Robots and trade: Implications for developing countries

Erhan Artuc
World Bank

Paulo Bastos
World Bank

Alexander Copestake
Oxford University

Bob Rijkers
World Bank

1. Introduction

Modern industrial robots can perform a variety of repetitive tasks with consistent precision and are increasingly used in a wide range of industries and applications. The global operational stock of industrial robots reached a record high of 2.7 million units last year (IFR, 2020) and robot adoption is projected to grow steadily. The accelerating automation of industrial production has stoked concerns that large swaths of the workforce, especially the unskilled, may suffer wage and job losses (e.g., Bloom et al., 2018). These fears are in part predicated on the experience of OECD countries, where robot adoption has contributed to productivity growth at the expense of the employment share and wages of low-skilled workers (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020). Recent estimates suggest that around 14% of jobs across the OECD area are at risk of disappearing because of automation, while another 32% are likely to see significant changes (OECD, 2018).

While robotization has been especially pronounced in advanced economies, workers in developing countries could also be at risk. Low-skilled workers, for whom robots substitute particularly well, are disproportionately located in developing countries. Robotization might move production closer to consumers in high-income markets and undermine prospects for industrialization and export-led development (Rodrik, 2018; Hallward-Driemeier and Nayyar, 2019). Developing countries are particularly exposed to automation-induced trade declines, since reduced trade and communication barriers have allowed the offshoring of repetitive and labor-intensive tasks to low wage countries (Grossman and Rossi-Hansberg, 2008; Antras, 2015; World Bank, 2020). Low-income countries may lack the skills and infrastructure that are needed to meaningfully participate in emerging global value chains, as automation diminishes the importance of low labor costs as a determinant of international competitiveness (Rodrik, 2018).

In this chapter, we first use a Ricardian framework to examine the impact on developing countries of robotization in developed countries. Drawing on Artuc, Bastos and Rijkers (2018), in Section 2 we present theory and evidence indicating that robot adoption in the high-wage advanced economies promoted trade between developed and developing countries. We highlight that such adoption can ultimately benefit workers in developing countries, particularly through lower prices and increased demand for intermediate inputs. The impact of robotization is shown to depend on the initial degree of robotization. In Section 3, we extend this framework by adding China explicitly to the calibrated model, noting that its robot stock has expanded rapidly in recent years to become by far the world's largest (in absolute terms). We analyze the impact of China's subsidies for robotization, as described in Cheng et al. (2019), and find ambiguous effects on wages of Chinese workers depending on the size of the subsidy. Interestingly, as China increasingly subsidizes industrial robots, its pattern of comparative advantage becomes more similar to that of OECD countries, which reduces its total trade with them. The opposite conclusion applies to trade between China and developing countries.

The Ricardian framework we adopt focuses on long-run and aggregate effects and abstracts from adjustment costs. In the short run workers cannot move freely across sectors, regions and occupations. In Section 4 we consider broader empirical evidence on the impacts of robotization in developed countries on workers in developing countries. Alongside support for the long-run predictions of the Ricardian model, we catalog evidence of negative short-run employment effects in the local labor markets of some middle-income countries, particularly for the least mobile workers previously performing tasks that can now be executed by robots. These adverse impacts on local labor markets highlight the role for policy to alleviate distributional issues arising from frictions during the automation transition. We also look beyond comparative statics and note that developed-country automation could exacerbate 'premature de-industrialization' (Rodrik, 2016) by discouraging investment in sectors with the highest growth potential. This in turn may help explain the emergence of robot subsidies in some developing economies, particularly China.

Furthermore, robot adoption may be driven by factors other than just the relative prices of robots and workers. Within each country, larger and typically less labor-intensive firms are more likely to be able to afford the fixed costs of upgrading production technology, while firms engaged in complex production networks may attach higher value to the increased precision and reliability enabled by robotics. In Section 5 we therefore move beyond relative prices to provide new evidence on firm-level drivers of adoption in developing countries, while in Section 6 we consider the impact of this adoption on firm-level outcomes. Our empirical analysis draws on firm-level data from 10 developing countries. We find support for both the scale and precision hypotheses, aligning with firm-level evidence from developed countries. After adopting robots, these initially larger and more globally connected firms tend to expand further. These firm-level mechanisms help to explain why we observe more and earlier robot adoption in developing countries than our stylized Ricardian model would predict. But they also add a firm-side element to the earlier distributional concerns: it is not just relatively disadvantaged workers who are most threatened by robotization, but also smaller, less productive, less internationally active firms. Given that low-skilled workers are also disproportionately more likely to work in these firms, the dual threat is a key issue for policymakers to consider.

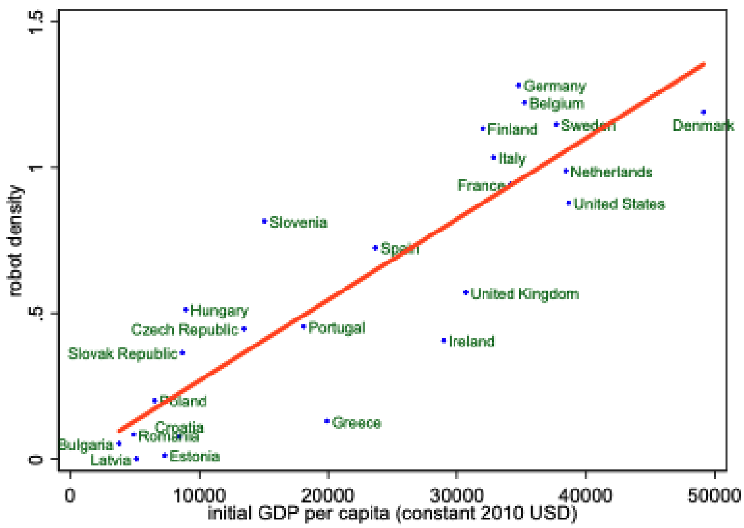
We conclude by surveying these opportunities and challenges for developing countries raised by automation. In the long run, industrial robots in developed countries could promote trade between advanced and developing countries, and enhance global welfare. And while China's growing robotization (driven in part by subsidies) might reduce productivity differences with advanced economies, and thereby the gains from inter-industry trade with them, it need not hinder future prospects for industrialization and export-led growth in lower-income countries. However, technological change, both in advanced and developing countries, necessitates labor-market adjustment and can create severe distributional tensions, which are not limited to the transition period. As robots catch up with humans in many abilities, so policy must keep pace with adoption.

2. Implications of robotization in advanced economies for developing countries

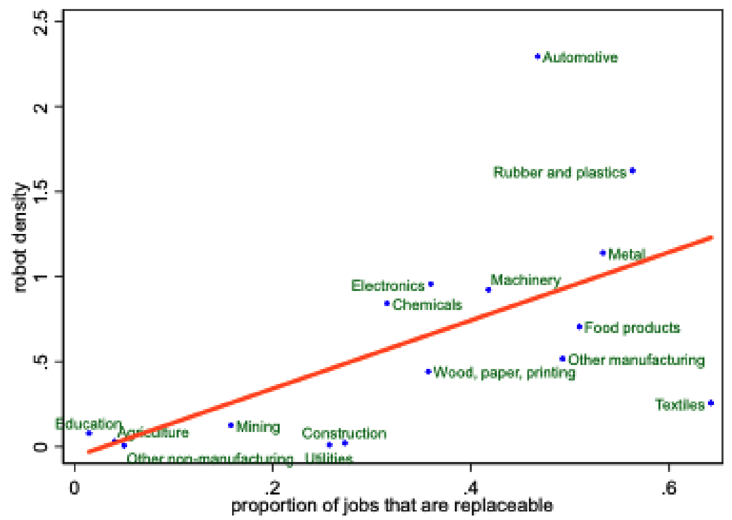
Drawing on Artuc, Bastos and Rijkers (2018), we first use a Ricardian framework to examine the impact on developing countries of robotization in developed countries. We start by inspecting drivers of robot adoption at the country and industry level (see Figure 1). High-wage rich countries tend to use more robots (Panel A), suggesting that the potential for cost savings is an important determinant of adoption. There is wide variation across industries in the proportion of jobs that are replaceable (calculated using the share of occupations involving tasks that can potentially be performed by robots, following Graetz and Michaels 2018), and this indeed predicts realized robot density (Panel B).

Figure 1: Robotization across countries and sectors

Panel A: Robot adoption is higher in richer countries



Panel B: Sectors in which automation is feasible adopt more robots



Notes: Panel A depicts the relationship between average robot density by country (averaged across years) and the initial GDP per capita. Panel B depicts the relationship between average robot density by sector (averaged across countries and years) and the share of replaceable jobs in the industry, as measured in Graetz and Michaels (2018), using the distribution of hours worked across occupations and industries from the 1980 US Census. Robot density is defined as the log of one plus the number of robots in use per million worker-hours. *Source:* Artuc, Bastos and Rijkers (2018).

Motivated by these patterns, the multi-country, multi-sector Ricardian model features: (i) a higher cost of labor in the North, and (ii) an industry-specific robotization frontier (i.e. the range of tasks for which humans are substitutable by robots varies across sectors).[1] The model features two-stage production, with intermediate goods produced in the first stage and final goods produced in the second stage. In the production process, robots can take over some tasks previously performed by humans.[2]

In the model, a subset of tasks required in the production of intermediate and final goods can be executed either by workers or robots, while other tasks can only be performed by humans. The range of tasks that can be performed by robots varies across sectors. The industry-specific robotization frontier, relative factor prices and productivity determine the extent of robot use within sectors. Production of each final-good variety further requires a composite intermediate good from the same industry. In equilibrium, varieties of intermediate inputs and final goods are sourced from the country that supplies at the lowest price. Thus, there are two layers of competition: (1) between robots and workers in factor markets; and (2) between countries in sector-specific product markets for inputs and outputs.[3] Relative production costs (driven by factor prices and technology) determine country-specific robotization and trade patterns.

With many countries in the model, a fall in the global price of industrial robots initially induces robotization in Northern countries, defined as those with a higher initial cost of labor.[4] This shift impacts relative production costs between countries, and therefore trade patterns. Producers substitute robots for domestic labor in automatable tasks, leading to lower costs of production in Northern countries, and hence to an increase in exports to Southern countries.[5] The more striking growth in same-sector imports from Southern countries reflects the sum of two competing forces. On one hand, lower costs in Northern countries make domestic producers and input suppliers there more competitive relative to foreign ones, which lowers the demand for goods produced abroad as consumers and producers substitute them with domestic goods. On the other hand, the increased scale of production in Northern countries also leads to an overall surge in the demand for intermediate inputs. If these are sourced from abroad, imports from lower-wage Southern countries in these industries can rise.

The two-stage production structure helps us to differentiate comparative advantage patterns for intermediate inputs and final goods, as well as the differences in the demand. Robotization in Northern countries increases productivity of North in both stages of production but does not

[1] A technical outline of the model is provided in the Appendix.

[2] The model combines elements from a large number papers in the literature, including Grossman and Rossi-Hansberg (2008), Eaton and Kortum (2002), Acemoglu and Restrepo (2020), Caliendo and Parro (2015), Lee and Yi (2018) and Artuc and McLaren (2015).

[3] Offshoring in the model takes place through imports of intermediate inputs, which embody tasks performed abroad. This allows us to calibrate all trade flows, production functions and labor shares using the World Input-Output Database. Given our focus on industrial robots and trade in goods, the distinction between offshored tasks and intermediate inputs is largely semantic (Grossman and Rossi-Hansberg 2008). Future research could extend the model by allowing direct offshoring of tasks, to consider cases where this distinction is more substantive (e.g. in services trade).

[4] Throughout this paper, the set of tasks that can feasibly be performed by robots is fixed. Increased robotization results only from a fall in the price of existing robots, not an expansion in their functionality. Technological advances which enable robots to perform new tasks, or indeed create new human-only tasks, are a distinct issue, which we leave to other work (e.g. Acemoglu and Restrepo, 2018).

