Robots, Tasks, and Trade[*]

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Abstract

This paper examines the effects of robotization on trade patterns, wages and welfare. It develops a Ricardian model with two-stage production and trade in intermediate and final goods in which robots can take over some tasks previously performed by humans in a subset of industries. An increase in robot adoption in the North reduces the cost of production and thereby impacts trade in final and intermediate goods with the South. The empirical analysis uses ordinary least squares and instrumental-variable regressions exploiting variation in exposure to robots across countries and sectors. Both reveal that greater robot intensity in own production leads to: (i) a rise in imports sourced from less developed countries in the same industry; and (ii) an even stronger increase in exports to those countries. Counterfactual simulations indicate that Northern robotization raises domestic welfare, but initially depresses wages. However, this adverse effect is likely to be reversed by further reductions in robot prices. Northern robotization may lead to higher wages and welfare in the South.

Keywords: Automation, robots, tasks, jobs, wages, trade, intermediate inputs, global value chains, gains from trade

JEL Classification: F1; J23; J24; O3; O4

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1 Introduction

Recent and prospective advances in automation, robotics and artificial intelligence have renewed concerns about the potential disruptive impacts of technological change on labor markets (Brynjolfsson and McAfee, 2014; Ford, 2015). Modern industrial robots can be programmed to perform a variety of repetitive tasks with consistent precision, and are increasingly used in a wide range of industries and applications.[1] A growing body of evidence reveals that their adoption has had important implications for productivity and labor markets in high-income countries. Exploiting variation in robot usage across industries and countries, Graetz and Michaels (2018) find that increased robot density raised productivity and wages, but reduced the employment share of low-skilled workers. Focusing on local labor markets in the United States, Acemoglu and Restrepo (2017b) document large and robust negative effects of robots on employment and wages across commuting zones.[2]

So far, the adoption of industrial robots has been largely confined to a relatively small number of high-income nations. Yet this does not necessarily mean that poorer countries have remained insulated from their impacts. In an integrated global economy, the adoption of industrial robots in high-income nations might have important implications for relative production costs and international specialization. If tasks that were commonly performed by low-skill workers in the South can now be executed by relatively inexpensive robots at home, the scope for North-South trade might be reduced. By potentially shutting developing countries out of global value chains, robotization might adversely impact wages and welfare, even in nations that have not yet adopted this technology (Rodrik, 2018).

In this paper, we examine the implications of industrial robotization for North-South trade, wages and welfare. We first develop a Ricardian trade theory with two-stage production in which robots can take over some tasks previously performed by humans, building on Eaton and Kortum (2002), Artuc and McLaren (2015), Caliendo and Parro (2015) and Acemoglu and Restrepo (2017b). In the model, a subset of tasks required in the production of intermediate and final goods can be executed either by workers or robots, while other tasks can only be performed by humans.

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[1] Robots are therefore different from other types of industrial machinery which can only be used to perform a specific application in a specific sector.

[2] Other recent contributions on the drivers and impacts of automation include Acemoglu and Restrepo (2017a, 2018a,b,c). A related strand of earlier work examines impacts of other technologies on wage inequality, jobs and employment polarization, including widely cited papers by Feenstra and Hanson (1999), Autor, Levy, and Murname (2003), Goos and Manning (2007), Michaels, Natraj, and Van Reenen (2007), Autor, Dorn, and Hanson (2015) and Akerman, Gaarder, and Mogstad (2015). Costinot and Werning (2018) offer a theoretical analysis of how tax policy can optimally be used to address the distributional impacts of technological change.

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

A fall in the price of industrial robots initially induces robotization in the North, where the cost of labor is relatively higher to begin with. This shift impacts relative production costs between countries, and therefore trade patterns. Robots replace domestic labor within sectors, leading to lower costs of production in the North, and hence to an increase in exports to the South. The effect of Northern robotization on imports sourced from the South in the same sector is theoretically ambiguous. On the one hand, robotization makes Northern producers more competitive, which implies that some varieties that were previously imported from the South are now sourced domestically. On the other hand, robotization leads to an expansion in the scale of production, which raises the demand for inputs sourced from the South.

Simple OLS regressions using country-industry panel data on trade and industrial robots over the last two decades—including country-pair-year and industry-year fixed effects—point to a robust positive relationship between robot intensity in own production and imports sourced from less developed countries. They also reveal an even stronger association with exports to these countries. Robotization thus leads to a significant reduction in net imports from less developed countries within the same sector. However, there are reasons to be concerned that these relationships reflect various forms of endogeneity. Robotization may in part be a response to changing trade patterns—for instance, trade may alter the incentives of Northern producers to automate their production. To address this possibility, as well as biases associated with omitted variables and measurement error, we implement an instrumental variable strategy motivated by our theory, exploiting variation in the exposure to robotization across countries and sectors. Specifically, we use the triple interaction between pre-determined country-wide labor costs (which govern the incentives to robotize), the share of workers engaged in replaceable tasks in the industry (as a proxy for the feasibility of automation), and the global stock of robots (as a proxy for the price of robots) as instrument for robotization at the country-industry-year level. As an alternative

IV strategy, we also present regressions in which we use sector-specific robotization trends in countries with similar income levels as an instrument for own robotization. In both cases, the IV results point to an even stronger effect of robot adoption on trade. According to our preferred IV estimates, a 10% increase in robot density in Northern countries is associated with a 6.1% increase in their imports from less developed countries and an 11.8% increase in their exports to these countries, such that net sectoral imports from the South decline by 5.7%. In line with the key mechanisms emphasized by our theory, the positive impact of Northern robotization on imports from the South is mainly driven by exchanges of parts and components.

Armed with these reduced-form partial equilibrium estimates, we return to the theoretical model to study quantitatively the general equilibrium effects of reductions in robot prices on wages and welfare in the North and the South, using counterfactual simulations. We find that, as robots become cheaper, they replace Northern workers in a wider range of tasks. Displaced workers must seek employment in other sectors of the economy. While overall production expands, aggregate labor demand falls during this process, depressing Northern wages. Robotization nevertheless leads to domestic welfare gains, as the income losses associated with lower labor income are more than compensated for by productivity gains, lower consumer prices, and increased income from the rental rate of robots. Interestingly, the quantified model points to an important non-linearity in the relationship between wages and robot prices. As robot adoption deepens in the North, production in the robotized sector continues to expand, thus raising demand for the tasks in which robotization is technologically unfeasible. As we move closer to the robotization frontier, this effect fully offsets the direct negative impact of robotization on sectoral labor demand. Eventually, the share of labor in the robotized sector starts to expand, thereby raising overall labor demand and leading to higher wages in the North.

Even if production in the South is not subject to robotization, Southern wages and welfare are impacted by robot-induced shifts in international specialization. While robotization makes Northern producers more competitive, it also raises demand for Southern inputs. Because of this increase in demand and lower consumer prices, aggregate welfare is likely to increase in the South. Welfare gains in the South are likely to be even more pronounced if robotization also becomes feasible there. Since trade in intermediate and final goods is the main channel by which Northern robotization impacts welfare in the South, the importance of this channel would be even greater if trade costs were lower.

In addition to the articles mentioned above, this paper adds to a growing literature that

builds on Eaton and Kortum (2002) to examine the implications of different aspects of globalization for welfare and income distribution, including influential contributions by Yi (2003), Dekle, Eaton, and Kortum (2008), Chor (2010), Waugh (2010), Fieler (2011), Arkolakis, Costinot, and Rodriguez-Clare (2012), Ramondo and Rodriguez-Clare (2013), Caliendo and Parro (2015), Donaldson (2018) and Caliendo, Dvorkin, and Parro (forthcoming).[3] Most closely related to this paper, Parro (2012) and Burstein, Cravino, and Vogel (2013) quantify multi-sector variants of Eaton and Kortum (2002) to study the impact of trade in capital equipment on the skill premium. In contrast to this body of work, we focus on the effects of robotization on trade patterns, wages and welfare for a *given level* of trade costs, and we use the model to empirically estimate the causal effects of robots on North-South trade. In addition, we emphasize non-linearities in the degree of substitutability between robots and workers, depending on the range of tasks in which robots have replaced humans and the distance to the robotization frontier. Acemoglu and Restrepo (2017b) explore links between robots and trade across US commuting zones in the context of an extended Armington (1969) model. But, unlike us, they do not focus on the interplay between robots and North-South trade driven by input-output linkages and comparative advantage, do not estimate causal effects of robots on trade flows, and do not explore quantitatively how further advances in robotization are expected to impact international specialization, wages and welfare in the North and the South.

More generally, our paper contributes to a broader literature focusing on links between international trade and technology, including contributions by Freund and Weinhold (2004), Verhoogen (2008), Lileeva and Trefler (2010), Bustos (2011), Bøler, Moxnes, and Ulltveit-Moe (2015), Burstein, Morales, and Vogel (2016), Bloom, Draca, and Van Reenen (2016), Burstein and Vogel (2017), Atkin, Khandelwal, and Osman (2017), Fort (2017), Autor, Dorn, Hanson, Pisano, and Shu (2017), Bastos, Silva, and Verhoogen (2018), Bastos, Dias, and Timoshenko (2018) and Akcigit, Ates, and Impullitti (2018).

The remainder of the paper proceeds as follows. Section 2 outlines the theoretical framework and derives implications for empirical work. Section 3 presents the empirical strategy for examining the causal impacts of robots on trade between developed and developing countries. Section 4 describes the data employed in the empirical analysis, before Section 5 presents the econometric results. Section 6 uses our quantitative model to examine general equilibrium effects of further reductions in robot prices on North-South trade patterns, wages and welfare. Section 7 concludes

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[3]See Eaton and Kortum (2012) for a survey of this literature.

the paper.

2 A Ricardian theory of robots, tasks and trade

We develop a multi-sector, multi-country Ricardian model with two-stage production and trade in intermediate and final goods in which robots can replace labor in a subset of industries. The model builds on Eaton and Kortum (2002), Caliendo and Parro (2015), Artuc and McLaren (2015) and Acemoglu and Restrepo (2017b). We denote countries by m and n and sectors by i. We denote production stages by s, where $s = 1$ refers to intermediate inputs (first stage) and $s = 2$ refers to final goods (second stage).[4] All markets are perfectly competitive. Workers can move freely across stages and sectors but are immobile across countries. Robots are equally available in all countries, at the same (exogenous) rental rate. They are owned by residents of the country that robotizes production.

2.1 Preferences

The representative household in country m maximizes utility by consuming a composite of final good varieties $Q_2^{m,i}$. Preferences are described by a Cobb-Douglas utility function, given by

$$U^m = \prod_i \left(Q_2^{m,i} \right)^{\gamma^{m,i}}, \tag{1}$$

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

2.2 Varieties and production stages

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

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[4]For simplicity, we assume a two-stage production process. However, as discussed below, the key mechanisms we emphasize would also apply in a multi-stage setting. Leading trade theories with multi-stage production include Yi (2003, 2010), Antras and Chor (2013), Antras and de Gortari (2017), Fally and Hillberry (2018) and Lee and Yi (2018).

Production of these varieties, both in the first and second stages, requires three types of inputs: a fixed factor specific to the industry-stage; a composite task input; and a composite first stage output from the same industry, $Q_1^{m,i}$. Thus, a set of tasks are performed on the composite intermediate input with the help of fixed factors to produce variety ω. If ω belongs to stage one, it is used to produce the composite intermediate input $Q_1^{m,i}$; if not, it belongs to the composite final good $Q_2^{m,i}$. Notice that composite $Q_1^{m,i}$ is only used to produce other varieties, while composite $Q_2^{m,i}$ is only demanded by consumers.

The amounts of tasks and fixed factors used in the production of ω are denoted as $T^{m,i}(\omega)$ and $F_s^{m,i}(\omega)$ respectively, where $\omega \in S_s^i$. The production function of variety ω is given by the following Cobb-Douglas technology

$$q^{m,i}(\omega) = z^{m,i}(\omega) \left(F_s^{m,i}(\omega)\right)^{\alpha_F^{m,i}} \left(Q_1^{m,i}(\omega)\right)^{\alpha_M^{m,i}} \left(T^{m,i}(\omega)\right)^{\alpha_T^{m,i}}, \tag{2}$$

where $z^{m,i}(\omega)$ is the productivity drawn from a *Frechet* distribution with shape parameter θ. For simplicity, we assume that fixed factors can be used to produce any variety ω in industry i and stage s. Therefore, they are specific to the industry-stage but not to the variety. The production technology is constant returns to scale, where $\alpha_F^{m,i} + \alpha_M^{m,i} + \alpha_T^{m,i} = 1, \forall\{m,i\}$.

Let $P_s^{m,i}$ denote the price of the composite good from stage s. The cost of producing $z^{m,i}(\omega)$ units of ω can be expressed as a Cobb-Douglas function

$$c_s^{m,i} = \psi_1^{m,i} \left(r_{s,F}^{m,i}\right)^{\alpha_F^{m,i}} \left(P_1^{m,i}\right)^{\alpha_M^{m,i}} \left(w_T^{m,i}\right)^{\alpha_T^{m,i}}, \tag{3}$$

where $\psi_1^{m,i}$ is a fixed constant, $w_T^{m,i}$ is the price of the composite task input, and $r_{s,F}^{m,i}$ is the rental rate of fixed factors.[5]

2.3 Composite intermediate and final goods

Consumers and producers demand varieties and source them both internationally and domestically. Producers in sector i and country m minimize the costs associated with input $Q_1^{m,i}$ by sourcing variety $\omega \in S_1$ from the lowest cost suppliers across all countries.[6] Similarly, consumers demand final good varieties $\omega \in S_2$ from the lowest cost suppliers across all countries.

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[5]Appendix A1 provides the expressions for the price and cost multipliers $\psi_1^{m,i}$, ψ_2^i, ψ_3^i,..., etc. These multipliers are constants which can conveniently be ignored by the reader.

[6]As is standard in trade models, only varieties are traded. Composite intermediate goods are produced using varieties that can be sourced domestically or internationally.

The aggregation process for the composite good of sector i and stage s in country m is given by:

$$Q_s^{m,i} = \left[\int_{S_s^i} \left(q^{m,i}(\omega) \right)^{\frac{\sigma-1}{\sigma}} d\omega \right]^{\frac{\sigma}{\sigma-1}},$$ (4)

where $\sigma > 0$ and $q^{m,i}(\omega)$ is the demand from the lowest cost supplier across countries.

Demand for $\omega \in S_s^i$ is given by

$$q^{m,i}(\omega) = \left(\frac{p^{m,i}(\omega)}{P_s^{m,i}} \right)^{-\sigma} Q_s^{m,i},$$ (5)

where unit price of the composite stage s good is $P_s^{m,i}$.

The lowest price for $\omega \in S_s^i$ across all suppliers is:

$$p^{m,i}(\omega) = \min_n \left\{ \frac{c_s^{n,i} \tau^{m,n,i}}{z^{n,i}(\omega)} \right\},$$ (6)

where $\tau^{m,n,i}$ denotes trade costs between origin n and destination m.

The price of the composite good of sector i and stage s can be expressed as the following function:

$$P_s^{m,i} = \psi_2^i \left[\sum_n \left(\psi_1^{n,i} \tau^{m,n,i} \left(r_{s,F}^{n,i} \right)^{\alpha_F^{n,i}} \left(P_1^{n,i} \right)^{\alpha_M^{n,i}} \left(w_T^{n,i} \right)^{\alpha_T^{n,i}} \right)^{-\theta} \right]^{-\frac{1}{\theta}}.$$ (7)

From (7) it is clear that the price of this composite good is positively associated with trade costs, factor prices and the price of the intermediate composite in the supplier country.

2.4 Robots and tasks

The production of composite task input for variety ω requires performing tasks $k \in [0,1]$. We assume that tasks from 0 to K^i can be performed by robots or humans, while tasks between K^i and 1 can only be performed by workers. In some industries, robotization is not feasible, and hence $\exists i : K^i = 0$. The subset of tasks that can be robotized is thus given by K^i, while the subset of tasks that cannot be robotized is given by $1 - K^i$. We denote the automatable tasks with T_A and non-automatable tasks with T_N. We assume that the robotization frontier and the

productivity of robots are industry specific, but not stage specific.[7]

We denote labor and robots with subscripts L and R respectively. In order to perform one unit of task k of variety ω within industry i, $\phi_L^i \zeta_L(k)$ labor units are required. If $k < K^i$, then alternatively $\phi_R^i \zeta_R(k)$ robot units can perform the same task. The wage per unit of labor is denoted by w_L^m, while the rental rate of one robot unit is denoted by w_R. We assume that $\zeta_R(k)$ and $\zeta_L(k)$ are distributed $Weibull$ with shape parameter ν.

Thanks to the distributional assumptions, the optimal set of tasks performed by robots is given by a simple expression:

$$K_R^{m,i} = \frac{(\phi_R^i w_R)^{-\nu}}{(\phi_R^i w_R)^{-\nu} + (\phi_L^i w_L^m)^{-\nu}} K^i, \tag{8}$$

where $K_R^{m,i}$ depends only on: (i) the automation frontier, K^i, (ii) the elasticity of substitution between robots and workers, $1 + \nu$; and (iii) the productivity-adjusted relative price of workers and robots, $\phi_L^i w_L / \phi_R^i w_R$. Producers use robots if $\zeta_L(k)\phi_L^i w_L / \zeta_R(k)\phi_R^i w_R > 1$ for a given task k, and employ workers otherwise. The top panel of Figure 1 displays the relationship between these productivity-adjusted relative prices (on the vertical axis) and the set of tasks performed by robots (on the horizontal axis). In equilibrium, the set of robotized tasks is given by $K_R^{m,i}$. A decline in the rental rate of robots, w_R, leads to an increase in the number of robotized tasks.

The average unit cost of tasks from 0 to K^i is given by the following CES function:

$$w_{T_A}^{m,i} = \psi_3^i \left((\phi_R^i w_R)^{-\nu} + (\phi_L^i w_L^m)^{-\nu} \right)^{-\frac{1}{\nu}}, \tag{9}$$

and depends on wages, the unit cost of robots, and the elasticity of substitution between robots and workers. Since tasks between K^i and 1 can only be performed by workers, their average cost is given by

$$w_{T_N}^{m,i} = \psi_3^i \phi_L^i w_L^m, \tag{10}$$

where $w_{T_A}^{m,i} < w_{T_N}^{m,i}$. Thus, the average cost of tasks that can be robotized is always smaller than the average cost of tasks that cannot be robotized.

Using (8)-(10), the relative cost of producing one unit of task with and without robots can be

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[7]It is straightforward to relax this assumption and make robotization stage-specific. We chose to model robotization as a stage-neutral process due to lack of information on how robots are allocated across production stages within industries.

expressed as:

$$\Omega^{m,i} = \psi_5^i \frac{w_T^{m,i}}{w_L^m},$$

$$= 1 - K^i + K^i \left(1 - \frac{K_R^{m,i}}{K^i}\right)^{\frac{1}{\nu}}, \tag{11}$$

where ψ_5^i is a constant. The relative cost variable in (11) is equal to one if there is no robotization, and it is minimized if robot rental rate is zero. Related to the cost reduction variable, equilibrium labor demand per unit of task can be expressed as

$$\Xi^{m,i} = \psi_5^i \frac{L^{m,i}}{T^{m,i}},$$

$$= 1 - K^i + K^i \left(1 - \frac{K_R^{m,i}}{K^i}\right)^{1+\frac{1}{\nu}}. \tag{12}$$

where $T^{m,i}$ is the total task output and $L^{m,i}$ is the total labor demand in industry i of country m.[8]

While $\Omega^{m,i}$ is the price of a task relative to wages, $\Xi^{m,i}$ is the number of workers demanded in equilibrium to produce a unit of task. Using these two variables, it is possible to express tasks and task prices in terms of labor and wages, and substitute out robot demand. Note that the cost share of robots in the total cost of all tasks will be simply equal to $1 - \frac{w_L^m L^{m,i}}{w_T^{m,i} T^{m,i}} = 1 - \frac{\Xi^{m,i}}{\Omega^{m,i}}$. Equations (8), (11) and (12) show the relationship between wages, cost of tasks, labor demand and task demand for given robot prices and robotization frontier.

