients of regression (9) on employment of different occupational groups. $\Delta log(tools)$ and $\Delta log(robots)$ are instrumented by the interaction of tariff changes with the share of replaceable occupations, as defined in (10) and (11). *robots* and *tools* denote the imports in dollars of robots and tools, respectively, in the past 5 years. The difference is taken over the past 5 years. The controls are the growth rate of the left-hand-side variable between 1993 and 1997, tariff change on sectoral output, the tariff change on inputs excluding capital, and year fixed effects. Standard errors are clustered at the region–sector level.

Table B.24: **Occupations, Labor-Saving, and Labor-Augmenting Machines – Year and Sector Fixed Effects**

	(1) $\Delta\log(\textit{Managers})$	(2) $\Delta\log(\textit{HS Professionals})$	(3) $\Delta\log(\textit{Technical Workers})$	(4) $\Delta\log(\textit{Adm Workers})$	(5) $\Delta\log(\textit{Operational Workers})$
$\Delta log(tools)$	-0.0652	-0.0235	0.270***	0.0331	0.372***
	(0.0683)	(0.0653)	(0.0633)	(0.0553)	(0.0944)
$\Delta log(robots)$	0.0925	0.0376	-0.193***	0.00600	-0.331***
	(0.0605)	(0.0469)	(0.0582)	(0.0672)	(0.114)
N	46061	20100	71851	132273	146863

Description: This table shows the coefficients of regression (9) on employment of different occupational groups. $\Delta log(tools)$ and $\Delta log(robots)$ are instrumented by the interaction of tariff changes with the share of replaceable occupations, as defined in (10) and (11). *robots* and *tools* denote the imports in dollars of robots and tools, respectively, in the past 5 years. The difference is taken over the past 5 years. The controls are the growth rate of the left-hand side variable between 1993 and 1997, tariff change on sectoral output, the tariff change on inputs excluding capital, year fixed effects, and sector fixed effects. Standard errors are clustered at the region–sector level.

Table B.25: **Occupations, Labor-Saving, and Labor-Augmenting Machines – Market Fixed Effects**

	(1) $\Delta\log(\textit{Managers})$	(2) $\Delta\log(\textit{HS Professionals})$	(3) $\Delta\log(\textit{Technical Workers})$	(4) $\Delta\log(\textit{Adm Workers})$	(5) $\Delta\log(\textit{Operational Workers})$
$\Delta log(tools)$	-0.0647	-0.0172	0.216***	0.0589	0.360***
	(0.0598)	(0.0663)	(0.0572)	(0.0532)	(0.0836)
$\Delta log(robots)$	0.0826	0.0306	-0.0951*	-0.0156	-0.290***
	(0.0515)	(0.0457)	(0.0507)	(0.0627)	(0.101)
N	46040	20087	71797	132235	146841

Description: This table shows the coefficients of regression (9) on employment of different occupations. Instead of using all machines, we limit the sample to machines that have text similarity to robot or tool above the median. $\Delta log(tools)$ and $\Delta log(robots)$ are instrumented by the interaction of tariff changes with the share of replaceable occupations, as defined in (10) and (11). *robots* and *tools* denote the imports in dollars of robots and tools, respectively, in the past 5 years. The difference is taken over the past 5 years. The controls are the growth rate of the left-hand-side variable between 1993 and 1997, tariff change on sectoral output, the tariff change on inputs excluding capital, year fixed effects, and region-sector fixed effects. Standard errors are clustered at the region–sector level.

B.3.5 Higher Degree of Text Similarity

Table B.26: Effect of Tools and Robots on Employment When Limiting the Sample to High Text Similarity Machines

	(1)	(2)	(3)	(4)	(5)	(6)
	$\Delta \log(Employment)$	$\Delta \log(Employment)$	$\Delta \log(Employment)$	$\Delta \log(Employment)$	$\Delta \log(Employment)$	$\Delta \log(Employment)$
$\Delta log(tools)$	0.147***	0.123***	0.111***	0.264***	0.220***	0.206***
	(0.0311)	(0.0312)	(0.0260)	(0.0640)	(0.0497)	(0.0481)
$\Delta log(robots)$	-0.0470***	-0.0321***	-0.0291***	-0.161***	-0.139***	-0.112***
	(0.0123)	(0.0120)	(0.0106)	(0.0423)	(0.0355)	(0.0312)
N	228871	194694	194693	194694	194693	194674

Description: This table shows the coefficients of regression (9) on employment. Instead of using all machines, we limit the sample to machines that have text-similarity to robot or tool above the median. $\Delta log(tools)$ and $\Delta log(robots)$ are instrumented by the interaction of tariff changes with the share of replaceable occupations, as defined in (10) and (11). *robots* and *tools* denote the imports in dollars of robots and tools, respectively, in the past 5 years. The difference is taken over the past 5 years. All specifications have year fixed effects. In column 1, there are no controls other than year fixed effects. Column 2 adds the baseline controls, i.e., growth rate of employment between 1993 and 1997, the tariff change on sectoral output, the tariff change on inputs excluding capital, and year fixed effects. Column 3 adds region FE to the baseline controls. Column 4 adds sector FE to the baseline controls. Column 5 includes as controls the baseline controls, region FE, and sector FE. Column 6 includes sector–region FEs and the baseline controls. Standard errors are clustered at the region–sector level.

Table B.27: Effect of Tools and Robots on the Labor Market When Limiting the Sample to High Text Similarity Machines

	(1)	(2)	(3)	(4)	(5)
	$\Delta wage$	Δ*Wage Bill*	Δ*H.S. Drop. or Less*	Δ*H.S. Complete*	Δ*Some College or More*
$\Delta log(tools)$	0.0470***	0.267***	0.258***	0.0320	0.0230
	(0.0149)	(0.0574)	(0.0537)	(0.0390)	(0.0401)
$\Delta log(robots)$	-0.0188*	-0.157***	-0.185***	0.00227	0.000831
	(0.0108)	(0.0412)	(0.0376)	(0.0237)	(0.0231)
N	194693	194693	185421	111126	72897

Description: This table shows the coefficients of regression (9) on labor market outcomes. Instead of using all machines, we limit the sample to machines that have text similarity to robot or tool above the median. $\Delta log(tools)$ and $\Delta log(robots)$ are instrumented by the interaction of tariff changes with the share of replaceable occupations, as defined in (10) and (11). *robots* and *tools* denote the imports in dollars of robots and tools, respectively, in the past 5 years. The difference is taken over the past 5 years. The controls are the growth rate of the left hand side variable between 1993 and 1997, tariff change on sectoral output, the tariff change on inputs excluding capital, region fixed effects, and sector fixed effects. Standard errors are clustered at the region–sector level.

Table B.28: Effect of Tools and Robots on Different Occupations When Limiting the Sample to High Text Similarity Machines

	(1)	(2)	(3)	(4)	(5)
	Δ*Managers*	Δ*HS Professionals*	Δ*Technical Workers*	Δ*Adm Workers*	Δ*Operational Workers*
$\Delta log(tools)$	-0.0410	0.00346	0.137***	-0.00155	0.261***
	(0.0579)	(0.0597)	(0.0443)	(0.0432)	(0.0650)
$\Delta log(robots)$	0.0359	-0.00600	-0.0248	0.0371	-0.168***
	(0.0282)	(0.0289)	(0.0236)	(0.0270)	(0.0385)
N	44921	19844	70112	128305	141991

Description: This table shows the coefficients of regression (9) on labor market outcomes. Instead of using all machines, we limit the sample to machines that have text similarity to robot or tool above the median. $\Delta log(tools)$ and $\Delta log(robots)$ are instrumented by the interaction of tariff changes with the share of replaceable occupations, as defined in (10) and (11). *robots* and *tools* denote the imports in dollars of robots and tools, respectively, in the past 5 years. The difference is taken over the past 5 years. The controls are the growth rate of the left-hand-side variable between 1993 and 1997, tariff change on sectoral output, the tariff change on inputs excluding capital, region fixed effects, and sector fixed effects. Standard errors are clustered at the region–sector level.

C Appendix for Quantitative Model

C.1 Additional Equations

Firms. Consider a firm's choice of technology $l \in \{R, T\}$. Based on the properties of the Fréchet distribution and the firm's profit maximization, the expenditure share by firm i on tasks performed with technology l equals the following:

$$\pi_n^{s,l}(i) = \frac{T_n^{s,l}(i)(\Theta_n^{s,l})^{-\tilde{\theta}}}{(\Phi_n^s(i))^{-\tilde{\theta}}},$$

where $\Phi_n^s(i) = \left(\sum_{l=1}^{L} T_n^{s,l}(i)(\Theta_n^{s,l})^{-\tilde{\theta}}\right)^{-\frac{1}{\tilde{\theta}}}$ denotes the cost index of the value-added component of the firm's output. The price of the firm's value added is as follows: $p_n^{s,VA}(i) = \gamma \Phi_n^s(i)$. According to the firm's production function, Equation (14), and the firm's profit maximization, the firm's output price equals the following:

$$p_n^s(i) = \left[p_n^{s,VA}(i)\right]^{\gamma^s} \prod_{s'=1}^{S} \left[P_n^{s'}\right]^{\gamma^{ss'}}, \tag{C.1}$$

where $P_n^{s'}$ denotes the composite goods price in region n, sector s'.