[5] In the model, which assumes full employment, the displaced workers compete for the remaining non-automated tasks, bidding down wages and generating a second-order increase in hiring.

necessarily reduce the demand for intermediate inputs produced by South, since the scale effect can potentially dominate the substitution effect.

Between 1995 and 2015, the production expansion effect seems to have dominated. Indeed, empirical results in Artuc, Bastos and Rijkers (2018) show that the robot-induced surge in Northern imports from the South is concentrated in intermediate inputs such as parts and components. To gauge the relationship between robotization and North-South trade, the empirical analysis combined robot stock data from the International Federation of Robotics, labor hours data from EU KLEMS, and trade data for 1995-2015 from CEPII BACI. The following baseline specification was estimated:

$$Trade_{nmit} = \beta Robots_{nit} + \Psi_{nmt} + \Lambda_{it} + \epsilon \qquad (1)$$

where $Trade_{nmit}$ denotes the log of (1+exports) from developed country n to developing country m in sector i and year t or alternatively the log of (1+imports) sourced from developed country n in sector i and year t; $Robots_{nit}$ denotes a measure of robot usage in country n in sector i in year t; Ψ_{nmt} denotes a fixed effect by exporter-importer-year; Λ_{it} denotes an industry-year fixed effect; and ϵ the error term. Equation (1) includes exporter-importer-year fixed effects both to allow for pair-specific shocks (such as fluctuations in relative income and exchange rates) and to control for country pair specific determinants of trade (e.g., distance, having a common language etc.). It further includes industry-year fixed effects to account for factors that are specific to each industry in each year. Standard errors are clustered by developed country. To address the possibility of reverse causality in the relationship between robotization and trade, as well as potential biases caused by omitted variables or measurement error, an instrumental-variables approach was followed. Specifically, the analysis uses the triple interaction between the (pre-determined) share of workers engaged in replaceable tasks in each sector, the country's initial income per capita, and the global stock of robots as an instrument for robotization.[6]

The instrumental-variables estimates reveal that a 10% increase in robot density in a robotizing industry in the North boosts its exports to the South by 11.8%. Surprisingly, it also induces a 6.1% increase in its imports from the South within the same broad sector. The latter effect is primarily driven by imports of parts and components.[7] These empirical results can be explained by two key features of the Ricardian trade model with a multi-stage production technology: (1) productivity effects of robotization in the North, such that replacing workers with (cheaper) robots increases output and exports; and (2) trade in intermediate goods, such that an expansion in Northern final production can increase imports of inputs from the South within the same broad sector.[8]

Given these patterns, how are further reductions in robot prices likely to impact global trade, wages and welfare? To answer this question, the Ricardian model was calibrated with three

[6] Following Graetz and Michaels (2018), we measure replaceability by comparing robot applications recorded by the IFR with three-digit occupation names and descriptions in the US Census, then aggregating to the industry level using the occupation-composition of industries. See Artuc et al. (2018) for further details of the empirical strategy and variable construction.

[7] When running separate regressions for intermediates vs. other goods, the respective increases in imports from the South are 6.8% and 5.6% (using the Broad Economic Categories (BEC) classification of goods) or 8.6% and 4.9% (using the classification from Schott, 2004).

[8] Specifically, the net increase in imports of parts and components implies that the robotization-induced scale effect, which increases demand for imported intermediates, outweighs any robotization-based reshoring (i.e., substitution effects from increased robot use by Northern intermediates producers).

countries and three sectors. In particular, the quantitative model features a representative high-income Northern country, a representative country in the South, and a group of other (lower-income) developed countries.[9][10] Among the three sectors considered, two sectors are tradable and the other sector is non-tradable. Production is subject to robotization in just one of the tradable sectors, consisting of the automotive, rubber and plastic, electronics, chemicals, metal and machinery industries. The non-robotized tradable sector consists of all other manufacturing industries, including food and textiles, agriculture, mining and utilities. The non-tradable sector consists of construction and services.

Simulating the impact of future reductions in robot prices offers several insights, which are illustrated in Figure 2. As robot prices decline, producers in the North, who face higher wages, will adopt progressively more robots (Panel A). When prices decline even further it also becomes profitable for less developed countries, where producers face lower labor costs, to robotize production. Robot adoption is associated with an initial reduction in the number of jobs in the automating sector (Panel B). Yet once all tasks that can be automated are performed by robots, further reductions in robot prices boost the demand for labor in the robotized sector, because they make workers in those sectors more productive. The impact of automation on jobs is thus state-dependent: while industrial robots compete with workers in the early stages of adoption, they complement them in subsequent stages, since we assume that the range of automatable tasks is fixed. This also explains the U-shaped relationship between robot prices and wages in North and "Other" (Panel C).[11] Interestingly, lower robot prices also gradually raise the wages of workers in the South.[12] As robot prices fall, aggregate welfare increases in all countries, but more so in the countries that adopt more robots (Panel D).

[9] We use the World Input Output Database (WIOD) to calibrate international trade, production functions and labor shares. In the baseline simulation, we use WIOD data for 2005 to calibrate initial trade patterns. We group countries into three broad categories, based on their income per capita, robot density and data availability. The group of countries in the North is composed of Belgium, Germany, Denmark, Finland, France, Italy, Netherlands, Sweden and the United States. The group of countries in the South is composed of Brazil, China, India, Indonesia, Mexico, Turkey and Taiwan, China. Based on these two groupings, we construct the representative countries in the North and South. The group of other developed countries results from the aggregation of other OECD and EU countries for which data are available in WIOD. This group consists of Australia, Austria, Bulgaria, Canada, Czech Republic, Spain, the United Kingdom, Greece, Croatia, Hungary, Ireland, Portugal, the Slovak Republic, Poland, Norway and Switzerland. Various robustness checks in Artuc et al. (2018) find that results are qualitatively robust across a variety of alternative groupings.

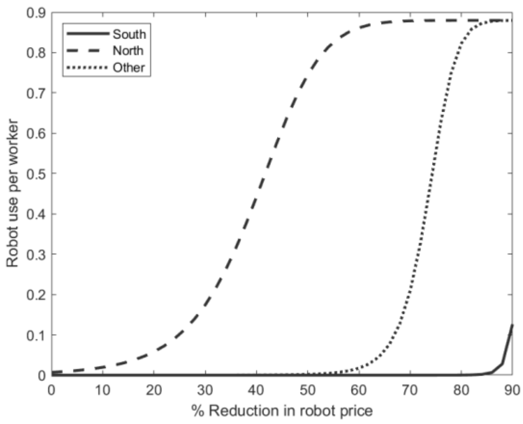
[10] This setup is suitable for illuminating the relevant dynamics without losing tractability. If we were to aggregate within groups, rather than averaging to create representative countries, the North would account for more than 50% of world GDP, and the bulk of world trade would occur within the North. This setting would underrepresent the importance of North-South trade, and trade as share of GDP would be very small. To avoid this aggregation bias, we instead construct representative countries in the North and the South. Considering a relatively large group of other developed countries is also important to allow for the possibility that competitiveness gains associated with robot adoption in the North translate into higher demand for its final-goods exports.

[11] Broadly, lower robot prices initially cause displacement of human labor at the 'extensive margin', but subsequently reduce costs and increase productivity at the 'intensive margin' (Acemoglu and Restrepo, 2019). Such sequencing could help explain differing empirical findings on the impact of robots: countries in the displacement phase (e.g., the USA (Acemoglu and Restrepo, 2020)) may experience larger wage declines from additional robotization than countries further ahead in the process of adoption (e.g., Germany (Dauth et. al, 2021)).

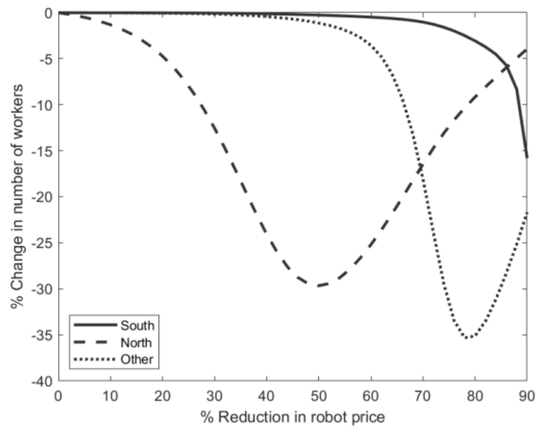
[12] However, for a sufficiently large reduction in robot prices (greater than 85% in Figure 2 Panel A) the South in turn adopts robots, lowering Southern wages (Panel C) due to the initial substitution effect of robot adoption.

Figure 2: Effects of robot price reductions

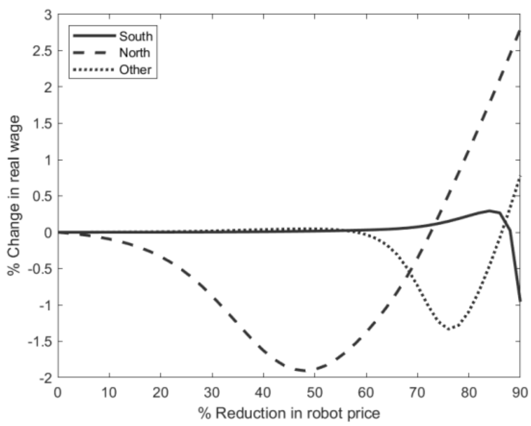
Panel A: Robot use in robotized industry



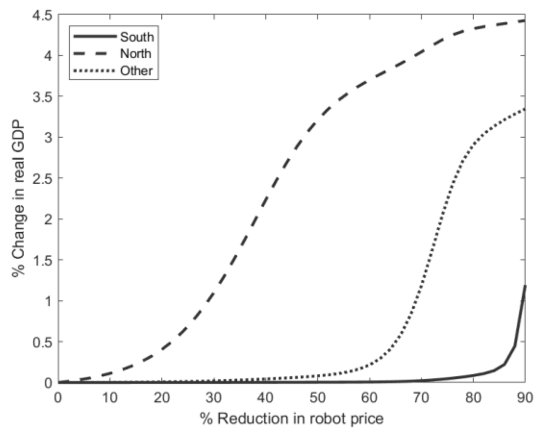
Panel B: Labor use in robotized industry



Panel C: Wages



Panel D: Welfare (Real GDP)



Notes: this figure presents results from simulations of the effects of lower robot prices on robot use, labor allocation, wages and welfare. As robot prices fall, initially only North adopts robots (Panel A for a 0-60% reduction in robot price), then Other also adopts (60-85%). Eventually these are both fully robotized; beyond 85% all effects are driven by Southern robotization. *Source:* Artuc, Bastos and Rijkers (2018).

Turning to trade flows, as Northern producers in the robotized industry demand progressively more intermediate inputs to enable their expansion of production (shown in Figure 3 Panel A), their demand for Southern exports of intermediates surges (Panel B).[13] Underlying this increased demand are two forces, decomposed in Panel C. The scale effect is the increase in Northern demand resulting from their higher productivity when using robots. This is offset by a substitution effect, in which the increased productivity of Northern producers raises the share of total demand that they supply (e.g., a reduction in the share of goods imported), which necessarily implies a lower share for Southern producers.[14] The same two forces also apply to Southern exports of final goods to the North (Panel D). In this case the scale effect is weaker, because it only includes higher Northern demand for final goods – i.e. it excludes the extra demand for intermediate inputs caused by the expansion of Northern final-good producers. Nonetheless, in both cases the scale effect dominates, causing a rise in total Southern exports to the North.[15]

---

[13] We place particular emphasis on the trade results because they illuminate the various mechanisms behind the modelled impacts on wages and GDP, and because they relate most closely to our core regressions.

[14] This effect could theoretically drive 'reshoring' of production.