A reduction in robot prices leads to a decline in the cost of production between tasks 0 and K^i, thereby lowering the average cost of production. This cost reduction will change relative production costs across countries. Some varieties that were previously imported can now be sourced domestically. We can express the new unit price function as

$$c_s^{m,i} = \psi_4^{m,i} \left(r_{s,F}^{m,i}\right)^{\alpha_F^{m,i}} \left(P_1^{m,i}\right)^{\alpha_M^{m,i}} \left(\Omega^{m,i} w_L^m\right)^{\alpha_T^{m,i}}, \tag{13}$$

where $\Omega^{m,i} \in [0,1]$ is the cost reduction implied by robotization from (11), with costs reductions decreasing in $\Omega^{m,i}$.[9]

The bottom panel in Figure 1 shows how $\Omega^{m,i}$ and $\Xi^{m,i}$ change as the rental rate of robots

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[8]See Appendix A.2 for the definition of ψ_5^i and the derivation of (11) and (12).

[9]That is, $\Omega^{m,i} = 1$ implies no cost reduction, while $\Omega^{m,i}$ closer to 0 denote larger costs reductions.

declines. As w_R decreases the average cost of performing tasks declines (i.e. $\Omega^{m,i}$ falls). This also means that wages relative to the unit cost of tasks increase. However, at the same time, demand for labor for a given number of tasks also declines (i.e. $\Xi^{m,i}$ falls). This decline in labor demand is faster than the decline in unit cost, which can potentially push the wages down and decrease employment in the robotized sector. However, with lower costs, production in the robotized industry also increases, which can raise labor demand and therefore wages. The direction and the magnitude of the impact of robotization on sectoral employment and wages is thus theoretically ambiguous.

2.5 Prices and international trade

Using (7) and $\Omega^{m,i}$, the price of the composite good from industry i and stage s can be expressed as

$$P_s^{m,i} = \psi_2^i \left[\sum_n \left(\psi_4^{n,i} \tau^{m,n,i} \left(r_s^{n,i} \right)^{\alpha_F^{n,i}} \left(P_1^{n,i} \right)^{\alpha_M^{n,i}} \left(\Omega^{n,i} w_L^n \right)^{\alpha_T^{n,i}} \right)^{-\theta} \right]^{-\frac{1}{\theta}}. \tag{14}$$

Therefore, we can now express the price of composite good as a function of wages, w_L^n (which can be measured). In each country, varieties are sourced from the country that charges the lowest price. The probability that country n charges the lowest price in country m for a stage s variety is given by

$$\pi_s^{m,n,i} = \left(\frac{\psi_4^{n,i} \tau^{m,n,i} \left(r_{s,F}^{m,i} \right)^{\alpha_F^{m,i}} \left(P_1^{n,i} \right)^{\alpha_M^{n,i}} \left(\Omega^{n,i} w_L^n \right)^{\alpha_T^{n,i}}}{P_s^{m,i} / \psi_2^i} \right)^{-\theta}. \tag{15}$$

Equation (15) represents the relative demand for each country in stage s of sector i. It is analogous to the gravity equation derived in Eaton and Kortum (2002) and others, with an additional variable measuring the *cost reduction implied by robotization*, $\Omega^{m,i}$. We present the equilibrium conditions and close the model in the next subsection.

2.6 Equilibrium

The value of output in country m stage s and industry i is denoted by $Y_s^{m,i}$. Total demand for $Q_s^{m,i}$ is given by the sum of demand by wage earners, fixed factor owners, producers and robot

owners. Consumer demand for final good varieties of sector i is given by

$$Q_2^{m,i} = \frac{1}{P_2^{m,i}} \gamma^{m,i} \sum_j \sum_s \left(\alpha_T^{m,j} + \alpha_F^{m,j} \right) Y_s^{m,j}, \tag{16}$$

The first-stage composite output is demanded for production of variety ω in both stages. Because of the Cobb-Douglas structure, total demand for the first-stage composite is a share of the total production in sector i:

$$Q_1^{m,i} = \frac{1}{P_1^{m,i}} \sum_s \alpha_M^{m,i} Y_s^{m,i}, \tag{17}$$

The expenditure of country m on country n output in industry i is given by

$$Y_s^{m,n,i} = \pi_s^{m,n,i} Y_s^{m,i}, \tag{18}$$

where

$$\begin{aligned} Y_s^{m,i} &= \sum_n Y_s^{m,n,i} \\ &= P_s^{m,i} Q_s^{m,i}. \end{aligned} \tag{19}$$

The balance of trade is given by

$$B^m = \sum_n \sum_s Y_s^{n,m,i} - \sum_n \sum_s Y_s^{m,n,i}, \tag{20}$$

and is assumed to be constant.

Nominal factor prices (the rental rate for fixed factors and the wage rate) can be expressed, respectively, as:

$$r_{s,F}^{m,i} = \frac{\alpha_F^{m,i} Y_s^{m,i}}{F_s^{m,i}}, \tag{21a}$$

$$w_L^m = \frac{\alpha_T^{m,i} Y_s^{m,i}}{L_s^{m,i}} \frac{\Xi^{m,i}}{\Omega^{m,i}}, \tag{21b}$$

where $\Xi^{m,i}$ is a measure of labor demand, as defined in (12) and derived in Appendix A2. The total number of workers in each country is fixed $L^m = \sum_i \sum_s L_s^{m,i}$. Since workers are perfectly mobile, wages are equalized across sectors and production stages.

The consumer price index in country m is given by

$$P^m = \exp\left(\sum_j \gamma^{m,j} \log P_2^{m,j}\right). \tag{22}$$

2.7 Implications of robotization for North-South trade within industries

As shown in (8), the subset of tasks subject to robotization (thus the number of robots) is inversely related to the rental rate of robots, w_R, and positively associated with wages w_L^m. A fall in the rental rate of industrial robots initially induces robotization in more developed countries, where the cost of labor is relatively higher to begin with. This shift influences relative production costs across countries ($\Omega^{m,i}$ declines more in countries with higher wages), thereby impacting trade patterns. Robots replace domestic labor within sectors, leading to lower costs of production in the North, and hence to an increase in exports to the South. The effect of Northern robotization on imports sourced from the South is theoretically ambiguous. On the one hand, robotization makes Northern producers more competitive, which implies that some varieties that were previously imported from the South are now sourced domestically. On the other hand, robotization leads to an expansion in the scale of production, which raises the demand for first-stage varieties sourced from the South.[10] Notice that robotization impacts productivity gains through both the fall in $\Omega^{m,i}$ and robot-induced fall in input prices, $P_1^{m,i}$.

3 Econometric method

Motivated by our theory, we now describe the econometric strategy for examining whether and how the adoption of industrial robots in advanced economies impacted trade flows with developing countries within industries. We adopt the following baseline econometric specification:

$$Trade_{nmit} = \beta Robots_{nit} + \Psi_{nmt} + \Lambda_{it} + \epsilon \tag{23}$$

where $Trade_{nmit}$ denotes the log of (1+ exports) from developed country n to developing country m in sector i and year t or alternatively the log of (1+imports) sourced from developed country

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[10]For simplicity, we assume a two-stage production process. However, the key mechanisms we emphasize would also apply in a multi-stage setting. As long as the South has a comparative advantage in some intermediate stages of production, a robot-induced expansion in Northern production would raise the demand for Southern inputs. At the same time, the shift in relative production costs implied by robotization would reduce the demand for imports from the South. The net effect on imports from South is generally ambiguous.

n in sector i and year t; $Robots_{nit}$ denotes a measure of robot usage in country n in sector i in year t; Ψ_{nmt} denotes a fixed effect by exporter-importer-year; Λ_{it} denotes an industry-year fixed effect; and ϵ the error term. We include exporter-importer-year fixed effects both to allow for pair-specific shocks (such as fluctuations in income, population and exchange rates) and to control for country pair specific determinants of trade (e.g. distance, having a common language etc.). We further include industry-year fixed effects to account for factors that are specific to each industry in each year. Standard errors are clustered by developed country.

An important concern is that robotization is potentially endogenous. It may be a response to, rather than a cause of, changing trade patterns. For example, increased trade may influence the decisions of Northern producers to robotize their production. Indeed, existing evidence suggests that increased trade may drive technology adoption through several channels, and in different directions. Using data for Europe, Bloom, Draca, and Van Reenen (2016) find that greater import competition from China is associated with higher patenting, expanded investment in IT and higher TFP. Conversely, Autor, Dorn, Hanson, Pisano, and Shu (2017) find that increased Chinese competition led to a reduction in firm-level and technology class-level patent production in the US; while Pierce and Schott (2018) find that US industries more exposed to increased import competition experienced a relative decline in investment. The implications of increased exports to the South for technology adoption are also ambiguous. Although a body of evidence suggests that exporting has positive effects on technology adoption (Lileeva and Trefler, 2010; Bustos, 2011; Atkin, Khandelwal, and Osman, 2017), a related strand of work suggests that such effects may depend on the income level of export destinations. In particular, exporting to less developed countries might lead to an expansion of less technology-intensive production lines within firms (Verhoogen, 2008; Bastos and Silva, 2010; Bastos, Silva, and Verhoogen, 2018).

To address this possibility of reverse causality in the relationship between robotization and trade, as well as biases caused by omitted variables or measurement error, we adopt an instrumental variables approach. Specifically, we use the triple interaction between the (pre-determined) share of workers engaged in replaceable tasks in each sector, the country's initial income per capita, and the global stock of robots as instrument for robotization. Alternatively, we use industry-level trends in robot adoption in other countries with similar levels of income as instrument for own robotization.

4 Data and descriptive statistics

4.1 Data sources

The empirical analysis in this paper combines and examines several sources of panel data for the period 1995-2015, which we can link through a consistent definition of industries. In this section, we provide a brief description of each data source, while giving further details in Appendix B.1.

The stock of industrial robots by industry, country and year comes from the International Federation of Robotics (IFR). These data are based on yearly surveys of robot suppliers, and cover about 90 percent of the industrial robots market. The IFR measures both deliveries and stocks of "multipurpose manipulating industrial robots" based on the definitions of the International Organization for Standardization.[11] The data are disaggregated roughly at the three-digit level for manufacturing and roughly at the two-digit level for non-manufacturing activities. The IFR data are regarded as the best source of information on industrial robots (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2017b). Nonetheless, these data have some limitations. First, about 30 percent of industrial robots are not classified into any industry. Following Acemoglu and Restrepo (2017b), we allocate these unclassified robots to industries in the same proportion as observed in the classified data. Second, the IFR data do not cover "dedicated industrial robots", which are defined as automatically controlled machines for only one industrial application. Third, the IFR data have incomplete coverage for a number of countries; as a result our panel is unbalanced. We construct the robot stock for each country-sector-year using the perpetual inventory method assuming a depreciation rate of 10%. We prefer this measure over the measure of the robots stock reported by the IFR because that measure assumes that robots do not depreciate for a period of 12 years, yet lose all their economic value after exactly 12 years. We believe that gradual depreciation is a more plausible description of reality, but use the IFR measure of the robots stock in our robustness tests.

We complement the IFR data with information on labor hours, material inputs, IT capital, and non-IT capital by industry-country-year from EU KLEMS. These data were originally reported for 28 industries, which were mapped into the 16 sectors we use in the analysis. Table A1 in the Appendix provides details on the exact correspondence we employed.

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[11]According to this definition, a machine is considered to be an industrial robot if it is an "Automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which may be either fixed in place or mobile for use in industrial automation applications". Each element of the definition is essential for a machine to be considered an industrial robot. Common applications of industrial robots include assembling, dispensing, handling, processing, and welding (all of which are common in manufacturing).

Following Graetz and Michaels (2018), we constructed an industry-level measure of replace-ability using data from IFR on robot applications, the US census of occupational classifications and the distribution of hours worked across occupations and industries from the 1980 US Census. The IFR distinguishes between different applications of robots, including (among others) welding, processing, and assembling (International Federation of Robotics, 2012). Using the 2000 Census three-digit occupations, we assign a replaceability value of one to a three-digit occupation if the name and/or description of at least one of the five-digit occupations included in it contains at least one of the IFR application categories and zero otherwise. We assume that services occupations are not replaceable by industrial robots and remove occupations that our text analysis algorithm identifies as being potentially replaceable by robots but we believe are not, such as "agricultural inspectors" and "artillery and missile officers". We then map our replaceability measure into the 1990 Census occupational classification, which is available for the 1980 and 2000 censuses. If several 2000 occupations map into one 1990 occupation, then we assign the 1990 occupation a replaceability value of one if and only if at least one of the corresponding 2000 occupations has a value of one. To measure replaceability at the industry level, we first assign these variables to each individual in the 1980 IPUMS Census based on their reported 1990 occupation. We then assign to each individual one of our 28 EU KLEMS industries based on a crosswalk to the 1990 Census industry classification. We compute the fraction of replaceable hours for each of the 16 industries by dividing the sum product of replaceability and annual hours worked by the total sum of hours worked (applying person weights both when computing the numerator and the denominator). The replaceability values represent an upper bound to the share of hours that may be performed by robots—occupations are classified as replaceable even if only a small proportion of their work can be replaced by robots.

We combined this information with product-level bilateral data on trade and import tariffs. Trade data come from BACI, the World trade database developed by CEPII, building on original data provided by the COMTRADE database of the United Nations Statistical Division. These data contain annual information on bilateral exports and imports at the HS 6-digit product disaggregation for 224 countries. In our final estimation sample we focus on trade between 26 OECD countries for which we have both EU KLEMS and IFR data (Northern countries), and 181 non-OECD (Southern countries). We exclude from our analysis OECD countries for which we do not have either IFR or EU KLEMS data. Annual data on bilateral applied tariffs by country and product (SITC 2-dig., Rev. 4) come from the TRAINS database of the United Nations Conference

on Trade and Development. The tariff data are generally available for the period of analysis, but the extent of time coverage differs considerably across countries. The product-level trade and tariff data were also mapped into the 16 sectors we use in the analysis, as detailed in Table A1 in the Appendix.

4.2   Descriptive statistics

To set the stage for the analysis that follows, we first document trends in robotization. Robot utilization varies widely not only across sectors, but also across countries. Figure 2 plots the evolution of robot adoption by country, and shows that robotization is most advanced in high-wage countries such as Germany, Denmark and Belgium. It also shows that robotization remains limited in lower wage countries such as Romania and Bulgaria, though these countries are adopting progressively more robots. Figure 3 provides evidence that robot adoption across countries is closely aligned with GDP per capita. This evidence is consistent with the prediction of our theoretical model that incentives for robot adoption are greater among countries with higher productivity and labor costs.

Figure 4 shows the evolution of the stock of robots per million hours across sectors. Automotives, rubber and plastics, and metal are the sectors in which robotization is most pronounced and has been advancing most rapidly. By contrast, the adoption of industrial robots in education, agriculture, construction, utilities and other non-manufacturing sectors remains limited. These differences in the extent of robot adoption across sectors reflect in part the technological feasibility adoption. Figure 5 plots average adoption of robots across sectors over our entire sample period against the share of jobs in a sector that are replaceable. The association between adoption and replaceability is clearly positive, with sectors where a larger share of tasks can potentially be performed by robots indeed using more robots, as also shown by Graetz and Michaels (2018).

In sum, robot adoption has increased significantly over time, although at different speeds in different countries and sectors, which is convenient for identification. Figures A1 and A2 in the Appendix display clearly the extent of variation in robot adoption across sectors, countries and time. In addition, the strong correlations of robot usage with both replaceability and initial GDP per capita suggest the triple interaction between the degree of sectoral replaceability, the initial GDP per capita and the price of robots (proxied by the global robot stock) is a suitable instrument for robotization. Indeed, Figures A3 and A4 in the Appendix show that the change in robot density observed between the initial and final years of our sample period is positively

correlated with initial income per capita and the share of replaceable tasks in the sector.[12]

5 Partial equilibrium estimates: Robots and North-South trade

This section reports the OLS and IV estimates of the effects of robotization in advanced economies on their exports and imports with less developed countries.

5.1 Baseline estimates

Table 1 reports our baseline estimates of how robotization in Northern countries impacted their trade with non-OECD countries. All specifications control for importer-exporter-year fixed effects as well as industry-year fixed effects. Standard errors are clustered by Northern country. Our main result is that robotization in the North catalyzes trade by inducing a significant increase in imports from and an even bigger surge in exports to non-OECD countries. As a consequence, net imports from these countries decline significantly. According to our OLS estimates a 10 percentage points increase in the number of robots per million hours in developed countries is associated with both a 1.5 percentage points increase in imports from non-OECD countries and a 4.1 percentage points increase in exports to non-OECD countries, as shown in columns (1) and (2) respectively. Net imports from the South would thus reduce by 2.6 percentage points, as is documented in column (3).

The estimated association between robot intensity and trade flows strengthens substantially when the extent of robotization is instrumented using the triple interaction between the share of jobs in a sector that are replaceable (which serves as a proxy for the technological feasibility of robotization), a country's initial GDP per capita (which serves as a proxy for labor costs and hence the economic incentives to robotize) and the global robot stock (which serves as a proxy for the rental rate of robots). The estimates in columns (4)-(6) suggest that a 10 percentage points increase in robot adoption is now associated with a 6.1 percentage points increase in imports from and a 11.8 percentage points increase in exports to non-OECD countries. Net imports would fall by 5.7 percentage points. The fact that IV estimates are higher than OLS estimates could reflect a local average treatment effect or attenuation bias associated with measurement error in our robotization variable, and lends credence to a causal interpretation of the association between robotization and trade. Note also that our instrument performs well and strongly predicts robot

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[12]Figures A3 reveals that Denmark is an outlier with regard to changes in robot density. The econometric results reported below do not depend on its inclusion in the estimation sample.

adoption: the Kleibergen-Paap statistic is 111.8.

5.2 Robustness

In this section we report the results of several robustness tests to our baseline analysis. A potential concern about the baseline results is that the association between trade and robotization could reflect complementary investments in other forms of technological progress and/or changes in the intensity of material inputs or capital usage. To assess this possibility, in Table 2 we add to the baseline specifications presented in Table 1 controls for ICT capital, non-ICT capital and material inputs. We also control for bilateral import tariffs applied by developed countries. The inclusion of these controls does not appreciably alter the estimated magnitude of the association between robot adoption and trade flows.

Another potential concern is that the baseline estimates might be driven by a select few sectors. To assess whether this is the case, in Table 3 we exclude the automotive, rubber and plastics, and metal industries, the three sectors in which automation is most widespread. If anything, excluding these sectors magnifies the estimated elasticity of trade flows with respect to robot use. Moreover, results remain statistically significant.

Our baseline estimation period includes the great depression of 2008/2009. We therefore worry that our results might be influenced by cyclical variations associated with the crisis. To address this concern, Panel A in Table 4 restricts the sample to the pre-crisis (i.e. pre 2008) period, whereas panel B presents estimates for the post-crisis (i.e. post 2009) period. The results suggest that the estimated impact of robotization on trade was qualitatively similar in the pre- and post-crisis periods. In both cases, the estimates of the relationship between robot adoption and trade suggest that robotization catalyzes trade, but reduces net imports from developing countries.

As an additional robustness check, we use variations over longer time periods (i.e., over 5-year intervals) for identification, instead of the yearly variation we exploit in the baseline analysis. The results are presented in Table A3 in the Appendix. Reassuringly, they are qualitatively similar to those of the baseline analysis. In Table A4 in the Appendix, we assess the sensitivity of the results to using an alternative proxy for automation. Specifically, we use the natural log of the IFR stock of robots per million hours worked, instead of the robot stock we constructed using the perpetual inventory method. The results obtained using this alternative measure are very similar to those obtained using our preferred measure. In Table A5, we assess the impact of extreme values by excluding the top 1% of observations of both the automation and each of the dependent

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variables. The estimates remain very similar, suggesting that our baseline estimates are not driven by outliers. In Table A6, we use the inverse hyperbolic sine of the regression variables (instead of adding one and taking the log) to account for zeros. The results are robust to this alternative transformation.

Finally, in Table 5 we consider specifications using alternative instruments, notably average robot usage per million hours in the same sector in countries at very similar levels of GDP per capita. This alternative IV strategy follows closely that adopted by Acemoglu and Restrepo (2017b) in their analysis of the local labor market impacts of robotization in the US. We report results both when instrumenting robot intensity with robotization in the two most similar countries in terms of GDP per capita as well as the four most similar countries. Both instruments perform reasonably well, in the sense that they have explanatory power in predicting robotization (albeit that they are significantly weaker than our preferred instrument). The resulting coefficient estimates are marginally different from those obtained using our preferred IV, but the overall pattern of results remains essentially unchanged.

Overall, these results provide robust evidence that robot adoption by Northern producers stimulates their imports from less developed countries and has an even larger impact on their exports to developing countries, such that their net imports from developing countries decline.

