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Automation-Induced Reshoring and Potential Implications for Developing Economies

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Abstract

Technological progress in automation technologies, such as Artificial Intelligence (AI), is expected to impact production activities beyond the home country adopting them as countries interact within the global trade system. Firms tend to offshore production activities to other countries when it is more profitable to produce elsewhere than at home. The adoption of automation technologies reduces the cost of producing in the home country, making previous offshore locations relatively less attractive. From a global perspective, the altered cost structure induces reshoring: a reorganization of production activities back home or to other lower-cost locations. Developing economies, which previously served as low-cost locations, could be adversely impacted by experiencing a drop in the production of the affected sectors and goods. This paper analyses the potential effect of automation on the global portfolio of trade specialization based on the principle of comparative advantage, employed in an extension of Duchin's World Trade Model to include non-tradable sectors. Through scenario-based analyses within the global economic context and using data, primarily, from the World Input-Output Database (WIOD) and the International Assessment of Adult Competencies (PIAAC), we find that countries in lower-income Asia are likely to be the most adversely affected by reshoring induced by automation in advanced economies.

Keywords: Reshoring, Automation, Specialization, Developing Countries, Advanced Countries

JEL: D33; E25; F14; F17; F47; J21; O33

1. Introduction

The past decade has been characterized by growing scholastic interest in the possible effects of new technologies in the wake of advances in automation technologies. Mobile Robotics, 3-D printing, Internet of Things, and Machine Learning are among the areas experiencing notable developments. Novel automation technologies currently possess the capacity to replace a variety of both manual and cognitive tasks. They can manage customer relations through chatbots, identify accounting miscalculations, accurately diagnose sicknesses, and monitor social media content, among others (Howard & Borenstein, 2020; Ivanov et al., 2020; Prettner and Bloom, 2020).

Given the early development and adoption of smart automation technologies in the advanced world, most of the research focused on industrialized economies. The seminal paper by Frey and Osborne (2017) estimated that about 47 percent of US jobs face high automation risk (a risk level above 70 percent). Several other studies followed: for instance, Arntz et al. (2017) argued that it is critical to account for differences in tasks performed under the same job as doing so reduced the estimated proportion of US jobs at high risk of automation. Previous work mainly concentrated on the within-country effects of automation technologies on employment and wages in the advanced world (Acemoglu and Restrepo, 2018; Gadberg et al., 2020). Relatively fewer studies have focused on the developing world such as Li et al, 2020, which documented the movement of labour from manufacturing to services in China.

In recent years, reports suggest that the impacts of automation-based technologies on output and workers can spill over geographical borders. Some industrial giants that formerly offshored parts of their production to lower-wage developing countries have been reported to relocate or reshore their production activities amidst rising wages in emerging markets and declining automation costs.[1] Adidas established Speedfactories in Ansbach, Germany, and Atlanta, USA, with the view to automating production using additive manufacturing.[2] Firms such as General Electric, Bosch, Philips, and Caterpillar have also been featured in the discussion (The Economist, 2013; Fratocchi et al., 2014; The Economist, 2017). The anecdotal evidence seems to indicate that, even if the diffusion and adoption of automation technologies in developing countries are limited by existing structural bottlenecks, as

[1] Offshoring and reshoring are both complex phenomena and can involve multiple motivations beyond labour costs such as flexibility to quickly meet changing demand, quality considerations, among others. Labour cost minimization is, however, a commonly cited reason for both phenomena (Johansson et al., 2019; Dachs et al., 2019). This study analyses the cross-border impact of automation-driven reshoring through the cost-channel.

[2] The Robotreport indicated that Adidas eventually shut down the Speedfactories, citing that it was still more profitable to operate in Asia since over 90% of their products are manufactured there. Available at: https://www.therobotreport.com/adidas-closing-german-us-robot-speedfactories/

surmised by World Bank (2016), developing countries could still be negatively impacted by automation efforts in industrialized economies.

The academic literature is trailing anecdotal evidence with regards to studying the potential impacts of automation spillover through reshoring, despite the need for a rigorous appreciation. In the International Business (IB) literature, where the study of offshoring is not new, but reshoring is relatively more recent, most of the studies have ignored technological change as one of the key drivers of reshoring (Dachs et al., 2019). Likewise, in the fields of the economics of technological change and international economics, research on the automation-reshoring relationship is thin albeit budding. Carbonero et al. (2018), one of the early studies, found that the adoption of robots in advanced countries has reduced offshoring and further decreased employment in emerging economies by 5 percent. However, robot exposure only accounts for a limited proportion of existing automation technologies. Moreover, most of the existing papers do not fully capture reshoring, which represents a generic relocation of production activities including but not limited to backshoring (production repositioning back home) (Albertoni et al., 2017; Di Mauro et al., 2018).

This paper bridges these gaps by analysing the effect of automation on the global reorganization of production activities between advanced and developing economies, thereby addressing the phenomena of off- and re-shoring. To conduct the analysis, the study extends the World Trade Model (WTM) proposed by Duchin (2005) to include non-tradable sectors and considers changes in the optimal international allocation of production activities under different (automation) scenarios. The WTM compares production costs globally and (re-)allocates production at the sector level under free trade. We construct the automation scenarios by estimating the labour-reducing risk of automation at the sector level. Our primary data sources are the World Input-Output Database (WIOD) and the International Assessment of Adult Competencies (PIAAC).

The paper is organized as follows. Section 2 reviews the literature on reshoring and its linkages with automation. Section 3 of the study presents our extended WTM model, as well as its empirical application and data sources. Section 4 reports and discusses the results and section 5 provides the summary and conclusion of the analysis.

2. Related Literature: Offshoring, Reshoring, and Automation

The literature on reshoring is recent and derives from older literature on offshoring. It is, therefore, worth succinctly introducing the offshoring literature. The theoretical roots that explain the motivations of offshoring date to the seminal contribution by Coase (1937). The paper explains why firms exist, arguing that they do because markets are not without transaction costs. The presence of transaction costs necessitates the existence of firms to offer an alternate means of allocating resources and organizing production.

Buckley and Casson (1976) extended the previous work to the multinational firm and introduced the internalization theory. The central idea is that firms "internalize" (i.e. conduct certain value chain activities internally) to exploit and develop firm-specific advantages in knowledge and intermediate products instead of relying on markets as an external coordinating mechanism. From this viewpoint, variations in value chain activities are influenced by underlying factors such as changing costs in the global economic system (Casson, 2013). Thus, the internalization theory adopts a systemic view of global product fragmentation.

The eclectic paradigm by Dunning (1977;1980), also known as the OLI framework, focuses more on heterogeneous firm characteristics and builds on the internalization theory by considering three main advantages. First, ownership advantages (O) denote the extent to which a firm holds (or can own) assets that its (potential) competitors do not hold, such as the ownership of capital, patents, or intellectual property rights. Second, location advantages (L) relate to the benefits of complementing the assets owned with the resources or conditions abroad such as lower labour costs, favourable government policies, and nearness to markets. Third, internalization advantage (I) refers to the advantage of making use of the assets rather than selling or leasing them.[3] Put simply, Dunning's theory stipulates that the OLI advantages are linked and essential for the internationalization of production. Greater ownership advantages tend to increase the internalization advantage, and these advantages combined with more attractive foreign location advantages provide a strong incentive to offshore.

