Robots, Tools, and Jobs:

Evidence from Brazilian Labor Markets

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Abstract

How do robots and tools affect employment and labor market inequality? Using natural language processing and an instrumental variable approach, we discover that robots lead to a sizable decrease in the employment and wages of low-skilled workers in operational occupations. However, tools, i.e., machines that complement labor, lead 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 labor market inequality and increased welfare without significantly affecting employment.

Key Words: robots, automation, tools, labor-saving, labor-augmenting
JEL: J23, J24, F63

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1 Introduction

Technological progress has drastically reduced the cost of automation. From 1995 to 2016, the price of imported industrial robots in Brazil fell by about 40%, making automation increasingly accessible to firms.[1] As a result, robot adoption surged across industries, raising concerns among economists and policymakers that automation could displace workers and drive widespread job losses (Acemoglu and Restrepo 2020, Humlum 2021, Hubmer and Restrepo 2021, Martinez 2021, Boustan et al. 2022).

However, technological progress has also reduced the cost of labor-augmenting machines. For example, the price of power tools imported by Brazilian firms decreased by about 20% over the same period.[2] These cheaper tools could make workers more productive and raise both employment and wages, unlike the expected effects of robots. As a result, it is unclear whether technological progress in machinery ultimately harms or benefits workers; the overall effect depends on the relative strength of these two opposing forces.

In this paper, we study how robots and tools, i.e., machines that complement labor, affect employment and welfare. While the impact of robots on employment is ambiguous (Acemoglu and Restrepo 2020), our model predicts that cheaper tools increase low-skilled employment and reduce inequality. To bring the model to the data, we use natural language processing to classify 535 different machines imported by Brazilian firms into two categories: those that are more likely to replace workers, which we refer to as robots, and those that are more likely to complement workers, which we refer to as tools. Exploiting a policy reform that lowered import tariffs on capital goods as an instrument (Dix-Carneiro and Kovak 2017, 2019), we show that tools reinstate as many workers as robots displace. Overall, cheaper machinery over the past few decades has raised welfare without significantly reducing employment.

Our first step is to study the effects of robots and tools in a simple theoretical framework. To do so, we expand the model of Acemoglu and Restrepo (2020) to include tools. In the model, firms produce by performing tasks with robots or with workers. Workers can be low-skilled, who operate tools, or high-skilled, who provide managerial and service inputs. Because tools complement low-skilled workers, a decrease in the price of tools increases their employment and decreases inequality. Robots, however, raise inequality but have an

[1] Graetz and Michaels (2018) also show a sizable decrease in the international price of industrial robots.
[2] Power tools include chainsaws, bandsaws, angle grinders, and other hand-operated equipment.

uncertain effect on employment. The degree to which robots and tools affect the labor market will depend on the model's particular parameters, which we identify with the data.[3]

There are two challenges in bringing the model to the data: classification and identification. The first challenge involves distinguishing machines that replace workers from those that complement them. Previous studies have addressed this classification challenge by focusing exclusively on industrial robots, which made up just 0.5% of all machine types and 3% of Brazil's capital imports in 2019. This approach reduces the risk of misclassification but significantly limits the scope of analysis. The second challenge lies in identifying exogenous variations in machine adoption to separate their effects from other shocks in the labor market.

To tackle the first challenge, we classify machines as robots or tools using natural language processing and detailed machine descriptions from administrative import data for Brazil. Inspired by Argente et al. (2020), we compare the description of each machine to two sets of reference text: one describing automation technologies (e.g., industrial robots) and the other describing worker-operated tools (e.g., power tools). A machine is labeled a robot if its description is more similar to the automation reference text than to the tool reference text.

To validate the classification algorithm, we perform a battery of tests. First, we show that the machines most associated with robots are "industrial robots" and other numerically controlled machines.[4] The machines most associated with tools consist of a variety of hand-operated equipment. These results indicate that the algorithm effectively captures intuitive distinctions between labor-replacing and labor-augmenting machines. Second, the words relevant to the classification algorithm are those directly associated with robots, such as "automatic" or "numeric," or those associated with the use of tools, such as "hand" and "operate." Having words associated with robots or with tools significantly increases the likelihood of a machine being classified accordingly.

We address the identification challenge by using tariff changes at the machine level as instruments for their adoption. Due to pressure from the Southern Common Market (Mercosur), at the beginning of the 2000s, the Brazilian government reduced import tariffs on capital goods from 14% to 8%, with rates varying across machines. Because tariffs affect

[3] In the quantitative model, we allow robots to complement high-skilled workers. We find that, quantitatively, this force is not significant.

[4] Supporting this classification, Boustan et al. (2022) show that the rise of numerically controlled machines has also led to the displacement of workers and an increase in automation.

the final price of imported machines and are unrelated to labor market shocks (Dix-Carneiro and Kovak 2017), they provide a valid instrument for the imports of robots and tools.[5] Several pieces of evidence support the assumption that capital tariff changes were exogenous to local labor markets in Brazil. First, tariff changes are not correlated with past labor market trends. Second, tariff changes are not correlated with campaign contributions, showing that political meddling in the determination of tariffs is unlikely. Third, tariffs are not correlated with other relevant policies of the period, such as subsidized loans or federal procurement. Finally, the policy reformed was pushed by the other Mercosur members and not Brazil itself.

We find that tools increase the employment and wages of low-skilled workers who operate machinery. A 1% increase in tool adoption increases the employment and wages of low-skilled workers by 0.17% and 0.04%, respectively, without any significant effect on high-skilled workers. The effect of tools is larger on operational and technical workers, i.e., those who directly operate machinery.

Robots, meanwhile, disrupt the labor market. A 1% increase in robot adoption reduces employment by 0.22%, an effect seven times larger than that reported by Acemoglu and Restrepo (2020).[6] As with tools, the impact is concentrated among low-skilled workers in operational occupations. Taken together, these results suggest that if the adoption of tools and robots increases by the same amount, the net effect on employment would be close to zero.

Our estimates of the employment effect of robots are substantially larger than those reported in previous studies, which can be explained by omitted variable bias in the traditional specification. An increase in robot adoption also leads to an increase in tool adoption. Our quantitative model rationalizes this relationship through the productivity effect: as robots become more widely used, productivity and output rise, which in turn increases the demand for tools, which are machines that increase employment. As a result, specifications that omit tools do not identify the true effect of robots, but instead estimate a net effect that combines the negative impact of robots with the positive impact of tools. Supporting this interpretation, we show that removing tools from our baseline specification delivers an estimated

[5]To isolate the effect of tariffs on machines, we control for tariffs on the final goods and other inputs of each sector.

[6]Acemoglu and Restrepo (2020) find that a 1% increase in robot adoption decreases employment by 0.003%. Dauth et al. (2021), Rodrigo (2022), and Graetz and Michaels (2018) find no significant effect of robots on employment.

coefficient that is statistically indistinguishable from that in Acemoglu and Restrepo (2020).

To move from the relative effects identified in the data to aggregate effects, we build a quantitative model with multiple sectors and regions calibrated to match the empirical findings. In the model, firms choose between adopting robots, which replace labor and require high-skilled operators, and using tools, which complement workers. They acquire robots and tools domestically and internationally. Workers decide whether to enter the labor force and choose their skill level, region, and sector. We calibrate the model's key parameters to replicate the empirical estimates of the effects of robots and tools on employment.

The model shows that the decline in the prices of robots and tools over the past 20 years has increased welfare and reduced inequality, with little effect on overall employment. The employment loss from cheaper robots is offset by the employment gain from cheaper tools. As a result, aggregate employment remains unchanged. However, lower capital costs reduce final goods prices, raise production, and increase welfare. Because tools complement low-skilled workers, their increased adoption leads to a decline in the skill premium. Therefore, technological progress in machinery has increased welfare and lowered inequality without significantly affecting employment.

Our main contribution is to add tools to the theoretical, empirical, and quantitative analysis of automation, leading to new conclusions and policy implications. Graetz and Michaels (2018) and Acemoglu and Restrepo (2020) show that automation decreases low-skilled employment and wages. Several economists have expanded their analyses to study the effect of automation at the firm level (Hubmer and Restrepo 2021, Humlum 2021, Martinez 2021), and on inequality (Adachi 2022, Acemoglu and Restrepo 2022, Cheng et al. 2021). Several papers have used import data to measure the degree of automation of different sectors and firms, such as Humlum (2021). Boustan et al. (2022), similarly to us, expand the analysis beyond industrial robots and show that computer numerical control has replaced semi-skilled manufacturing workers. Gregory et al. (2021) also study the interaction between international trade and automation.

We make several contributions to the automation literature. First, we expand the scope of the literature beyond industrial robots, which represented only 3% of capital imports and 0.5% of machinery products in Brazil in 2019.[7] We do so by using text analysis to classify machines as technologies associated with automation or those that complement workers.

[7]By contrast, according to our definition, robots account for 11% of capital imports and 10% of machinery products, while tools make up the remaining 89% and 90%, respectively.

Second, we propose a new instrument for the adoption of robots and tools exploiting variation on capital tariffs, an instrument that can be used in other contexts. Third, 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. Fourth, we highlight that previous research has underestimated the impact of robots on the labor market by not controlling for the associated increase in the adoption of tools. Lastly, we use our quantitative model to study capital taxation in an economy with robots and tools.

The paper is organized as follows. Section 2 discusses the simple model. Section 3 presents the data and Section 4 presents 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

We first analyze how tools and robots affect the labor market with a simple model, the implications of which are subsequently tested with data. We make three contributions to the canonical framework of Acemoglu and Restrepo (2020). First, we introduce tools as a form of capital that complements workers in their tasks. Second, we develop a new technology choice model and derive closed-form solutions for the effects of robots and tools on employment and wages. Third, we account for worker heterogeneity, which enables us to study the impact of robots and tools on inequality.

The model offers three new insights. First, a decrease in the price of tools boosts the employment of low-skilled workers, primarily due to the complementarity between low-skilled workers and tools. Second, the impact of tools on high-skilled workers is uncertain, as high-skilled and low-skilled workers are substitutes. Third, while an increase in the adoption of robots increases inequality, a rise in the adoption of tools decreases it.

2.1 Model Setup

Environment. There are two sectors: one with tasks that can be automated and another that cannot be easily automated.[8] The automatable sector has a representative firm that performs a set of production tasks. Each task can be performed by robots or by workers using tools.

There are two types of workers: low-skilled workers, who operate tools for production, and high-skilled workers, who manage low-skilled workers in performing tasks. The wages of high-skilled and low-skilled workers, w_H and w_L, are determined endogenously. In this section, we assume that robots and tools are imported with exogenous prices P_R and P_T.[9]

The economy's aggregate output combines the automatable and non-automatable sectors' output:

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

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 $\psi > 1$.[10]

Representative Firm and Tasks. A representative firm in the automatable sector produces by combining output from a continuum of tasks, $\nu \in [0, 1]$. The production function for the automatable sector is:

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

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 by either robots or workers using tools:

$$y(\nu) = y_R(\nu) + y_T(\nu),$$

[8] The relevant assumption for our results is that there are different sectors with different shares of tasks that can be automated. To keep the model simple, we assume only two sectors with one of them not using capital. In the quantitative model, we relax this assumption, allowing for several sectors with differing degrees of automatability.

[9] In the quantitative model to be introduced in Section 7, both types of capital are produced both abroad and domestically. In this case, capital prices will be affected by domestic policies.

[10] Similar assumptions are made by Acemoglu and Restrepo (2020, 2022), among others.

where $y_R(\nu)$ and $y_T(\nu)$ are the outputs of task ν, using robots or tools, respectively.[11] The production function of task ν with robots is:

$$y_R(\nu) = Z_R(\nu) k_R(\nu), \tag{1}$$

where $Z_R(\nu)$ is the productivity of robots in task ν and $k_R(\nu)$ denotes the quantity of robots. The marginal cost of completing task ν with robots is $\frac{P_R}{Z_R(\nu)}$.

Alternatively, task ν can be completed with workers and tools. Low-skilled workers use tools to produce intermediate goods, which are further combined with managerial and service inputs from high-skilled workers. The production function is the following:

$$y_T(\nu) = Z_T(\nu) \left[(\ell_H(\nu))^{\frac{\sigma-1}{\sigma}} + \left((\ell_L(\nu))^{\delta} (k_T(\nu))^{1-\delta} \right)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}, \tag{2}$$

where $Z_T(\nu)$ is the productivity of using tools for task ν, $\ell_L(\nu)$ is the number of low-skilled workers involved in the task, $\ell_H(\nu)$ is the number of high-skilled workers, 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. This assumption follows from the observation that most tools—such as drill presses, mechanical lathes, welding machines, and other physically intensive industrial equipment—are typically operated by low-skilled workers. Furthermore, as we will demonstrate empirically, this assumption explains the positive effect of tool adoption on the employment of low-skilled workers.

The firm chooses the least costly technology with which to complete task ν:

$$c(\nu) = \min \left\{ \frac{P_R}{Z_R(\nu)}, \frac{\left((w_H)^{1-\sigma} + \left(w_L^{\delta} P_T^{1-\delta} \right)^{1-\sigma} \right)^{\frac{1}{1-\sigma}}}{Z_T(\nu)} \right\}.$$

[11] We assume that robots do not require high-skilled workers. In Section 6, we show that the empirical results are consistent with this assumption. In the quantitative model, we relax this assumption by allowing high-skilled workers to work with robots. We show that this margin is not quantitatively relevant.

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

Task Heterogeneity. Tasks are heterogeneous in the relative productivity of robots and tools, which follows a Fréchet distribution i.i.d. across tasks (ν) and technologies (l):

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

θ, the shape parameter, governs the elasticity of substitution between technologies.[13] T_l, the scale parameter, determines the mean relative productivity of technology l.

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.[14] Therefore,

$$p_N = 1.$$

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

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

where A_H and A_L are parameters that affect the levels of labor supply.[15] 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.[16]

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.

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

[14] 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 instead assume that the non-automatable sector relies on a factor other than labor. This assumption helps us to eliminate the confounding effect of sector labor composition on inequality and enables us to focus on the impact of robots and tools. We relax this assumption in the quantitative model in Section 7.

[15] 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.

[16] 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:*

$$\frac{d\log \ell_L}{d\log P_R} = \beta_R^L \left[(1-s_A)(1-\psi)+\theta\right] \tag{3}$$

$$\frac{d\log \ell_H}{d\log P_R} = \beta_R^H \left[(1-s_A)(1-\psi)+\theta\right], \tag{4}$$

where $\beta_R^L > 0$, $\beta_R^H > 0$, and s_A denotes the share of the automatable sector in total output.

The impact of robots on employment depends on two opposing forces: the productivity effect and the displacement effect. The productivity effect is represented by the first term in Equations (3) and (4): $(1-s_A)(1-\psi)$. As the price of robots decreases, the automatable sector firm becomes more productive and expands, which increases the demand for all workers. The displacement effect, denoted by θ, arises from an increase in the share of tasks performed by robots, which reduces the demand for workers. The overall effect of robots on employment is determined by the relative strength of these two opposing forces.[17]

Tools Increase Employment of Low-Skilled Workers. Proposition 2 shows that cheaper tools increase the demand for low-skilled workers. Since tools complement low-skilled labor, more affordable tools decrease the marginal cost of producing with low-skilled workers, encouraging the firm to hire more of them.

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

$$\frac{d\log \ell_L}{d\log P_T} = \beta_T^L \left[(1-s_A)(1-\psi)(1-s_R) - \theta s_R + \frac{s_{T,H}(1-\sigma)(\xi+1)}{s_{T,H}(\sigma-1)+(1-s_{T,H})(\xi+\sigma)}\right] < 0, \tag{5}$$

where $\beta_T^L > 0$, s_R denotes the share of robots in automatable sector output, and $s_{T,H}$ denotes the cost share of high-skilled workers in the tool technology.

[17] This result highlights the importance of the production function described in Equation (2), where high- and low-skilled workers are combined to complete a task. Suppose that, instead, they perform different tasks, with low-skilled tasks being exposed to automation while high-skilled tasks are not. In this case, a decrease in the price of robots will increase the employment of high-skilled workers due to the productivity effect. This outcome contradicts the empirical findings presented later.

When the price of tools decreases, three forces affect the demand for low-skilled workers: the productivity effect, the reinstatement effect, and the complementarity effect. The productivity effect, captured by $(1 - s_A)(1 - \psi)(1 - s_R)$, and the reinstatement effect, captured by $-\theta s_R$, both lead to an increase in the demand for low-skilled workers as tools become cheaper—similar to the case of robots.

The complementarity effect refers to the third term in Equation (5). When tools become cheaper, firms prefer to use more low-skilled workers with tools instead of high-skilled workers for the tasks already performed with tools, further raising the demand for low-skilled workers. Because all forces are in the same direction, a reduction 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 decrease in the price of tools on high-skilled employment is uncertain because the substitution from high-skilled to low-skilled workers reduces 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*

$$\frac{d \log \ell_H}{d \log P_T} = \beta_T^H \left[(1 - s_A)(1 - \psi)(1 - s_R) - \theta s_R + (\sigma - 1) \right], \tag{6}$$

where $\beta_T^H > 0$.

When the prices of tools decrease, three forces affect the demand for high-skilled workers: the productivity, reinstatement, and substitution effects. As with low-skilled workers, the productivity and reinstatement effects push toward higher demand for high-skilled labor. However, the substitution effect, captured by $(\sigma - 1)$ in Equation 6, works in the opposite direction. As tools become cheaper, firms use more low-skilled workers for each task done by labor, substituting high-skilled workers. The net effect of cheaper tools on high-skilled employment is ambiguous, depending on the relative strength of these opposing forces.

Robots Increase Inequality and Tools Decrease It. Machines affect inequality because high- and low-skilled workers have different relationships with robots and with tools. When the price of robots decreases, if the displacement effect dominates the productivity effect, the demand for both worker types declines. However, the wage of low-skilled workers declines more. Proposition 4 formalizes this result.

Proposition 4. *Suppose* $(1-s_A)(1-\psi)+\theta > 0$*, 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 decreases, there is a greater demand for low-skilled workers because they complement the use of tools. As a result, the skill premium decreases.

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 increase inequality and might decrease employment, tools increase low-skilled employment and decrease inequality. In the following sections, we test these predictions with data. We identify the particular machines that are the most similar to the model's definition of robots and tools. Then, using data from Brazil, we study their effects on the labor market.

3 Data

We construct a dataset combining labor market outcomes with detailed information on machine imports by sector, region, and year in Brazil. Specifically, we observe the value of each imported machine—defined at the 6-digit Harmonized System (HS) level—for every sector–region–year cell.[18] Using text analysis, we classify each machine as either a robot or a tool, following the model.

Labor Market Information. The main source of labor market information is the RAIS dataset—*Relação Anual de Informações Sociais*—a matched employer–employee adminis-

[18]These data were also used by de Souza (2020).

trative dataset collected by the Brazilian Ministry of Labor. RAIS covers the universe of formal employment relationships in Brazil from 1997 to 2014. Its reliability and richness have made it a widely used source in empirical research across various fields of economics.[19] For our purposes, we use RAIS to calculate total employment and average wages by sector, region, and year—variables affected by the adoption of robots and tools according to our model. In addition, we compute average years of education, employment, and wages by educational group, and employment by occupation group.[20]

Import Data at the Product–Sector–Region Level. We use monthly import data from the Brazilian Secretary of International Trade covering 1997 to 2014. The dataset includes detailed information on each import transaction, such as product description, city of the importing establishment, quantity and value imported, and the product's classification under the HS code—a standardized international nomenclature used to identify traded goods.[21]

To identify the sector of the firm importing each product, we merge this dataset with confidential administrative records that report the sector of the importing establishment.[22] This enables us to assign each imported machine to the sector of the firm that uses it, rather than relying on aggregate input–output tables. By combining sector and location, we construct a final dataset with imports of each product by sector, microregion, and year.

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

4 Machine Classification

A key challenge in understanding the effects of automation and linking the model to the data is the wide variety of machines that firms adopt, which extends beyond just industrial robots. In our dataset, manufacturing firms import 535 different machinery products at the HS 6-digit level. To avoid misclassification, previous works have typically focused on a single machine type, industrial robots. While this strategy minimizes classification error, it

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

[20] A microregion, which is defined by the Brazilian Institute of Geography and Statistics, is made up of municipalities that are economically connected. There are 558 microregions in the sample.

[21] Products are classified at the 8-digit level in the Brazilian nomenclature, which consists of the first 6 digits of the international HS code plus 2 digits specific to Mercosur.

[22] To preserve firm anonymity, this dataset is not publicly available.

drastically narrows the scope of the analysis. In Brazil, industrial robots accounted for just 3% of capital imports and only 0.5% of machinery products in 2019.

To bring the model to the data, we develop a text-based method to classify machines. Inspired by Argente et al. (2020), we measure the similarity between machine descriptions and reference texts representing robots and tools. The procedure consists of four steps. First, we use HS codes to extract the official descriptions of machines imported by Brazilian firms. Second, we compile a set of reference texts that characterize machines that automate tasks done by workers (robots) and machines that are hand operated by workers (tools). Third, we compute the textual similarity between each machine description and the reference texts. Finally, we classify each machine as a robot or a tool based on the reference text to which it is most similar. We describe each step of the procedure in detail below.[23]

Sample Selection: Identifying Relevant Production Machinery. We focus on machines used directly in the production process, rather than those used in administrative or support functions. The import data include all types of goods purchased by firms, including intermediate inputs, office equipment, durable goods, and a variety of capital goods. However, not all of these are relevant for studying the effects of automation and labor-augmenting technologies. Since the model focuses on machinery that either substitutes for or complements labor in production, we restrict the sample to capital goods used in core production activities across tradable sectors such as manufacturing, mining, and agriculture.

