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Abstract

This paper investigates the effect of robotization in high-income countries on firm-level North-South trade along the value chain. Using a novel combination of data sources including firm-level export data, input-output linkages, and robot adoption, we show contrasting implications for Southern firms. Increased exposure to robot adoption in the destination country of exports reduces firm-level exports in case of robot adoption in the same industry. However, the opposite holds when accounting for input-output linkages and trade along the value chain. We outline a North-South trade model with endogenous robot adoption that accounts for the different channels shown in the data. Our findings highlight the importance of taking into account supply chain linkages and suggest net positive effects for Southern exporters.

JEL-Codes: D200, F140, L200, O330.

Keywords: robotization, firm-level trade, value chain linkages, sourcing.

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1 Introduction

The use of industrial robots has experienced a remarkable increase in recent decades, especially in high-income countries.[1] These trends have had disruptive effects on domestic markets, which spurred research on the economic effects of automation on firm-level productivity and labor market outcomes.[2] However, robotization does not only influence domestic markets but can spill over globally through supply chains and affect firms in developing countries through two opposing mechanisms. On the one hand, automation in high-income countries might trigger a *shift in relative production costs*, eroding the cost advantage of labor-abundant low-income countries.[3] This could decrease demand for goods from the global South and negatively affect local economic development (Rodrik, 2018). On the other hand, firms that adopt robots might become more *efficient* and expand production, leading to higher demand for intermediates goods, which would also benefit developing countries (Artuc et al., 2023).

Our paper investigates the effect of robotization in the global North on firm-level exports from Latin American countries to the North across sectors and along the value chain. In contrast to previous studies, we evaluate the impact of robotization in the North on *firm-level* North-South trade along the *value chain*. This allows us to take into account inter-country input-output linkages that channel the impact of automation from Northern countries to firms in the global South. Our results indicate a negative effect of robot adoption on Southern exports in case of robot adoption in the same industry, but the opposite effect holds when accounting for trade along the value chain. To guide our empirical analysis, we outline a two-country North-South trade model that incorporates these opposing mechanisms. In the model, we consider industry-specific automation shocks that change the trade-off between sourcing and vertical integration in the North. The model highlights that the position in the global value chain is crucial to identify the effects of robotization on North-South trade.

The main contribution of this paper is threefold. First, the highly disaggregated firm-level data allow us to evaluate exposure of southern firms to shocks in different

[1] According to the International Federation of Robotics, the stock of industrial robots rose by a factor of 5 between 1993 and 2015 in North America, Europe, and Asia (Dauth et al., 2021). The adoption of robots has predominantly occurred within a limited subset of high-income countries.

[2] A large literature discusses the relation between robot adoption and labor market outcomes, but there is no consensus regarding the impact of robotization on the composition of workers and worker displacement. Several papers suggest that technology causes a displacement effect and increases demand for high-skilled workers, leading to skill-biased technological change (Autor et al., 2003; Acemoglu and Autor, 2011; Akerman et al., 2015; Acemoglu and Restrepo, 2020). However, recent evidence also suggests no change in the composition of the workforce in response to adoption of automation technologies (Hirvonen et al., 2022).

[3] Automation might reduce production costs in high-income countries, such that low-income, labor abundant countries may lose their relative cost advantage in producing formerly labor-intensive goods.

industries across destination countries and along the value chain. For this purpose, we use data for the universe of exports by firm, product and destination of four Latin American countries from the World Bank Exporter Dynamics Database and Brazil's foreign trade secretariat. Hence, our paper takes on the perspective of Southern firms to evaluate the effect of automation on North-South trade. Second, we combine country and sector-level data on robot adoption from the International Federation of Robots (IFR) with commodity-level input-output tables from the Bureau of Economic Analysis (BEA) to create a novel data set, where automation shocks in the destination country are mapped to the exported products using *same industry linkages* (direct linkages) as well as *value-chain linkages* (indirect linkages). Using allocation coefficients, we show that it is crucial to account for value-chain linkages when evaluating the effect of automation on Southern firms, as the sign and magnitude of the effect depend on the type of linkage. Third, we setup a North-South model of trade that incorporates endogenous robot investments and gives rise to the two opposing channels shown in the empirical analysis.

In the theoretical framework, heterogeneous firms located in the North require two types of intermediate goods for the production of a differentiated final good. We distinguish these two inputs according to the available sourcing options. The first input is demanded from the same industry in which the firm is active, and can be either sourced from the South or produced under vertical integration in the North. In contrast, the second input has to be sourced from another industry in the South. This implies that final-good firms have no expertise to produce this type in the North, which reflects goods in which developing countries have a comparative advantage.[4] Intermediate inputs are produced under perfect competition with labor as the only factor of production. While there is a marginal cost advantage in the South due to lower wages, sourcing within-industry inputs is associated with higher fixed costs compared to vertical integration. This trade-off implies that only the most productive firms will source within-industry inputs from the South.

We use this model to derive two testable predictions on how automation affects North-South trade flows. For this purpose, we introduce an endogenous automation choice of final-good firms in the North. Under vertical integration, a positive automation shock reduces costs of automation, which results in lower marginal production costs. As a consequence, the competitive advantage in the South is reduced and the share of firms that source from this region is reduced. The change in relative costs due to automation thus reduces trade flows in the same industry from South to North. In contrast, final-good firms that automate production in the North become more efficient

[4]We show that the model's main implications also hold when allowing for a range of between-industry inputs that are only partially sourced from the South.

and demand more intermediate goods from other industries. Additionally, the lower automation costs enable lower productivity firms to be active under vertical integration in the North. Both effects cause an increase in trade flows between industries (along the value chain) from South to North. Hence, the theoretical analysis shows that the effect of automation on trade flows from Southern countries depends on the question whether the automation shock occurs in the same industry or in another industry. Accounting for industry-specific shocks and the position in the global value chain is thus crucial to identify the effects of robotization.

Literature Robotization is often discussed as the third big economic transformation in modern times (Baldwin and Forslid, 2020)[5], which emphasizes the importance of understanding its effects on firms and workers. Our paper is related to a strand of this literature that investigates the impact of robots on firms, though most of the papers focus on the effects on domestic markets. The literature shows sizable productivity gains from robot adoption for domestic firms (Koch et al., 2021), how automation augments labor productivity (Graetz and Michaels, 2018), increases value-added (Acemoglu et al., 2020) and boosts competitiveness (Bonfiglioli et al., 2020). While the literature agrees on the overall gains of robotization for adopting firms, the impact on domestic workers remains disputed. In a recent literature survey, Aghion et al. (2022) show two contrary views on the impact of robots on labor demand. The optimistic perspective suggests that through increased productivity firms expand market shares, potentially benefiting employment and wages. The pessimistic view emphasizes that the growth in labor demand applies mainly to complementary tasks but potentially leads to displacement of labor-intensive tasks by robots.[6]

While this literature focuses on outcomes for domestic firms and workers, the important role of global value chains implies that automation has also an impact on the (international) sourcing decision of firms and can thereby affect the economies of trading partners abroad. Echoing the views on the domestic employment effects of automation, two different channels for the effect of automation on international trade are conceivable. First, automation might put low-skilled and replaceable jobs at risk not only at home, but also abroad due to a change in relative production costs. This

[5]The first transformation being the industrial revolution in the 18th century and the second being the service transformation during the middle of last century.

[6]Using data for US local labor markets, Acemoglu and Restrepo (2019) provide evidence that the negative effect on employment and wages dominates. Based on Spanish firm-level data, however, Koch et al. (2021) find evidence for positive employment effects in robot-adopting firms and negative employment effects for firms which do not adopt robots. For the German labor market, Dauth et al. (2021) show a nuanced picture, as robot adoption leads to job reallocation between sectors, from manufacturing to services. Graetz and Michaels (2018) suggest that robotization has no significant effect on total employment but reduces low-skilled workers' employment share.

could especially affect trade flows between the global North and South. If robots can take over tasks at lower costs which were originally performed by low-skilled workers in the South, the current pattern of relative cost advantages might change and production sites might increasingly be relocated to the North (i.e. production reshoring). On the other hand, productivity gains for robot-adopting firms in the North might also translate into increasing demand for intermediate goods coming from the South, with positive implications for trade and growth.

The empirical findings regarding the impact of automation in the global North on trading partners in the global South are to some extent inconclusive. There is limited evidence for automation-induced reshoring from South to North. Krenz et al. (2021) show, based on a cross-country framework, a strong association between automation and reshoring at the macro level. Using Spanish firm-level data, Stapleton and Webb (2020) find that robot adoption had no impact on the offshoring activity of firms in case they were already offshoring to low-income countries, but robot adoption increased offshoring activities of firms that had not yet offshored to such countries. In total, they cannot detect a clear effect on the value of imports from developing countries. Taking the perspective of a country from the global South, Faber (2020) finds evidence that robot adoption in the US had a negative effect on local employment and exports in Mexico. Similar findings are reported by Stemmler (2023) for Brazil and Kugler et al. (2020) for Colombia. On the other hand, Artuc et al. (2022) provide support for a productivity channel of automation and argue that in the long run, developing countries will profit from robot adoption in the Global North through an increase in global demand for intermediate and final goods.

These results show that the impact of automation in the global North on the economies in the South is still largely debated. So far, the literature has mostly investigated the impact of automation shocks for the products in the same industry or for final versus intermediate goods. However, the majority of products are used in multiple industries. For this reason, we contribute to this literature by carefully taking into account supply chain linkages at the product level when estimating the effect of robot adoption in the global North on Southern countries. Moreover, we will do so by exploiting firm-level data, which allow us to account for heterogeneous effects across sectors and countries within a firm.

In analyzing the decision between outsourcing and vertical integration in a North-South model of trade, our paper builds on Antràs and Helpman (2004, 2006). Our approach, however, differs as we abstract from headquarter services and contractual frictions in the relationship between final-good firms and input suppliers. We rather focus on the implications of automation on trade flows when the available sourcing options differ across inputs and when accounting for endogenous robot investments.

Our analysis also relates to the task-based approach of modelling automation (Acemoglu and Restrepo, 2018a,b; Koch et al., 2021), where robot adoption substitutes for tasks previously performed by labor. Artuc et al. (2023) analyze this channel in a multi-sector and multi-country Ricardian model of trade. As the labor-replacing effect of automation is counteracted by an increase in productivity of Northern producers, the impact on trade flows from the South is theoretically ambiguous. While abstracting from substitution between labor and robots, we provide additional implications how robotization affects trade flows across different types of inputs. An industry-specific automation shock in our framework increases the incentives for firms to vertically integrate production of intermediates within this industry. In contrast, between-industry inputs benefit from a productivity-enhancing effect of automation leading to larger trade flows from the South.

Hence, our model is related to studies that analyze the effects of reshoring due to automation on labor market outcomes (Krenz et al., 2021). Allowing firms to choose the level of automation is common with Bonfiglioli et al. (2020), and the productivity-enhancing effect of this choice relates to models with offshoring (Grossman and Rossi-Hansberg, 2008), technology adoption (Bustos, 2011) and quality differentiation (Kugler and Verhoogen, 2012; Flach and Unger, 2022).

The reminder of this paper is structured as follows: Section 2 presents the theoretical framework. The sources used to build the firm-level data accounting for linkages along the value chain and summary statistics are described in Section 3. In the subsequent Section 4 we describe the empirical strategy of the paper. Section 5 presents the empirical results of our analysis. Section 6 concludes.

2 North-South model of trade and automation

In this section, we develop a North-South model of international trade. Heterogeneous final-good firms are located in the North and decide whether to source inputs from the South or to vertically integrate production in the North. After describing preferences and the technology of firms, we introduce an automation choice and analyze the implications for the sourcing decision. We use the framework to derive testable predictions regarding the effects of automation on trade flows from South to North.