5.3 Heterogeneity and mechanisms

We proceed by examining the extent to which our baseline estimates vary with stage of development among non-OECD countries. To this end, Table 6 splits the sample into high-income non-OECD trading partners (Panel A) and the remainder countries, i.e. low and middle income nations, which comprise the bulk of our sample (Panel B). The estimates reveal that robotization significantly promotes both imports from and exports to both sets of countries. They further suggest that the positive impact of robotization on imports is especially pronounced in high-income non-OECD countries. According to our preferred IV estimates these effects are even stronger than the impact on exports to high-income trading partners. The null hypothesis that automation did not impact net imports from high-income non-OECD destinations is not rejected. By contrast, net imports from low- and middle-income destinations are significantly negatively correlated with robotization in the North.

In our theory, trade in intermediate goods is the key channel whereby robotization may stimulate imports from the South. To assess the extent to which the data provide support to this

mechanism, we examine if the effects of robotization on imports are heterogeneous across intermediate and other goods. Although it is empirically challenging to precisely identify imports of intermediate goods (and distinguish them from imports of other goods), we use two product-level classifications that have been widely adopted in the literature to achieve this objective. First, the BACI data set makes it possible to distinguish between intermediate inputs from other goods using the Broad Economic Categories Classification of the UN (see Appendix B.1 for details). Second, we adopt the approach proposed by Schott (2004), who identifies as inputs only those goods for which the product codes explicitly contain the words "parts" or "components". For both these classifications, the IV estimates in columns (2) and (4) in Table 7 reveal that robotization has a considerably stronger positive impact on imports of intermediate than on other goods.

6   Counterfactual simulations

In this section, we use our theory to perform counterfactual simulations on the general equilibrium effects of reductions in robot prices on trade patterns, wages and welfare in the North and the South. To approximate the setting we explored in the regressions, we calibrate a model with three countries and three sectors. We consider a representative high-income Northern country, a representative country in the South, and a group of other (lower-income) developed countries. The existence of a group of other developed countries allows us to examine the extent to which the quantified model is able to reproduce the relative trade effects we documented in the regressions.[13]

Among the three sectors considered, two sectors are tradable and the other sector is non-tradable. Production may be subject to robotization only in one of the tradable sectors. This sector consists of automotive, rubber and plastic, electronics, chemicals, metal and machinery industries. The non-robotized tradable sector consists of all other manufacturing industries, including food and textiles, agriculture, mining and utilities. The non-tradable sector consists of construction and services.

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[13]If we were to aggregate all groups, the North would account for more than 50% of world GDP, and the bulk of world trade would occur within the North. This setting would underrepresent the importance of North-South trade, and trade as share of GDP would be very small. To avoid this aggregation bias, we construct instead representative countries in the North and the South. Considering a relatively large group of other developed countries is also important to allow for the possibility that competitiveness gains associated with robot adoption in the North translate into higher demand for its final-goods exports.

6.1 Data and calibration

We use the World Input Output Database (WIOD) to calibrate international trade, production functions and labor shares. In the baseline simulation, we use WIOD data for 2005 to calibrate initial trade patterns. We group countries into three broad categories, based on their income per capita, robot density and data availability. The group of countries in the North is composed of Belgium, Germany, Denmark, Finland, France, Italy, Netherlands, Sweden and the United States. The group of countries in the South is composed of Brazil, China, India, Indonesia, Mexico, Turkey and Taiwan, China. Based on these two groupings, we construct the representative countries in the North and South. The group of other developed countries results from the aggregation of other OECD and EU countries for which data are available in WIOD. This group consists of Australia, Austria, Bulgaria, Canada, Czech Republic, Spain, the United Kingdom, Greece, Croatia, Hungary, Ireland, Portugal, the Slovak Republic, Poland, Norway and Switzerland.[14] As detailed in Appendix B3, we have performed robustness checks using a variety of alternative groupings, and found that the results are qualitatively robust.

In the model, workers are perfectly mobile across sectors. Wages are therefore similar across sectors within countries, but differ across countries due to productivity differences. We assume that initial wages are proportional to the average GDP per capita of each group in thousands of U.S. dollars. We set initial wages to 39.5 in the North, 26.7 in Other, and 5.7 in the South. According to our calculations, the average ratio of replaceable tasks in the robotized tradeable sector defined above is approximately 50%, thus we set $K^i = 0.5$ for this sector and set $K^i = 0$ for the non-robotized sector.[15] We assume that the effective initial robot price (rental rate) is equal to 59, i.e. $\frac{\phi_R^i}{\phi_L^i} w_R = 59$. This parameterization ensures that initial robotization in the North is equal to that observed in the data, whereas robotization in Other and South is negligible.[16] We then examine the effects of exogenous reductions in the effective rental rate of robots, from the initial level to 5. This decline in the effective rental rate of robots can be caused by a decline in nominal robot prices and/or an increase in the productivity of robots. We assume that the first and second stage have similar production processes. We calibrate the labor share using information

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[14]We excluded small countries (with population up to 3 million) and the Russian Federation (which is neither a member of the OECD nor the EU). We also excluded the Republic of Korea and Japan, which have high robot stocks according the IFR, but were not included in the empirical analysis due to lack of data on labor hours by industry.

[15]We also experimented with $K^i = 0.8$ for the robotized sector and the qualitative implications were unchanged.

[16]We assume that the price of one robot is equal to $125,000, that robots can work 365 days per year and 24 hours per day, and can be rented for 10% of their price for a year. Then the implied cost of robots relative to the cost of tasks in robotized sector is equal to 1.3% both in the IFR data and in the calibrated model.

on the wage bill from WIOD. The fixed factor share is set to be equal to one minus the labor and intermediate input share. We take the number of workers in each sector from WIOD and assume that the share of workers in the first and second stages is proportional to the relative size of each stage. Since the utility function is assumed to be Cobb-Douglas, the elasticity of substitution between composites of different sectors is equal to one. The Cobb-Douglas shares are calibrated from WIOD. We set the elasticity parameter $\theta = 5$, so that the trade elasticity is equal to -6. We assume that the elasticity of substitution between robots and workers is high and equal to 10, thus we set $\nu = 9$.[17] Appendix B3 provides details on the data and additional parameters we use to calibrate the model, the solution method, and robustness checks.

6.2 Effects of Northern robotization on North-South trade

We first examine if the calibrated model is able to qualitatively reproduce the key empirical findings we documented above. The upper-left panel of Figure 6 shows how increased robot density in the North in the tradeable sector in which automation is feasible impacts exports to the South. The diagram depicts the percentage change of exports from North to South (relative to the exports from other countries to the South) in the industry that is subject to robotization. Consistent with the regressions discussed in section 5, the quantified model reveals that increased robotization in the North (reflecting a fall in robot prices) leads to a relative expansion of exports to the South. This effect is driven by robot-induced gains in Northern competitiveness in this industry. Perhaps more surprisingly, the upper-right panel of Figure 6 shows that the South also experiences a relative increase in sectoral exports to the North (relative to the exports of other countries to the North). This expansion is driven by the growth of exports of intermediate inputs, reflecting increased demand for these goods by final good producers in the North. The model is therefore able to replicate the main empirical finding reported in the previous section. Importantly, the lower panel of Figure 6 reveals that these relative trade impacts reflect a surge in North-South trade flows not only in relative, but also in absolute terms. Total trade flows increase: the lower-left panel of Figure 6 shows that Northern robotization leads to an increase in the value of exports from North to South; the lower-right panel shows that it also leads to an increase in the value of exports from South to North, which is driven by the expansion of

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[17]Although there are no explicit estimates of the elasticity of substitution between robots and workers in the literature, they are perceived to be highly substitutable. Acemoglu and Restrepo (2017b) assume that the elasticity is infinite. As detailed in Appendix B3, we performed sensitivity tests using different values for this elasticity, and found that the results remain qualitatively unchanged.

intermediate goods trade.

6.3 Effects of robot price reductions on trade, wages and welfare

Like in the IV regressions presented above, in our model the relative increase in robot density observed in Figure 6 results from the interaction between an exogenous decline in robot prices, differences in labor costs across countries (reflecting productivity differences) and the sector-specific robotization frontier. The upper-left panel of Figure 7 shows how a reduction in robot prices impacts robot adoption (as proxied by robots per worker) in the sector in which automation is feasible. The upper-right panel shows how falling robot prices influence the response of the ratio between the unit cost of tasks and the wage rate. We observe that a fall in robot prices (common to all countries) initially leads to increased adoption in the North, where the cost of labor (and thus the cost saving associated with robotization) is relatively higher to begin with. As robot prices decline further, the other (lower-income) developed countries also begin to adopt. Interestingly, the quantified model suggests that robotization will only become profitable in the South in the face of a very substantial decline in robot prices.

The lower-left panel in Figure 7 indicates that increased robot adoption in the North initially depresses labor demand, and thereby leads to a fall in the real wage of Northern workers (lower-right panel). As the price of robots declines, a larger share of tasks previously performed by humans is now performed by robots. Workers are therefore displaced from the sector that is subject to automation and must seek employment in other sectors of the economy. While overall production expands as a result of increased robot adoption, aggregate labor demand falls during this process, depressing real wages in the North. Interestingly, however, Figure 7 points to an important non-linearity in the relationship between wages and robot prices: as robot prices decline further, Northern wages start recovering and eventually rise above the level that was observed initially. While robot adoption deepens in the North, production in the robotized sector continues to expand, thereby raising demand for the tasks in which robotization is technologically unfeasible. As we move closer to the robotization frontier in the sector, this effect fully offsets the direct negative impact of robots on sectoral labor demand. Eventually, the share of labor in the robotized sector starts to expand, thereby raising aggregate labor demand and wages in the North. Aggregate welfare in the North always increases, as the income losses associated with lower labor income are more than offset by the gains associated with increased production, lower consumer prices and increased income from the rental rate of robots (Figure 8).

Even if production in the South is not subject to robotization, real wages and welfare are impacted by Northern automation. Increased robotization and reduced wages make Northern producers more competitive. This leads to an increase in Northern exports in the robotized industry, and to a corresponding reduction in final goods exports from the South in this sector. At the same time, the South expands its exports of intermediates in this sector. Both total real exports and exports measured as a share of GDP increase in the South (see top panels of Figure 8). As shown in Figures 7 and 8, real wages and welfare tend to increase in the South, reflecting also lower consumer prices. These effects are reinforced when robot prices decline further and the other countries in the North also find it optimal to robotize their own production. Welfare gains in the South are likely to be even more pronounced if robotization also becomes feasible there.

6.4 The role of trade frictions

As emphasized above, trade in intermediate and final goods is the key channel whereby Northern robotization impacts real wages and welfare in the South. A natural question is, then, how trade costs modulate the impact of robot price reductions on Southern workers and consumers. To answer this question, we perform counterfactual simulations on the effects of robot price reductions under two different trade cost scenarios. First, we consider a frictionless trade scenario, in which trade frictions are assumed to fall down to zero (from the level that was initially observed in the 2005 data). We then compute the new equilibrium associated with frictionless trade, and examine the effects of reductions in robot prices from this point. Similarly, we consider a high trade costs scenario, in which the level of trade frictions are assumed to be twice of the level that was initially calibrated.

Figure 9 displays the effects of Northern robotization on North-South trade under the frictionless trade regime. The figure reveals that the effects of Northern robotization on exports to the South in this sector remain qualitatively similar, but the rate of change is now considerably higher. Robotization still makes final-goods producers in the North more competitive, and the associated impact on their exports is now considerably higher. At the same time, the automation-induced expansion of production continues to have a positive effect on exports of intermediates from the South to the North. The magnitude of this effect is now considerably stronger, generating a sizable impact on total exports from the South to the North in the robotized sector.

Figure 10 depicts the impacts of robot price reductions on robot use, labor allocation, wages and real GDP under frictionless trade. Interestingly, we observe that robot price reductions lead

to relatively lower robot use by other countries than in the baseline simulations. Under frictionless trade, production in other countries is less shielded from Northern competition in the robotized sector. Therefore, there is more scope for robot-induced changes in international specialization, implying that robot adoption in this sector proceeds at a relatively slower pace. At the same time, the positive effects of Northern robotization on real wages and welfare in the South are now more significant. Since trade is the key channel by which Northern robotization benefits Southern workers and consumers, a reduction in trade frictions amplifies the importance of this channel. By the same token, Figures A5 and A6 in the Appendix reveal that the importance of this channel would be reduced if trade frictions were higher than in the baseline simulation.

7 Concluding remarks

Recent empirical evidence reveals that the adoption of modern industrial robots has already had important implications for productivity and labor markets in high-income countries. This paper has shown that even though less developed nations have not yet adopted these technologies on a large scale, they have not remained insulated from their impacts. Northern robotization impacts international trade in intermediate and final goods, and thereby also impacts wages and welfare in other countries.

We have developed a task-based Ricardian theory featuring two-stage production and trade in intermediate and final goods to examine the implications of industrial robotization for North-South trade, wages and welfare. In the model, a subset of tasks required in the production of intermediate and final goods can be performed either by workers or robots, while other tasks can only be executed by humans. Robots compete with human labor in factor markets, while countries compete in sector-specific product markets for inputs and outputs. Relative production costs determine country-specific robotization and trade patterns. A fall in the global price of industrial robots initially induces adoption in the North, where the cost of labor (and consequently cost savings associated with automation) is (are) relatively higher to begin with. Robots replace domestic labor, leading to lower production costs and higher exports. Imports from the South may rise or fall, depending on the extent to which Northern production requires intermediate inputs from the South. The stronger the dependence of Northern producers on inputs from the South, the more likely it is that Northern automation will catalyze, rather than curb, imports from the South.

Simple OLS regressions using panel data by country and sector on trade and robots point to a positive relationship between robot intensity in own production and imports sourced from less developed countries. They also reveal an even stronger association with exports to these countries. The direction of causality is further supported by an instrumental variable strategy motivated by our theory, exploiting variation in exposure to robotization across countries and sectors. The positive impact of Northern robotization on imports from the South is mainly driven by exchanges of parts and components, which attests to the importance of explicitly modeling input-output linkages. Models that only consider final goods trade would fail to anticipate the sizable surge in imports of intermediates from the South that Northern robotization induces.

We then turned back to our theoretical model to study quantitatively the effects of robot price reductions on wages and welfare, both in the North and in the South. Increased robot adoption in the North initially depresses labor demand, and therefore leads to lower wages. Nevertheless, robotization induces welfare gains, as the income losses associated with lower labor income are more than offset by the gains associated with increased production, lower prices, and increased income from the rental rate of robots. Interestingly, the model points to an important non-linearity in the relationship between wages and robot prices. As robot adoption proceeds in the North, production in the robotized sector continues to expand, thereby raising demand for the tasks in which robotization is technologically unfeasible. Eventually, the share of labor in the robotized sector starts to expand, thereby raising overall labor demand and leading to higher wages in the North.

Even if production in the South is not subject to robotization, Southern wages and welfare are impacted by robot-induced shifts in international specialization. While robotization makes Northern producers more competitive, it also raises demand for Southern inputs. Real wages and welfare are likely to increase in the South, reflecting also lower consumer prices. Welfare gains in the South are likely to be even more pronounced if robotization also becomes feasible there. Given that trade in intermediate and final goods is the key channel whereby Northern robotization impacts wages and welfare in the South, the importance of this channel is magnified if trade frictions are removed.

Although our model relies on static mechanisms, the main channels we emphasize may have important implications for the link between openness and economic development. Buera and Oberfield (2017) emphasize that international trade is an important channel behind the transmission and diffusion of best practices across countries, and has therefore been an important driver of

the post-war growth miracles experienced by China, the Republic of Korea and Taiwan, China. If Northern robotization leads to an increase in trade flows with the South, the relative importance of this channel may be amplified. Exploring these issues in the context of a dynamic model of trade and growth is an important task for future human research.

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Figure 1: Tasks performed by robots, unit cost and labor demand
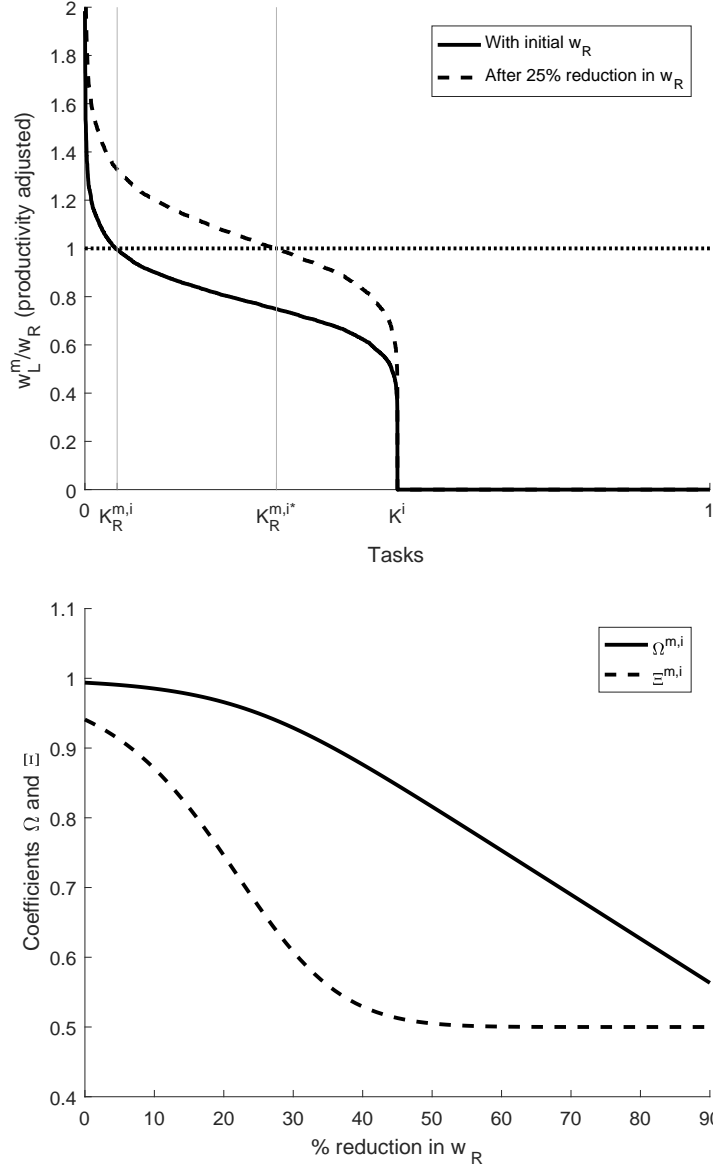
Notes: The upper panel depicts the relationship between the relative factor prices and the optimal set of tasks performed by robots. The horizontal axis shows the robotization frontier, K^i, the set of tasks initially performed by robots, $K_R^{m,i}$, and the number of tasks performed by robots after a 25% reduction in robot rental rates, $K_R^{m,i*}$. The vertical axis shows the effective relative cost of labor to robots (after taking productivity into account), $\phi_L^i \zeta_L(k) w_L^m / \phi_R^i \zeta_R(k) w_R$. The lower panel shows the values of the price of a task relative to wages, $\Omega^{m,i}$, and the number of workers demanded in equilibrium to produce a unit of task, $\Xi^{m,i}$, (vertical axis) for a given reduction in w_R (horizontal axis). The robotization frontier, K^i, is assumed to be 0.5 and other parameter values are taken from the calibration exercise in Section 6.