We isolate production machines from other imported products in three steps. First, we restrict the dataset to capital goods using the official classification provided by the Secretary of International Trade. This step removes non-durable intermediate goods, such as raw materials. Second, we further narrow the sample to capital goods that have been imported at least once by firms in production sectors. This step excludes products not used in production, such as MRI scanners and military equipment. It also removes goods typically imported and sold through retail channels, like office equipment and computers.

Third, we remove HS codes corresponding to durable intermediate inputs that are not directly involved in production tasks, such as furniture. To do so, we restrict the sample to HS chapters 82 to 90, which include hand tools, metal items, mechanical appliances, and precision instruments.[24]

[23]Similar classification includes Kogan et al. (2023) and Dechezleprêtre et al. (2021), who classify patents rather than machines.

[24]We also remove boilers (8402, 8404), furnaces (8416), cooling equipment (8418), office machines (8472),

Reference Text. Following Argente et al. (2020), we use Wikipedia as the source for reference texts describing robots and tools. Wikipedia is one of the few publicly available sources that provides detailed descriptions of a wide variety of machines, including their applications and functional characteristics. An important advantage of using Wikipedia is that it organizes articles into thematic categories, which enables us to systematically collect machine descriptions without hand-picking individual pages. For robots, we use all articles under the "Industrial robots" category. For tools, we include articles from the "Power tools," "Hand tools," and "Cutting tools" categories, which focus on machines that complement workers in production tasks. A full list of the articles used is provided in Appendix B.1.1.

Text Similarity. After removing stop-words and lemmatizing the text, we compute the cosine similarity between each machine description and the set of Wikipedia reference articles. The algorithm represents each document as a vector, where each entry corresponds to a word: the entry equals 1 if the word appears in the document and 0 otherwise. The dimension of the vector is equal to the number of different words in all the combined documents. The similarity between two documents is then measured by the cosine distance between their corresponding vectors. A detailed explanation of the method and the weighting scheme is provided in Appendix B.1.2, following Argente et al. (2020).

Classification. We classify each machine as a robot or a tool based on its closest similarity among the Wikipedia reference articles. Let s_{jw} denote the text similarity between machine j and Wikipedia article w. The closest article is defined as $w_j^* = \arg\max_w s_{jw}$. If w_j^* belongs to a Wikipedia category associated with automation, we classify machine j as a robot; otherwise, we classify it as a tool.[25]

Validation of Machine Classification. In Section B.1.4, we validate our classification through a number of exercises. First, the classification delivers intuitive results: the machines most associated with robots are "industrial robots" and other numerically controlled machines, while those most associated with tools are various hand-operated pieces of equipment. Second, the words relevant to the classification algorithm are directly related to robots—such as "automatic," "robotic," "control," and "numerical"—or to the use of tools—such as

mold bases (8480), lighting and display equipment (8513, 8516, 8517, 8519, 8521, 8525, 8526, 8527, 8528, 8531, 8537, 8539), rafts (8907), medical instruments (9018–9022), and measuring devices (9023, 9028).

[25]Some machines may not fall clearly into either category or may share features of both. To address this, in the robustness section, we restrict the analysis to machines with the highest similarity scores relative to the reference texts and show that our results remain unchanged.

"tool," "operate," "handle," and "hand." Third, machines containing words associated with robots, such as "automatic," have a significantly higher probability of being classified as robots. Similarly, machines with words related to tools, such as "tool" or "operate," are more likely to be classified as tools.[26]

Alternative Classification Methods. In the robustness section, we explore two alternative strategies for classifying machines. First, instead of using the full set of production machines, we restrict the sample to those with text similarity scores above the median for either robots or tools. This approach excludes machines that are harder to classify, reducing the risk of misclassification. Second, we implement a classification procedure based on a large language model, which assigns each machine to either the robot or tool category based on its description. Our main conclusions are robust to these two alternative classification strategies.

5 Empirics

In this section, we present the empirical strategy used to estimate the impact of robots and tools on local labor markets. Since machine adoption is likely correlated with local economic conditions, we use tariff reductions on robots and tools as instruments for their adoption. These tariff changes were imposed by the Southern Common Market (Mercosur), among which Brazil is a member, and are plausibly exogenous to local labor market dynamics in Brazil.[27] By comparing employment growth across microregions in Brazil with different levels of exposure to lower capital tariffs, we identify the broader effects of robots and tools on labor markets—not just on the firms that adopt them—following an approach similar to Graetz and Michaels (2018), Acemoglu and Restrepo (2020), and Dauth et al. (2021), among others.

In this section, we explain how we identify the impact of robots and tools on local labor markets. We do this by comparing employment growth in markets with different levels of exposure to a decrease in tariffs on robots or tools. By studying how machine adoption affects the market as a whole, we capture the broader impact of robots, not just on the firms that adopt them.

[26] In Section B.1.3, we discuss summary statistics of robots and tools in Brazil.

[27] Mercosur is a regional trade bloc with a common external tariff, similar to the European Union.

5.1 Empirical Model

Main Empirical Model. Our main specification is the following:

$$\Delta \log(y_{r,s,t}) = \theta^R \Delta \log\left(robots_{r,s,t}\right) + \theta^T \Delta \log\left(tools_{r,s,t}\right) + X'_{r,s,t}\Theta + \mu_r + \mu_s + \mu_t + \epsilon_{r,s,t}. \quad (7)$$

The dependent variable, $\Delta \log(y_{r,s,t}) = \log(y_{r,s,t}) - \log(y_{r,s,t-5})$, is the five-year change in the log of a labor market outcome—such as employment or wages—in region r, sector s, and year t. We adopt a long-difference model because machine investments are typically lumpy and their effects on labor market outcomes unfold gradually. Each region r corresponds to a Brazilian microregion, the equivalent of a commuting zone in the US. Each sector s corresponds to a 4-digit CNAE 2.0 code. We restrict the sample to agriculture, mining, and manufacturing sectors, as they are the main adopters of production machines. The sample contains a total of 181 sectors and 538 microregions.

On the right-hand side, $robots_{r,s,t}$ is defined as 1 plus the total value in US dollars of robot imports over the previous five years. Therefore, $\Delta \log\left(robots_{r,s,t}\right)$ is the growth rate in robot imports by region r and sector s in year t. Similarly, $\Delta \log\left(tools_{r,s,t}\right)$ measures the growth rate in the imports of tools.

Fixed Effects Control for Differential Trends. As controls, we include a set of pre-period variables and fixed effects. $X_{r,s,t}$ contains the pre-period growth rate of the outcome variable $y_{r,s,t}$, which helps capture underlying labor market trends, as well as the tariff change on sectoral output and the tariff change on inputs excluding capital.[28] μ_r and μ_s are region and sector fixed effects. Because the model is specified in differences, these fixed effects absorb potential differential trends across regions and sectors. μ_t is a time fixed effect that controls for shocks common to all regions and sectors in a given year.

5.2 Instrument and First Stage

To identify the causal effect of robots and tools, we use heterogeneous exposure to tariffs across markets as instruments. Without exogenous variation, it is difficult to disentangle the impact of robots and tools from confounding labor market shocks. For example, a sector-specific demand shock could simultaneously increase investment and labor demand, making

[28] We also control for routine task content and manual task content, which are defined later.

it unclear whether observed changes are driven by the machines or by the demand shock.

Institutions: Lower Capital Tariffs due to Pressure from Mercosur. In the early 2000s, Brazil reduced import tariffs on capital goods—including robots and tools—from 14% to an average of 8%. This tariff change resulted from broader negotiations within Mercosur. At the time of Mercosur's formation, the members agreed that capital tariffs would converge to a common rate of 14% by 2001 (Mercosur Common Market Council 1994). However, Brazil was the only country to fully implement this commitment on schedule, leading to a significant unilateral reduction in capital tariffs at the start of the decade.

Argentina's economic crisis in 2001 reopened capital tariff negotiations within Mercosur. With the exception of Brazil, member countries advocated for further reductions in capital goods tariffs—particularly on goods not produced within the bloc—as a means to stimulate investment (Mercosur Common Market Council 2001, 2003a). These negotiations led to a bloc-wide agreement to lower capital tariffs (Mercosur Common Market Council 2003b), introducing a tiered system with rates ranging from 0% to 13%, according to which high-tech capital goods not produced within Mercosur faced the lowest tariffs (Mercosur Common Market Council 2005). As part of this agreement, Brazil implemented significant tariff reductions between 2000 and 2004. This externally imposed policy change generated variation in capital prices that is plausibly exogenous to local labor market conditions, providing a credible source with which to identify the effects of robots and tools.[29]

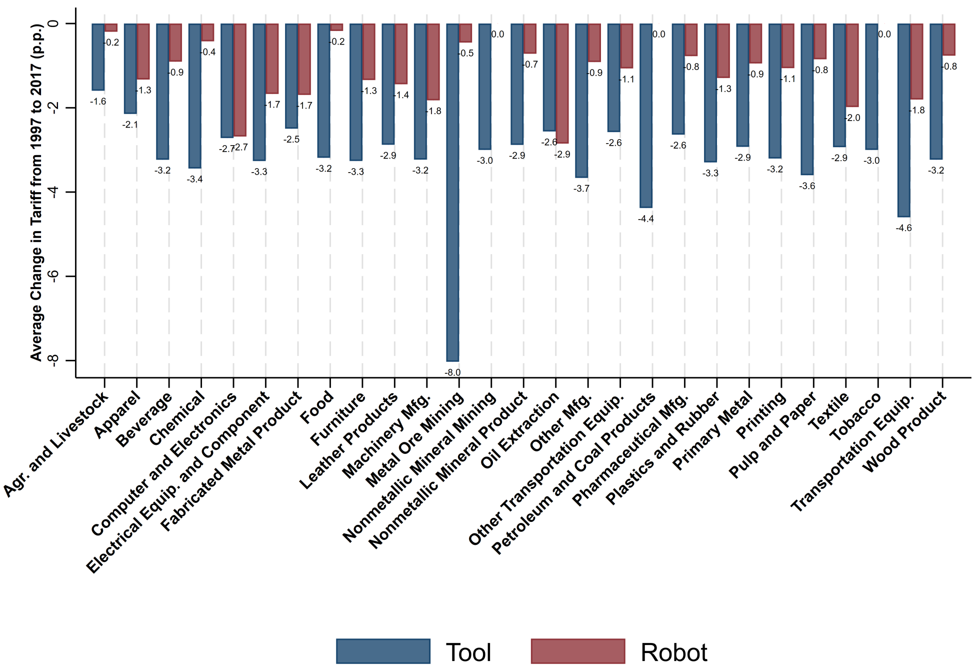
Tariffs on Robots and Tools as the Instrument. The tariff on robots imported by sector s in year t is given by

$$\tau^R_{s,t} = \sum_m \lambda_{R,m,s} \times \tau_{m,t} \times \mathbb{I}\left\{m \textit{ is a robot}\right\} \times \mathbb{I}\left\{m \textit{ is an input to sector } s\right\}, \tag{8}$$

where $\tau_{m,t}$ is the average import tariff on machine m in year t, $\mathbb{I}\left\{m \textit{ is a robot}\right\}$ is a dummy taking the value of 1 if machine m is classified as a robot, and $\mathbb{I}\left\{m \textit{ is an input in sector } s\right\}$ is a dummy taking the value of 1 if machine m has ever been imported by firms in sector s, i.e., if it is an input to sector s. $\lambda_{R,m,s}$ is the share of machine m among all robot imports by sector s in 1998. Therefore, $\tau^R_{s,t}$ is the average import tariff on robots of sector s in year t. We calculate the tariff on tools in a similar way.

[29]As part of the validation exercise, we show that sectors with higher tariff reductions exhibited parallel parallel trends with those experiencing smaller changes before the tariff cuts.

Figure 1: **Tariff Changes on Robots and Tools Between 1997 and 2014**



Description: This figure shows the average tariff changes in robots and tools in different 2-digit CNAE sectors.

Figure 1 plots the average changes in robot and tool tariffs across broadly defined sectors between 1997 and 2014. Since different sectors imported different machines, and each machine experienced different tariff reductions, the extent of tariff reduction varied across sectors. This variation provides sector-specific exposure to changes in the cost of adopting robots and tools, which we exploit in the instrument.

Heterogeneous Exposure to Tariff Changes. In addition to using tariff changes, we exploit heterogeneity in how markets respond to changes in the prices of robots and tools. Autor and Dorn (2013), Graetz and Michaels (2018), and Acemoglu and Restrepo (2020) argue that robots are more likely to replace workers in jobs that are intensive in routine tasks. Therefore, regions and sectors with a higher share of these tasks should respond more to robot tariff changes, as they have greater potential for automation. We build on this idea to construct the instrument as follows:[30]

$$IV^{robots}_{r,s,t} = Routine\ Task\ Content_{r,s,0} \times \tau^{R}_{s,t}, \tag{9}$$

[30]A similar approach is used by Graetz and Michaels (2018), Bonfiglioli et al. (2020), and Acemoglu and Restrepo (2022), among others. In Section B.3.2, we use only tariffs as instruments and show that the results are still the same.

where $Routine\ Task\ Content_{r,s,0}$ is the average routine task content among workers in region r and sector s in 1998.[31] $\tau^R_{s,t}$ is the tariff on robots used by sector s at time t weighted by pre-period trade flows, as defined in Equation (8).

We create a similar instrument for the adoption of tools. As described in Section 4, machines that are manually operated are more likely to be classified as tools. Therefore, regions and sectors with a higher share of manual tasks are more likely to adopt tools when their prices fall. The instrument for tools is defined as:

$$IV^{tools}_{r,s,t} = Manual\ Task\ Content_{r,s,0} \times \tau^T_{s,t}, \tag{10}$$

where $Manual\ Task\ Content_{r,s,0}$ is the average manual task content among workers in region r and sector s in 1998.[32] $\tau^T_{s,t}$ is the average tariff on tools used by sector s at time t.[33]

First Stage. Using the instruments, we estimate the first-stage equations as follows:

$$\Delta log(robots_{r,s,t}) = \pi_{1,1}\Delta IV^{robots}_{r,s,t} + \pi_{1,2}\Delta IV^{tools}_{r,s,t} + X'_{r,s,t}\Pi_1 + \mu_r + \mu_s + \mu_t + \epsilon_{r,s,t} \tag{11}$$

$$\Delta log(tools_{r,s,t}) = \pi_{2,1}\Delta IV^{robots}_{r,s,t} + \pi_{2,2}\Delta IV^{tools}_{r,s,t} + X'_{r,s,t}\Pi_2 + \mu_r + \mu_s + \mu_t + \epsilon_{r,s,t}, \tag{12}$$

where $\Delta \log(robots_{r,s,t})$ and $\Delta \log(tools_{r,s,t})$ are the five-year changes in robot and tool imports, and $\Delta IV^{robots}_{r,s,t}$ and $\Delta IV^{tools}_{r,s,t}$ are the corresponding five-year changes in the instruments. To facilitate the interpretation of the coefficients, we normalize the instruments to have a standard deviation of one. The control vector $X_{r,s,t}$ is the same as in Equation (7) and includes changes in output tariffs and in input tariffs (excluding capital goods) to account for potential spurious correlations between the instruments and other tariff changes. We also include controls for the levels of routine and manual task content to capture structural differences across labor markets that may be correlated with trends in machine adoption. Importantly, we do not control for the levels of robot and tool tariffs, as this variation is exogenous and should be absorbed in the first-stage coefficients.

[31] Following the literature, routine task content is measured as the average of two O*NET scores for each occupation: the degree of automation and the importance of repeating the same task. This measure is then aggregated to the region-sector level using the occupational employment shares at the beginning of the period.

[32] Manual task content is constructed by averaging all O*NET questions related to the use of hand tools at the occupation level. This measure is then aggregated to the region–sector level using the occupational employment shares at the beginning of the period.

[33] Figure B.5 shows the distribution of manual and routine task content across Brazilian microregions.

5.3 Validation

A natural identification concern is that trends or other shocks correlated with the instrument could bias the estimated effects. To validate the identification strategy, we show that the instrument 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. Table B.3 in the appendix reports the correlation between our instrument and several major policies implemented during the period, including subsidized credit, public procurement, and campaign contributions. The results show no significant correlation, suggesting that the instrument is not affected by political connections or byconcurrent policy interventions. These findings reinforce our argument that the tariff changes were externally imposed by Mercosur and are plausibly unrelated to domestic political influence or policy targeting in Brazil.

Pre-period Trends. In Table B.4, we run a regression of the instruments on pre-period changes in employment and wages to ensure that changes in tariffs are not correlated with pre-period trends in the labor market. The left-hand side contains the change in labor market outcomes from 1993 to 1997. The right-hand side contains the change in the instrument from 1997 to 2002. For this test, we remove pre-period changes from the set of controls. There is no correlation between the instrument and pre-period trends.

Other Shocks. During the period of analysis, the Brazilian economy experienced a sharp rise in global prices of raw materials and agricultural goods, an event commonly referred to as the commodity boom. To ensure that our results are not driven by this shock, Table B.3 shows that our instruments are not correlated with changes in import prices. While there is a statistically weak correlation between the robot instrument and export prices, it is not economically significant, suggesting that the commodity boom is unlikely to bias our estimates.

6 Empirical Results

In this section, we show that robots and tools have opposing effects on employment: while robots reduce employment, tools increase it. These effects are concentrated among low-skilled production workers in occupations directly involved in operating machinery. Our estimates indicate a substantially larger negative impact of robots on employment than previously reported in the literature. This difference arises from a bias in earlier studies, which typically do not account for the simultaneous adoption of tools. Because robot adoption increases firm productivity, it often leads to greater demand for labor-complementary technologies like tools. When tools are omitted from the analysis, their positive employment effect is incorrectly attributed to robots, biasing the estimated impact of robots toward zero.

Significant First Stage. Table 1 shows that higher tariffs significantly reduce the adoption of robots and tools in more exposed markets, as expected. In the baseline specification (columns 2 and 5), a one standard deviation increase in the robot or tool instrument leads to a 64% and 34% decline in their imports, respectively. The corresponding F-statistics are well above the conventional threshold of 10, addressing any concern about weak instruments. Moreover, these results are robust to alternative functional forms: columns 1–4 in Table B.5 use the inverse hyperbolic sine transformation, and columns 5–8 in Table B.5 examine the binary probability of importing at least one robot or tool—both confirming the negative relationship between the instrument and imports of machines. In addition, as shown in Section B.3.2, we find that higher tariffs reduce imports even without interacting them with task content, reinforcing the strength and validity of our identification strategy.

Table 1: **First Stage: Effect of Instruments on the Adoption of Robots and Tools**

	(1) Δ log *Robots*	(2) Δ log *Robots*	(3) Δ log *Robots*	(4) Δ log *Tools*	(5) Δ log *Tools*	(6) Δ log *Tools*
ΔIV^{robots}	-0.6366***	-0.6420***	-0.6328***	-0.7334***	-0.7417***	-0.7172***
	(0.0331)	(0.0329)	(0.0330)	(0.0332)	(0.0328)	(0.0333)
ΔIV^{tools}	0.2230***	0.1919***	0.2036***	-0.2771***	-0.3466***	-0.3041***
	(0.0255)	(0.0255)	(0.0261)	(0.0417)	(0.0416)	(0.0425)
R^2	0.315	0.338	0.388	0.497	0.523	0.549
F-statistic	120.168	119.354	202.091	138.921	143.671	222.011
N	204,070	204,069	204,049	204,070	204,069	204,049
Region FE	–	✓	–	–	✓	–
Sector FE	✓	✓	–	✓	✓	–
Region–Sector FE	–	–	✓	–	–	✓

Description: This table shows the coefficients of the first stage, i.e., regressions (11) and (12). IV^{tools} is the interaction between the shares of manual occupations and the tariffs on tools. IV^{robots} is the interaction between the shares of replaceable occupations and the tariffs on robots. *Robots* and *Tools* denote the imports in US 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, the average routine task content in 1997, the average manual task content in 1997, 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 (in parentheses) are clustered at the region–sector level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Robots Increase the Adoption of Tools. Table 1 also shows that tool adoption responds to changes in the price of robots. Column 5 reports that a one standard deviation increase in the robot instrument leads to a 74% decrease in tool imports. In our quantitative model, this pattern is rationalized by the productivity effect: as robots become cheaper and raise firm productivity, firms expand production and increase their demand for tools.

The effect of robots on the adoption of tools has important implications for identification: if robot adoption leads to greater tool adoption, failing to control for tools—as is common in the literature—biases the estimated effect of robots. In such cases, the estimated coefficient captures the net effect of robots and tools, rather than the true causal effect of robots alone.