Sectoral Production and Trade. Due to the constant return to scale and perfect competition, the output price index at the region–sector level (the price index associated with y_n^s) is determined by firm-level prices as follows:

$$[p_n^s]^{1-\theta} = \frac{1}{A_n^s}\left[\int_0^1 (p_n^s(i))^{1-\theta} di\right]^{1-\theta} \tag{C.2}$$

Sector s in region n has the following expenditure share on the output from region n':

$$\pi_{nn'}^s = \frac{(p_{n'}^s h_{nn'}^s t_{nn'}^s)^{1-\epsilon^s}}{(P_n^s)^{1-\epsilon^s}} \tag{C.3}$$

Capital Goods Sector. Using Equation (15), we observe that the production of investment goods decreases with the cost of capital production, $\Sigma_n^{s,l}$. Therefore, an increase in capital import tariffs can reduce investment:

$$I_n^{s,l} = \left(\frac{(1-\xi^l) P_n^{s,l}}{\Sigma_n^{s,l}} \right)^{\frac{1-\xi^l}{\xi^l}} . \tag{C.4}$$

Worker's Problem. Consider workers of type $e \in \{H, L\}$. Solving the worker's intratemporal problem, the time t utility equals the following:

$$u_{n,t}^{s,e} = \begin{cases} \frac{a_{n,t}^{s,e}(1-B) w_{n,t}^{s,e}}{P_{n,t}} & s \in \{1, ..., S\}, \\ \frac{a_{n,t}^{s,e}(1-B) b_n}{P_{n,t}} & s = S+1, \end{cases} \tag{C.5}$$

$$\text{where } P_n = \prod_{s=1}^{S} (P_n^s)^{\alpha^s} . \tag{C.6}$$

The probability that a type-e worker in region n, sector s will choose region n', sector s' in the next period equals the following:

$$s_{n'n,t}^{s's,e} = \frac{\exp(\lambda^e \beta v_{n',t+1}^{s',e} - \kappa_{n'n,t}^{s's,e})^{1/\rho^e}}{\sum_{n'=1}^{N} \sum_{s'=1}^{S+1} \exp(\lambda^e \beta v_{n',t+1}^{s',e} - \kappa_{n'n,t}^{s's,e})^{1/\rho^e}}. \tag{C.7}$$

Therefore, $1/\rho^e$ indicates the migration elasticity. It determines how easily workers of each type can switch sectors and locations based on their lifetime utility in the destination sector and location.

The following share of entrants will choose to become high-skilled:

$$\tilde{s}_{n,t}^{s,H} = \frac{\exp(\beta v_{n,t+1}^{s,H} - f^H)^{1/\tilde{\rho}}}{\exp(\beta v_{n,t+1}^{s,H} - f^H)^{1/\tilde{\rho}} + \exp(\beta v_{n,t+1}^{s,L})^{1/\tilde{\rho}}}, \tag{C.8}$$

where $1/\tilde{\rho}$ measures the skill choice elasticity.

According to the worker's problem, labor supply at the level of regions or sectors will follow the following law of motion:

$$l_{n',t+1}^{s',H} = \zeta^H \sum_{n=1}^{N} \sum_{s=1}^{S+1} s_{n'n,t}^{s's,H} l_{n,t}^{s,H} + \left((1-\zeta^H) l_{n,t}^{s,H} + (1-\zeta^L) l_{n,t}^{s,L} \right) \tilde{s}_{n,t}^{s,L}, \tag{C.9}$$

and

$$l_{n',t+1}^{s',L} = \zeta^L \sum_{n=1}^{N} \sum_{s=1}^{S+1} s_{n'n,t}^{s's,L} l_{n,t}^{s,L} + \left((1-\zeta^H) l_{n,t}^{s,H} + (1-\zeta^L) l_{n,t}^{s,L} \right) \tilde{s}_{n,t}^{s,L}. \tag{C.10}$$

C.1.1 Market-Clearing Conditions

Robot Capital. The market-clearing condition for robot capital at the region–sector level is the following:

$$R_n^{s,R} K_n^{s,R} = \int_{i=0}^{1} \frac{T^{s,R}(i)(R_n^{s,R})^{-\tilde{\theta}}}{(\Phi_n^s(i))^{-\tilde{\theta}}} \frac{(p_n^s(i))^{-\theta}}{(p_n^s)^{-\theta}} \gamma^s p_n^s Y_n^s di, \tag{C.11}$$

where $\frac{(p_n^s(i))^{-\theta}}{(p_n^s)^{-\theta}} \gamma^s p_n^s Y_n^s$ refers to firm i's value added and $\frac{T^{s,R}(i)(R_n^{s,R})^{-\tilde{\theta}}}{(\Phi_n^s(i))^{-\tilde{\theta}}}$ is the share of robot capital in the firm's value added. Integrating all firms in this region–sector, we get the total demand for the robot capital, which is equal to the supply of capital.

Tool Capital. Similarly, the market-clearing condition for tool capital is the following:

$$R_n^{s,T} K_n^{s,T}(i) = \int_{i=0}^{1} (1-\delta) \frac{\left(([w_n^{s,2}]^{\delta} \left[R_n^{s,T}\right]^{1-\delta}) \right)^{1-\sigma}}{(\Theta_n^{s,T}(i))^{1-\sigma}} \frac{(\Theta_n^{s,T}(i))^{-\tilde{\theta}}}{(\Phi_n^s(i))^{-\tilde{\theta}}} \frac{(p_n^s(i))^{-\theta}}{(p_n^s)^{-\theta}} \gamma^s p_n^s Y_n^s di. \tag{C.12}$$

High-skilled Workers. The market-clearing condition for high-skilled workers is the following:

$$w_n^{s,H} l_n^{s,H} = \int_{i=0}^{1} \frac{A^{s,T}(i)(w_n^{s,H})^{1-\sigma}}{(\Theta_n^{s,T}(i))^{1-\sigma}} \frac{(\Theta_n^{s,T}(i))^{-\tilde{\theta}}}{(\Phi_n^s(i))^{-\tilde{\theta}}} \frac{(p_n^s(i))^{-\theta}}{(p_n^s)^{-\theta}} \gamma^s p_n^s Y_n^s di. \tag{C.13}$$

Low-skilled Workers The market-clearing condition for low-skilled workers is the following:

$$w_n^{s,L} l_n^{s,L} = \int_{i=0}^{1} \delta \frac{\left(\left[w_n^{s,L}\right]^{\delta} \left[R_n^{s,T}\right]^{1-\delta} \right)^{1-\sigma}}{(\Theta_n^{s,T}(i))^{1-\sigma}} \frac{(\Theta_n^{s,T}(i))^{-\tilde{\theta}}}{(\Phi_n^s(i))^{-\tilde{\theta}}} \frac{(p_n^s(i))^{-\theta}}{(p_n^s)^{-\theta}} \gamma^s p_n^s Y_n^s di. \tag{C.14}$$

Composite Goods. Composite goods are consumed and used as production inputs. Therefore, their market-clearing condition is the following:

$$X_n^s = \underbrace{P_n^s C_n^s}_{\text{Consumption}} + \sum_{s'=1}^{S} \gamma^{s's} (\underbrace{\sum_{n'=1}^{N} X_{n'}^{s'} \pi_{n'n}^{s'}}_{\text{Sector } s' \text{ domestic sales}} + \underbrace{EF_n^{s'} (p_n^{s'})^{1-\sigma^{s'}}}_{\text{Sector } s' \text{ exports}}), \tag{C.15}$$

where EF_n^s, an exogenous parameter, governs the size of the foreign demand. Regional consumption of sectoral composite goods equals the following:

$$P_n^s C_n^s = \alpha^s \left(\sum_{s=1}^{S} (w_n^{s,H} l_n^{s,H} + w_n^{s,L} l_n^{s,L} + R_n^{s,R} K_n^{s,R} + R_n^{s,T} K_n^{s,T}) + TDG_n \right), \tag{C.16}$$

where TDG_n denotes the trade deficit and the tariff revenue in the composite goods sectors and equals the following:

$$TDG_n = \sum_{s=1}^{S} (X_n^s \pi_{nN+1}^s - EF_n^s (p_n^s)^{1-\sigma^s}). \tag{C.17}$$

Region n, sector s output is used both for domestic expenditure and for exports. Therefore, its market-clearing condition is the following:

$$p_n^s Y_n^s = \underbrace{\sum_{n'=1}^{N} X_{n'}^s \pi_{n'n}^s}_{\text{Domestic sales}} + \underbrace{EF_n^s (p_n^s)^{1-\sigma^s}}_{\text{Exports}}. \tag{C.18}$$

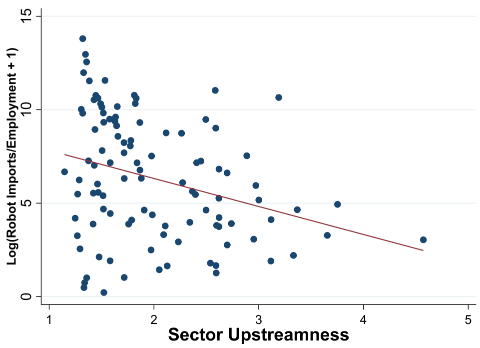
The foreign transfer equals the trade deficit due to trade in composite goods and imported capital goods:

$$TD_n = TDG_n + \sum_{s=1}^{S} \left(\Sigma_n^{s,T} M_n^{s,T} \frac{\left[h_{nN+1}^{s,T} t_{N+1}^{s,T} \right]^{1-\sigma^T}}{\left[\Sigma_n^{s,T} \right]^{1-\sigma^T}} + \Sigma_n^{s,R} M_n^{s,R} \frac{\left[h_{nN+1}^{s,R} t_{N+1}^{s,R} \right]^{1-\sigma^R}}{\left[\Sigma_n^{s,R} \right]^{1-\sigma^R}} \right). \tag{C.19}$$

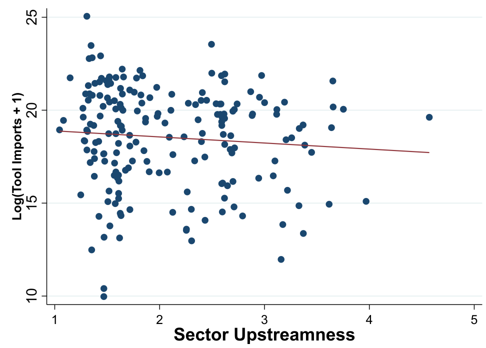
Equilibrium. The equilibrium is defined as a set of prices $\left\{ w_n^{s,H}, w_n^{s,L}, R_n^{s,R}, R_n^{s,T}, p_n^s, P_n^s, b \right\}$, such that workers' value functions follow Equation (18), sector–region and skill choice prob-

Figure C.1: Robots, Tools, and Sector Upstreamness

(a) Robot Imports and Sector Upstreamness



(b) Tool Imports and Sector Upstreamness



Description: This figure shows the estimated coefficients of model B.2 on employment and average wage of firms adopting labor-augmenting machines. For each firm importing a labor-augmenting machine, we create a control firm that matches in terms of employment, share of high-school dropouts, age, and sector in the three years before the adoption of the machine. The sample is from 1997 to 2015. Standard errors are clustered at the firm level.

abilities follow Equations (C.7) and (C.8), the supply of labor follows Equations (C.9) and (C.10), the supply of capital follows Problem (16), and market-clearing conditions (C.11)–(C.15) and (20) hold.[40]

C.2 Parameterization

Firm-level Productivity We assume that the firm-level high-skilled worker-augmenting productivity, $A_{n,t}^{s,T}(i)$, and robot-augmenting productivity, $T_{n,t}^{s,R}(i)$, follow joint log-normal distributions. They are independent across regions, sectors, firms, and time, but are correlated within a firm. The reason for this within-firm correlation is that the high-tech firms that are better at utilizing robots may also be better at utilizing high-skilled workers. Assume that $A^{s,T}(i) = \exp(\mu_1^s + \sigma_1^s Z_1^s(i))$ and $T^{s,R}(i) = \exp(\mu_2^s + \sigma_2^s Z_2^s(i))$ and that $Z_1^s(i)$ and $Z_2^s(i)$ are random variables that follow a bi-variate normal distribution:[41]

$$\begin{pmatrix} Z_1^s \\ Z_2^s \end{pmatrix} = \mathcal{N}\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho^s \\ \rho^s & 1 \end{pmatrix}\right). \tag{C.20}$$

[40] Since we focus on steady state-to-steady state changes, we omit the time dimension from the prices under consideration.