Empirical work in the international business (IB) strand of literature has closely followed the theoretical contributions by investigating the main motivations of offshoring, with an emphasis on estimating their effect sizes via regression frameworks. Through probit analyses based on the German Manufacturing Survey, for

[3] The study of offshoring is well-established with multiple theories proposed to explain the phenomenon based on the relative costs and benefits of offshoring, including internalization theory, OLI framework, resource-based view, and transaction cost economics (TCE). However, internalization theory and OLI theory are the most widely used theoretical lenses. It is also worth noting that, while TCE and internalization theory are similar, the latter is broader and further assumes awareness of existing costs. Bounded rationality plays a more important role in TCE (Foss, 2003; Delis et al, 2019; Dachs et al, 2019).

instance, Kinkel and Maloca (2009) found that, "the reduction of labour costs is the most important single motive for production offshoring activities".

Generally, previous studies on the organization of global production networks tended to focus on offshoring as a uni-directional phenomenon. However, recent reports have indicated a possible counter-trend whereby firms reverse their offshoring decision and relocate production networks or reshore (Economist, 2013; 2017). The IB literature noted the reversal of offshoring early, but it was viewed as stemming from managerial mistakes: miscalculations of the risks of offshoring (Kinkel and Maloca, 2009).[4] Reshoring was, however, subsequently recognized as the change of a completely rational offshoring decision, motivated by changes in the host or home country conditions (Di Mauro et al., 2018).

The motivations for reshoring are discussed within the existing theories of offshoring. Through the perspectives of the internalization and OLI theories, for instance, reshoring is explained in terms of the declining advantages of ownership, location, and internalization. Concerning the location advantages more specifically, the rise of labour costs in developing countries has been identified as a major driver of reshoring due to an emerging disincentive to operate certain value chain activities in these countries (Casson, 2013; Dachs et al., 2019). These studies also generally support the view that different sectors or firms in a given country may be simultaneously offshoring and backshoring at any given time. Thus, determining the magnitude of ultimate impacts on an economy depends on the relative strengths of offshoring and backshoring activities.

Some recent studies have confined reshoring to backshoring or back-reshoring, which refers to the relocation of production activities back to the home country (Delis et. al., 2019; Faber, 2020). However, reshoring is broader than backshoring; it can additionally involve a relocation of value chain activities from a host country to another country other than the home country (Albertoni et al., 2017; Di Mauro et al., 2018).

Following the earlier work on offshoring, the international business (IB) strand of literature has centred empirical analyses on identifying the most important drivers of reshoring. Like the offshoring literature, labour cost differences stand out as one of the most important considerations in the newer reshoring literature (Johansson et al., 2019; Delis et. al., 2019). Technological change has been largely ignored as a driver of reshoring in the IB strand of literature. Dachs et al., 2019 stress this point and argue, consistent with the reported anecdotal evidence, that Industry 4.0 will likely positively

[4] This perspective is rooted in Transaction Cost Economics theory as it attributes a reduction in offshoring or reshoring to bounded rationality in determining foreign location costs.

affect reshoring by making labour arbitrage less attractive as factor cost advantages in foreign locations are counteracted.[5]

The economics literature is witnessing increasing interest in linking automation technologies to reshoring and employment. This attention is mainly driven by concerns that the adoption of new automation technologies in the advanced world could drive reshoring, as labour cost advantages in developing economies that serve as host countries are eroded, which could in turn adversely impact production and employment in the developing world. De Backer et al. (2018) described this phenomenon as *botsourcing*. The paper concluded that the use of robots is not yet triggering backshoring based on their full sample covering 2000 to 2014. Conversely, Carbonero et al. (2018) found that offshoring to emerging economies decreased because of automation efforts in advanced economies. Due to the focus on robots, these studies do not substantially account for disembodied technological change present in the advancement of algorithms and software.

Besides, most of the recent studies employ regression frameworks involving some measure of reshoring or offshoring such as the share of imported intermediate inputs in the same industry over total non-energy intermediates (Feenstra and Hanson 1996; Faber 2020). Krentz et al. (2021) also proposed a new reshoring measure based on the premise that earlier measures merely capture a reduction in offshoring, which is not necessarily equivalent to reshoring. The paper measures reshoring as the time-difference between the ratio of domestic to foreign inputs over a present and past period. However, the measure equates reshoring to backshoring and thereby does not fully address reshoring. Besides, the use of regression approaches does not provide a system's view that incorporates critical interdependences within the global economy, such as the coexistence of offshoring and backshoring.

The World Trade Model (WTM) proposed by Duchin (2005) possesses properties useful for analysing the global consequences of automation-driven reshoring, taking into account relevant interdependences during trade. It is a linear program that determines worldwide outputs and factor inputs (in the primal program) and world prices (in the dual program) based on each country's comparative advantage in the global economy. The model is an extension of the 2-country, 2-good, 2-factor World Model of Leontief et al. (1977) to an m-country, n-good, k-factor case, and is an alternative to more complex models (such as Computable General Equilibrium models that requires additional assumptions to be operationalized). Strømman and Duchin (2006) extended the model to determine bilateral trade flows. Several other extensions and applications have been suggested, such as the use of the model to analyse scenarios about potential changes in the future (Dilekli and Cazcarro, 2019;

[5] Another technology-backshoring channel that authors point out is flexibility. In addition to the labour cost channel, they argue that Industry 4.0 technologies promise flexibility in production which could induce firms to backshore or reshore close to advanced-country customers.

Rocco et al, 2020). Our analysis extends the WTM to include non-tradable sectors as doing so addresses extreme specialization, which is a limitation of the original WTM.

The analytical prowess of the WTM can be coupled with recent literature that estimates the risk of automation to construct alternative scenarios of automation-induced reshoring. The seminal work by Frey and Osborne (2017) asserted that new automation technologies are smarter: they can also perform varied cognitive tasks in addition to manual tasks. The study estimated that about 47 percent of total US employment is at a high risk of automation. This was achieved by first asking experts to hand-assign binary values to 70 jobs (1 for jobs that are expected to be automated; 0 otherwise). Machine learning algorithms then linked them with job descriptions to predict their automation risks. This relationship was extrapolated to their entire dataset. Job descriptions in the O*NET database were used to determine the automation risks to various jobs depending on whether the tasks that they embodied were difficult to automate.

Logit regressions can also be estimated to compute the risks conditional on tasks, according to Nedelkoska and Quintini (2018). Foster-McGregor et al. (2019) aggregate the individual-level risks to the sector and country levels using their employment shares as weights. Nii-Aponsah, (2022) further breaks down risks to different workers in the gender, age, and skills labour market dimensions and includes "learning" tasks to capture labour adaptive capacity, which can reduce the automation risk of workers. We employ the latter approach, which encompasses a broader set of bottleneck tasks, to compute automation risks. Automation scenarios can be constructed by reducing labour coefficients in the input-output framework (Leontief and Duchin, 1984). Our approach reduces labour coefficients to create automation scenarios using automation risk estimates instead of assumptions on parameters, which was done in previous work.

By coupling automation-risk estimates with our WTM with non-tradables model (henceforth WTMNT), this study offers a unified analysis that bridges existing gaps in both economics and IB literature. The estimated automation risks capture automation technologies beyond robots. In addition, the WTMNT can be implemented as a general equilibrium scenario-based analysis that accounts for intersectoral relations in intermediate inputs. It is, thus, suitable for analysing the changing patterns of trade from a system's perspective. In this sense, it is linked with the internalization theory. Furthermore, since an automation-induced change in the global production cost structure drives the worldwide reorganization of intermediate inputs and production activities in this framework, reshoring is captured in its broad sense.