Table 2: **Effect of Robots and Tools on Employment**

	(1) Δ log *Employment*	(2) Δ log *Employment*	(3) Δ log *Employment*	(4) Δ log *Employment*	(5) Δ log *Employment*
Δ log(Robots)	-0.1056***	-0.0941***	-0.2333***	-0.2245***	-0.2258***
	(0.0159)	(0.0142)	(0.0335)	(0.0322)	(0.0330)
Δ log(Tools)	0.1545***	0.1496***	0.1826***	0.1738***	0.1942***
	(0.0224)	(0.0213)	(0.0266)	(0.0245)	(0.0258)
N	204,070	204,069	204,070	204,069	204,049
Region FE	–	✓	–	✓	–
Sector FE	–	–	✓	✓	–
Region–Sector FE	–	–	–	–	✓

Description: This table shows the coefficients of regression (7) on employment. Δ log(Tools) and Δ log(Robots) are instrumented according to Equations (9) and (10). *Robots* and *Tools* denote the imports in US dollars of robots and tools, respectively, in the past 5 years. The difference is taken over the past 5 years. All specifications include year fixed effects as control. Column 1 contains the baseline controls, i.e., the growth rate of employment between 1993 and 1997, the tariff change on sectoral output, the tariff change on inputs excluding capital, the average routine task content in 1997, and the average manual task content in 1997. Column 2 adds a region fixed effect to the controls. Column 3 adds a sector fixed effect to the controls. Column 4 includes as controls the baseline controls, region FE, and sector FE. Column 5 includes sector–region fixed effects and the baseline controls. Standard errors (in parentheses) are clustered at the region–sector level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Robots Decrease Employment. Table 2 shows the effect of robots and tools on employment. Across all specifications, robot adoption significantly decreases employment. In the main specification (column 5), a 1% increase in robot adoption reduces employment by 0.22%.

Effect of Robots on Employment Is Larger than Identified in Other Papers. Table 3 compares our estimated elasticity of employment with those reported in the existing literature. For consistency, we convert all estimates into elasticities, i.e., the effect of a 1% increase in robot adoption on employment. Our baseline estimate shows that a 1% increase in robot adoption reduces employment by 0.22%. In contrast, estimates from previous studies range from -0.01% to 0.007%, with most being statistically insignificant.

Table 3: **Effect of Robots on Employment According to the Literature**

Source	Effect of Robots on Employment
Baseline (Table 2)	-0.2245***
	(0.0322)
Acemoglu and Restrepo (2020)	-0.0064***
	(0.0014)
Graetz and Michaels (2018)	+0.0076
	(0.0633)
Dauth et al. (2021)	-0.0114
	(0.0402)
Baseline Without Controlling for Tools (Table 4)	+0.0037
	(0.0179)

Description: This table compares the estimated elasticities of employment with respect to robot adoption across key papers in the literature. To make the results comparable, we express all estimates as the effect of a 1% increase in robot adoption on employment. The first line shows the baseline estimates in column 4 of Table 2. Acemoglu and Restrepo (2020) find that one additional robot per thousand workers reduces the employment-to-population ratio by 0.002. Given that one additional robot per thousand workers corresponds to a 47.6% increase in the robot stock, and that the US employment-to-population ratio was 59.3% in 2014, their estimate implies that a 1% increase in robot adoption decreases employment by 0.0064%. Graetz and Michaels (2018) report that a 1% increase in robot adoption raises aggregate hours worked by 0.03%. Using US aggregate data, where a 1% increase in hours worked corresponds to a 0.436% increase in employment, we infer that a 1% increase in robot adoption would increase employment by approximately 0.007%. Dauth et al. (2021) find that one robot per thousand workers reduces the employment-to-population ratio by 0.0357. Using the same conversion approach as in Acemoglu and Restrepo (2020), this implies an elasticity of employment with respect to robot adoption of about -0.011. The last line shows the estimates from column 4 of Table 4. Standard errors are in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Ignoring Tools Biases Estimated Effects of Robots Toward Zero. The much larger effect of robots we estimate compared to previous studies can be explained, in part, by a key difference in identification: we account for the adoption of tools. As shown in Table 1, cheaper robots lead not only to greater robot adoption but also to an increase in tool adoption, and tools increase employment. Omitting tools from the specification introduces an omitted variable bias, biasing the estimated effect of robots toward zero. In regressions that do not control for tool adoption, the estimated coefficient captures the net effect of robots and tools combined, rather than the true causal effect of robots alone.

The last line of Table 3 illustrates this bias: when we exclude tools from the specification and instrument robot adoption using only the robot instrument from Equation (9), the estimated effect becomes non-significant and closely matches the smaller estimates reported in previous studies, such as Graetz and Michaels (2018), Acemoglu and Restrepo (2020), and Dauth et al. (2021). Table 4 further shows that, across different specifications, the estimated effect of robots on employment remains much smaller as long as tool adoption is not controlled for.[34] As we show in Section 6.1, this omitted variable bias is specific to tools: controlling for other types of inputs, such as materials, does not materially affect the results.

Instrumenting robot adoption with robot imports in other countries—a common ap-

[34]Table B.6 presents the first stage corresponding to these regressions.

proach in the literature—also leads to biased estimates when tools are omitted. As shown in Section B.3.1, foreign robot imports are positively correlated with local tool adoption, reinforcing the idea that robots and tools are adopted together in the same market. When tools are not controlled for, the estimated effect of robots reflects the combined impact of both technologies, biasing the coefficient toward zero. Once we control for tools, the estimated effect of robot adoption on employment becomes significantly stronger, confirming that the bias is not specific to our main instrument but a broader identification issue.

Table 4: **Effect of Robots on Employment Without Controlling for Tools**

	(1) Δ log *Employment*	(2) Δ log *Employment*	(3) Δ log *Employment*	(4) Δ log *Employment*	(5) Δ log *Employment*
Δ log(Robots)	0.0050	0.0046	0.0047	0.0037	0.0222
	(0.0057)	(0.0061)	(0.0182)	(0.0179)	(0.0180)
N	204,070	204,069	204,070	204,069	204,049
Controls	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Region FE	–	✓	–	✓	–
Sector FE	–	–	✓	✓	–
Reg-Sec FE	–	–	–	–	✓

Description: This table shows the coefficients of regression (7) on employment but without controlling for tools. Δ log(Robots) is instrumented by IV^{robots}. *Robots* denote the imports in US dollars of robots in the past 5 years. The difference is taken over the past 5 years. All specifications include year fixed effects as control. Column 1 contains the baseline controls, i.e., the growth rate of employment between 1993 and 1997, the tariff change on sectoral output, the tariff change on inputs excluding capital, the average routine task content in 1997, and the average manual task content in 1997. Column 2 adds a region fixed effect to the controls. Column 3 adds a sector fixed effect to the controls. Column 4 includes as controls the baseline controls, region FE, and sector FE. Column 5 includes sector–region fixed effects and the baseline controls. Standard errors (in parentheses) are clustered at the region–sector level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Tools Increase Employment by as Much as Robots Decrease It. Table 2 shows that tools have a strong positive effect on employment. A 1% increase in tool adoption raises employment by 0.17%. This effect is robust across specifications: columns 1 to 6 report elasticities ranging from 0.15 to 0.19.

Because the magnitude of the tool effect is similar—but opposite in sign—to that of robots, increasing the adoption of both technologies by the same amount results in little net change in employment. In our main estimates, the difference between the negative effect of robots and the positive effect of tools is not statistically significant, suggesting that their opposing impacts effectively cancel each other out.

Robots and Tools Affect Employment of Low-Skilled Workers. Table 5 reports the effects of robots and tools on employment and wages by educational group. Columns 1 and

Table 5: **Effect of Robots and Tools on Different Educational Groups**

	(1) Δ log *H.S. Drop.*	(2) Δ log *Wage H.S. Drop.*	(3) Δ log *H.S. Complete*	(4) Δ log *Wage H.S. Complete*	(5) Δ log *College*	(6) Δ log *Wage College*
Δ log(Robots)	-0.2283***	-0.0482***	-0.0377	-0.0232**	-0.0226	-0.0107
	(0.0324)	(0.0098)	(0.0279)	(0.0110)	(0.0232)	(0.0120)
Δ log(Tools)	0.1683***	0.0433***	0.0946***	0.0083	0.0468*	0.0209
	(0.0247)	(0.0074)	(0.0274)	(0.0107)	(0.0255)	(0.0130)
N	194,269	194,269	116,352	116,352	75,878	75,878
Region FE	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓	✓

Description: This table shows the coefficients of regression (7) on employment in different occupations. $\Delta log(Tools)$ and $\Delta log(Robots)$ are instrumented according to Equations (9) and (10). *Robots* and *Tools* denote the imports in US dollars of robots and tools, respectively, in the past 5 years. The left-hand side of each column is the number of workers in different occupations. The controls are the growth rate of the left-hand-side variable between 1993 and 1997, the tariff change on sectoral output, the tariff change on inputs excluding capital, the average routine task content in 1997, the average manual task content in 1997, year fixed effects, region fixed effects, and sector fixed effects. Columns 1 and 2 show the effect of robots and tools on employment and monthly earnings of workers who have less education than a high-school diploma. Columns 3 and 4 show the effects on workers with a high-school diploma. Columns 5 and 6 show the effect on workers with at least some college education. Standard errors (in parentheses) are clustered at the region–sector level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

2 show results for workers without a high-school diploma, columns 3 and 4 for those with a high-school diploma, and columns 5 and 6 for workers with at least some college education.

The effects of robots and tools are concentrated among low-educated workers. A 1% increase in robot adoption decreases the employment and wages of workers without a high-school diploma by 0.22% and 0.04%, respectively. For workers with more education, the estimated effects are smaller and less precisely estimated. By contrast, tools significantly increase employment for low-skilled workers, almost fully offsetting the negative effect of robots.

Robots and Tools Affect Workers Operating Machines or Supporting Production. Table 6 breaks down the effects of robots and tools on different occupational groups. Column 1 shows the effects on managers, while column 2 covers science professionals—engineers, chemists, and other STEM college graduates. Column 3 presents the effects on technical workers, such as mechatronics specialists, chemistry and electronics technicians, and others in STEM-related fields without a college degree; notably, 62.8% of workers in this category have not completed high-school. Column 4 reports results for administrative workers, who support production workers. Column 5 focuses on operational workers, who are directly responsible for running machinery.

The results show that the effects of robots and tools are concentrated among operational

Table 6: **Effect of Tools and Robots on Different Occupations**

	(1) Δ log *Managers*	(2) Δ log *Science Professionals*	(3) Δ log *Technical Workers*	(4) Δ log *Adm Workers*	(5) Δ log *Operational Workers*
Δ log(Robots)	0.0140	0.0140	-0.0256	-0.1331***	-0.1936***
	(0.0231)	(0.0321)	(0.0256)	(0.0270)	(0.0386)
Δ log(Tools)	0.0135	0.0116	0.0905***	0.1086***	0.2318***
	(0.0271)	(0.0392)	(0.0302)	(0.0248)	(0.0341)
N	46,422	20,288	72,857	134,132	149,619
Region FE	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓

Description: This table shows the coefficients of regression (7) on employment in different occupations. $\Delta log(Tools)$ and $\Delta log(Robots)$ are instrumented according to Equations (9) and (10). *Robots* and *Tools* denote the imports in US dollars of robots and tools, respectively, in the past 5 years. The left-hand side of each column is the number of workers in different occupations. The controls are the growth rate of the left-hand-side variable between 1993 and 1997, the tariff change on sectoral output, the tariff change on inputs excluding capital, the average routine task content in 1997, the average manual task content in 1997, year fixed effects, region fixed effects, and sector fixed effects. In column 1, it is the number of managers, i.e., 1-digit CBO 2002 occupations 0 and 1; in column 2, it is the number of science professionals, i.e., 1-digit CBO 2002 occupation 2; in column 3, it is the number of technical workers, i.e., 1-digit CBO 2002 occupation 3; in column 4, it is the number of administrative workers, i.e., 1-digit CBO 2002 occupations 4 and 5; and in column 5, it is the number of operational blue-collar workers, i.e., 1-digit CBO 2002 occupations 6 and 7. Standard errors (in parentheses) are clustered at the region–sector level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

and technical workers—those who directly work with machines—and among administrative staff, who are hired to support production workers. Robots reduce employment in these groups, while tools increase it. By contrast, we find little to no effect on managers and science professionals.

6.1 Robustness

The main empirical results show that robots reduce the employment of low-skilled operational workers, while tools increase it by a similar magnitude. In this section, we demonstrate that this conclusion is robust to a range of tests, including alternative identification strategies, the inclusion of additional controls, and different methods for classifying machines as robots or tools.

Imports 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.

Tariffs as Instruments. In Section B.3.2, we reproduce the main regressions but use only 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 an equal magnitude.

Controlling for Other Inputs. Robots or tools may lead to the adoption of other inputs. If these inputs directly affect the labor market, not controlling for them would also bias the estimates. In Panel A of Table B.13 and Table B.14, we add imports of intermediate inputs (that are neither robots nor tools) as controls in the baseline specification. We still find that tools increase employment for low-skilled workers, while robots decrease it.

Controls. In Panels B to F of Table B.13 and Table B.14, we show that the results are robust to adding or removing controls. We try five different specifications. First, we remove region and sector fixed effects, which capture regional and sectoral trends. Second, we add only a sector fixed effect. Third, we control for joint sector–region fixed effects, which controls for market-specific trends. Fourth, concerned with potential shocks to the growth rate of large regions, we control for initial period employment interacted with a year fixed effect. Fifth, concerned with trends in the growth rate of labor outcomes, we add as a control pre-period growth rates interacted with year fixed effects. In all these specifications, we still find that low-skilled workers who directly operate machines are more affected by both robots and tools.

Higher Degree of Text Similarity. Some machines might be similar to both robots and tools. It is also possible that not all machines fall into these two categories. To deal with this, Section B.3.4 shows the main results restricting the sample to the set of machines that have a cosine text similarity above the median. We still find that robots decrease employment while tools increase it.

Machine Classification with Large Language Model. In Section B.3.6, we use a large language model to classify machines as robots or tools. A machine is classified as a robot if Gemini identifies it as performing tasks independently of workers, and as a tool if it primarily assists workers in performing their tasks. Table B.18 confirms our baseline findings: robots reduce employment—particularly among low-skilled workers—while tools increase it.

Effect of Robots and Tools on Informality. Brazil's large informal labor market raises the concern that automation could have affected informality, either directly or through general equilibrium effects. While large firms that import robots and tools are unlikely to increase informal hiring—due to frequent labor inspections—we cannot rule out broader labor market spillovers. Unfortunately, no dataset provides annual sector-level data on informal employment at sufficient granularity. As an indirect test, we examine whether robot and tool adoption affected the number of fines issued for hiring informal workers. In this period, there were 12 million fines for hiring workers informally in Brazil. If informality had expanded (or contracted), we would expect a corresponding rise (or fall) in these violations. Table B.17 in the Appendix shows no significant effect, suggesting that machine adoption has not meaningfully altered the size of the informal sector.

7 Quantitative Model

The empirical findings reveal a trade-off between inequality and productivity: greater 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. 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 and to study the policy implications.

To interpret the empirical elasticities and capture important elements of the economy, we add other features to our simple model. First, we introduce multiple regions and sectors, which enables us to reproduce the regressions with model–simulated data. Second, we extend the production function such that production with robots also requires high-skilled workers, which is intuitive and helps us match the empirical elasticity of robot adoption on high-skilled employment. Third, we introduce heterogeneous firms, following Koch et al. (2021), which allows for rich variation in production technologies across firms. This heterogeneity is crucial for matching the finding that cheaper robots increase tool adoption. Finally, the model allows for both local production and imports of robots and tools, reflecting the reality that changes in tariffs only partially affect the final price of robots and tools.

7.1 Demographics

There are $n \in \{1, ..., N\}$ regions and $s \in \{1, ..., S\}$ sectors. We denote workers in sector $S + 1$ as being outside the labor force. There are five agents in the economy: intermediate goods producers, composite goods 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, and rent them to firms. Workers choose their education level, region, and sector of employment. The government taxes income and imports. It also provides social security to workers outside the labor force.

7.2 Intermediate Goods Producers

Production Function with Input–Output Connections. Firms perform a set of tasks and use inputs from different sectors. The output of firm i in region n and sector s is:

$$y_n^s(i) = \left[\frac{1}{\gamma^s} \left(\int_0^1 [y_n^s(i,\nu)]^{\frac{\lambda-1}{\lambda}} \, d\nu \right)^{\frac{\lambda}{\lambda-1}} \right]^{\gamma^s} \prod_{s'=1}^{S} \left[\frac{1}{\gamma^{ss'}} M_n^{ss'}(i) \right]^{\gamma^{ss'}}, \tag{13}$$

where, similar to the simple model, $y_n^s(i,\nu)$ denotes firm i'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. Technology is constant return to scale: $\gamma^s + \sum_{s'=1}^{S} \gamma^{ss'} = 1$.

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

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

where $y^{s,R}n(i,\nu)$ denotes the output of task ν produced by firm i in sector s and region n using robots, and $y^{s,T}n(i,\nu)$ denotes the output of task ν produced using tools and workers. If firm i performs task ν with robots, the production function is:

$$y_n^{s,R}(i,\nu) = Z_n^{s,R}(i,\nu) \left(\ell_n^{s,H,R}(i,\nu) \right)^{\eta} \left(K_n^{s,R}(i,\nu) \right)^{1-\eta},$$

where $Z_n^{s,R}(i,\nu)$ is firm i's productivity in completing task ν with robots, $K_n^{s,R}(i,\nu)$ is robot capital, and $\ell_n^{s,H,R}(i,\nu)$ is the number of high-skilled workers operating robots. η is the expenditure share on high-skilled workers if the firm completes the task with robots.

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

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

where $Z_n^{s,T}(i,\nu)$ is the productivity of tools for firm i in sector s and region n in task ν.

$A_n^{s,H}(i)$ is the productivity of high-skilled workers at firm i. $\ell_n^{s,H,T}(i,\nu)$ and $\ell_n^{s,L}(i,\nu)$ are, respectively, the number of high-skilled and low-skilled workers. $K_n^{s,T}(i,\nu)$ is the amount of tools and $\delta_n^s(i)$ denotes the share of low-skilled workers in their output with tools at firm i.

Firm Heterogeneity. Firms are heterogeneous along several dimensions: the productivity of robots, $Z_n^{s,R}(i,\nu)$; the productivity of tools, $Z_n^{s,T}(i,\nu)$; the productivity of high-skilled workers, $A_n^{s,H}(i)$; and the share of low-skilled workers in their production with tools, $\delta_n^s(i)$. 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):

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

θ is the shape parameter that determines the elasticity of substitution between technologies. $T_n^{s,l}(i)$ is the scale parameter that governs the level of robot and tool adoption.

Joint Distribution of Factor Bias and Robot Productivity. We assume that $A_n^{s,H}(i)$, $T_n^{s,R}(i)$, and $\frac{\delta_n^s(i)}{1-\delta_n^s(i)}$ follow a joint log-normal distribution.[35] These draws are independent across regions, sectors, firms, and time, but are correlated within a firm (see Section C.2 for details). We denote the key parameters as follows: the mean of $\delta_n^s(i)$ represented by μ_δ, and the correlation between $\log\left(T_n^{s,R}(i)\right)$ and $\log\left(\frac{\delta_n^s(i)}{1-\delta_n^s(i)}\right)$ represented by $\rho_{T^R,\delta}$. The within-firm correlation arises because firms with a comparative advantage in using robots likely employed a higher share of low-skilled workers, as robots primarily replace low-skilled labor (see empirical evidence presented in Acemoglu et al. 2020, Koch et al. 2021).

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

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

where A_n^s denotes region–sector 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

[35] We normalize $T_n^{s,T}(i) \equiv 1$.

substitution ϵ^s, which is also the trade elasticity:[36]

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

where $n' = N + 1$ indicates the international market and $y_{nn'}^s$ denotes output flowing from region n' to region n. Inter-region trade and imports incur a trade cost and importers pay tariffs to the Brazilian government. We present equations of the price indices in Section C.1.

7.3 Capital Goods Sector

In the capital goods sector, capitalists own capital producers who produce robots and tools using domestic final goods and imported capital. Capitalists make inter-temporal investment decisions, owning the capital and renting it to firms.[37]

Capital Producers. Every region–sector has a robot and tool producer. The production of these goods combines domestic final goods with imported capital. The production of investment goods of type $l \in \{R, T\}$ has decreasing returns to scale, as follows:[38]

$$\begin{aligned} &\max_{M_n^{s,l}} \Pi_n^{s,l,P} = P_n^{s,l} I_n^{s,l} - \Sigma_n^{s,l} M_n^{s,l},\ l \in \{R, T\} \\ &\text{s.t. } I_n^{s,l} = (M_n^{s,l})^{1-\xi^l},\ \xi^l \in (0,1) \\ &\Sigma_n^{s,l} = \left([P_n]^{1-\epsilon^l} + \left[h_{nN+1}^{s,l} t^{s,l} \right]^{1-\epsilon^l} \right)^{\frac{1}{1-\epsilon^l}}, \end{aligned} \tag{14}$$

where $M_n^{s,l}$ is a composite good combining domestic final goods and imported capital, $\xi^l \in (0, 1)$ is the degree of decreasing return to scale, $P_n^{s,l}$ is the price of capital good l, and $\Sigma_n^{s,l}$ is the cost index. $h_{nN+1}^{s,l}$ denotes the trade cost of importing capital l by region n sector s, and $t^{s,l} = 1 + \tau^{s,l}$, where $\tau^{s,l}$ is the tariff on capital imported by sector s. ϵ^l denotes the trade elasticity for capital goods.