[15] Future research with more granular data on robot use (i.e., distinguishing between robots used in the production of final vs. intermediate goods) could also separate these mechanisms in reduced-form empirics. Here, our

We also investigate the dependence of these results on the specific parameters chosen for the model. Figure A1 in the Appendix repeats Figure 3 Panels C and D for different values of the trade elasticity.[16] All the results are qualitatively robust, with only the size of the effects changing. For instance, while substitution effects are very large in the high-trade-elasticity case, the scale effect always dominates.[17] In contrast, Figure A2 repeats the baseline simulations with a lower elasticity of substitution between robots and workers, such that robots are modelled as being more similar to conventional capital.[18] Compared to Figure 2, we see that investment in robots is more gradual as their prices fall (Panel A), and Northern producers in the robotized industry actually increase their total labor use for large price reductions (Panel B). Since workers are less easily substitutable, wages rise almost monotonically in North (Panel C), in stark contrast to the baseline U-shaped relationship in which Northern wages initially fall substantially as robots displace workers. Nonetheless, Southern wages fall, along with South's exports to the North in the robotized sector (Panel D). The substitution effect is now much stronger than the scale effect, so exports of final goods collapse in the robotized sector. Thus, our conclusions above are specific to automation *per se*, as opposed to capital investments that complement Northern workers. The key characteristic of robots, that they substitute particularly well for human workers for a sizable subset of tasks in manufacturing industries, is critical in generating state-dependent comparative statics.

---

regressions focus on the net effect, which we can observe. In the simulations, we have experimented with a larger trade elasticity and found that, for final goods, the substitution effect could indeed outweigh the scale effect – but only for a very high trade elasticity (Figure A1 Panel B).

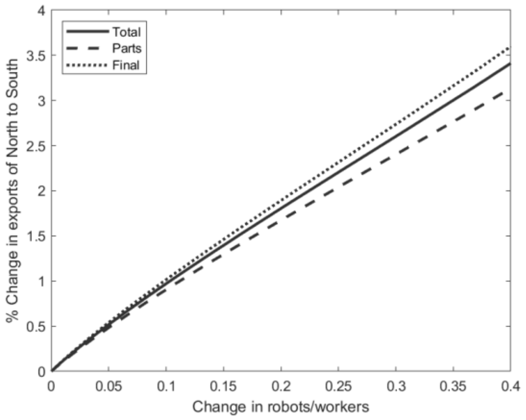
[16] Specifically, Figure A1 uses trade elasticities of 2 and 10, whereas the baseline model uses 4.

[17] The paths of other key variables (e.g., labor use, wages, welfare) are almost unchanged across the various trade elasticity scenarios.

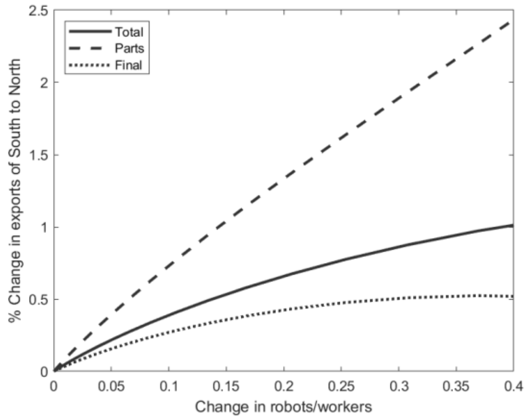
[18] Specifically, Figure A2 uses an elasticity of substitution between robots and workers of 3, rather than 10 in the baseline model. The trade elasticity is reset to 4.

Figure 3: Effects of robot adoption on trade in the robotized industry

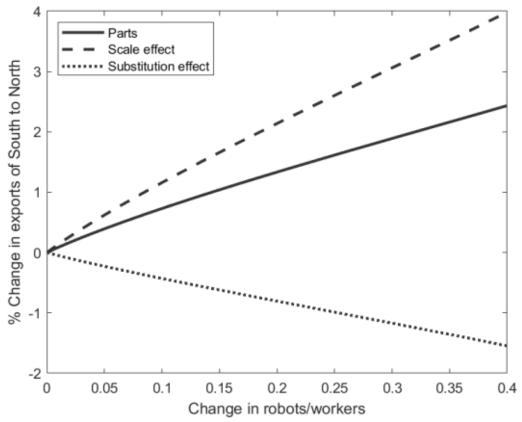
Panel A: North's exports to South



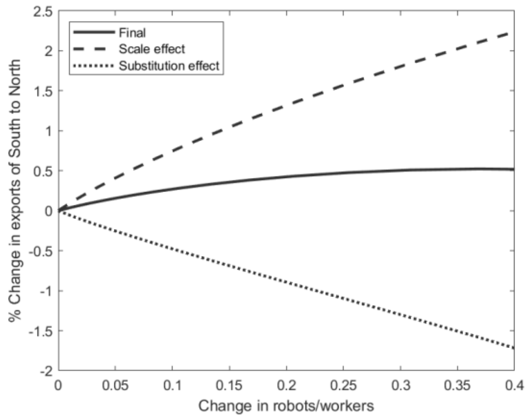
Panel B: South's exports to North



Panel C: South's exports to North, parts only



Panel D: South's exports to North, final only



Notes: this figure presents results from simulations of the effects of increased robot density (resulting from lower robot prices, as per Figure 2 Panel A) on North-South trade in the robotized industry. Panels C and D decompose the mechanisms underpinning the impacts in Panel B, on South's exports of intermediate and final goods respectively.

Robustness, indirect effects and heterogeneity

Artuc, Bastos and Rijkers (2018) run extensive robustness checks on the core empirical predictions of the model, which analyze bilateral trade flows as a function of automation in developed countries.[19] Yet such automation could also have indirect effects, by increasing competition in developing countries' other export markets. If North automates, and so increases its exports to Other, this could displace Southern exports to Other. A commonly held concern is that automation in developed countries could shut developing countries out of global value chains.

In the calibrated model, however, such effects are small. Figure 2 shows that automation in developed countries (corresponding to a 0-60% reduction in robot prices in Panel A) leads to only a very small reduction in labor use in the robotized industry in South (Panel B). We evaluate whether this prediction is realistic using World KLEMS data (Jorgenson, 2017) that allow us to move beyond bilateral trade flows.[20] We regress industry i log employment or value added y_{mit} in developing country m on its exposure to developed-country automation, measured by robot intensity in developed countries n, weighted by their share of m's baseline exports:

$$y_{mit} = \beta \cdot \ln\left(1 + \sum_{k \in n} \omega_{mkit_0} Robots_{kit}\right) + \Psi_{mt} + \Lambda_{it} + \epsilon_{mit} \tag{2}$$

where ω_{mkit_0} is baseline exports in industry i from m to k, as a share of total exports of i from m to all n, and $Robots_{kit}$ is the number of robots per million worker hours in country-industry ki. Table 1 shows only a weak negative relationship between exposure to foreign robotization and value added as well as employment. These results are robust to instrumenting exposure to developed country-automation with the log of the baseline-weighted product of replaceability, initial GDP per capita and the global robot stock (as described for regression (1) above). While data availability limits the sample substantially relative to the regressions with bilateral trade flows, these results are consistent with the those from the calibrated model. Indirect effects do not seem to play an important role; the key conclusion – that Northern automation increases Southern imports and exports – is not affected.

[19] In particular, Artuc, Bastos and Rijkers (2018) check that the results are not driven by a select few sectors, the financial crisis, tariff patterns or correlations between robotization and other types of investment. The results are also robust to alternative specifications using the inverse hyperbolic sine, variation over longer time periods, alternative instruments, and an alternative proxy for automation.

[20] Specifically, we use an unbalanced panel of value added and employment data from Russia, China, India, Cyprus, Colombia, Costa Rica, El Salvador, Honduras, Peru and the Dominican Republic between 1980 and 2016.

Table 1: Exposure to foreign robotization, employment and value added

	ln Value Added		ln Employment	
	(1)	(2)	(3)	(4)
Exposure to developed-country robotization	-0.107	-0.261	0.295	-0.663
	(0.233)	(0.495)	(0.976)	(1.858)
Observations	1,676	1,169	1,676	1,169
Specification	OLS	2SLS	OLS	2SLS
Kleibergen-Paap rk Wald-F		14.218		14.218
Country-Year FE	Y	Y	Y	Y
Industry-Year FE	Y	Y	Y	Y

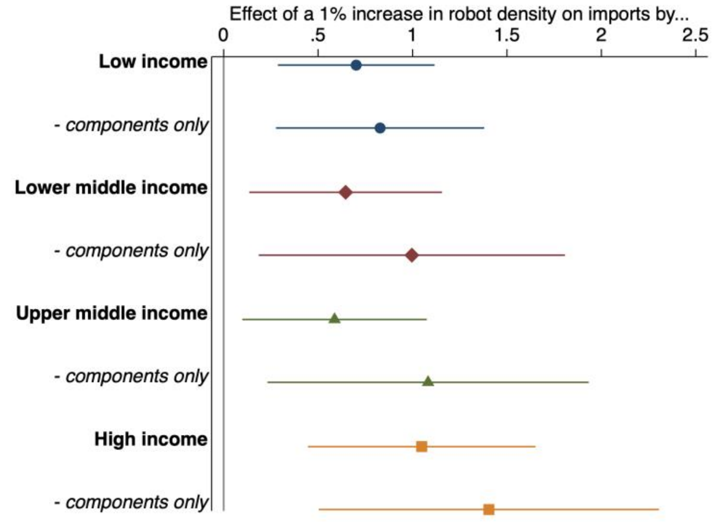
Notes: Standard errors in parentheses, clustered at the country-industry level. (Insufficient variation to cluster at country- or industry-level alone.) *** p<0.01, ** p<0.05, * p<0.1. Unbalanced panel of industry-level data between 1980 and 2016. Models (2) and (4) instrument exposure with the log of the baseline-weighted product of replaceability, initial GDP per capita and the global robot stock. *Source:* World KLEMS.

These average impacts may mask heterogeneity across different types of developing countries. Whilst the available input-output data used to quantify trade models do not make it possible to credibly simulate fine-grained country-level heterogeneity across a wide range of developing countries, we can use the empirical approach outlined above to examine how different types of countries are impacted by automation. In a new extension, we run the model above separately within sub-samples by income level and region.

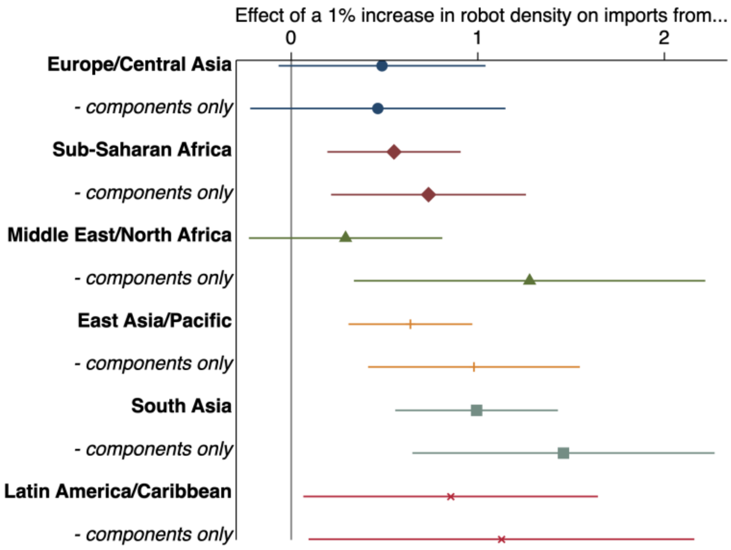
The results are shown in Figure 4. First, we find robust effects on imports at all income levels (Panel A): in each case, robotization significantly raises both total imports and imports of parts and components from developing countries. The scale effect of robotization on imports from developing countries thus appears to consistently outweigh the substitution effect within sectors. Second, we examine the effect of developed-country robotization on imports from developing countries in particular regions. We find that the effects are strongest in South and East Asia and Latin America, with slightly less of an effect in Sub-Saharan Africa, a mixed picture in the Middle East/North Africa, and no significant effect in Europe and Central Asia. This points to factors beyond relative prices driving the heterogeneity – particularly regional trade linkages and global value chain participation, which are particularly strong in South and East Asia. These mechanisms are investigated in more detail in Section 5.

