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GVCs meet robots: smiling, smirking or flattening? The case of the automotive value chain

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ABSTRACT

The paper contributes to the fast-growing literature on the structural dynamics of digitalization with a focus on robotization, and its heterogeneous diffusion and impact along and within global value chains. Specifically, building on an innovative granular analysis of the International Federation of Robotics (IFR) dataset, we provide new empirical evidence of the disproportional distribution of robotization across countries, sectors and along different stages and production functions of global value chains (GVCs). Moreover, with specific reference to the automotive sector, we identify some features that characterize industrial robots' adoption across different applications and along different stages of the automotive value chain. Such characteristics are also assessed through a sectoral case study analysis based on primary data collection conducted in the automotive sector in South Africa.

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GVC; automotive; robotization; upgrading; governance

1. Introduction

The emergence, effective deployment, and diffusion of new technologies clustered around Industry 4.0 (Sung 2018) are increasingly altering the nature of manufacturing production, blurring the boundaries between physical and digital production technologies and systems. Advances in intelligent automated systems, robotization, and data analytics – IoT, digital platforms, and digital supply chains – generate significant opportunities to accelerate innovation and increase the value-added content of production in manufacturing industries (Peruzzini, Grandi, and Pellicciari 2017; Szalavetz 2019).

Industry 4.0 is a broad trend toward automation and data-enabled exchange in manufacturing technologies (Kargermann, Wahlster, and Helbig 2013). Although digitalization and automation trends encompass the use and integration of a bundle of technologies (Andreoni and Anzolin 2020; Frank, Dalenogare, and Ayala 2019; Tortorella and Fettermann 2018) whose effects are hard to disentangle, one notable exception is the literature on industrial robots (IRs). IRs are one of the few technologies that received extensive

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attention due to their direct and often quantifiable effect on production processes and labour and the availability of a global dataset (e.g. the International Federation of Robotics).

Despite an extensive literature on adopting robots and their effects on manufacturing production and employment, most of the analyzes take a normative approach, considering IRs as an off-the-shelf and one-fits-all technology, which hardly applies to how industrial robots function in the manufacturing realm. First, existing works tend to be at the country level, thus being sector and firm-agnostic; robot adoption is highly influenced by heterogeneity at the sectoral and at firm level, yet few studies take a sectoral approach unpacking the diversity across different manufacturing sub-sector and even fewer a firm-level unit of analysis (Anzolin, Andreoni, and Zanfei 2020; Cheng et al. 2019; Dachs, Fu, and Jäger 2022; Zhao et al. 2022). Second, the high concentration of IRs in a few sectors would call for a global value chain perspective to study the adoption and the impact of IRs across different stages of specific sectoral value chains. Third, although IRs are not new, technological advances in the last decades have increased the type of applications that IRs can perform, and yet the impact of different applications for value distribution across the value chain is neglected in the current literature. By exploring these research gaps, we will provide evidence on some structural determinants for robot adoption, with implications for businesses and policymakers interested in spurring the adoption of IRs.

This paper aims to contribute to the fast-growing literature on the Industry 4.0 trend by analyzing country and firm-specific dynamics of robotization and how IRs are deployed across sectors and stages of GVCs, with a specific focus on automotive. Specifically, building on an innovative granular analysis of the International Federation of Robotics (IFR) dataset, we provide new empirical evidence of the distribution of robotization across countries, sectors and along different stages and production functions of the value chain (GVCs); on this latter aspect, we provide a case study on the automotive sector, where we identify different characteristics of robotization within final assemblers and suppliers. The qualitative case study analysis is part of a four-year research programme on robotization in the automotive sector with a focus on OEMs in South Africa. Several rounds of interviews were conducted between 2018 and 2022. The benchmark year for the international benchmark and value chain analysis is 2017 (IFR 2018).[1]

The empirical results indicate that robotization is not only a sector-specific phenomenon – automotive and electronics account for more than 56% of total robots in operation by 2017 – but that robots are disproportionally distributed along functional stages of the value chain. The matching of robotization data against a detailed set of functional stages reveals how robotization concentrates on a subset of production applications. By increasing productivity, process reliability and product quality, robotization is likely to be a major driver of value addition in these specific functional stages and the related applications at the GVC level. Industrial robots' adoption represents a process upgrading strategy and, depending on the application and production process, it can entail product and functional upgrading too (Lin, Xiao, and Yin 2022); the actual firm-level space to increase value-added and the market value of specific functions is highly sector and institution-specific (Pipkin and Fuentes 2017).