Figure 2: Average robotization by country
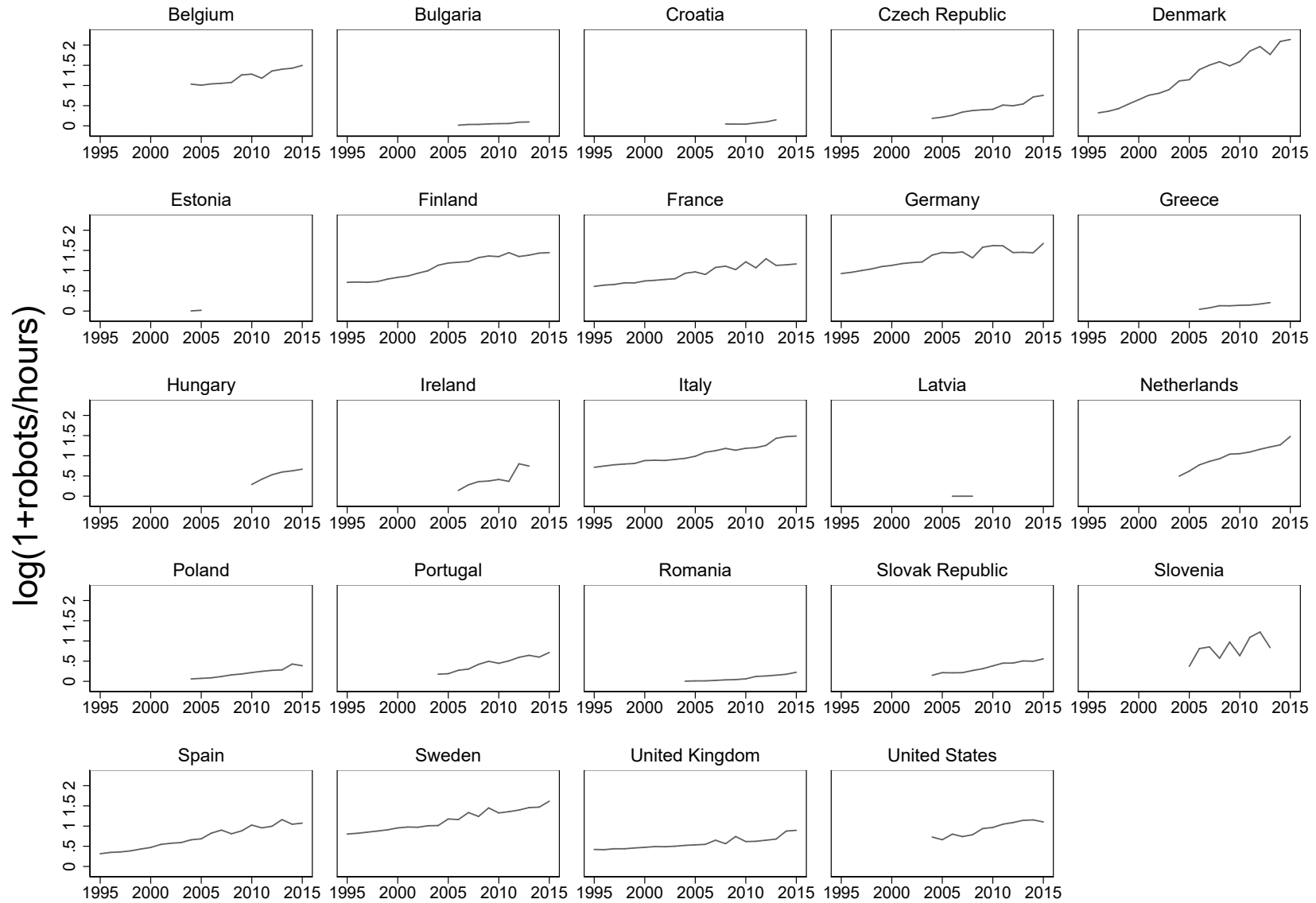
Notes: Figure depicts the stock of industrial robots by country (averaged across sectors).

Figure 3: Robotization and initial GDP per capita
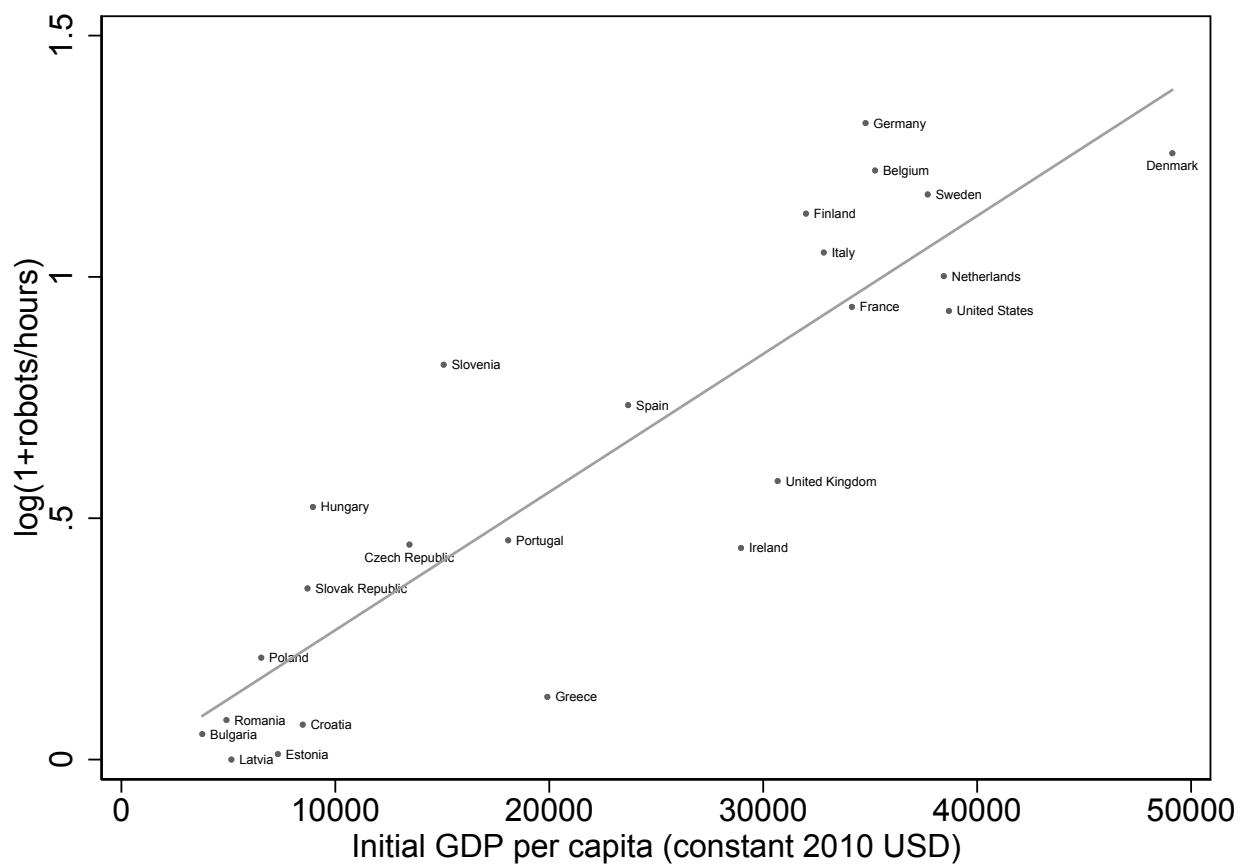
Notes: Figure depicts the relationship between average robot density by country (averaged across years) and the initial GDP per capita.

Figure 4: Average robotization by sector
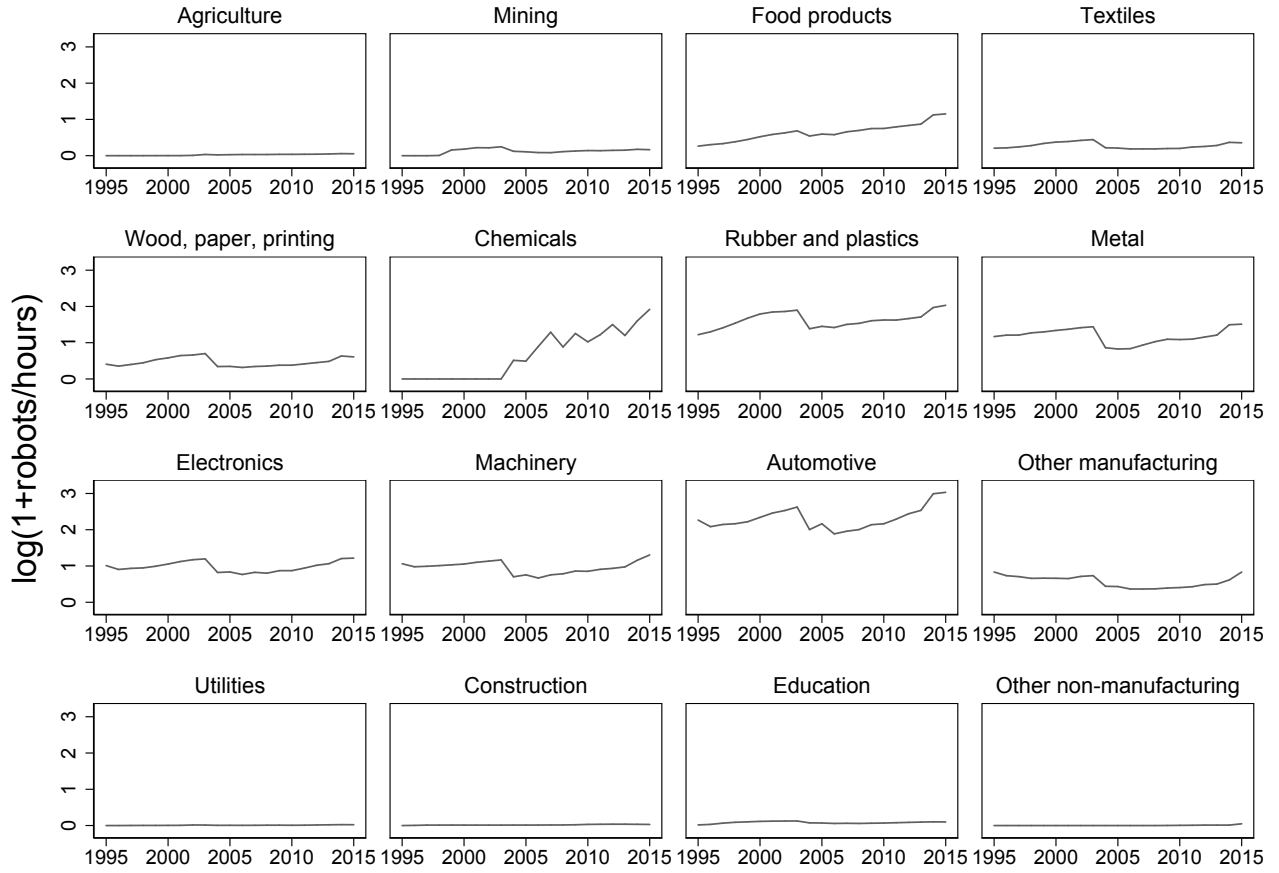
Notes: Figure depicts the stock of industrial robots by sector (averaged across countries).

Figure 5: Robotization and replaceability
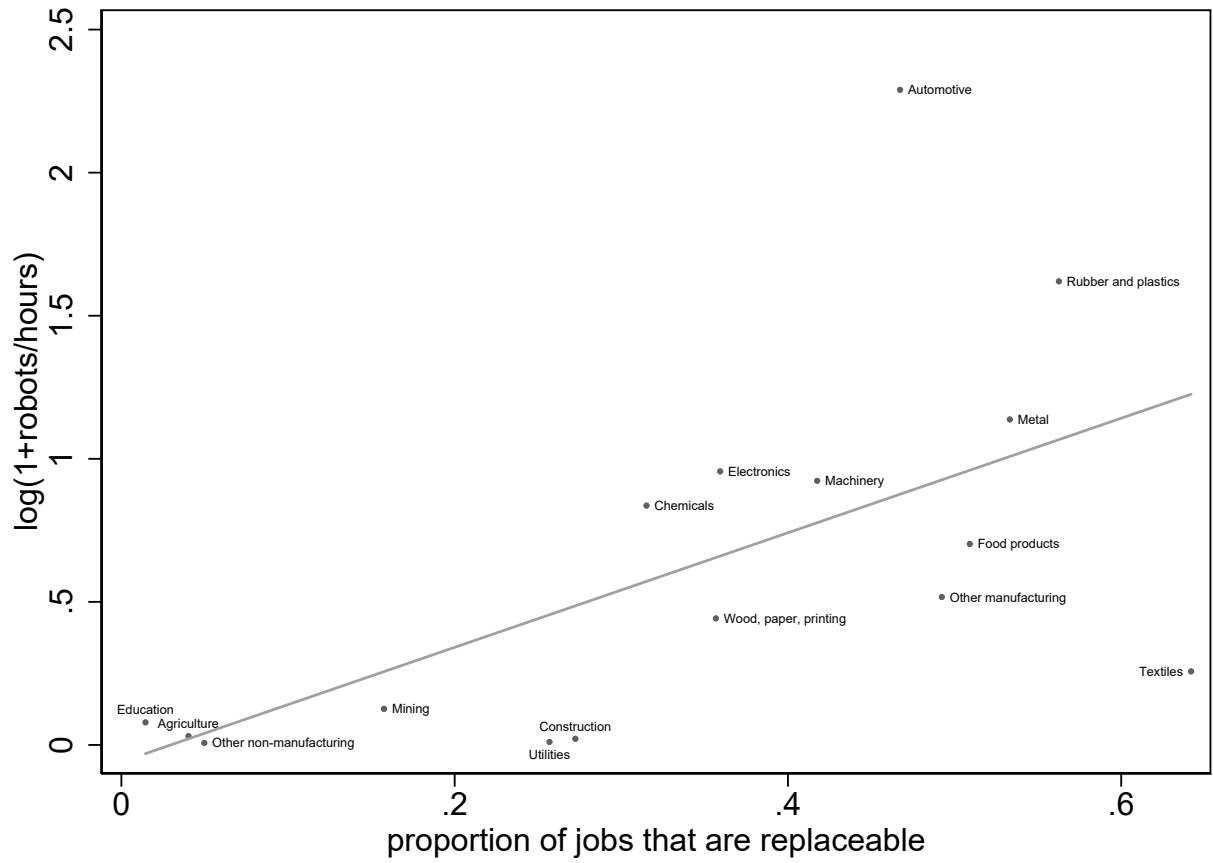
Notes: Figure depicts the relationship between average robot density by sector (averaged across countries and years) and the share of replaceable jobs in the industry.

Figure 6: Effects of Northern robotization on North-South trade
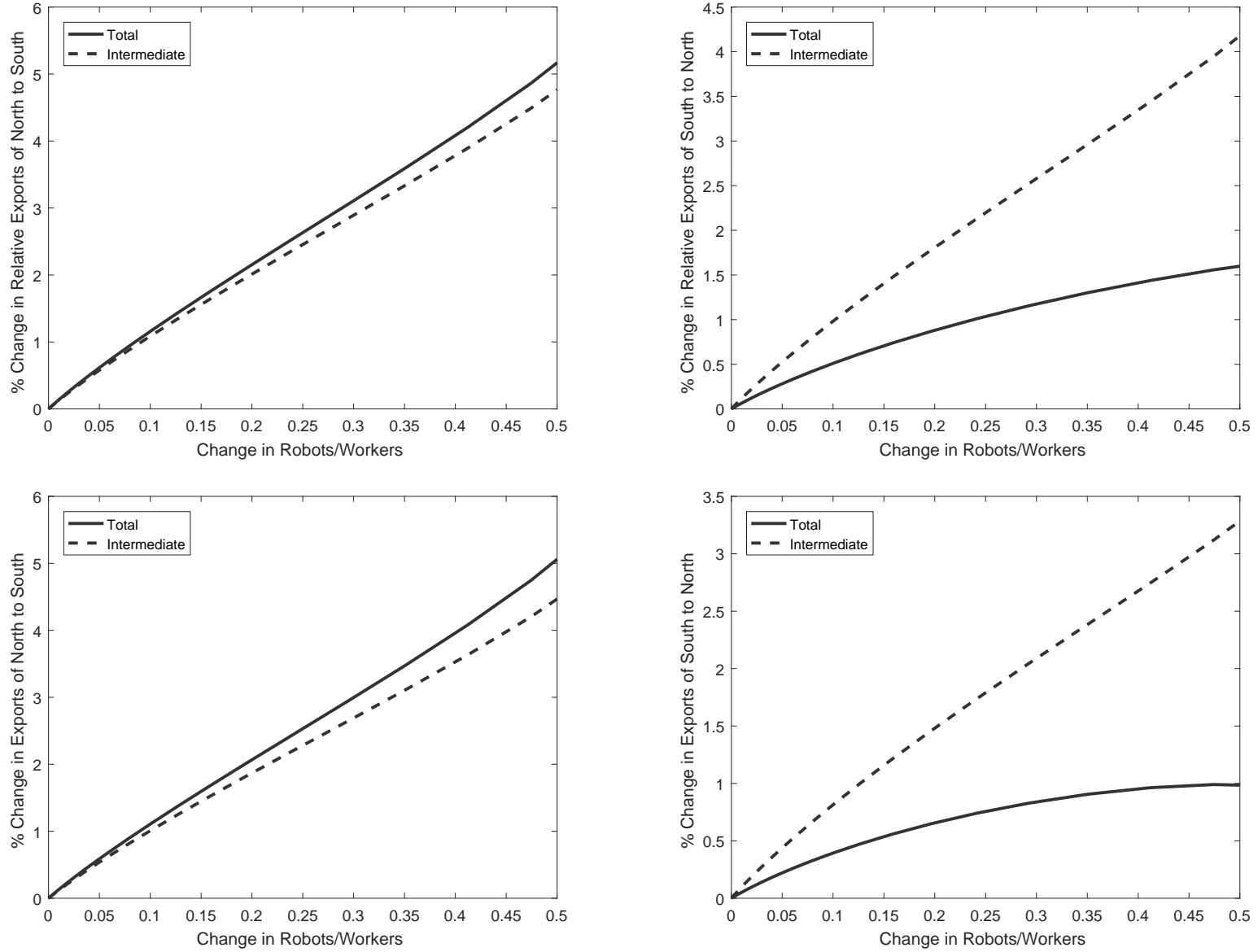
Notes: Figure depicts the results of counterfactual simulations on the effects increased robot density in the North on North-South trade flows in the industry in which production is robotized. The upper panel presents relative effects on exports of the representative country in the North or South (relative to other developed countries). The lower panel presents absolute impacts on real export values of the representative country in the North or South. The thick line refers to total exports, while the dashed line refers to exports of intermediate goods.

Figure 7: Effects of robot price reductions on robot use, cost reduction, labor allocation and wages
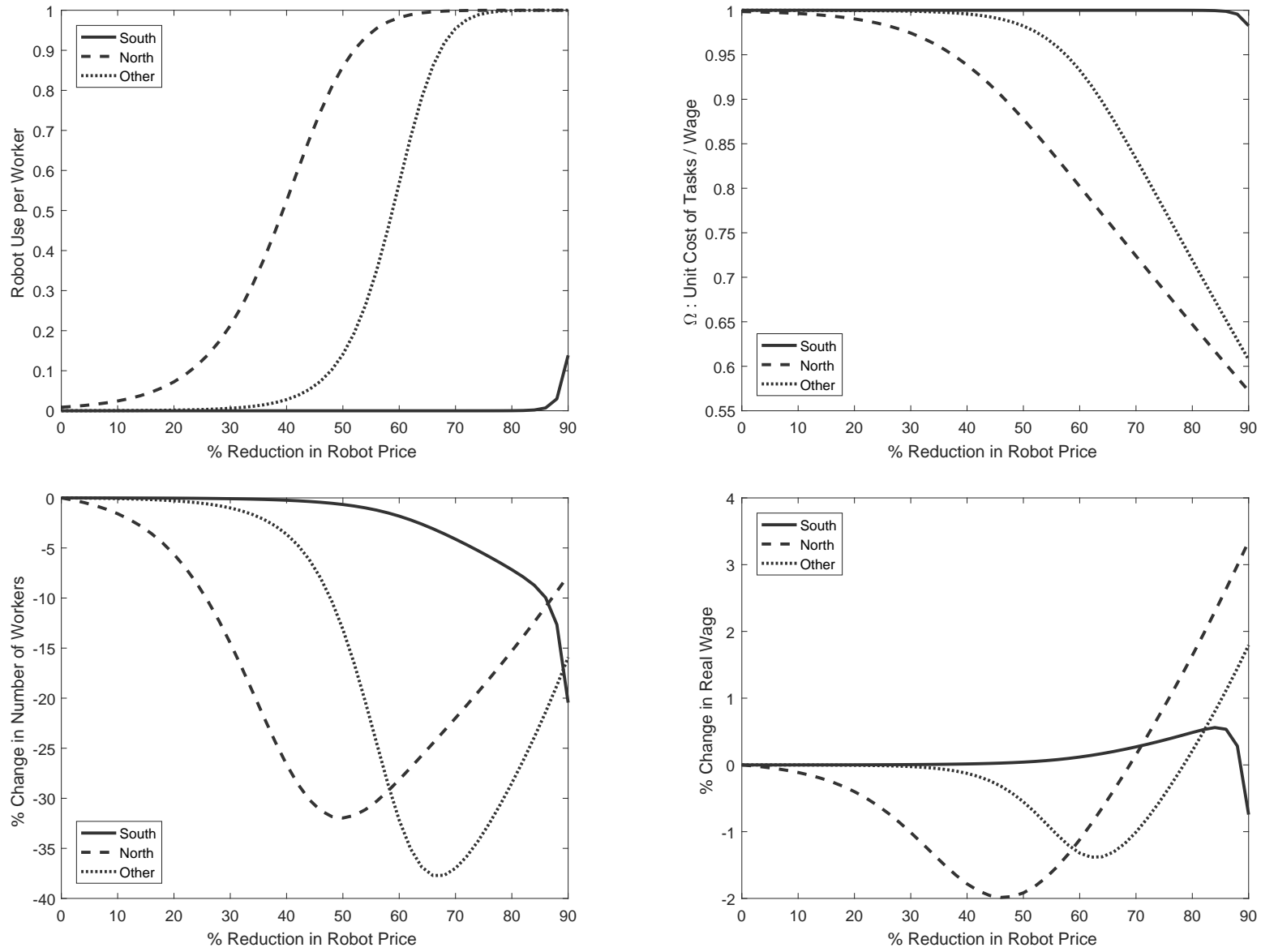
Notes: Figure depicts the results of counterfactual simulations on the effects of reductions in robot prices on robot use per worker in the robotized sector (upper-left panel), robot-induced cost reduction (upper-right panel), number of workers in the robotized sector (lower-left panel) and real wages (lower-right panel). The long-dashed line refers to the representative higher-income country in the North, the thick line refers to the South, while the short-dashed line refers to other lower-income Northern countries.