Figure 4: Heterogeneity of effects of Northern robotization on North-South trade

Panel A: Heterogeneity across income levels of importers



Panel B: Heterogeneity across regions



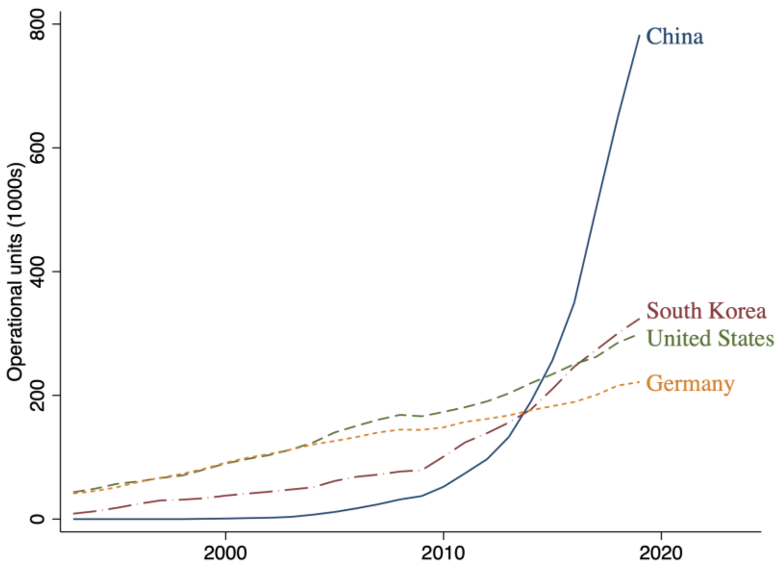
Notes: this figure presents IV estimates of the heterogeneous effects of increased robot density in the OECD on imports from developing countries, using the empirical approach outlined in equation (1).

3. Implications of growing robotization in China

While global robot use has been increasing steadily, adoption of industrial robots has been especially rapid in China – particularly in the last few years (see Figure 5). This adds an extra dimension to the mechanisms described above. Rather than technological progress leading to an exogenous fall in robot prices, which encourages high-wage countries to automate, China's robotization has been supported by large subsidies and a plethora of government programs. Faced with a rapidly ageing population, robotization has been promoted by various levels of government (Cheng et al., 2019). The Ministry of Industry and Information Technology (MIIT) released its 'Guidance on the Promotion and Development of the Robot Industry' in 2013, which aimed for a robot density of 10 per 1000 workers in factories. Subsequently, the 2015

‘Made in China 2025’ program raised this to 15; the Robotics Industry Development Plan released in 2016 by the MIIT, National Development and Reform Commission, and Minister of Finance further encouraged robot use in a broader range of sectors, including services. At a regional level, examples of automation-promoting initiatives include the government of Guangdong Province’s USD150 billion fund to invest in automation technology (Yang, 2017).

Figure 5: China's robot stock has grown rapidly



Notes: This figure shows the operational stock of robots over time for leading countries. China’s robot stock has expanded rapidly, such that it is now the largest of any country. Note, however, that the robot stock per manufacturing worker in China continues to be considerably smaller than in the OECD. *Source:* International Federation of Robotics.

To study the impact of automation subsidies in China, we use the framework of Artuc, Bastos and Rijkers (2018) with four countries.[21] The simulations include : (i) a representative country for the South (an average of Turkey, Taiwan, Mexico, Indonesia, India, Brazil, Mexico), (ii) a representative country for the North (an average of high automation counties, USA, Denmark, etc. excluding the outliers of Korea and Japan), (iii) the large ‘Other’ country, containing the totality of the OECD, and (iv) China. Everything in the model operates as before, except we now include a subsidy such that the robot price in China is $(1 - subsidy) \times price$.[22] This therefore increases robot investment in China in an analogous way to the global price reductions modelled in Figure 2 Panel A.

In the quantified model, China’s robot subsidies now push them closer to the comparative advantage profile of developed countries, and away from that of developing countries. Specifically, we find that robotization increases significantly with subsidies, so labor use in the robotized industry in China initially declines as the subsidy rises (first part of Figure 6 Panel A).[23] This reduces labor demand, and so lowers wages (first part of Panel B). However, beyond

[21] Adding an additional country to the model, as opposed to re-calibrating South to represent China, allows us to consider the impact of subsidies on China’s trade with both developed and developing countries.

[22] The subsidy is financed by taxing all Chinese factors of production in proportion to income.

[23] The strength of this effect depends on the level of initial robot prices. If robot prices are already low (so automation levels in the world are already high) then subsidies are more effective, as at this point even small subsidies tip robots into being the cheaper production option in China. This is the scenario shown in the graphs. Versions for a starting point of high robot prices and low automation levels are qualitatively similar, but with the

a threshold level – approximately a 60% subsidy in the figures – further subsidies increase labor demand and wages. Once all automatable tasks are performed by robots instead of humans, additional subsidies simply lower production costs and expand output. In other words, there is a robotization frontier beyond which further declines in robot prices are unambiguously beneficial for workers. From this point, further subsidies encourage additional investment in a technology that is now complementary to the remaining human workers.[24]

Turning to trade flows, exports by China's robotized sectors increase unambiguously with subsidies, while China's imports in those sectors decrease unambiguously. As China's robot subsidies push it closer to the relative productivity profile of high-income countries (and further away from that of low-income countries), classical comparative advantage discourages trade with high-income countries and encourages it with low-income countries. We see in Panel C that China's trade with the North may increase for lower subsidy levels, but will probably decline over time as subsidies continue and China's specialization patterns become more similar to those in the OECD. In contrast, China's trade with the South increases unambiguously (Panel D), because subsidies make China more different to other developing countries, as its comparative advantage moves to robot-intensive sectors.

Once again, these aggregate effects result from several interacting mechanisms. Consider, for instance, total Chinese imports of goods produced in the robotized sector in the South (Panels E and F). Subsidies in China increase Chinese productivity and output in this sector, which increases imports from the South through both elements of the scale effect (i.e. general consumption plus higher demand for intermediate goods). Yet subsidies also further reduce the relative competitiveness of Southern producers in the robotized sector, reducing Chinese imports from the South (the substitution effect). For large subsidies (approximately greater than 60%), the substitution effect increasingly outweighs the scale effect, so total Chinese imports of robotized-sector goods from the South fall. Once again, this is most pronounced in final goods – since the offsetting scale effect is larger for parts, because they benefit from both elements of the scale effect.[25]

Interestingly, other countries' wages and labor allocations are hardly impacted by China's subsidies. The subsidy increases both total imports from and exports to developing countries, which nets out the impact on wages. The impact on labor use in the automatable sector is noticeable, but small, since developing country labor markets are only indirectly exposed to robotization in China through international trade. Therefore, the subsidy in China causes a modest labor shift in developing countries from automatable industries to non-automatable industries, with only marginal impacts on wages.

Accounting for continued population ageing in China would strengthen these results. As documented by Acemoglu and Restrepo (2021), middle-aged workers have a comparative advantage over older workers in manual production tasks, such that demographic changes that reduce their share of the population raise labor costs in manufacturing. Thus continued ageing

impact of the subsidy only kicking in once it reaches a higher level (60%+) – effectively all the action in the graphs shifts rightwards.

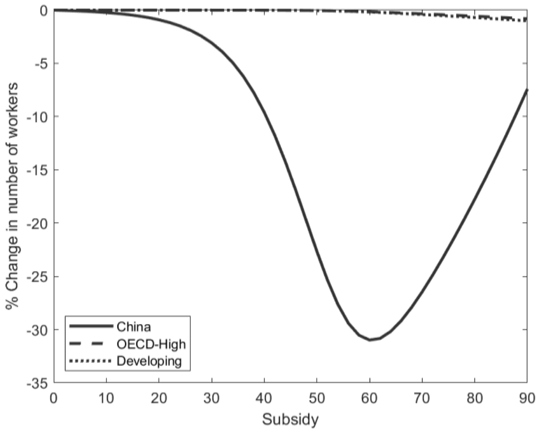
[24] In the very long run, new tasks can be created and/or some existing tasks can become obsolete – thus the robotization frontier can also move, which is an aspect omitted from our model. Depending on the direction of the shift of the robotization frontier, labor demand can increase or decrease.

[25] How do these falls in imports from the South relate to the increasing overall imports from the South in Panel D? Note that Panel D shows total trade, so also includes the non-robotized tradeable sector. As China specialises in the robotized sector, it increases its imports in this other sector, generating a net increase in aggregate imports from the South.

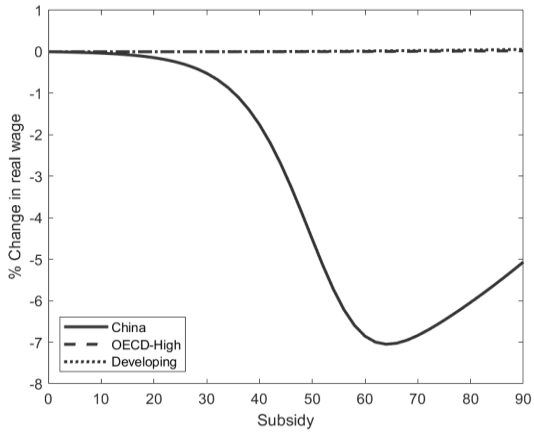
would further increase the relative attractiveness of robots, paralleling and reinforcing the impacts that we find for a robot subsidy.

Figure 6: Simulated effects of increased Chinese robot subsidies

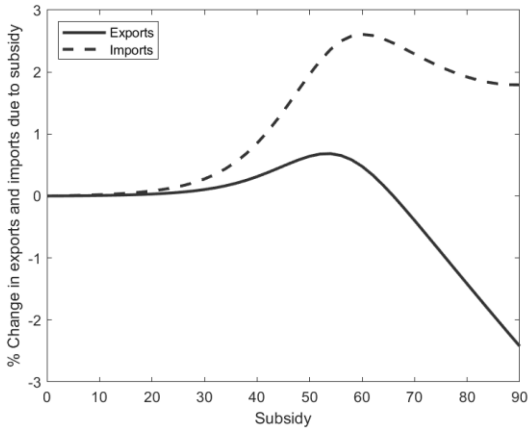
Panel A: Labor use in robotized industry



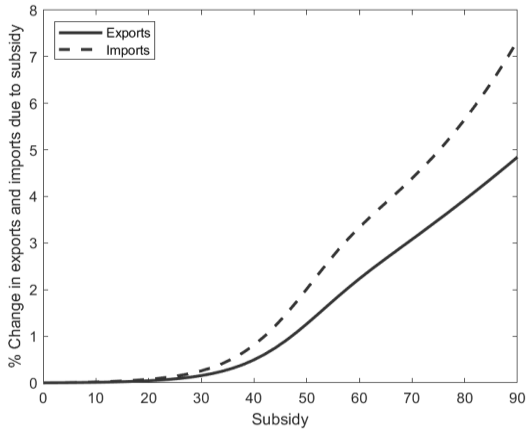
Panel B: Wages



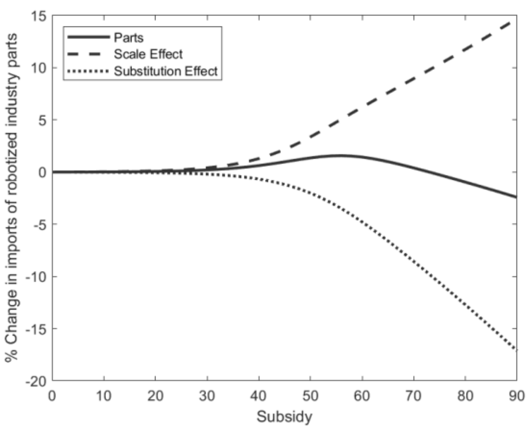
Panel C: Trade with high income countries



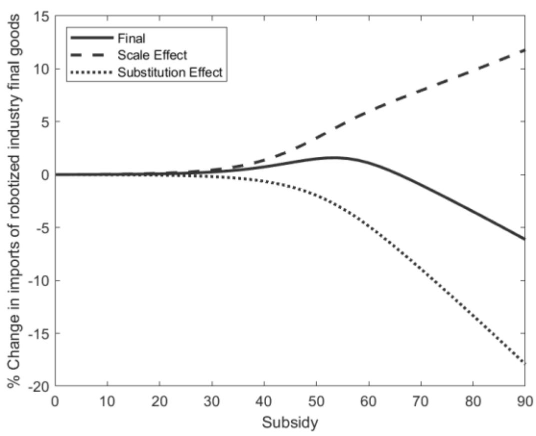
Panel D: Trade with developing countries



Panel E: Rob. ind. imports from South, parts



Panel F: Rob. ind. imports from South, final



Notes: This figure presents results from simulations of the effects of Chinese robot subsidies on labor use in the robotized industry, wages and trade. Everything in the model operates as before, except that there is now an extra country, calibrated to fit China, which subsidizes robots such that the robot price there is $(1 - subsidy) \times price$.