2.1 Preferences

The demand side is based on Antràs and Helpman (2004). The world is populated by a unit measure of consumers with identical preferences given by:

$$U = x_0 + \frac{1}{\mu}\sum_{j=1}^{J} X_j^{\mu}, 0 < \mu < 1,$$

where x_0 is the consumption of a homogeneous good, and μ captures the substitutability of consumption goods between different sectors j and with respect to the outside good. Aggregate consumption in sector j follows from a constant elasticity of substitution (CES) function:

$$X_j = \left[\int_i x_j\left(i\right)^{\alpha} di\right]^{\frac{1}{\alpha}}, \quad 0 < \alpha < 1.$$

From the consumer's maximization problem it follows that the inverse demand function for each variety i in sector j is given by:

$$p_j\left(i\right) = X_j^{\mu-\alpha} x_j\left(i\right)^{\alpha-1}, \tag{1}$$

where $p_j\left(i\right)$ denotes the price and $x_j\left(i\right)$ the quantity of a single variety i in sector j. We follow Antràs and Helpman (2004) and assume that $\alpha > \mu$, so that varieties within a sector are more substitutable for each other than they are for the outside good or for varieties from a different sector.

2.2 Technology

Final-good firms located in the North differ in productivity θ and require two-variety specific inputs according to the following Cobb-Douglas production function:

$$x_j\left(i\right) = \theta\left(\frac{m_j\left(i\right)}{\eta_j}\right)^{\eta_j}\left(\frac{m_k\left(i\right)}{1-\eta_j}\right)^{1-\eta_j}, \quad 0 < \eta_j < 1. \tag{2}$$

The intermediate input $m_j\left(i\right)$ comes from the same industry as the final-good firm. In contrast, a second input is required that has to be sourced from another industry k. The parameter η_j captures the intensity of production in inputs used from the same industry. Intermediate inputs are produced under perfect competition with labor as the only factor of production, so that one unit of labor is needed to produce one unit of input. We further assume that labor supply is perfectly elastic in each country but immobile across countries. The wage rate in the North is larger than in the South

$\left(w^N > w^S\right)$. For the sake of simplicity, we abstract from hold-up problems in the context of incomplete contracts between final-good firms and intermediate goods suppliers (Antràs and Helpman, 2004, 2006). As our focus is on the impact of automation choices along the global value chain, we do not consider headquarter services as input in the production process but rather focus on intermediate goods coming from different industries.

In particular, we distinguish the two variety-specific inputs according to the available sourcing options. The final-good firm can either produce the within-industry input, $m_j(i)$, under vertical integration in the North with wage rate w^N, or source it from the South at cost τw^S, where $\tau > 0$ captures trading costs between South and North. We assume that the marginal cost when sourcing from the South are lower compared to production under vertical integration $\left(\tau w^S < w^N\right)$. Accordingly, we define the relative marginal cost advantage of sourcing as $\hat{w} \equiv w^N / \left(\tau w^S\right) > 1$. Each decision is associated with additional fixed costs, which are larger in case of sourcing from the South compared to vertical integration in the North $\left(f_O^S > f_V^N\right)$. This difference captures additional costs of searching and organizing trade relationships for the supply of inputs from the South. We assume that final-good producers have no expertise to produce intermediate inputs from other industries, $m_k(i)$, under vertical production in the North. Hence, these inputs will be always sourced from the South. We show in Section 2.5 that our main results hold when relaxing this assumption and allowing that between-industry inputs can also be partly produced under vertical integration.

2.3 Automation choice and sourcing decision

We now allow firms in the North to invest in automation within their industry. Automation reduces marginal production costs of within-industry inputs under vertical integration, and thus influences the sourcing decision. Hence, final-good producers decide whether vertical integration with automation in the North is profitable compared to sourcing of within-industry inputs $m_j(i)$ from the South.

In particular, firms choose the optimal level of automation $a_j(i)$, which reduces marginal production costs in case of vertical integration in the North given by $w^N/a_j(i)$. Automation is associated with endogenous innovation costs: $\kappa_j/\xi_j a_j(i)^{\xi_j}$, where $\kappa_j > 0$ is a cost parameter, and $\xi_j > 0$ determines the convexity of the investment cost function.[7] In choosing the optimal level of automation, firms minimize the following cost function:

$$\min_a C_j(i) = \frac{w^N}{a_j(i)} m_j(i) + \frac{\kappa_j}{\xi_j} a_j(i)^{\xi_j} m_j(i) \tag{3}$$

[7]The specification of endogenous fixed costs is related to modeling approaches in the quality and trade literature (Kugler and Verhoogen, 2012; Flach and Unger, 2022).

From the cost minimization problem in Equation (3) it follows that the optimal automation choice is given by:

$$a_j = \left(\frac{w^N}{\kappa_j}\right)^{\frac{1}{1+\xi_j}}. \tag{4}$$

The optimal level of automation in Equation (4) increases in the Northern wage rate w^N due to higher cost saving incentives, and decreases in the innovation cost parameter κ_j. With the possibility to automate production in the North, the decision whether to vertically integrate or to outsource depends not only on the relative wage costs $\hat{w}$ but also on automation costs. Hence, we summarize the marginal cost advantage of sourcing from the South compared to vertical integration with automation in the North in one statistic, $\psi_j \equiv \frac{\xi_j+1}{\xi_j}\frac{\hat{w}}{a_j}$. We impose the following restrictions on the optimal automation level:

Condition 1 $\frac{\xi_j+1}{\xi_j} < a_j < \frac{\xi_j+1}{\xi_j}\hat{w}$.

The first part of the inequality in Condition 1 will ensure a sufficiently large automation level that reduces marginal production cost under vertical integration compared to a situation without automation. It bounds the investment cost parameter κ_j from above. If this inequality is violated, firms would have no incentive to automate production as the additional innovation costs outweigh the efficiency gain in production. Instead, the second inequality in Condition 1 is satisfied whenever the investment cost parameter κ_j is sufficiently large and is obtained by imposing that $\psi_j > 1$. This ensures that there is still a marginal cost advantage of sourcing from the South compared to vertical integration with automation. Otherwise, no firm will have an incentive to pay the higher fixed costs of sourcing and vertical integration with automation is always the preferred choice.

As we have expressed both benefits and costs of automation per unit of intermediate input in Equation (3), the optimal automation choice is independent of firm productivity and thus we have dropped the firm index i in Equation (4). In Section 2.5, we show that the main implications of our framework hold with an alternative specification where the level of automation is positively related to firm productivity following recent evidence (Bonfiglioli et al., 2020; Koch et al., 2021). The productivity-enhancing effect of automation is common with models in which robotization additionally serves as a substitute for tasks previously performed by labor (Acemoglu and Restrepo, 2018a,b; Artuc et al., 2023; Koch et al., 2021). While we abstract from this substitution effect, our approach with two distinct intermediate inputs allows us to focus on the differential implications of automation on North-South trade.

Under vertical integration with automation in the North, profits of a final-good producer can be written as follows:

$$\pi_j(i)_V^N = r_j(i) - C_j(i) - \tau w^S m_k(i) - f_V^N, \tag{5}$$

where revenues are given by $r_j(i) = p_j(i)\, x_j(i)$. We abstract from additional fixed cost for sourcing between-industry inputs. As these intermediates are always demanded from the South, introducing fixed cost would not change the sourcing decision of firms with respect to within-industry inputs.[8]

By taking into account the demand in Equation (1) and the production technology in Equation (2), as well as the optimal automation level (4), profit maximization implies that the relative input choice is given by:

$$\frac{m_j(i)}{\eta_j} = \frac{1}{\psi_j}\frac{m_k(i)}{1-\eta_j}. \tag{6}$$

Lower automation costs captured by a decrease in κ_j reduce the relative marginal cost advantage of sourcing ψ_j. This increases the incentive to use inputs from the same industry, $m_j(i)$, produced under vertical integration in the North compared to sourcing of inputs, $m_k(i)$, from the South. To analyze the impact of automation on firm performance, and ultimately the sourcing decision, we define the effective marginal production costs under vertical integration and automation in the North as follows:

$$c_{j,V}^N \equiv \left(\frac{\xi_j+1}{\xi_j}\frac{w^N}{a_j}\right)^{\eta_j}\left(\tau w^S\right)^{1-\eta_j}. \tag{7}$$

By taking into account the relative use of inputs in Equation (6), the optimal output choice of firms implies that revenues are a function of effective marginal production costs: $r_j(i)_V^N = X_j^{\frac{\mu-\alpha}{1-\alpha}}\left(\frac{\alpha\theta}{c_{j,V}^N}\right)^{\frac{\alpha}{1-\alpha}}$. Accordingly, profits in Equation (5) are given by $\pi_j(i)_V^N = (1-\alpha)\, r_j(i)_V^N - f_V^N$.

As an alternative to vertical integration with automation, final-good firms can decide to purchase within-industry inputs from the South (besides the sourcing of intermediates from other industries). In this case, profits are given by:

$$\pi_j(i)_O^S = r_j(i) - \tau w^S\left[m_j(i) + m_k(i)\right] - f_O^S. \tag{8}$$

In comparison to Equation (5), sourcing within-industry inputs is associated with higher fixed costs $\left(f_O^S > f_V^N\right)$, while trade costs $\tau > 0$ have to be paid for both types of intermediate goods. Hence, the marginal cost of sourcing both inputs from the

[8] We relax this assumption in Section 2.5 by allowing for a range of between-industry inputs that are only partially sourced from the South.

South can be defined as $c_{j,O}^{S} \equiv \tau w^{S}$. Profit maximization implies that the relative input choice is given by $m_j(i)/m_k(i) = \eta_j/(1-\eta_j)$. Thus, the profits with sourcing of both inputs are given by $\pi_j(i)_O^S = (1-\alpha) r_j(i)_O^S - f_O^S$, where revenues are $r_j(i)_O^S = X_j^{\frac{\mu-\alpha}{1-\alpha}} \left(\frac{\alpha\theta}{c_{j,O}^{S}}\right)^{\frac{\alpha}{1-\alpha}}$. The underlying trade-off implies that the most productive firms will find it more profitable to source inputs from the South as incurring additional fixed cost pays off to a larger extent in terms of marginal cost savings. Hence, the comparison of profits, $\pi_j\left(\theta_O^S\right)_O^S = \pi_j\left(\theta_O^S\right)_V^N$, leads to a cutoff productivity for sourcing inputs from the South:

$$\theta_O^S = \frac{c_{j,O}^{S}}{\alpha X_j^{\frac{\mu-\alpha}{\alpha}}} \left(\frac{f_O^S - f_V^N}{1-\alpha} \frac{1}{1-(1/\psi_j)^{\frac{\alpha\eta_j}{1-\alpha}}}\right)^{\frac{1-\alpha}{\alpha}}. \tag{9}$$

Higher relative marginal cost in the North (captured by an increase in ψ_j), ceteris paribus, raise the incentive to source inputs from the South for lower productivity firms. This effect shows up in Equation (6) by a decrease in the cutoff productivity. In contrast, higher relative fixed costs of sourcing $\left(f_O^S - f_V^N\right)$ reduce the profitability of sourcing compared to vertical integration and thus increase the cutoff productivity. Note that the assumption $\psi_j > 1$ in Condition 1 ensures a well-defined selection pattern with $\theta_O^S > 0$.

To fully characterize the sorting pattern of firms, we additionally consider the decision to integrate in the North or to exit the market, which follows from the condition $\pi_j\left(\theta_V^N\right)_V^N = 0$, yielding the following cutoff productivity:

$$\theta_V^N = \frac{c_{j,V}^{N}}{\alpha X_j^{\frac{\mu-\alpha}{\alpha}}} \left(\frac{f_V^N}{1-\alpha}\right)^{\frac{1-\alpha}{\alpha}}. \tag{10}$$

Comparing Equations (6) and (10) leads to the following condition.