3. Empirical Approach

Our approach to analysing the impact of automation on reshoring is based on input-output economics. We formulate a model, based on Duchin (2005), that uses linear programming to allocate production across countries in an optimal way (minimizing production costs) given the desired level of final demand (private and government consumption plus investment). We will set this model up using empirical data from the World Input-Output Database (WIOD) and compare outcomes using actual data on labour input coefficient (i.e., labour productivity), and using alternative labour input coefficients that have changed, in part of the world, due to automation. We will first explain the theory of the model and our adaptation of it that allows for non-tradeable sectors and then present the empirical results.

3.1 The World Trade Model with Non-Tradables (WTMNT)

Duchin's original World Trade Model (WTM) is an input-output-based linear program with *m* countries, *n* goods/sectors, and *k* factors. The primal version of the program minimizes the global cost of factor use subject to country-specific factor prices, technologies, consumption requirements, and factor endowments and thereby determines the world allocation of inputs and outputs according to each country's comparative advantage. The WTM model treats demand as exogenous. The dual version of the program determines world prices for traded goods, and shadow prices in the form of factor scarcity rents and benefit-of-trade rents.

Our preference for a linear input-output based model over more complex ones, such as the Computable General Equilibrium (CGE) models, stems from the fact that these alternative models generally require additional assumptions about agents' behaviour, market structure, and elasticities and are therefore more difficult to operationalize (Rocco et al, 2020). The linear input-output-based model is sufficient to address the objective of our research.

In a model similar in spirit, ten Raa and Mohnen (2001) considered a linear program where final demand is maximized in a free trade model with one country (Canada) and the rest of the world. Following them we introduce non-tradables in the WTM model, hence the denomination WTMNT (WTM with non-tradables). It is more realistic to allow for non-tradables because some services are location-bounded, and some others are produced locally for reasons of self-sufficiency. Moreover, it diminishes the possibility of extreme specialization when a single country produces all the global output in a given sector.

Table 1 presents the key variables of the model, together with their dimensions and indications as to whether they are endogenous or exogenous. The notations are the same as in Duchin (2005), with some additions, including: $y_{0,i}$ (final demand for tradable sectors only), $y_{1,i}$ (final demand for non-tradable sectors only), $p_{1,i}$ (prices of non-tradable commodities), and matrices J_0 and J_1, which select the tradable and non-tradable sectors, respectively.

Table 1: Key Parameters of the World Trade Model with Non-Tradables

Symbol	Dimension	Description	Category
A_i	*n x n*	Matrix of inter-industry production coefficients in country *i*	Exogenous
F_i	*k x n*	Matrix of factor inputs per unit of output in country *i*	Exogenous
x_i	*n x 1*	Vector of output in country *i*	Endogenous
y_i	*n x 1*	Vector of domestic final demand for all sectors in country *i*	Exogenous
$f_{nt,i}$	*k x 1*	Vector of factor use when there is no trade by country *i*	Exogenous
f_i	*k x 1*	Vector of factor endowments in country *i*, where *fi ≥ fnt,i*	Exogenous
π_i	*k x 1*	Vector of factor prices in country *i*	Exogenous
$p_{nt,i}$	*n x 1*	Vector of commodity prices in country *i* if there is no trade	Endogenous
p_0	*n0 x 1*	Vector of world prices per tradable good	Endogenous
r_i	*k x 1*	Vector of factor scarcity rents in country *i*	Endogenous
α_i	*scalar*	benefit-of-trade shadow price in country *i*	Endogenous
$y_{0,i}$	*n0 x 1*	Vector of domestic consumption for tradable sectors in country *i*	Exogenous
$y_{1,i}$	*n1 x 1*	Vector of domestic consumption for non-tradable sectors in country *i*	Exogenous
$p_{1,i}$	*n1 x 1*	Vector of prices for non-tradable goods during trade in country *i*	Endogenous
J_o	*n0 x n*	Matrix that selects the tradable sectors	Exogenous
J_1	*n1 x n*	Matrix that selects the non-tradable sectors	Exogenous

Note: There are a total of *m* countries, *n* sectors/goods, and *k* factors. *n0* and *n1* denote the number of tradable and non-tradable sectors, respectively, and add up to the total *n* sectors.

The WTMNT entails a primal formulation (also referred to as the quantity model) and a dual formulation (also termed the price model). In line with the duality theorem, the primal and dual problems of the WTMNT return the same optimal value. The primal program minimizes global production factor costs by solving for the optimal global allocation of outputs and factor use across countries and sectors, subject to four sets of restrictions. First, a materials balance constraint assures that worldwide production satisfies global final demand requirements for all tradable goods and domestic production satisfies domestic demand for each non-tradable good.[6] Second, the endowment constraints (given by: $-F_i x_i \geq -f_i$ for each *i*) imply that the total quantity of a given factor used by a country must not exceed the total endowment of the factor in the country in question. Third, for each country a benefit-of-trade constraint (given by: $-p_{nt,i}'(I - A_i)x_i \geq -p_{nt,i}'y_i$ for each *i*) is imposed to

[6] We make no distinction between commodities and sectors as the input-output data that we use are constructed under the industry technology model. All commodities produced by a given sector use the same technology. Under the commodity technology model, the number of commodities may exceed the number of industries as each commodity has its own technology wherever it is produced (ten Raa and Mohnen, 2001 used the commodity technology model).

ensure that its imports at autarky prices are worth at least as much as its exports.[7] The autarky prices are equal to average costs, given exogenous factor requirements and factor prices. Fourthly, a non-negativity constraint is imposed because outputs cannot be negative.

Primal Problem of the World Trade Model with Non-Tradables:

Minimize $z = \sum_i \pi_i{}' F_i x_i$

Subject to:

$$\begin{bmatrix} J_o(I - A_1) & \cdots & J_o(I - A_m) \\ J_1(I - A_1) & & 0 \\ & \ddots & \\ 0 & & J_1(I - A_m) \\ -F_1 & & 0 \\ & \ddots & \\ 0 & & -F_m \\ -p'_{nt,1}(I - A_1) & & 0 \\ & \ddots & \\ 0 & & -p'_{nt,m}(I - A_m) \end{bmatrix} \begin{bmatrix} x_1 \\ \vdots \\ x_m \end{bmatrix} \geq \begin{bmatrix} \sum_i y_{0,i} \\ y_{1,1} \\ \vdots \\ y_{1,m} \\ -f_1 \\ \vdots \\ -f_m \\ -p_{nt,1}{}' y_1 \\ \vdots \\ -p_{nt,m}{}' y_m \end{bmatrix} \tag{1}$$

with

$x_i \geq 0, \forall\, i$

Dual Problem of the World Trade Model with Non-Tradables:

Maximize $z = p'_0 \sum_i y_{0,i} + \sum_i p'_{1,i} y_{1,i} - \sum_i r'_i f_i - \sum_i \alpha_i (p'_{nt,i} y_i)$

Subject to:

[7] Proposition 4 of Duchin (2005) shows that: $-p_{nt,i}{}'(I - A_i)x_i \geq -p_{nt,i}{}' y_i \rightarrow \pi_i{}' F_i x_{nt,i} \geq \pi_i{}' F_i x_i$. Thus, the benefit-of-trade constraint assures that country i enters trade only if its total factor cost in free trade, ($\pi_i{}' F_i x_i$) is no greater than the corresponding cost in autarky ($\pi_i{}' F_i x_{nt,i}$). Intuitively, a country would not accept to enter free trade if it exported some of its factor endowments at autarky prices (rather than higher world prices which embody benefit-of-trade rents).