4. Broader evidence: global value chains, frictions and de-industrialization

Our findings dovetail with empirical evidence from other recent studies. Robotization by Spanish firms increased their demand for inputs from developing countries, and also led them to increase their number of affiliates in developing countries (Stapleton and Webb, 2020).[26] Robot usage has also promoted greenfield FDI from high-income countries to low-income countries (Hallward-Driemeier and Nayyar, 2019). This evidence is particularly informative about future trends because greenfield FDI decisions are a forward-looking indicator of where production is expected – unlike trade flows, which reflect past investment decisions. In contrast to fears of automation driving mass reshoring, there is reason to be cautiously optimistic that the positive scale/productivity effect of developed country automation on offshoring may outweigh the negative substitution effect.

However, the focus of our Ricardian model is on long run and aggregate effects. In the short run, workers cannot move freely across sectors or between sub-national regions. Sector-specific skills, frictions and sunk investments could drive transitional unemployment and growing inequality; workers in robot-competing sectors and localities could lose out from Northern robotization. Recent studies find evidence for such effects. To gauge the impact of US robots on employment in Colombia, Kugler et al. (2020) use employer-employee matched data from social security records. They measure exposure to US robotization by combining baseline Colombian local labor market-industry employment shares with industry-time robot adoption in the US, and find that such exposure reduces employment and earnings in Colombia. Their estimates imply that, between 2011 to 2016, the adoption of 70,000 new robots in the US led to the cumulative loss of between 63,000 and 100,000 Colombian jobs. The negative effects are largest for women, older and middle-aged workers, and those employed in small and medium-size businesses – groups which may be least mobile across locations or industries to find new employment.

Similarly, Faber (2020) examines the impact of US robotization on employment in Mexican local labor markets between 1990 and 2015. He combines initial Mexican local labor market-industry employment shares with a measure of offshorability and changes in US robot intensity, and again finds a sizeable negative impact on Mexican employment. Although Mexico also automated industrial production in this period, and the coarse industry-level robots data make it difficult to distinguish between the effects of robotization in the US and at home, he finds that the burden of robotization falls most heavily on low-educated machine operators in the manufacturing sector – again, a group likely to be less mobile across locations and occupations. Also focusing on Mexico, but over 2004-2014 Artuc, Christiaensen and Winkler (2019) find less of an effect of US robotization on Mexican regional exports and local labor markets. They find evidence that the informal sector expands, acting as an ‘employment buffer’ as in Dix-Carneiro et al. (2019), but that automation nonetheless hits the unskilled and other already-disadvantaged workers hardest. Wage inequality thus increases, especially in the local labor markets most exposed to foreign automation. Taken together, this evidence suggests that while robotization could promote trade and increase real wages in developing countries in the

[26] Interestingly, Stapleton and Webb (2020) illuminate a firm-level analogue of the contrasting forces in our model, finding that firm-level sequencing matters for the net impact of robotization on offshoring. For firms that had not yet offshored any production, robotization simply allowed them to expand, which caused them to begin new offshoring. In contrast, for firms that had already offshored some production, there was also a negative effect on offshoring – as robots allowed some previously-offshored production to be automated domestically. In the Spanish case they find that the effect for the former group dominates, with robotization in the full sample having a net positive impact on imports from lower-income countries.

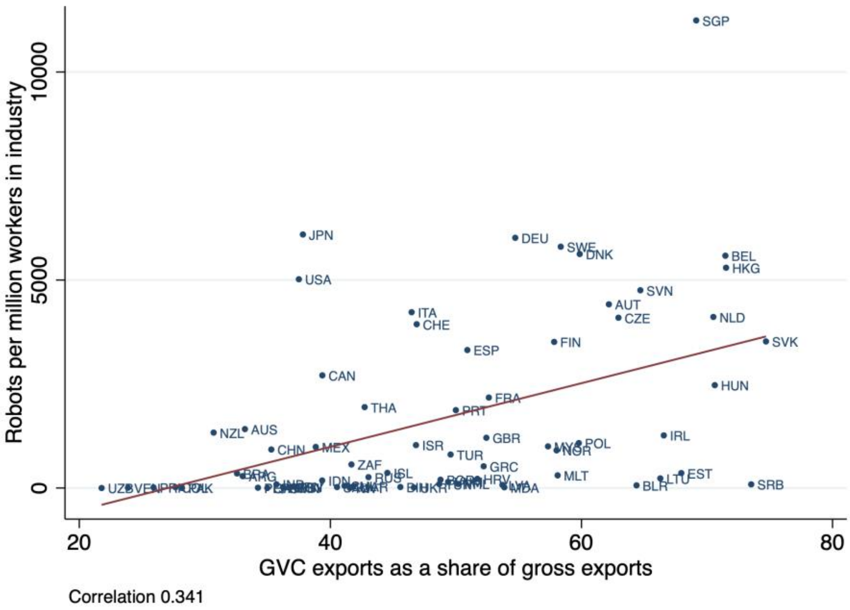
medium and long run, in the short run governments will need to be attentive to those workers and regions that are most vulnerable in the transition.

Furthermore, long-run risks are non-negligible. The model described above focuses on static gains from trade. Over time, developed-country robotization could also push developing economies away from some sectors with higher long-run potential for learning-by-doing or technology transfers. This could compound existing difficulties in trying to grow technology-intensive 'infant industries' to a competitive scale, and exacerbate 'premature de-industrialization' (Rodrik, 2016). Such dynamics may help explain why some developing countries, such as China, have opted to subsidize robots.

5. Robot adoption in developing countries: beyond relative prices

The Ricardian model described above abstracts from firm-level heterogeneity in order to emphasize country- and sector-level effects. In reality, many factors beyond robot prices, wages and subsidies will influence the incentives to adopt robots. First, we can conceptualize robotization as a one-off or per-period fixed cost that lowers marginal production costs. In this case, we might expect only larger, more productive, export-oriented firms to undertake such investment, in the spirit of Melitz (2003) and Bustos (2011). Alternatively, robotization could be conceptualized as an upgrade to product quality – for instance, by allowing greater precision and reliability, as discussed in Verhoogen (2008) and Rodrik (2018). These attributes may be most valued by firms that are tightly integrated into complex production networks, involving the coordination and assembly of many interdependent components (Kremer, 1993; Verhoogen, 2008; Demir et al., 2021). The cost of producing a defective widget compounds rapidly if its failure negates all the other inputs into a complex final product. By this reasoning, we might then expect more automation in firms that are tightly integrated into global value chains, where the costs of errors (or the payoffs to quality) are highest. Such mechanisms will drive some robot adoption within developing countries, despite the availability of cheap labor. A first glance at high-level cross-country correlations do indeed point to a positive association between GVC participation and robot adoption (Figure 7).

Figure 7: Robot use and participation in global value chains

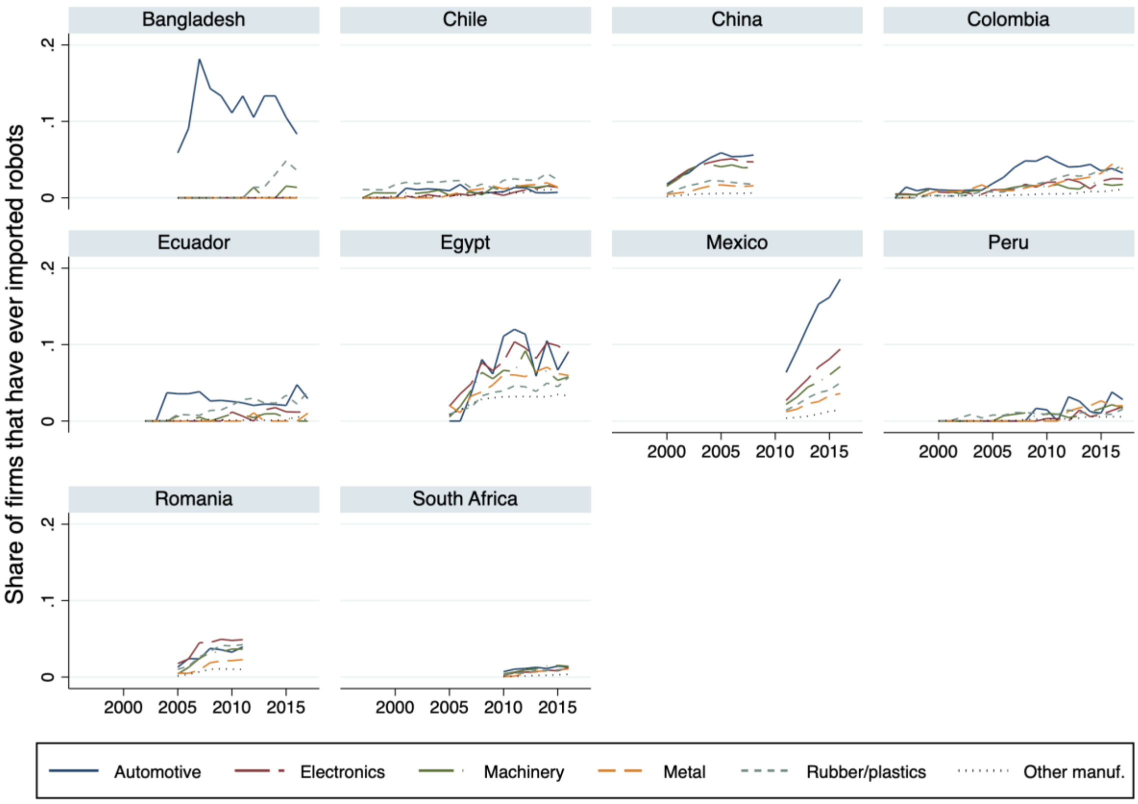


Notes: This graph shows the correlation between robot density and GVC participation in 2015, using the data and methodology outlined in the World Development Report 2020 (World Bank, 2020). GVC exports are defined as those crossing more than one border. One outlier (Republic of Korea) is excluded from the graph for clarity, but is included in the correlation calculation.

To investigate such relationships further, we use the near-universe of firm-level trade transactions from ten developing countries, identifying automation events from imports of industrial robots.[27] The shares of firms that have ever imported robots are shown in Figure 8. Consistent with the patterns presented in Section 2, the electronics and automotive sectors have the highest shares of robot use. Defining 'automators' as firms that import robots at some point in the sample period, we regress automator status on a range of firm characteristics, using only observations prior to the first observed robot purchase by each firm.[28] The resulting ex-ante correlations are shown in Figure 9.[29] Firms adopting robots are larger, more diversified across products (yet simultaneously more specialized in their core products), and more integrated with GVCs. This resonates with the literature on technology adoption. Firms adopting robots in developed countries are generally larger, more productive and growing faster (Humlum, 2019; Koch et al., 2019; Acemoglu et al., 2020; Bonfiglioli et al., 2020). In China firms that adopt robots also tend to be larger, have more capital per worker, pay higher wages, and are less likely to be state-owned (Cheng et al., 2019).

