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Trade Specialisation in Products Embedding Automation Technologies: Cross-Country Evidence and the Case of Poland*

Specjalizacja handlowa w produktach związanych z automatyzacją – analiza międzynarodowa i przypadek Polski

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Abstract

Using a large sample of 160 economies observed over three decades since the mid-1990s, this paper documents patterns of trade specialisation in products embedding automation technologies. We draw on HS 6-digit trade data matched with product-level taxonomies identifying automation-related export lines to quantify the importance of such products in national export structures. Despite the rising value of global trade in automation products, their share in total exports remains small—negligible in low-income economies and not exceeding 2.5% in high-income countries. Between 1995 and 2019, Poland experienced a rise in automation-related exports, in terms of both value and as a share of total exports (reaching 2.5% in 2019). Export specialisation in products embedding automation technologies, measured by the revealed comparative advantage index, is positively correlated with income per worker. However, automation-related exports have not played a significant role in economic convergence. By contrast, technological trade in the broad sense is among factors driving global productivity convergence. The paper also discusses the limitations of trade data in capturing international trends in automation technology.

Streszczenie

W artykule wykorzystano dane dotyczące 160 gospodarek (obserwowanych od połowy lat 90. XX w.) do opisu trendów w handlu produktami związanymi z automatyzacją. W analizie użyto danych handlowych na poziomie 6-cyfrowej dezegregacji HS połączonych z taksonomiami produktów technologicznych, które pozwalają na identyfikację linii eksportowych związanych z automatyzacją oraz pomiar ich znaczenia w krajowych strukturach handlu. Pomimo wzrostu wartości globalnego handlu produktami związanymi z automatyzacją mają one niewielki udział w oficjalnie zarejestrowanym eksporcie (od nieistotnego w gospodarkach

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o niskich dochodach do 2,5% całkowitego eksportu krajów o wysokich dochodach). W latach 1995–2019 Polska odnotowała wzrost eksportu związanego z automatyzacją zarówno pod względem jego wartości, jak i udziału w eksporcie całkowitym (2,5% w 2019 r.). Specjalizacja eksportowa w produktach związanych z automatyzacją, mierzona wskaźnikiem ujawnionej przewagi komparatywnej, jest dodatnio skorelowana z poziomem dochodu na pracownika, ale nie odegrała statystycznie znaczącej roli w globalnym procesie konwergencji ekonomicznej. Handel szeroko rozumianymi produktami technologicznymi należy natomiast do czynników warunkujących ogólnoświatową konwergencję. W artykule opisano także ograniczenia związane z użyciem danych handlowych do pomiaru międzynarodowych trendów w rozwoju technologii cyfrowych.

Słowa kluczowe:
eksport, konwergencja, automatyzacja, przewaga komparatywna

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Introduction

Given the rapid technological change of recent decades [**Growiec, 2022**; **WIPO, 2024a**], a burgeoning body of literature has examined the economic effects of digital technologies, including ICT, industrial robots, and artificial intelligence (AI) [see, among others, **Brynjolfsson, McAfee, 2011**, **2014**; **Brynjolfsson et al., 2019**; **Graetz, Michaels, 2018**; **Parteka, Kordalska, 2023**; **Restrepo, 2023**; **Growiec, 2023**; **Prettner, Bloom, 2020**]. These technologies are often intangible, which poses serious problems in their quantification and in assessing their actual economic impact. In particular, the contribution of digitally-driven technological innovation to registered productivity growth results has proven weak. This disappointing outcome has fuelled a vivid debate on the so-called "modern productivity paradox" [**Brynjolfsson et al., 2019**; **Acemoglu et al., 2014**; **Kromann et al., 2020**; **Parteka, Kordalska, 2023**; **Venturini et al., 2022**; **Pieri et al., 2018**].

Available proxies for quantifying the pace and effects of digital progress include measures of intangible investment and capital stock (as in the EUKLEMS & INTANProd database; **Bontadini et al., 2024**); the number of installed industrial robots, often used as a proxy for automation [**IFR, 2023**; **Acemoglu et al., 2020**; **Graetz, Michaels, 2018**; **Ballestar et al., 2020**; **Cséfalvay, 2020**; **Koch et al., 2021**]; AI-related patents and scientific publications [**Venturini, 2022**; **Parteka, Kordalska, 2023**; **Foster-McGregor et al., 2019**]; and measures of occupational exposure to ICT/software, robots or AI [**Brynjolfsson et al., 2018**]. This paper explores another, less common dimension: information contained in trade data matched with product-level taxonomies that identify products associated with the so-called Fourth Industrial Revolution, 4IR[1] [**Foster-McGregor et al., 2019**; **Castellani et al., 2022**; **Domini et al., 2021**]. Our analysis focuses specifically on products embedding automation technologies [**Domini et al., 2021**; **Acemoglu, Restrepo, 2022**].

The purpose of this paper is twofold. First, we aim to quantify cross-country differences in trade specialisation in products embedding automation technologies. To this end, we analyse patterns of revealed comparative advantage in automation goods using product-level trade statistics covering a broad panel of 160 countries. Given the profile of the journal, we present trade-based evidence for the specific case of Poland. To the best of our knowledge, no such study has yet been conducted.[2]

Second, we seek to evaluate the implications of trade in products embedding automation technologies for economic growth, with a particular focus on its role in the process of cross-country economic convergence. This aspect of the analysis is motivated by the observation that digital technologies tend to be highly clustered in both production and adoption [**Venturini, 2022**; **Foster-McGregor et al., 2019**]. Looking at global

[1] The related literature employs various terms to describe technological advancements driven by the development of digital technologies – such as the *digital revolution* [**Brynjolfsson, McAfee, 2011**; **Growiec, 2023**], *4IR* [**Schwab, 2024**; **Castellani et al., 2022**; **Venturini, 2022**]; *industry 4.0* [**Growiec, 2023**]; *intelligent* (or *smart*, *brilliant*) *technologies* [**Brynjolfsson, McAfee, 2014**; **Venturini, 2022**]. For the sake of simplicity, we adopt the term *4IR*, while acknowledging the caveats and simplifications associated with its use [**Growiec, 2023**].

[2] Among the studies on digital technological progress in Poland, **Jabłońska and Mućk** [**2024**] provide a set of stylised facts, based on survey results, about the adoption of automation among Polish firms. **Arendt et al.** [**2023**] study the evolution of the Polish labour market due to digitisation. **Hardy et al.** [**2016**] document changes in the task content of jobs—and their degree of routinisation—in Poland between 1996 and 2014.

technology production patterns, Switzerland, Sweden, the United States, Singapore, and the United Kingdom lead the 2024 Global Innovation Index, GII [WIPO, 2024b], while China remains the only middle-income economy in the GII top 30. Frontier research in AI is also highly concentrated: more than 75% of the world's granted AI patents originate from East Asia and the Pacific, with China alone accounting for 61% (AI Index Report 2024[3], data for 2022). Technology adoption shows similar clustering. According to the International Federation of Robotics[4] [IFR, 2023; Müller, 2023], 79% of global robot installations are concentrated in just five countries: China, Japan, the United States, South Korea, and Germany. These patterns make it crucial to assess whether such concentration affects global income distribution and the catching-up process.

The rest of the paper is structured as follows. In Section 2, we review the literature on quantifying recent waves of technological progress (including automation) and summarise the key empirical findings on cross-country differences in production and adoption. In Section 3, we describe the dataset used in this paper, the methods that allow us to quantify technological trade specialisation and present the main stylised facts on trade in products embedding automation technologies. Section 4 discusses the results linking productivity growth to technological specialisation patterns in a sample of 160 countries. Section 5 concludes. A replication package accompanies the paper to facilitate the reproduction of the empirical findings[5].