$$\begin{bmatrix} (I-A_1')J_0' & (I-A_1')J_1' & & 0 & -F_1' & & 0 & -(I-A_1')p_{nt,1} & & 0 \\ \vdots & & \ddots & & & \ddots & & & \ddots & \\ (I-A_m')J_0' & 0 & & (I-A_m')J_1' & 0 & & -F_m' & 0 & & -(I-A_m')p_{nt,m} \end{bmatrix}$$

$$\begin{bmatrix} p_0 \\ p_{1,1} \\ \vdots \\ p_{1,m} \\ r_1 \\ \vdots \\ r_m \\ \alpha_1 \\ \vdots \\ \alpha_m \end{bmatrix} \leq \begin{bmatrix} F_1{}'\pi_1 \\ \vdots \\ F_m{}'\pi_m \end{bmatrix} \qquad (2)$$

with

$p_0, p_{1,i}, r_i, \alpha_i \geq 0, \forall\, i$

In the dual problem, the objective is to maximize the total value of factor income including scarcity rents and benefit of trade rents. The dual model takes final demand as exogenous and solves for world prices of traded commodities (p_0), domestic prices of non-tradables ($p_{1,i}$), as well as country-specific scarcity rents (r_i) and rent corresponding to the benefit of trade constraints (α_i). The objective function is subject to two constraints. The first constraint assures that, in each economy, commodity prices and rents do not exceed the cost of inputs per unit of output. The second constraint restricts prices and rents to non-negative values. Because the minimal production costs from the primal model correspond to the maximum factor income of the dual model, the optimal values are shared between the two models:

Common Optimal Value of the World Trade Model with Non-Tradables:

$$p_0' \sum_i y_{0,i} + \sum_i p_{1,i}' y_{1,i} - \sum_i r_i' f_i - \sum_i \alpha_i (p_{nt,i}' y_i) = \sum_i \pi_i{}' F_i x_i \qquad (3)$$

By the Duality Theorem of linear programming, the primal and dual programs must yield the same optimal result (Luenberger, 1989). In our context, the implication is that prices for tradable and non-tradable commodities cover production costs, and by the complementary slackness condition, production does not take place in sectors where production cost exceeds the market value of output. Factors of production receive scarcity rents over and above the exogenous country-specific factor prices when they are fully utilized. Factor prices are not equalized across countries since the production factors are considered to be immobile. If a factor of production is not fully utilized, it earns just the exogenous factor price. Intuitively, a country earns rents for the commodity-incorporated exports of its endowments. We expect the optimal global production cost of our world trade model with non-tradables to exceed the optimal cost of a world trade model with all commodities tradable, but to be lower than the optimal solution under no trade. The reason is that trade provides more opportunities to minimize costs whereas non-tradables restrict this range of possibilities.[8]

To evaluate the effect of automation on the international division of labour, we compare a baseline scenario (using actual data) with an automation scenario (constructed by reducing the labour coefficients by risks of automation estimates). We construct the risk of automation for different country-sectors in line with recent literature (Nedelkoska and Quintini, 2018; Foster-McGregor et al., 2019; Nii-Aponsah, 2022). Put simply, the approach uses logit regressions to predict automation risks to individual workers in different country-sectors based on the automation bottleneck tasks that they perform and aggregates their risks to the country-sector level using the formula below.[9]

$$\rho_{ri} = \frac{\sum_k \rho_{rik} S_{rik}}{\sum_k S_{rik}} \tag{4}$$

ρ_{ri} is the risk of automation for sector *i* in country *r*. It is summed over all *k* workers in sector *i*; ρ_{rik} indicates the risk of automation of worker k in sector *i* and country *r*, and S_{rik} is the associated full final PIAAC sampling weight of individual k in sector *i* and country *r*.

Because the automation scenario is constructed by reducing labour coefficients (mainly in advanced country-sectors) by their corresponding automation risks, labour costs become cheaper in the advanced world.[10] This results in a reorganization of (intermediate) inputs and production activity *away* from sectors (in developing countries) where production factors are relatively more expensive, which in turn changes output and income between (comparable) scenarios.

[8] If there are no non-tradable sectors, the approach simplifies to Duchin's WTM. If all sectors are non-tradable, the benefit-of-trade constraints are not imposed and the WTMNT simplifies to the No Trade model.

[9] Automation bottleneck-tasks are those tasks performed by workers that are difficult to automate. This analysis uses the set of tasks in Nii-Aponsah (2022), which includes 'learning' tasks to account for the fact that labour adaptive capacity also reduces the automation exposure of workers.

[10] The automation risks were separately computed for 2-digit sectors in the following advanced countries: Belgium, Czech, Denmark, France, Greece, Italy, Japan, Republic of Korea, Netherlands, Poland, Russia, Slovakia, Slovenia, Spain, and UK. For the remaining advanced country-sectors in WIOD but not in PIAAC, we use the automation risks computed from the combined sample of the above-listed advanced economies.

4. Empirical Findings

This section presents the findings of our analysis based on the approach explained in the previous section. As explained in detail in Appendix C, our data are taken from an actual description of the global economy (the WIOD database). This describes a situation in which trade takes place, and the appendix explains how we calculate autarky values of the variables based on these data. However, trade in this real-world situation is not as far-developed as the WTM (or WTMNT) linear programs predict, for example, because the models do not include any transportation or other trading costs. Therefore, the autarky (no-trade) linear program as well as the WTM and WTMNT linear programs are abstractions that are necessarily different from the actual data observed in the WIOD.

The main focus of our analysis is the impact of automation on the distribution of production across the world. For this, we specify two automation scenarios, which entail changing the labour coefficients according to the automation risk estimates that were discussed above. In the first automation scenario, only the developed world implements automation technology, and hence the labour coefficients only change in the developed countries. In the second automation scenario, automation is global, i.e., all countries have lower labour coefficients.

The simplest way to implement the three scenarios (baseline and automation) in the three models (No Trade model, WTMNT, and WTM) is to impose the labour and capital endowments as they appear in the data. In this case, either capital or labour may provide a constraint in each particular country, but it is generally the case that (global) final demand is satisfied while some countries do not become constrained in any production factor. The reason is that each of the three models assumes that the final demand is exogenous and equal to what we observe in the real-world input-output table, and those values correspond to a situation in which no country produces at full capacity. This is the first way in which we solve our models, but we only use this to broadly check the consistency of the solutions obtained under autarky, WTM, and WTMNT.

Table 2 presents the optimal values for these model solutions. The left column uses factor coefficients as they are observed in the data, while the middle column assumes that automation takes place in developed countries, and the rightmost column assumes that automation takes place in all countries. In each of the three columns, the results confirm Duchin's basic result that trade permits countries with comparative advantage to produce goods to satisfy worldwide consumption requirements at a lower global cost than autarky. This is seen from the fact that the bottom line (WTM) in the table has lower values than the top line (no trade, or autarky). The WTMNT is an intermediate case where some but not all of the benefits of trade are reaped. Furthermore, automation reduces global factor costs by improving productivity and thus reducing the cost of labour in output.