Condition 2 $\theta_O^S > \theta_V^N \qquad if \qquad \frac{f_O^S}{f_V^N} > \psi_j^{\frac{\alpha\eta_j}{1-\alpha}}.$

Note that Condition 1 regarding the innovation cost function implies that the right-hand side of the inequality in Condition 2 is larger than one. Hence, it states that the relative fixed costs of sourcing in the South have to be higher than the relative marginal cost savings accounting for the optimal automation choice.

Lemma 1 *If Condition 2 is satisfied, then the most productive final-good producers with $\theta \geq \theta_O^S$ source both inputs from the South. Firms with $\theta_V^N \leq \theta < \theta_O^S$ vertically integrate production of within-industry inputs in the North, while the least productive firms with $\theta < \theta_V^N$ exit.*

The sorting pattern of firms into outsourcing and vertical integration is depicted in the left part of Figure 1.

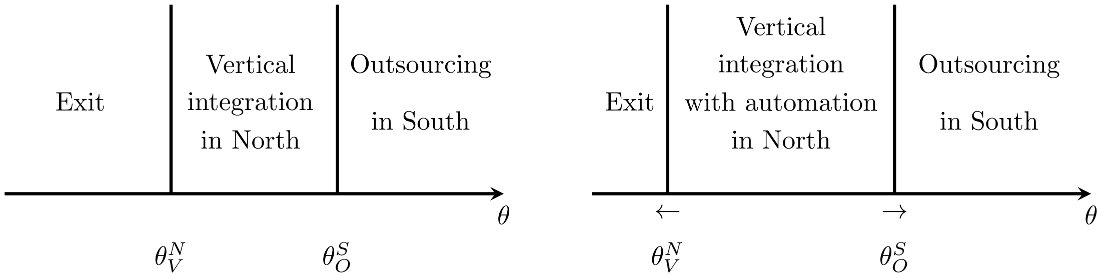


Figure 1: Sorting pattern of firms before (left) and after automation shock (right)

2.4 The impact of automation on trade flows

Within our framework we analyze the implications of an industry-specific automation shock reflected by a reduction in the innovation cost parameter κ_j. This shock increases the level of automation in Equation (4) and thus reduces effective marginal production costs under vertical integration in the North as shown by Equation (7). The lower incentive to purchase inputs from the same industry from the South leads to an increase of the cutoff productivity for sourcing in Equation (6). Additionally, the cutoff level in Equation (10) decreases as the lower marginal innovation cost of automation enables lower productivity firms to enter the market under vertical integration. These adjustments are depicted in the right part of Figure 1, and clearly lead to a decreasing share of active firms that outsource, which is given by:

$$\chi_O^S = \frac{1 - G\left(\theta_O^S\right)}{1 - G\left(\theta_V^N\right)}, \tag{11}$$

where $G(\theta)$ is the cumulative distribution function of productivity draws. As only firms with productivity $\theta \geq \theta_O^S$ source inputs from the same industry, total trade flows of within-industry inputs from South to North can be written as follows:

$$T_j^{N,S} = M_e \int_{\theta_O^S}^{\infty} \tau w^S m_j(\theta)\, dG(\theta), \tag{12}$$

where M_e denotes the mass of entrants, and firm-level trade flows are given by $\tau w^S m_j(\theta)$.

Proposition 1 *A positive automation shock in industry j (induced by a reduction in the cost parameter κ_j) reduces trade flows in the same industry $T_j^{N,S}$ from South to North.*

Proof. See Appendix A. ■

This result is driven by the fact that automation narrows the cost advantage of sourced inputs compared to production under vertical integration, and thus reduces the share of firms that purchase intermediate goods from the same industry from the South in Equation (11). As a consequence, the rise in the cutoff productivity θ_O^S clearly decreases trade flows from South to North. While this effect holds for a general distribution, we provide an explicit solution for Proposition 1 by assuming that productivity is Pareto distributed in Appendix A.

To account for linkages along global value chains, we further consider the implications of the automation shock for trade flows from South to North between industries (i.e. indirect linkages along the value chain). For firms with productivity $\theta_V^N \leq \theta < \theta_O^S$ that already automate before the shock, there is a positive intensive margin effect on between-industry inputs through a reduction in marginal cost $c_{j,V}^N$. These final-good producers become more efficient and thus demand more inputs from other industries. As described above, the share of firms that produce under vertical production increases. This selection effect is the second force behind the positive demand shock on between-industry inputs. Aggregate between-industry trade flows from South to North induced by firms that vertically integrate production are given by:

$$T_{k,V}^{N,S} = M_e \int_{\theta_V^N}^{\theta_O^S} \tau w^S m_k(\theta)\, dG(\theta). \tag{13}$$

Both the intensive margin effect and the increasing share of active firms under vertical integration contribute to the positive effect of automation on trade flows in Equation (13). As firms with $\theta \geq \theta_O^S$ demand between-industry inputs from the South as well, total trade flows along the value chain from South to North are defined as $T_k^{N,S} \equiv T_{k,V}^{N,S} + T_{k,O}^{N,S}$, where trade induced by fully outsourcing firms is given by:

$$T_{k,O}^{N,S} = M_e \int_{\theta_O^S}^{\infty} \tau w^S m_k(\theta)\, dG(\theta). \tag{14}$$

The lower share of outsourcing firms captured by an increase in the cutoff level θ_O^S clearly decreases trade flows in Equation (14) and thus counteracts the positive effect in Equation (13).

Proposition 2 *A positive automation shock in industry j (a reduction in the cost parameter κ_j) increases total trade flows between industries along the value chain $T_k^{N,S}$ from South to North.*

Proof. See Appendix A. ■

Proposition 2 shows that the positive effects of automation driven by firms that vertically integrate inputs dominate the counteracting selection effect induced by a lower fraction of outsourcing firms. In contrast to Proposition 1, intermediate inputs from other industries than where the automation shock occurs benefit from the higher efficiency of final-good producers and thus face an increase in demand. Hence, the theoretical analysis shows that automation shocks in the North will affect trade flows from Southern countries differently across industries. Before taking these opposing predictions to the data, we discuss the robustness of results with respect to extensions of our theoretical framework.

2.5 Discussion and extensions

Our analysis is related to Artuc et al. (2023) who investigate the implications of automation in a multi-sector and multi-country Ricardian model of trade. While following a task-based approach which explains the substitution of labor by automated tasks, they conclude that the effect of robotization in the North on trade flows from the South is theoretically ambiguous. We contribute to this question by showing that reductions in sector-specific automation costs incentivize final-good producers in the North to vertically integrate the production of intermediate goods that were previously sourced from the South. This channel reduces trade in within-industry inputs from South to North. In contrast, the productivity-enhancing effect of automation increases demand for inputs sourced from different industries in the South. Hence, our model highlights the important role of supply chain linkages to differentiate between positive and negative effects of automation on North-South trade.

In the following, we relax assumptions of our theoretical framework with respect to sourcing of between-industry inputs and the automation choice. We discuss the main implications of these extensions, while relegating technical details to Appendix B.

Vertical integration of between-industry inputs: In our baseline model, we have assumed that between-industry inputs are always sourced from the South. We extend our framework by allowing for a continuum of between-industry inputs m_k used for production in Equation (2). For technological reasons, we now assume that final-good producers have the expertise to produce a fraction $\bar{v}$ of these inputs under vertical integration, while the share $(1 - \bar{v})$ will be sourced from the South.[9] Marginal production costs increase with $\bar{v}$, as the higher wage costs in the North have to be paid to a larger fraction of inputs. We further assume that automation decisions also apply

[9]This assumption is related to the task-based approach of automation, where a share of tasks is assumed to be offshoreable.

to the share of vertically integrated between-industry inputs. Hence, for this fraction of intermediates, firms face the same cost minimization problem as for within-industry inputs in Equation (3). A positive automation shock now also affects the fraction of vertically integrated between-industry inputs, which implies a stronger decline of relative marginal costs c_V^N/c_O^S compared to the baseline model.

This additional channel does not change the main implication in Proposition 1 that higher automation in the North reduces within-industry trade flows from the South. While this effect is still driven by the decreasing share of outsourcing firms, it becomes quantitatively stronger with increasing $\bar{v}$, as a higher fraction of vertically integrated between-industry inputs reinforces the cost-reducing effect of automation. The larger efficiency gain leads to a stronger increase in demand for between-industry inputs from the South. Hence, compared to Proposition 2, there is an additional intensive margin effect that reinforces the positive impact of automation. This channel, however, is counteracted by a decline of the share of outsourcing firms. In Appendix B.1, we show that the intensive margin effect dominates over the whole range of $\bar{v} \in [0, 1]$. Hence, the result in Proposition 2 holds in the extended framework with a continuum of inputs as well.

Alternative automation choice: Firms choose the optimal degree of automation per unit of intermediate inputs as shown in Equation (3). This modelling approach implies that the automation choice in Equation (4) is the same for all firms independent of their productivity. While this assumption considerably simplifies the analysis, it does not capture that more productive firms tend to invest more in robotization (Koch et al., 2021; Bonfiglioli et al., 2020). To account for this fact, we consider an alternative specification, where automation increases the effectiveness of within-industry inputs in the production function, while firms face endogenous fixed costs that increase in the level of automation.[10] As a consequence, the optimal automation choice is positively related to sales and thus to firm productivity. This implies that vertical integration with the possibility to automate production of within-industry inputs is not only profitable for lower productivity firms that cannot afford the higher fixed costs of outsourcing but also for the most productive firms. Compared to the selection pattern in Figure 1, there is an additional group of highly productive firms, with $\theta > \overline{\theta}_V^N$, that prefers vertical integration over outsourcing. We illustrate this selection pattern in Figure 5, and provide the technical details including the implications for trade-flows from South to North in Appendix B.2. As in the baseline model, a positive automation shock reduces the share of outsourcing firms and thus within-industry trade flows from South to North in line with Proposition 1. While selection into ver-

[10] In a related model of monopolistic competition, Bonfiglioli et al. (2020) allow for endogenous automation choice, where firms differ in automation costs.

tical integration reduces between-industry trade flows among outsourcing firms, there is a positive impact on the same type of trade flows induced by firms choosing vertical integration as highlighted in Proposition 2. This effect works through both the intensive and the extensive margin, which now captures that also more productive firms select into vertical integration.

3 Data

To test the two main predictions of the model, we combine firm-level data with input-output linkages and data on robot adoption. One challenge of our empirical analysis is to account for the proper automation shock that exporters face in their destination countries and across industries and products. Most of the literature maps robotization shocks only to goods within the same industry (see Jurkat et al. (2022) for a literature overview). Consider the example of the textile industry: the analysis of shocks within the same industry implicitly assumes that exports of textiles respond to changes in robot adoption in the textile industry, but not in other industries along the value chain. However, value-chain linkages are important to fully quantify the impact of robot adoption on textile exporters: producers are not only affected by automation in their own industry, but also in all other industries that use textile products as inputs (e.g. automobile industry, furniture). To account for these linkages, we construct a novel data set, where automation shocks are mapped to firm-level exports using direct linkages (i.e. linkages in the same industry) as well as value chain linkages (between industries) at the product level using allocation coefficients. The following section describes the data.

Firm-level data: We use detailed firm-level trade data for four Latin American countries (Mexico, Brazil, Peru and Uruguay), which accounted for 68.5 % of Latin American exports in the year 2019.[11] The data cover the universe of exports by firm, HS (Harmonized System) 6-digit products, destination country of exports and year over the period 2001-2007. Firm-level data for Mexico, Peru and Uruguay come from the World Bank Exporter Dynamics Database. The data for Brazil comes from SECEX (Brazilian Foreign Trade Secretariat) for the same period. The analysis is supplemented by data on bilateral trade flows by HS 6-digit products from BACI (Gaulier and Zignago, 2010). We follow Fernandes et al. (2016) and create a time-consistent HS classification for all products in our sample. Moreover, we exclude all products which form part of HS chapter 27 (hydrocarbons such as oil, petroleum,

[11]Numbers are based on data from the Inter-American Development Bank on goods exports of Latin American countries, which in turn are based on official data from national sources.