Capitalists and Dynamic Problem. Capitalists accumulate capital from capital producers to maximize their lifetime utility. Each region–sector has a capitalist that invests in

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

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

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

robot and tool capital. Their problem is given by:

$$\max_{I_{n,t}^{s,l}} \sum_{t=0}^{\infty} \beta^t \log(C_{n,t}^{s,l}),\ l \in \{R,T\} \tag{15}$$
$$\text{s.t. } K_{n,t+1}^{s,l} = (1-\delta)K_{n,t}^{s,l} + I_{n,t}^{s,l}$$
$$P_{n,t}C_{n,t}^{s,l} = (1-B)(R_{n,t}^{s,l}K_{n,t}^{s,l} - P_{n,t}^{s,l}I_{n,t}^{s,l} + \Pi_n^{s,l,P}).$$

$R_{n,t}^{s,l}K_t$ indicates the capitalist's rental income and $\Pi_n^{s,l}$ the profit of capital producers, which is owned by capitalists. Capitalists spend on investment, $P_{n,t}^{s,l}I_{n,t}^{s,l}$, and on the consumption of local final goods after paying taxes at a rate of B.

7.4 Workers

Workers' Dynamic Problem. Workers maximize lifetime utility by choosing consumption, the sector that they want to work in, and the region that they want to live in. The problem is dynamic because to change region–sectors, workers must pay a migration cost that depends on their current region–sector. If a worker is in the outside sector, they receive social insurance payments, otherwise they receive a wage associated with that region–sector. We present detailed equations of the workers' migration problem in Section C.1. The workers' problem closely follows Artuç et al. (2010), Caliendo et al. (2019), and Kleinman et al. (2023).

Human Capital Choice. To account for changes in the supply of skills due to the prices of tools and robots, we assume that in each year a fraction of workers exit the labor market and are replaced by entrants who choose their skill type. These entrants are in the same sector and region as those exiting and choose their skill level for the next period by comparing the present value utility of high- and low-skilled workers. Entrants need to pay a cost to become high-skilled. We present these equations in Section C.1.

Government. The government taxes workers, capitalists, and imports to subsidize social security for workers outside of the labor force. The payment to those not in the labor force is endogenously determined by the government's budget constraint, as follows:

$$(1-B)b\sum_{n=1}^{N}(\ell_n^{S+1,H}+\ell_n^{S+1,L}) =$$
$$B\sum_{s=1}^{S}\sum_{n=1}^{N}\left(w_n^{s,H}\ell_n^{s,H}+w_n^{s,L}\ell_n^{s,L}+R_n^R K_n^R-\Sigma_n^R M_n^R+R_n^T K_n^T-\Sigma_n^T M_n^T\right)+TD_n. \quad (16)$$

The left-hand side is 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, trade deficit, and tariff revenues from abroad, TD_n.

8 Model Estimation

The model is calibrated in two steps. First, we set parameters that are either standard in the literature or directly estimated from Brazilian data. In particular, we calibrate the model to match employment, capital imports, and worker flows across sector–region cells. Second, we calibrate the parameters of the production function and firm heterogeneity to replicate the labor market effects of cheaper robots and tools. To do so, we simulate in the model the same tariff reductions observed in the data. We then apply the same empirical strategy used in the empirical analysis, using exposures to tariffs as an instrument, to identify their effect on imports and employment. We then choose the technology and firm heterogeneity parameters to match the estimated effects of lower capital tariffs. To validate the strategy, we show that the model can match several non-targeted moments of the Brazilian economy.

8.1 Calibration

We calibrate externally five groups of parameters: the labor and skill supply elasticities, the exit rate by skill group, the trade elasticity, the input–output coefficients, and the government fiscal policy. To calibrate these parameters, we follow the approach developed by others in the literature.

Labor and Skill Supply Elasticities. We estimate the labor supply 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. We instrument current wages with past wages, which are unlikely to correlate with current amenity shocks, following Artuç et al. (2010), Dix-Carneiro (2014), and Caliendo et al. (2019). We define high-skilled workers as those who have a high-school degree or higher, and low-skilled workers as those who have not completed high-school. We present the details of calibrating these parameters in Section C.3.

Exit Rates by Skill Group. Exit rates by skill group are calibrated to match movements out of the labor force from RAIS in an average year. They are 3.5% for high-skilled workers and 6.1% for low-skilled workers.

Trade Elasticities of Robots and Tools. Local capital production is combined with imports of robots and tools with a CES aggregator. The elasticity on this aggregator, known as the trade elasticity, is estimated by regressing changes in robot and tool imports on changes in their tariffs, controlling for region and sector fixed effects. We estimate robot trade elasticity to be 7.81 and tool trade elasticity to be 5.59.[39]

Parameters from the Literature. 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).

8.2 Simulated Methods of Moments (SMM)

We estimate the parameters related to technology choice to replicate the identified effects of robots and tools on high-skilled and low-skilled employment, as well as the effects of robot and tool tariffs on their adoption. To do so, we begin with the model in 1997 as the initial equilibrium, apply the actual tariff changes to it, and compute the resulting changes in employment using the model. With model-simulated data, we reproduce the main empirical strategy exploiting heterogeneous exposure to tariff changes across markets. We select the parameters such that the regression coefficients from the model-simulated data match our empirical estimates. Below, we describe how each parameter is primarily informed by different targeted moments.

θ Is Identified from the Effect of Robots on Low-Skilled Workers. θ, the elasticity of substitution between technologies, is identified from the effect of robots on low-skilled employment. When robots and tools are easily substitutable, a reduction in the price of

[39]These estimates are similar to what Parro (2013) obtained for overall capital goods.

robots will result in a greater decline in low-skilled employment due to displacement effect.

ζ Is Identified from the Effect of Tools on High-Skilled Workers. ζ, the elasticity of substitution between high- and low-skilled workers, is identified from the effect of tools on high-skilled employment. A large elasticity of substitution between high- and low-skilled workers implies that the substitution effect is strong, leading to a smaller—and potentially negative—impact of tools on high-skilled employment. To match the empirical finding that cheaper tools have no significant effect on high-skilled workers, ζ should be set such that the substitution effect approximately offsets the productivity and reinstatement effects on high-skilled workers.

η Is Identified from the Effect of Robots on High-Skilled Workers. η, the share of high-skilled workers in the output produced with robots, is calibrated to match the effect of robots on high-skilled employment. A larger value implies stronger complementarity between robots and high-skilled workers, meaning that cheaper robots would lead to an increase in high-skilled employment.

μ_δ Is Identified from the Effect of Tools on the Employment of Low-Skilled Workers. μ_δ is the average share of low-skilled workers in the output they produce with tools. A larger value implies that tools require a greater use of low-skilled workers, meaning that when tools become cheaper, the demand for low-skilled workers rises more strongly.

$\rho_{T^R,\delta}$ Is Identified from the Effect of Robots on Imports of Tools. Cheaper robots affect the demand for tools through the same channels that they affect the demand for low-skilled workers: the productivity, replacement, and substitution effects. However, because of the correlation between robot productivity and the low-skilled labor share in tool-based production, $\rho_{T^R,\delta}$, these forces impact tools and low-skilled workers differently. When the correlation is high, a decrease in the price of robots leads to a sharper drop in the demand for low-skilled workers than for tools because firms adopting robots are more intensive in low-skilled labor than in tools.

Other Parameters Estimated by SMM. Besides the key parameters related to technology choice, we estimate several other production and trade parameters by SMM. Specifically, we estimate the mean, standard deviation, and correlations of robot and high-skilled worker productivity by targeting cross-region-sector imports of robots and high-skilled employment data. We estimate region-sector level productivity by targeting region-sector employment and wage. We also estimate trade cost parameters from region-sector imports and migration cost parameters from cross-region-sector worker flows. We compute these data moments using 1997 data, representing the initial equilibrium. We detail the estimation procedure in Section C.4.

Table 7: **Key Estimated Parameters Governing Technology Choice**

Parameter	Name	Value
θ	Elasticity of substitution between robots and tools	14.88
ζ	Elasticity of substitution between high- and low-skilled workers in tool technology	3.49
η	Share of high-skilled workers in output produced with robots	0.06
μ_δ	Average low-skilled share in tool technology across firms	0.50
$\rho_{T^R,\delta}$	Correlation between robot productivity and low-skilled share in tool technology across firms	0.53

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.

Estimation Results. Table 7 presents estimates of key parameters governing robot and tool technologies. The remaining ones are presented in Table C.5.[40] The elasticity of substitution between robots and tools is 14.88, showing that these technologies are close substitutes.

The elasticity of substitution between high- and low-skilled workers, ζ, is estimated at 3.49. To compare it with values commonly reported in the literature, we follow the approach of Katz and Murphy (1992), Krusell et al. (2000), and Ciccone and Peri (2005), deriving the relationship between factor shares and the skill premium to recover the implied aggregate elasticity of substitution. Based on this aggregation, the implied elasticity is 1.72, which closely matches the estimate of 1.4 found by Katz and Murphy (1992) and de Souza (2020).

High-skilled workers account for 6% of the output produced with robots, based on the calibrated value of η, which explains the small effect of robot adoption on high-skilled employment observed in the data. The productivity of robots and the share of low-skilled workers in tool-based production are positively correlated, with a correlation coefficient of 0.53. This implies that firms that are intensive in robot adoption are also relatively intensive in low-skilled labor, a pattern documented by Koch et al. (2021).

[40]Table C.4 shows that we accurately match the targeted moments. Figure C.1 shows that the model can replicate region–sector level distributions of employment and imports and migration shares observed in the data, which disciplines the parameters related to productivity, trade, and migration cost.

Table 8: **Non-targeted Moments**

Moment Name	**Data**	**Model**
Labor share	0.57	0.65
Skill premium	2.98	3.82
Aggregate elasticity of substitution between high- and low-skilled workers without capital	1.4	1.76
High-skilled share in population	0.21	0.20
Trade balance	-2.6%	-4.7%

Description: This table presents non-targeted moments of the Brazilian economy as observed in both the data and the model. The data for labor share is sourced from FRED (`https://fred.stlouisfed.org/series/LABSHPBRA156NRUG`). The skill premium is calculated with RAIS. The high-low skill substitution elasticity is acquired from de Souza (2020). The model moments are computed using corresponding variables in the baseline year. Section C.5 presents the formula used to compute the high-low skill substitution elasticity.

Non-Targeted Moments. Table 8 shows statistics of non-targeted moments. The model closely matches the observed labor share and skill premium in the data. It also replicates the aggregate elasticity of substitution between high- and low-skilled workers without capital, as estimated by Katz and Murphy (1992) and de Souza (2020). In addition, the model matches the observed share of high-skilled workers in the population and Brazil's trade deficit as a percentage of GDP.

9 Quantitative Results

If Prices of Robots and Tools Decrease Equally, Aggregate Employment Is Not Affected. Figure 2 shows the aggregate effects of changes in the prices of robots and tools.[41] Each plot displays changes in robot and tool prices along the x-axis, with the corresponding changes in aggregate employment, GDP, welfare, and the skill premium on the y-axis. The figure illustrates three different scenarios: one in which only the price of robots changes, one in which only the price of tools changes, and one in which both prices change simultaneously.

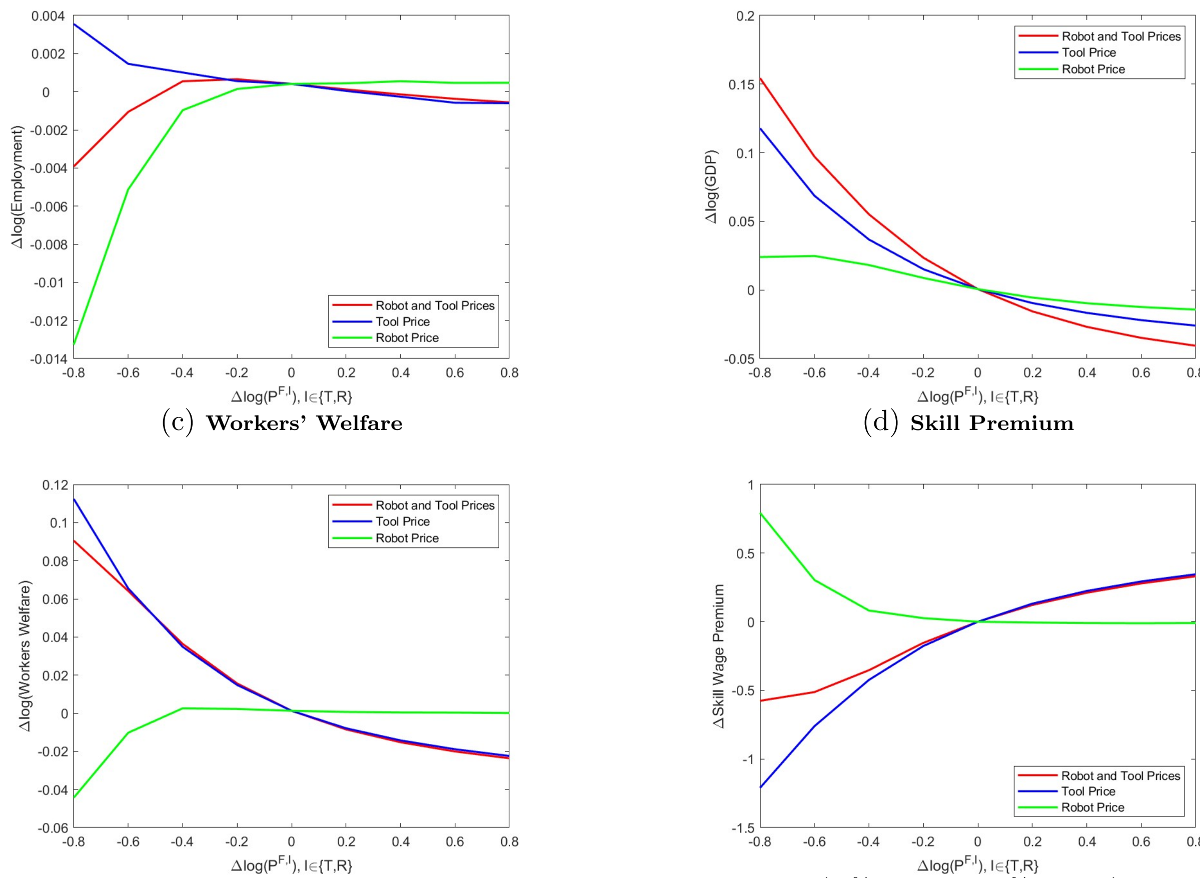
Figure 2 shows that less expensive robots decrease employment and welfare while increasing GDP and skill premium. An 80% drop in the price of robots would decrease employment by 1.4%. While robots do complement high-skilled workers, the proportion of high-skilled workers involved in robot technology is relatively low. Therefore, the substitution effect dominates and robots decrease employment. Because low-skilled workers are replaced by robots, their welfare decreases. GDP increases from lower robot prices because firms become more productive with less expensive capital. Skill premium increases because robots lead to more layoffs of low-skilled workers.

[41] Formulas used to compute these aggregate statistics in the model are provided in Section C.5.

Figure 2: **Aggregate Effects of Robots' and Tools' Import Price Changes**

(a) **Employment** (b) **GDP**

(c) **Workers' Welfare** (d) **Skill Premium**



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.

According to Figure 2, if the prices of robots and tools fell by the same amount, welfare would increase and inequality would decrease without a significant effect on employment. The red line in Figure 2 plots changes in employment, GDP, workers' welfare, and skill premium from the same price changes to both machines. Tools and robots have the opposite effect on the labor market. Robots replace low-skilled workers in their tasks, whereas tools reinstate them. GDP and welfare, meanwhile, increase significantly from the reduced machine costs. Inequality decreases because tools are complements to low-skilled workers.

Cheaper Robots and Tools Increased Welfare and Decreased Inequality. Between 1997 and 2014, the after-tariff import price of robots and tools fell by 49.4% and 42.3%, respectively. Table 9 displays the effects of reduced capital goods prices on the Brazilian economy. The first line shows the effects of changes in both capital prices. On the second

Table 9: **Aggregate Effects of Reduced International Capital Goods Prices**

	Robot Price Chg.	Tool Price Chg.	Employment	GDP	Workers' Welfare	Skill Premium
Robots and Tools	-49.4%	-42.3%	-0.3%	6.1%	3.2%	-8.5%
Tools	0	-42.3%	0.1%	3.9%	3.7%	-12.2%
Robots	-49.4%	0	-0.5%	2.0%	-0.5%	3.8%

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.

Table 10: **Optimal Tariffs on Robots and Tools**

Tariff Objective	Employment	GDP	Workers' Welfare	Skill Premium	Robot Tariff	Tool Tariff
GDP	0.0%	2.5%	1.4%	1.2%	-7.2%	2.7%
-Skill Premium	-0.1%	-0.0%	1.5%	-1.5%	65.2%	-0.2%
Welfare	0.0%	1.4%	1.7%	-0.5%	13.8%	-1.1%

Description: This table presents the change in employment, GDP, workers' welfare, and skill premium from different tariffs in robots and tools. Tariffs are set on the imports of robots and tools to maximize GDP or welfare, or to minimize the skill premium. Appendix C.6 lays out the problem of the government. The first line shows the effect of tariffs that maximize GDP, the second line shows the effect of tariffs that minimize inequality, and the last line shows the effect of tariffs that maximize workers' welfare.

line, only the tool price changes, and on the third line, only the robot price changes.

Less expensive robots and tools led to large GDP gains and decreased inequality in Brazil, with limited impact on aggregate employment. Because both machines enhanced productivity, GDP increased. Moreover, because tools are complements to low-skilled workers, inequality in the labor market decreased and overall welfare increased.

Taxing Robots Increases Welfare. Robots and tools introduce a trade-off between productivity and redistribution. Robots increase productivity, while tools reduce inequality. Table 10 highlights this trade-off. It shows the optimal budget-neutral tariffs on robots and tools to fulfill different objectives of the government.[42]

In particular, to maximize welfare, the government should tax robots and subsidize tools. On the one hand, subsidizing robots increases production, which benefits workers by increasing overall consumption. On the other hand, tools increase the demand for low-skilled workers, transferring income to workers with higher marginal utility. According to Table 10, the redistribution effect is stronger and the optimal policy is to weakly discourage robot adoption by imposing a 14% tariff on robots.

[42]We present the government's optimal tariff problem in Section C.6. The government optimally sets import tariffs/subsidies on robots and tools to achieve one of three policy objectives: (1) maximizing GDP, (2) maximizing workers' welfare, or (3) minimizing the skill premium (inequality). To ensure that we find an interior solution, we require that the government maintains a balanced budget for these subsidies and tariffs: The tariffs collected from robot and tool imports cannot exceed the subsidies paid for them.

10 Conclusion

Technological progress over the past few decades has led to cheaper robots and tools. In this paper, 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. Employing 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 and propose a new instrument to identify their effects. In addition, 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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Online Appendix
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Robots, Tools, and Jobs: Evidence from Brazilian Labor Markets

by Gustavo de Souza and Haishi Li

A Appendix for Simple Model

We derive the proofs for Section 2.

A.1 Equilibrium of Simple Model

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

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

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

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

Without loss of generality, we normalize the economy's total output, PY, to 1. 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 changes on the employment of high-skilled and low-skilled workers can be summarized as follows:

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

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

in which $\Delta = 1-\sigma-(1-s_A)(1-\psi)+[(1-s_A)(1-\psi)+\theta]\,s_R$ summarizes the impact of tools 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.

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

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 Δ, we show that $\Delta+(1-s_A)(1-\psi)+\sigma-1 = \left[\underbrace{(1-s_A)(1-\psi)}_{\text{Productivity Effect},<0} + \underbrace{\theta}_{\text{Substitution Effect},>0}\right] s_R$.

Proof of Proposition 2: The sign of $\frac{\mathrm{dlog}\,l_L}{\mathrm{dlog}\,P_T}$ 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 Δ and collect the terms:

$$
\begin{aligned}
&-\left(\Delta\left[(1-s_{T,H})(\xi+\sigma)+s_{T,H}(\sigma-1)\right]+(\sigma-1)(\xi+\sigma)\right) \\
&=\left((1-s_{T,H})(\xi+\sigma)+s_{T,H}(\sigma-1)\right)\left((1-\psi)(1-s_A)(1-s_R)-\theta s_R+\frac{(1-\sigma)s_{T,H}(\xi+1)}{(1-s_{T,H})(\xi+\sigma)+s_{T,H}(\sigma-1)}\right). \qquad \text{(A.5)}
\end{aligned}
$$

Equation (A.5) is negative because all terms in the equation are negative.

Proof of Proposition 3: The sign of $\frac{\mathrm{dlog}\,l_H}{\mathrm{dlog}\,P_T}$ is determined by the sign of $-\Delta$, which can be further decomposed into the productivity effect, the reinstatement effect, and the substitution effect: $-\Delta = \underbrace{(1-s_A)(1-\psi)(1-s_R)}_{\text{Productivity Effect},<0} + \underbrace{-\theta s_R}_{\text{Reinstatement Effect},<0} + \underbrace{\sigma-1}_{\text{Substitution Effect},>0}$.