Figure 8: Effects of reductions in robot prices on exports, real GDP and consumer prices

Notes: Figure depicts the simulated effects of reductions in robot prices on total exports (upper-left panel), ratio of exports and GDP (upper-right panel), real GDP (lower-left panel) and consumer prices (lower-right panel). Robotization occurs only in the sector in which the North has a comparative advantage. The long-dashed line refers to the North, the thick line refers to the South, while the short-dashed line refers to other developed countries.

Figure 9: Effects of Northern robotization on North-South trade (frictionless trade)
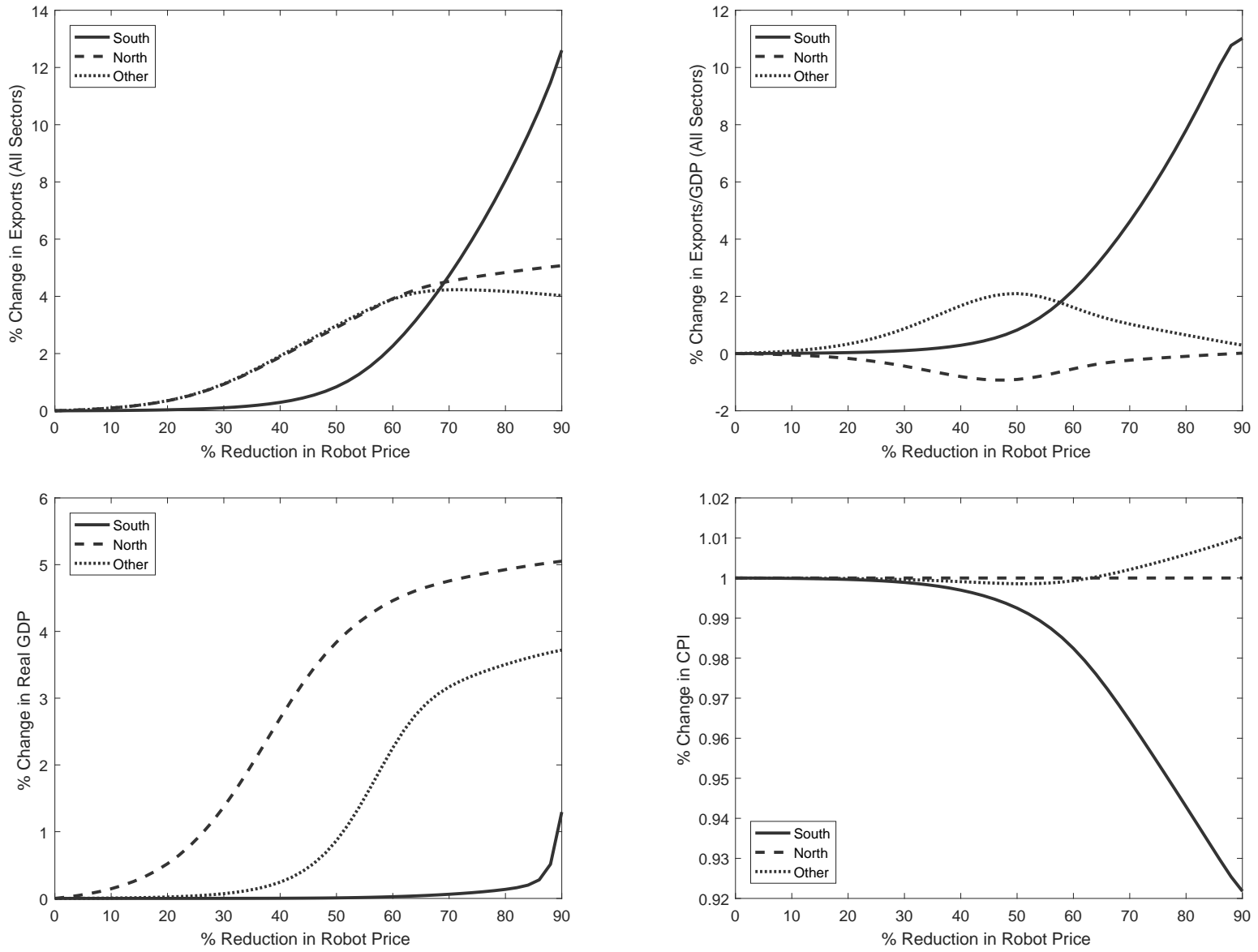

Notes: Figure depicts the results of counterfactual simulations on the effects increased robot density in the North on North-South trade flows in the industry in which production is robotized, assuming frictionless trade. The upper panel presents relative effects on exports of the representative country in the North or South (relative to other developed countries). The lower panel presents absolute impacts on real export values of the representative country in the North or South. The thick line refers to total exports, while the dashed line refers to exports of intermediate goods.

Figure 10: Effects of robot price reductions on robot use, labor allocation, wages and real GDP (frictionless trade)
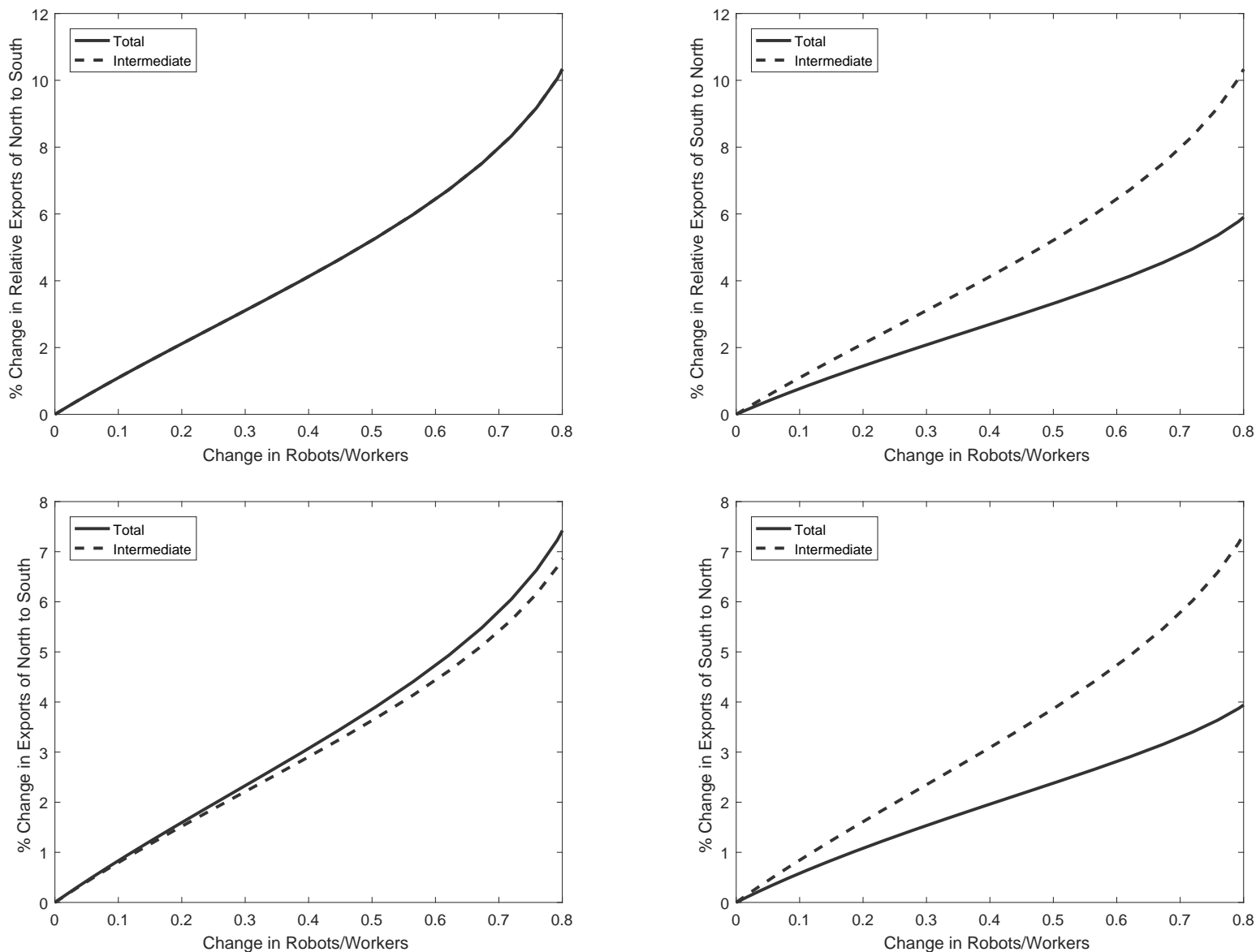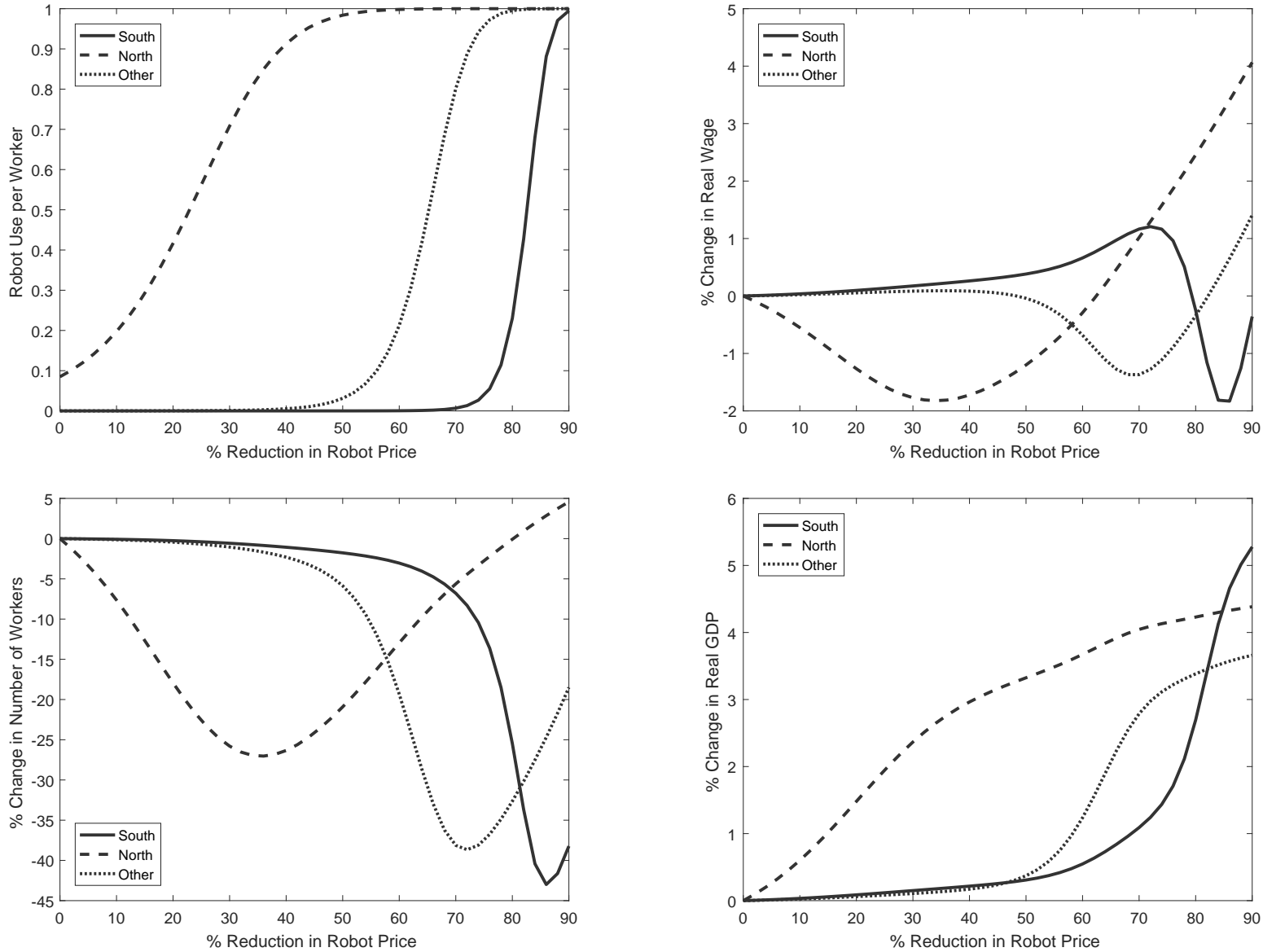
Notes: Figure depicts the results of counterfactual simulations on the effects of reductions in robot prices on robot use per worker in the robotized sector (upper-left panel), number of workers in the robotized sector (lower-left panel), real wages (upper-right panel) and real GDP (lower-right panel), assuming frictionless trade. The long-dashed line refers to the representative higher-income country in the North, the thick line refers to the South, while the short-dashed line refers to other lower-income Northern countries.

Table 1: The impact of robotization on North-South trade

Dependent variable:	OLS			IV		
	$log(1+imp)$ (1)	$log(1+exp)$ (2)	$log(\frac{1+imp}{1+exp})$ (3)	$log(1+imp)$ (4)	$log(1+exp)$ (5)	$log(\frac{1+imp}{1+exp})$ (6)
$log(1+\frac{robots}{hours})$	0.1534**	0.4117***	-0.2583***	0.6144***	1.1839***	-0.5695***
	(0.0690)	(0.1238)	(0.0684)	(0.2156)	(0.3146)	(0.1529)
First stage:						
*Replaceability * initial GDPpc * global robot stock*				0.0027***	0.0027***	0.0027***
				(0.0003)	(0.0003)	(0.0003)
Observations	888,813	888,813	888,813	888,813	888,813	888,813
R^2	0.6351	0.7738	0.3912	0.6314	0.7655	0.3887
Kleibergen-Paap rk Wald F-stat				111.795	111.795	111.795
Importer-exporter-year effects	Y	Y	Y	Y	Y	Y
Industry-year effects	Y	Y	Y	Y	Y	Y

Notes: Table reports OLS and IV results of equation (23) in text, using the baseline estimation sample. Columns (1)-(3) report the OLS results, while columns (4)-(6) report the IV and corresponding first stage estimates. Robust standard errors clustered by developed country are presented in parentheses. ***1% level, **5% level, *10% level.

Table 2: Additional controls

Dependent variable:	OLS			IV		
	$log(1+imp)$	$log(1+exp)$	$log(\frac{1+imp}{1+exp})$	$log(1+imp)$	$log(1+exp)$	$log(\frac{1+imp}{1+exp})$
	(1)	(2)	(3)	(4)	(5)	(6)
$log(1+\frac{robots}{hours})$	0.1694**	0.4309***	-0.2615***	0.6370***	1.2130***	-0.5760***
	(0.0635)	(0.1216)	(0.0712)	(0.2145)	(0.3175)	(0.1561)
$log\ (1+material\ inputs)$	0.0029	0.0939	-0.0910	-0.1710	-0.1970	0.0259
	(0.1013)	(0.1662)	(0.1140)	(0.1227)	(0.2142)	(0.1225)
$log\ (1+IT\ capital)$	4.8065	7.8370	-3.0306	12.0230***	19.9068**	-7.8838
	(3.9050)	(7.3223)	(6.2491)	(3.4734)	(8.7868)	(7.4821)
$log\ (1+non\text{-}IT\ capital)$	-19.3898**	-31.3726*	11.9828	-31.2832***	-51.2645***	19.9813*
	(7.2922)	(16.5164)	(11.0901)	(7.2316)	(15.6678)	(11.3884)
$log\ (1+tariffs)$	0.5462***	0.2371	0.3091***	0.5589***	0.2584*	0.3005***
	(0.0725)	(0.1650)	(0.0989)	(0.0643)	(0.1500)	(0.0925)
First stage:						
*Replaceability * initial GDPpc * global robot stock*				0.0027***	0.0027***	0.0027***
				(0.0003)	(0.0003)	(0.0003)
Observations	888,813	888,813	888,813	888,813	888,813	888,813
R^2	0.6354	0.7742	0.3913	0.6318	0.7659	0.3889
Kleibergen-Paap rk Wald-F-stat				105.254	105.254	105.254
Importer-exporter-year effects	Y	Y	Y	Y	Y	Y
Industry-year effects	Y	Y	Y	Y	Y	Y

Notes: Table reports OLS and IV results of equation (23) in text, using the baseline estimation sample. Columns (1)-(3) report the OLS results, while columns (4)-(6) report the IV and corresponding first stage estimates. Robust standard errors clustered by developed country are presented in parentheses. ***1% level, **5% level, *10% level.

Table 3: Excluding top-3 most robotized sectors: automotives, rubber and plastics, metal

Dependent variable:	OLS			IV		
	$log(1+imp)$	$log(1+exp)$	$log(\frac{1+imp}{1+exp})$	$log(1+imp)$	$log(1+exp)$	$log(\frac{1+imp}{1+exp})$
	(1)	(2)	(3)	(4)	(5)	(6)
$log(1+\frac{robots}{hours})$	0.2009*	0.4443***	-0.2434***	0.8618**	1.6272***	-0.7654***
	(0.0987)	(0.1571)	(0.0811)	(0.3259)	(0.4248)	(0.1765)
First stage:						
*Replaceability * initial GDPpc * global robot stock*				0.0023***	0.0023***	0.0023***
				(0.0002)	(0.0002)	(0.0002)
Observations	722,592	722,592	722,592	722,592	722,592	722,592
R^2	0.6163	0.7595	0.3723	0.6106	0.7446	0.3670
Kleibergen-Paap rk Wald-F-stat				115.011	115.011	115.011
Importer-exporter-year effects	Y	Y	Y	Y	Y	Y
Industry-year effects	Y	Y	Y	Y	Y	Y

Notes: Table reports OLS and IV results of equation (23) in text, excluding the top-3 most robotized sectors from the baseline estimation sample (automotives, rubber and plastics, metal). Columns (1)-(3) report the OLS results, while columns (4)-(6) report the IV and corresponding first stage estimates. Robust standard errors clustered by developed country are presented in parentheses. ***1% level, **5% level, *10% level.

Table 4: Excluding the 2008/2009 financial crisis

	OLS			IV		
Dependent variable:	$log(1+imp)$	$log(1+exp)$	$log(\frac{1+imp}{1+exp})$	$log(1+imp)$	$log(1+exp)$	$log(\frac{1+imp}{1+exp})$
	(1)	(2)	(3)	(4)	(5)	(6)
A. Pre 2008						
$log(1+\frac{robots}{hours})$	0.1016	0.3297**	-0.2280**	0.6520***	1.2577***	-0.6057***
	(0.0728)	(0.1441)	(0.0848)	(0.2317)	(0.3405)	(0.1946)
First stage:						
*Replaceability * initial GDPpc * global robot stock*				0.0035***	0.0035***	0.0035***
				(0.0006)	(0.0006)	(0.0006)
Observations	417,799	417,799	417,799	417,799	417,799	417,799
R^2	0.6343	0.7777	0.3985	0.6297	0.7670	0.3953
Kleibergen-Paap rk Wald-F-stat				32.893	32.893	32.893
B. Post 2009						
$log(1+\frac{robots}{hours})$	0.1767**	0.4181***	-0.2414***	0.6058**	1.0963***	-0.4904***
	(0.0747)	(0.1155)	(0.0658)	(0.2318)	(0.3318)	(0.1514)
First stage:						
*Replaceability * initial GDPpc * global robot stock*				0.0026***	0.0026***	0.0026***
				(0.0003)	(0.0003)	(0.0003)
Observations	351,008	351,008	351,008	351,008	351,008	351,008
R^2	0.6363	0.7725	0.3870	0.6327	0.7653	0.3852
Kleibergen-Paap rk Wald-F-stat				101.515	101.515	101.515
Importer-exporter-year effects	Y	Y	Y	Y	Y	Y
Industry-year effects	Y	Y	Y	Y	Y	Y

Notes: Table reports OLS and IV results of equation (23) in text, excluding 2008/2009 from the baseline estimation sample. Columns (1)-(3) report the OLS results, while columns (4)-(6) report the IV and corresponding first stage estimates. Robust standard errors clustered by developed country are presented in parentheses. ***1% level, **5% level, *10% level.