Table 2: Global Factor Use Cost (US$ millions), Baseline and Automation Scenarios

Model	Baseline	Developed world Automation	Global Automation
No Trade Model	74,366,875	60,592,661	51,120,128
World Trade Model with Non-Tradables	49,897,034	38,361,280	35,259,063
World Trade Model	34,884,787	23,956,648	21,521,377

Note: In both baseline and automation scenarios, global factor use cost of the World Trade Model with Non-Tradables lies between the Duchin's No Trade Model and World Trade Model.

A second possible way to solve the models assumes that each country produces at maximum capacity of at least one production factor. This is achieved by progressively increasing global final demand, by multiplying the final demand vector by ever-larger scalar numbers, until a solution to the linear program becomes infeasible. Note that this means that final demand increases everywhere in the world by the same multiplicative factor. At the maximum feasible multiplication factor, at least one of the endowment constraints for labour and capital is binding in all countries (i.e., factor use equals factor endowments). We solved the model in this way, but do not document the results to save space (these results are available on request).

Furthermore, we consider a third way to solve the models, which is focused on the implications of labour rather than capital being the scarce factor, under a situation of full employment (i.e., a binding labour constraint) in every country. This is implemented by first increasing capital endowments in every country to (very) large amounts, to ensure that capital never becomes the binding factor, and then progressively increasing final demand until labour becomes binding in every country, in the same way as before. Obviously, this yields a hypothetical solution to the linear programs, not only in the sense that full employment is reached globally, but also in the sense that final demand is at the maximum possible value given the state of technology in every country.

Solving the models in this way yields a very specialized international distribution of labour. In the baseline scenario, in 19 of the 44 tradeable sectors, production takes place in just one country, 14 other sectors have production concentrated in 2 countries, and 5 sectors concentrated in 3 countries, leaving 6 sectors with more than 3 countries. The largest number of countries in which production takes place for a single sector is 11, which happens in wholesale trade.

Table 3: Shares of Global GDP and share of rents in GDP, Baseline Scenario

	Shares of global total					Shares of GDP in country group	
	Actual GDP (data)	Factor price income	Scarcity rents	Benefit of trade rents	Total GDP	Scarcity rents	Benefit of trade rents
NA&A	0.276	0.241	0.257	0.000	0.246	0.968	0.000
EU	0.240	0.225	0.221	0.517	0.233	0.878	0.090
H'Asia	0.084	0.096	0.073	0.000	0.070	0.955	0.000
L'Asia	0.178	0.175	0.173	0.158	0.173	0.930	0.037
LAM	0.045	0.052	0.087	0.230	0.092	0.880	0.101
ROW	0.176	0.211	0.189	0.094	0.186	0.942	0.021

Table 3 documents the shares of global GDP of 6 country groups in these optimizations, as well as the share of rents related to the shadow prices in each of the country groups. In this case, i.e., the baseline scenario without labour saving due to automation, the maximum feasible multiplication factor for final demand was 1.606. The table also documents the share of global GDP of the country groups in the actual data.

The country groups are as follows:

- North America (comprising USA and Canada) and Australia (NA&A);
- Europe (EU): Austria, Belgium, Bulgaria, Switzerland, Cyprus, Czech Republic, Germany, Denmark, Spain, Estonia, Finland, France, United Kingdom of Great Britain and Northern Ireland, Greece, Croatia, Hungary, Ireland, Italy, Lithuania, Luxembourg, Latvia, Malta, Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, and Sweden;
- High-income Asia (H'Asia), which includes Taiwan, Japan, and Korea;
- Lower-income Asia (L'Asia), which includes China, India, and Indonesia;
- Latin America (LAM), covering Brazil and Mexico;
- Rest of the World (ROW): Russian Federation, Turkey, and WIOD-ROW.

We note that in Table 3, the optimization assigns a much higher share of GDP to LAM as compared to the actual data, and a slightly higher share to ROW. The 4 other country groups get a smaller share of global GDP than what they have in the actual data. In this particular setup, i.e., production at global full employment, scarcity rents (for labour, as capital is never scarce) are the largest share of GDP in each region, and benefit-of-trade rents are much smaller shares, which are highest in EU and LAM. Factor payments at exogenous factor prices represent a very small share of GDP.

Next, we present the results of the optimizations where labour saving is introduced. We still focus on the results corresponding to the full employment setup, as in Table 3. If automation/labour saving is introduced in the developed countries, which are the NA&A, EU, and H'ASIA groups, plus the Russian Federation (part of ROW), we are able to multiply final demand by 2.440. If labour saving is global, then we are able to multiply by 2.492. Table 4 shows the shares of production value of each country group in each broad sector and the changes of this in the automation scenarios relative to the baseline. The table only includes sectors that were treated as tradeable in the analysis.

Table 4: Shares of sectoral GDP and changes relative to Baseline Scenario

	A: Agriculture, Forestry, and Fisheries	B: Mining	C: Manufacturing	JK: Trade, Hotels, Restaurants	MN: Services
Baseline					
NA&A	95.6	12.9	1.3	0	0
EU	4.4	36.4	18.9	27.1	0.6
H'ASIA	0	0	20.7	17.4	3.6
L'ASIA	0	28.4	51.8	20.3	28.9
LAM	0	22.3	0	26.8	43.1
OTH	0	0	7.3	8.3	23.7
Developed countries automation					
NA&A	77.1 (-18.5)	13.6 (0.8)	24 (22.7)	40.3 (40.3)	0 (0)
EU	22.9 (18.5)	8.8 (-27.7)	46.8 (27.9)	43.2 (16.1)	0.6 (0)
H'ASIA	0 (0)	0 (0)	19.1 (-1.6)	0 (-17.4)	4.8 (1.1)
L'ASIA	0 (0)	37.7 (9.4)	10.1 (-41.6)	9.7 (-10.6)	43.8 (14.9)
LAM	0 (0)	24.5 (2.2)	0 (0)	0 (-26.8)	3.7 (-39.4)
OTH	0 (0)	15.3 (15.3)	0 (-7.3)	6.8 (-1.6)	47.1 (23.3)
Global automation					
NA&A	80.4 (-15.2)	0 (-12.9)	22.7 (21.4)	10.7 (10.7)	4.6 (4.6)
EU	19.6 (15.2)	2.5 (-34)	42.8 (23.9)	12.6 (-14.5)	12.4 (11.8)
H'ASIA	0 (0)	30 (30)	18 (-2.7)	0 (-17.4)	0 (-3.6)
L'ASIA	0 (0)	67.5 (39.1)	9 (-42.8)	48.6 (28.3)	40.4 (11.5)
LAM	0 (0)	0 (-22.3)	7.5 (7.5)	14 (-12.7)	38.2 (-4.9)
OTH	0 (0)	0 (0)	0 (-7.3)	14 (5.7)	4.4 (-19.3)

Note: Numbers between brackets are the changes relative to the baseline scenario

In the agriculture, forestry, and fisheries sector, production is concentrated in the NA&A group in the baseline, with a small part in EU, but nothing in the rest of the world. Automation shifts a part of the production from NA&A to EU, with little difference between the two automation scenarios.

In Mining, results are biased because we do not consider mineral resources as a separate production factor. Production is fairly spread out in the baseline scenario, and with the automation in the developed scenario, EU loses out an important part of its share, which is large in the baseline. In the global automation scenario, LAM and NA&A also lose, and L'ASIA becomes the largest producer.

In manufacturing, L'ASIA is by far the largest producer in the baseline, but it loses out most of its share in the developed world automation scenario, mostly to EU and NA&A. In the global automation scenario, L'ASIA loses an even larger part of its baseline share.