Literature review

The literature on the economic effects of technological progress has a long tradition, and technology is a vital component of economic growth models [Acemoglu, 2008]. Recent theoretical developments reflect the growing interest in the implications of digital progress for economic growth, productivity, and labour markets [Growiec, 2022; Acemoglu, 2025; Restrepo, 2023]. In particular, task-based models of production have gained prominence [Zeira, 1998; Autor et al., 2003; Acemoglu, Autor, 2011; Acemoglu, Restrepo, 2018; 2019, 2022]. In these models, production is represented as a continuum of tasks, with factors of production allocated to perform them. The assignment of tasks to factors is shaped by technology, while tasks can be partially or even fully automated [Growiec, 2022]. Task-based models offer a solid theoretical basis to study the implications of digital progress and automation for economic growth, productivity, employment, earnings and inequality (see Restrepo [2023] for a recent review).

In parallel, empirical economic research has grappled with the challenge of adequately quantifying digital progress driven, at least partly, by rapid advancements in intangible solutions. The first wave of related literature used mainly statistics on the adoption of information and communication technologies (ICTs) [Draca et al., 2007; Atalay et al., 2018; Jorgenson et al., 2008; van Ark et al., 2008; Inklaar et al., 2005; Oliner et al., 2008; Acemoglu et al., 2014; Pieri et al., 2018]. The development of automation, in turn, has been captured mainly through data on the introduction of industrial robots in manufacturing. Most studies follow the approach of Acemoglu and Restrepo [2018, 2019], using robot adoption statistics from the International Federation of Robotics (IFR). Much of this literature has focused on the labour market effects of automation, in particular its impact on occupational and wage structures, analysed from the perspective of workers, firms or industries (among many others: Acemoglu and Restrepo [2018, 2019, 2022]; Restrepo [2023]; Graetz and Michaels [2018]). A parallel strand of literature has addressed the productivity effects of automation [Ballestar et al., 2020; Kromann et al., 2020; Acemoglu et al., 2020; Graetz, Michaels, 2018; Koch et al., 2021]. Finally, research on the development of highly intangible AI technologies typically relies on data on AI-related patents or scientific publications [Van Roy et al., 2020; Parteka, Kordalska, 2023; Venturini, 2022; WIPO, 2024a].

Evidence on the scale and pace of digital progress and automation from the trade literature is far more limited. Notable exceptions include Castellani et al. [2024], who build on Caselli and Coleman's [2001] idea that

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[3] https://aiindex.stanford.edu/report/ (accessed on 6.11.2024).

[4] Access to the IFR database was made possible through financial support from the National Science Centre, Poland (grant number 2020/37/B/HS4/01302).

[5] Available upon request.

technology diffusion takes place through imports of equipment that embodies new technology[6]. Caselli and Coleman [2001] examined the diffusion of computers, while Castelani et al. [2022] used granular trade data to identify products related to advanced manufacturing technologies (AMT) — advanced industrial robots (AIR), additive manufacturing (AM), and the Industrial Internet of Things (IIoT) —for 28 European countries over 2009–2018. Few studies use a global sample: Foster-McGregor et al. [2019] combined trade and patent data, finding that although the share of 4IR products in global trade increased, it remains very small ("just 0.34% of total imports in 2000, falling slightly to 0.27% of total imports in 2016" [Foster-McGregor et al., 2019: 17]). They also document a high degree of international specialisation in 4IR technologies, with only the most developed countries and selected emerging economies playing a leading role in their development, production and use.

For Poland, to the best of our knowledge, no country-specific study has examined the recent evolution of trade in products embedding automation technologies. Some insights, however, emerge from multi-country studies. Poland is included in a sample of European economies analysed by Castellani et al. [2022]. They find that Poland ranks relatively high in terms of additive manufacturing (AM) and IIoT imports and net consumption [Castellani et al., 2022, Figure 1]. Between 2009 and 2018, Polish imports of industrial robots rose by 387%, close to the European average of 390% [Castellani et al., 2022, Table 2]. Over the same period, Polish imports of AM grew by 123%, compared to the EU average at 85%, while imports of IIoT increased by 86%, far above the EU average of 50%. Complementary evidence from automation-related studies suggests a similar pattern. Cséfalvay [2020] analysed patterns of robotisation in Central and Eastern Europe, reporting that robot density in Polish manufacturing was below the global average in 2015. Yet, in light of the most recent IFR data (see Section 3, Figure 3), the stock of industrial robots operating in Poland increased dramatically, from just 65 in 2004 to almost 14,000 in 2020.

The empirical literature on trade specialisation is extensive and uses a wide range of indices to capture trade (mainly exports) specialisation from different angles. One group of studies analyses comparative advantage [see Maneschi, 1998], the approach we follow in this paper (see Section 3). The revealed comparative advantage (RCA) index, commonly known as the Balassa index [Balassa, 1965], is the most widely used. It measures a country's relative production capability for specific goods or sectors (as reflected in trade data), building on the main assumption rooted in trade theory: the observed patterns of comparative advantage in trade flows proxy for underlying cross-country differences in relative productivity that cannot be directly observed. Yeats [1985], Vollrath [1991] and Laursen [2015] developed the original Balassa [1965] measure. More recently, French [2017] reviewed various variants of the RCA index based on Balassa's [1965] classic formula, including the Bilateral Balassa Index (BBI), as well as its more complex variants, such as the Regression-Based RCA Index (RBI) and the Gravity-Based RCA Index (GBI), which are well suited to revealing countries' underlying patterns of comparative advantage in terms of trade costs [Anderson, Yotov, 2010; Costinot et al., 2012; Caliendo, Parro, 2015; Levchenko, Zhang, 2016]. Another strand of trade specialisation literature focuses on diversification (reviewed in, among others, Cadot et al. [2013]; Parteka [2015]; Sarin et al. [2022]), where specialisation is understood as the opposite of product variety and is often measured inversely using inequality indices such as the Theil index [Cadot et al., 2011; Gnidchenko, 2021; Parteka, 2015; Parteka et al., 2025; Zarach, Parteka, 2023]. Moreover, international trade research often links specialisation patterns to the division of production/tasks across countries within global value chains by analysing vertical specialisation [Hummels et al., 2001; Pahl, Timmer, 2019] or functional specialisation [Timmer et al., 2019]. Finally, high-tech specialisation has been quantified using a wide range of approaches, from simple indicators of export technological intensity (e.g., a classification of exported products into technological categories [UNCTAD, 2025]) to more sophisticated methods based on economic complexity [Balland et al., 2022; Hidalgo, Hausmann, 2009; Felipe et al., 2012], technological capabilities [Archibugi et al., 2009; Archibugi, Coco, 2005], or specialisation in tech-related functions [Timmer et al., 2019].

6 A similar approach, involving the use of import data as a proxy for technology adoption, was employed by Caselli and Wilson [2004].

Empirical setting and key stylised facts

The data

We use product-level (HS 6-digit) export data from the BACI CEPII database, a widely used, clean trade dataset ready for comparisons across countries and time [Gaulier, Zignago, 2010][7]. The sample consists of 160 countries (listed in Table A1 in the Appendix) observed from 1996 to 2019. The final year of analysis is guided by data availability: country-level statistics from the Penn World Table, the key source of data on income per worker and other country-level variables [Feenstra et al., 2015] are available up to 2019. For each country and year, we merge product-level trade data with high-tech product taxonomy by Eurostat [2024] to quantify technologically advanced exports (313 product lines). Trade in products embedding automation technologies is computed as a subset of the export basket that contains products present in the taxonomy by Domini et al. [2021][8]. The group of traded products that embed automation technologies include industrial robots, dedicated machinery, numerically controlled machines, and several other automated intermediate goods. Using this approach, we identify product lines as "exports embedding automation technologies" and compute the values of "automation exports" for the countries in our sample. The list of product codes is provided in the Appendix (Table A2).