Table 5: Alternative instruments

Dependent variable:	IV			IV		
	$log(1+imp)$	$log(1+exp)$	$log(\frac{1+imp}{1+exp})$	$log(1+imp)$	$log(1+exp)$	$log(\frac{1+imp}{1+exp})$
	(1)	(2)	(3)	(4)	(5)	(6)
$log(1+\frac{robots}{hours})$	0.5825**	1.4069***	-0.8244***	0.5762**	1.2756**	-0.6995**
	(0.2333)	(0.3403)	(0.2576)	(0.2745)	(0.4565)	(0.2756)
First stage:						
$log(1+\frac{robots}{hours})$ in two countries	0.2743**	0.2743**	0.2743**			
with most similar GDP per capita	(0.1000)	(0.1000)	(0.1000)			
$log(1+\frac{robots}{hours})$ in four countries				0.3247**	0.3247**	0.3247**
with most similar GDP per capita				(0.1182)	(0.1182)	(0.1182)
Observations	786,797	786,797	786,797	854,589	854,589	854,589
R^2	0.6282	0.7608	0.3855	0.6255	0.7580	0.3874
Kleibergen-Paap rk Wald-F-stat	7.523	7.523	7.523	7.546	7.546	7.546
Importer-exporter-year effects	Y	Y	Y	Y	Y	Y
Industry-year effects	Y	Y	Y	Y	Y	Y

Notes: Table reports OLS and IV results of equation (23) in text, using the baseline estimation sample and alternative instruments. Columns (1)-(3) report the OLS results, while columns (4)-(6) report the IV and corresponding first stage estimates. Robust standard errors clustered by developed country are presented in parentheses. ***1% level, **5% level, *10% level.

Table 6: Heterogeneity by income level of non-OECD countries

	OLS			IV		
Dependent variable:	$log(1+imp)$	$log(1+exp)$	$log(\frac{1+imp}{1+exp})$	$log(1+imp)$	$log(1+exp)$	$log(\frac{1+imp}{1+exp})$
	(1)	(2)	(3)	(4)	(5)	(6)
A. High-income non-OECD countries						
$log(1+\frac{robots}{hours})$	0.3187***	0.4851***	-0.1664**	1.0488***	1.1087***	-0.0599
	(0.0800)	(0.1202)	(0.0626)	(0.2927)	(0.2944)	(0.1987)
First stage :						
*Replaceability * initial GDPpc * global robot stock*				0.0027***	0.0027***	0.0027***
				(0.0003)	(0.0003)	(0.0003)
Observations	80,080	80,080	80,080	80,080	80,080	80,080
R^2	0.6674	0.8266	0.3889	0.6593	0.8217	0.3886
Kleibergen-Paap rk Wald-F-stat				110.960	110.960	110.960
B. Low and middle-income non-OECD countries						
$log(1+\frac{robots}{hours})$	0.1370*	0.4044***	-0.2674***	0.5716**	1.1913***	-0.6197***
	(0.0688)	(0.1247)	(0.0702)	(0.2094)	(0.3193)	(0.1593)
First stage :						
*Replaceability * initial GDPpc * global robot stock*				0.0027***	0.0027***	0.0027***
				(0.0003)	(0.0003)	(0.0003)
Observations	808,733	808,733	808,733	808,733	808,733	808,733
R^2	0.6366	0.7677	0.3939	0.6333	0.7587	0.3908
Kleibergen-Paap rk Wald-F-stat				111.830	111.830	111.830
Importer-exporter-year effects	Y	Y	Y	Y	Y	Y
Industry-year effects	Y	Y	Y	Y	Y	Y

Notes: Table reports OLS and IV results of equation (23) in text, using the sub-samples for non-OECD countries depending on their level of income per capita. Columns (1)-(3) report the OLS results, while columns (4)-(6) report the IV and corresponding first stage estimates. Robust standard errors clustered by developed country are presented in parentheses. ***1% level, **5% level, *10% level.

Table 7: Imports of intermediates versus other goods

Dependent variable:	BEC classification		Schott (2004) classification	
	OLS	IV	OLS	IV
	$log(1+imp)$	$log(1+imp)$	$log(1+imp)$	$log(imp)$
	(1)	(2)	(3)	(4)
A. Intermediate goods				
$log(1+\frac{robots}{hours})$	0.1094	0.6815**	0.2132***	0.8566**
	(0.0788)	(0.3240)	(0.0573)	(0.3124)
First stage :				
*Replaceability * initial GDPpc * global robot stock*		0.0027***		0.0027***
		(0.0003)		(0.0003)
Observations	888,813	888,813	888,813	888,813
R^2	0.5137	0.5027	0.5278	0.5101
Kleibergen-Paap rk Wald-F-stat		111.795		111.795
B. Other goods				
$log(1+\frac{robots}{hours})$	0.1507***	0.5627***	0.1136*	0.4929**
	(0.0511)	(0.1680)	(0.0619)	(0.1906)
First stage :				
*Replaceability * initial GDPpc * global robot stock*		0.0027***		0.0027***
		(0.0003)		(0.0003)
Observations	888,813	888,813	888,813	888,813
R^2	0.6259	0.6226	0.6246	0.6220
Kleibergen-Paap rk Wald-F-stat		111.795		111.800
Importer-exporter-year effects	Y	Y	Y	Y
Industry-year effects	Y	Y	Y	Y

Notes: Table reports OLS and IV results of equation (23) in text, using the sub-samples for imports of intermediate and other goods. Columns (1)-(3) report the OLS results, while columns (2)-(4) report the IV and corresponding first stage estimates. Robust standard errors clustered by developed country are presented in parentheses. ***1% level, **5% level, *10% level.

A.1 Price and cost multipliers

The expressions for the price and cost multipliers are:

$$\psi_1^{m,i} \;=\; \left(\alpha_F^{m,i}\right)^{-\alpha_F^{m,i}} \left(\alpha_M^{m,i}\right)^{-\alpha_M^{m,i}} \left(\alpha_T^{m,i}\right)^{-\alpha_T^{m,i}}, \tag{A1a}$$

$$\psi_2^i \;=\; \left[\Gamma\left(\frac{\sigma+1-\theta}{\theta}\right)\right]^{\frac{1}{1-\sigma}}, \tag{A1b}$$

$$\psi_3^i \;=\; \Gamma\left(1+\frac{1}{\nu}\right), \tag{A1c}$$

$$\psi_4^{m,i} \;=\; \psi_1^{m,i}\left(\psi_3^i \phi_L^i\right)^{\alpha_T^{m,i}}, \tag{A1d}$$

$$\psi_5^i \;=\; \left(\Gamma\left(1+\frac{1}{\nu}\right)\phi_L^i\right)^{-1}. \tag{A1e}$$

A.2 Allocation of tasks and robotization

A.2.1 Optimal allocation of tasks

The optimal number of robots relative to workers does not depend on the production stage, since the production technology and the cost structure of tasks are identical across stages within an industry and country. Therefore, the solution does not depend on the stage of production and we can omit subscript s.

Efficiency implies that robotized tasks $(T_A^{m,i})$ and non-robotized tasks $(T_N^{m,i})$ are performed at a certain proportion (like a Leontief production function):

$$T^{m,i} = \frac{T_A^{m,i}}{K^i} = \frac{T_N^{m,i}}{1-K^i}. \tag{A2}$$

In order to derive the CES task production function, we define

$$b_R^i \;=\; \left(\Gamma\left(1+\frac{1}{\nu}\right)\phi_R^i\right)^{-\frac{1}{1+\nu}}, \tag{A3a}$$

$$b_L^i \;=\; \left(\Gamma\left(1+\frac{1}{\nu}\right)\phi_L^i\right)^{-\frac{1}{1+\nu}}, \tag{A3b}$$

and production tasks per worker below and above K, respectively, as

$$T_A^{m,i} \;=\; \left(b_R^i (R^{m,i})^{\frac{1}{1+\nu}} + b_L^i (L_A^{m,i})^{\frac{1}{1+\nu}}\right)^{1+\nu}, \tag{A4a}$$

$$T_N^{m,i} \;=\; (b_L^i)^{1+\nu} L_N^{m,i}. \tag{A4b}$$

The labor endowment is optimally split by producers into the two segments of the tasks space.

A.2.2 Optimal allocation of labor

Producers have to allocate workers to tasks optimally, under the production of tasks outlined above. The subset of tasks produced by workers between 0 and K is given by

$$K_{A,L}^{m,i} = \frac{(\phi_L^i w_L^m)^{-\nu}}{(\phi_R^i w_R)^{-\nu} + (\phi_L^i w_L^m)^{-\nu}} K^i. \tag{A5}$$

Similarly, the subset of tasks produced by robots between 0 and K is given by

$$K_R^{m,i} = \frac{(\phi_R^i w_R)^{-\nu}}{(\phi_R^i w_R)^{-\nu} + (\phi_L^i w_L^m)^{-\nu}} K^i. \tag{A6}$$

The ratio of tasks produced by workers between K and 1 is given by

$$K_{N,L}^{m,i} = 1 - K^i. \tag{A7}$$

The number of workers performing tasks below and above K to produce $T^{m,i}$ units of tasks is given, respectively, by

$$L_A^{m,i} = T^{m,i} K_{A,L}^{m,i} \frac{w_{T_A}^{m,i}}{w_L^m}, \tag{A8a}$$

$$L_N^{m,i} = T^{m,i} K_{N,L}^{m,i} \frac{w_{T_N}^{m,i}}{w_L^m}, \tag{A8b}$$

where the total labor demand is $L^{m,i} = L_A^{m,i} + L_N^{m,i}$.

A.2.3 Production cost with robotization

The overall cost reduction in producing tasks implied by robotization is given by

$$\Omega^{m,i} = \frac{K^i w_{T_A}^{m,i} + (1 - K^i) w_{T_N}^{m,i}}{w_{T_N}^{m,i}}, \tag{A9}$$

where $0 < \Omega^{m,i} \leq 1$. The average cost of automatable tasks is

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

while the average cost of tasks from K^i to 1 is

$$w_{T_N}^{m,i} = \psi_3^i \phi_L^i w_L^m,$$

thus

$$w_T^{m,i} = K^i w_{T_A}^{m,i} + (1 - K^i) w_{T_N}^{m,i}.$$

Note that

$$\frac{w_{T_A}^{m,i}}{w_{T_N}^{m,i}} = \left(1 - \frac{K_R^{m,i}}{K^i} \right)^{\frac{1}{\nu}}. \tag{A10}$$

Using the expressions above we can re-write (A9) as

$$\Omega^{m,i} \;=\; K^i \frac{w^{m,i}_{T_A}}{w^{m,i}_{T_N}} + 1 - K^i,$$

$$\;=\; 1 - K^i + K^i \left(1 - \frac{K^{m,i}_R}{K^i} \right)^{\frac{1}{\nu}}.$$

A.2.4 Production function with robotization

We can take the optimality conditions above and derive an expression for the number of worker per unit task

$$T^{m,i} \;=\; \frac{\psi^i_5 L_N}{1 - K^i},$$

$$\frac{\psi^i_5}{T^{m,i}} \;=\; \frac{1 - K^i}{L^{m,i}_N},$$

$$\psi^i_5 \frac{L^{m,i}}{T^{m,i}} \;=\; \frac{1 - K^i}{L^{m,i}_N} L^{m,i},$$

$$\Xi^{m,i} \;=\; \frac{(1 - K^i)(L^{m,i}_A + L^{m,i}_N)}{L^{m,i}_N}.$$

Then the expression for $\Xi^{m,i}$ can be simplified as

$$\Xi^{m,i} \;=\; \frac{(1 - K^i)(L^{m,i}_A + L^{m,i}_N)}{L^{m,i}_N},$$

$$\;=\; \frac{\left(1 - K^i\right) \left(\frac{K^{m,i}_{A,L} w^{m,i}_{T_A}}{w^m_L} + \frac{K^{m,i}_{N,L} w^{m,i}_{T_N}}{w^m_L} \right)}{\frac{K^{m,i}_{N,L} w^{m,i}_{T_N}}{w^m_L}},$$

$$\;=\; \left(1 - K^i\right) \left(\frac{K^{m,i}_{A,L} w^{m,i}_{T_A}}{K^{m,i}_{N,L} w^{m,i}_{T_N}} + 1 \right),$$

$$\;=\; \left(1 - K^i\right) \left(\frac{(K^i - K^{m,i}_R) w^{m,i}_{T_A}}{(1 - K^i) w^{m,i}_{T_N}} + 1 \right),$$

$$\;=\; \left(\left(K^i - K^{m,i}_R\right) \frac{w^{m,i}_{T_A}}{w^{m,i}_{T_N}} + \left(1 - K^i\right) \right).$$

Finally, we plug (A10) into the expression:

$$\Xi^{m,i} \;=\; K^i \left(1 - \frac{K^{m,i}_R}{K^i} \right) \left[\left(1 - \frac{K^{m,i}_R}{K^i} \right)^{\frac{1}{\nu}} \right] + \left(1 - K^i\right),$$

$$\;=\; \left(1 - K^i\right) + K^i \left(1 - \frac{K^{m,i}_R}{K^i} \right)^{1 + \frac{1}{\nu}}.$$

The production function of varieties can be re-written with the introduction of robotization

$$q\left(\omega\right) = z(\omega)\left(\psi_5^i\right)^{\alpha_T^{m,i}}\left(F_s^{m,i}(\omega)\right)^{\alpha_F^{m,i}}\left(Q_1^{m,i}(\omega)\right)^{\alpha_M^{m,i}}\left(\frac{L^{m,i}(\omega)}{\Xi^{m,i}}\right)^{\alpha_T^{m,i}},\tag{A11}$$

where $\psi_5^i = \left(\Gamma\left(1+\frac{1}{\nu}\right)\phi_L^i\right)^{-1}$.

A.2.5   Labor and robot demand

Thanks to the CES structure, robot demand is given by

$$R^{m,i} = L_A^{m,i}\frac{\phi_L^i}{\phi_R^i}\left(\frac{w_L^m}{w_R}\right)^{1+\nu},\tag{A12}$$

the cost share of labor in producing T is given by

$$\frac{w_L^m L^{m,i}}{w_T^{m,i} T^{m,i}} = \frac{\Omega^{m,i}}{\Xi^{m,i}},\tag{A13}$$

and the cost share of robots is

$$\frac{w_R R^{m,i}}{w_T^{m,i} T^{m,i}} = 1 - \frac{\Omega^{m,i}}{\Xi^{m,i}}.\tag{A14}$$

The demand for robots can alternatively be expressed as

$$R^{m,i} = L^{m,i}\left(\frac{\Xi^{m,i}}{\Omega^{m,i}} - 1\right)\frac{w_L^{m,i}}{w_R}.$$

A.2.6   Preferences with CES utility function

Assume that preferences are described by a CES utility function (rather than a Cobb-Douglas), given by

$$U^{m,i} = \left(\sum_i \widetilde{\gamma}^{m,i}(Q_2^{m,i})^\rho\right)^{\frac{1}{\rho}},\tag{A15}$$

where $\widetilde{Q}_2^{m,i}$ is the amount of final goods from sector i demanded by consumers in country m, $\widetilde{\gamma}^{m,i}$ is a constant, and the elasticity of substitution is defined as $\frac{1}{1-\rho}$.

The budget share of i is now a variable equal to

$$\gamma^{m,i} = \frac{\left(\widetilde{\gamma}^{m,i}\left(P^{m,i}\right)^{-\rho}\right)^{\frac{1}{1-\rho}}}{\sum_j\left(\widetilde{\gamma}^{m,j}\left(P^{m,j}\right)^{-\rho}\right)^{\frac{1}{1-\rho}}},\tag{A16}$$

and the consumer price index in country m is equal to

$$P^m = \left(\sum_j \widetilde{\gamma}^{m,j} \left(P_2^{m,j} \right)^{\frac{-\rho}{1-\rho}} \right)^{\frac{1-\rho}{-\rho}}. \tag{A17}$$

B.1 Data sources and description

This appendix provides further details about the data used in the empirical analysis. The set of developed countries included in our estimation sample is: Belgium, Bulgaria, Croatia, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Netherlands, Poland, Portugal, Romania, Slovak Republic, Slovenia, Spain, Sweden, United Kingdom and United States. For each of these countries, the estimation sample includes all years for which the IFR data are available during the period 1995-2015. We examine bilateral trade flows between these countries and all non-OECD countries included in BACI. Table A1 reports the final list of sectors used and their correspondence with the sectors defined in the original data sets.

Industrial robots: The stock of industrial robots by industry, country and year comes from the International Federation of Robotics (IFR). These data are based on yearly surveys of robot suppliers, and currently cover 75 countries (about 90 percent of the industrial robots market). The IFR measures deliveries of "multipurpose manipulating industrial robots" based on the definitions of the International Organization for Standardization. The data are disaggregated roughly at the three-digit level for manufacturing and roughly at the two-digit level for non-manufacturing. We focus only on tradable sectors, which are listed in Table A1.

To calculate a measure of the robot stock per sector, we use the perpetual inventory method assuming a depreciation rate of 10%, following Graetz and Michaels (2018).[18] We initialize the series using the IFR measure of the stock of robots per sector in 1993. For countries for which the 1993 sectoral breakdown of the stock of robots is not available, we initialize the series using the initial robots stock for the first year for which it is available.[19]

The IFR data are regarded as the best source of information on industrial robots (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2017b). Nonetheless, these data have some limitations. First, about 30 percent of industrial robots are not classified into any industry. Following Acemoglu and Restrepo (2017b), we allocate these unclassified robots to industries in the same proportion as in the classified data. Second, the IFR data do not cover "dedicated industrial robots", which are defined as automatically controlled machines for only one industrial application. Third, the time coverage of the IFR data varies substantially across countries. Moreover, a detailed sectoral breakdown of the robot stock and deliveries is not always available for all years even when countries are included in the IFR, so that our panel is unbalanced.[20]

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[18]While the IFR data contain measures of the robot stock, we prefer to use estimates based on the perpetual inventory method because the IFR measures are based on the assumption that the service lifetime of a robot is exactly 12 years, exhibiting no depreciation whatsoever for the first 12 years and losing all their functionality after the 12th year.

[19]For countries for which we have data on the aggregate (i.e. country-wide) stock of robots in years prior to having the sectoral breakdown, we deflate the initial stock per sector as follows. We first construct a deflator by dividing the sum of the IFR robot stock reported for each sector by the aggregate robot stock calculated using the perpetual inventory method. We then use this deflator to obtain the sector-specific series.

[20]Up until 2010 robots used in Mexico and Canada are reported as being used in the United States. To account for the attendant over-reporting of robots usage in the US, we first calculate what share of robots in the NAFTA area were being used in the United States in 2011 and subsequently correct the US series assuming that during the period prior to 2011 robots usage in the US, Canada and Mexico grew at equal pace.

Labor hours and other inputs: Data on labor hours, material inputs, IT capital, non-IT capital by industry-country-year come from EU KLEMS (Timmer, van Moergastel, Stuivenwold, Ypma, O'Mahony, and Kangasniemi, 2007). These data were originally reported for 28 industries, which were mapped into the sectoral classification of the IFR data (see Table A1).

Replaceability: Following Graetz and Michaels (2018), we constructed an industry-level measure of replaceability using data from IFR on robot applications, the US census of occupational classifications and the distribution of hours across occupations and industries from the 1980 US Census. The IFR distinguishes between different applications of robots, including (among others) welding, processing, and assembling (International Federation of Robotics, 2012). We take the 2000 Census three-digit occupations and assign a replaceability value of one to the three-digit occupation if the name and/or description of at least one of the SOC five-digit occupations included in it contains at least one of these IFR application categories and zero otherwise. Note that we assume that services occupations (occupations with SOC codes < 45000) are not replaceable. In addition, this procedure inadvertently identifies some occupations as potentially replaceable by robots that presumably are not, such as "agricultural inspectors", "infantry", and "airport cargo handling supervisors". These are typically occupations that include tasks and/or titles such as "repair", "inspect", "drive", "maintain", "actor" etc. We remove such cases from the list of potentially replaceable occupations.