[41] We assume that these parameters depend on the sector instead of the region, since they govern the relative importance of high-skilled workers and robots in the technology of production. Therefore, they are more likely to be affected by the sector for which the technologies are developed than by the location in which they are used.

The average high-skilled worker and robot productivity μ_1^s and μ_2^s, their standard deviations σ_1^s and σ_2^s, and the correlation ρ^s are the parameters we will estimate.

Trade and Migration Costs We assume that the domestic trade cost follows Equation (C.21). The trade cost from region n' to region n is a function of several factors: (1) whether the origin is identical to the destination, (2) whether the two regions share a border, (3) the distance between the two regions, (4) the proximity of the origin and destination to the nearest coast, and (5) the number of ports present in the origin and destination. Additionally, trade cost depends on the sector of the traded products. We consider two measures of sector heterogeneity that may influence trade costs: (1) the degree of a sector's upstream position and (2) the share of high-skilled workers in sectoral employment. These sectoral variables, along with their interactions with the geographical variables mentioned above, affect trade costs.

$$\begin{aligned}
\log(h^s_{nn'}) = {} & \beta^0 \mathbf{1}(n'=n) + \beta^1 \text{Contig}_{n'n} + \beta^2 \log(\text{Dist to Coast}_n) + \beta^3 \log(\text{Dist to Coast}_{n'}) \\
& + \beta^4 \mathbb{N}(\text{Ports})_n + \beta^5 \mathbb{N}(\text{Ports})_{n'} + \beta^6 \log(\text{Dist}_{n'n}) + \beta^7 \text{Contig}_{n'n} \log(\text{U}^s) \\
& + \beta^8 \log(\text{Dist to Coast}_n) \log(\text{U}^s) + \beta^9 \log(\text{Dist to Coast}_{n'}) \log(\text{U}^s) \\
& + \beta^{10} \mathbb{N}(\text{Ports})_n \log(\text{U}^s) + \beta^{11} \mathbb{N}(\text{Ports})_{n'} \log(\text{U}^s) + \beta^{12} \log(\text{Dist}_{n'n}) \log(\text{U}^s) \\
& + \beta^{13} \mathbf{1}(n'=n) \log(\text{U}^s) + \beta^{14} \log(\text{U}^s) + \beta^{15} \mathbf{1}(n'=n) \log(\text{high-skilled labor share}^s) + \beta^{16} \text{Contig}_{n'n} \log(\text{high-skilled labor share}^s) \\
& + \beta^{17} \log(\text{Dist to Coast}_n) \log(\text{high-skilled labor share}^s) + \beta^{18} \log(\text{Dist to Coast}_{n'}) \log(\text{high-skilled labor share}^s) \\
& + \beta^{19} \mathbb{N}(\text{Ports})_n \log(\text{high-skilled labor share}^s) + \beta^{20} \mathbb{N}(\text{Ports})_{n'} \log(\text{high-skilled labor share}^s) + \beta^{21} \log(\text{high-skilled labor share}^s) \\
& + \beta^{22} \log(\text{Dist}_{n'n}) \log(\text{high-skilled labor share}^s). \qquad \text{(C.21)}
\end{aligned}$$

We assume that the non-tariff trade barrier faced by a region–sector when importing composite goods (Equation (C.22)), as well as robot (Equation (C.23)) and tool capital (Equation (C.24)), depends on several factors: (1) the distance to the coast, (2) the number of ports in the region, (3) the sector's upstreamness, and (4) the sector's high-skilled employment share. Additionally, the interactions between geographical and sectoral variables are taken into account. Moreover, an intercept term is included to account for the home bias against imports.

$$\log(h^{s}_{nN+1}) = \beta^{23}\log(\text{Dist to Coast}_n) + \beta^{24}\mathbb{N}(\text{Ports})_n + \beta^{25}\log(\text{Dist to Coast}_n)\log(\text{U}^s) + \beta^{26}\mathbb{N}(\text{Ports})_n\log(\text{U}^s) + \beta^{27}\log(\text{U}^s)$$
$$+ \beta^{28} + \beta^{29}\log(\text{Dist to Coast}_{n'})\log(\text{high-skilled labor share}^s) + \beta^{30}\mathbb{N}(\text{Ports})_{n'}\log(\text{high-skilled labor share}^s)$$
$$+ \beta^{31}\log(\text{high-skilled labor share}^s). \tag{C.22}$$

$$\log(h^{s,R}_{nN+1}) = \beta^{1,R}\log(\text{Dist to Coast}_n) + \beta^{2,R}\mathbb{N}(\text{Ports})_n + \beta^{3,R}\log(\text{Dist to Coast}_{n'})\log(\text{U}^s) + \beta^{4,R}\mathbb{N}(\text{Ports})_{n'}\log(\text{U}^s) + \beta^{5,R}\log(\text{U}^s)$$
$$+ \beta^{6,R} + \beta^{7,R}\log(\text{Dist to Coast}_{n'})\log(\text{high-skilled labor share}^s) + \beta^{8,R}\mathbb{N}(\text{Ports})_{n'}\log(\text{high-skilled labor share}^s)$$
$$+ \beta^{9,R}\log(\text{high-skilled labor share}^s). \tag{C.23}$$

$$\log(h^{s,T}_{nN+1}) = \beta^{1,T}\log(\text{Dist to Coast}_n) + \beta^{2,T}\mathbb{N}(\text{Ports})_n + \beta^{3,T}\log(\text{Dist to Coast}_{n'})\log(\text{U}^s) + \beta^{4,T}\mathbb{N}(\text{Ports})_{n'}\log(\text{U}^s) + \beta^{5,T}\log(\text{U}^s)$$
$$+ \beta^{6,T} + \beta^{7,T}\log(\text{Dist to Coast}_{n'})\log(\text{high-skilled labor share}^s) + \beta^{8,T}\mathbb{N}(\text{Ports})_{n'}\log(\text{high-skilled labor share}^s)$$
$$+ \beta^{9,T}\log(\text{high-skilled labor share}^s). \tag{C.24}$$

The migration cost depends on the migration origin region–sector and the migration destination region–sector. We assume that the migration cost is a function of the same geographical variables that affect the domestic trade cost. In addition, they are also influenced by the absolute values of the difference between the upstreamness and the high-skilled labor shares of the origin sector and the destination sector. We also include in the migration cost the interactions between the geographical distances and the sectoral differences. The migration cost is parameterized as follows:

$$\log(\kappa^{s's}_{n'n}) = \gamma^0\mathbf{1}(n'=n) + \gamma^1\text{Contig}_{n'n} + \gamma^2\log(\text{Dist}_{n'n}) + \gamma^3|\log(\text{U}^{s'}) - \log(\text{U}^s)| + \gamma^4\text{Contig}_{n'n}|\log(\text{U}^{s'}) - \log(\text{U}^s)|$$
$$+ \gamma^5\log(\text{Dist}_{n'n})|\log(\text{U}^{s'}) - \log(\text{U}^s)| + \gamma^6\mathbf{1}(n'=n)|\log(\text{U}^{s'}) - \log(\text{U}^s)| + \gamma^7|\text{high-skilled labor share}^{s'} - \text{high-skilled labor share}^s|$$
$$+ \gamma^8\text{Contig}_{n'n}|\text{high-skilled labor share}^{s'} - \text{high-skilled labor share}^s|$$
$$+ \gamma^9\log(\text{Dist}_{n'n})|\text{high-skilled labor share}^{s'} - \text{high-skilled labor share}^s|$$
$$+ \gamma^{10}\mathbf{1}(n'=n)|\text{high-skilled labor share}^{s'} - \text{high-skilled labor share}^s|. \tag{C.25}$$

C.3 Estimation

In the first step, we calibrate a set of parameters outside the model. Table C.3 summarizes these parameters.

Trade Elasticities We calibrate sectoral trade elasticities for the composite goods to the estimates acquired in De Souza and Li (2022).[42] Using a specification similar to the one developed in Section 5, we estimate robot and tool capital trade elasticities to 5.64 and 3.11, respectively.