Building on the empirical result, we indicate that robot adoption can lead to a reshaping of those value chains with high industrial robot adoption. One of the main references is a paper on additive manufacturing and GVC restructuring (Rehnberg and Ponte 2018), contributing to the growing literature that examines recent production technologies and their relationship with value chain structures and governance. Our analysis complements the data analysis of IRs with a firm-level case study on the automotive sector, where we find that the structural dynamics of robotization are both functional stage and application-specific and that there are some cascade effects along the supply chain, although they are limited to specific type of applications and businesses.

The paper is structured as follows: in section 2, we present the theoretical background and highlight different characteristics of robotization by focusing on the structural drivers and dynamics at the firm and value chain levels. Section 3 introduces the methodology adopted and the two levels of analysis. Section 4 presents evidence of industrial robot applications. Based on this data, the paper focuses on a case study regarding the automotive industry, which is discussed in section 5. Section 6 concludes.

2. Theoretical background

2.1. Structural drivers of robotization

Over the last two decades, robotization has been driven by various opportunities and constraints. Some are reminiscent of challenges faced during the First Industrial Revolution, such as the need to increase productivity and address worker fatigue (Mokyr, Vickers, and Ziebarth 2015). Other factors have emerged due to technological advancements, new organizational models, and evolving market quality requirements. One major opportunity is the replacement of workers in repetitive, routinized tasks, particularly those posing safety challenges. Large-scale production activities, like those in metal and chemical industries, involve continuous processes of interrelated tasks that have been automated to cut costs and improve reliability (OECD 2017).

The literature observes three main drivers. First, productivity is a primary motivator for adopting robots (Graetz and Michaels 2018; Michalos et al. 2010). In sectors like automotive and metals, early adopters of IRs achieved significant productivity gains by automating simple, repetitive tasks (Eric, Guerzoni, and Nuccio 2018; Nisen 2014). Second, IRs offer superior performance in executing critical and complex tasks with high precision and quality, improved dexterity, real-time adaptation and standard conformity (Anzolin and Andreoni 2023). For instance, painting and other dispensing applications solved complexity issues and safety requirements (Hassan and Liu 2017). The task specificity of robot adoption is key as it brings new processing methods, new production processes and inspection methods (Cheng and Yuan 2020). A study on the Brazilian aviation sector highlighted that high precision requirements and process standardization in drilling applications were major drivers of robotization (Barbosa and de Andrade Bezerra 2019). Third, flexibility is another driver, yet the complexity raised by the deployment of flexible machines on the shop floor makes it challenging in certain sectors that still work better on high volume low variety. There are several issues with flexible manufacturing systems (Mehrabi, Ulsoy, and Koren 2000): they can be expensive, include unnecessary functions, lack adequate system software, are not highly reliable, and are subject to obsolescence due to technological advances. Frank, Dalenogare, and Ayala (2019) confirmed these findings, noting that flexible production lines were not adopted in any mature clusters they studied. Similarly, productivity, rather than flexibility, is a stronger driver of automation in Brazil (Dalenogare et al. 2018). Automated solutions and robots can also increase complexity and introduce rigidities in production lines. A study of manufacturing firms in Japan and Sweden revealed that workstations with industrial robots tend to have higher rigidity (Hedelind and Jackson 2011).

How robotization can increase productivity, performance, and flexibility is highly sector and application specific. This is because robotization entails both technological and organizational integration within production plants (section 2.2) and value chain governance and upgrading strategies (section 2.3).