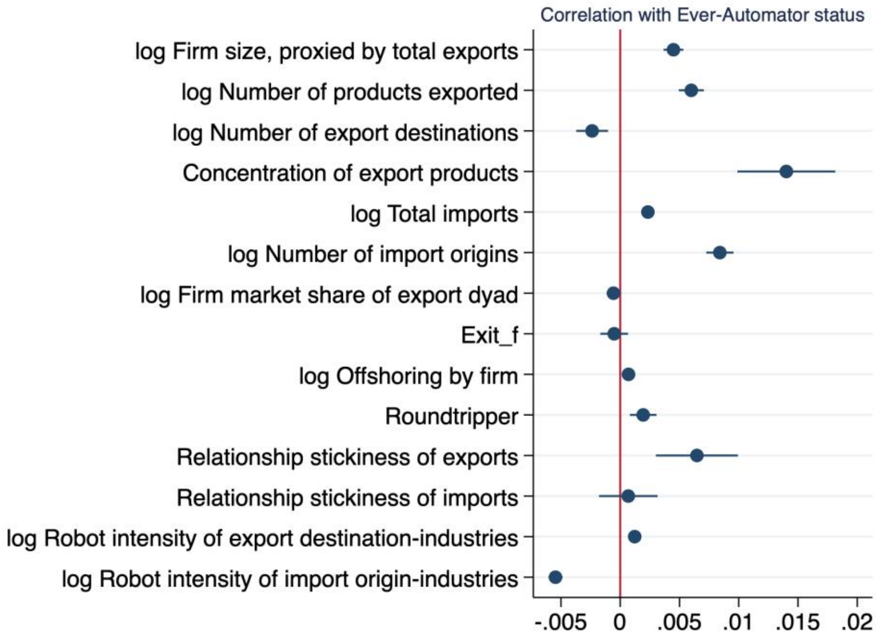
[27] Source: The World Bank's Exporter Dynamics Database, which covers all trade transactions except those of oil and arms. We use data from importer-exporters in Bangladesh, Chile, China, Colombia, Ecuador, Egypt, Mexico, Peru, Romania and South Africa, which contain 10,312 separate robot purchases by 4646 distinct firms.
[28] We also include industry-year and country-year fixed effects and cluster at the firm level.
[29] Concentration is measured by a Herfindahl index of export sales, using each firm-product's share of total firm exports. Market shares are the firm's share of total sales from the home country to each given export destination, which are then averaged across all the firm's export dyads. Offshoring is the sum of imports in the same HS4 category as goods sold by the firm, following the 'narrow' measure of Hummels et al. (2014). Roundtripper is a dummy that takes value one only for firms which export and import the same HS6 product to the same partner in a given year. Relationship stickiness is a weighted average across either exports or imports of the measure of Martin et al. (2020).

Figure 8: Share of firms that imported robots by country and industry



Notes: The figure draws on data from the World Bank's Exporter Dynamics Database, which covers all trade transactions except those of oil and arms. We use data from importer-exporters in Bangladesh, Chile, China, Colombia, Ecuador, Egypt, Mexico, Peru, Romania and South Africa, which contain 10,312 separate robot purchases by 4,646 distinct firms. Note that the range of years displayed for each country varies, according to the current availability of customs data in the EDD.

Figure 9: Ex-ante correlates of automation



Notes: Confidence intervals shown for 95% significance level. Fixed effects: industry-year, country-year. Standard errors clustered at the firm level. *Source:* the World Bank's Exporter Dynamics Database.

We supplement this evidence with detailed firm-level data from the Vietnam Technology and Competitiveness Surveys 2010-14. These data record explicitly whether a firm uses computer-operated machines, and are also not restricted to firms that trade internationally. Table 2 shows summary statistics for automating vs. non-automating firms. The patterns are similar: in general, automators are larger, pay higher wages, are more likely to export and to be foreign owned. Moving to partial correlations in Table 3, and accounting for province, industry and year fixed effects, we find that automators have more assets, earn higher revenues, pay higher wages, are more likely to be foreign-owned, and have higher levels of labor productivity.

Table 2: Summary statistics for automating vs. non-automating firms in Vietnam

	(1) Computer operated machines=0				(2) Computer operated machines=1				(1)-(2)	
	Mean	SD	Min	Max	Mean	SD	Min	Max	Diff	S.E.
log employment	4.092	1.367	0.693	10.091	4.907	1.413	0.693	9.429	-0.814***	(0.027)
log avg. wage	3.401	0.632	0.000	10.085	3.736	0.599	0.065	8.405	-0.335***	(0.011)
Exporter	0.391	0.488	0.000	1.000	0.609	0.488	0.000	1.000	-0.218***	(0.009)
log revenues	9.580	1.989	0.000	16.604	10.952	2.046	0.000	16.952	-1.372***	(0.038)
log leverage	0.420	0.194	0.000	0.693	0.430	0.179	0.000	0.693	-0.010**	(0.003)
log fixed assets	8.363	2.073	0.000	17.279	9.990	2.134	0.000	16.395	-1.627***	(0.040)
State-owned	0.435	0.496	0.000	1.000	0.330	0.470	0.000	1.000	0.105***	(0.009)
Privately-owned	0.370	0.483	0.000	1.000	0.265	0.441	0.000	1.000	0.105***	(0.008)
Foreign-owned	0.195	0.396	0.000	1.000	0.405	0.491	0.000	1.000	-0.210***	(0.009)
N (obs.)	28097				3141				31238	

Notes: Standard errors in parentheses, clustered by firm. Data for the 2010-2013 period. Leverage is normalized to lie between 0 and 1. *Source:* Vietnam Technology and Competitiveness Surveys.

Surveying this evidence, it seems likely that domestic robot adoption will primarily help the largest, most productive and most globally integrated firms in developing countries. Smaller and less productive firms miss out, in line with Rodrik (2018) and Goger et al. (2014).

Table 3: Firm-level correlates of automation in Vietnam

Dep. variable: Firm with computer-operated machines		
	(1)	(2)
log employment	-0.001	0.003
	(0.003)	(0.004)
log avg. wage	0.025***	0.017***
	(0.004)	(0.004)
Exporter	0.014	0.012
	(0.007)	(0.008)
log revenues	0.008***	0.007**
	(0.002)	(0.002)
log leverage	-0.041**	-0.039**
	(0.013)	(0.013)
log fixed assets	0.022***	0.022***
	(0.002)	(0.002)
State-owned	0.006	0.001
	(0.005)	(0.005)
Foreign-owned	0.031**	0.030**
	(0.010)	(0.011)
Province-Industry FE	N	Y
Industry FE	Y	N
Year	Y	Y
N (obs.)	31233	31109
R2	0.077	0.145
F-stat	72.458	59.066

Notes: Standard errors in parentheses, clustered by firm. Firm-level data for the 2010-2013 period. Leverage is normalized to lie between 0 and 1. *Source:* Vietnam Technology and Competitiveness Surveys.

6. Firm-level implications

Larger, internationally active firms are more likely to adopt robots. How do they change ex-post? Drawing on firm-level data for ten developing countries, we address this question using an event study approach (based on Bessen et al., 2020). We estimate:[30]

$$\ln Y_{ft} = \sum_{s\neq-1,s=-2}^{2} \beta_s \times AutoEvent_{ft-s} + \alpha \cdot X_{ft} + \alpha_{ct} + \alpha_{it} + \alpha_f + \epsilon_{ft} \qquad (3)$$

where X_{ft} controls for firm age. An automation event is defined as a period in which the firm spends more than three times its average cost-share on robots, not including robot purchases in the current period. Specifically:

$$AutoEvent_{f\tau} = 1\left\{\frac{RobotPurchases_{f,t=\tau}}{\overline{TotalNonRobotImports}_f} \geq 3 \times \frac{\overline{RobotPurchases}_{f,t\neq\tau}}{\overline{TotalNonRobotImports}_f}\right\} \qquad (4)$$

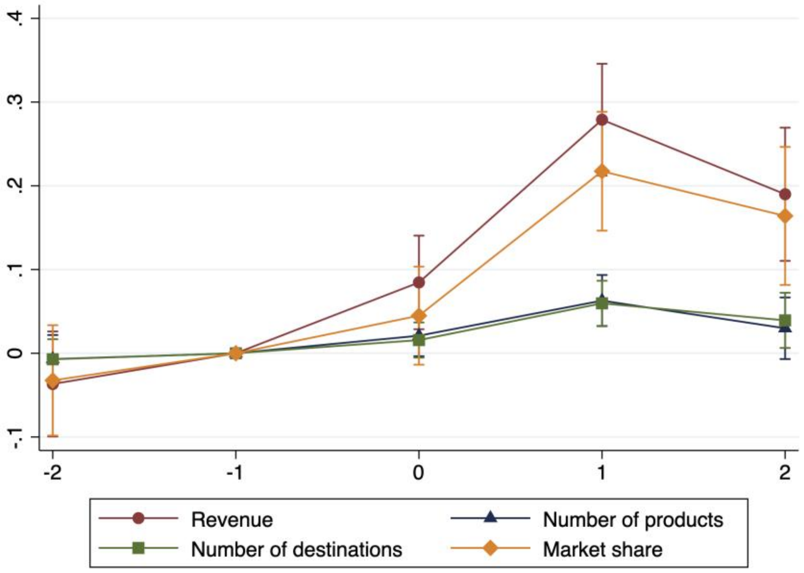
To mitigate selection effects, e.g. automators being particularly well-managed, we restrict our main sample to only firms that do, at some point, automate. Thus the relevant counterfactual, against which the effect captured by β is measured, is the trend in firms that do automate, but not in the same period as the firm under consideration. We find that, after adopting robots, firms increase their exports and market share, and expand their range of export products and

[30] We use a four-year window to maximise the number of automation events for which pre- and post-trends can be detected, given the short panel lengths in some of our countries. Results are qualitatively robust to using a longer window and fewer observations.

destinations (Figure 10). Robotizing firms are not only larger ex-ante; their adoption of robots also coincides with a further expansion ex-post.[31]

In other words, we have evidence consistent with robotization boosting the growth of initially larger firms in developing countries. Robotization could thus contribute to increasing the average firm size in developing countries, and thereby raise aggregate productivity (Hsieh and Klenow, 2014). Yet this evidence also adds a firm-side element to the earlier distributional concerns: it is not just more disadvantaged workers who are most threatened by robotization, but also smaller, less productive, less internationally active firms.[32] Given that low-skilled workers are also more likely to work at such firms, this dual threat is a key issue for policymakers to consider. As Rodrik (2018) notes, a key objective will be to "disseminate throughout the rest of the economy the capabilities already in place in the most advanced parts of the productive sector". In the meantime, robot adoption may place temporary support systems – whether state welfare systems, social networks or the informal sector (Dix-Carneiro et al., 2019; Dix-Carneiro and Kovak, 2019) – under increasing strain. Reaping the benefits of robot adoption at home and abroad, whilst mitigating the downsides, will be a key policy challenge.

Figure 10: Impact of robot adoption on firm export outcomes



Notes: All variables in logs. Confidence intervals shown for 95% significance level. Standard errors clustered at the firm level. *Source:* the World Bank's Exporter Dynamics Database.

[31] If we expand the sample to include never-adopters, rather than only not-now-adopters, the relative post-adoption expansion is even larger.

[32] This aligns with findings from developed countries that large firms adopting robots expand at the expense of more labor-intensive competitors (Koch et al., 2019; Acemoglu et al., 2020). Smaller and less productive firms may also be more vulnerable to automation-driven business-stealing from abroad (Aghion et al., 2020).

7. Conclusion

Industrial robots will place conflicting pressures on developing countries. In the long run, robot adoption in developed countries will most probably catalyze international trade and enhance global welfare. This conclusion is likely to be reinforced by the fact that other new technologies – such as high-speed internet and digital platforms – will further reduce the costs of trading and coordinating across borders (Brynjolfsson et al., 2019; Freund and Weinhold, 2002, 2004) and will create entirely new products and tasks (Acemoglu and Restrepo, 2018; Nakamura and Zeira, 2018). Furthermore, China's growing robotization (driven in part by subsidies) might reduce productivity differences with advanced economies (and thereby the gains from inter-industry trade with them), and need not hinder prospects for industrialization and export-led growth in lower-income countries.