To quantify specialisation in technologically advanced products, particularly in automation-related goods, we use a variant of the Balassa index of revealed comparative advantage (RCA) [Balassa, 1965; Laursen, 2015][9] computed over a set of technologically advanced goods (T) and another set of products embedding automation technologies (AT):

$$RCA_{it}^{k} = \frac{s_{it}^{k}}{w_{it}^{k}} = \frac{X_{it}^{k}/X_{it}}{X_{wt}^{k}/X_{wt}} \vee k = \{T, AT\} \tag{1}$$

where $s^{T}_{it} = \frac{X_{it}^{T}}{X_{it}}$ reflects the share of technologically advanced products in country i's export (X) structure at time t while $w^{T}_{it} = X_{wt}^{T}/X_{wt}$ is the analogous share computed with global export data. Similar shares are used to compute RCA in automation-related exports (i.e. specialisation in products belonging to the AT category). RCA values above 1 indicate a comparative advantage in technologically advanced products (T) or exports embedding automation technologies (AT), depending on the specification. The correlation between RCA^{T} *and* RCA^{AT} is low: 0.37, so they deliver different information.

Additionally, we compute indices similar to (1) at the product (p) level:

$$RCA_{ipt}^{k} = \frac{X_{ipt}^{k}/X_{it}}{X_{wpt}^{k}/X_{wt}} \vee k = \{T, AT\} \tag{2}$$

This allows us to measure the number of technological/automation-related products in which a particular country/group of countries has a comparative advantage (i.e. the number of products in the T or AT domain with $RCA_{ipt} > 1$).

7 We keep 4985 product codes and stick to 96 HS classification to ensure data consistency across time. The same procedure was adopted by Parteka et. al [2025].

8 Domini et al. [2021] measure automation technology adoption via imports of automation technologies (including: industrial robots, numerically controlled machines, and automatic machine tools) based on Acemoglu and Restrepo's [2022] categorisation, assuming that their acquisition represents tangible asset investment. We rely on the matching procedure between the detailed (8-digit) product codes listed in Domini et al. [2021] and the HS 6-digit export data from BACII developed by Parteka et al. [2025].

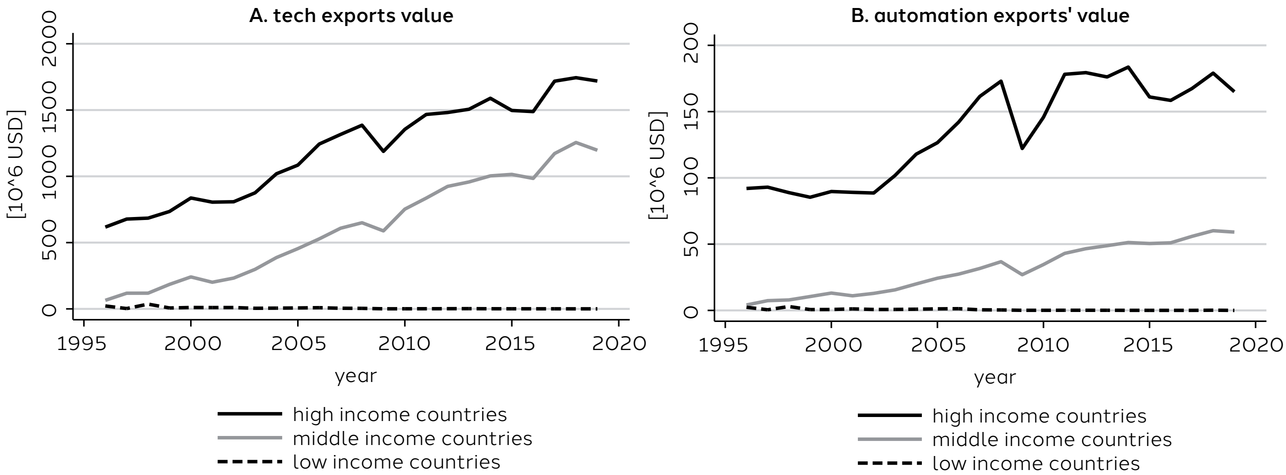
9 The related literature employs the revealed technological advantage index (RTA) to quantify the degree of technological specialisation of countries using patent data as a proxy for technological activity [Bahar et al., 2020; Foster McGregor et al., 2019; Soete, 1987]. The construction of such patent-based RTA is analogous to Balassa's [1965] Revealed Comparative Advantage (RCA) index used in international trade.

Global patterns of trade in products embedding automation technologies

Figure 1 shows the evolution of technologically advanced exports (their value) by country income group (Figure 1A) and the corresponding trend referring to exports embedding automation technologies (Figure 1B). Unsurprisingly, the value of tech exports has been rising. They originate mainly from high-income countries (in 2019, roughly 40% more than from middle-income countries). Also, the value of exports embedding digital technologies has been increasing: such exports from high-income countries almost doubled between 1996 and 2019 and registered rapid growth in middle-income economies. In turn, high-tech and automation exports originating from low-income countries are practically negligible.

Figure 2 shows the relative importance (i.e. share) of tech products and automation products in the total trade of the three groups of countries. To avoid bias due to the presence of very big economies in the sample, within each income group, the share is weighted by country size in terms of population. The share of exports of technologically advanced products (Figure 2A) in high-income countries reached its peak in 2000 when, on average, such exports accounted for approximately 22% of total trade. Since then, this share has declined, standing at 15% in 2019. Middle-income countries sharply increased the importance of tech exports in their trade structures between the mid-1990 s and the global financial crisis period. Afterwards, the share of tech exports ranged between 11% and 13% of the total trade of middle-income economies.

Figure 1. Value of technologically advanced exports (plot A) and exports of automation products (plot B) by income group, 1996–2019

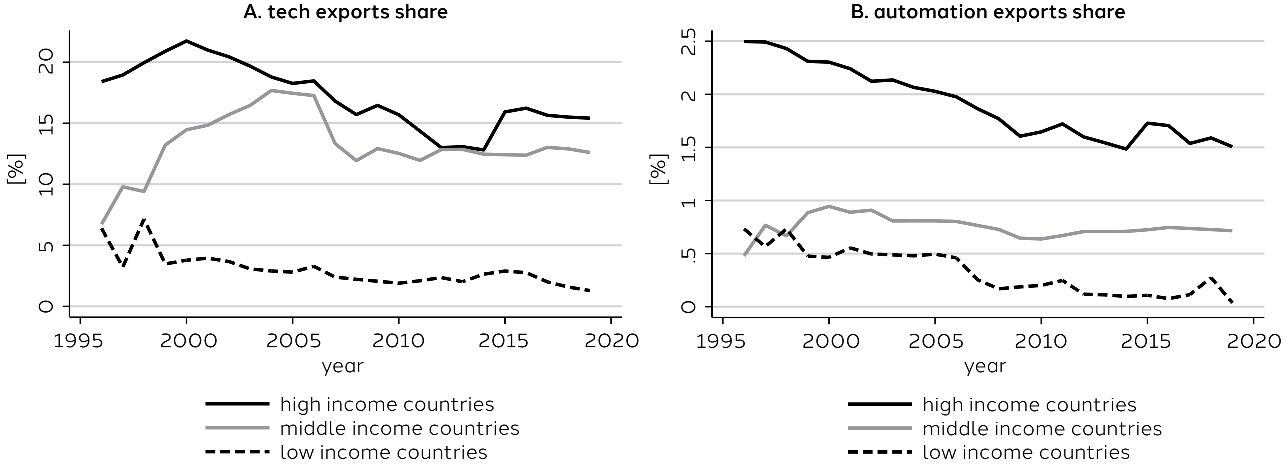


Notes: Countries are divided into income groups according to the World Bank's classification. Upper-middle and lower-middle-income countries merged into one group. Technologically advanced exports were identified using the classification of Eurostat [2024], and automation exports were identified using the taxonomy of Domini et al. [2021].