2.2. Structural dynamics of robotization: technological and organizational integration

Robot adoption within existing production plants and several interconnected production facilities along GVC requires technological and organizational integration. Technological integration assures that the different technology components are properly integrated, that is, the companies have the right mix of hardware, connectivity and software and meet the 'digital capability threshold' required to operate each one of them, and all of them together as a system in a cost and quality effective manner (Sturgeon 2017). Technology integration requires a series of pre-conditions to be satisfied both in terms of infrastructure and skills (Andreoni, Chang, and Labrunie 2021; Chuang 2024), as well as advanced capabilities for organizational integration. Organizational integration is important both at the single company and at the supply chain levels. Challenges at the company level are mainly related to the variety and complexity of the different tasks and processes that have to be managed within a robotic cell, and to the integration of a new IR cell into an existing production line (i.e. the retrofitting process) (Kolla et al. 2022; Uyeh et al. 2022). Both types of integration, organizational and technological, affect the workforce and require increasingly highly skilled workers. Indeed, when IRs replace workers to execute skilled-intensive tasks, IRs also require high-skill activities to handle and monitor the process, thus presenting a complementarity between IRs adoption and high-skill labour (De Backer et al. 2018).

When applying IRs or other automated and digital technologies, the capability gap between leading multinational companies and first-tier suppliers, and the even wider gap with second and third tiers SMEs, can be such that the advantages offered by the integration of intelligent automated systems and robots do not materialize or spread along the chain. In some cases, such capability gap discourages leading OEMs and first-tier suppliers from linking backwards domestically. Thus, a technology upgrading opportunity can turn into an industrialization bottleneck for local suppliers when system integrators and assemblers have to rely on the importation of components more than local insourcing from developing countries. Therefore, automation opportunities (e.g. safety improvements, productivity increases, better product quality, etc.) must be balanced with feasibility issues.

2.3. Robots and (global) value chains

According to ISO 8373:2012, industrial robots are defined as 'an automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications'. These robots have evolved from simple robotic arms to complex machines that offer increased intelligence, flexibility, and the ability to perform multiple complex tasks. For example, in automotive plants, multiple robots collaborate on assembly and spot-welding operations (Michalos et al. 2010). More recently, coordination has extended to machines and humans, with cobots working alongside human workers on assembly lines (Calitz, Poisat, and Cullen 2017; Vahedi-Nouri et al. 2024).

Emerging literature explores how robotization is redesigning production processes within plants and along global value chains. Frank, Dalenogare, and Ayala (2019) study on Brazilian firms reveals that industrial robots adoption increases with firm size, suggesting that readiness for Industry 4.0 involves integrating rather than merely substituting technologies. De Backer et al. (2018) examined the impact of robotization on production organization through offshoring and backshoring. Their analysis indicates that while robotization may reduce offshoring trends from developed to developing countries, there is no significant evidence of backshoring. Interestingly, they found a small GVC integration and upgrading effect from robot adoption in developed countries but no consistent evidence for emerging markets, pointing to other dynamics that might be critical to promote developmental returns to upgrading (Pipkin and Fuentes 2017). Lee, Qin, and Li (2022) observe that improvement effects from robotization are greater if robots have applications in high-tech industries.

In the automotive sector, which accounts for over 35% of total industrial robots in manufacturing, Organizational differences are important in the decision to use automated technologies (Krzywdzinski 2021). His analysis of production processes indicates how technology intensity varies across tasks and processes. Anzolin, Andreoni, and Zanfei (2020) further studied the correlation between robotization and FDIs in the automotive sector, finding a correlation at the OEM level but more scattered data at the component level, suggesting that other local ecosystems elements influence robot diffusion (Anzolin, Andreoni, and Zanfei 2022).

As production processes become increasingly global, robotization offers opportunities for technological upgrading within GVCs. The installation of IRs already had an impact on the comparative advantage of countries and the division of labour in GVCs (Yuan and Lu 2023); replacing low-end labour with IRs improves productivity, optimization and learning mechanisms (Duan et al. 2023; Sun and Hou 2021). Upgrading involves improving a firm's ability to move to more profitable, technologically sophisticated niches (Gereffi 1999). This concept has evolved into a four-fold categorization: product, process, functional, and inter-sectoral upgrading (Humphrey and Schmitz 2002; Kaplinsky and Morris 2000; Ponte, Sturgeon, and Dallas 2019). Robots offer a direct possibility for process and functional upgrading in production.