In Trade, Hotels, and Restaurants, LAM, L'ASIA, and H'ASIA are the large losers in the developed world automation scenario, while NA&A and EU gain. In the global automation scenario, L'ASIA becomes the winner instead of EU and NA&A.

Finally, in the business services sector, LAM loses in the developed world automation scenario, with L'ASIA and ROW as the gainers. In the global automation scenario, ROW is the only big loser.

Table 5 presents the GDP data for the developed world automation scenario, in the form of differences to the baseline of Table 3. Hence in each of the columns for shares of the global total, the numbers in Table 5 will add to zero. The table shows that the developed countries will gain significantly in GDP, with EU gaining the most (6.5 points), and NA&A and H'ASIA gaining marginally less. L'ASIA loses the most (7 points), closely followed by ROW. In terms of the components of GDP, EU gains most in terms of the benefit-of-trade rents, which become almost one-third of the total GDP in the EU group.

Table 5: Shares of Global GDP and share of rents in GDP, Differences of Developed world Automation scenario to Baseline Scenario

	Shares of global total				Shares of GDP in country group	
	Factor price income	Scarcity rents	Benefit of trade rents	Total GDP	Scarcity rents	Benefit of trade rents
NA&A	0.045	0.074	0.000	0.049	-0.040	0.000
EU	0.018	0.008	0.404	0.065	-0.243	0.214
H'Asia	-0.009	0.058	0.044	0.048	-0.046	0.037
L'Asia	-0.038	-0.062	-0.158	-0.070	-0.029	-0.037
LAM	-0.010	-0.012	-0.230	-0.026	0.073	-0.101
ROW	-0.005	-0.067	-0.060	-0.066	-0.098	0.008

In Table 6, we document the results of the global automation scenario. Again, the table reports differences from the baseline scenario of Table 3. In terms of total GDP, the ROW country group is the big winner (+6 points). H'ASIA also gains, but marginally, and EU stays virtually constant, but at a very small positive difference. The other country groups lose in terms of the global GDP share, with L'ASIA as the largest loser (-4.4 points). However, the benefits of trade rents shift towards L'ASIA in this case. Scarcity rents now fall very significantly as a share of GDP in all country groups.

Table 6: Shares of Global GDP and share of rents in GDP, Differences of global Automation scenario to Baseline Scenario

	Shares of global total				Shares of GDP in country group	
	Factor price income	Scarcity rents	Benefit of trade rents	Total GDP	Scarcity rents	Benefit of trade rents
NA&A	0.057	-0.209	0.000	-0.019	-0.912	0.000
EU	0.040	-0.081	-0.068	0.003	-0.725	-0.052
H'Asia	-0.008	0.025	0.000	0.018	-0.671	0.000
L'Asia	-0.025	-0.135	0.387	-0.044	-0.853	0.048
LAM	0.002	0.049	-0.224	-0.017	-0.407	-0.100
ROW	-0.065	0.352	-0.094	0.060	-0.369	-0.021

5. Summary and Conclusions

The objective of this study is to use an input-output-based model of global trade to investigate the possible consequences of the introduction of automation technologies on global development. The main results are obtained under the assumption that labour is the scarce production factor (and that capital is abundant everywhere in the world). Broadly, the analysis finds that the adoption of new automation technologies in advanced economies is likely to lead to significant relocation of production, including a fair amount of reshoring of production activities away from developing countries, back to developed countries. As the main part of the analysis assumes full employment, the consequences of this relocation are experienced in the form of a changing global distribution of income (GDP).

The results revealed that lower-income Asia is likely to be the most adversely impacted developing region in a scenario where automation takes place in the advanced world only. In this case, the advanced regions of the world gain a significant share of global GDP. The loss in lower-income Asia was especially manifest in manufacturing. When automation takes place globally, i.e., also in developing countries, the "rest of the world" category appears as a main winner. However, again, lower-income Asia loses out the most in terms of the share of global GDP, with manufacturing likely to experience the hardest hit. We also find that advanced economies adopting automation technologies would rather benefit via growth in incomes including positive factor earnings.

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APPENDIX A

The No Trade model represents a generalization of the static, one-country input-output model to the case of m closed economies. The No Trade quantity model (equation A1) determines sectoral outputs based on their existing endowments in the absence of trade. Each country *i* produces a vector of sectoral outputs when there is no trade (denoted as $\mathbf{x_{nt,i}}$) to satisfy its own demand, given as $\mathbf{y_i}$. The model additionally finds the quantity of factors that are used or would have been used in the absence of trade. For country *i*, this is given by $\mathbf{f_{nt,i}} = \mathbf{F_i x_{nt,i}}$.

The dual problem indicated by equation A2 represents the No Trade price model. It solves for commodity prices for each country-sector in the absence of trade. Finally, equation A3 indicates and ensures that, for each country, the value of final demand is equal to the value of factor payments. Hence, it assures that solution to the primal problem equals that of the dual, consistent with the duality theorem.

$(\mathrm{A1})$: **No-Trade Quantity Model:**

$$\begin{bmatrix} (\mathrm{I}-\mathrm{A}_1) & & 0 \\ & \ddots & \\ 0 & & (\mathrm{I}-\mathrm{A}_m) \\ -\mathrm{F}_1 & & 0 \\ & \ddots & \\ 0 & & -\mathrm{F}_m \end{bmatrix} \begin{bmatrix} \mathrm{x}_{nt,1} \\ \vdots \\ \mathrm{x}_{nt,m} \end{bmatrix} = \begin{bmatrix} \mathrm{y}_1 \\ \vdots \\ \mathrm{y}_m \\ -\mathrm{f}_{nt,1} \\ \vdots \\ -\mathrm{f}_{nt,m} \end{bmatrix}$$

$(\mathrm{A2})$: **No-Trade Price Model:**

$$\begin{bmatrix} (\mathrm{I}-\mathrm{A}'_1) & & 0 & -\mathrm{F}'_1 & & 0 \\ & \ddots & & & \ddots & \\ 0 & & (\mathrm{I}-\mathrm{A}'_m) & 0 & & -\mathrm{F}'_m \end{bmatrix} \begin{bmatrix} \mathrm{P}_{nt,1} \\ \vdots \\ \mathrm{P}_{nt,m} \\ \pi_1 \\ \vdots \\ \pi_m \end{bmatrix} = \begin{bmatrix} 0 \\ \vdots \\ 0 \end{bmatrix}$$

$(A3)$: **No-Trade Income Equations:**

$$\mathrm{P}'_{nt,i}\mathrm{y}_i = \pi'_i\mathrm{F}_i\mathrm{x}_{nt,i} = \pi'_i\mathrm{f}_{nt,i}\ , \forall\, i$$

APPENDIX B

Table B1: Wage and Capital Rental Rates

Country	Wage Rate	Rental Rate
Australia	66.059	0.149
Austria	55.563	0.085
Belgium	67.030	0.100
Bulgaria	8.676	0.052
Brazil	10.978	0.094
Canada	52.824	0.184
Switzerland	87.113	0.143
China	6.601	0.097
Cyprus	32.139	0.103
Czech Republic	18.665	0.072
Germany	50.901	0.107
Denmark	69.931	0.112
Spain	41.158	0.090
Estonia	20.705	0.097
Finland	60.464	0.108
France	60.390	0.097
United Kingdom	56.280	0.123
Greece	26.078	0.118
Croatia	20.199	0.064
Hungary	14.808	0.062
Indonesia	2.498	0.063
India	1.503	0.062
Ireland	58.095	0.150
Italy	46.378	0.083
Japan	42.264	0.142
Republic of Korea	33.607	0.062
Lithuania	16.202	0.114
Luxembourg	85.786	0.156
Latvia	16.384	0.101
Mexico	10.383	0.173
Malta	28.506	0.099
Netherlands	56.433	0.107
Norway	88.512	0.195
Poland	15.497	0.208
Portugal	25.128	0.072

Romania	8.718	0.090
Russian Federation	13.822	0.103
Slovakia	19.946	0.074
Slovenia	29.891	0.062
Sweden	60.816	0.150
Turkey	8.335	0.121
Taiwan	34.863	0.064
United States	62.729	0.141
ROW	6.716	0.102

Notes: The table presents the wage and capital rental rates computed per country. The wage rate is in thousands of US dollars: that is, the total labour compensation (US$ millions) divided by total employment (in thousands). The rental rate of capital is computed as the total capital compensation (US$ millions) divided by the total PPP-adjusted capital (in US$ millions).