Table 1: Export shares *(in %)* in 2001

	Brazil	Mexico	Peru	Uruguay
A: By Destination Region				
OECD	66.75	96.22	76.64	42.17
Rest Latin America	17.13	3.77	11.95	44.50
Rest of World	16.12	1.01	11.41	13.33
B: By Sector Group				
Agriculture & Mining	18.17	10.99	20.75	14.07
High Manufacturing	25.54	60.65	0.74	0.93
Other Manufacturing	56.29	28.35	78.50	85.00
Number of observations	236,451	202,646	40,985	8,731

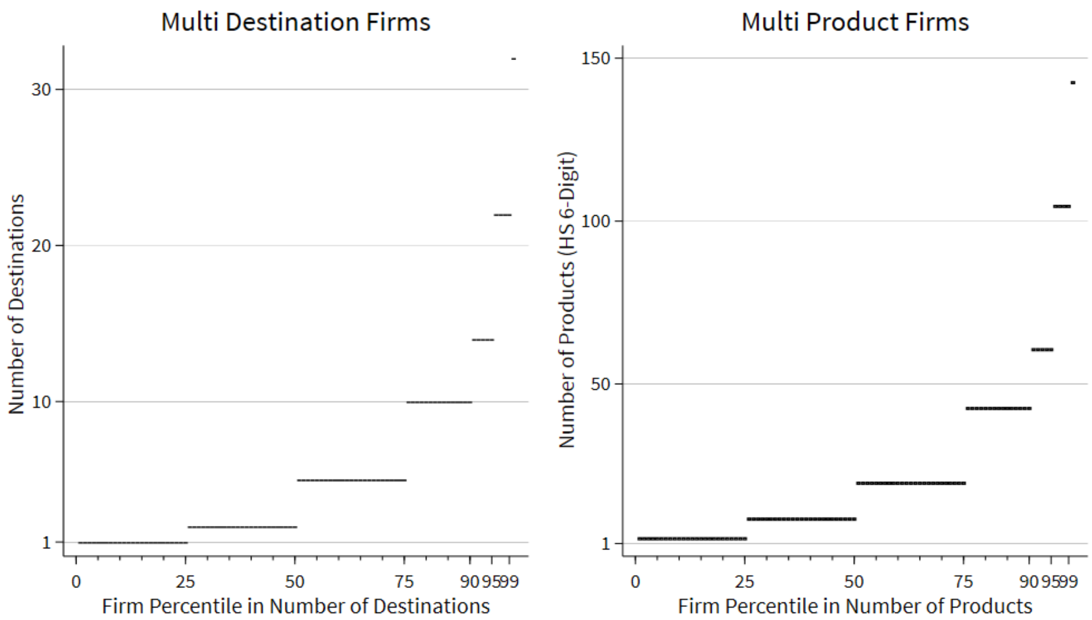
natural gas, coal etc.).

Table 1 shows how exports of the four Latin American countries are distributed by destination region and sector group in the year 2001. Panel A shows that the OECD is an important destination region, with an export share of approximately 60 %, while the respective export share to other Latin American countries is in general relatively low. This is crucial for our research question, as it implies that shocks in OECD countries have important implications for exporters in Brazil, Mexico, Peru and Mexico. Panel B shows how exports are distributed across sectors.[12] Perhaps surprisingly, in the first year of our sample firm-level exports to OECD countries are not concentrated in agriculture but rather span a large number of products. This is another advantage for our empirical analysis using this period, as several types of goods are affected by shocks in Northern countries. There is also large heterogeneity across countries: while Mexico predominantly exports high manufacturing products (automotive, electronics and other vehicles industries), exports of the remaining countries are mainly based on agriculture and basic manufacturing. As a small Latin American country, Uruguay has the lowest share of exports to OECD countries.

Figure 2 shows the distribution of firms by number of destination countries and number of HS 6-digit products exported by a firm. The median firm from the four Latin American countries exports to two destinations worldwide and to two OECD countries. Among the top 10 % exporters, there is a strong increase of number of destination

[12] *Agriculture & Mining* contain following industries: Agriculture, Forestry, Fishing, Minerals, Mining and Quarrying. *High Manufacturing* consists of the Automotive, Electronics and Other Vehicles industries. *Other* covers the remaining manufacturing industries.

Figure 2: Distribution of multi destination & multi product firms exporting to the OECD



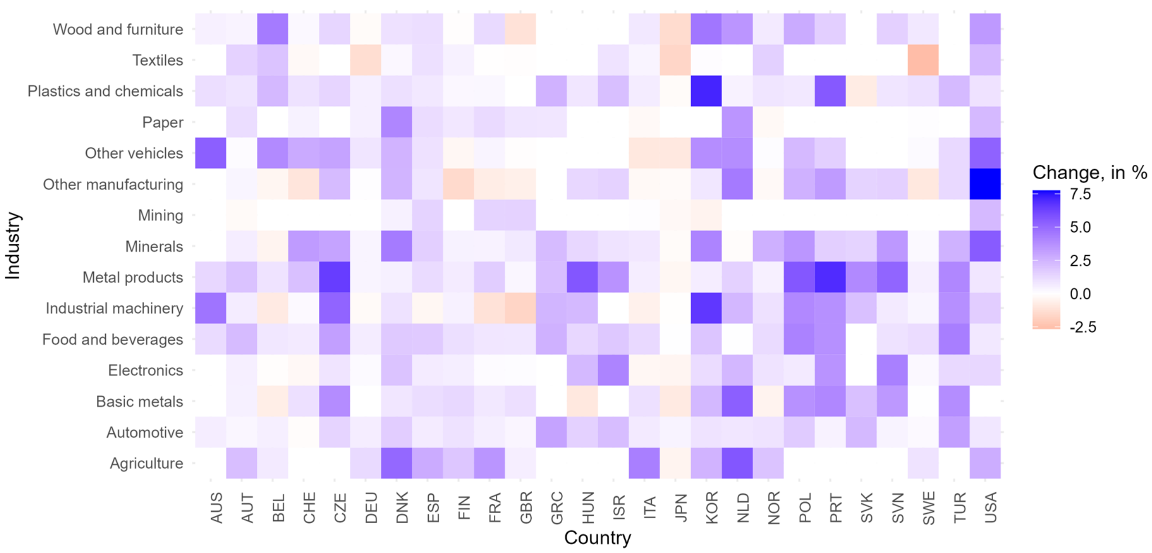
countries, which allows us to exploit not only variation between firms but also within firms across destinations. When looking at the number of products exported by a firm (right panel in Figure 2), we observe a strong increase in the top 5 %, but also other smaller firms export more than one product. This provides an additional source of variation, as products from the same firm might be used as inputs to different industries.[13]

Industrial Robots: The stock of industrial robots by industry, country and year comes from the International Federation of Robotics (IFR). This dataset is based on yearly surveys of robot suppliers, and currently covers 75 countries (about 90 percent of the industrial robots market). We use data for a 20 year time frame between 1998 and 2018. The IFR measures deliveries of multipurpose industrial robots based on the definitions of the International Organization for Standardization.

Figure 3 illustrates the change of robot stocks between 2001 and 2007 across industries and countries for OECD countries. As shown in the figure, there is large heterogeneity across countries and industries. This is important for our empirical analysis, as it

[13] As is usually the case in this type of customs data, the original database contains commercial intermediaries which exported more than a hundred HS 6-digit products. For Brazilian firms, we can directly drop commercial intermediaries using the industry classification of the firm. For the other countries in the sample, we have restricted the sample to only keep exporters of up to 150 different HS 6-digit products. We conduct robustness analyses using different threshold values.

Figure 3: Change in robot stocks in OECD countries, 2001-2007



shows that the changes in robot adoption that we exploit are not confined to specific industries or countries.

The IFR data is arguably the most reliable source for comparing robot stocks across countries (Artuc et al., 2019). However, the data has limitations that we take into account. First of all, about 30 % of industrial robots are not classified into any industry. Following Acemoglu et al. (2020), we allocate these stocks in the same proportion as observed in the classified data. Moreover, sector-specific robot stock data is available from 2004 onwards for some of the destination countries in our sample. For the previous years, sector shares are extrapolated - for each country we impute the industry stock based on the industry shares of the first year for which industry data exists.

Input-Output Tables: To account for global value chain linkages when estimating the effect of robotization in the global North on Latin American exports, we make use of the 1997 US Benchmark Input-output (I-O) tables from the Bureau of Economic Analysis (BEA). One important advantage of BEA in comparison to other input-output tables is the availability of input-output linkages for 405 commodities instead of aggregate sectors.[14] As argued by Acemoglu et al. (2009) and Alfaro et al. (2016), due to their detailed nature these I-O tables provide general information on technology-based input-flows across industries, and to this extent can be applied to other country-settings. By using I-O tables before our sample periods starts, we ensure that we measure linkages that are not endogenous to robotization in the 2000's (Acemoglu

[14] For comparison, the World Input-Output Database (WIOD) 2016 Release covers 56 sectors (Timmer et al., 2016).

et al., 2016; Bown et al., 2020). We match the I-O commodities to HS6 products by using the concordance table provided on the BEA website.

To account for input-output linkages we construct the following adjusted stock of robots

$$robots_{pdt}^{IO} = \sum_{s} \omega_{ps}\, robots_{sdt}, \tag{15}$$

which is a weighted average of robot stocks in year t in the importing country d across all industries indexed by s. The weights ω_{psd} are allocation coefficients that refer to the share of products p's total sales which are used as inputs in the production of sector s and are constructed based on the 1997 US I-O tables. More formally, the allocation coefficients are calculated as

$$\omega_{ps} = \frac{\alpha_{ps}}{\sum_s \alpha_{ps}}, \tag{16}$$

where α_{ps} is the value of product p purchased by industry s. Following Alfaro et al. (2016), we derive these allocation coefficients after applying an open-economy and net-inventories correction to the values in the BEA's 1997 use table. Hence, the adjusted stock of robots in Equation (15) is a weighted average of robot stocks related to the industries which purchase product p as inputs. Thereby, we ensure that our measure of robotization takes into account input-output linkages and not exclusively within-industry linkages.

The variable $robots_{pdt}^{IO}$ includes linkages between industries as well as linkages within the same industry. Hence, in a modified calculation of the IO-adjusted robot stock, we exclude within-industry linkages by setting the respective allocation coefficient for sales in the same industry to zero. Results using this specification are shown by the variable $(robots_{between}^{IO})_{pdt}$. We report our empirical results for the total effect $(robots_{total}^{IO})_{pdt}$ as well as only for linkages between industries along the value chain $(robots_{between}^{IO})_{pdt}$.

4 Empirical Strategy

In this section we test the two main predictions from the theoretical model. We take the perspective of southern countries and provide first empirical evidence on the impact of robot adoption in the North on firm-level exports of Latin American countries. Our preferred specification is based on the Poisson pseudo-maximum-likelihood (PPML) estimator, as it accounts for sample attrition in the data.[15] In our main specification, the robot stock is divided by the value added of the respective industry. This normalisation allows for a better comparison of the development of the robot stock across different industries: If the robot adoption rate of an industry rises faster than the value added of this industry, this indicates a higher robot intensity of the industry. The opposite is true for industries where robot use grows slower than value added.