Source: Author's own elaboration using data from BACI CEPII.

One striking fact emerges: the share of automation products in countries' exports is tiny (Figure 2B). In the case of high-income countries, it never reached 3% of total exports, and, despite the rising value of such exports (Figure 1), their share declined from 2.5% in 1996 to 1.5% in 2019. In middle-income economies, the share of automation exports has consistently remained below 1%, while in low-income countries it is practically negligible. The pattern shown in Figures 1B and 2B is in line with the findings of Foster-McGregor et al. [2019], who also documented a rise in 4IR technologies over the last two decades (similar to the evolution shown in Figure 1B), combined with a minimal share of 4IR products (including automation goods) in total trade. The suspiring decline in the share of automation-related exports in high-income economies (Figure 2B) is likely due to the limitations of existing taxonomies of technologically sophisticated products, including automation-related goods. In particular, these classifications are time-invariant and therefore may fail to adequately capture recent advances in automation technologies and related areas.

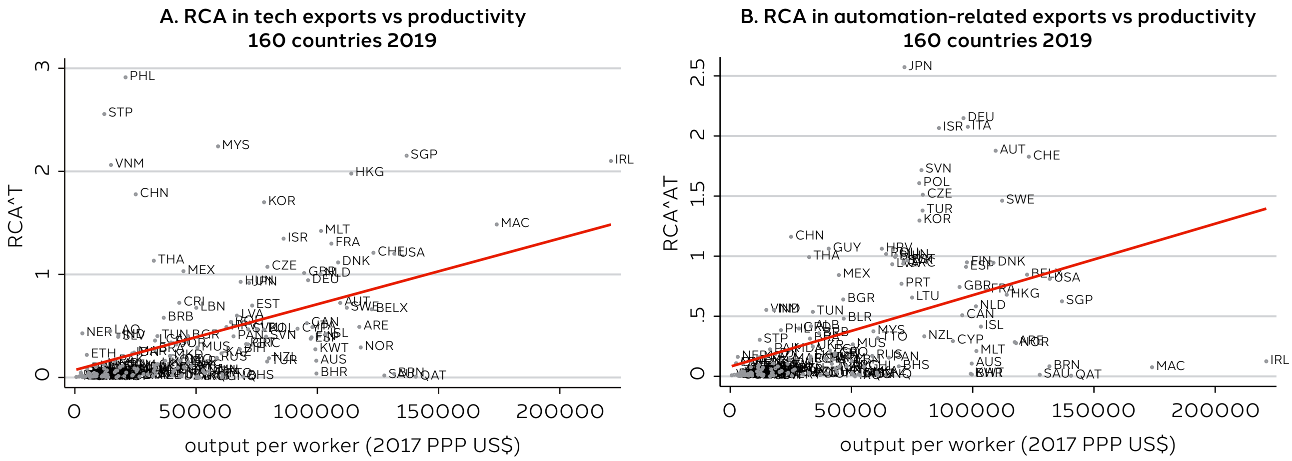
Figure 2. Shares of technologically advanced exports (plot A) and exports of automation products (plot B) in total country exports, by income group, 1996–2019



Notes: Countries are divided into income groups according to the World Bank's classification. Upper-middle and lower-middle-income countries merged into one group. Technologically advanced exports were identified using the Eurostat [2024] classification, and automation exports were identified using the taxonomy of Domini et al. [2021]. Within each income group, the shares are weighted by country size (population).
Source: Author's own elaboration using data from BACI CEPII.

Figure 3 depicts the relationship between the two types of RCA indices (RCA_{it}^{T}, RCA_{it}^{AT}) – eq. (1) – and output per worker across a sample of 160 countries in 2019)[10]. Unsurprisingly, the correlation is positive, though cross-country dispersion around the trend is noticeable. Figure 3R in the Appendix is based on the symmetric transformation of the RCA [Dalum et al., 1998] and log labour productivity.

Figure 3. RCA in technologically advanced products (plot A) and in automation-related products (plot B), against productivity levels, 2019



Source: Author's own elaboration using data from BACI CEPII and PWT.

The evidence based on product-level RCA indices (eq. 2) is shown in Table 1. Even in high-income countries, the average share of exports embedding automation technologies (s^{AT}) is low, at just 1.5%. For comparison, more than 15% of their exports can be classified as high-tech. The average number of automation products with revealed comparative advantage increases with income: from just one product in the low-in-

[10] Figure 3R in the Appendix shows analogous plots obtained using the symmetric transformation of RCA and log of labour productivity. Table A4 in the Appendix reports high (over 0.9) correlation coefficients between regular and symmetric RCA indices, and, additionally, the correlation between RCAs and alternative measures of specialisation such as the Herfindahl-Hirschman Index, Theil index or Gini index. The correlation between these indices and RCA (or SRCA) is low because they measure different aspect of specialisation, namely the degree of product variety within the group of technologically advanced products (Table A4_A) and automation-related products (Table A4_B).

come group to 32 in the high-income category. This clearly indicates which countries lead in exporting products embedding digital technologies. A similar pattern holds for *RCA* in technologically advanced products (Table 1, column 4).

Table 1. Export shares of technologically advanced (T) and automation technology (AT) products, and revealed comparative advantage (RCA) patterns by income group, 2019

	s^{AT} (1)	s^{T} (2)	Number of products with $RCA^{AT}>1$ (3)	Number of products with $RCA^{T}>1$ (4)
Low-income countries	0.035%*	1.3%*	1	2
Medium-income countries	0.71%*	12.6%*	7	13
High-income countries	1.5%*	15.4%*	32	48
China	1.5%	30%	107	109
Germany	2.8%	16%	144	141
India	0.7%	7%	42	45
Japan	3.4%	15.6%	107	121
Poland	2.1%	7.9%	45	29
USA	1.1%	20.5%	47	155

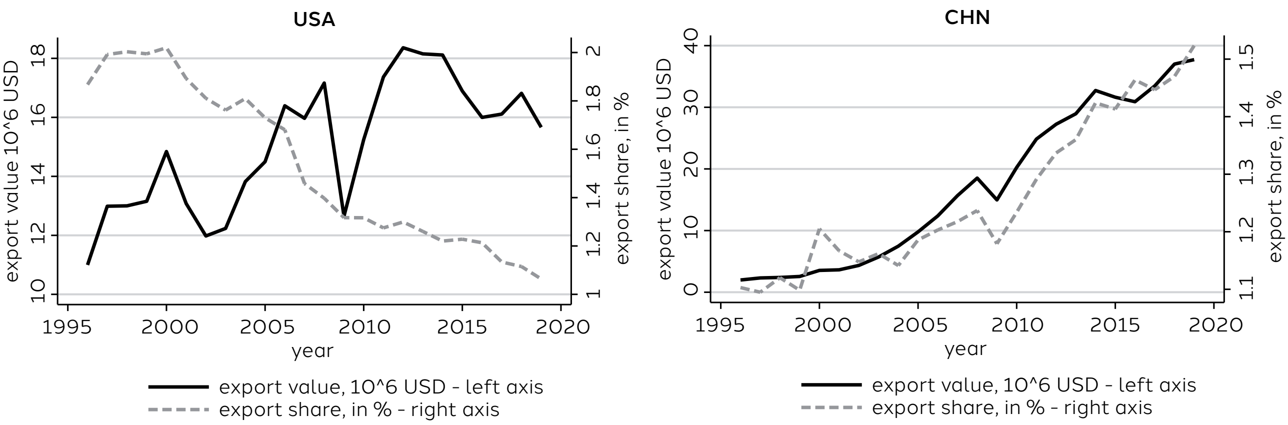
Notes: Averages within income groups, * weighted averages (by country size).

Source: Author's own calculations using a sample of 160 countries.