We estimate the trade elasticity of different types of capital goods by studying how tariff changes affect changes in imports at the regional and sectoral levels.[43] For robots:

$$\Delta \log \left(Import^R_{is,t} \right) = \theta^R \Delta \log \left(tariff^R_{s,t} \right) + Fixed\ effect_i + Fixed\ effect_s + Fixed\ effect_t + \epsilon_{ist}, \tag{C.26}$$

where $\Delta \log(Import^R_{is,t})$ is the log change in robot imports in region i, sector s, from year $t-5$ to year t. $\log(tariff^R_{s,t})$ is the log change in a weighted average[44] tariff on robots in region i, sector s, from year $t-5$ to year t. θ^R is the trade elasticity for robots. Similarly, we estimate the following for tools:

$$\Delta \log \left(Import^T_{is,t} \right) = \theta^R \Delta \log \left(tariff^T_{s,t} \right) + Fixed\ effect_i + Fixed\ effect_s + Fixed\ effect_t + \epsilon_{is}, \tag{C.27}$$

where θ^T is the trade elasticity for tools. Table C.1 shows the parameters estimated based on Equations (C.26) and (C.27), along with other robustness tests. Estimators from the main specification suggest the elasticities of $\theta^R = -5.64$ and $\theta^T = -3.11$.[45]

[42] In De Souza and Li (2022), we utilize anti-dumping investigations and anti-dumping tariffs and a difference-in-differences strategy to study the effect of tariffs. We use the products and sectors that are investigated for dumping but do not receive tariff protection as the control group.

[43] We leverage variations across both regions and sectors to increase statistical power. Different regions import distinct capital goods, resulting in varying tariffs when measured using sector-level weighted averages.

[44] We calculate the average tariff on robot products using product-level import value as weight.

[45] This implies that $\epsilon^R = 1 - \theta^R = 6.64$ and $\epsilon^T = 1 - \theta^T = 4.11$.

Table C.1: **Trade Elasticity of Capital Goods**

	Measured by 5-Year Change			Measured by 1-Year Change		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Trade Elasticity of Robots						
θ^R	-19.58***	-5.637***	-6.079***	-1.932***	-1.940***	-2.001***
	(2.477)	(1.391)	(1.465)	(0.440)	(0.529)	(0.517)
Observation	325271	325271	325271	400501	400501	400501
R^2	0.029	0.220	0.221	0.000	0.009	0.009
Year FE	N	Y	Y	N	Y	Y
Sector FE	N	Y	Y	N	Y	Y
Region FE	N	Y	Y	N	Y	Y
Control	N	N	Y	N	N	Y
	(7)	(8)	(9)	(10)	(11)	(12)
Panel B. Trade Elasticity of Tools						
θ^T	-12.64***	-3.108*	-3.815**	-1.473***	-4.702***	-4.572***
	(1.242)	(1.684)	(1.863)	(0.207)	(0.667)	(0.658)
Observation	325271	325271	325271	400501	400501	400501
R^2	0.009	0.348	0.349	0.000	0.013	0.013
Year FE	N	Y	Y	N	Y	Y
Sector FE	N	Y	Y	N	Y	Y
Region FE	N	Y	Y	N	Y	Y
Control	N	N	Y	N	N	Y

Description: FE = fixed effects. This table presents trade elasticities estimated from Equations (C.26) and (C.27). θ^R is the trade elasticity of labor-saving capital goods. θ^T is the trade elasticity of labor-augmenting capital goods. Controls include the tariff change on sectoral output and input. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Migration Elasticities We apply the method used by Artuç et al. (2010), Dix-Carneiro (2014), and Caliendo et al. (2019) to estimate the migration elasticities for both skill types. Manipulating Equation (C.7), we can express migration shares as a function of wages and migration shares in the next period, and the coefficient in front of wages indicates the the migration elasticity. We conduct an instrumental variable regression using lagged wages as the instrument for the next period's wages in order to identify the coefficient. We estimate the migration elasticity (the inverse of ρ^e, $e \in \{1, 2\}$) to be 0.167 for high-skilled workers and 0.141 for low-skilled workers. These estimates are consistent with our intuition that high-skilled workers should be more mobile than low-skilled workers. In studies using US state–sector level migration data, Artuç et al. (2010) found a migration elasticity of 0.532 and Caliendo et al. (2019) found a migration elasticity of 0.495. We estimate lower mobility rates based on Brazilian data, which is in accordance with our intuition that population mobility is lower in developing countries than in advanced economies.

With Equation (C.7), the log difference between the probability of migrating from region n-sector j to region i-sector k and the probability of staying in region n-sector j is the following:

$$\log(s^{kj,e}_{in,t}) - \log(s^{jj,e}_{nn,t}) = \frac{\zeta^e \beta}{\rho^e} v^{k,e}_{i,t+1} - \frac{\zeta^e \beta}{\rho^e} v^{j,e}_{n,t+1} - \frac{1}{\rho^e} . \kappa^{kj,e}_{in,t}. \tag{C.28}$$

Use Equation (18) to substitute the value functions:

$$\begin{aligned}\log(s^{kj,e}_{in,t}) - \log(s^{jj,e}_{nn,t}) = \frac{\zeta^e \beta}{\rho^e} \Bigg(& \log(a^{k,e}_{i,t+1}) + \log(\frac{w^{k,e}_{i,t+1}}{P_{i,t+1}}) + \rho^e \log(\sum_{n'=1}^{N} \sum_{s'=1}^{S+1} \exp(\zeta^e \beta v^{s',e}_{n',t+2} - \kappa^{s'k,e}_{n'i,t+1})^{1/\rho^e}) \\ & - \log(a^{j,e}_{n,t+1}) - \log(\frac{w^{j,e}_{n,t+1}}{P_{n,t+1}}) - \rho^e \log(\sum_{n'=1}^{N} \sum_{s'=1}^{S+1} \exp(\zeta^e \beta v^{s',e}_{n',t+1} - \kappa^{s'j,e}_{n'n,t})^{1/\rho^e}) \Bigg) - \frac{1}{\rho^e} \kappa^{kj,e}_{in,t}.\end{aligned} \tag{C.29}$$

To substitute the region–sector–level expected value, use Equation (C.7) again at time $t+1$:

$$\begin{aligned}\log(s^{kj,e}_{in,t+1}) - \log(s^{kk,e}_{ii,t+1}) = & -\frac{1}{\rho^e} \kappa^{kj,e}_{in,t+1} - \log(\sum_{n'=1}^{N} \sum_{s'=1}^{S+1} \exp(\zeta^e \beta v^{s',e}_{n',t+2} - \kappa^{s'j,e}_{n'n,t+2})^{1/\rho^e}) \\ & + \log(\sum_{n'=1}^{N} \sum_{s'=1}^{S+1} \exp(\zeta^e \beta v^{s',e}_{n',t+2} - \kappa^{s'k,e}_{n'i,t+2})^{1/\rho^e}).\end{aligned} \tag{C.30}$$

Plug Equation (C.30) into Equation (C.29):

$$\begin{aligned}\log(s^{kj,e}_{in,t}) - \log(s^{jj,e}_{nn,t}) = & \frac{\zeta^e \beta}{\rho^e} \left(\log(\frac{w^{k,e}_{i,t+1}}{P_{i,t+1}}) - \log(\frac{w^{j,e}_{n,t+1}}{P_{n,t+1}}) \right) + \zeta^e \beta \left(\log(s^{kj,e}_{in,t+1}) - \log(s^{kk,e}_{ii,t+1}) \right) \\ & + \frac{\zeta^e \beta}{\rho^e} \kappa^{kj,e}_{in,t+1} - \frac{1}{\rho^e} \kappa^{kj,e}_{in,t} + \frac{\zeta^e \beta}{\rho^e} \left(\log(a^{k,e}_{i,t+1}) - \log(a^{j,e}_{n,t+1}) \right).\end{aligned} \tag{C.31}$$

Accordingly, our estimation equation will be:

$$\log(s^{kj,e}_{in,t}) - \log(s^{jj,e}_{nn,t}) - \zeta^e \beta (\log(s^{kj,e}_{in,t+1}) - \log(s^{kk,e}_{ii,t+1})) = \frac{\zeta^e \beta}{\rho^e} (\log(w^{k,e}_{i,t+1}) - \log(w^{j,e}_{n,t+1})) + \phi_{i,t} + \phi_{n,t} + \epsilon^{kj,e}_{in,t}. \tag{C.32}$$

This amounts to regressing the log difference between the probability of mitigating from region n-sector j to region i-sector k and the probability of remaining in region n-sector j. This is adjusted by the log difference between the probability of mitigating from region n-sector j to region i-sector k and the probability of staying in region i-sector k during the subsequent period. The dependent variable is the log difference in wages between region i-sector k and region n-sector j. Fixed effect controls are included to address the region-level price indices. Since the continuation probability for each worker type, ζ^e, and the discount factor, β, are both known, the inverse of the migration probability, ρ^e, can be obtained from the estimated coefficient.

Comparing Equations (C.31) and (C.32), the error term, $\epsilon_{in,t}^{kj,e}$, absorbs migration costs and region–sector level amenities. To address potential bias, similar to Caliendo et al. (2019), we use past wages (in $t-1$) as instruments for the wages in $t+1$.[46] The identifying assumption is that past wages are uncorrelated with current and future migration costs and future amenities.

Table C.2: **Migration Elasticity and Skill Choice Elasticity**

	Migration Elasticity				Skill Choice Elasticity	
	$\frac{1}{\rho^H}$		$\frac{1}{\rho^L}$		$\frac{1}{\tilde{\rho}}$	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
Parameters	0.141***	0.167***	0.131***	0.141***	0.022***	0.076***
	(0.005)	(0.006)	(0.008)	(0.010)	(0.0004)	(0.018)
Observation	255,321	251,838	345,991	344,822	94,836	94,089
Origin–Year FE	Y	Y	Y	Y	Y	Y
Destination–Year FE	Y	Y	Y	Y	Y	Y
R^2	0.109	0.003	0.136	0.001	0.197	-0.202
First stage F-statistic		257.42		164.50		20.46

Description: FE = fixed effects. This table presents migration elasticities and skill choice elasticities estimated from Equations (C.32) and (C.36). ρ^H is the inverse of the migration elasticity of high-skilled workers. ρ^L is the inverse of the migration elasticity of low-skilled workers. $\tilde{\rho}$ is the skill choice elasticity. 2SLS specifications use wages in the previous period as instruments. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Columns (1)-(4) of Table C.2 show the parameters estimated from Equation (C.32). The 2SLS estimators imply migration elasticities of $\frac{1}{\rho^H} = 0.167$ and $\frac{1}{\rho^L} = 0.141$.

[46] Similar to Artuç et al. (2010) and Caliendo et al. (2019), we use $(\log(w_{i,t-1}^{k,e}) - \log(w_{n,t-1}^{j,e}))$ to instrument for $(\log(w_{i,t+1}^{k,e}) - \log(w_{n,t+1}^{j,e}))$.