Proof of Proposition 4: Equivalently, we demonstrate that

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

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.3) and (A.4), 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

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

$\frac{\operatorname{dlog} w_H}{\operatorname{dlog} P_T} > \frac{\operatorname{dlog} w_L}{\operatorname{dlog} P_T}$ 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. $\frac{\operatorname{dlog} \ell_H}{\operatorname{dlog} P_T} > \frac{\operatorname{dlog} \ell_H}{\operatorname{dlog} P_T}$ 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. Equation (A.6) shows that a country's GDP can be increased by lowering the cost of either tools or robots:

$$\begin{aligned}\operatorname{dlog}(Y) = &-\frac{s_A(1-s_R)(1-s_{T,H})(1-\delta)(\xi+\sigma)(\xi_2+1)}{\Delta\left[(1-s_{T,H})\delta(\xi+\sigma)+s_{T,H}(1+\xi+(\sigma-1)\delta)\right]+(1+\xi+(\sigma-1)\delta)(\xi+\sigma)}\operatorname{dlog} P_T \\ &-\frac{s_A s_R\left[(\xi+1)(\xi+1)+(\xi+1)(\sigma-1)s_{T,H}\delta+(\xi+1)(\sigma-1)(1-s_{T,H})\right]}{\Delta\left[(1-s_{T,H})\delta(\xi+\sigma)+s_{T,H}(1+\xi+(\sigma-1)\delta)\right]+(1+\xi+(\sigma-1)\delta)(\xi+\sigma)}\operatorname{dlog} P_R. \end{aligned} \tag{A.6}$$

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

$$\operatorname{dlog} P = s_A s_R \operatorname{dlog} P_R + s_A(1-s_R)s_{T,H}\operatorname{dlog} w_H + s_A(1-s_R)(1-s_{T,H})\delta\operatorname{dlog} w_L + s_A(1-s_R)(1-s_{T,H})(1-\delta)\operatorname{dlog} P_T.$$

Plugging in $\operatorname{dlog} w_H$ and $\operatorname{dlog} w_L$ according to Equations (A.3) and (A.4), we get Equation (A.6).

B Appendix for the 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 those in Argente et al. (2020).

Parsing and Lemmatization. Documents are tokenized into 1-grams (individual words) and lemmatized to their root forms using the WordNet database (wordnet.princeton.edu) to consolidate grammatical variants.

Selection and Vectorization. Common words appearing in over 80% of documents are dropped. Each document k is then represented by a binary vector c_k, where $c_{km} = 1$ if word m appears in document k, and 0 otherwise.

Normalization. Words are weighted by term-frequency-inverse-document-frequency (TF-IDF) scores:

$$\omega_m = \log\left(\frac{K+1}{d_m+1}\right) + 1,$$

where d_m is the number of documents containing word m. Document vectors are normalized to have unit ℓ_2 norm:

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

Final Classification. Cosine similarities between machine vectors and Wikipedia article vectors are computed. Each machine j is classified as robotic if its most similar article $w_j^* = \arg\max_w s_{jw}$ corresponds to an automation-related topic.

B.1.3 Summary Statistics of Robots and Tools

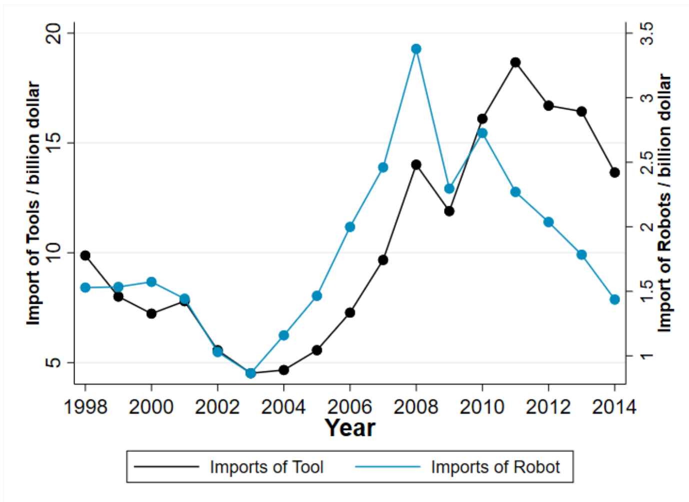
The following three facts highlight the importance of tools among firms in Brazil.

Imports of Tools Are about 10 Times the Imports of Robots. Figure B.1a shows that imports of tools are about 10 times those of robots, with both being strongly correlated over time.

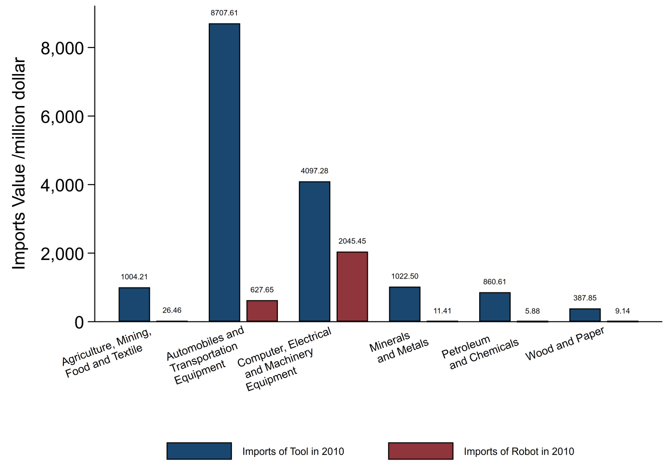
Robot Adoption Is Concentrated in a Few Sectors, Whereas Tools Are Common in All Sectors. Figure B.1b shows that tool imports are widespread across most sectors, while robot imports are concentrated in the transportation and electrical equipment industries.

Figure B.1: **Summary Statistics**

(a) **Robot and Tool Adoption over Time**



(b) **Robot and Tool Adoption by Sector**



(c) **Average Price of Robots and Tools over Time**

Description: Panel (a) shows the total imports of machines classified as robots or tools in real 2010 US dollars. Panel (b) shows the imports of robots and tools in 2010 by large sectors. Panel (c) shows the average prices of robots and tools over time. The prices are calculated by dividing import values by import weights.

Robots and Tools Have Become Cheaper Over Time. Figure B.1c shows the average price of robots and tools over time. Since 1998, their prices have decreased by 49% and 42%, respectively, which explains the large increase in the adoption of robots and tools.

B.1.4 Validation of Machine Classification

In this section, we discuss the validation exercises.

Relevant Machines. Machines strongly associated with robots or tools can be recognized by human inspection. Table B.1 lists the top five machines most similar to the tools.

The machines most associated with robots include industrial robots, numerically controlled machines, and lifting equipment such as traveling cranes. This finding aligns with previous studies: Boustan et al. (2022) show that numerically controlled machines replace less-educated workers performing routine tasks, similar to industrial robots, and Acemoglu and Restrepo (2019) argue that both contribute equally to automation. Additionally, Adachi (2022) notes that industrial robots specializing in picking, packaging, and material handling perform tasks similar to those handled by cranes and other lifting machinery.

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

Panel B of Table B.1 shows the top five machines with the highest similarity to tools. Most of these are hand-operated and used to work with wood or metal.[43]

Words Driving Classification. We show that the key words used to classify machines are related to automation or the handling of equipment. This rules out the possibility that the algorithm uses counter-intuitive words to classify machines.[44]

Figure B.2a shows the most common words among robots, with terms such as "process," "automatic," and "control," which are directly linked to automation. Words such as "unit," "datum," and "industrial" appear often among "automatic" or "numerical control." Figure B.2b shows the common words among machines classified as tools, including synonyms such as "tool," "instrument," and "apparatus," and worker-related terms such as "work" and "hand." Other frequent terms, such as "part" and "incl," are common in tool product names.

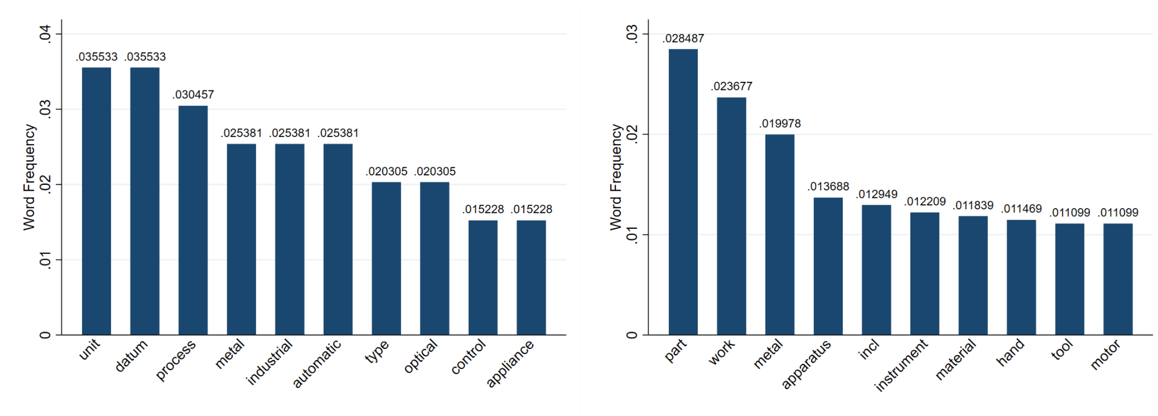
Figure B.3 shows the importance of robot- and tool-related words to the classification algorithm. We proceed in two steps. First, we select five robot-related words ("automatic," "numeric," "control," "robot," "program") and five tool-related words ("tool," "hand," "use," "handle," "instrument"). Second, we re-

[43]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.

[44]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.

Figure B.2: **Distribution of Words among Machines Classified as Robots or Tools**

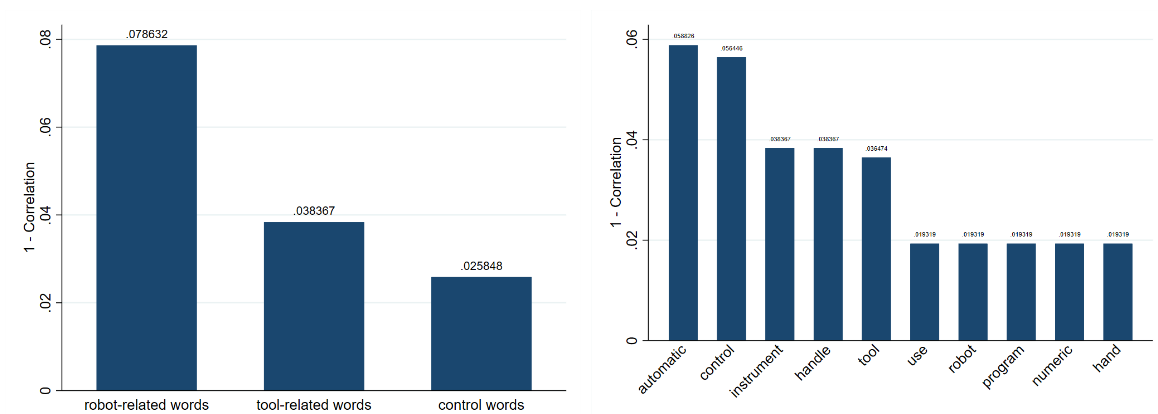
(a) **Common Words among Robots** (b) **Common Words among Tools**



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

Figure B.3: **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 robots 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 five words from the vocabulary 30 times and plot their correlation under "control words." Figure B.3b repeats this exercise for each robot- and tool-related word.

move each set of words from the vocabulary, rerun the classification, and compute the correlation between classifications with and without the selected words. Figure B.3 plots one minus this correlation: a higher value indicates that removing the word substantially alters the classification. As a baseline, we randomly remove five words 30 times and average the resulting correlations. According to Figure B.3, words intuitively associated with automation or the handling of equipment are key to the classification algorithm. Figure B.3a shows that, as expected, words associated with robots and tools are relevant to the machine classification. Figure B.3b shows that the words "automatic," "control," and "instrument" are the most important for the machine classification.

Table B.2 shows the effect of different words on the probability of a machine being classified as a robot. Words associated with automation strongly increase the probability of robot classification, whereas

Table B.2: **Correlation Between Words and Classification**

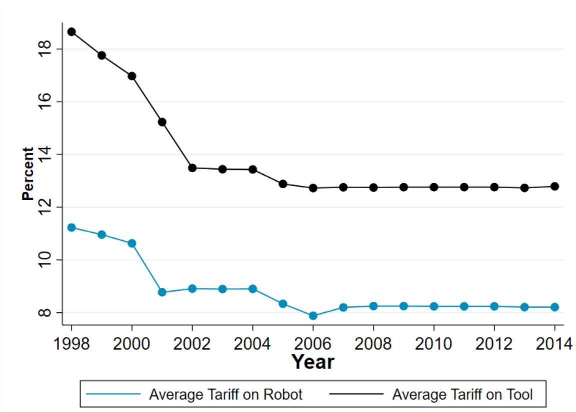
Dependent Variable: $\mathbb{I}(Robot)$									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\mathbb{I}(contain\ \text{"}automatic\text{"})$	0.358***								
	(0.0724)								
$\mathbb{I}(contain\ \text{"}numeric\text{"})$		0.537***							
		(0.111)							
$\mathbb{I}(contain\ \text{"}control\text{"})$			0.209***						
			(0.0770)						
$\mathbb{I}(contain\ \text{"}robot\text{"})$				0.933***					
				(0.250)					
$\mathbb{I}(contain\ \text{"}tool\text{"})$					-0.0745				
					(0.0489)				
$\mathbb{I}(contain\ \text{"}hand\text{"})$						-0.0498			
						(0.0418)			
$\mathbb{I}(contain\ \text{"}use\text{"})$							-0.0411		
							(0.0468)		
$\mathbb{I}(contain\ \text{"}handle\text{"})$								0.0224	
								(0.0777)	
$\mathbb{I}(contain\ \text{"}instrument\text{"})$									0.0208
									(0.0456)
N	405	405	405	405	405	405	405	405	405
R^2	0.057	0.055	0.018	0.033	0.006	0.004	0.002	0.000	0.001

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. Standard errors are in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

tool-related words such as "hand" and "tool" have negative but non-significant effects.

B.1.5 Other Tables and Figures

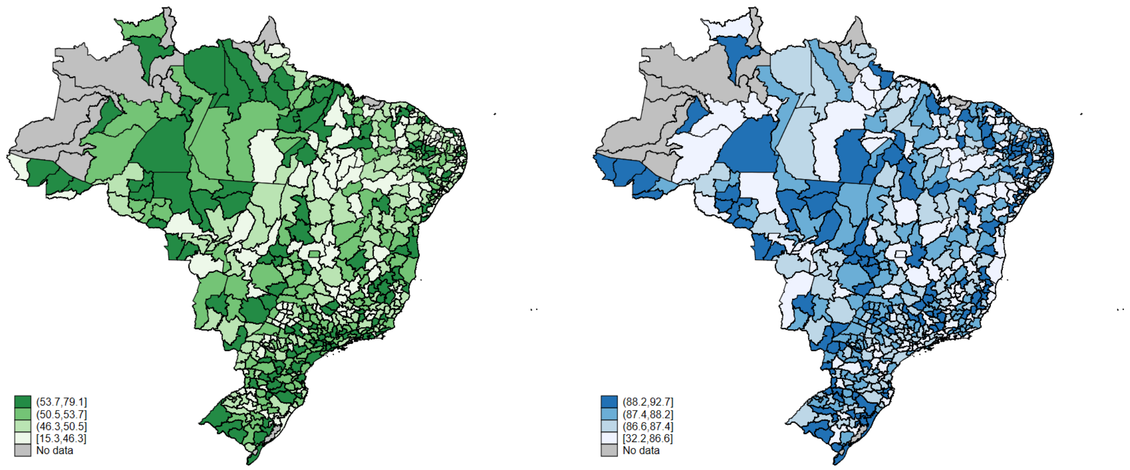
Figure B.4: **Tariffs on Robots and Tools over Time**



Description: This figure plots the average import tariffs on robots and tools in Brazil over time. Tariffs are weighted by the import share in 1997.

Figure B.5: **Manual and Routine Task Content across Regions**

(a) **Routine Task Content** (%) (b) **Manual Task Content** (%)



Description: This figure plots the average routine and manual task content in different microregions in Brazil in 1997. The routine task content for each occupation is constructed averaging the O*NET questions on the degree of automation and the importance of doing the same task. The manual task content for each occupation is constructed averaging all the O*NET questions related to the use of hand tools.

B.2 Empirics

Table B.3: **Validation: Political Connections and Other Policies**

	(1) Δ log *Subsidized Loan*	(2) Δ log *Federal Procurement*	(3) Δ log *Campaign Contribution*	(4) Δ log *International Import Price*	(5) Δ log *International Export Price*
$\Delta IV^{robots}_{r,s,t}$	-0.0063	0.1699	0.1239	0.0078	0.0067
	(0.1024)	(0.1248)	(0.0768)	(0.0074)	(0.0084)
$\Delta IV^{tools}_{r,s,t}$	0.1411	-0.0556	-0.0767	-0.0019	0.0069*
	(0.1066)	(0.1227)	(0.0665)	(0.0035)	(0.0040)
N	56545	56545	56545	158944	70048

Description: This table shows the coefficients of regression (11) on outcomes related to the prominent policies of the period. In the first column, the left-hand side is the total loans made by the BNDES; in the second column, it is the total federal procurement; in the third column, it is the total campaign contributions made by firms; in the fourth column, it is the price of imports; and in the last column it is the average price of exports. Standard errors (in parentheses) are clustered at the region–sector level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table B.4: **Validation: Pre-Period Labor Market Outcomes**

	(1) Δ log *Employment*	(2) Δ log *Earnings*	(3) Δ log *Wage Bill*	(4) Δ log *Avg. Yrs. Edu.*	(5) Δ log *H.S. Drop.*	(6) Δ log *H.S. Complete*
$\Delta IV^{robots}_{r,s,t}$	-0.0182	-0.0279	-0.0146	0.0281	-0.0503	0.0170
	(0.0405)	(0.0734)	(0.0232)	(0.0697)	(0.0774)	(0.0777)
$\Delta IV^{tools}_{r,s,t}$	0.0130	0.0407	-0.00783	0.0361	0.0783	0.00178
	(0.0144)	(0.0327)	(0.00720)	(0.0239)	(0.0590)	(0.0672)
N	11692	11692	11582	11398	6758	4704
R^2	0.032	0.571	0.002	0.600	0.270	0.240

Description: This table shows the coefficients of regression (11) on the growth rate of different labor market variables in the pre-period. In the first column, the left-hand side is employment growth; in the second column, it is average monthly wage; in the third column, it is wage bill; in the fourth column, it is average years of education; in the fifth column, it is the number of workers with less education than a high school diploma; and in the last column, it is the number of workers with high school. Standard errors (in parentheses) are clustered at the region–sector level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

B.3 Empirical Results

Table B.5: **First Stage with Alternative Measures**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ΔIHS *Robots*	ΔIHS *Robots*	ΔIHS *Tools*	ΔIHS *Tools*	$\Delta\mathbb{I}$ *Robots*	$\Delta\mathbb{I}$ *Robots*	$\Delta\mathbb{I}$ *Tools*	$\Delta\mathbb{I}$ *Tools*
ΔIV^{robots}	-0.6946***	-0.6834***	-0.7703***	-0.7438***	-0.0694***	-0.0650***	-0.0351***	-0.0325***
	(0.0348)	(0.0350)	(0.0340)	(0.0345)	(0.0037)	(0.0038)	(0.0025)	(0.0025)
ΔIV^{tools}	0.2006***	0.2144***	-0.3695***	-0.3221***	0.0019	0.0051	-0.0367***	-0.0298***
	(0.0272)	(0.0278)	(0.0440)	(0.0449)	(0.0035)	(0.0036)	(0.0047)	(0.0047)
N	204069	204049	204069	204049	204069	204049	204069	204049
R^2	0.339	0.388	0.529	0.555	0.324	0.355	0.537	0.561
F	124.001	209.476	144.064	221.878	106.643	168.107	56.185	78.694

Description: This table shows the coefficients of the first stage, i.e., regressions (11) and (12). In columns 1–4, the left-hand side uses the inverse hyperbolic sine of robot and tool imports. In columns 5–8, the left-hand side is a dummy taking 1 if the market has imported at least one robot or tool 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, the average routine task content in 1997, the average manual task content in 1997, and year fixed effects. Columns 1, 3, 5, and 7 have sector and region fixed effects, and columns 2, 4, 6, and 8 have sector–region fixed effects. Standard errors (in parentheses) are clustered at the region–sector level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table B.6: **First Stage without Tools Instrument**

	(1)	(2)	(3)	(4)
	Δlog *Robots*	Δlog *Robots*	Δlog *Tools*	Δlog *Tools*
ΔIV^{Robots}	-0.6095***	-0.6001***	-0.8002***	-0.7661***
	(0.0320)	(0.0322)	(0.0320)	(0.0325)
N	204069	204049	204069	204049
R^2	0.337	0.388	0.523	0.549
F	165.679	267.169	177.888	264.715

Description: This table shows the coefficients of the first stage, i.e., regressions (11), but without controlling for tools, IV^{Tools}. Columns 1 and 3 have sector and region fixed effects, and columns 2 and 4 have sector–region fixed effects. Standard errors (in parentheses) are clustered at the region–sector level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

B.3.1 Robot and Tool Imports as Instruments and Comparisons with the Literature

Following the procedure adopted by Acemoglu and Restrepo (2020) and Dauth et al. (2021), among others, we instrument robot and tool adoption using their imports by other countries. The main results remain similar. Excluding tools biases the estimated effect of robots toward zero, consistent with previous findings.