To test Proposition 1 from the model, we first investigate the effect of robot adoption in Northern countries on firm-level exports in the same industry. Equation (17) estimates the average level effect for our sample:

$$X^o_{fpdt} = \exp\left[\zeta_{fpd} + \gamma_{odt} + \delta_{pt} + \pi_{sot} + \beta_1 asinh(robots_{sdt}) + \beta_2 \ln imp_{pdt}\right] \times \epsilon_{fpdt}, \quad (17)$$

where X^o_{fpdt} denotes exports of product p by firm f in origin country o to destination country d in year t. $robots_{sdt}$ refers to the stocks of robots in industry s in country d in year t. We use a two period model with t $\in$ {2001, 2007}. In this way, we evaluate the effect of robot adoption over the period on firm-level exports in year t. In our strictest specification for *direct linkages* (linkages within the same industry), we include four groups of fixed effects to account for different shocks. Firm-product-destination fixed effects (ζ_{fpd}) account for unobserved heterogeneity and industry-origin-time fixed effects (π_{sot}) control for industry-specific supply-side shocks in the origin country. Origin-destination-time fixed effects (γ_{odt}) account for any changes in the bilateral relationship between two countries in our sample that might affect trade flows and are common across products and firms. Lastly, we add product-time fixed effects (δ_{pt}) to account for product-specific shocks. We control for total imports of the destination country by product and time (captured by the coefficient β_2) to account for product-specific changes in demand in the destination. The standard errors ϵ_{fpdt} are clustered by sector-destination.

The main coefficient of interest in Equation (17) is β_1. Following Proposition 1 from the model, a positive automation shock in northern countries reduces the cost-advantage of southern countries, which implies lower within-industry trade flows from South to North. Hence, we expect $\beta_1 < 0$.

Some destination countries have zero robots stock for several industries in the first observation period. Following Burbidge et al. (1988) we use the inverse hyperbolic sine

[15] Santos Silva and Tenreyro (2006) highlight the potential pitfalls of log-linear estimations due to sample selection in the presence of zero trade flows and heteroskedasticity with the log transformation. They suggest the estimation of the gravity equation in their multiplicative form using PPML estimators.

transformation ($asinh$) in our main specification instead of logs. This transformation allows us to include observations with zero robots stock, while approximating logs for larger values. Another advantage of our approach is that the industry-specific shocks (Equation 17) and product-specific shocks (Equation 18) in the destination country of exports are, from the perspective of South American exporters, less subject to endogeneity concerns compared to changes in robot adoption in the home country.

As discussed in the model, the analysis of direct linkages might offer an incomplete picture of the impact that robot adoption has on North-South trade, as only the linkages within the same industry are considered. Hence, as one central contribution of our theoretical and empirical analysis, we investigate the effect of robot adoption along the value chain, whereby input-output linkages are taken into account. To test Proposition 2 from the model, we estimate the following equation:

$$X^{o}_{fpdt} = \exp\left[\zeta_{fpd} + \gamma_{odt} + \delta_{pt} + \pi_{sot} + \nu_{sdt} + \beta_1 asinh(robots^{IO}_{pdt}) + \beta_2 \ln imp_{pdt}\right] \times \epsilon_{fpdt} \tag{18}$$

The key difference between Equation (17) and Equation (18) is that we now include the product-specific adjusted stock of robots ($robots^{IO}_{pdt}$) shown in Equation (15) as main explanatory variable in this specification. As explained in Section 3, we thereby take into account supply chain linkages between the exported product p and all sectors in the destination country d which use this product as input. Alternatively, we exclude within-industry linkages and only consider linkages between industries when constructing the adjusted robot stock. We name this variable $asinh(robots^{IO}_{between})_{pdt}$. Another difference between Equation (17) and Equation (18) is that shocks in Equation (18) are product specific. Hence, we may include industry-destination-time fixed effects (ν_{sdt}) to account for industry-specific shocks in the destination country.

In Proposition 2 of the theoretical model, we show that a positive automation shock in industry j in the North increases total between-industry trade flows from South to North. In contrast to Equation (17), Equation (18) takes into account intermediate inputs from all other industries. Hence, we expect that $\beta_1 > 0$ in Equation (18), as automation in northern countries increases efficiency of final-good producers in the North, which leads to higher demand for intermediate inputs from the South. As outlined by the model, when accounting for both direct and indirect linkages, the positive effect dominates (i.e. $\beta_1 > 0$).

5 Empirical Results

5.1 Baseline Results

Table 2 shows our main results using PPML. We first estimate Equation (17) to test Proposition 1 from the model and provide evidence on the effect of robotization on exports in the same industry. As reported in column 1, robot adoption in OECD countries is associated with a reduction in firm-level exports of Latin American countries when solely considering direct linkages (in the same industry), in accordance with Proposition 1 from the theory.

However, the opposite holds when we account for value chain linkages, as shown in columns 2 and 3. We estimate Equation (18) to test Proposition 2 from the model and provide evidence on the effect of robot adoption along the value chain. Column 2 reports results for linkages along the value chain excluding direct linkages (in the same industry) whereas column 3 reports the total effect, which includes linkages in the same industry, shown by $asinh(robots^{IO}_{total})_{pdt}$. We find a positive effect of robot adoption on firm-level exports to OECD countries along the value chain (column 2). When both direct and indirect linkages are taken into account (column 3), the positive effect persists, which is in line with Proposition 2 from the model. Moreover, as suggested by the model, the coefficient shown in column 3 is larger in magnitude when compared with column 2.

The baseline results include the most stringent specification regarding fixed effects. The estimations include interacted firm-product-destination fixed effects (ζ_{fpd}), origin-destination-time fixed effects (γ_{odt}) and product-time fixed effects (δ_{pt}). γ_{odt} fixed effects absorb any time-varying changes in a bilateral relationship between two countries, which are important to rule out confounding factors related to changes in trade policy and country-specific policies, for instance. δ_{pt} effects help mitigate endogeneity concerns related to changes in demand for specific products, such as a commodity boom over this period. All regressions control for total imports of the destination country from the rest of the world at the product level ($\ln imp_{pdt}$) to account for changes in competition faced by Latin American firms in the destination country - for instance, changes in competition caused by the rise of Chinese exports to OECD countries.

In addition, we account for industry-specific supply and demand shocks by including industry-origin-time fixed effects π_{sot} and industry-destination-time fixed effects ν_{sdt} - note that ν_{sdt} can only be included for the analysis along the value chain shown in columns 2 and 3, as in this case the shocks vary across products within an industry.

Table 2: Baseline Results

Dependent Var: X_{fpdt}	Direct linkages (1)	Indirect linkages (2)	Total (3)
$asinh(robots)_{sdt}$	-0.0377*		
	(0.0217)		
$asinh(robots^{IO}_{between})_{pdt}$		0.245***	
		(0.0563)	
$asinh(robots^{IO}_{total})_{pdt}$			0.179***
			(0.0690)
Total Imp of Dest$_{pdt}$	0.696***	0.666***	0.664***
	(0.0622)	(0.0509)	(0.0502)
Observations	248,990	243,770	243,770
Firm-product-destination FE	Yes	Yes	Yes
Origin-destination-time FE	Yes	Yes	Yes
Product-time FE	Yes	Yes	Yes
Industry-destination-time FE	Yes	Yes	Yes
Industry-origin-time FE		Yes	Yes

Note: Robust standard errors clustered by SD in parentheses: *** p<0.01, ** p<0.05, * p<0.1

5.2 Robustness Checks

This section provides three main robustness analyses. First, Appendix C provides extensions of the baseline results using different specifications with respect to fixed effects. Tables C1 to C3 provide robustness checks for direct linkages (Table C1), indirect linkages (Table C2) and the combined total effect (Table C3). The coefficients shown in Tables C1 to C3 reveal that the results remain robust when accounting for different groups of fixed effects, which reinforces that results are not driven by the choice of a full set of controls.

Second, in the results shown in section 5.1, all specifications include interacted firm-product-destination fixed effects. Hence, the estimations only include firm-product-destination observations that prevail throughout the whole period. This implies that firms that exit the market due to a decline in demand or low productivity are not considered in the analysis. This creates an upward bias in the estimates, as only those firms that survive are considered. At the same time, the analysis also does not account for firms entering the market. In this case, the impact is underestimated and the results are biased downwards. To rule out both sources of bias, we create a balanced data set. For all firm-product-destination combinations which are observed in the first period but no exports exists in the last, zero trade flows are included for the last period. The same applies for firms for which no trade flows are observed in the first period but in the last. Results including zero trade flows are presented in Table 3. The coefficients remain negative for the direct linkages in the same industry (column 1) and positive when accounting for value chain linkages (columns 2 and 3), such that a bias of the baseline estimations can be ruled out in both directions. As for the baseline results, Tables C4 to C6 in Appendix C provide robustness checks using a different group of fixed effects. Table C4 reports results for direct linkages, Table C5 shows indirect linkages and Table C6 shows the total effect.

Finally, the results could be biased due to firm-level productivity shocks or other firm-level changes that exporters in Latin American countries undergo, such as firm-level robot adoption. Hence, in additional regressions, we include firm-time fixed effects in the balanced data set, allowing us to account for time-varying firm heterogeneity. As shown in Table 4, the coefficients remain robust and with similar magnitudes in comparison to Table 3, which reinforces the robustness of the results.

Table 3: Baseline Results with Control for Market Entry and Exit

Dependent Var: X_{fpdt}	Direct linkages (1)	Indirect linkages (2)	Total (3)
$asinh(robots)_{sdt}$	-0.0251		
	(0.0348)		
$asinh(robots^{IO}_{between})_{pdt}$		0.230***	
		(0.0598)	
$asinh(robots^{IO}_{total})_{pdt}$			0.192**
			(0.0846)
Total Imp of Dest_{pdt}	0.961***	0.929***	0.928***
	(0.0903)	(0.0802)	(0.0803)
Observations	1,718,062	1,693,893	1,693,893
Firm-product-destination FE	Yes	Yes	Yes
Origin-destination-time FE	Yes	Yes	Yes
Product-time FE	Yes	Yes	Yes
Industry-destination-time FE	Yes	Yes	Yes
Industry-origin-time FE		Yes	Yes

Note: Robust standard errors clustered by SD in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Table 4: Baseline Results with Control for Market Entry and Exit and Firm FE

Dependent Var: X_{fpdt}	Direct linkages (1)	Indirect linkages (2)	Total (3)
$asinh(robots)_{sdt}$	-0.0289		
	(0.0404)		
$asinh(robots^{IO}_{between})_{pdt}$		0.241***	
		(0.0744)	
$asinh(robots^{IO}_{total})_{pdt}$			0.154*
			(0.0883)
Total Imp of Dest_{pdt}	1.143***	1.052***	1.052***
	(0.0936)	(0.0787)	(0.0786)
Observations	1,014,016	997,674	997,674
Firm-product-destination FE	Yes	Yes	Yes
Origin-destination-time FE	Yes	Yes	Yes
Product-time FE	Yes	Yes	Yes
Industry-destination-time FE	Yes	Yes	Yes
Industry-origin-time FE		Yes	Yes
FT FE	Yes	Yes	Yes

Note: Robust standard errors clustered by SD in parentheses: *** p<0.01, ** p<0.05, * p<0.1

6 Conclusion

This paper investigates the effect of robot adoption in high-income countries on firm-level North-South trade across products and along the value chain. Using detailed firm-level data by product and destination country of exports, we take on the perspective of southern firms to evaluate the effect of automation in the North on exports from the South. This is one relevant dimension, as the effect of robotization, which takes place predominantly in high-income countries, is not confined by geographical boundaries but can spill over globally through supply chains and affect all trading partners.

One key contribution of our paper is the analysis of firm-level exposure to shocks across destinations and along the value chain. For this purpose, we create a novel data set, where automation shocks are mapped to exported products using *same industry linkages* as well as *value-chain linkages*. We show that robot adoption in OECD countries is associated with a reduction in exports of Latin American countries when solely considering effects in the same industry. However, once we account for input-output linkages and trade along the value chain, the opposite holds: we find a positive effect of robot adoption on firm-level exports to OECD countries.