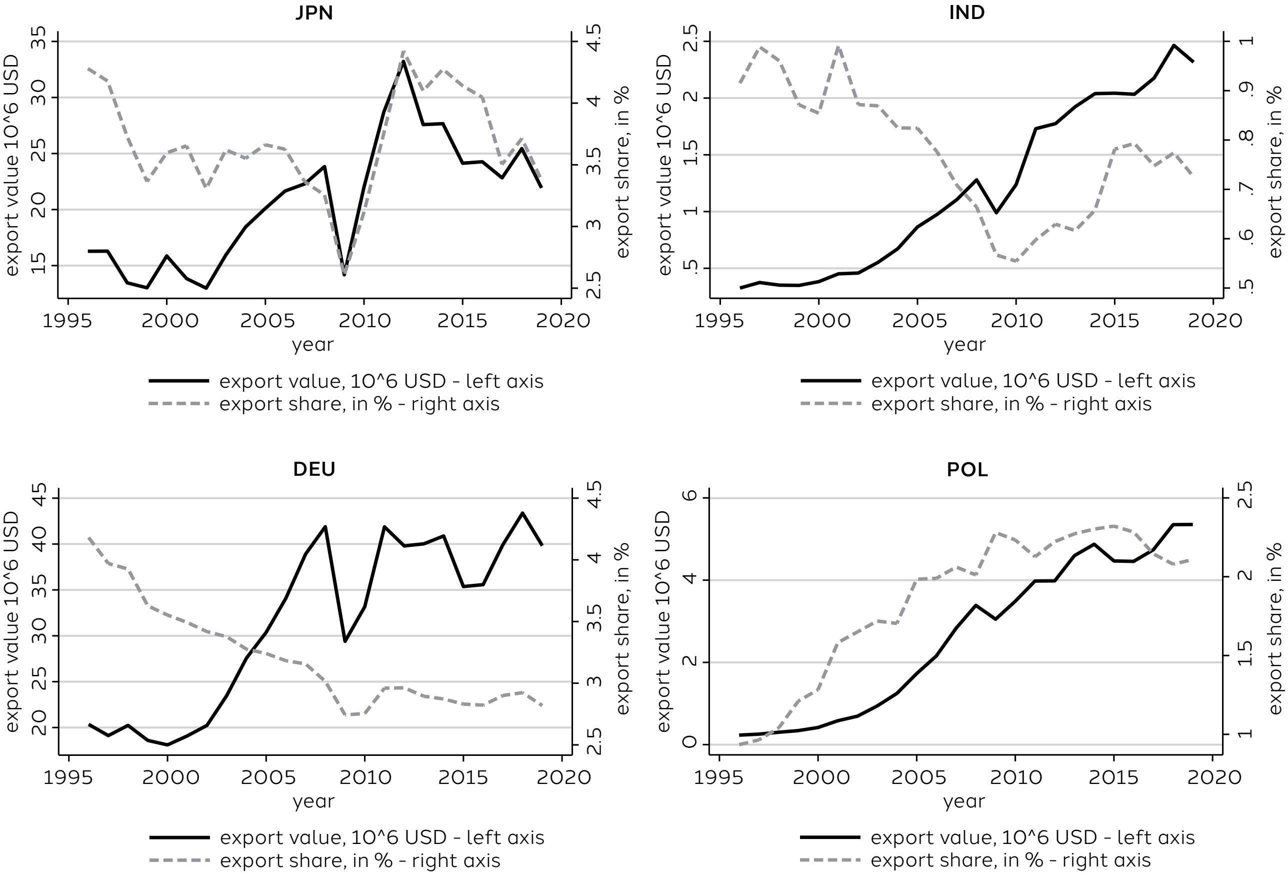
Country-specific evidence on automation technology exports and the case of Poland

The evidence discussed so far points to significant cross-country heterogeneity. While part of this is visible in average trends by income groups, specific country-level evidence on automation trends provides additional insights (Table 1). Figure 4 illustrates the evolution of exports embedding automation technologies in selected economies, showing both their value (left axis) and share in total exports (right axis). We focus on the two leading global exporters (the United States and China), two other Asian economies (Japan and India), as well as Poland and Germany (see also Table 1). Between 1996 and 2019, China sharply expanded its automation-related exports, almost quadrupling the value of trade in products embedding automation technologies. The share of such products in total Chinese exports also increased, from around 1% in the late 1990s to 1.5% in 2019.

Figure 4. Exports of products embedding automation technologies – value and share in total exports, selected countries (1996-2019)



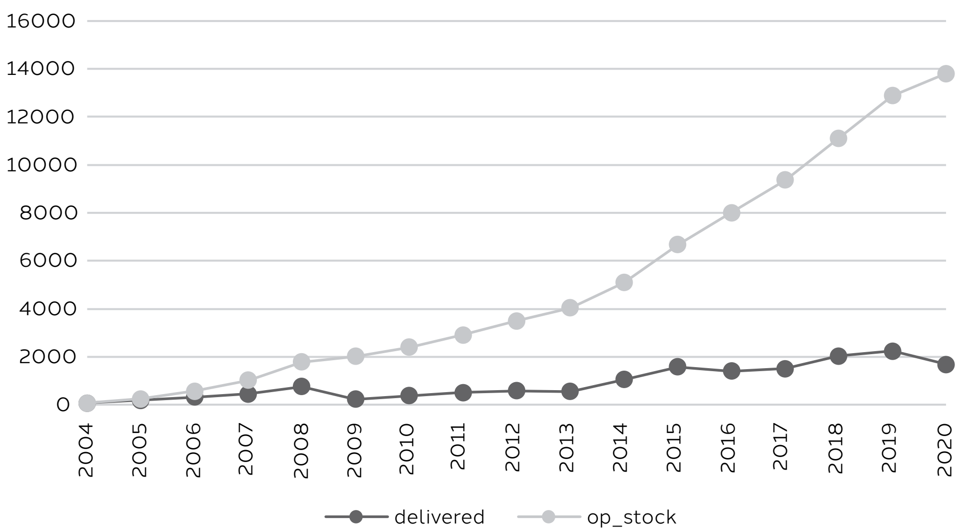
cont. Figure 4



Notes: products embedding automation technologies were identified using the classification of products from Domini et al. [2021].
Source: Author's own elaboration using data from BACI CEPII.

The United States—China's main competitor in global trade, especially in terms of exports—experienced a different trend: while the value of automation exports rose, their share in total exports declined. Germany also saw a decline in the share of automation exports; the *AT* share fell from over 4% in 1996-relatively high compared to other countries—to 2.7% in 2019. Meanwhile, the value of automation technology exports originating from Poland rose considerably, from nearly negligible in 1996 to almost USD 6 billion in 2019. During the same period, their share in Poland's total exports more than doubled—from 1% in 1996 to 2.4% in 2019.

Figure 5. Industrial robots in Poland - delivered and operating stock in manufacturing, 2004–2020



Source: Author's own elaboration using data from the International Federation of Robotics, Version 4.0 [IFR, 2023].

A breakdown of subcategories of products embedding automation technologies in selected countries (WITS data, Table A5) reveals that Poland is primarily specialised in textile machinery (more than 35% of all automation-related exports in 2023), followed by industrial tools (22.6%) and machinery and mechanical appliances (16%). Importantly, the product composition has shifted: textile machinery increased from 11% of automation exports in 1996 to 35.4% in 2023, while machine tools declined from nearly 37% to just 10% over the same period. Although the use of industrial robots in Poland has expanded significantly (Figure 5), they account for only a marginal share of exports (0.23% in 2023). Although the use of industrial robots in Poland has increased significantly (Figure 5), they play a marginal role in automation exports (0.23% in 2023).