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

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

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

where $IMP^{robots}_{s,t}$ and $IMP^{tools}_{s,t}$ are the imports of robots and tools by sector s in the US and Europe in the past 5 years, respectively. 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 an increase in their quality.

Results. Table B.7 shows that robot and tool imports in Brazil are positively correlated with those in the US and Europe. The cross-elasticities are also large and significant, implying that increased imports of robots (tools) in developed countries lead to higher adoption of tools (robots) in Brazil. This implies that removing tools from specification (7) will lead to a downward bias in the estimated effect of robots.

Table B.7: **First Stage with Imports by Other Countries as the Instrument**

	(1) Δlog Robots	(2) Δlog Robots	(3) Δlog Robots	(4) Δlog Tools	(5) Δlog Tools	(6) Δlog Tools
$\Delta \log(IMP^{robots})$	0.8662***	1.2012***	1.2046***	0.3118***	-0.0696	0.0301
	(0.0803)	(0.0375)	(0.0340)	(0.1115)	(0.0572)	(0.0509)
$\Delta \log(IMP^{tools})$	0.0979***	0.1210***	0.1260***	0.1453*	0.1729**	0.1502**
	(0.0304)	(0.0296)	(0.0276)	(0.0856)	(0.0702)	(0.0665)
N	189456	132513	132512	189456	132513	132512
R^2	0.104	0.052	0.105	0.055	0.055	0.119
F	64.366	238.328	279.666	5.719	8.283	7.825

Description: This table shows the coefficients of the first stage, i.e., regressions (B.1) and (B.2). 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. 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 (in parentheses) are clustered at the region–sector level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table B.8 shows that, using imports by other countries as instruments, it is still true that tools increase employment and earnings, whereas robots decrease them. The estimated effect of robots is larger than previously found in the literature. Compared to the elasticities identified in Section 6, tools also positively affect the employment of workers with college or more education, but to a lesser extent than their effects on low-skilled workers.

Table B.8: **Effect of Robots and Tools with Imports by Other Countries as the Instrument**

	(1) Δlog Employment	(2) Δlog Earnings	(3) Δlog Wage Bill	(4) Δlog H.S. Drop.	(5) Δlog H.S. Complete	(6) Δlog College or More
Δ log(Robots)	-0.119***	-0.0253**	-0.144***	-0.181***	-0.0431**	0.0502*
	(0.0427)	(0.0123)	(0.0530)	(0.0404)	(0.0201)	(0.0272)
Δ log(Tools)	0.643***	0.188***	0.831***	0.600***	0.0325	0.383***
	(0.207)	(0.0611)	(0.258)	(0.220)	(0.111)	(0.137)
N	189456	189456	189456	178163	161605	101569
R^2	-2.037	-2.118	-2.792	-1.868	-0.004	-0.689

Description: This table shows the coefficients of regression (7) on the labor market using as the instrument the imports of robots and tools by the US and Europe. Δ log(Robots) and Δ log(Tools) are instrumented by imports of robots and tools by other countries, as defined in (B.1) and (B.2). Standard errors (in parentheses) are clustered at the region–sector level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table B.9 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.7, 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.9: **Effect of Robots with Imports by Other Countries as the Instrument and Without Controlling for Tools**

	(1) Δlog *Employment*	(2) Δlog *Earnings*	(3) Δlog *Wage Bill*	(4) Δlog *H.S. Drop.*	(5) Δlog *H.S. Complete*	(6) Δlog *College or More*
Δ log(Robots)	-0.0483**	-0.00470	-0.0530**	-0.127***	-0.0421**	0.0166
	(0.0195)	(0.00500)	(0.0213)	(0.0195)	(0.0197)	(0.0200)
N	189456	189456	189456	178163	161605	101569
R^2	-0.006	-0.000	-0.005	-0.027	-0.003	0.000

Description: This table shows the coefficients of regression (7) without controlling for the adoption of tools. Δ log(Robots) is instrumented by imports of robots by other countries. Standard errors (in parentheses) are clustered at the region–sector level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

B.3.2 Tariff Instrument

Table B.10: **Tariff Instrument: Employment, Robots, and Tools**

	(1) Δlog *Employment*	(2) Δlog *Employment*	(3) Δlog *Employment*	(4) Δlog *Employment*	(5) Δlog *Employment*
Δ log(Robots)	-0.0878**	-0.0781**	-0.2355***	-0.2272***	-0.2264***
	(0.0351)	(0.0311)	(0.0735)	(0.0713)	(0.0748)
Δ log(Tools)	0.1355***	0.1314***	0.1727***	0.1644***	0.1804***
	(0.0502)	(0.0471)	(0.0504)	(0.0462)	(0.0524)
N	204812	204811	204812	204811	204791

Description: This table shows the coefficients of regression (7) on employment. Δ log(Tools) and Δ log(Robots) are instrumented by the average tariffs on robots and tools, as described in 8. All specifications have year fixed effects. Column 1 contains 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 2 adds region fixed effect to the baseline controls. Column 3 adds sector fixed effect to the baseline controls. Column 4 includes as controls the baseline controls, region fixed effect, and sector fixed effect. Column 5 includes sector–region fixed effects and the baseline controls. Standard errors (in parentheses) are clustered at the sector–year level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table B.11: **Tariff Instrument: Labor Market, Robots, and Tools**

	(1) Δlog *Employment*	(2) Δlog *Earnings*	(3) Δlog *Wage Bill*	(4) Δlog *H.S. Drop.*	(5) Δlog *H.S. Complete*	(6) Δlog *College or More*
Δ log(Robots)	-0.227**	-0.0322	-0.260**	-0.234***	-0.0252	-0.0195
	(0.0713)	(0.0166)	(0.0809)	(0.0729)	(0.0398)	(0.0267)
Δ log(Tools)	0.164***	0.0391***	0.203***	0.159***	0.0782**	0.0407
	(0.0462)	(0.0112)	(0.0530)	(0.0480)	(0.0384)	(0.0292)
N	204811	204811	204811	194872	116352	75878

Description: This table shows the coefficients of regression (7) on labor market outcomes using tariffs as instrument. Δ log(Tools) and Δ log(Robots) are instrumented by the average tariffs on robots and tools. Standard errors (in parentheses) are clustered at the sector–year level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table B.12: **Tariff Instrument: Occupations, Robots, and Tools**

	(1) Δlog *Managers*	(2) Δlog *HS Professionals*	(3) Δlog *Technical Workers*	(4) Δlog *Adm Workers*	(5) Δlog *Operational Workers*
Δ log(Robots)	0.0235	0.0229	-0.0265	-0.1234***	-0.2223**
	(0.0250)	(0.0345)	(0.0453)	(0.0445)	(0.0990)
Δ log(Tools)	0.0037	-0.0003	0.0815	0.0927**	0.2091***
	(0.0296)	(0.0477)	(0.0548)	(0.0414)	(0.0780)
N	46422	20288	72857	134159	149619

Description: This table shows the coefficients of regression (7) on the employment in different occupations using tariffs as instrument. Standard errors (in parentheses) are clustered at the sector–year level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

B.3.3 Controls

Table B.13: **Labor Market, Robots, and Tools in Alternative Specifications**

	(1) Δlog *Employment*	(2) Δlog *Earnings*	(3) Δlog *H.S. Drop.*	(4) Δlog *Wage H.S. Drop.*	(5) Δlog *H.S. Complete*	(6) Δlog *Wage H.S. Complete*	(7) Δlog *College*	(8) Δlog *Wage College*
Panel A. Control for Imports of Intermediate Inputs								
Δ log(Robots)	-0.1548***	-0.0250***	-0.1609***	-0.0362***	-0.0289	-0.0177*	-0.0163	-0.0154
	(0.0283)	(0.0093)	(0.0292)	(0.0092)	(0.0276)	(0.0106)	(0.0238)	(0.0122)
Δ log(Tools)	0.1462***	0.0381***	0.1389***	0.0421***	0.0880***	0.0059	0.0407	0.0306*
	(0.0269)	(0.0087)	(0.0278)	(0.0087)	(0.0324)	(0.0124)	(0.0307)	(0.0156)
N	177211	177211	169565	169565	106189	106189	72376	72376
Panel B. Remove Region FE and Sector FE								
Δ log(Robots)	-0.1056***	-0.0337***	-0.1204***	-0.0400***	-0.0143	-0.0254***	0.0065	-0.0087
	(0.0159)	(0.0054)	(0.0157)	(0.0052)	(0.0148)	(0.0063)	(0.0123)	(0.0063)
Δ log(Tools)	0.1545***	0.0392***	0.1398***	0.0427***	0.0566**	0.0160	0.0213	0.0101
	(0.0224)	(0.0075)	(0.0222)	(0.0072)	(0.0242)	(0.0102)	(0.0212)	(0.0111)
N	204070	204070	194272	194272	116352	116352	75879	75879
Panel C. Add Only Sector FE								
Δ log(Robots)	-0.2333***	-0.0487***	-0.2409***	-0.0587***	-0.0394	-0.0267**	-0.0248	-0.0108
	(0.0335)	(0.0110)	(0.0340)	(0.0107)	(0.0286)	(0.0115)	(0.0235)	(0.0121)
Δ log(Tools)	0.1826***	0.0534***	0.1830***	0.0561***	0.0966***	0.0142	0.0539**	0.0211
	(0.0266)	(0.0087)	(0.0269)	(0.0085)	(0.0287)	(0.0115)	(0.0261)	(0.0133)
N	204070	204070	194272	194272	116352	116352	75879	75879
Panel D. Add Region-Sector FE								
Δ log(Robots)	-0.2258***	-0.0175*	-0.2371***	-0.0320***	-0.0359	-0.0218**	-0.0199	-0.0127
	(0.0330)	(0.0095)	(0.0329)	(0.0092)	(0.0275)	(0.0108)	(0.0225)	(0.0119)
Δ log(Tools)	0.1942***	0.0215***	0.1923***	0.0297***	0.1003***	0.0074	0.0463*	0.0241*
	(0.0258)	(0.0073)	(0.0256)	(0.0071)	(0.0269)	(0.0105)	(0.0248)	(0.0130)
N	204049	204049	194240	194240	116335	116335	75849	75849
Panel E. Add Initial Employment × Year FE								
Δ log(Robots)	-0.2145***	-0.0334***	-0.2184***	-0.0448***	-0.0303	-0.0218**	-0.0203	-0.0092
	(0.0324)	(0.0101)	(0.0326)	(0.0098)	(0.0278)	(0.0110)	(0.0234)	(0.0121)
Δ log(Tools)	0.1702***	0.0381***	0.1649***	0.0418***	0.0889***	0.0080	0.0456*	0.0198
	(0.0239)	(0.0074)	(0.0242)	(0.0073)	(0.0266)	(0.0105)	(0.0251)	(0.0127)
N	204069	204069	194269	194269	116352	116352	75878	75878
Panel F. Add Pre-period LHS Growth × Year FE								
Δ log(Robots)	-0.1897***	-0.0378***	-0.1878***	-0.0422***	-0.0357	-0.0171*	-0.0367*	-0.0145
	(0.0296)	(0.0097)	(0.0298)	(0.0093)	(0.0266)	(0.0102)	(0.0220)	(0.0112)
Δ log(Tools)	0.1426***	0.0434***	0.1348***	0.0435***	0.0842***	0.0063	0.0485**	0.0235*
	(0.0226)	(0.0074)	(0.0227)	(0.0071)	(0.0262)	(0.0102)	(0.0244)	(0.0123)
N	204069	204069	194269	194269	116352	116352	75878	75878

Description: This table shows the coefficients of regression (7) on employment and earnings of different educational groups. Δ log(Tools) and Δ log(Robots) are instrumented by the interaction of tariff changes with the share of replaceable occupations, as defined in (9) and (10). The controls are the growth rate of the left-hand-side variable between 1993 and 1997, the tariff change on sectoral output, the tariff change on inputs excluding capital, import of other inputs. Each panel reports coefficients estimated using an alternative specification which differs from the baseline as suggested by the panel name. Columns 1 and 2 show the effect of robots and tools on employment and earnings. Columns 3 and 4 show the effect on workers who have less education than a high-school diploma. Columns 5 and 6 show the effect on workers with a high-school diploma. Columns 7 and 8 show the effect on workers with at least some college education. Standard errors (in parentheses) are clustered at the region–sector level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table B.14: **Occupations, Robots, and Tools in Alternative Specifications**

	(1) Δlog *Managers*	(2) Δlog *HS Professionals*	(3) Δlog *Technical Workers*	(4) Δlog *Adm Workers*	(5) Δlog *Operational Workers*
Panel A. Control for Imports of Intermediate Inputs					
Δ log(Robots)	0.0318	0.0184	-0.0283	-0.1043***	-0.1580***
	(0.0252)	(0.0356)	(0.0268)	(0.0264)	(0.0369)
Δ log(Tools)	-0.0136	0.0081	0.1001***	0.0906***	0.2221***
	(0.0354)	(0.0531)	(0.0377)	(0.0289)	(0.0396)
N	44303	19525	69025	122064	132237
Panel B. Remove Region FE and Sector FE					
Δ log(Robots)	0.0271**	0.0473***	0.0465***	-0.0485***	-0.0638***
	(0.0122)	(0.0166)	(0.0142)	(0.0135)	(0.0196)
Δ log(Tools)	0.0040	-0.0127	0.0375	0.0885***	0.1623***
	(0.0229)	(0.0294)	(0.0256)	(0.0217)	(0.0295)
N	46426	20292	72858	134134	149620
Panel C. Add Only Sector FE					
Δ log(Robots)	0.0146	0.0139	-0.0268	-0.1352***	-0.2035***
	(0.0232)	(0.0319)	(0.0259)	(0.0275)	(0.0405)
Δ log(Tools)	0.0148	0.0091	0.0928***	0.1142***	0.2425***
	(0.0274)	(0.0384)	(0.0308)	(0.0260)	(0.0364)
N	46425	20292	72858	134134	149620
Panel D. Add Region-Sector FE					
Δ log(Robots)	0.0175	0.0159	-0.0184	-0.1398***	-0.1855***
	(0.0230)	(0.0334)	(0.0250)	(0.0271)	(0.0384)
Δ log(Tools)	0.0072	0.0013	0.0851***	0.1243***	0.2333***
	(0.0273)	(0.0412)	(0.0294)	(0.0255)	(0.0342)
N	46405	20278	72802	134096	149596
Panel E. Add Initial Employment $\times$ Year FE					
Δ log(Robots)	0.0146	0.0175	-0.0185	-0.1267***	-0.1732***
	(0.0231)	(0.0328)	(0.0255)	(0.0271)	(0.0379)
Δ log(Tools)	0.0120	0.0079	0.0832***	0.1057***	0.2198***
	(0.0263)	(0.0385)	(0.0292)	(0.0242)	(0.0326)
N	46422	20288	72857	134132	149619
Panel F. Add Pre-period LHS Growth $\times$ Year FE					
Δ log(Robots)	-0.0018	0.0041	-0.0239	-0.1105***	-0.1473***
	(0.0217)	(0.0302)	(0.0238)	(0.0249)	(0.0344)
Δ log(Tools)	0.0242	0.0173	0.0750***	0.0831***	0.1888***
	(0.0260)	(0.0378)	(0.0285)	(0.0229)	(0.0305)
N	46422	20288	72857	134132	149619

Description: This table shows the coefficients of regression (7) on employment in different occupations. Δ log(Tools) and Δ log(Robots) are instrumented by the interaction of tariff changes with the share of replaceable occupations, as defined in (9) and (10). The controls are the growth rate of the left-hand-side variable between 1993 and 1997, the tariff change on sectoral output, the tariff change on inputs excluding capital, import of other inputs. Each panel reports coefficients estimated using an alternative specification which differs from the baseline as suggested by the panel name. In column 1, it is the number of managers, i.e., 1-digit CBO 2002 occupations 0 and 1; in column 2, it is the number of science professionals, i.e., 1-digit CBO 2002 occupation 2; in column 3, it is the number of technical workers, i.e., 1-digit CBO 2002 occupation 3; in column 4, it is the number of administrative workers, i.e., 1-digit CBO 2002 occupations 4 and 5; and in column 5, it is the number of operational blue-collar workers, i.e., 1-digit CBO 2002 occupations 6 and 7. Standard errors (in parentheses) are clustered at the region–sector level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

B.3.4 Higher Degree of Text Similarity

Table B.15: **Effect of Tools and Robots on Employment When Limiting the Sample to High Text Similarity Machines**

	(1) Δ log *Employment*	(2) Δ log *Earnings*	(3) Δ log *Wage Bill*	(5) Δ log *H.S. Drop.*	(6) Δ log *H.S. Complete*	(7) Δ log *College or More*
Δ log(Robots)	-0.156***	-0.0452***	-0.201***	-0.183***	0.00572	0.00119
	(0.0294)	(0.00919)	(0.0341)	(0.0299)	(0.0268)	(0.0227)
Δ log(Tools)	0.225***	0.0521***	0.277***	0.222***	0.102***	0.0536*
	(0.0322)	(0.00989)	(0.0373)	(0.0330)	(0.0339)	(0.0306)
N	204069	204069	204069	194269	116352	75878

Description: This table shows the coefficients of regression (7) on employment. Instead of using all machines, we limit the sample to machines that have text similarity to robot or tool above the median. Standard errors (in parentheses) are clustered at the region–sector level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table B.16: **Effect of Tools and Robots on Different Occupations When Limiting the Sample to High Text Similarity Machines**

	(1) Δ*log* *Managers*	(2) Δ*log* *HS Professionals*	(3) Δ*log* *Technical Workers*	(4) Δ*log* *Adm Workers*	(5) Δ*log* *Operational Workers*
Δ log(Robots)	0.0284	0.0069	-0.0306	-0.0619**	-0.1784***
	(0.0215)	(0.0293)	(0.0244)	(0.0259)	(0.0374)
Δ log(Tools)	0.0135	0.0226	0.1116***	0.1448***	0.2993***
	(0.0320)	(0.0417)	(0.0356)	(0.0319)	(0.0469)
N	46422	20288	72857	134132	149619

Description: This table shows the coefficients of regression (7) 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. Standard errors (in parentheses) are clustered at the region–sector level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

B.3.5 Test on Informality

Table B.17: **Effect of Tools and Robots on Informal Infractions**

	(1) Δ*log* No. of firms with informal infraction	(2) Δ*log* No. of firms under inspection with no infraction	(3) Δ*log* No. of firms under inspection with infraction	(4) Δ*log* No. of informal infractions	(5) Δ*log* No. of inspections with infraction	(6) Δ*log* No. of inspections with no infraction
Δ log(*tool*)	-0.1431	0.0129	-0.0804	-0.0371	0.0052	-0.3257*
	(0.3233)	(0.0509)	(0.1405)	(0.3112)	(0.0611)	(0.1881)
Δ log(*robots*)	0.3373	-0.0671	0.0556	0.1397	-0.0852	0.3704
	(0.5287)	(0.0926)	(0.1988)	(0.5012)	(0.1122)	(0.2637)
N	2864	57963	19594	2864	57963	19594

Description: This table shows the coefficients of regression (7) on informal infractions. Standard errors (in parentheses) are clustered at the region–sector level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

B.3.6 LLM Classification

To classify machines as robots or tools, we use the following prompt in Gemini. The prompt provides a description of robot and tools inspired by the model and examples of machines classified in each, a technique know as n-shot prompting.

I want to classify a set of product codes into two groups according to their relation to labor. There are two broad categories. The first broad category of machines I call "robots". Those are machines that perform tasks done by *workers, such as industrial robots. Those machines usually do not require a direct operator and are programmable. Examples of robots are industrial robot, cartesian coordinate robot, robotic arm, SCARA, articulated robot, parallel manipulator, anything that is propelled by itself, and other numerically controlled machines. Anything propelled by itself should be consiered a robot.*

The second broad category of machines I call "tools". Those are machines that increase the productivity of workers on tasks that they already perform, such as power tools. Machines that require a worker operating them are usually a tool. Examples of tools are 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, jacks, hoists, tractors, vacuum cleaners, mowers, winches, pulley, tackles, and a wrench.

In case the product is ambiguous and it could be either a robot or a tool depending of the model and year of creation, assume that it is a tool.

Based on my examples above, respond with a 1 if the following is a robot and 0 otherwise: {product_description}. DO NOT RESPOND WITH ANYTHING OTHER THAN JUST A 1 OR JUST A 0.