Table B2: Unemployment and Capacity Utilization Rates and Endowments

Country	**Unemployment Rates**	**Utilization Rate**	**Labour Endowments**	**Capital Endowments**
Australia	0.061	**0.807**	12630.970	3853254.340
Austria	0.056	0.843	4522.664	1799661.465
Belgium	0.085	0.793	4973.546	1718103.032
Bulgaria	0.114	0.708	4064.507	345607.892
Brazil	0.067	0.812	111454.320	9906947.677
Canada	0.069	**0.757**	19819.395	3815900.173
Switzerland	0.048	0.823	5342.725	1659750.859
China	0.041	**0.808**	895065.016	47588887.250
Cyprus	0.161	0.539	426.064	92823.333
Czech Republic	0.061	0.83	5441.719	1267763.743
Germany	0.05	0.843	44944.222	12203407.692
Denmark	0.069	0.797	2970.882	952204.449
Spain	0.244	0.758	23775.146	5785034.249
Estonia	0.074	0.73	668.322	108688.219
Finland	0.087	0.79	2735.384	772933.644
France	0.103	0.819	30425.817	9145075.259
United Kingdom	0.061	0.82	32725.530	7630980.072
Greece	0.265	0.677	5390.586	888305.689
Croatia	0.173	0.69	1898.319	258341.617
Hungary	0.077	0.803	4588.544	874450.860
Indonesia	0.041	0.762	175928.794	7138622.884
India	0.041	**0.762**	686582.749	16108945.715
Ireland	0.119	0.787	2171.897	775667.236
Italy	0.127	0.737	27906.894	9537647.597
Japan	0.036	**0.808**	63520.616	12992606.687

Republic of Korea	0.031	**0.808**	25225.960	7558787.873
Lithuania	0.107	0.749	1474.401	196765.330
Luxembourg	0.059	0.662	430.175	150809.231
Latvia	0.109	0.722	1007.325	128581.092
Mexico	0.048	0.731	40967.290	4744019.747
Malta	0.057	0.781	205.346	39773.625
Netherlands	0.074	0.802	9426.442	2798388.038
Norway	0.035	0.799	2846.042	1057938.509
Poland	0.09	0.772	17110.318	1169459.961
Portugal	0.139	0.784	5278.655	1207756.659
Romania	0.068	0.794	9446.245	1109364.289
Russian Federation	0.052	0.623	78330.609	5774669.717
Slovakia	0.132	0.807	2560.631	633354.244
Slovenia	0.097	0.803	1040.795	238944.459
Sweden	0.08	0.809	5160.239	1455057.992
Turkey	0.099	0.754	35873.493	3643533.177
Taiwan	0.053	**0.808**	21343.755	2547302.944
United States	0.062	0.757	166013.492	53547021.046
ROW	**0.056**	**0.771**	1412079.744	88892206.754

Notes: Table B2 reports 2014 unemployment rates from World Development Indicators (2021) and the 2014 annual average of the capacity utilization rates from Eurostat and OECD statistics, coupled with labour and capital endowments computed from WIOD. We determined the utilization rates in **bold** (due to a lack of reliable data) as follows. China, Taiwan, Republic of Korea and Japan are the average of the utilization rates for the USA, Germany, and Switzerland. Canada is assumed to have a similar utilization rate to the USA, Australia to Slovakia, and India to Indonesia. The unemployment and utilization rates for ROW are the averages of the developing region sample of Brazil, China, Indonesia, India, Mexico, and Turkey.

Table B3: Weighted Average Automation Risks of Advanced Country-Sectors

Sector in Advanced Region	**Overall weighted Automation Risks**
Crop and animal production, hunting, and related service activities	0.621
Forestry and logging	0.589
Fishing and aquaculture	0.672
Mining and quarrying	0.555
Manufacture of food products, beverages, and tobacco products	0.75
Manufacture of textiles, wearing apparel and leather products	0.67
Manufacture of wood and products of wood and cork, except furniture…	0.694
Manufacture of paper and paper products	0.723
Printing and reproduction of recorded media	0.697
Manufacture of coke and refined petroleum products	0.743
Manufacture of chemicals and chemical products	0.707
Manufacture of basic pharmaceutical products and pharmaceutical preparations	0.677
Manufacture of rubber and plastic products	0.752

Manufacture of other non-metallic mineral products	0.740
Manufacture of basic metals	0.744
Manufacture of fabricated metal products, except machinery and equipment	0.734
Manufacture of computer, electronic and optical products	0.732
Manufacture of electrical equipment	0.755
Manufacture of machinery and equipment, not elsewhere classified (n.e.c.)	0.731
Manufacture of motor vehicles, trailers, and semi-trailers	0.774
Manufacture of other transport equipment	0.738
Manufacture of furniture; other manufacturing	0.679
Repair and installation of machinery and equipment	0.614
Electricity, gas, steam, and air conditioning supply	0.603
Water collection, treatment, and supply	0.721
Sewerage; waste collection, treatment, and disposal activities; materials recovery…	0.718
Construction	0.353
Wholesale and retail trade and repair of motor vehicles and motorcycles	0.654
Wholesale trade, except for motor vehicles and motorcycles	0.704
Retail trade, except for motor vehicles and motorcycles	0.698
Land transport and transport via pipelines	0.732
Water transport	0.782
Air transport	0.726
Warehousing and support activities for transportation	0.782
Postal and courier activities	0.84
Accommodation and food service activities	0.432
Publishing activities	0.633
Motion picture, video and television programme production, sound recording…	0.625
Telecommunications	0.637
Computer programming, consultancy, and related activities; information service…	0.645
Financial service activities, except insurance and pension funding	0.836
Insurance, reinsurance, and pension funding, except compulsory social security	0.746
Activities auxiliary to financial services and insurance activities	0.659
Real estate activities	0.534
Legal and accounting activities; activities of head offices; management consultancy…	0.435
Architectural and engineering activities; technical testing and analysis	0.445
Scientific research and development	0.539
Advertising and market research	0.429
Other professional, scientific, and technical activities; veterinary activities	0.412
Administrative and support service activities	0.524
Public administration and defence; compulsory social security	0.591
Education	0.091

Human health and social work activities	0.101
Other service activities	0.199
Activities of households as employers; undifferentiated goods- and services-producing…	0.05
Activities of extraterritorial organizations and bodies	0

Notes: The table reports the average share of workers at risk of automation in advanced country-sectors. The third column presents the overall weighted average risk estimate for each sector in the advanced region.