The concept of upgrading, which involves moving away from low value-adding stages of production by outsourcing them to locations with cost advantages (Baldwin 2013) has often been presented through the smiling curve. Traditionally, production stages are seen as having less value addition potential compared to pre-production (R&D, prototyping) and post-production (distribution, MRO services) stages, which are closer to knowledge creation and markets. The outsourcing processes that characterized most manufacturing firms since the 1980s increased the deepening of the smiling curve. Recent studies argue that increasing automation and digitalization could reshape the smiling curve pattern along value chains, adjusting value addition scope across sectoral value chain stages (Fernández-Macías 2018; Krzywdzinski and Jo 2022). While industrial robots are a source of upgrading across different sectoral value chains, an increasing number of contributions discuss the developmental returns to upgrading, providing evidence that upgrading does not always relate to higher value-added (Pipkin and Fuentes 2017; Rehnberg and Ponte 2018), and that downgrading could in certain cases lead to windows of value-adding opportunities (Ponte and Ewert 2009). There are cases where upgrading does not materialize to increase firm's competitiveness or it spurs only shortlisted benefits (Dussel Peters 2008). High value-adding dynamics are deeply affected by industry specificities and their governance structures, and by the role of institutions, which are closely linked to the outcome of upgrading.

3. Methods

In this paper, our aim is to provide new evidence on the structural dynamics of industrial robots' adoption. We proceed in two main directions, (i) unpacking and examining the IFR data and, on this basis, (ii) addressing specific research questions through an in-depth case study. Our approach is based on abductive reasoning as we moved from an observation (both quantitative and qualitative) to a theory that accounts for what we observed (Timmermans and Tavory 2012). We used a mixed methods approach where the quantitative analysis serves as a first step to then narrowing down to a specific sectoral case study where we gathered primary data through semi-structured interviews.

First, we had access to the International Federation of Robotics dataset, which is the only global dataset available on industrial robots. The IFR data provides annual figures on the operational stock and market value of industrial robots, expressed in number of units adopted, covering all major industrialized and middle-income countries, including a large number of fast industrialisers and emerging economies. The robots included are based on the definition of the International Organisation for Standardization mentioned above, and they are classified according to ISIC rev. 4 classification. The two most critical information reported in the IFR dataset and used for this paper are (i) the robots applications and (ii) the sector where robots are adopted. One of the main limitations of the dataset is that it does not allow to match applications and sectors, i.e. it is not possible to see which applications belong to which sector. While this can be partially deducted for certain applications, e.g. welding in the automotive and metal sectors and the two categories of cleanroom for FPD and cleanroom for semiconductors, this is not the case for example with material handling or packaging applications. Despite this limitation, we provide a matching analysis whereby robots applications are linked to functional stages of a generic multi-stages value chain. In doing so, we aim at capturing where robots are mostly affecting existing GVCs and, potentially, if and how they are changing the technological upgrading and value addition dynamics.

Second, our qualitative research is an exploratory case study conducted to better understand the adoption dynamics of disruptive technology within a real-life context, which seems to be an unexplored phenomenon. This study draws on six months of research on the automotive industry in South Africa with a focus on technology adoption. This paper is the result of a four-year project on the use of industrial robots and other automation and digital technologies in the South African automotive context (Anzolin and Andreoni 2023; Anzolin 2024). The use of a qualitative in-depth methodology allows us to understand and analyze the dynamics that characterize robots' adoption along different stages of the value chain, to go beyond the idea that the availability of a set of technologies is an enabling factor *per se*. Specifically, and with a focus on robotization, this methodology allows to disentangle three main elements: (i) the complexity of such technology, (ii) the main challenges related to its adoption and (iii) how the interrelations between different players play a role in the adoption of industrial robots within the automotive sector.

We presented an in-depth case study through semi-structured interviews conducted using open-ended questions focusing on the specific topics of technology adoption. The selected interviewees are either part of the manufacturing division or in charge of plant direction and they are all highly knowledgeable on automated manufacturing due to their specific engineering background and several years of experience in the sector. We followed a purposeful sampling technique where the cases are 'rich examples of the phenomenon of interest, but not highly unusual cases … cases that [can] illuminate the nature of the [phenomenon]' (Patton 2002, 234). Specifically, we focused on OEMs and suppliers that produce metal commodities in the automotive sector; while the dynamic observed is not transferrable to other commodities, the technology involved makes it transferrable across firms active in the same sector/application. The snowballing technique also favour the case study from OEM to tier 2 supplier (Noy 2008). Among the six OEMs interviewed, we consider one OEM[2] (Firm A) characterized by a long-term presence in South Africa and with an already planned expansion in the next couple of years. Second, we analyzed the case of Firm B, which is a Tier 1 company directly supplying Firm A. Lastly, from Firm B we reached the third firm (Firm C) which is a direct supplier of Firm B.