We then map the resulting replaceability measure into the 1990 Census occupational classification, which is available for the 1980 and 2000 censuses. If several 2000 occupations map into one 1990 occupation, then we assign the 1990 occupation a replaceability value of one if and only if at least one of the corresponding 2000 occupations has a value of one. To arrive at a measure of replaceability at the industry level, we first assign individuals in the 1980 IPUMS Census a replaceability score based on the 1990 occupation they report (assuming the value 1 if the occupation is replaceable, and 0 if it is not). We then assign each individual to one of our 28 EU KLEMS industries based on a crosswalk to the 1990 Census industry classification. We compute the fraction of replaceable hours for each of the 16 robot-using industries by dividing the sum product of replaceability and annual hours worked by the total sum of hours worked (applying person weights both when computing the numerator and the denominator). The replaceability values represent an upper bound to the share of hours that is replaceable, because occupations are classified as replaceable if only a part of their work can be replaced by robots; this part need not be large.

Bilateral trade data: Product-level bilateral trade data come from BACI. This data set is the World trade database developed by the CEPII, building on original data provided by the COMTRADE database of the United Nations Statistical Division. BACI is constructed using an original procedure that reconciles the declarations of the exporter and importer. This harmonization procedure makes it possible to extend considerably the number of countries for which trade data are available. BACI provides bilateral values and quantities of exports at the HS 6-digit product disaggregation, for 224 countries and is available from 1995 onwards. CEPII developed original statistical procedures to reconcile data reported by almost 150 countries to the United Nations Statistics Division. First, as import values are reported CIF (cost, insurance and freight) while exports are reported FOB (free on board), CIF costs are estimated and removed from imports values to compute FOB import values. Second, the reliability of country reporting is assessed based on the reporting distances among partners. These reporting qualities are used as weights in the reconciliation of each bilateral trade flow twice reported. Due to the use of this double information on each flow, BACI ends up covering a large set of countries not reporting at a given level of the product classification. The data set gives information about the value (in thousands of US dollars) and the quantity (in tons) of trade. Gaulier and Zignano (2010) provide

a detailed description of the BACI data set.

Import tariffs: We use annual data on bilateral applied import tariffs by country and product (SITC 2-dig., Rev. 4) from the TRAINS database of the United Nations Conference on Trade and Development. While these data span our sample period, the extent of time coverage differs considerably across countries.

Initial GDP per capita: We use data on GDP per capita of each developed country (in constant 2000 USD) from the World Development Indicators of the World Bank. We use values for the first year the country is observed in the estimation sample.

B.2   Variable definitions and summary statistics

This section describes in detail the variables used in the econometric analysis. Table A2 provides summary statistics on each of these variables.

$log\,(1+exp)$: logarithm of one plus the FOB value of bilateral exports in thousands of US dollars of developed country n to developing country m in sector i in year t.

$log\,(1+imp)$: logarithm of one plus the FOB value of bilateral imports in thousands of US dollars from developed country n to developing country m in sector i in year t.

$log(1+\frac{robots}{hours})$: logarithm of one plus the ratio between the stock of robots and the number of working hours (in millions) in developed country n in sector i in year t. The stock of robots was estimated suing the perpetual inventory method based on the observed stock of robots in the IFR data and using a depreciation rate of 10%.

$log(1+\frac{obs.robots}{hours})$: logarithm of one plus the ratio between the stock of robots and the number of work hours (in millions) in developed country n in sector i in year t. The stock of robots was directly observed in the IFR data set.

$Initial\ GDPpc$: GDP per capita (in constant 2000 USD) of developed country n in the first year the country is observed in the estimation sample.

$Replaceability$: proportion of US jobs in 1980 that were in occupations that are replaceable by robots.

$Global\ robot\ stock$: global stock of robots. The stock of robots was estimated using the perpetual inventory method based on the observed stock of robots in the IFR data and using a depreciation rate of 10%.

$log\,(1+material\ inputs)$: logarithm of one plus the expenditure on material inputs in developed country n in sector i in year t.

$log\,(1+IT\ capital)$: logarithm of one plus the expenditure on IT capital in developed country n in sector i in year t.

$log\,(1+non\text{-}IT\ capital)$: logarithm of one plus the expenditure on non-IT capital in developed country n in sector i in year t.

$log\,(1+tariff)$: logarithm of one plus the ad valorem import tariff applied by developed country n to developing country m in sector i in year t.

B.3 Counterfactual simulations

B.3.1 Computation of production and consumption shares

The production and consumption shares are calibrated using WIOD. The production share parameter of inputs, $\alpha_M^{m,i}$, is calculated by dividing the stage one expenditure by the total output of a given industry. The labor share parameter, $\alpha_T^{m,i}$, is calibrated using the wage bill (adjusted using equation (A14) with the equilibrium share of robots, initial wages and initial robot rental rate). The consumption share parameter, $\gamma^{m,i}$, is calibrated using the expenditure on stage two outputs. All calibrated parameters, initial wages and robot prices are reported in Table A7.

B.3.2 Computation of the trade matrix

We index South as $m = 1$, Other as $m = 2$ and North as $m = 3$. We index individual countries with $\widetilde{m}$ and $\widetilde{n}$, and country sets with m and n. Define $N_1 = 7$, $N_2 = 1$ and $N_3 = 9$, $M_1 =$Brazil, China, ..., $M_2 =$Australia, Austria, ..., and $M_3 =$Belgium, Germany, ... Let $Y_s^{\widetilde{m},\widetilde{n},i}$ denote the trade flow between $\widetilde{m}$ and $\widetilde{n}$ for industry i and stage s. The structure of WIOD is similar to OECD input-output tables, with multiple countries in each column and row. A row reveals how output of a given industry for a specific country is used across different columns. Take an entry from the database. If both its row and column correspond to an industry within the sector, we consider that entry as a part of the first stage output of the sector. The other entries, including those that correspond to consumption by households or government, are considered a part of second stage output. For a given entry, a country in the row is the origin country, while the country in the column is the destination country. We construct $Y_s^{\widetilde{m},\widetilde{n},i}$ for each individual country. We define the trade matrix between m and n as

$$Y_s^{m,n,i} = \begin{cases} \frac{1}{N_m N_n} \sum_{\widetilde{m} \in M_m} \sum_{\widetilde{n} \in M_n} Y_s^{\widetilde{m},\widetilde{n},i}, & m \neq n \\ \frac{1}{N_m} \sum_{\widetilde{m} \in M_m} Y_s^{\widetilde{m},\widetilde{m},i}, & m = n \end{cases} \tag{A18}$$

Additionally, we assume that all NT sector output is final.

B.3.3 Solution method

We follow the solution methods of Caliendo and Parro (2015) and Caliendo, Dvorkin, and Parro (forthcoming), and calculate the new equilibrium after an exogenous reduction of robot prices using changes in variables from their initial values. For the purpose of the solution, we can treat first and second stage production as different industries, and impose that first stage output is only demanded by producers as intermediate inputs, while second stage output is only used for final household consumption. Our model then becomes a special case of Caliendo and Parro (2015) with additional task structure involving robots and additional fixed factors. The task structure does not affect the solution method significantly. The only difference (with regard to the solution method) is the inclusion of cost reduction variable $\Omega^{m,i}$, and the related labor demand variable, $\Xi^{m,i}$. Given the exogenous effective robot rental rate, $\frac{\phi_R^i}{\phi_L^i} w_R$, it is straightforward to solve for $\Omega^{m,i}$ using (11). We then plug the change in the cost reduction parameter into the equation used in the solution. Similarly, we can solve for the labor demand variable $\Xi^{m,i}$ using (12). The changes in labor allocations can be easily solved jointly with the changes in equilibrium wages, productivity and cost reduction using (21b). Apart from the variables $\Xi^{m,i}$ and $\Omega^{m,i}$, the solution is similar to other papers in the literature, and therefore we omit further details.

B.3.4   Robustness checks

Alternative country groupings: We performed several checks to assess the extent to which our results are sensitive to different country groupings. We first used individual countries from the North (rather than the average). We confirmed that the results are robust for almost all countries. The results only change qualitatively when North consists of only the United States. Since the United States accounts for a large share of world GDP, and trade accounts for a small share of output, their imports from the South do not increase with domestic robotization, similar to the counterfacual exercise with high trade costs presented in the Appendix. For all other outcomes, the results are qualitatively similar to the baseline simulations. In addition, we performed simulations with different country groupings.

Alternative parameters: We also performed several checks to assess if our results are sensitive to the choice for some key parameters. In the baseline calibration, we assume that the elasticity of substitution between robots and workers is equal to 10, thus we set $\nu = 9$. In alternative simulations, we assumed elasticities of substitution between 5 and 30, and the qualitative implications were unchanged. The results also remained qualitatively similar under different robotization frontiers (such as $K^i = 0.8$) and different elasticities of substitution across products from different industries (with values between 1 and 5).

Figure A1: Robotization by country-sector

log(1+robots/hours)

56
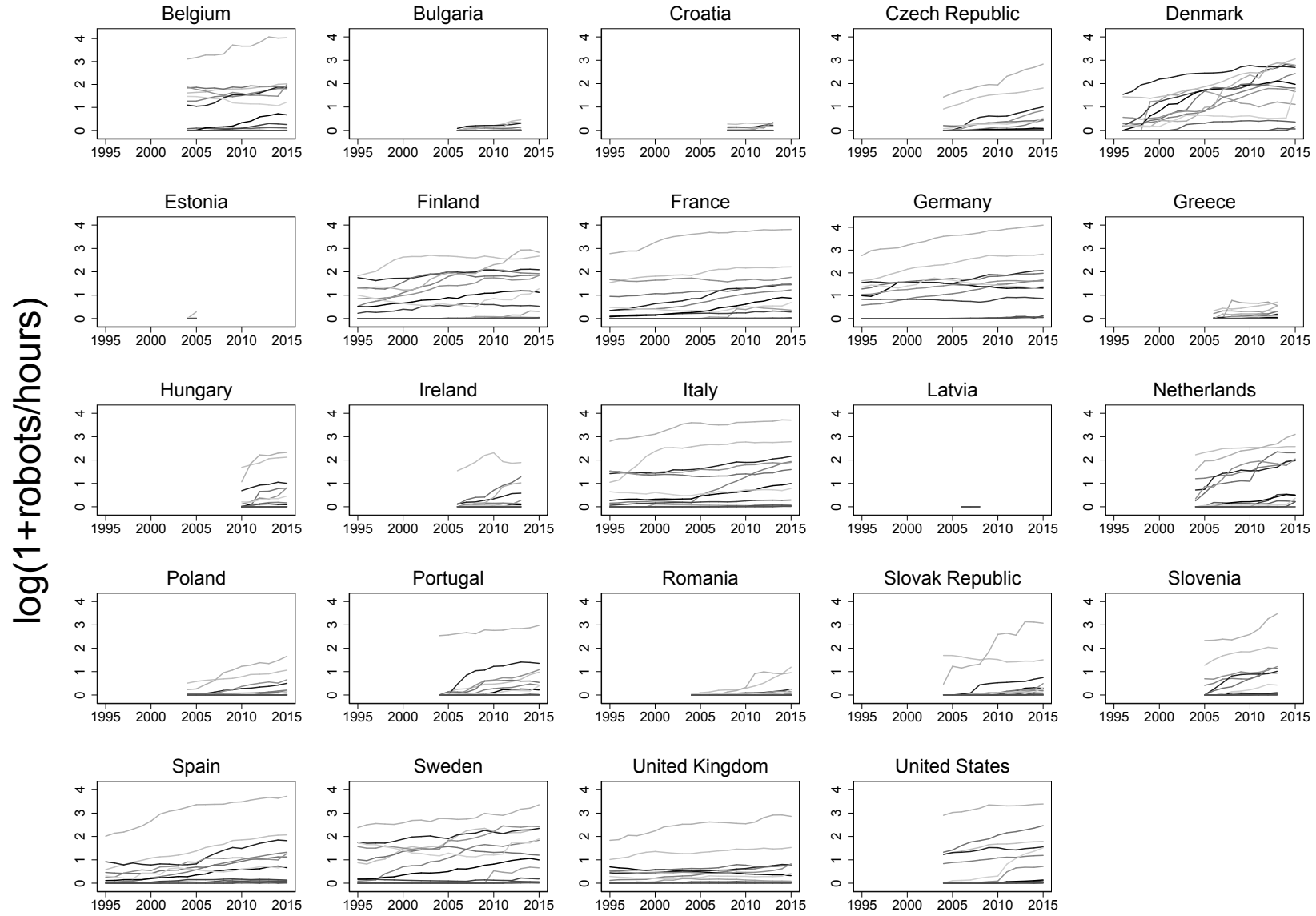
Figure A2: Robotization by sector-country
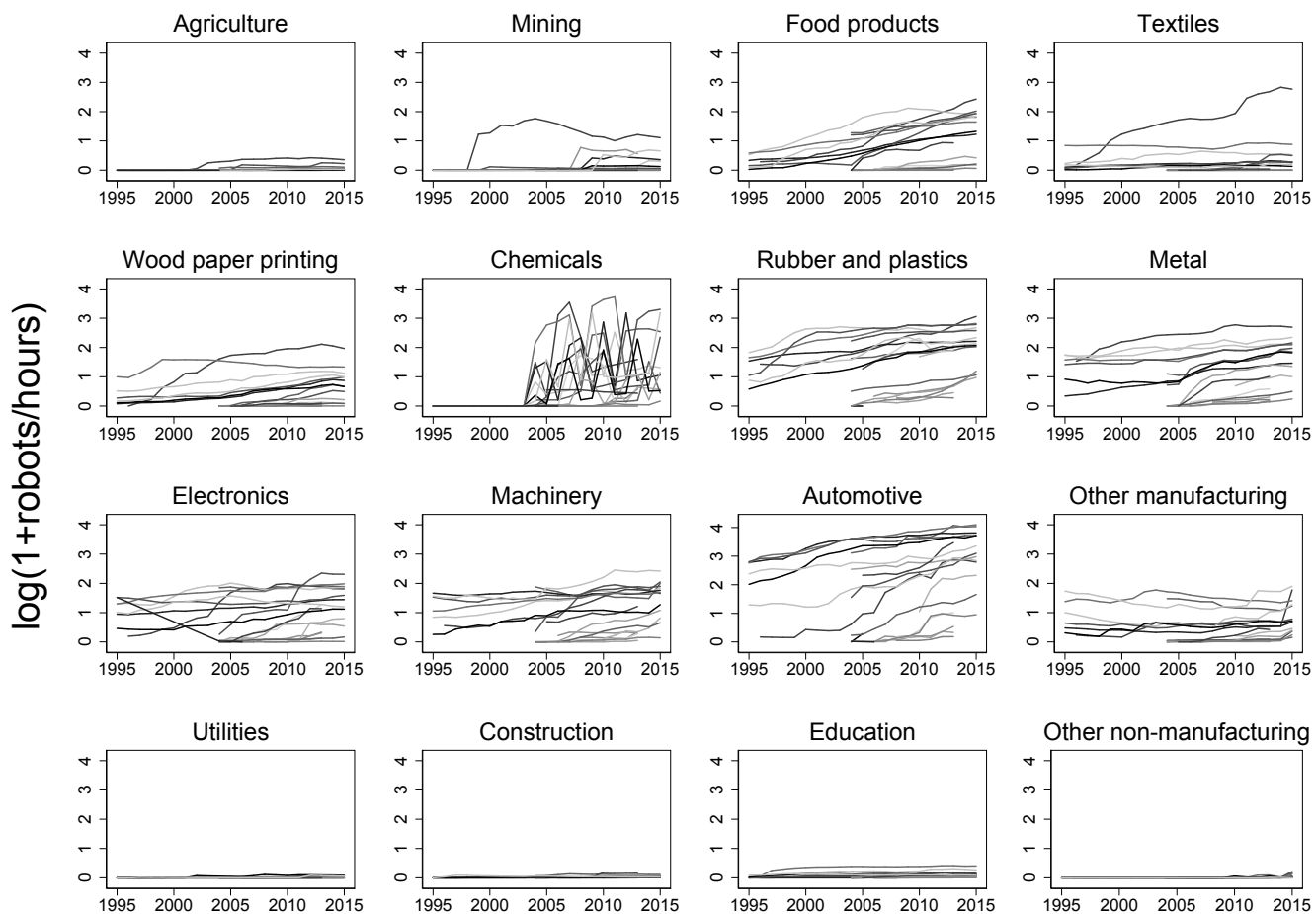
Notes: Figure depicts the stock of industrial robots by sector-country.

Figure A3: Changes in robotization and initial GDP per capita
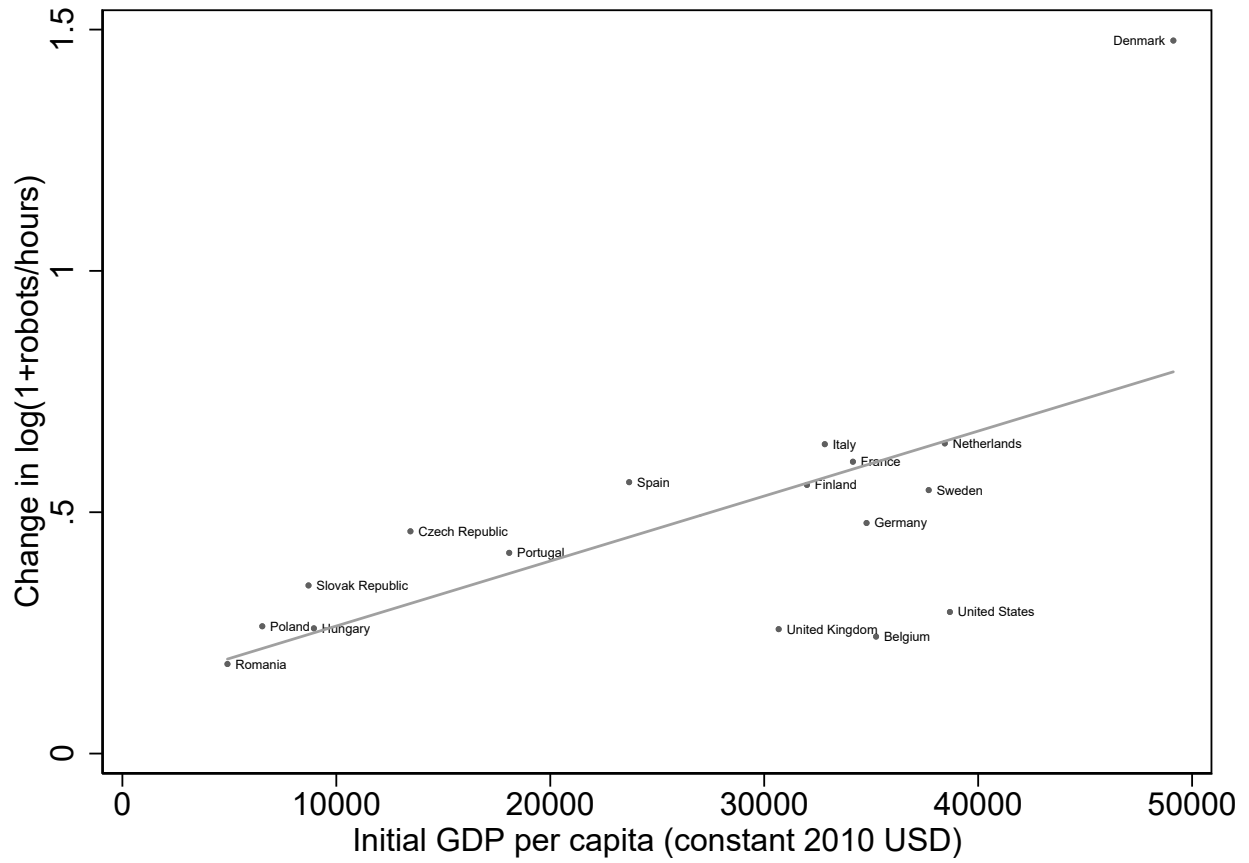
Notes: Figure depicts the relationship between the change in the robot density by country between the first and final years of the sample and the initial GDP per capita.