The role of automation technology trade in economic growth

A model of technology-driven convergence

To assess the economic role of technologically advanced exports--particularly in the growth process—we estimate a conditional convergence model [**Kremer et al., 2022**], linking GDP per worker growth rates (*gGDPpw*, computed as the log difference) in country *i* to lagged levels of output per worker (*GDPpw*) and a set of control variables:

$$gGDPpw_{it} = \beta_0 + \beta_1 \ln GDPpw_{it-1} + \beta_2 TECH_{it} + \gamma X_{it} + D_i + D_t + \epsilon_{it}. \tag{3}$$

The key control variable, reflecting the technological content of exports (*TECH*), is represented either by the share of products embedding automation technology in a country's total exports (s_{it}^{AT}) or by the export share of all technologically advanced products (s_t^{T}). The set of other r.h.s. variables (X) includes the human capital index (*HC*) from PWT 10.0, the share of fuel exports (*FUEL*) based on CEPII export data, and FDI inflows (as % of GDP) from the World Bank. Country- and time-specific fixed effects (D_i and D_t) account for unobservable factors. Table A3 in the Appendix reports the coefficients of correlation between explanatory variables. In most cases, they are low, so collinearity is not a major concern.

The convergence process is indicated by a negative and statistically significant coefficient $\hat{\beta}_1 < 0$. If tech-driven conditional convergence is confirmed, then $\hat{\beta}_2 > 0$. To address potential endogeneity in the model, we apply GMM estimation with lags.

Empirical results

The IV estimation results reported in Table 2 prove productivity convergence ($\hat{\beta}_1 < 0$). Focusing on the key variables (in bold), there is a weak positive relationship between productivity growth and the share of tech exports, s_{it}^{T} (sign of a conditional convergence process, columns 2–4). However, we find no statistically significant relationship between exports of products embedding automation technologies (s_{it}^{AT}) and output per worker growth (columns 5–7).

Table 2. Benchmark estimation results

Dep.var.: $gGDPpw_{it}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ln $GDPpw_{it-1}$	−0.07939*** (−4.71)	−0.08066*** (−4.72)	−0.10930*** (−10.83)	−0.11027*** (−10.76)	−0.07961*** (−4.71)	−0.10773*** (−10.82)	−0.10871*** (−10.72)
FUEL		0.08509*** (4.28)	0.10687*** (4.18)	0.08924*** (4.49)	0.08118*** (4.14)	0.09976*** (3.99)	0.08408*** (4.28)
HC			−0.03152 (−0.84)			−0.03222 (−0.85)	
FDI			−0.00013* (−2.23)	−0.00015* (−2.12)		−0.00012* (−2.11)	−0.00015* (−2.02)

cont. Table 2

Dep.var.: $gGDPpw_{it}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)
s^T		**0.07534*** (2.35)	**0.09265**** (3.18)	**0.09535**** (3.07)			
s^{AT}					**0.23662** (1.06) (1.06)	**0.47327** (1.50) (1.50)	**0.40000** (1.43) (1.43)
R2_a	0.130	0.136	0.179	0.180	0.136	0.178	0.179
N	3520	3520	2998	3498	3520	2998	3498
idstat	7077.183	7073.309	6341.907	7267.199	7100.444	6373.37	7299.84
idp	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: Country and time dummies are included in all specifications. *,**,*** denote significance at the 1%, 5%, 10% levels respectively; robust standard errors in brackets.

Source: Author's own calculations.

We conducted a series of robustness checks to assess the sensitivity of the benchmark results. The outcomes are reported in the Appendix. Specifically, we employed alternative taxonomies of technological products (Table A6), using the UNCTAD[11] classification of high-tech goods and a taxonomy of 4IR exports proposed by **Foster-McGregor et al.** [**2019**]. We also considered an alternative measure of labour productivity (Table A7) and modified the set of control variables when estimating model (3), including data on natural resource exports [**Zarach, Parteka, 2023**]. These changes do not alter the key finding: trade in automation technologies does not play a statistically significant role in the productivity convergence process.

Concluding remarks

This paper examines export specialisation in products embedding automation technologies, using product-level trade data for 160 countries (spanning a wide range of income per capita levels) over the period from 1996 to 2019. Despite rapid global digital progress and the rising export value of products embedding automation technologies, our analysis shows that their role in export structures remains negligible. Even in high-income countries, such products account for no more than 2.5% of total exports.

This study confirms that revealed comparative advantage in automation exports is positively correlated with income per worker. However, we do not find evidence that trade in automation-related products has a statistically significant effect on cross-country productivity differences or on the conditional productivity convergence process. We do, nonetheless, observe differences across countries. China stands out as a country increasing both the value and share of automation-related exports, while Poland shows rising exports of products embedding automation technologies, combined with progress in manufacturing automation, as measured by robot adoption.

Our results demonstrate that trade statistics provide a useful alternative means of quantifying the global spread of automation-related technologies. Such data is easily accessible for a long time horizon and for many countries, as also highlighted by **Castellani et al.,** [**2022**], who used trade data to study European economies. Evidence based on product-level trade data can complement other measures of digital progress, including ICT and robot adoption data [**Acemoglu, Restrepo, 2022**; **Restrepo, 2023**; **Acemoglu et al., 2020**; **Ballestar et al., 2020**; **Cséfalvay, 2020**; **Graetz, Michaels, 2018**; **Koch et al., 2021**; **IFR, 2023**], patents and scientific publications [**Venturini, 2022**; **Parteka, Kordalska, 2023**; **Foster-McGregor et al., 2019**], and the development of open-source software (e.g. **Lohmann et al., 2024**; AI-related evidence based on GitHub[12]).

However, a trade-based approach has important limitations. Measurement of automation-related technologies via trade statistics remains imperfect. Consequently, evidence on the scale of trade in products that

11 https://unctadstat.unctad.org/en/classifications.html, file "Product by technological categories SITC Rev. 3", (accessed on 13.11.2024).

12 For instance, the software development contributions to public AI projects across countries and over time are provided here: https://oecd.ai/en/data?selectedArea=ai-software-development (accessed on 13.11.2024).

embed automation technologies is sensitive to how such products are defined. For instance, the classification of 4IR exports offered by **Foster-McGregor et al.** [**2019**] is highly conservative, covering only 21 products of nearly 5,000 HS 6-digit codes. As a result, the importance of such a small number of products in total exports is insignificant. The classification we use [**Domini et al., 2021**] is broader (190 products), but still represents only a small fraction of traded goods. Moreover, much of the trade in automation and related technologies takes place in services. ICT services, for example, accounted for 6.2% of total world trade in 2005, rising to 13% in 2023.[13] This illustrates how the intangible nature of digital technologies (including automation) makes them difficult to capture in product-level trade statistics, leading to potential severe underestimation of their true economic role. In addition, available taxonomies of technologically advanced goods are time-invariant, which is problematic in the case of dynamically developing technologies. This problem reflects a broader limitation of international trade data, where product classifications are revised only infrequently.

These limitations point to a clear direction for further research: re-examining and developing alternative ways of quantifying the digital economy and its impact using trade statistics and other data. A particularly pressing challenge is measuring the role of generative AI (GenAI), a small but rapidly growing subset of AI technologies worldwide [**WIPO, 2024a**]. Also, further analysis of the composition of automation-related exports could provide new insights into country-specific patterns of trade specialisation.

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[13] Source: UNCTAD, International trade in ICT services, https://unctadstat.unctad.org/datacentre/dataviewer/US.TradeServICT (accessed on: 26.09.2025).