Table B.18: **Labor Market, Robots, and Tools Using LLM Classification**

	(1) Δ*log* *Employment*	(2) Δ*log* *Earnings*	(3) Δ*log* *H.S. Drop.*	(4) Δ*log* *Wage H.S. Drop.*	(5) Δ*log* *H.S. Complete*	(6) Δ*log* *Wage H.S. Complete*	(7) Δ*log* *College*	(8) Δ*log* *Wage College*
Δ log(Robots)	-0.6867***	-0.1640**	-0.6204***	-0.1868**	-0.1633	-0.0226	-0.0671*	-0.0258
	(0.2452)	(0.0645)	(0.2376)	(0.0741)	(0.1070)	(0.0322)	(0.0355)	(0.0177)
Δ log(Tools)	0.6667***	0.1640**	0.6310**	0.1910**	0.2823	0.0155	0.1350	0.0487
	(0.2450)	(0.0645)	(0.2459)	(0.0768)	(0.1806)	(0.0542)	(0.0873)	(0.0433)
N	205609	205609	195678	195678	116912	116912	76057	76057

Description: This table shows the coefficients of regression (7) on employment and earnings of different educational groups. Δ log(Tools) and Δ log(Robots) are instrumented by the interaction of tariff changes with the share of replaceable occupations, as defined in (9) and (10). Departing from the baseline classification, we use Google Gemini, a large language model, to define robots and tools. The controls are the growth rate of the left-hand-side variable between 1993 and 1997, the tariff change on sectoral output, the tariff change on inputs excluding capital, import of other inputs. Standard errors (in parentheses) are clustered at the region–sector level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

C Appendix for Quantitative Model

C.1 Additional Equations

Firm Technology Choice and Production. The expenditure share by firm i on tasks performed with technology $l \in \{R, T\}$ equals the following:

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

where $\Phi_n^s(i) = \left(\sum_{l=1}^{L} T_n^{s,l}(i)\left(\Theta_n^{s,l}(i)\right)^{-\theta}\right)^{-\frac{1}{\theta}}$ 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: $p_n^{s,VA}(i) = \bar{\gamma}\Phi_n^s(i)$.[45] The firm's output price equals the following:

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

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

Sectoral Production and Trade. The output price index at the region–sector level (the price index associated with y_n^s) is defined as follows:

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

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 $t^s = 1 + \tau^s$. Include the foreign price p_{N+1}^s in the importing cost h_{nN+1}^s. Consequently, the composite goods price is:

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

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

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

[45] γ is the Gamma constant.

Capital Goods Sector. Using Equation (14), we observe that investment decreases with the cost of capital production:

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

Workers' Dynamic Problem. Following Artuç et al. (2010), Caliendo et al. (2019), and Kleinman et al. (2023), among others, a worker of type e has the following recursive utility:

$$\begin{aligned} \mathbb{V}_{n,t}^{s,e} &= \log(u_{n,t}^{s,e}) + \max_{n' \in \{1,2,\ldots,N\}, s' \in \{1,\ldots,S,S+1\}} \left\{ \lambda^e \beta \mathbb{E}_t \left(\mathbb{V}_{n',t+1}^{s',e} \right) - \kappa_{n'n,t}^{s's} + \rho^e \epsilon_{n',t}^{s',e} \right\}, e \in \{H, L\}, \\ \text{where } u_{n,t}^{s,e} &= \max_{\left\{ C_{n,t}^{ss',e} \right\}} a_{n,t}^{s,e} \prod_{s'=1}^{S} \left(\frac{C_{n,t}^{ss',e}}{\alpha^{s'}} \right)^{\alpha^{s'}} \quad \text{s.t.} \quad \sum_{s'=1}^{S} P_{n,t}^{s'} C_{n,t}^{ss',e} = (1-B) w_{n,t}^{s,e}, \end{aligned} \tag{C.1}$$

where $\mathbb{V}_{n,t}^{s,e}$ is the value function of a worker in region n, sector s, and skill level e at time t. Workers choose their location next period, n', sector, s', and consumption of sectoral goods, $\left\{ C_{n,t}^{ss',e} \right\}$. $\alpha^{s'}$ and $a_{n,t}^{s,e}$ are parameters of the utility function representing the sectoral consumption shares and consumption shifters.

With probability $1 - \lambda^H$, a high-skilled worker dies, which is similar for low-skilled workers with probability $1 - \lambda^L$. The dead worker is replaced by an entrant in the same region–sector, who decides whether to become a high- or low-skilled worker.

$\kappa_{n'n,t}^{s's}$ is the mobility cost from region n, sector s to region n', sector s'. $\epsilon_{n',t}^{s',e}$ is a preference shock for regions and sectors following a Type-I extreme value distribution i.i.d. across regions, sectors, and time.[46] The income of a worker in the outside sector is equal to the social insurance payment: $w_{n,t}^{S+1,e} = b$.

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

$$v_{n,t}^{s,e} = \log(a_{n,t}^{s,e}) + \log(1-B) + \log \left(\frac{w_{n,t}^{s,e}}{P_{n,t}} \right) + \rho^e \log \sum_{n'=1}^{N} \sum_{s'=1}^{S+1} \exp(\lambda^e \beta v_{n',t+1}^{s',e} - \kappa_{n'n,t}^{s',s,e})^{1/\rho^e}. \tag{C.2}$$

This problem can be solved as follows. Consider workers of type $e \in \{H, L\}$'s intratemporal problem. Time t utility equals the following:

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

$$u^{s,e}_{n,t} = \begin{cases} \frac{a^{s,e}_{n,t}(1-B)w^{s,e}_{n,t}}{P_{n,t}} & s \in \{1, ..., S\}, \\ \frac{a^{s,e}_{n,t}(1-B)b}{P_{n,t}} & s = S+1, \end{cases}$$
$$\text{where } P_n = \prod_{s=1}^{S} (P^s_n)^{\alpha^s}.$$

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, where $1/\rho^e$ denotes the migration elasticity:

$$s^{s's,e}_{n'n,t} = \frac{\exp(\lambda^e \beta v^{s',e}_{n',t+1} - \kappa^{s's,e}_{n'n,t})^{1/\rho^e}}{\sum_{n'=1}^{N}\sum_{s'=1}^{S+1}\exp(\lambda^e \beta v^{s',e}_{n',t+1} - \kappa^{s's,e}_{n'n,t})^{1/\rho^e}}. \tag{C.3}$$

Human Capital Choice. At the end of period t, a proportion $1-\lambda^e$ workers die and are replaced with entrants. These entrants are in the same sector and region as those exiting and choose their skill level for the next period. Their problem is given by:

$$\max\left\{\beta v^{s,H}_{n,t} - f^H + \tilde{\rho}\tilde{\epsilon}^{s,H}_{n,t}, \beta v^{s,L}_{n,t} + \tilde{\rho}\tilde{\epsilon}^{s,L}_{n,t}\right\}, \tag{C.4}$$

where f^H denotes the fixed cost of becoming high-skilled and $\tilde{\epsilon}^{s,e}_{n,t}$ is a preference shock.[47]

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

$$\tilde{s}^{s,H}_{n,t} = \frac{\exp(\beta v^{s,H}_{n,t+1} - f^H)^{1/\tilde{\rho}}}{\exp(\beta v^{s,H}_{n,t+1} - f^H)^{1/\tilde{\rho}} + \exp(\beta v^{s,L}_{n,t+1})^{1/\tilde{\rho}}}, \tag{C.5}$$

where $1/\tilde{\rho}$ measures the skill choice elasticity. According to the workers' problem, labor supply at the level of regions or sectors will follow the following law of motion:

$$l^{s',H}_{n',t+1} = \lambda^H \sum_{n=1}^{N}\sum_{s=1}^{S+1} s^{s's,H}_{n'n,t} l^{s,H}_{n,t} + \left((1-\lambda^H)l^{s,H}_{n,t} + (1-\lambda^L)l^{s,L}_{n,t}\right)\tilde{s}^{s,H}_{n,t} \tag{C.6}$$
$$l^{s',L}_{n',t+1} = \lambda^L \sum_{n=1}^{N}\sum_{s=1}^{S+1} s^{s's,L}_{n'n,t} l^{s,L}_{n,t} + \left((1-\lambda^H)l^{s,H}_{n,t} + (1-\lambda^L)l^{s,L}_{n,t}\right)\tilde{s}^{s,L}_{n,t}. \tag{C.7}$$

C.1.1 Market-Clearing Conditions

Robot Capital. The market-clearing condition for robot capital is the following:

$$R^{s,R}_n K^{s,R}_n = (1-\eta)\int_{i=0}^{1} \frac{T^{s,R}(i)(\Theta^{s,R}_n)^{-\theta}}{(\Phi^s_n(i))^{-\theta}} \frac{(p^s_n(i))^{1-\phi}}{(p^s_n)^{1-\phi}} \gamma^s p^s_n Y^s_n di. \tag{C.8}$$

[47] $\tilde{\epsilon}^{s,e}_{n,t}$ follows a Type-I extreme value distribution and is i.i.d. across regions, sectors, time, and skill types.

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

$$R_n^{s,T}K_n^{s,T} = \int_{i=0}^{1}(1-\delta_n^s(i))\frac{\left(\left[w_n^{s,L}\right]^{\delta_n^s(i)}\left[R_n^{s,T}\right]^{1-\delta_n^s(i)}\right)^{1-\sigma}}{\left(\Theta_n^{s,T}(i)\right)^{1-\sigma}}\frac{(\Theta_n^{s,T}(i))^{-\theta}}{(\Phi_n^s(i))^{1-\theta}}\frac{(p_n^s(i))^{1-\phi}}{(p_n^s)^{1-\phi}}\gamma^s p_n^s Y_n^s di.$$

High-skilled Workers. Their market-clearing condition is the following:

$$w_n^{s,H}l_n^{s,H} = \int_{i=0}^{1}\frac{A^{s,H}(i)(w_n^{s,H})^{1-\sigma}}{(\Theta_n^{s,T}(i))^{1-\sigma}}\frac{(\Theta_n^{s,T}(i))^{-\theta}}{(\Phi_n^s(i))^{-\theta}}\frac{(p_n^s(i))^{-\phi}}{(p_n^s)^{-\phi}}\gamma^s p_n^s Y_n^s di + \eta\int_{i=0}^{1}\frac{T^{s,R}(i)(\Theta_n^{s,R})^{-\theta}}{(\Phi_n^s(i))^{-\theta}}\frac{(p_n^s(i))^{1-\phi}}{(p_n^s)^{1-\phi}}\gamma^s p_n^s Y_n^s di.$$

Low-skilled Workers. Their market-clearing condition is the following:

$$w_n^{s,L}l_n^{s,L} = \int_{i=0}^{1}\delta_n^s(i)\frac{\left(\left[w_n^{s,L}\right]^{\delta_n^s(i)}\left[R_n^{s,T}\right]^{1-\delta_n^s(i)}\right)^{1-\zeta}}{(\Theta_n^{s,T}(i))^{1-\zeta}}\frac{(\Theta_n^{s,T}(i))^{-\theta}}{(\Phi_n^s(i))^{-\theta}}\frac{(p_n^s(i))^{1-\phi}}{(p_n^s)^{1-\phi}}\gamma^s p_n^s Y_n^s di.$$

Composite Goods. Composite goods are consumed and used as production inputs:

$$X_n^s = \underbrace{P_n^s C_n^s}_{\text{Consumption}} + \sum_{s'=1}^{S}\gamma^{s's}(\underbrace{\sum_{n'=1}^{N}X_{n'}^{s'}\pi_{n'n}^{s'}}_{\text{Sector } s' \text{ domestic sales}} + \underbrace{EF_n^{s'}(p_n^{s'})^{1-\epsilon^{s'}}}_{\text{Sector } s' \text{ exports}}), \tag{C.9}$$

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

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

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

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

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

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

Equilibrium. The equilibrium is defined as 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 (C.2), sector–region and skill choice probabilities follow Equations (C.3) and (C.5), labor supply follows Equations (C.6) and (C.7), capital supply follows (15), and market-clearing conditions (C.8)–(C.9) and (16) hold.[48]

C.2 Parameterization

Firm-level Productivity. We assume that the log of firm-level high-skilled worker-augmenting productivity, $\log\left(A^{s,H}_{n,t}(i)\right)$, the log of robot-augmenting productivity, $\log\left(T^{s,R}_{n,t}(i)\right)$, and the logit of low-skilled worker share in tool technology, $\log\left(\frac{\delta^s_n(i)}{1-\delta^s_n(i)}\right)$, follow joint normal distributions. They are independent across regions, sectors, firms, and time, but are correlated within a firm. The within-firm correlation reflects the idea that firms employing more low-skilled workers tend to adopt robots, and firms with a lower low-skilled labor share and higher robot share tend to use more high-skilled workers.

Specifically, we assume that $A^{s,H}_n(i) = \exp\left(\mu_H + \sigma_H Z^s_{n,H}(i)\right)$, $T^{s,R}_n(i) = \exp\left(\mu_R + \sigma_R Z^s_{n,R}(i)\right)$, and $\delta^s_n(i) = \frac{\exp\left(\mu_L+\sigma_L Z^s_{n,L}(i)\right)}{1+\exp\left(\mu_L+\sigma_L Z^s_{n,L}(i)\right)}$, where Z_H, Z_R, and Z_L follow multivariate normal:

$$\begin{pmatrix} Z_H \\ Z_R \\ Z_L \end{pmatrix} = \mathcal{N}\left(\begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho_{A^H,T^R} & \rho_{A^H,\delta} \\ \rho_{A^H,T^R} & 1 & \rho_{T^R,\delta} \\ \rho_{A^H,\delta} & \rho_{T^R,\delta} & 1 \end{pmatrix}\right). \tag{C.10}$$

We estimate $\left\{\mu_H, \mu_R, \mu_L, \sigma_H, \sigma_R, \sigma_L, \rho_{A^H,T^R}, \rho_{A^H,\delta}, \rho_{T^R,\delta}\right\}$ with Simulated Method of Moments.

Trade and Migration Costs. We assume that domestic trade cost follows (C.11), depending on whether regions are contiguous, proximity to the coast, the number of ports, and sectoral characteristics such as upstreamness and high-skilled labor share.

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

We assume that the non-tariff trade barrier faced by a region–sector when importing composite goods (Equation C.12), as well as robot (Equation C.13) and tool capital (Equation C.14), 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. The interactions between the geographical and sectoral variables are taken into account. Moreover, an intercept term is included to account for the home bias

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

against imports.

$$\log(h^{s}_{nN+1}) = \beta^{23}\log(\text{Dist to Coast}_n) + \beta^{24}\mathbb{N}(\text{Ports})_n + \beta^{25}\log(\text{Dist to Coast}_n)\log(\text{U}^s) + \beta^{26}\mathbb{N}(\text{Ports})_n\log(\text{U}^s) + \beta^{27}\log(\text{U}^s)$$
$$+ \beta^{28} + \beta^{29}\log(\text{Dist to Coast}_{n'})\log(\text{high-skilled labor share}^s) + \beta^{30}\mathbb{N}(\text{Ports})_{n'}\log(\text{high-skilled labor share}^s)$$
$$+ \beta^{31}\log(\text{high-skilled labor share}^s). \tag{C.12}$$

$$\log(h^{s,R}_{nN+1}) = \beta^{1,R}\log(\text{Dist to Coast}_n) + \beta^{2,R}\mathbb{N}(\text{Ports})_n + \beta^{3,R}\log(\text{Dist to Coast}_{n'})\log(\text{U}^s) + \beta^{4,R}\mathbb{N}(\text{Ports})_{n'}\log(\text{U}^s) + \beta^{5,R}\log(\text{U}^s)$$
$$+ \beta^{6,R} + \beta^{7,R}\log(\text{Dist to Coast}_{n'})\log(\text{high-skilled labor share}^s) + \beta^{8,R}\mathbb{N}(\text{Ports})_{n'}\log(\text{high-skilled labor share}^s)$$
$$+ \beta^{9,R}\log(\text{high-skilled labor share}^s). \tag{C.13}$$

$$\log(h^{s,T}_{nN+1}) = \beta^{1,T}\log(\text{Dist to Coast}_n) + \beta^{2,T}\mathbb{N}(\text{Ports})_n + \beta^{3,T}\log(\text{Dist to Coast}_{n'})\log(\text{U}^s) + \beta^{4,T}\mathbb{N}(\text{Ports})_{n'}\log(\text{U}^s) + \beta^{5,T}\log(\text{U}^s)$$
$$+ \beta^{6,T} + \beta^{7,T}\log(\text{Dist to Coast}_{n'})\log(\text{high-skilled labor share}^s) + \beta^{8,T}\mathbb{N}(\text{Ports})_{n'}\log(\text{high-skilled labor share}^s)$$
$$+ \beta^{9,T}\log(\text{high-skilled labor share}^s). \tag{C.14}$$

The migration cost depends on both the origin and destination region–sector pairs. They are modeled as a function of the same geographical variables that influence domestic trade costs, as well as the absolute differences in sectoral upstreamness and high-skilled labor shares. Interactions between geographical distances and sectoral differences are also incorporated. The migration cost is parameterized as follows:

$$\log(\kappa^{s's}_{n'n}) = \chi^0\mathbf{1}(n'=n) + \chi^1\text{Contig}_{n'n} + \chi^2\log(\text{Dist}_{n'n}) + \chi^3|\log(\text{U}^{s'}) - \log(\text{U}^s)| + \chi^4\text{Contig}_{n'n}|\log(\text{U}^{s'}) - \log(\text{U}^s)|$$
$$+ \chi^5\log(\text{Dist}_{n'n})|\log(\text{U}^{s'}) - \log(\text{U}^s)| + \chi^6\mathbf{1}(n'=n)|\log(\text{U}^{s'}) - \log(\text{U}^s)| + \chi^7|\text{high-skilled labor share}^{s'} - \text{high-skilled labor share}^s|$$
$$+ \chi^8\text{Contig}_{n'n}|\text{high-skilled labor share}^{s'} - \text{high-skilled labor share}^s|$$
$$+ \chi^9\log(\text{Dist}_{n'n})|\text{high-skilled labor share}^{s'} - \text{high-skilled labor share}^s|$$
$$+ \chi^{10}\mathbf{1}(n'=n)|\text{high-skilled labor share}^{s'} - \text{high-skilled labor share}^s|. \tag{C.15}$$

C.3 Estimation

In the first step, we calibrate a set of parameters, including trade elasticities for capital and non-capital goods, migration and skill-choice elasticities, workers' exit rates, social insurance benefits, and input–output coefficients. Table C.1 summarizes these parameters.

Table C.1: **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	5.59	Estimated
ϵ^R	Robot capital goods trade elasticity	7.81	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
λ^H	Continuation probability of high-skilled workers	0.965	Data
λ^L	Continuation probability of low-skilled workers	0.939	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 the parameters in the model that are externally calibrated.

Trade Elasticities. We calibrate sectoral trade elasticities for the composite goods to the estimates from De Souza and Li (2022).[49] Using a specification similar to Section 5, we estimate robot and tool capital trade elasticities as 7.81 and 5.59, respectively.

We estimate the trade elasticities of different types of capital goods by studying how tariff changes affect changes in imports at the regional and sectoral levels.[50] For robots:

$$\Delta \log \left(Import^R_{is,t} \right) = \theta^R \Delta \log \left(Tariff^R_{s,t} \right) + Fixed\ effect_i + Fixed\ effect_s + Fixed\ effect_t + \epsilon_{ist}, \tag{C.16}$$

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[51] tariff on robots in region i, sector s, from year $t-5$ to year t. We estimate an identical specification for tools.

Table C.2 shows the parameters estimated based on Equation (C.16), along with other robustness tests. The main specification (column 2) suggests the elasticities of $\theta^R = -6.81$ and $\theta^T = -4.59$.[52]

Table C.2: **Trade Elasticities 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	-19.20***	-6.813***	-6.493***	-1.808***	-1.788***	-1.889***
	(2.431)	(1.523)	(1.503)	(0.433)	(0.523)	(0.496)
R^2	0.029	0.223	0.225	0.000	0.009	0.009
	(7)	(8)	(9)	(10)	(11)	(12)
Panel B. Trade Elasticity of Tools						
θ^T	-14.13***	-4.594***	-4.707**	-1.323***	-5.456***	-5.260***
	(1.246)	(1.654)	(1.880)	(0.196)	(0.718)	(0.696)
R^2	0.012	0.341	0.343	0.000	0.013	0.013
Observation	322981	322981	322981	397715	397715	397715
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 Equation (C.16). 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 are 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.3), migration shares can be expressed as a function of wages and future migration shares, with the wage coefficient capturing migration elasticity. We use an instrumental variable regression with lagged wages to identify this coefficient. We estimate the migration elasticity (the inverse of ρ^e, $e \in \{H, L\}$) as 0.167 for high-skilled workers and as 0.141 for low-skilled workers (Table C.3), consistent with our intuition

[49] De Souza and Li (2022) use a difference-in-differences strategy based on anti-dumping investigations, comparing sectors facing investigations but no tariffs with a control group.

[50] We leverage variations across both regions and sectors, whereby different regions import distinct capital goods, generating variation in sector-level weighted tariffs.

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

[52] Therefore $\epsilon^R = 1 - \theta^R = 7.81$ and $\epsilon^T = 1 - \theta^T = 5.59$.

that high-skilled workers are more mobile. Compared to US-based studies—Artuç et al. (2010) (0.532) and Caliendo et al. (2019) (0.495)—our Brazilian estimates are lower, reflecting lower mobility typical of developing countries.

Equation (C.3) shows that the log difference between the probabilities of (1) migrating from region n-sector j to region i-sector k and (2) staying in region n-sector j is the following:

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

Substituting the region–sector-level expected value, our estimation equation will be:

$$\log(s^{kj,e}_{in,t}) - \log(s^{jj,e}_{nn,t}) - \lambda^e\beta(\log(s^{kj,e}_{in,t+1}) - \log(s^{kk,e}_{ii,t+1})) = \frac{\lambda^e\beta}{\rho^e}(\log(w^{k,e}_{i,t+1}) - \log(w^{j,e}_{n,t+1})) + \phi_{i,t} + \phi_{n,t} + \epsilon^{kj,e}_{in,t}. \tag{C.17}$$

The error term, $\epsilon^{kj,e}_{in,t}$, absorbs migration costs and region–sector-level amenities. To address potential endogeneity, similar to Caliendo et al. (2019), we use past wages (in $t-1$) as instruments for the wages in $t+1$.[53] The identifying assumption is that past wages are uncorrelated with current and future migration costs and amenities.