We rationalize these opposing effects in a North-South model of trade, where final-goods producers in the North decide whether to source inputs from the South or to vertically integrate production. Lower automation costs increase the incentive to reshore production and thus reduce the demand for sourced inputs, while the productivity-enhancing effect works in the opposite direction. Consistent with the theoretical analysis, our empirical findings suggest that it is important to account for the effects along the value chain when evaluating the impact of robotization on North-South trade, as the sign and magnitude of the effect depend on the type of linkage. Future research might further investigate the impact of industrial robot adoption in the global North on the industry composition and the quality of the exported products from the global South.

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A Proof of Propositions

Proof of Proposition 1. As described in Section 2.3, final-good producers with $\theta \geq \theta_O^S$ source within-industry inputs from the South. Each of these firms induces the following trade flow of intermediates from South to North:

$$\tau w^S m_j(\theta) = \frac{\eta_j c_{j,O}^S}{\theta} x_j(\theta)_O^S = \alpha \eta_j X_j^{\frac{\mu-\alpha}{1-\alpha}} \left(\frac{\alpha \theta}{c_{j,O}^S} \right)^{\frac{\alpha}{1-\alpha}}, \tag{A1}$$

where we have used the production function in Equation (2) and the profit-maximizing input choice and output under sourcing. To explicitly solve for aggregate trade flows, we assume that productivity follows a Pareto distribution, $G(\theta) = 1 - \theta^{-k}$, with shape parameter $k > 1$. We further impose that $k(1-\alpha) > \alpha$ to ensure a well-defined equilibrium. Under this assumption and by using Equation (A1), within-industry flows of intermediate inputs from South to North can be written as follows:

$$T_j^{N,S} = \alpha \eta_j M_e X_j^{\frac{\mu-\alpha}{1-\alpha}} \left(\frac{\alpha}{c_{j,O}^S} \right)^{\frac{\alpha}{1-\alpha}} \frac{k(1-\alpha)}{k(1-\alpha)-\alpha} \left(\theta_O^S\right)^{\frac{\alpha - k(1-\alpha)}{1-\alpha}}, \tag{A2}$$

where the cutoff productivity of outsourcing θ_O^S in Equation (6) increases with automation and thus clearly decreases trade flows in Equation (A2). *QED.*

Proof of Proposition 2. For final-good producers with productivity $\theta_V^N \leq \theta < \theta_O^S$, the between-industry trade flow of intermediate goods from the South is given by:

$$w^S m_k(\theta) = \alpha (1-\eta_j) X_j^{\frac{\mu-\alpha}{1-\alpha}} \left(\frac{\alpha \theta}{c_{j,V}^N} \right)^{\frac{\alpha}{1-\alpha}}. \tag{A3}$$

To obtain this result, we have combined the production function in Equation (2), relative input choice in Equation (6), and optimal output as described in Section 2.3. We have further used the definition of marginal cost with vertical integration and automation in Equation (7). With Pareto distributed productivity, inserting firm-level flows from Equation (A3) into Equation (13) and solving the integral yields:

$$T_{k,V}^{N,S} = \alpha (1-\eta_j) M_e X_j^{\frac{\mu-\alpha}{1-\alpha}} \left(\frac{\alpha}{c_{j,V}^N} \right)^{\frac{\alpha}{1-\alpha}} \frac{k(1-\alpha)}{k(1-\alpha)-\alpha} \left[\left(\theta_V^N\right)^{\frac{\alpha-k(1-\alpha)}{1-\alpha}} - \left(\theta_O^S\right)^{\frac{\alpha-k(1-\alpha)}{1-\alpha}} \right].$$

Nominal demand for between-industry inputs of final-good producers with productivity $\theta \geq \theta_O^S$ can be written as follows:

$$w^S m_k(\theta) = \alpha(1-\eta_j) X_j^{\frac{\mu-\alpha}{1-\alpha}} \left(\frac{\alpha\theta}{c_{j,O}^S}\right)^{\frac{\alpha}{1-\alpha}}. \tag{A4}$$

Inserting Equation (A4) into Equation (14) and solving for the integral under the assumption of Pareto distributed productivity leads to:

$$T_{k,O}^{N,S} = \alpha(1-\eta_j) M_e X_j^{\frac{\mu-\alpha}{1-\alpha}} \left(\frac{\alpha}{c_{j,O}^S}\right)^{\frac{\alpha}{1-\alpha}} \frac{k(1-\alpha)}{k(1-\alpha)-\alpha} \left(\theta_O^S\right)^{\frac{\alpha-k(1-\alpha)}{1-\alpha}}.$$

We define the relative cutoff productivity $\hat{\theta} \equiv \theta_O^S/\theta_V^N > 1$, where the inequality holds under Condition 2. Additionally, the relative marginal cost advantage of sourcing compared to vertical integration under automation is determined by $\psi_j \equiv \frac{\xi_j+1}{\xi_j}\frac{\hat{w}}{a_j}$. Using these definitions and taking into account both types of firms, total between-industry trade flows from South to North can be derived as follows:

$$\begin{aligned} T_k^{N,S} &\equiv T_{k,V}^{N,S} + T_{k,O}^{N,S} \\ &= (1-\eta_j)\mathit{\Gamma} M_e X_j^{\frac{k(\mu-\alpha)}{\alpha}} \left(f_V^N\right)^{\frac{\alpha-k(1-\alpha)}{\alpha}} \left(c_{j,V}^N\right)^{-k} \left[1 + \left(\psi^{\frac{\alpha\eta_j}{1-\alpha}} - 1\right)\hat{\theta}^{\frac{\alpha-k(1-\alpha)}{1-\alpha}}\right], \end{aligned} \tag{A5}$$

where $\mathit{\Gamma} \equiv \frac{k\alpha^{k+1}(1-\alpha)^{\frac{k(1-\alpha)}{\alpha}}}{k(1-\alpha)-\alpha}$. The impact of an automation cost shock on total between-industry trade flows in Equation (A5) is given by the following elasticity:

$$\frac{\partial \ln T_k^{N,S}}{\partial \ln \kappa_j} = -k\frac{\partial \ln c_{j,V}^N}{\partial \ln \kappa_j} + \frac{k\eta_j \psi_j^{\frac{\alpha\eta_j}{1-\alpha}} \hat{\theta}^{\frac{\alpha-k(1-\alpha)}{1-\alpha}}}{1 + \left(\psi_j^{\frac{\alpha\eta_j}{1-\alpha}} - 1\right)\hat{\theta}^{\frac{\alpha-k(1-\alpha)}{1-\alpha}}} \frac{\partial \ln \psi_j}{\partial \ln \kappa_j} < 0. \tag{A6}$$

The first term on the right-hand side of Equation (A6) captures the increase in marginal production cost, with $\frac{\partial \ln c_{j,V}^N}{\partial \ln \kappa_j} = \frac{\eta_j}{1+\xi_j} > 0$. From Equation (A5) it follows that this cost effect influences trade flows negatively through the intensive margin, where the elasticity is governed by the Pareto shape parameter k. The second term on the right-hand side of Equation (A6) is a counteracting selection effect. As $\frac{\partial \ln \psi_j}{\partial \ln \kappa_j} = \frac{1}{1+\xi_j} > 0$, higher costs for automation incentivize more firms to select into sourcing from the South, resulting in larger between-industry trade flows to the North. Comparing the two counteracting effects shows that the overall impact of automation costs on trade flows in Equation (A6) is negative as long as $\hat{\theta} > 1$, which is satisfied under Condition 2. Hence, a reduction in automation costs leads to an increase of total between-industry trade flows. *QED.*

B Extensions of theoretical model

B.1 Vertical integration of between-industry inputs

We extend the baseline model by allowing for a continuum of between-industry inputs in Equation (2), so that $m_k(i) = \int_0^1 m_k(v)\,dv$. Let us further assume that a fraction $\bar{v}$ of these inputs cannot be outsourced for technological reasons, while the share $(1-\bar{v})$ is produced in the South. Hence, the marginal cost for between-industry inputs is given by $c_k = \bar{v}w^N + (1-\bar{v})\,\tau w^S$. Analogous to the baseline model, revenues with outsourcing of within-industry inputs can be written as $r_j(i)_O^S = X_j^{\frac{\mu-\alpha}{1-\alpha}} \left(\frac{\alpha\theta}{c_{j,O}^S}\right)^{\frac{\alpha}{1-\alpha}}$, where marginal cost are now given by $c_{j,O}^S = \left(\tau w^S\right)^\eta c_k^{1-\eta}$.

Regarding automation under vertical integration, we assume that the cost minimization problem in Equation (3) applies to the share $\bar{v}$ of between-industry inputs as well, implying an identical automation level for these intermediates, $a_k = \left(\frac{w^N}{\kappa_j}\right)^{\frac{1}{1+\xi_j}}$. Profit maximization leads to the following marginal cost under vertical integration of within-industry inputs and automation:

$$c_{j,V}^N \equiv \left[\frac{\xi_j+1}{\xi_j}\frac{w^N}{a_j}\right]^{\eta_j} \left[\tau w^S \left(1+\bar{v}\left(\psi_j-1\right)\right)\right]^{1-\eta_j}.$$

Note that setting $\bar{v}=0$ leads to the marginal cost in Equation (7) of the main text. Hence, the term $(1+\bar{v}(\psi_j-1))$ captures the additional cost disadvantage of vertically integrated between-industry inputs relative to outsourcing. To compare the two decisions, we define $\Lambda_j \equiv \frac{1+\bar{v}(\hat{w}-1)}{1+\bar{v}(\psi_j-1)} > 1$, which reflects the cost advantage of vertically integrated intermediates with automation following from Condition 1. This allows us to write the relative marginal cost of sourcing compared to vertical integration as follows:

$$\hat{c}_j \equiv \frac{c_{j,V}^N}{c_{j,O}^S} = \frac{\psi_j^{\eta_j}}{\Lambda_j^{1-\eta_j}} > 1. \tag{B1}$$

Note that relative marginal costs in Equation (B1) decrease in $\bar{v}$ through an increase in Λ_j, as a higher share of intermediate inputs benefits from automation compared to outsourcing. Following the main analysis, we set $\pi_j(i)_O^S = \pi_j(i)_V^N$ to determine the cutoff productivity of outsourcing:

$$\theta_O^S = \frac{c_{j,O}^S}{\alpha X_j^{\frac{\mu-\alpha}{\alpha}}} \left(\frac{f_O^S - f_V^N}{1-\alpha}\frac{1}{1-(1/\hat{c}_j)^{\frac{\alpha}{1-\alpha}}}\right)^{\frac{1-\alpha}{\alpha}}. \tag{B2}$$

Additionally, the cutoff productivity of vertical integration follows from a zero-profit condition $\pi_j(i)_V^N = 0$, leading to $\theta_V^N = \frac{c_{j,V}^N}{\alpha}\left(\frac{f_V^N}{(1-\alpha)X_j^{\frac{\mu-\alpha}{1-\alpha}}}\right)^{\frac{1-\alpha}{\alpha}}$. Comparison of the two cutoff levels leads to the following condition:

$$\theta_O^S > \theta_V^N \qquad if \qquad \frac{f_O^S}{f_V^N} > \hat{c}_j^{\frac{\alpha}{1-\alpha}}.$$

As the relative marginal cost under partial integration of between-industry inputs in Equation (B1) are smaller than in the baseline model with $\bar{v} = 0$, the selection condition requires lower relative fixed costs compared to Condition 2.