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Appendix

Table A1. The list of countries in the sample

Exporter	Country name
ALB	Albania
DZA	Algeria
AGO	Angola
ARG	Argentina
ARM	Armenia
AUS	Australia
AUT	Austria
AZE	Azerbaijan
BHS	Bahamas
BHR	Bahrain
BGD	Bangladesh
BRB	Barbados
BLR	Belarus
BELX	Belgium and Luxembourg
BLZ	Belize
BEN	Benin
BTN	Bhutan
BOL	Bolivia (Plurinational State of)
BIH	Bosnia Herzegovina
BRA	Brazil
BRN	Brunei Darussalam
BGR	Bulgaria
BFA	Burkina Faso
BDI	Burundi
CPV	Cabo Verde
KHM	Cambodia
CMR	Cameroon
CAN	Canada
CAF	Central African Rep.
TCD	Chad
CHL	Chile

cont. Table A1

Exporter	Country name
CHN	China
HKG	China, Hong Kong SAR
MAC	China, Macao SAR
COL	Colombia
COM	Comoros
COG	Congo
CRI	Costa Rica
HRV	Croatia
CYP	Cyprus
CZE	Czechia
CIV	Côte d'Ivoire
COD	Dem. Rep. of the Congo
DNK	Denmark
DJI	Djibouti
DOM	Dominican Rep.
ECU	Ecuador
EGY	Egypt
SLV	El Salvador
GNQ	Equatorial Guinea
EST	Estonia
ETH	Ethiopia
FJI	Fiji
FIN	Finland
FRA	France
GAB	Gabon
GMB	Gambia
GEO	Georgia
DEU	Germany
GHA	Ghana
GRC	Greece
GRD	Grenada
GTM	Guatemala
GIN	Guinea
GNB	Guinea-Bissau
GUY	Guyana
HTI	Haiti
HND	Honduras
HUN	Hungary
ISL	Iceland
IND	India
IDN	Indonesia
IRN	Iran
IRQ	Iraq
IRL	Ireland
ISR	Israel
ITA	Italy
JAM	Jamaica
JPN	Japan
JOR	Jordan

cont. Table A1

Exporter	Country name
KAZ	Kazakhstan
KEN	Kenya
KWT	Kuwait
KGZ	Kyrgyzstan
LAO	Lao People's Dem. Rep.
LVA	Latvia
LBN	Lebanon
LBR	Liberia
LTU	Lithuania
MDG	Madagascar
MWI	Malawi
MYS	Malaysia
MDV	Maldives
MLI	Mali
MLT	Malta
MRT	Mauritania
MUS	Mauritius
MEX	Mexico
MNG	Mongolia
MAR	Morocco
MOZ	Mozambique
MMR	Myanmar
NPL	Nepal
NLD	Netherlands
NZL	New Zealand
NIC	Nicaragua
NER	Niger
NGA	Nigeria
NOR	Norway
OMN	Oman
PAK	Pakistan
PAN	Panama
PRY	Paraguay
PER	Peru
PHL	Philippines
POL	Poland
PRT	Portugal
QAT	Qatar
KOR	Rep. of Korea
MDA	Rep. of Moldova
ROU	Romania
RUS	Russian Federation
RWA	Rwanda
LCA	Saint Lucia
VCT	Saint Vincent and the Grenadines
STP	Sao Tome and Principe
SAU	Saudi Arabia
SEN	Senegal
SLE	Sierra Leone

cont. Table A1

Exporter	Country name
SGP	Singapore
SVK	Slovakia
SVN	Slovenia
ESP	Spain
LKA	Sri Lanka
SDN	Sudan
SUR	Suriname
SWE	Sweden
CHE	Switzerland
SYR	Syria
MKD	TFYR of Macedonia
TJK	Tajikistan
THA	Thailand
TGO	Togo
TTO	Trinidad and Tobago
TUN	Tunisia
TUR	Turkey
TKM	Turkmenistan
USA	USA
UGA	Uganda
UKR	Ukraine
ARE	United Arab Emirates
GBR	United Kingdom
TZA	United Rep. of Tanzania
URY	Uruguay
UZB	Uzbekistan
VEN	Venezuela
VNM	Vietnam
YEM	Yemen
ZMB	Zambia
ZWE	Zimbabwe

Source: Author's own elaboration.

Table A2. Products embedding automation technologies - HS product codes

Label	HS codes
Industrial robots	847950
Machines & mechanical appliances nes	847989
Numerically controlled machines	84563011, 84563019, 84573010, 845811, 845891, 845921, 845931, 84594010, 845951, 845961, 846011, 846021, 846031, 84604010, 84613010, 84614011, 84614031, 84614071, 84621010, 846221, 846231, 846241, 84629120, 84629920
Machine tools	845600–846699, 846820–846899, 851511–851519
Tools for industrial work	820200–821299
Welding machines	851521, 851531, 851580, 851590
Weaving and knitting machines	844600–844699 and 844700–844799
Other textile dedicated machinery	844400–845399
Conveyors	842831–842839
Regulating instruments	903200–903299

Source: Domini et al. [2021] based on Acemoglu and Restrepo [2018].

Table A3. Table of correlation coefficients between explanatory variables

	lagged productivity	share of tech exports	share of automation exports	share of fuel exports	human capital index	avg trade costs	distance from the main markets
lagged productivity	1.0000						
share of tech exports	0.3125	1.0000					
share of automation exports	0.3705	0.3559	1.0000				
share of fuel exports	0.1559	−0.2481	−0.2727	1.0000			
human capital index	0.7572	0.3656	0.5100	−0.1080	1.0000		
avg trade costs	−0.3970	−0.2121	−0.2659	0.0743	−0.4867	1.0000	
distance from the main markets	−0.5132	−0.3281	−0.5214	0.0986	−0.5126	0.3486	1.0000

Source: Author's own calculations.

Table A4. Table of correlation coefficients between RTA indices (regular and symmetric) and other indices of export specialisation (Herfindahl-Hirschman Index, Gini index, Theil index)

A. Indices computed with respect to the group of technologically advanced products (T)

	RCA^T	*SRCA^T*	*Herf^T*	*Gini^T*	*Theil^T*
RCA^T	1.0000				
SRCA^T	0.9251	1.0000			
Herf^T	0.0451	0.0189	1.0000		
Gini^T	0.2902	0.3106	0.4238	1.0000	
Theil^T	0.3555	0.3648	0.6549	0.8888	1.0000

B. Indices computed with respect to the group of automation-related products (AT)

	RCA^AT	*SRCA^AT*	*Herf*	*Gini*	*Theil*
RCA^AT	1.0000				
SRCA^AT	0.9184	1.0000			
Herf^AT	−0.2190	−0.2938	1.0000		
Gini^AT	−0.0399	0.0155	0.0020	1.0000	
Theil^AT	−0.0354	0.0227	0.3357	0.8472	1.0000

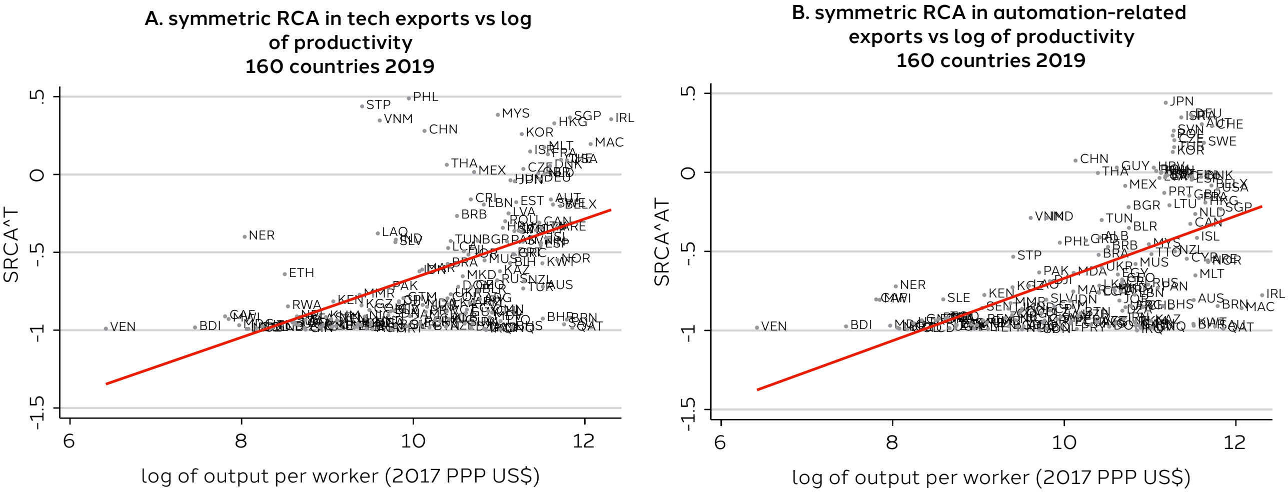
Source: Author's own calculations.