At the same time, trade and technological change will necessitate labor market adjustment and could create severe distributional tensions both during and after the transition to automated production. Robot adoption in developing countries could exacerbate disparities between, on the one hand, the more advanced internationally active firms that account for a large share of exports, and on the other hand the small-scale, informal firms that account for a large share of low-skilled and manual employment. These firm-level disparities may also accentuate income disparities across households in developing countries. Furthermore, over time developed-country automation could discourage developing countries from investing in some sectors with high growth potential, contributing to 'premature de-industrialization' (Rodrik, 2016). Weighing these risks against the potential gains from specializing in labor-intensive exports will be a difficult balancing act. Informing policies that harness the growth potential of globalization and technological progress while ensuring the attendant gains are equitably shared is thus an important task for future research.

Appendix

This section provides an overview of the model; further details can be found in Artuc et al. (2018). The task-based Ricardian framework combines several ideas from the literature: productivity differences across countries and sectors (Eaton and Kortum, 2002), two-stage production with trade in intermediates and final goods (Yi, 2003; Caliendo and Parro, 2015) and feasible robotization of some tasks previously performed by humans (Acemoglu and Restrepo, 2020).

We denote countries by m and n, sectors by i, and production stages by s, where $s = 1$ refers to intermediate inputs (first stage) and $s = 2$ refers to final goods (second stage). Workers are mobile across stages and sectors, but not across countries. Robots are equally available in all countries, at the same (exogenous) rental rate, and are owned by residents of the country that robotizes production. The representative household in country n maximises Cobb-Douglas utility

$$U^n = \prod_i \left(Q_2^{n,i}\right)^{\gamma^{n,i}}$$

where $Q_2^{n,i}$ is the amount of composite final good from sector i demanded by consumers in country n, and $\gamma^{n,i}$ is a constant with $\sum_i \gamma^{n,i} = 1$. The composite final good $Q_2^{n,i}$ results from the aggregation of final stage varieties by consumers, as described in detail below.

A continuum of varieties $\omega \in [0,1]$ is produced in each sector i of country n. These varieties can be produced either as intermediate inputs in the first stage or as final goods in the second stage. We define the set of first and second stage varieties in industry i respectively as S_1^i and S_2^i, such that $S_1^i \cup S_2^i = \{0,1\}$. The production function for varieties ω is:

$$q^{n,i}(\omega) = z^{n,i}(\omega)\left(F_s^{n,i}(\omega)\right)^{\alpha_F^{n,i}}\left(Q_1^{n,i}(\omega)\right)^{\alpha_M^{n,i}}\left(T^{n,i}(\omega)\right)^{\alpha_T^{n,i}}$$

where $Q_1^{n,i}$ is a first stage composite, $F_s^{n,i}(\omega)$ is a fixed factor specific to the industry-stage, $T^{n,i}(\omega)$ is a composite task input, and $z^{n,i}(\omega)$ is productivity drawn from a $Frechet$ distribution with shape parameter θ. Aggregation of stage s varieties $\omega \in S_s^i$ then yields the stage s composite good $Q_s^{n,i}$.

The production of the composite task input $T^{n,i}$ for variety ω requires performing a range of tasks $k \in [0,1]$. We assume that tasks from 0 to K^i can be performed by robots or humans, while tasks between K^i and 1 can only be performed by workers. In some industries, robotization is not feasible, and hence $\exists i : K^i = 0$. The subset of tasks that can be robotized is thus given by K^i, while the subset of tasks that cannot be robotized is given by $1 - K^i$. The robotization frontier and the productivity of robots are assumed to be industry specific, but not stage specific.

To perform one unit of task k of variety ω within industry i, $\phi_L^i \zeta_L(k)$ labor units are required. If $k < K^i$, $\phi_R^i \zeta_{\mathrm{R}}(\mathrm{k})$ robot units can perform the same task. $\zeta_R(k)$ and $\zeta_L(k)$ are distributed $Weibull$ with shape parameter ν. Thanks to the distributional assumptions, the optimal set of tasks performed by robots is then given by the expression

$$K_R^{n,i} = \frac{\left(\phi_R^i w_R\right)^{-\nu}}{\left(\phi_R^i\, w_R\right)^{-\nu} + \left(\phi_L^i\, w_L^n\right)^{-\nu}} K^i$$

and depends upon the automation frontier K^i, the elasticity of substitution between robots and workers $1+\nu$, and the productivity-adjusted relative price of workers versus robots $\phi_L^i\, w_L^n / \phi_R^i\, w_R$. The average unit cost of tasks from 0 to K^i is given by the standard CES function

$$w_{T_A}^{n,i} = \psi_3^i\left(\left(\phi_R^i\, w_R\right)^{-\nu} + \left(\phi_L^i\, w_L^n\right)^{-\nu}\right)^{-\frac{1}{\nu}}$$

and depends on wages w_L^n, the unit cost of robots w_R and the elasticity of substitution between robots and workers.[33] Similarly, the unit cost of tasks from K^i to 1 is $w_{T_N}^{n,i} = \psi_3^i \phi_L^i w_L^n$. Combining these expressions, the cost of producing a task with robots, relative to the cost of producing it without robots, is:

[33] Parameters ψ throughout denote various constants.

$$\Omega^{n,i} = 1 - K^i + K^i \left(1 - \frac{K_R^{n,i}}{K^i}\right)^{\frac{1}{\nu}}$$

Intuitively, robots bring no cost benefit (i.e. $\Omega^{n,i}$=1) if there is no potential for robotization in an industry ($K_i = 0$), while the relative cost is minimized (i.e. $\Omega^{n,i}$ is close to zero) if robots are free to rent ($w_R = 0$) and can be used for all tasks ($K_i = 1$). Analogously, labor demand per task is

$$\Xi^{\mathrm{n,i}} = 1 - K^i + K^i \left(1 - \frac{K_R^{n,i}}{K^i}\right)^{1+\frac{1}{\nu}}$$

such that labor demand is lower when robots (i) are cheaper, or (ii) can be used more widely.

We can use $\Omega^{n,i}$ to express the unit price of output under robotization:

$$c_s^{n,i} = \psi_4^{n,i} \left(r_{s,F}^{n,i}\right)^{\alpha_F^{n,i}} \left(P_1^{n,i}\right)^{\alpha_M^{n,i}} \left(\Omega^{n,i} w_L^n\right)^{\alpha_T^{n,i}}$$

where $P_1^{n,i}$ is the price of (first-stage) inputs. A larger cost reduction from robotizing (i.e., $\Omega^{n,i}$ closer to zero) lowers output prices. This in turn raises the probability that country n is the lowest-priced provider of a stage s variety to country m:

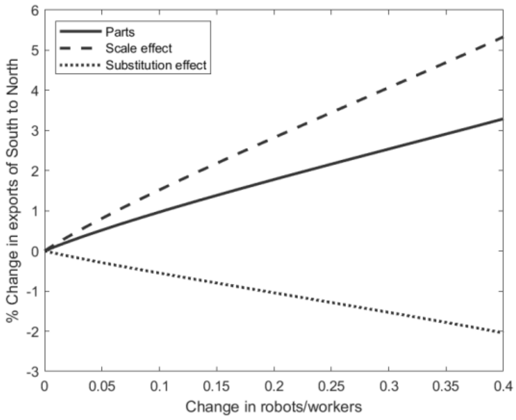
$$\pi_s^{m,n,i} = \left(\frac{\psi_{s,4}^{n,i}\, \tau^{m,n,i} \left(r_{s,F}^{m,i}\right)^{\alpha_{s,F}^{m,i}} \left(P_1^{n,i}\right)^{\alpha_{s,M}^{n,i}} \left(\Omega^{n,i}\, w_L^n\right)^{\alpha_{s,T}^{n,i}}}{P_s^{m,i}/\psi_2^i}\right)^{-\theta}$$

In other words, robotization at home increases exports to other countries. In the calibrated model, initial higher wages lead the richer Northern countries n to adopt more robots than Southern countries m. Declines in robot prices then induce further robotization, which disproportionately lowers production costs in the North and thus increases exports to the South and to the third country ('Other').

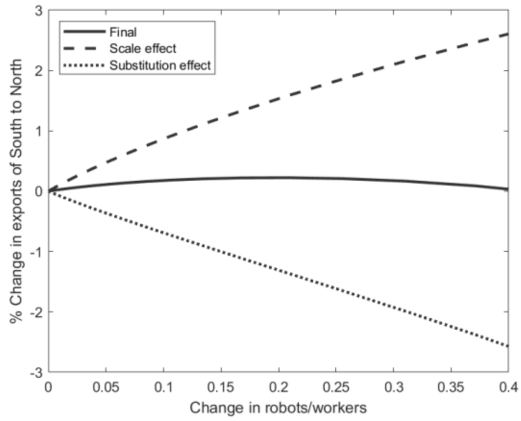
In contrast, the effect of Northern robotization on imports sourced from the South is theoretically ambiguous. On the one hand, robotization makes Northern producers more competitive at home (i.e. $\pi_s^{n,n,i}$ is larger), which implies that some varieties that were previously imported from the South are now sourced domestically. On the other hand, robotization leads to an expansion in the scale of production, which raises demand for first-stage varieties sourced from the South (i.e. $Q_1^{m,i}$ is larger).

Figure A1: South's exports to North in the robotized industry

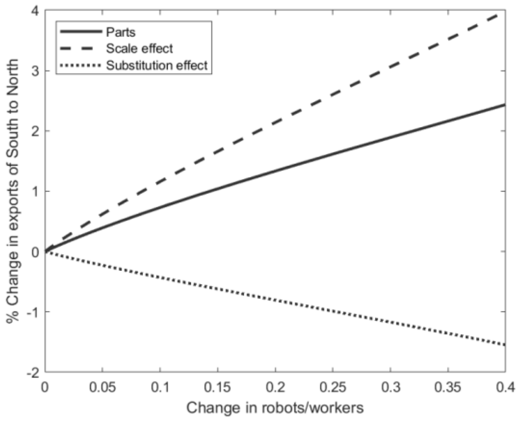
Panel A: Parts only, high trade elasticity



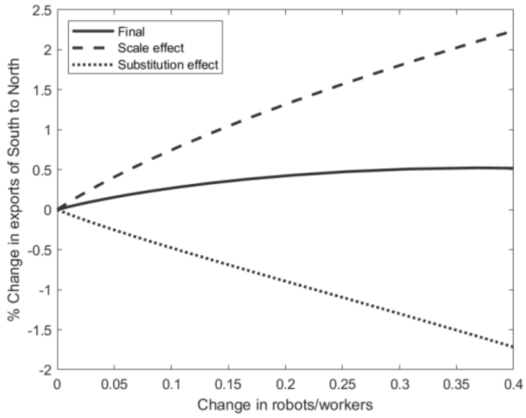
Panel B: Final goods only, high trade elasticity