Skill Choice Elasticity Using a similar approach, we estimate the skill choice elasticity of entrants, referred to as those entering the Brazilian matched employer–employee data for the first time. Equation (C.33) demonstrates that the share of new workers in a region–sector choosing to become high-skilled depends on the relative value functions of high-skilled and low-skilled workers. Equation (C.36) enables the value functions to be inverted and rewritten as migration shares, forming our estimation equation. We use lagged wages as instruments for migration shares.

We estimate the skill choice elasticity for new workers as follows. Compute the log difference between the probabilities of becoming a high-skilled versus a low-skilled worker in region n-sector s and in region n'-sector s'. Take the log difference between the two region-sectors and plug it into Equation (C.8):

$$\begin{aligned}&\Big(\log(\tilde{s}^{s,H}_{n,t}) - \log(\tilde{s}^{s,L}_{n,t})\Big) - \Big(\log(\tilde{s}^{s',H}_{n',t}) - \log(\tilde{s}^{s',L}_{n',t})\Big)\\ =&\frac{\beta}{\tilde{\rho}}(v^{s,H}_{n,t+1} - v^{s',H}_{n',t+1}) - \frac{\beta}{\tilde{\rho}}(v^{s,L}_{n,t+1} - v^{s',L}_{n',t+1})\end{aligned} \tag{C.33}$$

With Equation (C.7), we can express the value functions as migration shares and migration costs:

$$v^{s,e}_{n,t+1} - v^{s',e}_{n',t+1} = \frac{\rho^e}{\zeta^e\beta}\Big(\log(s^{ss,e}_{nn,t}) - \log(s^{s's,e}_{n'n,t})\Big) - \frac{1}{\zeta^e\beta}\kappa^{s's,e}_{n'n,t}, e \in \{1,2\}. \tag{C.34}$$

Plug Equation (C.34) into Equation (C.33):

$$\begin{aligned}&\Big(\log(\tilde{s}^{s,H}_{n,t}) - \log(\tilde{s}^{s,L}_{n,t})\Big) - \Big(\log(\tilde{s}^{s',H}_{n',t}) - \log(\tilde{s}^{s',L}_{n',t})\Big)\\ =&\frac{1}{\tilde{\rho}}\left[\frac{\rho^H}{\zeta^H}\Big(\log(s^{ss,H}_{nn,t}) - \log(s^{s's,H}_{n'n,t})\Big) - \frac{\rho^L}{\zeta^L}\Big(\log(s^{ss,L}_{nn,t}) - \log(s^{s's,L}_{n'n,t})\Big)\right] - (\frac{1}{\zeta^H}\kappa^{s's,H}_{n'n,t} - \frac{1}{\zeta^L}\kappa^{s's,L}_{n'n,t}).\end{aligned} \tag{C.35}$$

Equation (C.35) leads to our estimation equation:

$$\begin{aligned}&\left(\log(\tilde{s}^{s,H}_{n,t}) - \log(\tilde{s}^{s,L}_{n,t})\right) - \left(\log(\tilde{s}^{s',H}_{n',t}) - \log(\tilde{s}^{s',L}_{n',t})\right)\\ =&\frac{1}{\tilde{\rho}}\left[\frac{\rho^H}{\zeta^H}\left(\log(s^{ss,H}_{nn,t}) - \log(s^{s's,H}_{n'n,t})\right) - \frac{\rho^L}{\zeta^L}\left(\log(s^{ss,L}_{nn,t}) - \log(s^{s's,L}_{n'n,t})\right)\right] + \epsilon^{ss'}_{nn',t}.\end{aligned} \tag{C.36}$$

Similar to the estimation of migration elasticities, we use wages at $t-1$ as instruments.[47] The identifying assumption is that past wages are uncorrelated with current migration costs.

Columns (5)-(6) of Table C.2 show the parameters estimated from Equation (C.36). The 2SLS estimator implies a skill choice elasticity of $\frac{1}{\tilde{\rho}} = 0.076$.

Other Parameters Calibrated Outside the Model Using the Brazilian matched employer–employee data, we calibrate workers' exit rates by type. In order to measure exit rates, we calculate, for an average year, the percentage of each type of worker who leaves the labor market and never returns. We calibrate the input-output coefficients, final consumption shares, and social insurance tax rates based on the values obtained in De Souza and Li (2022).

Table C.3: **Parameters Calibrated outside the Model**

Parameters			Targeted Moments
Variable	Var. Name	Value	Source
ϵ^s	Sectoral trade elasticities	3.7199 (mean)	De Souza and Li (2022)
ϵ^T	Tool capital goods trade elasticity	4.11	Estimated
ϵ^R	Robot capital goods trade elasticity	6.64	Estimated
ρ^H	Migration elasticity of high-skilled workers (inverse)	5.99	Estimated
ρ^L	Migration elasticity of low-skilled workers (inverse)	7.09	Estimated
$\tilde{\rho}$	Skill choice elasticity (inverse)	13.16	Estimated
ζ^H	Exit rate of high-skilled workers	0.035	Data
ζ^L	Exit rate of low-skilled workers	0.061	Data
$\gamma^{ss'}$	Input-output coefficient	Varies	De Souza and Li (2022)
α^s	Final consumption share	Varies	De Souza and Li (2022)
B	Social insurance tax rate	10.3%	"Government transfer rate" ("Renda de transferências governamentais") in the IPEA's database
β	Discount factor	0.96	Numerous

Description: This table presents model parameters that are externally calibrated.

C.4 Estimation

We estimate the remaining parameters using the Simulated Method of Moments (SMM), dividing them into two groups: cross-sectional and dynamic moments. We treat the Brazilian economy in 1997 as the initial steady state (t_0). The cross-sectional moments govern the economy's static aspects, while dynamic moments dictate its response to shocks (change

[47]The instruments are $[\log(w^{k,H}_{i,t-1}) - \log(w^{j,H}_{n,t-1}) - (\log(w^{k,L}_{i,t-1}) - \log(w^{j,L}_{n,t-1})]$.

from t_0 to t_1). To estimate parameters governing cross-sectional moments, we target Brazilian trade, employment, and migration in 1997 using the model's initial steady state. For dynamic moments, we replicate the empirical analysis in Section 5 using simulated data, searching for parameters related to production technologies involving robots or tools, namely $\left\{\tilde{\theta}, \theta, \sigma, \delta\right\}$ (elasticity of substitution between robots and tools, elasticity of substitution across firms, elasticity of substitution between high-skilled workers and the low-skilled-worker-tool bundle, and low-skilled workers' share in the low-skilled-worker-tool bundle). We use these four parameters to target four key empirical results – the impact of robot and tool imports on high-skilled and low-skilled employment – by replicating the instrumental variables(IV) regression with model simulated data, reflecting the change from initial to final steady states. In the SMM algorithm, we minimize the sum of squared differences between data moments and model counterparts, treating all moments with equal weight.

In particular, we estimate the trade cost-related parameters described in Section C.2 by targeting region–sector imports of robots, tools, and non-capital goods. In order to estimate migration cost-related parameters, we target migration shares from one region–sector to another. In order to estimate region–sector level productivity, we target the wage and employment of high-skilled and low-skilled workers by region and sector. To estimate the fixed cost of becoming a high-skilled worker, we target the annual average share of high-skilled workers among entrants.

We estimate the four key parameters – $\left\{\tilde{\theta}, \theta, \sigma, \delta\right\}$ – governing robot and tool technologies, which determine the impact of their capital imports on high-skilled and low-skilled employment. We target coefficients summarizing these effects, as presented in Section 6, and consider the following regression:[48]

$$\Delta \log(l_n^{s,e}) = \theta^{R,e} \Delta \log(robots_n^s) + \theta^{T,e} \Delta \log(tool_n^s) + \epsilon_n^{s,e}, e \in \{H, L\}, \tag{C.37}$$

where changes from the initial steady state to the final steady state in type-e employment,

[48] In the empirical counterpart of this regression in Section 5, we include additional controls, such as fixed effects for regions and sectors, output tariffs, other input tariffs, and pre-period growth. According to the data, these control variables are necessary because a number of shocks have affected both the labor market and the import of machinery. Model simulated data, however, do not contain such shocks, so we do not include additional controls in these regressions.

robot capital goods imports, and tool capital goods imports are represented by $\Delta \log(l_n^{s,e})$, $\Delta \log(robots_n^s)$, and $\Delta \log(tool_n^s)$, respectively.

Similar to the section 5, we use the exposures to robot and tool capital goods tariff changes as instruments for the changes in imports. As a measure of routine task shares in the model, we use the share of low-skilled workers and tools in region–sector value added in the initial steady state. Therefore, the instruments constructed with model-simulated data are the following:

$$\Delta IV_n^{s,R} = \frac{w_{n,t_0}^{s,L} l_{n,t_0}^{s,L} + R_{n,t_0}^{s,T} K_{n,t_0}^{s,T}}{\gamma^s p_{n,t_0}^s y_{n,t_0}^s} \Delta\tau^{s,R} \tag{C.38}$$

for robots, and

$$\Delta IV_n^{s,T} = (1 - \frac{w_{n,t_0}^{s,L} l_{n,t_0}^{s,L} + R_{n,t_0}^{s,T} K_{n,t_0}^{s,T}}{\gamma^s p_{n,t_0}^s y_{n,t_0}^s}) \Delta\tau^{s,T} \tag{C.39}$$

for tools.

We employ the Mathematical Programming with Equilibrium Constraints (MPEC) algorithm (Su and Judd 2012) to solve the model, incorporating both initial and final steady states in the constraints. This method enables us to solve for initial and final steady states, the variable changes across steady states listed in Equations (C.37), (C.38), and (C.39), and the IV regression coefficients per Equation (C.37). We then compute model moments and include them in the objective function along with data moments.