Table A5. Shares of subcategories in total exports of products embedding automation technologies – selected countries

	USA	USA	CHN	CHN	JPN	JPN	IND	IND	DEU	DEU	POL	POL
	1996	2024	1996	2023	1996	2024	1996	2023	1996	2024	1996	2023
Industrial robots	0.49	0.68	0.02	0.69	1.33	2.73	0.00	0.34	0.74	1.25	0.00	0.23
Machines & mechanical appliances nes	29.76	53.48	8.27	17.35	24.11	59.03	5.73	16.18	9.75	28.98	12.72	16.11
Numerically controlled machines	2.07	1.17	1.18	2.08	7.85	2.82	0.89	1.32	5.79	3.79	2.43	0.95
Machine tools	28.28	13.36	18.57	17.66	28.64	12.43	13.86	15.76	26.45	24.38	36.74	10.11
Tools for industrial work	13.37	13.26	43.32	27.88	8.71	6.33	45.58	27.37	14.31	18.17	22.26	22.60
Welding machines	2.29	2.76	0.97	2.55	3.08	1.49	0.45	1.87	3.08	3.76	1.35	1.67
Weaving and knitting machines	0.28	0.07	0.54	1.35	2.78	0.70	0.71	0.46	2.49	0.35	0.56	0.02
Other textile dedicated machinery	9.12	3.51	23.44	18.85	14.33	3.63	29.77	24.54	27.28	7.41	11.14	35.42
Conveyors	2.34	2.59	1.10	3.96	1.88	0.68	0.35	1.05	2.70	3.38	8.99	4.09
Regulating instruments	11.99	9.11	2.60	7.64	7.28	10.15	2.66	11.10	7.40	8.53	3.79	8.81
TOTAL	100	100	100	100	100	100	100	100	100	100	100	100

Source: Author's own calculations using data from WITS.

Figure 3R. Symmetric RCA in technologically advanced products (plot A) and in automation-related products (plot B), against log of labour productivity, 2019



Source: Author's own elaboration using data from BACI CEPII and PWT.

Table A6. Estimation results – robustness 1 (alternative taxonomies of technological products)

Dep. var.: $gGDPpw_{it}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ln $GDPpw_{it-1}$	−0.07939*** (−4.71)	−0.08032*** (−4.71)	−0.10860*** (−10.80)	−0.10980*** (−10.72)	−0.07951*** (−4.71)	−0.10752*** (−10.83)	−0.10855*** (−10.72)
FUEL		0.08405*** (4.23)	0.10432*** (4.08)	0.08796*** (4.43)	0.08086*** (4.12)	0.09908*** (3.96)	0.08362*** (4.26)
HC			−0.03014 (−0.80)			−0.02635 (−0.70)	
FDI			−0.00013* (−2.13)	−0.00015* (−2.05)	−0.00012*	−0.00015* (−2.08)	(−2.01)
s^T		**0.05546** (1.77)	**0.06290*** (2.31)	**0.07290*** (2.39)			
s^{AT}					**−1.04542** (−0.83)	**−0.30688** (−0.21)	**−1.04915** (−0.81)
R2_a	0.130	0.136	0.178	0.179	0.136	0.178	0.179
N	3520	3520	2998	3498	3520	2998	3498
idstat	7077.183	7076.12	6349.249	7270.978	7106.543	6379.262	7306.118
idp	0	0	0	0	0	0	0

Notes: Country and time dummies are included in all specifications. *,**,*** denote significance at the 1%, 5%, 10% levels respectively; robust standard errors in brackets. Results obtained with high-tech products' classification UNCTAD[14] and a taxonomy of 4IR exports from Foster-McGregor et al. [2019].

Source: Author's own calculations.

Table A7. Estimation results – robustness 2 (change of the dependent variable: alternative measure of productivity)

Dep. var.: $gGDPpw_{it}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ln $GDPpw_{it-1}$	−0.07977*** (−4.94)	−0.08059*** (−4.92)	−0.10563*** (−10.24)	−0.11010*** (−11.63)	−0.07970*** (−4.92)	−0.10413*** (−10.20)	−0.10870*** (−11.59)
FUEL		0.09317*** (4.40)	0.11456*** (4.17)	0.10278*** (4.78)	0.08980*** (4.30)	0.10770*** (4.00)	0.09814*** (4.61)
HC			−0.04155 (−1.02)			−0.04148 (−1.01)	

14 https://unctadstat.unctad.org/en/classifications.html (file "Product by technological categories SITC Rev. 3").

cont. Table A7

Dep. var.: $gGDPpw_{it}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)
FDI			−0.00009 (−1.11)	−0.00008 (−0.96)		−0.00008 (−1.00)	−0.00007 (−0.86)
s^{T}		**0.06430** (1.73)	**0.08843*** (2.43)	**0.08629*** (2.38)			
s^{AT}					**0.13685** (0.43)	**0.39037** (0.94)	**0.37567** (0.98)
R2_a	0.157	0.164	0.201	0.206	0.163	0.200	0.205
N	3520	3520	2998	3498	3520	2998	3498
idstat	6699.296	6690.324	5802.762	6758.03	6715.214	5834.138	6789.372
idp	0	0	0	0	0	0	0

Notes: Country and time dummies are included in all specifications. *,**,*** denote significance at the 1%, 5%, 10% levels respectively; robust standard errors in brackets. Here: *GDPpw* measured in terms of output-side real GDP at chained PPPs (in mil. 2017US$) per person employed (Source: PWT 10.0).

Source: Author's own calculations.

Table A8. Estimation results – robustness 3 (change in the set of control variables: share of natural resource exports instead of fuel exports)

Dep. var.: $gGDPpw_{it}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ln $GDPpw_{it-1}$	−0.07939*** (−4.71)	−0.07957*** (−4.69)	−0.10744*** (−10.68)	−0.10869*** (−10.57)	−0.07859*** (−4.68)	−0.10606*** (−10.66)	−0.10726*** (−10.54)
FUEL		0.07225*** (4.43)	0.08721*** (4.33)	0.07144*** (4.34)	0.06914*** (4.28)	0.08284*** (4.19)	0.06761*** (4.14)
HC			−0.03310 (−0.88)			−0.03434 (−0.90)	
FDI			−0.00013* (−2.21)	−0.00015* (−2.10)	−0.00012*	−0.00015* (−2.11)	(−2.01)
s^{T}		**0.07498*** (2.35)	**0.08970**** (3.12)	**0.09303**** (2.99)			
s^{AT}					**0.27707** (1.26)	**0.53363** (1.71)	**0.43840** (1.60)
R2_a	0.130	0.136	0.179	0.179	0.136	0.179	0.178
N	3520	3520	2998	3498	3520	2998	3498
idstat	7077.183	7078.194	6349.971	7276.185	7102.729	6377.068	7305.1
idp	0	0	0	0	0	0	0

Notes: Country and time dummies are included in all specifications. *,**,*** denote significance at the 1%, 5%, 10% levels respectively; robust standard errors in brackets. *NR* measured in terms of the export share of products classified as natural resources (Source: Zarach and Parteka, 2024).

Source: Author's own calculations.