Panel C: Parts only, low trade elasticity

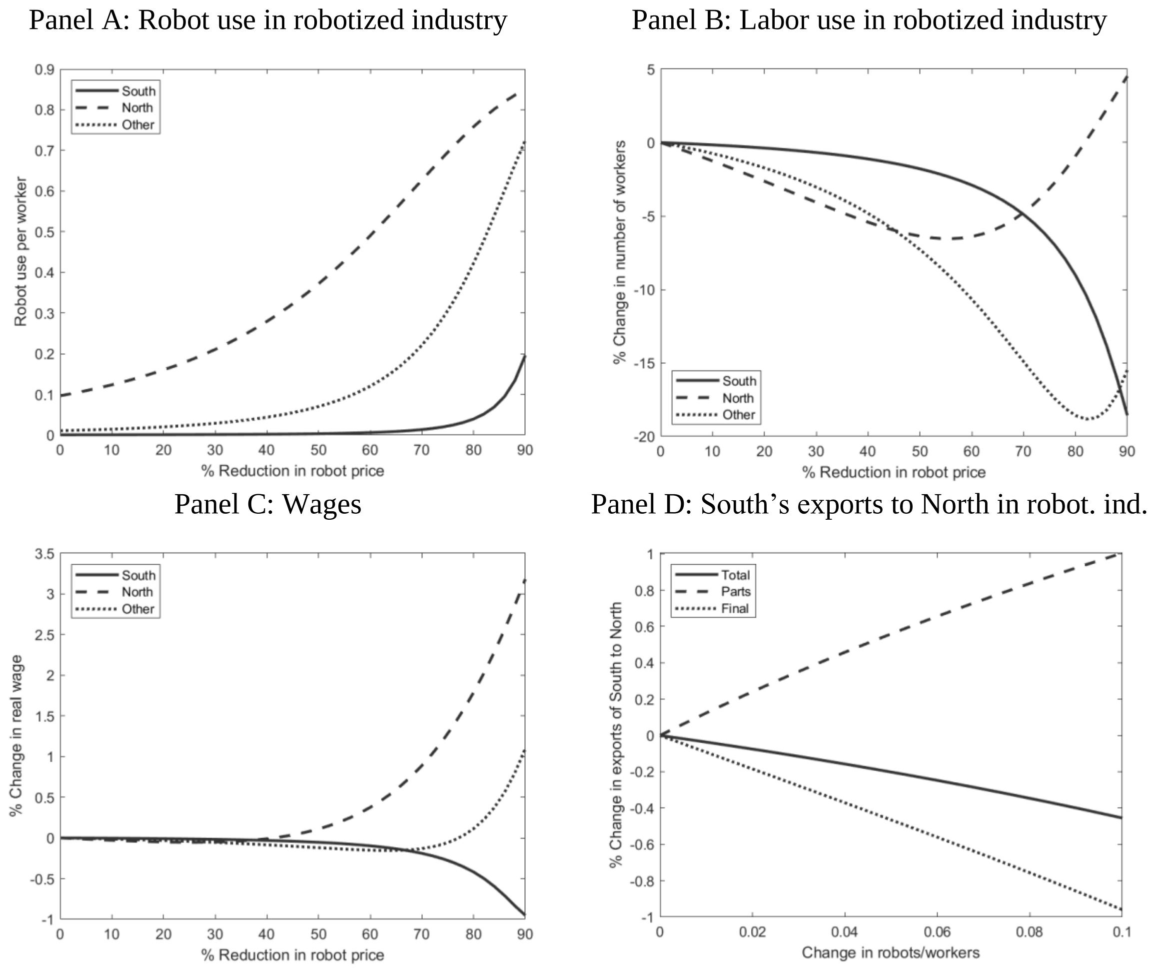


Panel D: Final goods only, low trade elasticity



Notes: this figure presents results from simulations of the effects of lower robot prices (and so increased robot usage) on Southern exports to North in the robotized industry, for a range of trade elasticities. Panels A and B show results for a trade elasticity of 10 (versus 4 in Figure 3 in the main text), while Panels C and D use a trade elasticity of 2. The results are qualitatively robust across all cases, with only the size of the effects changing. For full discussion, see Section 2 in the main text. Note the differential scaling of the y axes for the different scenarios.

Figure A2: Low elasticity of substitution between robots and workers



Notes: this figure presents results from simulations of the effects of lower robot prices on robot use, labor allocation, wages and trade, for a case with low elasticity of substitution between robots and workers. Specifically, this elasticity is 3 in these graphs, rather than 10 in the baseline case – so robots are thus modelled as being similar to conventional capital. For full discussion, see Section 2 in the main text.

References

Acemoglu, D., Lelarge, C., Restrepo, P., 2020. Competing with Robots: Firm-Level Evidence from France. AEA Papers and Proceedings 110, 383–388. https://doi.org/10.1257/pandp.20201003

Acemoglu, D., Restrepo, P., 2018. The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment. American Economic Review 108, 1488–1542. https://doi.org/10.1257/aer.20160696

Acemoglu, D., Restrepo, P., 2019. Automation and New Tasks: How Technology Displaces and Reinstates Labor. Journal of Economic Perspectives 33, 3–30. https://doi.org/10.1257/jep.33.2.3

Acemoglu, D., Restrepo, P., 2020. Robots and Jobs: Evidence from US Labor Markets. Journal of Political Economy. https://doi.org/10.1086/705716

Acemoglu, D., Restrepo, P., 2021. Demographics and Automation. The Review of Economic Studies. https://doi.org/10.1093/restud/rdab031

Aghion, P., Antonin, C., Bunel, S., Jaravel, X., 2020. What Are the Labor and Product Market Effects of Automation? New Evidence from France 47.

Antras, Pol (2015). Global production: Firms, Contracts, and Trade Structure, Princeton University Press.
Artuc, E., Bastos, P., Rijkers, B., 2018. Robots, Tasks and Trade. World Bank, Washington, DC. https://doi.org/10.1596/1813-9450-8674
Artuc, E., Christiaensen, L., Winkler, H., 2019. Does Automation in Rich Countries Hurt Developing Ones? Evidence from the U.S. and Mexico 59.
Artuç, E., McLaren, J., 2015. Trade policy and wage inequality: A structural analysis with occupational and sectoral mobility. Journal of International Economics 97, 278–294. https://doi.org/10.1016/j.jinteco.2015.06.001
Bessen, J., Goos, M., Salomons, A., van den Berge, W., 2020. Firm-Level Automation: Evidence from the Netherlands. AEA Papers and Proceedings 110, 389–393. https://doi.org/10.1257/pandp.20201004
Bloom, D., McKenna, M., Prettner, K., 2018. Demography, unemployment, and automation: Challenges in creating (decent) jobs until 2030. VoxEU.org. URL https://voxeu.org/article/demography-unemployment-and-automation (accessed 3.22.21).
Bonfiglioli, A., Gancia, G., Fadinger, H., Rosario Crino, 2020. Robot Imports and Firm-Level Outcomes 46.
Brynjolfsson, E., Hui, X., Liu, M., 2019. Does Machine Translation Affect International Trade? Evidence from a Large Digital Platform. Management Science 65, 5449–5460. https://doi.org/10.1287/mnsc.2019.3388
Bustos, P., 2011. Trade Liberalization, Exports, and Technology Upgrading: Evidence on the Impact of MERCOSUR on Argentinian Firms. The American Economic Review 101, 304–340. https://doi.org/10.1257/aer.101.1.304
Caliendo, L., Parro, F., 2015. Estimates of the Trade and Welfare Effects of NAFTA. The Review of Economic Studies 82, 1–44. https://doi.org/10.1093/restud/rdu035
Cheng, H., Jia, R., Li, D., Li, H., 2019. The Rise of Robots in China. Journal of Economic Perspectives 33, 71–88.
Das, M., 2018. Automation and job displacement in emerging markets: New evidence. VoxEU.org. URL https://voxeu.org/article/automation-and-job-displacement-emerging-markets (accessed 3.23.21).
Das, M., Hilgenstock, B., 2018. The Exposure to Routinization: Labor Market Implications for Developed and Developing Economies. IMF Working Papers 18, 1. https://doi.org/10.5089/9781484361900.001
Dauth, W., Findeisen, S., Suedekum, J., Woessner, N., 2021. The Adjustment of Labor Markets to Robots. Journal of the European Economic Association. https://doi.org/10.1093/jeea/jvab012
Demir, B., Fieler, A.C., Xu, D., Yang, K.K., 2021. O-Ring Production Networks (No. w28433). National Bureau of Economic Research, Cambridge, MA. https://doi.org/10.3386/w28433
Dix-Carneiro, R., Goldberg, P., Ulyssea, G., 2019. Trade and Informality in the Presence of Labor Market Frictions and Regulations 121.
Dix-Carneiro, R., Kovak, B.K., 2019. Margins of labor market adjustment to trade. Journal of International Economics 117, 125–142. https://doi.org/10.1016/j.jinteco.2019.01.005
Eaton, J., Kortum, S., 2002. Technology, Geography, and Trade. Econometrica 70, 1741–1779. https://doi.org/10.1111/1468-0262.00352
Faber, M., 2020. Robots and reshoring: Evidence from Mexican labor markets. Journal of International Economics 127, 103384. https://doi.org/10.1016/j.jinteco.2020.103384
Freund, C., Weinhold, D., 2002. The Internet and International Trade in Services. American Economic Review 92, 236–240. https://doi.org/10.1257/000282802320189320

Freund, C.L., Weinhold, D., 2004. The effect of the Internet on international trade. Journal of International Economics 62, 171–189. https://doi.org/10.1016/S0022-1996(03)00059-X
Goger, A., Hull, A., Barrientos, S., Gereffi, G., Godfrey, S., 2014. Capturing the Gains in Africa: Making the most of global value chain participation. OECD.
Graetz, G., Michaels, G., 2018. Robots at Work. The Review of Economics and Statistics 100, 753–768. https://doi.org/10.1162/rest_a_00754
Grossman, G., Rossi-Hansberg, E., 2008. Trading Tasks: A Simple Theory of Offshoring. American Economic Review, 98.
Hallward-Driemeier, M., Nayyar, G., 2019. Have Robots Grounded The Flying Geese? : Evidence From Greenfield FDI In Manufacturing. World Bank, Washington, DC. https://doi.org/10.1596/1813-9450-9097
Grossman and Rossi-Hansberg (2008). Trading tasks: A simple theory of offshoring, American Economic Review, 98(5), 1978-1997.
Humlum, A., 2019. Robot Adoption and Labor Market Dynamics 79.
Hsieh, Chang-Tai and Pete Klenow (2014). The life cycle of plants in India and Mexico, Quarterly Journal of Economics, 129: 1035-1084.
Hummels, D., Jørgensen, R., Munch, J., Xiang, C., 2014. The wage effects of offshoring: Evidence from Danish matched worker-firm data. The American Economic Review 104, 1597–1629.
IFR, 2020. World Robotics Report 2020.
Jorgenson, D.W., 2017. World KLEMS: Productivity and Economic Growth in the World Economy: An Introduction. International Productivity Monitor 33, 1–7.
Koch, M., Manuylov, I., Smolka, M., 2019. Robots and Firms (SSRN Scholarly Paper No. ID 3377705). Social Science Research Network, Rochester, NY.
Kremer, M., 1993. The O-Ring Theory of Economic Development. Q J Econ 108, 551–575. https://doi.org/10.2307/2118400
Kugler, A., Kugler, M., Ripani, L., Rodrigo, R., 2020. U.S. Robots and their Impacts in the Tropics: Evidence from Colombian Labor Markets (No. w28034). National Bureau of Economic Research, Cambridge, MA. https://doi.org/10.3386/w28034
Lee, E., Yi, K. 2018. Global value chains and inequality with endogenous labor supply. Journal of International Economics, 115.
Martin, J., Mejean, I., Parenti, M., 2020. Relationship stickiness and economic uncertainty 37.
Melitz, M.J., 2003. The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity. Econometrica 71, 1695–1725.
Nakamura, H., Zeira, J., 2018. Automation and unemployment: Help is on the way. VoxEU.org. URL https://voxeu.org/article/automation-and-unemployment-help-way (accessed 3.23.21).
OECD, 2018. Job Creation and Local Economic Development 2018: Preparing for the Future of Work (Text).
Rodrik, D., 2016. Premature deindustrialization. Journal of Economic Growth 21, 1–33.
Rodrik, D., 2018. New Technologies, Global Value Chains, and Developing Economies (No. w25164). National Bureau of Economic Research, Cambridge, MA. https://doi.org/10.3386/w25164
Stapleton, K., Webb, M., 2020. Automation, Trade and Multinational Activity: Micro Evidence from Spain. SSRN Journal. https://doi.org/10.2139/ssrn.3681143
Schott, P.K., 2004. Across-Product Versus Within-Product Specialization in International Trade. Q J Econ 119, 647–678. https://doi.org/10.1162/0033553041382201

World Bank (Ed.), 2020. World development report 2020: trading for development in the age of global value chains. World Bank Group, Washington.
Verhoogen, Eric (2008). Trade, quality upgrading and wage inequality in the Mexican manufacturing sector, Quarterly Journal of Economics, 123 (2): 489-530
Yang, Z., 2017. Who Will Satisfy China's Thirst for Industrial Robots?
Yi, K.-M., 2003. Can Vertical Specialization Explain the Growth of World Trade? Journal of Political Economy 111, 52–102.