Within-industry trade flows from South to North can still be expressed as in Equation (12), where the positive impact of automation works through a reduction in relative marginal cost (B1). Consequently, the cutoff productivity in Equation (B2) increases and the share of outsourcing firms decreases. Total between-industry trade flows from South to North are now given by:

$$\begin{aligned} T_k^{N,S} &= (1-\bar{v}) M_e \int_{\theta_V^N}^{\theta_O^S} \tau w^S m_k(\theta)\, dG(\theta) + (1-\bar{v}) M_e \int_{\theta_O^S}^{\infty} \tau w^S m_k(\theta)\, dG(\theta) \\ &= (1-\bar{v})(1-\eta_j)\,\Gamma M_e X_j^{\frac{k(\mu-\alpha)}{\alpha}} \left(f_V^N\right)^{\frac{\alpha-k(1-\alpha)}{1-\alpha}} \left(c_{j,V}^N\right)^{-k} \frac{1+\left(\Lambda\hat{c}_j^{\frac{\alpha}{1-\alpha}}-1\right)\hat{\theta}^{\frac{\alpha-k(1-\alpha)}{1-\alpha}}}{1+\bar{v}(\psi_j-1)}. \end{aligned}$$

Note that setting $\bar{v} = 0$ leads to Equation (A5). The impact of automation costs on total between-industry trade flows can be decomposed into an intensive and an extensive margin effect:

$$\frac{\partial \ln T_k^{N,S}}{\partial \ln \kappa_j} = \left.\frac{\partial \ln T_k^{N,S}}{\partial \ln \kappa_j}\right|_{IM} + \left.\frac{\partial \ln T_k^{N,S}}{\partial \ln \kappa_j}\right|_{EM},$$

where the change of the intensive margin can be written as follows:

$$\left.\frac{\partial \ln T_k^{N,S}}{\partial \ln \kappa_j}\right|_{IM} = -\frac{(k+1)\,\bar{v}\psi_j + k\eta_j(1-\bar{v})}{1+\bar{v}(\psi_j-1)}\frac{\partial \ln \psi_j}{\partial \ln \kappa_j} < 0, \tag{B3}$$

with $\frac{\partial \ln \psi_j}{\partial \ln \kappa_j} = \frac{1}{1+\xi_j} > 0$. This channel is counteracted by a positive extensive margin effect:

$$\left.\frac{\partial \ln T_k^{N,S}}{\partial \ln \kappa_j}\right|_{EM} = \frac{\left(\hat{c}\hat{\theta}\right)^{\frac{\alpha}{1-\alpha}}\chi_O^S\Psi}{\Lambda+\left(\hat{c}^{\frac{\alpha}{1-\alpha}}-\Lambda\right)\hat{\theta}^{\frac{\alpha}{1-\alpha}}\chi_O^S}\frac{\partial \ln \psi_j}{\partial \ln \kappa_j}, \tag{B4}$$

where $\Psi \equiv \frac{\bar{v}\psi_j+(1-\bar{v})\alpha\eta_j+[k(1-\alpha)-\alpha][\bar{v}\psi_j+(1-\bar{v})\eta_j]\frac{\hat{c}^{\frac{\alpha}{1-\alpha}}-\Lambda}{\hat{c}^{\frac{\alpha}{1-\alpha}}-1}}{(1-\alpha)[1+\bar{v}(\psi_j-1)]}$. If we set $\bar{v} = 0$, we obtain the

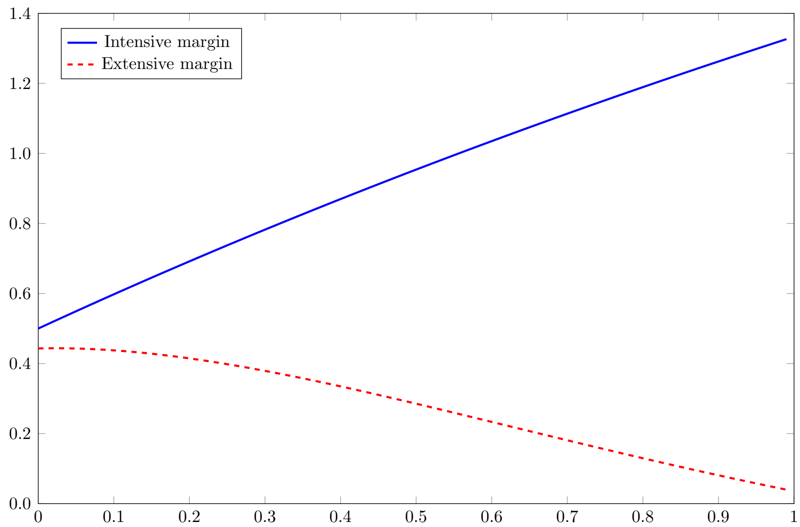

Figure 4: Intensive and extensive margin effects of automation as a function of $\bar{v}$ on the horizontal axis. *Notes:* The blue solid curve shows the intensive margin elasticity in Eq. (B3), the red dashed curve depicts the extensive margin effect in Eq. (B4). The curves are illustrated for the following parameter values: $k = 3$, $\alpha = 0.5$, $\eta = 0.5$, $\hat{w} = 1.3$, $\xi = 2$, $\kappa = 0.3$, and $f_O^S/f_V^N = 1.1$.

elasticity of trade flows in Equation (A6). The reactions of the two margins are illustrated in Figure 4. The intensive margin effect, expressed as absolute value, is clearly increasing in $\bar{v}$, as a higher fraction of vertically integrated inputs benefits from a reduction in automation costs. Note that this increased efficiency gain reduces the reaction of the share of outsourcing firms and thus the counteracting extensive margin effect. We use Equations (B3) and (B4) to derive a sufficient but not necessary condition that the intensive margin is the dominating force of the automation shock:

$$\frac{(k+1)\,\bar{v}\psi_j + k\eta_j\,(1-\bar{v})}{\bar{v}\psi_j + \alpha\eta_j\,(1-\bar{v})} > \frac{1}{1-\alpha} + \frac{k\,(1-\alpha)-\alpha}{1-\alpha}\,\frac{\hat{c}^{\frac{\alpha}{1-\alpha}} - \Lambda}{\hat{c}^{\frac{\alpha}{1-\alpha}} - 1}. \tag{B5}$$

The left-hand side of this condition has its maximum at $\bar{v} = 0$ with k/α, and is clearly decreasing in $\bar{v}$ under the assumption that the Pareto shape parameter is sufficiently large, $k > \alpha/\,(1-\alpha)$, with a minimum of $(k+1)$ at $\bar{v} = 1$. The right-hand side of Equation (B5) decreases in $\bar{v}$ as well, while the maximum at $\bar{v} = 0$ is exactly given by $(k+1)$:

$$\frac{\partial RHS}{\partial \bar{v}} = -\frac{\frac{\alpha(1-\eta_j)}{1-\alpha}\frac{\Lambda-1}{\Lambda}\hat{c}^{\frac{\alpha}{1-\alpha}} + \hat{c}^{\frac{\alpha}{1-\alpha}} - 1}{\left(\hat{c}^{\frac{\alpha}{1-\alpha}} - 1\right)^2}\frac{\partial \Lambda}{\partial \bar{v}} < 0,$$

where $\frac{\partial \Lambda}{\partial \bar{v}} > 0$, and $\hat{c} > 1$ follows from Equation (B1). This ensures that the intensive margin effect is strictly larger than the extensive margin effect over the whole range of $\bar{v} \in [0, 1]$. Hence, both Propositions in the main text still hold when allowing for partial vertical integration of between-industry inputs.

B.2 Alternative automation choice

In the baseline model, firms choose the optimal automation level by minimizing the marginal cost per unit of within-industry inputs as shown in Equation (3). This implies that the optimal automation choice is independent of firm productivity. As an alternative approach, we assume that automation increases the effectiveness of within-industry inputs in the production function:

$$x_j(i) = \theta \left(\frac{a_j(i)\, m_j(i)}{\eta_j} \right)^{\eta_j} \left(\frac{m_k(i)}{1-\eta_j} \right)^{1-\eta_j}, \tag{B6}$$

while firms face endogenous fixed costs $\frac{\kappa_j}{\xi_j} a_j(i)^{\xi_j}$. Hence, compared to Equation (5) in the main text, profits under vertical integration of within-industry inputs can be written as:

$$\pi_j(i)_V^N = r_j(i) - w^N m_j(i) - \tau w^S m_k(i) - \frac{\kappa_j}{\xi_j} a_j(i)^{\xi_j} - f_V^N.$$

By taking into account the demand function in Equation (1) and the production function (B6), profit maximization implies the following relative input choice: $\eta_j m_k(i) = (1-\eta_j)\, \hat{w} m_j(i)$. The optimal automation choice is given by:

$$a_j(i) = \left(\frac{\alpha \eta_j}{\kappa_j} r_j(i) \right)^{\frac{1}{\xi_j}}, \tag{B7}$$

so that firms with larger revenues choose higher innovation levels. Let us define the marginal cost under vertical integration without automation as $c_{j,V}^N \equiv \left(w^N\right)^{\eta} \left(\tau w^S\right)^{1-\eta_j}$. Then, the first-order condition with respect to the optimal output is given by:

$$x_j(i)^{1-\alpha} = \alpha X_j^{\mu-\alpha} \frac{\xi_j - \alpha\eta_j}{\xi_j} \frac{\theta}{a_j(i)^{\eta}\, c_{j,V}^N}. \tag{B8}$$

Combining Equations (B7) and (B8), we can write revenues under vertical integration as follows:

$$r_j(\theta)_N^V = X_j^{\frac{\mu-\alpha}{(1-\alpha)(1-\vartheta)}} \left(\frac{\xi_j - \alpha\eta_j}{\xi_j} \frac{\alpha\theta}{c_{j,V}^N} \right)^{\frac{\alpha}{(1-\alpha)(1-\vartheta)}} \left(\frac{\alpha\eta_j}{\kappa_j} \right)^{\frac{\vartheta}{1-\vartheta}},$$

where $\vartheta \equiv \frac{\eta}{\xi_j} \frac{\alpha}{1-\alpha}$. Hence, profits can be written as:

$$\pi_j(\theta)_V^N = r_j(\theta)_N^V \frac{\xi_j(1-\alpha) - \alpha\eta_j}{\xi_j} - f_V^N.$$

We assume that automation costs are sufficiently convex, $\xi_j > \frac{\alpha\eta_j}{1-\alpha}$, to ensure a well-defined equilibrium. As more productive firms have higher revenues, they will also invest more in automation according to Equation (B7), which is consistent with the modelling approach of Bonfiglioli et al. (2020). Note that considering additional fixed costs of automation would allow us to generate the result that only a share of firms use automation similar to Koch et al. (2021). We abstract from this as heterogeneity in firm-level adoption of robots is not the focus of our paper.