C.5 Estimation Results and Model Fit

Table 6 displays the estimated values of the key parameters that govern robot and tool technologies. Table C.5 presents the estimates of other parameters. As anticipated, more distant regions experience higher domestic trade costs. Upstream and low-skilled sectors also incur higher trade costs. In terms of import costs, greater distance increases the cost of importing sectoral goods, robot capital goods, and tool capital goods. Having more ports significantly reduces import costs. A home bias exists against importing all goods. Migration costs rise with the distance between regions and the differences in sector upstreamness and skill levels between origin and destination sectors. Furthermore, becoming a high-skilled worker incurs a fixed cost equivalent to 7.8 years of average high-skilled wages.

Table C.4 shows that we precisely match the key empirical moments with the four robot and tool technology parameters.

Table C.4: **Match of Key Moments**

Data Moments			Model Moments
Variable	Var. Name	Value	Value
$\theta^{R,H}$	Elasticity of high-skilled employment to robot import shock	-0.0190	-0.0190
$\theta^{T,H}$	Elasticity of high-skilled employment to tool import shock	0.0475	0.0477
$\theta^{R,L}$	Elasticity of low-skilled employment to robot import shock	-0.3590	-0.3590
$\theta^{T,L}$	Elasticity of low-skilled employment to tool import shock	0.2270	0.2270

Description: This table presents the model's performance in matching the key moments: the elasticities of region–sector level high-skilled and low-skilled employment with respect to the imports of robots and tools.

Table C.5: **Parameters Estimated in the Model (Cont'd): Other Parameters**

Parameter	Para. Name	Value	Targeted Moments
	Production		
ξ^R	Decreasing return to scale parameter of robot investment goods production	0.0505	
ξ^T	Decreasing return to scale parameter of tool investment goods production	0.0529	Imports of robots and tools by region and sector
A_n^s	Region-sector level productivity	10.6702 (mean)	
μ_1^s	Sector-specific mean (across firms) high-skilled worker productivity	0.2157 (mean)	
μ_2^s	Sector-specific mean (across firms) robot productivity	−1.3304 (mean)	
σ_1^s	Sector-specific standard deviation (across firms) high-skilled worker productivity	1.0146 (mean)	Wage and employment of high-skilled and low-skilled workers by region and sector
σ_2^s	Sector-specific standard deviation (across firms) robot productivity	1.5477 (mean)	
ρ^s	Sector-specific correlation (across firms) between high-skilled worker productivity and robot productivity	0.0765 (mean)	
	Trade		
	Elasticity of domestic composite goods trade cost w.r.t.		
β^0	$\mathbf{1}(n'=n)$	−1.1094	
β^1	$\text{Contig}_{n'n}$	−1.0054	
β^2	$\log(\text{Dist to Coast}_n)$	−0.6190	
β^3	$\log(\text{Dist to Coast}_{n'})$	−0.1693	
β^4	$\mathbb{N}(\text{Ports})_n$	0.3855	
β^5	$\mathbb{N}(\text{Ports})_{n'}$	0.1583	
β^6	$\log(\text{Dist}_{n'n})$	0.5764	
β^7	$\text{Contig}_{n'n}\log(\text{U}^s)$	0.6008	
β^8	$\log(\text{Dist to Coast}_n)\log(\text{U}^s)$	0.5956	
β^9	$\log(\text{Dist to Coast}_{n'})\log(\text{U}^s)$	0.0584	
β^{10}	$\mathbb{N}(\text{Ports})_n\log(\text{U}^s)$	−0.5528	
β^{11}	$\mathbb{N}(\text{Ports})_{n'}\log(\text{U}^s)$	−0.1227	
β^{12}	$\log(\text{Dist}_{n'n})\log(\text{U}^s)$	−0.2250	
β^{13}	$\log(\text{U}^s)$	3.3709	Region-sector level imports
β^{14}	$\mathbf{1}(n'=n)\log(\text{U}^s)$	1.6955	
β^{15}	$\mathbf{1}(n'=n)\log(\text{high-skilled labor share}^s)$	−3.4660	
β^{16}	$\text{Contig}_{n'n}\log(\text{high-skilled labor share}^s)$	−3.3575	
β^{17}	$\log(\text{Dist to Coast}_n)\log(\text{high-skilled labor share}^s)$	−0.3025	
β^{18}	$\log(\text{Dist to Coast}_{n'})\log(\text{high-skilled labor share}^s)$	−0.0936	
β^{19}	$\mathbb{N}(\text{Ports})_n\log(\text{high-skilled labor share}^s)$	0.0117	
β^{20}	$\mathbb{N}(\text{Ports})_{n'}\log(\text{high-skilled labor share}^s)$	0.0653	
β^{21}	$\log(\text{high-skilled labor share}^s)$	−2.8436	
β^{22}	$\log(\text{Dist}_{n'n})\log(\text{high-skilled labor share}^s)$		
	Elasticity of imported composite goods trade cost w.r.t.		
β^{23}	$\log(\text{Dist to Coast}_{n'})$	0.0313	
β^{24}	$\mathbb{N}(\text{Ports})_{n'}$	−0.0271	
β^{25}	$\log(\text{Dist to Coast}_{n'})\log(\text{U}^s)$	0.0179	
β^{26}	$\mathbb{N}(\text{Ports})_{n'}\log(\text{U}^s)$	−0.00015	
β^{27}	$\log(\text{U}^s)$	0.7177	
β^{28}	$\mathbf{1}(\text{Imported})$	3.0806	
β^{29}	$\log(\text{Dist to Coast}_{n'})\log(\text{high-skilled labor share}^s)$	0.1406	
β^{30}	$\mathbb{N}(\text{Ports})_{n'}\log(\text{high-skilled labor share}^s)$	0.0028	
β^{31}	$\log(\text{Dist}_{n'n})\log(\text{high-skilled labor share}^s)$	0.2701	
β^{32}	$\log(\text{high-skilled labor share}^s)$	−0.8755	
	Elasticity of imported robot capital goods trade cost w.r.t.		
$\beta^{1,R}$	$\log(\text{Dist to Coast}_{n'})$	0.1272	
$\beta^{2,R}$	$\mathbb{N}(\text{Ports})_{n'}$	−0.3827	
$\beta^{3,R}$	$\log(\text{Dist to Coast}_{n'})\log(\text{U}^s)$	0.0360	
$\beta^{4,R}$	$\mathbb{N}(\text{Ports})_{n'}\log(\text{U}^s)$	0.2446	
$\beta^{5,R}$	$\log(\text{U}^s)$	0.2990	Imports of robot capital by region-sector
$\beta^{6,R}$	$\mathbf{1}(\text{Imported})$	3.3035	
$\beta^{7,R}$	$\log(\text{Dist to Coast}_{n'})\log(\text{high-skilled labor share}^s)$	0.2522	
$\beta^{8,R}$	$\mathbb{N}(\text{Ports})_{n'}\log(\text{high-skilled labor share}^s)$	−0.1113	
$\beta^{9,R}$	$\log(\text{high-skilled labor share}^s)$	0.1457	
	Elasticity of imported tool capital goods trade cost w.r.t.		
$\beta^{1,T}$	$\log(\text{Dist to Coast}_{n'})$	0.3861	
$\beta^{2,T}$	$\mathbb{N}(\text{Ports})_{n'}$	−0.2617	
$\beta^{3,T}$	$\log(\text{Dist to Coast}_{n'})\log(\text{U}^s)$	−0.2514	
$\beta^{4,T}$	$\mathbb{N}(\text{Ports})_{n'}\log(\text{U}^s)$	0.2733	
$\beta^{5,T}$	$\log(\text{U}^s)$	0.6267	Imports of tool capital by region-sector
$\beta^{6,T}$	$\mathbf{1}(\text{Imported})$	2.7747	
$\beta^{7,T}$	$\log(\text{Dist to Coast}_{n'})\log(\text{high-skilled labor share}^s)$	0.2727	
$\beta^{8,T}$	$\mathbb{N}(\text{Ports})_{n'}\log(\text{high-skilled labor share}^s)$	−0.0602	
$\beta^{9,T}$	$\log(\text{high-skilled labor share}^s)$	0.3065	
	Labor Migration		
$f^H/\text{mean}(w_n^{s,H})$	Fixed cost of becoming high-skilled workers (relative to high-skilled wage)	3.5484	Share of new workers who are high-skilled
	Elasticity of migration cost w.r.t.		
γ^0	$\mathbf{1}(n'=n)$	−7.6297	
γ^1	$\text{Contig}_{n'n}$	−6.5904	
γ^2	$\log(\text{Dist}_{n'n})$	2.0054	
γ^3	$\lvert\log(\text{U}^{s'})-\log(\text{U}^s)\rvert$	5.4627	
γ^4	$\text{Contig}_{n'n}\lvert\log(\text{U}^{s'})-\log(\text{U}^s)\rvert$	6.4620	Share of high-skilled workers moving from one region-sector to another region-sector
γ^5	$\log(\text{Dist}_{n'n})\lvert\log(\text{U}^{s'})-\log(\text{U}^s)\rvert$	3.3443	Share of low-skilled workers moving from one region-sector to another region-sector
γ^6	$\mathbf{1}(n'=n)\lvert\log(\text{U}^{s'})-\log(\text{U}^s)\rvert$	2.2070	
γ^7	$\lvert\text{high-skilled labor share}^{s'}-\text{high-skilled labor share}^s\rvert$	6.2657	
γ^8	$\text{Contig}_{n'n}\lvert\text{high-skilled labor share}^{s'}-\text{high-skilled labor share}^s\rvert$	5.1353	
γ^9	$\log(\text{Dist}_{n'n})\lvert\text{high-skilled labor share}^{s'}-\text{high-skilled labor share}^s\rvert$	0.7093	
γ^{10}	$\mathbf{1}(n'=n)\lvert\text{high-skilled labor share}^{s'}-\text{high-skilled labor share}^s\rvert$	1.3961	

Description: This table presents the model parameters that are estimated with the SMM method within the model and focuses on the parameters related to production, trade, and migration. We present the key parameters related to robot and tool technologies in Table 6.