Table C.3: **Migration Elasticities and Skill Choice Elasticities**

	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.17) and (C.18). 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.

Skill Choice Elasticity. We estimate the skill choice elasticity of entrants using a similar approach to migration elasticities. We express the share of new workers choosing high-skilled employment in terms of value functions, which can then be rewritten as migration shares using Equation (C.18). We use lagged wages as instruments for migration shares.

Substituting the value function leads to our estimation equation:

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

$$
\begin{aligned}
&\left(\log(\tilde{s}^{s,H}_{n,t}) - \log(\tilde{s}^{s,L}_{n,t})\right) - \left(\log(\tilde{s}^{s',H}_{n',t}) - \log(\tilde{s}^{s',L}_{n',t})\right) \\
=&\frac{1}{\tilde{\rho}}\left[\frac{\rho^H}{\lambda^H}\left(\log(s^{ss,H}_{nn,t}) - \log(s^{s's,H}_{n'n,t})\right) - \frac{\rho^L}{\lambda^L}\left(\log(s^{ss,L}_{nn,t}) - \log(s^{s's,L}_{n'n,t})\right)\right] + \epsilon^{ss'}_{nn',t}.
\end{aligned} \tag{C.18}
$$

Similar to the estimation of migration elasticities, we use wages at $t-1$ as instruments.[54] The identifying assumption is that past wages are uncorrelated with current migration costs.

Columns (5) and (6) of Table C.3 show the parameters estimated from Equation (C.18). The 2SLS estimator implies a skill choice elasticity of $\frac{1}{\tilde{\rho}} = 0.076$.

Other Parameters Calibrated Outside the Model. Using RAIS, we calibrate workers' exit rate by type by computing the share of workers leaving the labor market each year. Input–output coefficients, final consumption shares, and social insurance tax rates are calibrated based on values reported in De Souza and Li (2022).

C.4 Estimation Results

Estimation Strategy. The model is first calibrated to the Brazilian economy in 1997. Next, we input observed changes in robot and tool tariffs between 1997 and 2010 and simulate the resulting changes in high- and low-skilled employment and trade. We estimate five key parameters, $\{\theta, \sigma, \eta, \mu_\delta, \rho_{T^R,\delta}\}$, by minimizing the distance between simulated regression coefficients and the empirical estimates from Section 6.[55]

$$
\begin{aligned}
&\Delta\log(\ell^{s,e}_n) = \theta^{R,e}\Delta\log(robots^s_n) + \theta^{T,e}\Delta\log(tool^s_n) + \epsilon^{s,e}_n, e \in \{H, L\} \\
&\Delta\log(robots^s_n) = \theta^{R,R}\Delta IV^{s,R}_n + \theta^{R,T}\Delta IV^{s,T}_n + \epsilon^{s,R}_n \\
&\Delta\log(tools^s_n) = \theta^{T,R}\Delta IV^{s,R}_n + \theta^{T,T}\Delta IV^{s,T}_n + \epsilon^{s,T}_n,
\end{aligned} \tag{C.19}
$$

where the first equation refers to the instrumental variable regression and the second and third equations refer to the first stage. Changes in type-e employment, robot capital goods imports, and tool imports are represented by $\Delta\log(\ell^{s,e}_n)$, $\Delta\log(robots^s_n)$, and $\Delta\log(tool^s_n)$, respectively.

$\Delta IV^{s,R}_n$ and $\Delta IV^{s,T}_n$ denote instruments for robots and tools in the model. Similar to 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 year. Therefore, the instruments constructed with model-simulated data are the following:

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

[55] Unlike the empirical regressions in Section 5, we do not include additional controls when using model data, since the simulated data are free from external shocks.

$$\Delta IV_n^{s,R} = \frac{w_n^{s,L}\ell_n^{s,L} + R_n^{s,T}K_n^{s,T}}{\gamma^s p_n^s y_n^s}\Delta\tau^{s,R} \tag{C.20}$$

for robots, and for tools:

$$\Delta IV_n^{s,T} = (1 - \frac{w_n^{s,L}\ell_n^{s,L} + R_n^{s,T}K_n^{s,T}}{\gamma^s p_n^s y_n^s})\Delta\tau^{s,T} \tag{C.21}$$

Besides the key parameters governing technology choice, we estimate the mean, standard deviation, and their correlations for high-skilled worker and robot productivity (μ_H, μ_R, σ_H, σ_R, ρ_{A^H,T^R}, $\rho_{A^H,\delta}$, see Section C.2) by targeting cross-region-sector high-skilled employment data and robot imports. We estimate the standard deviation for low-skilled share in tools, σ_δ, by targeting cross-region-sector low-skilled employment. We also estimate the trade cost and investment-related parameters described in Section C.2 by targeting region–sector imports of robots, tools, and non-capital goods. Productivity and comparative advantage parameters are estimated by matching region–sector wage and employment by skill. Migration cost parameters target migration flows, and the fixed cost of becoming high-skilled targets the share of high-skilled entrants.

We employ the mathematical programming with equilibrium constraints (MPEC) algorithm (Su and Judd 2012) to solve the model, incorporating both equilibria before and after tariff changes in the constraints. We compute the changes across equilibria listed in Equations (C.19), (C.20), and (C.21), and estimate the IV and first-stage coefficients per Equation (C.19). We compute model moments: the estimated IV and first-stage coefficients and model-predicted initial year's region–sector level imports of robots, tools, and non-capital goods, region-sector wage, employment of high/low-skilled workers, share of high/low-skilled workers moving from one region-sector to another region-sector, and share of new workers who are high skilled. In the SMM algorithm, we minimize the sum of squared differences between data moments and model counterparts, treating all moments with equal weight.

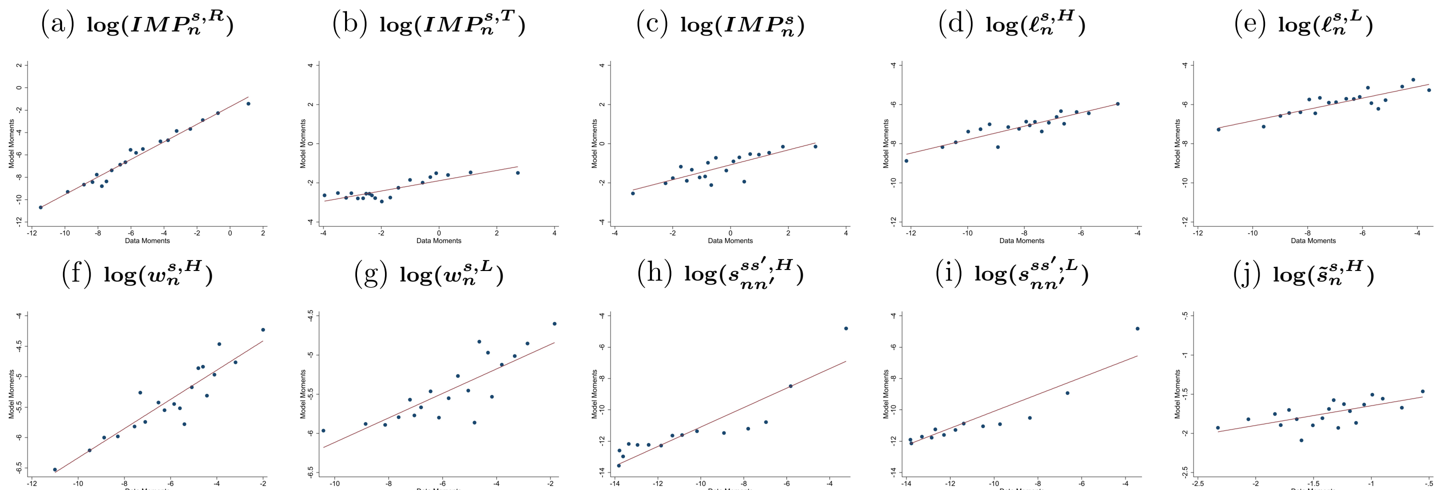
Table 7 displays the estimated key parameters that govern robot and tool technologies. Table C.5 presents the estimates of other parameters, showing that domestic trade costs increase with distance and sector upstreamness, while more ports reduce import costs. Migration cost rises with distance and sectoral differences, and becoming high-skilled incurs a fixed cost equivalent to 3.6 years of average high-skilled wages. Table C.4 shows that we successfully match the key empirical moments using the five robot and tool technology parameters. Figure C.1 shows that the model can generate region-sector level statistics similar to the data.

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

Data Moments		Model Moments
Moment Name	Value	Value
Elasticity of high-skilled employment to robot imports	-0.062	-0.061
Elasticity of high-skilled employment to tool imports	0.106	0.109
Elasticity of low-skilled employment to robot imports	-0.237	-0.241
Elasticity of low-skilled employment to tool imports	0.169	0.176
Elasticity of tool imports to robot instrument	-0.280	-0.305
Elasticity of tool imports to tool instrument	-0.063	-0.067
Elasticity of robot imports to robot instrument	-0.242	-0.241
Elasticity of robot imports to tool instrument	0.035	0.036

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 5) and the elasticities of robot and tool imports with respect to robot and tool instruments (Table 1). Robot and tool instruments measure region–sector-level exposures to robot and tool tariffs (Equations 9 and 10).

Figure C.1: **Model Fit in Matching Cross-sectional Moments of the Brazilian Economy**



Description: The figure presents the model's performance in matching cross-sectional moments of the Brazilian economy. Data moments are plotted on the horizontal axis and model moments are plotted on the vertical axis. Imports of robots, tools, and non-capital composite goods, wage and employment of high/low-skilled workers, share of high-/low-skilled workers moving from one region-sector to another region-sector, and share of new workers who are high-skilled are plotted. To avoid figure cluttering, the scatter plots are grouped into 20 bins where each bin contains the same number of points and the means of each bin along horizontal and vertical axes are plotted. The fitted line is in red.

C.5 Aggregate Statistics

We present the formulas for the aggregate statistics discussed in Sections 9 and C.4.

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

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

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

$$
\begin{aligned}
\text{dlog}(GDP) = \frac{1}{NGDP} \sum_{n=1}^{N} \sum_{s=1}^{S} & w_n^{s,H} \ell_n^{s,H} \,\text{dlog}(\ell_n^{s,H}) + w_n^{s,L} \ell_n^{s,L} \,\text{dlog}(\ell_n^{s,L}) \\
& + R_n^{s,R} K_n^{s,R} \,\text{dlog}(K_n^{s,R}) + R_n^{s,T} K_n^{s,T} \,\text{dlog}(K_n^{s,T}) \\
& + \xi^R P_n^{s,R} I_n^{s,R} \,\text{dlog}(I_n^{s,R}) + \xi^R P_n^{s,T} I_n^{s,T} \,\text{dlog}(I_n^{s,T}).
\end{aligned}
$$

Aggregate Elasticity of Substitution between High- and Low-skilled Workers Without Capital.

$$
\begin{aligned}
\sigma_n^{s,HL} = (\sigma - 1 - \theta) & \int s_n^{s,L}(i) s_n^{s,H,T}(i) \frac{1}{s_n^{s,T}(i)} di \\
+ (\theta - \phi + 1) & \int s_n^{s,L}(i) s_n^{s,H}(i) \frac{1}{s_n^{s}(i)} di \\
+ (\phi - 1) & \int s_n^{s,L}(i) s_n^{s,H}(i) di,
\end{aligned}
\tag{C.22}
$$

where i denotes a firm, $s_n^{s,H}(i)$ and $s_n^{s,L}(i)$ shares of region–sector total high- and low-skilled employment hired by firm i, $s_n^{s,H,T}(i)$ denotes the share of high-skilled workers working with tool technology in firm i among region–sector total high–skilled employment, $s_n^{s,T}(i)$ denotes the share of firm i's tool technology in region–sector value added, and $s_n^s(i)$ denotes the share of firm i in region-sector value added.

We take the average across regions and sectors to obtain the model moment in Table 8:

$$
\sigma^{HL} = \frac{1}{S} \frac{1}{N} \sum_{n=1}^{N} \sum_{s=1}^{S} \sigma_n^{s,HL}
$$

C.6 Optimal Robot and Tool Tariffs

In this section, we study the aggregate effects of optimally chosen tariffs or subsidies on robot and tool imports to achieve specific policy objectives: (1) maximizing GDP, (2) maximizing welfare, and (3) minimizing the skill premium (inequality). The government is required to maintain a balanced budget, meaning that tariff revenues must cover any subsidies provided:

$$
\begin{aligned}
& \max_{\{\tau_s^R, \tau_s^T\}} \text{Obj} \in \{\text{GDP, Workers' Welfare, -Skill Premium}\} \\
& \text{s.t. Equilibrium conditions (Equations C.8-C.9)} \\
& \sum_{n=1}^{N} \sum_{s=1}^{S} (IMP_n^{s,R} \tau^{s,R} + IMP_n^{s,T} \tau^{s,T}) \geq 0,
\end{aligned}
$$

where $IMP_n^{s,R}$ denotes the (pre-tariff) imports of robots and $IMP_n^{s,T}$ denotes the (pre-tariff) imports of tools.

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

Parameter	Para. Name	Value	Targeted Moments
	Production		
μ_H	Average productivity of high-skilled worker across firms	2.225	
μ_R	Average robot productivity across firms	2.195	
σ_H	Standard deviation of high-skilled productivity across firms	0.097	
σ_R	Standard deviation of robot productivity across firms	0.110	
σ_R	Standard deviation of low-skilled share in tool technology across firms	0.234	
ρ_{A^H,T^R}	Correlation between high-skilled productivity and robot productivity across firms	0.090	Wage and employment of high-skilled and low-skilled workers by region and sector
$\rho_{A^H,\delta}$	Correlation between high-skilled productivity and low-skilled share in tool technology across firms	-0.239	
ξ^R	Decreasing return to scale parameter of robot investment goods production	0.051	
ξ^T	Decreasing return to scale parameter of tool investment goods production	0.119	
ϕ	Elasticity of substitution across firms	3.009	
A_n^s	Region–sector-level productivity	10.562 (mean)	
	Trade		
	Change of log domestic trade cost w.r.t.		
β^0	$\mathbf{1}(n'=n)$	-0.872	
β^1	$\mathrm{Contig}_{n'n}$	-1.016	
β^2	$\log(\text{Dist to Coast}_n)$	-0.564	
β^3	$\log(\text{Dist to Coast}_{n'})$	-0.190	
β^4	$\mathbb{N}(\text{Ports})_n$	0.494	
β^5	$\mathbb{N}(\text{Ports})_{n'}$	0.151	
β^6	$\log(\text{Dist}_{n'n})$	0.714	
β^7	$\mathrm{Contig}_{n'n}\log(\mathrm{U}^s)$	1.492	
β^8	$\log(\text{Dist to Coast}_n)\log(\mathrm{U}^s)$	0.455	
β^9	$\log(\text{Dist to Coast}_{n'})\log(\mathrm{U}^s)$	0.028	
β^{10}	$\mathbb{N}(\text{Ports})_n\log(\mathrm{U}^s)$	-0.761	
β^{11}	$\mathbb{N}(\text{Ports})_{n'}\log(\mathrm{U}^s)$	-0.091	
β^{12}	$\log(\text{Dist}_{n'n})\log(\mathrm{U}^s)$	-0.186	
β^{13}	$\log(\mathrm{U}^s)$	3.222	Region–sector-level imports
β^{14}	$\mathbf{1}(n'=n)\log(\mathrm{U}^s)$	2.701	
β^{15}	$\mathbf{1}(n'=n)\log(\text{high-skilled labor share}^s)$	-3.648	
β^{16}	$\mathrm{Contig}_{n'n}\log(\text{high-skilled labor share}^s)$	-3.248	
β^{17}	$\log(\text{Dist to Coast}_n)\log(\text{high-skilled labor share}^s)$	-0.519	
β^{18}	$\log(\text{Dist to Coast}_{n'})\log(\text{high-skilled labor share}^s)$	-0.135	
β^{19}	$\mathbb{N}(\text{Ports})_n\log(\text{high-skilled labor share}^s)$	-0.079	
β^{20}	$\mathbb{N}(\text{Ports})_{n'}\log(\text{high-skilled labor share}^s)$	0.092	
β^{21}	$\log(\text{high-skilled labor share}^s)$	-3.100	
β^{22}	$\log(\text{Dist}_{n'n})\log(\text{high-skilled labor share}^s)$	0.394	
	Change of log composite goods import cost w.r.t.		
β^{23}	$\log(\text{Dist to Coast}_{n'})$	0.016	
β^{24}	$\mathbb{N}(\text{Ports})_{n'}$	-0.014	
β^{25}	$\log(\text{Dist to Coast}_{n'})\log(\mathrm{U}^s)$	0.089	
β^{26}	$\mathbb{N}(\text{Ports})_{n'}\log(\mathrm{U}^s)$	-0.080	
β^{27}	$\log(\mathrm{U}^s)$	1.369	
β^{28}	$\mathbf{1}(\text{Imported})$	2.728	
β^{29}	$\log(\text{Dist to Coast}_{n'})\log(\text{high-skilled labor share}^s)$	0.190	
β^{30}	$\mathbb{N}(\text{Ports})_{n'}\log(\text{high-skilled labor share}^s)$	-0.078	
β^{31}	$\log(\text{high-skilled labor share}^s)$	-0.749	
	Change of log imported robot capital goods trade cost w.r.t.		
$\beta^{1,R}$	$\log(\text{Dist to Coast}_{n'})$	0.148	
$\beta^{2,R}$	$\mathbb{N}(\text{Ports})_{n'}$	-0.298	
$\beta^{3,R}$	$\log(\text{Dist to Coast}_{n'})\log(\mathrm{U}^s)$	-0.024	
$\beta^{4,R}$	$\mathbb{N}(\text{Ports})_{n'}\log(\mathrm{U}^s)$	0.155	
$\beta^{5,R}$	$\log(\mathrm{U}^s)$	-0.182	Imports of robot capital by region–sector
$\beta^{6,R}$	$\mathbf{1}(\text{Imported})$	3.490	
$\beta^{7,R}$	$\log(\text{Dist to Coast}_{n'})\log(\text{high-skilled labor share}^s)$	0.220	
$\beta^{8,R}$	$\mathbb{N}(\text{Ports})_{n'}\log(\text{high-skilled labor share}^s)$	-0.086	
$\beta^{9,R}$	$\log(\text{high-skilled labor share}^s)$	-0.198	
	Change of log imported tool capital goods trade cost w.r.t.		
$\beta^{1,T}$	$\log(\text{Dist to Coast}_{n'})$	0.308	
$\beta^{2,T}$	$\mathbb{N}(\text{Ports})_{n'}$	-0.091	
$\beta^{3,T}$	$\log(\text{Dist to Coast}_{n'})\log(\mathrm{U}^s)$	-0.156	
$\beta^{4,T}$	$\mathbb{N}(\text{Ports})_{n'}\log(\mathrm{U}^s)$	-0.068	
$\beta^{5,T}$	$\log(\mathrm{U}^s)$	1.416	Imports of tool capital by region–sector
$\beta^{6,T}$	$\mathbf{1}(\text{Imported})$	2.156	
$\beta^{7,T}$	$\log(\text{Dist to Coast}_{n'})\log(\text{high-skilled labor share}^s)$	0.219	
$\beta^{8,T}$	$\mathbb{N}(\text{Ports})_{n'}\log(\text{high-skilled labor share}^s)$	-0.168	
$\beta^{9,T}$	$\log(\text{high-skilled labor share}^s)$	0.007	
	Labor Migration		
$f^H/\mathrm{mean}(w_n^{s,H})$	Fixed cost of becoming high-skilled workers (relative to high-skilled wage)	3.582	Share of new workers who are high-skilled
	Change of log migration cost w.r.t.		
χ^0	$\mathbf{1}(n'=n)$	-13.833	
χ^1	$\mathrm{Contig}_{n'n}$	-7.040	
χ^2	$\log(\text{Dist}_{n'n})$	1.500	
χ^3	$\lvert\log(\mathrm{U}^{s'})-\log(\mathrm{U}^s)\rvert$	7.386	
χ^4	$\mathrm{Contig}_{n'n}\lvert\log(\mathrm{U}^{s'})-\log(\mathrm{U}^s)\rvert$	6.899	Share of high-skilled workers moving from one region–sector to another region–sector
χ^5	$\log(\text{Dist}_{n'n})\lvert\log(\mathrm{U}^{s'})-\log(\mathrm{U}^s)\rvert$	2.386	Share of low-skilled workers moving from one region–sector to another region–sector
χ^6	$\mathbf{1}(n'=n)\lvert\log(\mathrm{U}^{s'})-\log(\mathrm{U}^s)\rvert$	-1.347	
χ^7	$\lvert\text{high-skilled labor share}^{s'}-\text{high-skilled labor share}^s\rvert$	7.310	
χ^8	$\mathrm{Contig}_{n'n}\lvert\text{high-skilled labor share}^{s'}-\text{high-skilled labor share}^s\rvert$	5.674	
χ^9	$\log(\text{Dist}_{n'n})\lvert\text{high-skilled labor share}^{s'}-\text{high-skilled labor share}^s\rvert$	2.312	
χ^{10}	$\mathbf{1}(n'=n)\lvert\text{high-skilled labor share}^{s'}-\text{high-skilled labor share}^s\rvert$	-0.664	

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 7.