Figure A4: Changes in robotization and replaceability
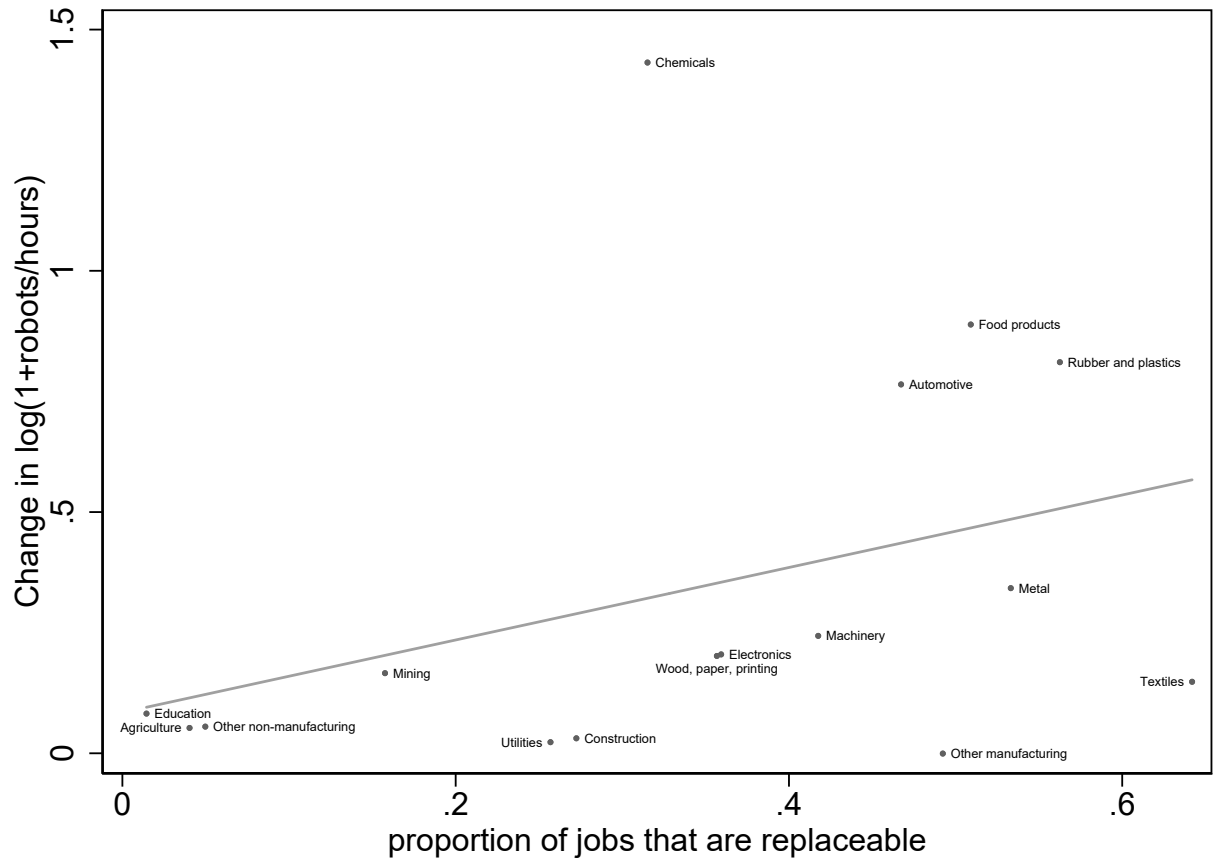
Notes: Figure depicts the relationship between the change in average robot density by sector between 1995 and 2015 and the industry's replaceability index.

Figure A5: Effects of Northern robotization on North-South trade (high trade costs)

Notes: Figure depicts the results of counterfactual simulations on the effects increased robot density in the North on North-South trade flows in the industry in which production is robotized, assuming that trade costs are twice as high as in the baseline 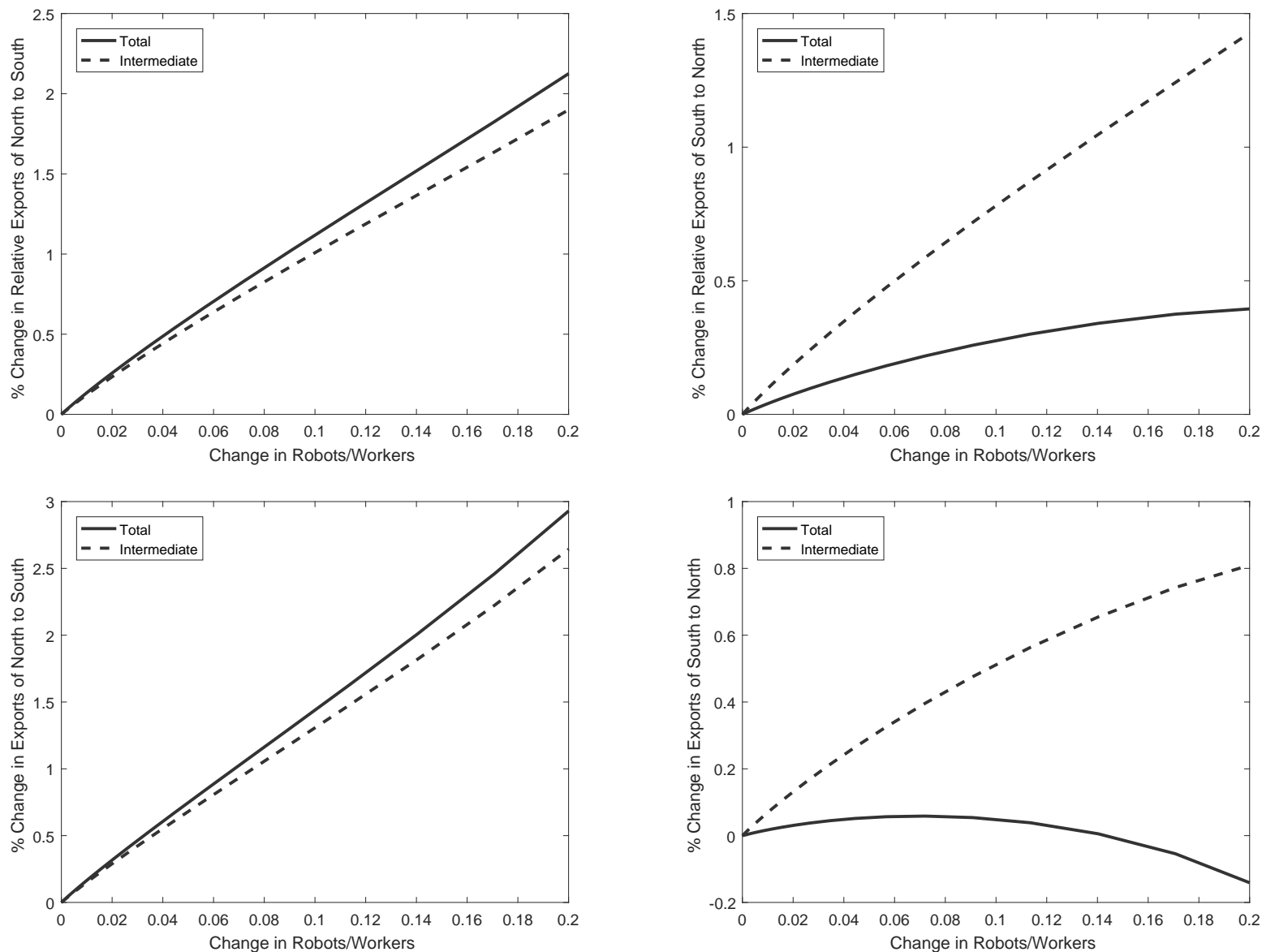simulation. The upper panel presents relative effects on exports of the representative country in the North or South (relative to other developed countries). The lower panel presents absolute impacts on real export values of the representative country in the North or South. The thick line refers to total exports, while the dashed line refers to exports of intermediate goods.

Figure A6: Effects of robot price reductions on robot use, labor allocation, wages and real GDP (high trade costs)
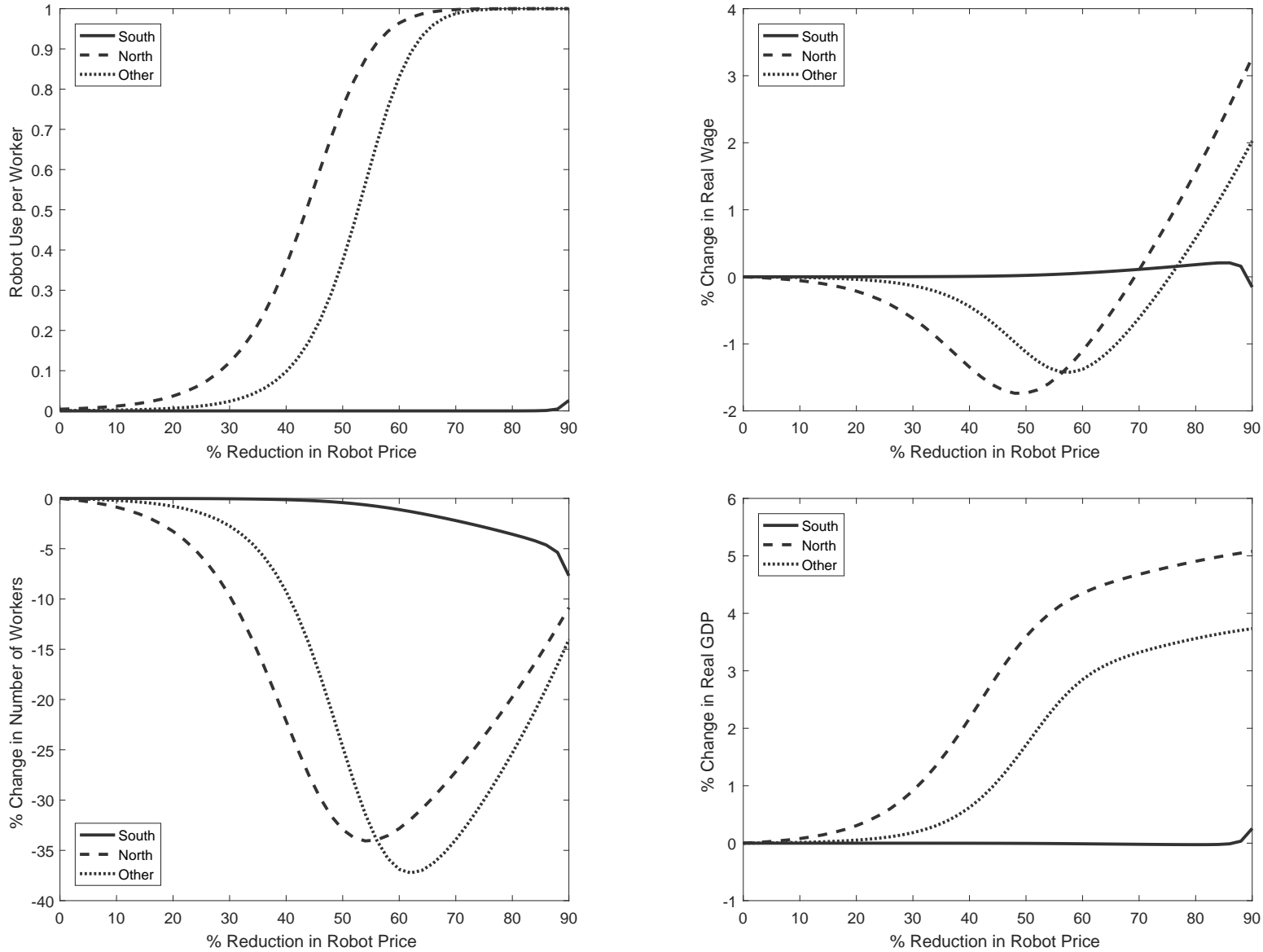
Notes: Figure depicts the results of counterfactual simulations on the effects of reductions in robot prices on robot use per worker in the robotized sector (upper-left panel), number of workers in the robotized sector (lower-left panel), real wages (upper-right panel) and real GDP (lower-right panel), assuming that trade costs are twice as high as in the baseline simulation. The long-dashed line refers to the representative higher-income country in the North, the thick line refers to the South, while the short-dashed line refers to other lower-income Northern countries.

Table A1: Industry classification

Label	IFR	EU KLEMS	BACI and TRAINS
Agriculture	A	A	111-322
Mining	C	B	510-990
Food Products	10-12	10-12	1010-1200
Textiles	13-15	13-15	1311-1520
Wood, paper, printing	16, 17-18	16-18	1610-1629, 1701-1820
Chemicals	19-21	19-21	1910-2100
Rubber and plastics	22, 229, 23	22-23	2211-2200, 2310-2399
Metal	24, 25	24-25	2410-2432, 2511-2599
Electronics	260-268, 271-275, 279	26-27	2610-2680, 2710-2790
Machinery	28, 289	28	2811-2829
Automotive	291-292, 2931-2934, 2939, 2999, 299, 30	29-30	2910-2930, 3011-3099
Other manufacturing	91	31-33	3100-3320
Utilities	E	D-E	3510-3900
Construction	F	F	4100-4390
Education	P	P	8510-8550
Other non-manufact.	90	45-47, 49-53, I, 58-63, K, L, M-N, O, Q, R, S, T, U	4510-8430, 8610-9900

Notes: Table reports the industry classification used in the analysis, as well as the corresponding codes in the IFR, EU KLEMS, BACI and TRAINS data sets. BACI and TRAINS are mapped from HS6 product codes to ISIC4 industry codes.

Table A2: Summary statistics, estimation sample, 1995-2015

	Mean	St. Dev.	Observations
	(1)	(2)	(3)
$log\ (1+exp)$	3.8384	3.9886	888,813
$log\ (1+imp)$	2.4173	3.5929	888,813
$log(1+\frac{robots}{hours})$	0.6211	0.8918	888,813
$log(1+\frac{obs.robots}{hours})$	0.7041	0.9813	888,813
$Initial\ GDPpc$	26791.2044	12687.1355	888,813
$Replaceability$	0.3397	0.1903	888,813
$Global\ robot\ stock$	17543.7724	11664.1515	888,813
$log\ (1+material\ inputs)$	0.1400	0.3013	888,813
$log\ (1+IT\ capital)$	0.0011	0.0057	888,813
$log\ (1+non\text{-}IT\ capital)$	0.0010	0.0042	888,813
$log\ (1+tariff)$	0.0102	0.1287	888,813

Notes: Table reports mens and standard deviations of the baseline estimation sample for the period 1995-2015.

Table A3: Long differences: 5-year intervals

Dependent variable:	OLS			IV		
	$log(1+imp)$	$log(1+exp)$	$log(\frac{1+imp}{1+exp})$	$log(1+imp)$	$log(1+exp)$	$log(\frac{1+imp}{1+exp})$
	(1)	(2)	(3)	(4)	(5)	(6)
$log(1+\frac{robots}{hours})$	0.1466*	0.3796***	-0.2329***	0.7252***	1.3597***	-0.6345***
	(0.0793)	(0.1273)	(0.0624)	(0.2217)	(0.3390)	(0.1938)
First stage:						
*Replaceability * initial GDPpc * global robot stock*				0.0041***	0.0041***	0.0041***
				(0.0004)	(0.0004)	(0.0004)
Observations	204,656	204,656	204,656	204,656	204,656	204,656
R^2	0.6361	0.7762	0.3935	0.6307	0.7634	0.3896
Kleibergen-Paap rk Wald F-stat				88.479	88.479	88.479
Importer-exporter-year effects	Y	Y	Y	Y	Y	Y
Industry-year effects	Y	Y	Y	Y	Y	Y

Notes: Table reports OLS and IV results of equation (23) in text, using data on 5-year intervals from the baseline estimation sample. Columns (1)-(3) report the OLS results, while columns (4)-(6) report the IV and corresponding first stage estimates. Robust standard errors clustered by developed country are presented in parentheses. ***1% level, **5% level, *10% level.

Table A4: Alternative robotization measure

Dependent variable:	OLS			IV		
	$log(1+imp)$	$log(1+exp)$	$log(\frac{1+imp}{1+exp})$	$log(1+imp)$	$log(1+exp)$	$log(\frac{1+imp}{1+exp})$
	(1)	(2)	(3)	(4)	(5)	(6)
$log(1+\frac{obs.robots}{hours})$	0.1387**	0.3854***	-0.2467***	0.5679***	1.0943***	-0.5264***
	(0.0669)	(0.1180)	(0.0646)	(0.1960)	(0.2843)	(0.1392)
First stage :						
*Replaceability * initial GDPpc * global robot stock*				0.0030***	0.0030***	0.0030***
				(0.0003)	(0.0003)	(0.0003)
Observations	888,813	888,813	888,813	888,813	888,813	888,813
R^2	0.6351	0.7739	0.3913	0.6313	0.7656	0.3890
Kleibergen-Paap rk Wald-F-stat				115.912	115.912	115.912
Importer-exporter-year effects	Y	Y	Y	Y	Y	Y
Industry-year effects	Y	Y	Y	Y	Y	Y

Notes: Table reports OLS and IV results of equation (23) in text, using the baseline estimation sample and an alternative robotization measure (the observed stock of robots, ignoring depreciation). Columns (1)-(3) report the OLS results, while columns (4)-(6) report the IV and corresponding first stage estimates. Robust standard errors clustered by developed country are presented in parentheses. ***1% level, **5% level, *10% level.

Table A5: Excluding outliers: robotization and dependent variables censored

Dependent variable:	OLS			IV		
	$log(1+imp)$ (1)	$log(1+exp)$ (2)	$log(\frac{1+imp}{1+exp})$ (3)	$log(1+imp)$ (4)	$log(1+exp)$ (5)	$log(\frac{1+imp}{1+exp})$ (6)
$log(1+\frac{robots}{hours})$	0.1771**	0.4384***	-0.2725***	0.5830**	1.1704***	-0.5942***
	(0.0738)	(0.1327)	(0.0720)	(0.2173)	(0.3223)	(0.1370)
First stage :						
*Replaceability * initial GDPpc * global robot stock*				0.0027***	0.0027***	0.0027***
				(0.0002)	(0.0002)	(0.0002)
Observations	870,826	871,295	870,942	870,826	871,295	870,942
R^2	0.6205	0.7624	0.4095	0.6179	0.7559	0.4070
Kleibergen-Paap rk Wald-F-stat				129.528	128.008	128.850
importer-exporter-year effects	Y	Y	Y	Y	Y	Y
Industry-year effects	Y	Y	Y	Y	Y	Y

Notes: Table reports OLS and IV results of equation (23) in text, excluding outliers from the baseline estimation sample (robotization and dependent variables censored). Columns (1)-(3) report the OLS results, while columns (4)-(6) report the IV and corresponding first stage estimates. Robust standard errors clustered by developed country are presented in parentheses. ***1% level, **5% level, *10% level.

Table A6: Using the inverse hyperbolic sine to account for zeros

Dependent variable:	OLS			IV		
	$sinh^{-1}(imp)$	$sinh^{-1}(exp)$	$sinh^{-1}(imp)-$ $sinh^{-1}(exp)$	$sinh^{-1}(imp)$	$sinh^{-1}(exp)$	$sinh^{-1}(imp)-$ $sinh^{-1}(exp)$
	(1)	(2)	(3)	(4)	(5)	(6)
$sinh^{-1}(\frac{robots}{hours})$	0.1431**	0.3479***	-0.2048***	0.5236***	0.9625***	-0.4389***
	(0.0621)	(0.1044)	(0.0560)	(0.1827)	(0.2513)	(0.1236)
First stage :						
Replaceability * init. GDPpc * global robot stock				0.0035***	0.0035***	0.0035***
				(0.0003)	(0.0003)	(0.0003)
Observations	888,813	888,813	888,813	888,813	888,813	888,813
R^2	0.6382	0.7753	0.3868	0.6349	0.7683	0.3850
Kleibergen-Paap rk Wald-F-stat				109.622	109.622	109.622
importer-exporter-year effects	Y	Y	Y	Y	Y	Y
Industry-year effects	Y	Y	Y	Y	Y	Y

Notes: Table reports OLS and IV results of equation (23) in text, using the inverse hyperbolic sine to account for zeros in the regression variables. Columns (1)-(3) report the OLS results, while columns (4)-(6) report the IV and corresponding first stage estimates. Robust standard errors clustered by developed country are presented in parentheses. ***1% level, **5% level, *10% level.

Table A7: Initial factor prices and other calibrated parameters

Initial wage in South			5.70	
Initial wage in Other			26.7	
Initial wage in North			39.5	
Initial rental rate of robots			59.0	
θ			5.00	
ν			9.00	

		sector X	sector Y	sector NT
	South	0.48	0.31	0.00
$\alpha_M^{m,i}$	Other	0.34	0.23	0.00
	North	0.34	0.21	0.00
	South	0.20	0.30	0.26
$\alpha_T^{m,i}$	Other	0.38	0.45	0.41
	North	0.36	0.49	0.40
	South	0.20	0.47	0.33
$\gamma^{m,i}$	Other	0.10	0.49	0.42
	North	0.13	0.59	0.28

Notes: Initial wages are calibrated with data on per capita GDP and expressed in thousands of USD. The initial effective rental rate of robots is $\frac{\phi_R^i}{\phi_L^i} w_R = 59$. The parameters θ and ν govern the trade elasticity and the elasticity of substitution between robots and workers, respectively. The Cobb-Douglas share parameters are calibrated using WIOD data.