C.6 Aggregate Statistics

Changes in employment of type $e \in \{H, L\}$ and total employment equal the following:

$$\text{dlog}(L^e) = \sum_{n=1}^{N} \sum_{s=1}^{S} \frac{l_{n,t_0}^{s,e}}{\sum_{n=1}^{N} \sum_{s=1}^{S} l_{n,t_0}^{s,e}} \text{dlog}(l_{n,t_0}^{s,e}),$$

and

$$\text{dlog}(L) = \frac{\sum_{n=1}^{N}\sum_{s=1}^{S} l_{n,t_0}^{s,H}}{\sum_{n=1}^{N}\sum_{s=1}^{S} l_{n,t_0}^{s,H} + l_{n,t_0}^{s,L}}\,\text{dlog}(L^H) + \frac{\sum_{n=1}^{N}\sum_{s=1}^{S} l_{n,t_0}^{s,L}}{\sum_{n=1}^{N}\sum_{s=1}^{S} l_{n,t_0}^{s,H} + l_{n,t_0}^{s,L}}\,\text{dlog}(L^L).$$

The skill premium at time t equals the following:

$$\text{Skill Premium} = \frac{\frac{1}{\sum_{n=1}^{N}\sum_{s=1}^{S} l_{n,t}^{s,H}}\sum_{n=1}^{N}\sum_{s=1}^{S} w_{n,t}^{s,H} l_{n,t}^{s,H}}{\frac{1}{\sum_{n=1}^{N}\sum_{s=1}^{S} l_{n,t}^{s,L}}\sum_{n=1}^{N}\sum_{s=1}^{S} w_{n,t}^{s,L} l_{n,t}^{s,L}}.$$

Average foreign price change for capital $l \in \{R, T\}$:

$$\text{Ave Price Chg. for } l = \sum_{n=1}^{N}\sum_{s=1}^{S} \frac{IMP_n^{s,l}}{\sum_{n=1}^{N}\sum_{s=1}^{S} IMP_n^{s,l}}\left(\text{dlog}(h_{n,N+1}^{s,l}) + \text{dlog}(t^{s,l})\right)$$

Average tariff for capital $l \in \{R, T\}$:

$$\text{Ave Tariff for } l = \sum_{n=1}^{N}\sum_{s=1}^{S} \frac{IMP_n^{s,l}}{\sum_{n=1}^{N}\sum_{s=1}^{S} IMP_n^{s,l}}\tau^{s,l}$$

The change in workers' welfare equals the weighted average of workers of both types from all regions and sectors:

$$\begin{aligned}
\text{dlog}\, v^{worker} &= \sum_{n=1}^{N}\sum_{s=1}^{S} \frac{l_{n,t_0}^{s,H}(v_{n,t}^{s,H} - v_{n,t_0}^{s,H}) + l_{n,t_0}^{s,L}(v_{n,t}^{s,L} - v_{n,t_0}^{s,L})}{\sum_{n=1}^{N}\sum_{s=1}^{S} l_{n,t_0}^{s,H} v_{n,t_0}^{s,H} + l_{n,t_0}^{s,L} v_{n,t_0}^{s,L}} \\
&= \sum_{n=1}^{N}\sum_{s=1}^{S} \frac{l_{n,t_0}^{s,H} v_{n,t_0}^{s,H}}{\sum_{n=1}^{N}\sum_{s=1}^{S} l_{n,t_0}^{s,H} v_{n,t_0}^{s,H} + l_{n,t_0}^{s,L} v_{n,t_0}^{s,L}} \frac{v_{n,t}^{s,H} - v_{n,t_0}^{s,H}}{v_{n,t_0}^{s,H}} \\
&+ \frac{l_{n,t_0}^{s,L} v_{n,t_0}^{s,L}}{\sum_{n=1}^{N}\sum_{s=1}^{S} l_{n,t_0}^{s,H} v_{n,t_0}^{s,H} + l_{n,t_0}^{s,L} v_{n,t_0}^{s,L}} \frac{v_{n,t}^{s,L} - v_{n,t_0}^{s,L}}{v_{n,t_0}^{s,L}}.
\end{aligned}$$

The change in national welfare equals the weighted average of workers of both types and capitalists from all regions and sectors:

$$\text{dlog}\, v^{national} = \sum_{n=1}^{N}\sum_{s=1}^{S} \frac{l_{n,t_0}^{s,H}(v_{n,t}^{s,H} - v_{n,t_0}^{s,H}) + l_{n,t_0}^{s,L}(v_{n,t}^{s,L} - v_{n,t_0}^{s,L}) + (v_{n,t}^{s,Cap,R} - v_{n,t_0}^{s,Cap,R}) + (v_{n,t}^{s,Cap,T} - v_{n,t_0}^{s,Cap,T})}{\sum_{n=1}^{N}\sum_{s=1}^{S} l_{n,t_0}^{s,H} v_{n,t_0}^{s,H} + l_{n,t_0}^{s,L} v_{n,t_0}^{s,L} + v_{n,t_0}^{s,Cap,R} + v_{n,t_0}^{s,Cap,T}},$$

where $v_{n,t_0}^{s,Cap,R}$ and $v_{n,t_0}^{s,Cap,T}$ denote the welfare (discounted utility) of robot and tool capitalists defined based on Equation (16).

According to the income approach, the country's normal GDP can be calculated by aggregating the wage bill, rental income, and profits generated by capitalists:

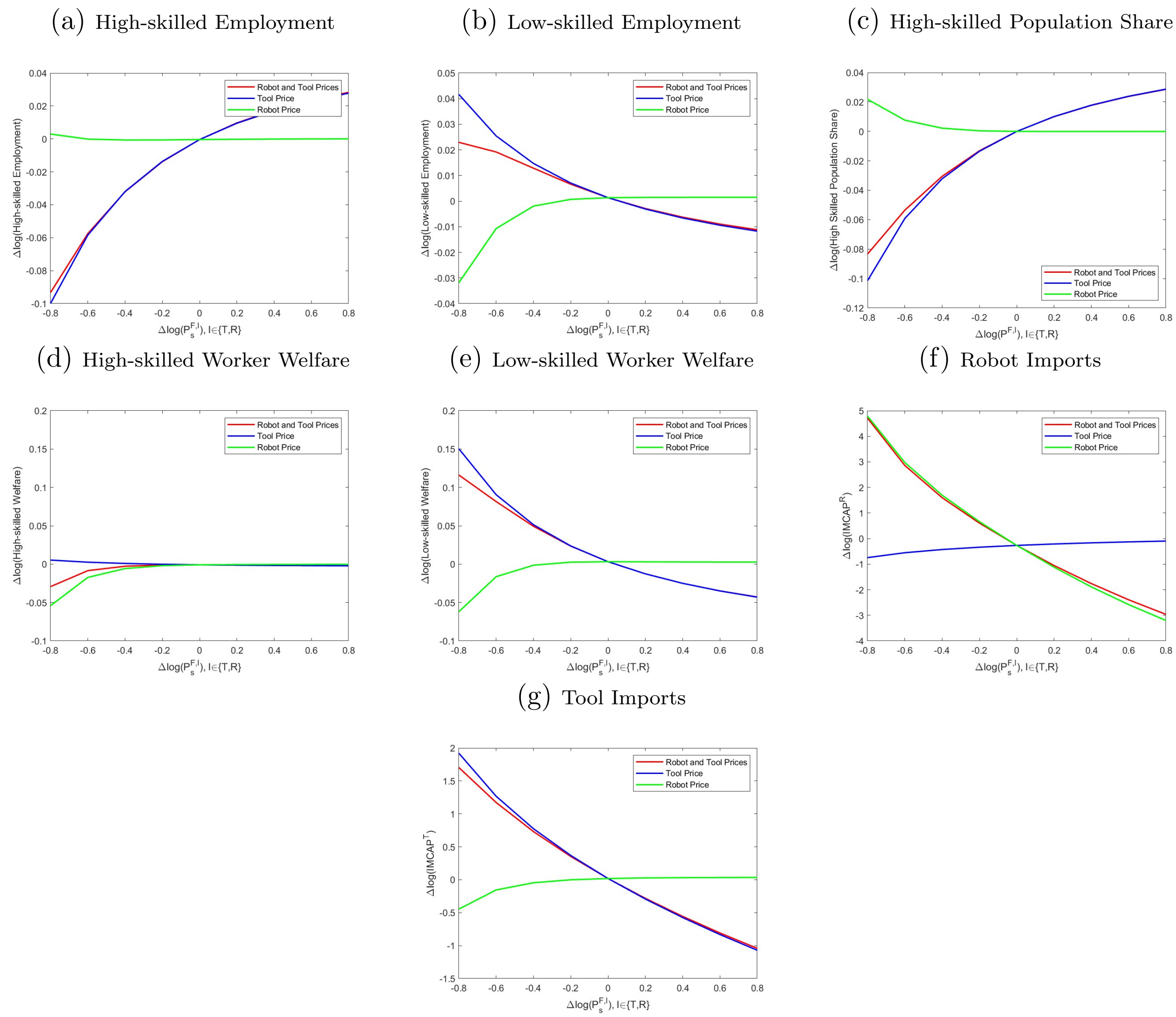
$$NGDP = \sum_{n=1}^{N} \sum_{s=1}^{S} w_n^{s,H} l_n^{s,H} + w_n^{s,L} l_n^{s,L} + (R_n^{s,R} K_n^{s,R} - \Sigma_n^{s,R} M_n^{s,R}) + (R_n^{s,T} K_n^{s,T} - \Sigma_n^{s,T} M_n^{s,T}).$$

The change in real GDP measures the change in quantity, while prices remain the same. Therefore,

$$\begin{aligned}
\mathrm{dlog}(GDP) = \frac{1}{NGDP} \sum_{n=1}^{N} \sum_{s=1}^{S} & w_n^{s,H} l_n^{s,H} \, \mathrm{dlog}(l_n^{s,H}) + w_n^{s,L} l_n^{s,L} \, \mathrm{dlog}(l_n^{s,L}) \\
& + R_n^{s,R} K_n^{s,R} \, \mathrm{dlog}(K_n^{s,R}) - \Sigma_n^{s,R} M_n^{s,R} \, \mathrm{dlog}(M_n^{s,R}) \\
& + R_n^{s,T} K_n^{s,T} \, \mathrm{dlog}(K_n^{s,T}) - \Sigma_n^{s,T} M_n^{s,T} \, \mathrm{dlog}(M_n^{s,T}).
\end{aligned}$$

C.7 Other Results

Figure C.2: **Aggregate Effects of Robot and Tool Import Price Changes**



Description: The figure illustrates the effects of varying robot and tool import prices (80% decrease to 80% increase) on high-low-skilled employment, high-skilled population share, high-low-skilled welfare, and robot and tool imports, relative to the initial steady state (1997). Red lines represent simultaneous robot and tool price changes, blue lines represent tool-only changes, and green lines represent robot-only changes. Uniform price changes across all sectors are considered.