We rather compare the profits under vertical integration with the profits when firms outsource within-industry inputs. Note that the profits under sourcing are given as in the main text. Let us define the relative sales between these two choices, $\hat{r}_j(\theta) \equiv \frac{r_j(\theta)_N^V}{r_j(\theta)_O^S}$. Comparing the profits under both modes of organizational choice, $\pi_j(\theta)_O^S > \pi_j(\theta)_V^N$, leads to the following condition:

$$(1-\alpha)\, r_j(\theta)_O^S \left[1 - (1-\vartheta)\, \hat{r}_j(\theta)\right] > f_O^S - f_V^N. \tag{B9}$$

Note that the left-hand side of this condition is inversely U-shaped in θ, where the derivative is given by $\frac{\partial LHS}{\partial \theta} = \frac{\alpha}{\theta}\left(r_j(\theta)_O^S - r_j(\theta)_N^V\right)$. We define the productivity level $\bar{\theta}$, at which the LHS is maximized as $\hat{r}_j\left(\bar{\theta}\right) = 1$. For $\theta < \bar{\theta}$, it holds that $\hat{r}_j(\theta) < 1$ and $\frac{\partial LHS}{\partial \theta} > 0$. In contrast, in the range $\theta > \bar{\theta}$ relative sales are larger, $\hat{r}_j(\theta) > 1$, which implies that $\frac{\partial LHS}{\partial \theta} < 0$. Intuitively, as the automation choice is positively related to sales, the most productive firms invest more, which additionally boosts their sales compared to outsourcing. To ensure an intersection of the two profit curves, the selection condition in Equation (B9) has to be satisfied when evaluated at the threshold value $\theta = \bar{\theta}$, leading to:

$$\frac{c_{j,V}^N}{c_{j,O}^S}\left(\frac{\kappa_j}{\alpha\eta_j}\right)^{\frac{\alpha}{\vartheta(1-\alpha)}} > \frac{\xi_j - \alpha\eta_j}{\xi_j}\left(\frac{f_O^S - f_V^N}{(1-\alpha)\,\vartheta}\right)^{\frac{\vartheta(1-\alpha)}{\alpha}}.$$

We assume in the following that this condition is satisfied, which implies that the production cost under vertical integration and the automation cost k_j have to be sufficiently large to ensure a productivity range where outsourcing is the most profitable choice of organization. If this condition is violated, then firms always prefer vertical integration of within-industry inputs over buying from the South.

Given this condition, we obtain two cutoff productivity levels for which firms are indifferent between outsourcing and vertical integration, so that Equation (B9) holds with equality. The first one with $\theta_O^S < \bar{\theta}$, determines the lowest productivity firm that chooses outsourcing. The second cutoff level $\bar{\theta}_V^N > \bar{\theta}$ is a threshold above which the most productive firms instead prefer vertical integration over outsourcing. The selection pattern is illustrated in Figure 5.

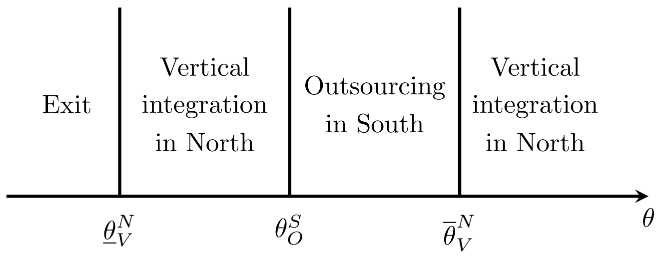

Figure 5: Sorting pattern of firms with alternative automation choice

The lower cutoff productivity for vertical integration is given by the zero-profit condition: $\pi_j\left(\underline{\theta}_V^N\right)_V^N = 0$, leading to $r_j\left(\underline{\theta}_V^N\right)_N^V = \frac{f_V^N}{(1-\alpha)(1-\vartheta)}$. From Equation (B9) it follows that the productivity cutoff θ_O^S is implicitly given by $r_j\left(\theta_O^S\right)_O^S\left[1-(1-\vartheta)\,\hat{r}_j\left(\theta_O^S\right)\right] = \frac{f_O^S - f_V^N}{1-\alpha}$. Hence, similar to Condition 2 in the main text, the fixed cost of outsourcing have to be sufficiently high compared to the fixed cost of vertical integration to ensure that $\underline{\theta}_V^N < \theta_O^S$.

Based on this selection pattern, only firms with productivity $\theta_O^S \leq \theta < \overline{\theta}_V^N$ source within-industry inputs from the South, so that trade flows of these intermediates to the North are given by:

$$T_j^{N,S} = M_e \int_{\theta_O^S}^{\overline{\theta}_V^N} \tau w^S m_j\left(i\right) dG\left(\theta\right).$$

As $\frac{\partial \overline{\theta}_V^N}{\partial \kappa_j} > 0$ and $\frac{\partial \theta_O^S}{\partial \kappa_j} < 0$, a positive automation shock that lowers κ_j clearly reduces within-industry trade flows in line with Proposition 1 in the main text. For these firms, between-industry trade flows are given by:

$$T_{k,O}^{N,S} = M_e \int_{\theta_O^S}^{\overline{\theta}_V^N} \tau w^S m_k\left(\theta\right)_O^S dG\left(\theta\right),$$

where $\tau w^S m_k\left(\theta\right)_O^S = \alpha\left(1-\eta_j\right) r_j\left(\theta\right)_O^S$. Accordingly, between-industry trade flows induced by firms that vertically integrate the production of within-industry intermediates can be written as:

$$T_{k,V}^{N,S} = M_e \int_{\underline{\theta}_V^N}^{\theta_O^S} \tau w^S m_k\left(\theta\right)_V^N dG\left(\theta\right) + M_e \int_{\overline{\theta}_V^N}^{\infty} \tau w^S m_k\left(\theta\right)_V^N dG\left(\theta\right),$$

with $\tau \omega^S m_k\left(\theta\right)_V^N = \frac{\alpha\left(\xi_j - \alpha\eta_j\right)}{\xi_j}\left(1-\eta_j\right) r_j\left(\theta\right)_V^N$. The impact of automation costs on these between-industry trade flows can be written as follows:

$$\frac{\partial \ln T_{k,V}^{N,S}}{\partial \ln \kappa_j} = -\frac{\vartheta}{1-\vartheta} - \zeta_1 \frac{\frac{\partial \ln \theta_V^N}{\partial \ln \kappa_j} - \left(\frac{\theta_V^N}{\theta_O^S}\right)^{\zeta_1} \frac{\partial \ln \theta_O^S}{\partial \ln \kappa_j} + \left(\frac{\theta_V^N}{\overline{\theta}_V^N}\right)^{\zeta_1} \frac{\partial \ln \overline{\theta}_V^N}{\partial \ln \kappa_j}}{1 - \left(\frac{\theta_V^N}{\theta_O^S}\right)^{\zeta_1} + \left(\frac{\theta_V^N}{\overline{\theta}_V^N}\right)^{\zeta_1}} < 0,$$

where $\zeta_1 \equiv \frac{k(1-\alpha)(1-\vartheta)-\alpha}{(1-\alpha)(1-\vartheta)}$. The first term on the right-hand side captures the efficiency loss of higher automation costs through the intensive margin of trade. Given the selection pattern described above, the extensive margin effect is now governed by changes of three cutoff productivity levels. Note that $\frac{\partial \theta_V^N}{\partial \kappa_j}, \frac{\partial \overline{\theta}_V^N}{\partial \kappa_j} > 0$, and $\frac{\partial \theta_O^S}{\partial \kappa_j} < 0$, so that the extensive margin effect is clearly negative. Hence, in line with Proposition 2, a positive automation shock increases between-industry trade flows of firms that vertically integrate production. This effect is counteracted by the negative impact of automation on between-industry trade flows caused by firms that outsource within-industry inputs:

$$\frac{\partial \ln T_{k,O}^{N,S}}{\partial \ln \kappa_j} = \frac{\zeta_2}{\left(\frac{\overline{\theta}_V^N}{\theta_O^S}\right)^{\zeta_2} - 1} \left[\frac{\partial \ln \overline{\theta}_V^N}{\partial \ln \kappa_j} - \left(\frac{\overline{\theta}_V^N}{\theta_O^S}\right)^{\zeta_2} \frac{\partial \ln \theta_O^S}{\partial \ln \kappa_j}\right] > 0.$$

where $\zeta_2 = \frac{k(1-\alpha)-\alpha}{1-\alpha}$. Note that this effect is entirely driven by the extensive margin as the fraction of outsourcing firms declines with automation.

C Further Empirical Results

Table C1: Robustness checks - direct linkages

Dependent Var: X_{fpdt}	(1)	(2)
$asinh(robots)_{sdt}$	-0.0361*	-0.0377*
	(0.0210)	(0.0217)
Total Imp of Dest$_{pdt}$	0.688***	0.696***
	(0.0602)	(0.0622)
Observations	248,992	248,990
FPD FE	Yes	Yes
ODT FE	Yes	Yes
PT FE	Yes	Yes
SOT FE		Yes

Note: Robust standard errors clustered by SD in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Table C2: Robustness checks - indirect linkages

Dependent Var: X_{fpdt}	(1)	(2)	(3)	(4)
$asinh(robots^{IO}_{between})_{pdt}$	0.0923***	0.0915***	0.241***	0.245***
	(0.0315)	(0.0315)	(0.0576)	(0.0563)
Total Imp of Dest$_{pdt}$	0.697***	0.703***	0.666***	0.666***
	(0.0599)	(0.0620)	(0.0508)	(0.0509)
Observations	243,861	243,861	243,770	243,770
FPD FE	Yes	Yes	Yes	Yes
ODT FE	Yes	Yes	Yes	Yes
PT FE	Yes	Yes	Yes	Yes
SDT FE			Yes	Yes
SOT FE		Yes		Yes

Note: Robust standard errors clustered by SD in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Table C3: Robustness checks - combined total effect

Dependent Var: X_{fpdt}	(1)	(2)	(3)	(4)
$asinh(robots^{IO}_{total})_{pdt}$	0.0720*	0.0724**	0.171**	0.179***
	(0.0373)	(0.0366)	(0.0719)	(0.0690)
Total Imp of Dest$_{pdt}$	0.691***	0.698***	0.665***	0.664***
	(0.0591)	(0.0611)	(0.0501)	(0.0502)
Observations	243,861	243,861	243,770	243,770
FPD FE	Yes	Yes	Yes	Yes
ODT FE	Yes	Yes	Yes	Yes
PT FE	Yes	Yes	Yes	Yes
SDT FE			Yes	Yes
SOT FE		Yes		Yes

Note: Robust standard errors clustered by SD in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Table C4: Direct linkages accounting for market entry and exit

Dependent Var: X_{fpdt}	(1)	(2)
$asinh(robots)_{sdt}$	-0.0172	-0.0251
	(0.0313)	(0.0348)
Total Imp of Dest$_{pdt}$	0.960***	0.961***
	(0.0883)	(0.0903)
Observations	1,718,028	1,718,062
FPD FE	Yes	Yes
ODT FE	Yes	Yes
PT FE	Yes	Yes
SOT FE		Yes

Note: Robust standard errors clustered by SD in parentheses:
*** p<0.01, ** p<0.05, * p<0.1

Table C5: Indirect linkages accounting for market entry and exit

Dependent Var: X_{fpdt}	(1)	(2)	(3)	(4)
$asinh(robots^{IO}_{between})_{pdt}$	0.0869**	0.0839**	0.225***	0.230***
	(0.0341)	(0.0343)	(0.0626)	(0.0598)
Total Imp of Dest$_{pdt}$	0.966***	0.966***	0.934***	0.929***
	(0.0869)	(0.0886)	(0.0796)	(0.0802)
Observations	1,693,992	1,694,037	1,693,896	1,693,893
FPD FE	Yes	Yes	Yes	Yes
ODT FE	Yes	Yes	Yes	Yes
PT FE	Yes	Yes	Yes	Yes
SDT FE			Yes	Yes
SOT FE		Yes		Yes

Note: Robust standard errors clustered by SD in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Table C6: Total effect accounting for market entry and exit

Dependent Var: X_{fpdt}	(1)	(2)	(3)	(4)
$asinh(robots^{IO}_{total})_{pdt}$	0.0794**	0.0719**	0.201**	0.192**
	(0.0343)	(0.0361)	(0.0967)	(0.0846)
Total Imp of Dest$_{pdt}$	0.962***	0.962***	0.933***	0.928***
	(0.0860)	(0.0879)	(0.0797)	(0.0803)
Observations	1,693,992	1,694,037	1,693,896	1,693,893
FPD FE	Yes	Yes	Yes	Yes
ODT FE	Yes	Yes	Yes	Yes
PT FE	Yes	Yes	Yes	Yes
SDT FE			Yes	Yes
SOT FE		Yes		Yes

Note: Robust standard errors clustered by SD in parentheses: *** p<0.01, ** p<0.05, * p<0.1