APPENDIX C

Data Sources, Construction of Variables, and Model Implementation

Data sources

To implement the WTMNT, we source data from the World Input-Output Database (2016) for all input-output data, and the International Assessment of Adult Competencies (2019) to estimate the automation risks. We also rely on PPP exchange rates from the International Comparison Program (2017), unemployment rates from the World Development Indicators (2021), and capacity utilization rates from Eurostat (2021) and the OECD statistics (2017).

The analysis uses data from WIOD's most recent World Input-Output Table (WIOT), which is for the year 2014 (the most recent year) throughout the analysis. The WIOT contains sector-by-sector data at the 2-digit ISIC rev. 3 level, covering 56 sectors and 43 countries. It also comprises a 44th country, termed Rest of the World (ROW), that proxies all non-WIOD countries to close the model of the world economy (Timmer et al., 2015). The table that we use specifies a full matrix of intermediate deliveries with all possible country-sector combinations in both the rows and columns, the matrix of final demand, with deliveries from all possible country-sector combinations to 5 final demand categories for each country, and vectors of value added and gross output for each country-sector combination. We aggregate the 5 final demand categories into just one category (which therefore includes household consumption, government consumption, and gross capital formation).

WIOD's Socio-economic accounts (SEA) data also deliver information on the quantity of factor inputs as well as their corresponding compensations (in millions of the national currency), also reported at the 2-digit ISIC rev. 3 level. We group the countries in the WIOD SEA and WIOT into advanced and developing countries. The advanced countries comprise 37 countries while the remaining 7 developing countries include Brazil, China, Indonesia, India, Mexico, Turkey, and ROW. The advanced economies include the following: Australia, Austria, Belgium, Bulgaria, Canada, Switzerland, Cyprus, Czech Republic, Germany, Denmark, Spain, Estonia, Finland, France, United Kingdom of Great Britain and Northern Ireland, Greece, Croatia, Hungary, Ireland, Italy, Japan, Republic of Korea, Lithuania, Luxembourg, Latvia, Malta, Netherlands, Norway, Poland, Portugal, Romania, Russian Federation, Slovakia, Slovenia, Sweden, Taiwan, and the United States.

Furthermore, the study uses PIAAC data to estimate the risk of automation needed to construct the automation scenarios, which are compared to the baseline scenarios. The PIAAC dataset, created by the OECD, is based on a survey that provides information on tasks that workers perform and the frequency with which they undertake them. Although the survey includes about 37 countries across three (3) rounds between 2011 and 2019, we use only countries with publicly available 4-digit-level ISCO-08 job codes and estimate the automation risks for 2-digit sectors, consistent with WIOD. The sample entails 20 advanced countries based on the 2020-2021 World Bank Income Classification system. The advanced countries include the following: Belgium, Chile, Czech Republic, Denmark, France, Greece, Hungary, Israel, Italy, Japan, the Republic of Korea, Lithuania, Netherlands, New Zealand, Poland, Russia, Slovakia, Slovenia, Spain, and the UK. We, however, compute the automation risks for countries in WIOD, which exclude Chile, Israel, and New Zealand.

Variables

From the raw input-output data, we first compute intermediate input coefficients in the usual way, yielding a square matrix with 44×56 rows and columns. Next, we calculate the autarky intermediate input coefficients (A_i), which, for each country including ROW, forms a square matrix with 56 rows and columns. To calculate these, we sum, in each column of the original (large) intermediate input coefficients matrix, the cells belonging to the same sector. This yields 56 values, which form the column of the autarky intermediate input coefficients matrix of the column-country in the original intermediate inputs matrix. For instance, if sector 1 in Germany needed to use \$10 million worth of sector 2 intermediate input domestically while importing (from the other 43 countries) \$2 million worth of sector 2 intermediate input to produce \$24 million worth of sector 1 output, then the autarky intermediate input coefficient in row 2, column 1 becomes $(10 + 2)/24$.

Final demand under autarky (y_i) is constructed using the same approach as autarky intermediate input coefficients. We first aggregate the 5 WIOD components of final demand (final consumption expenditure by households, final consumption expenditure by non-profit organisations serving households, final consumption expenditure by government, gross fixed capital formation, and changes in inventories and valuables) into a single vector. Then for every country, we aggregate all values in this vector for each of the 56 sectors.

The analysis further needs the factor inputs per unit output (F_i), which we calculate by dividing labour (number of persons engaged) and capital input quantities from the Socio-economic accounts (SEA) database by the corresponding country-sector outputs in the WIOT. Since the SEA database does not contain data for the Rest of the World (ROW), we calculate the ROW factor coefficients as the average over the corresponding developing countries-sectors (China, Brazil, India, Indonesia, Mexico, and Turkey). Thus, ROW is treated as primarily reflecting the developing world. Moreover, because capital is measured in national currencies, the study first adjusts it to US dollars by dividing capital by the PPP exchange rates from the International Comparison Program (2017). Capital is adjusted further by multiplying the PPP-adjusted capital by economy-wide capacity utilization rates in 2014 from Eurostat and the OECD statistics (see Appendix B for these data). This is to ensure that capital coefficients reflect capital use per unit output rather than capital stock per unit output.

Factor endowments (f_i) are calculated as follows. The aggregate capital endowments are the total PPP-adjusted capital from the WIOD SEA (without the utilization rate adjustment), whereas the implied aggregate labour endowments are determined by dividing the total number of persons engaged in each country from the WIOD SEA by 1 minus the unemployment rate from WDI (2021).[11] To determine ROW endowments, we first calculate the total ROW labour and capital use by multiplying the ROW factor input coefficients by output and summing them up. The employment and utilization rates for ROW are the averages over the rates for the developing-region sample: Brazil, China, Indonesia, India, Mexico, and Turkey.

Finally, the analysis needs the factor input prices (π_i). The wage rate is calculated by dividing total labour compensation (converted to \$ using the WIOD exchange rates) by the total number of persons engaged per country (labour input). The price of capital is determined likewise; that is, the capital cost is first converted by the WIOD exchange rate to US dollars and subsequently divided by the total PPP-adjusted capital stock (in this case unadjusted for utilization) in the country. Input prices for the ROW are the averages over the developing regions in the sample.

Implementation

We observed which fraction of the gross output of each sector is exported in the WIOT, and based on this, designated twelve sectors as non-tradable: electricity supply (D35), water supply (E36), construction (F), postal activities (H53), accommodation and food (I), real estate activities (L68), public administration and defence (O84), education (P85), health (Q), other services (R_S), activities of households as employers (T), and activities of extraterritorial organizations (U). Note that none of these are exactly non-tradable, i.e., we observe some trade even in these sectors, but trade is minor as compared to the tradeable sectors.

[11] Our analysis compares the computed labour and capital endowments per country with their corresponding No Trade endowments and uses the maximum endowments (in each scenario) to satisfy the restriction: $f_i \geq f_{nt,i}$.

Some other critical considerations before running the models are as follows. The WIOT contains some sectors that produce no gross output, for example, because these sectors are merged with other sectors for specific countries. We set the intermediate coefficients and final demands of these sectors to zero to assure that they also produce no output under both autarky (the No Trade) and trade (the WTMNT), and set the factor input coefficients to be prohibitively high to ensure that these sectors do not attract positive output in any of the optimization scenarios (we checked ex-post to make sure this indeed did not happen). We run the linear programming optimizations in Matlab using the linprog command for the baseline and automation scenarios.

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