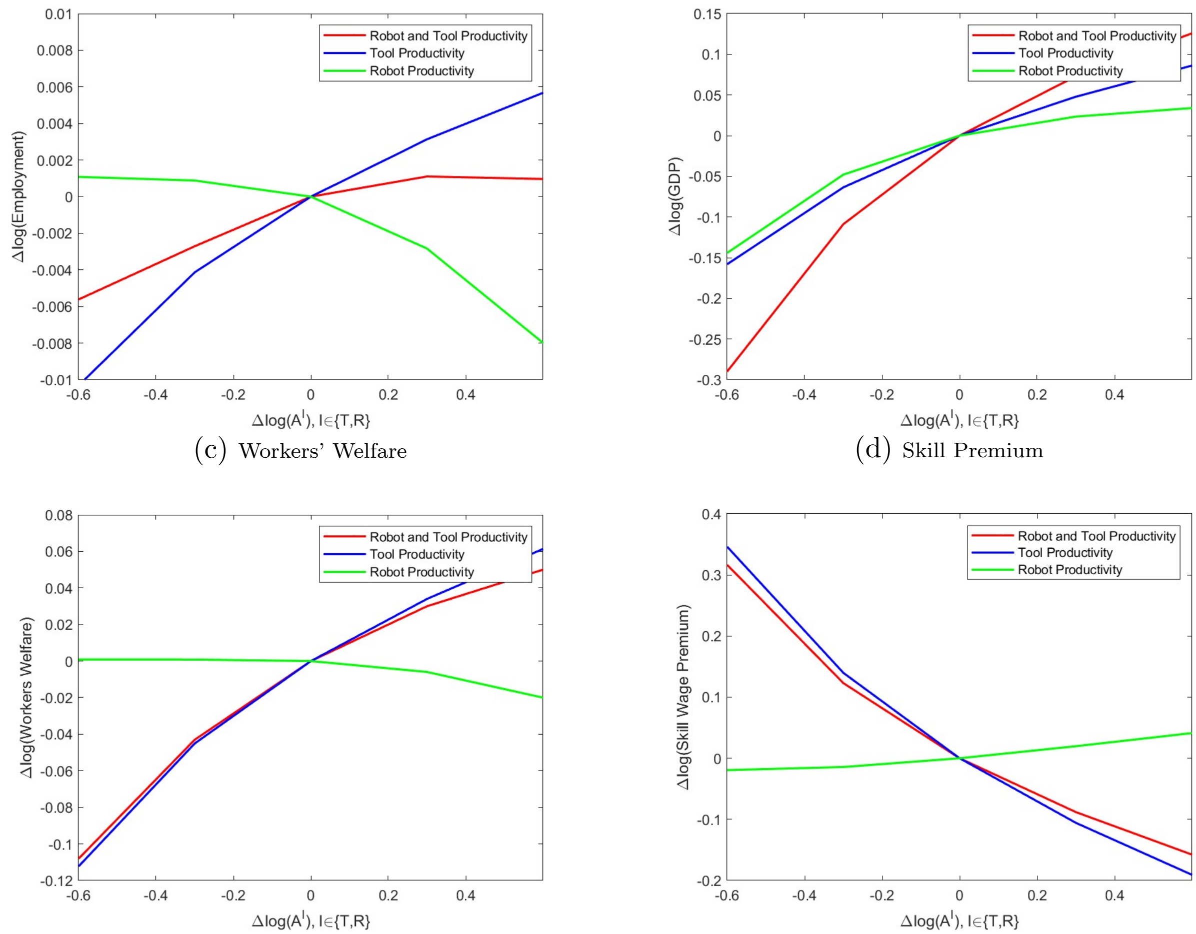
C.8 Effects of Capital Producers' Productivity Changes

Figure C.3a shows that a decrease in the productivity of robot producers or an increase in the productivity of tool producers can lead to a rise in aggregate employment. Enhancing the productivity of tool producers by 60% results in a 0.6% increase in employment, whereas raising the productivity of robot producers by 60% results in a 0.8% increase in employment.

Simultaneous productivity enhancements of a comparable magnitude for both robot and

Figure C.3: **Aggregate Effects of Robot and Tool Capital Producer Productivity Changes**

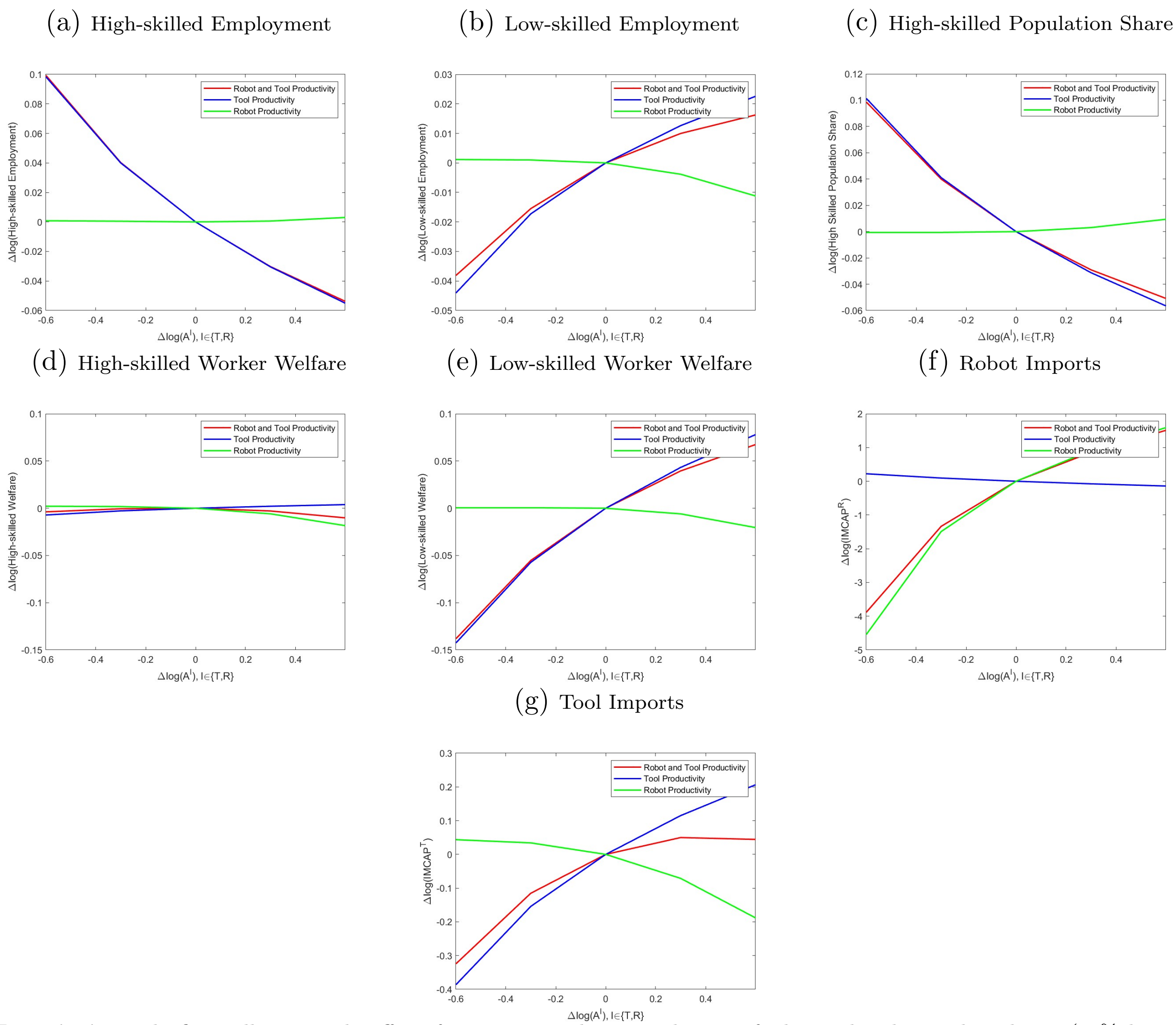
(a) Employment (b) GDP (c) Workers' Welfare (d) Skill Premium



Description: The figure illustrates the effects of varying productivity changes for robot and tool capital producers (60% decrease to 60% increase) on aggregate employment, GDP, workers' welfare, and skill premium, relative to the initial steady state (1997). Red lines represent simultaneous robot and tool capital producer productivity changes, blue lines represent tool-only changes, and green lines represent robot-only changes. Uniform capital producer productivity changes across all regions and sectors are considered.

tool producers, can significantly boost GDP while having little effect on employment and a positive effect on workers' welfare. Figure C.3b shows that an increase in the productivity of either robot or tool producers can lead to a rise in GDP; a 60% increase in the productivity of both robot and tool producers results in a 30% growth in GDP. Similar to the employment effects, workers' welfare also increases with tool producers' productivity but decreases with robot producers' productivity (Figure C.3c). However, the improvement in tool technology has a much greater positive impact on workers' welfare compared to the negative effect of advancements in robot technology. Figure C.3d shows that an increase in the productivity of robot producers or a decrease in the productivity of tool producers can significantly increase the skill premium and inequality. Tool productivity changes can affect the skill premium more substantially compared to robot productivity changes. We present the effects of productivity changes for robot and tool capital producers on other aggregate outcomes in Figure C.4.

Figure C.4: **Aggregate Effects of Robot and Tool Capital Producer Productivity Changes**



Description: The figure illustrates the effects for varying productivity changes of robot and tool capital producers (60% decrease to 60% increase) on high-skilled/low-skilled employment, high-skilled population share, high-skilled welfare, low-skilled welfare, robot imports, and tool imports, relative to the initial steady state (1997). Red lines represent simultaneous robot and tool capital producer productivity changes, blue lines represent tool-only changes, and green lines represent robot-only changes. Uniform capital producer productivity changes across all regions and sectors are considered.