The following company case studies will provide exploratory evidence of robotization dynamics in the automotive industry. Specifically, we address the following questions:

i to which extent robotization is characterized by application at different stages of the value chain and at different applications' levels;
ii if there are any 'cascade effects' due to robot's adoption at the OEM level leading to robotization along supply chain tiers.

4. GVCs meet robots: geographic diffusion, sectoral distribution and functional application of robots

4.1. Geographic and sectoral diffusion of robots: stocks and flows

By 2017, 95.9% of all industrial robots operational stock was present in 37 countries. Within this group of 'robotised countries', the stock of industrial robots is highly concentrated. The top ten countries capture 85.8% of world industrial operational robots alone, while the top five countries deploy 74.8% of all industrial robots in operation in the world by 2017. The top five countries include three leading industrialized nations – Japan, the United States and Germany – and two of the fastest industrialisers of the last century – China and South Korea. The exponential growth of China since 2012 put the country in the global leading position since 2016 when it replaced Japan (Andreoni, Frattini, and Prodi 2024) (Figure 1). In 2020 the top five countries still accounted for 73.1% (IFR 2022).

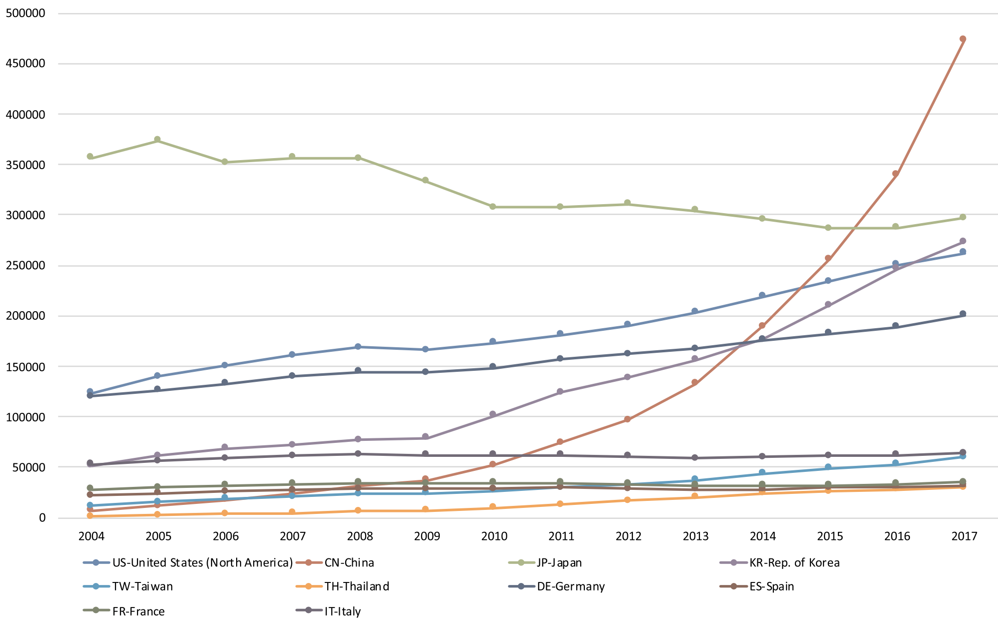

Figure 1. Operational stock of industrial robots for top 10 countries, 2004 –2017. Source: Authors based on IFR.

For what concerns sectoral distribution of industrial robots, the International Federation of Robotics (IFR) dataset reveals a high sectoral concentration. By 2017, a striking 88% of industrial robots was deployed in the manufacturing sector[3], with the remaining 1% in non-manufacturing sectors. Within manufacturing, the automotive sector is the industry deploying the greatest number of industrial robots (Table 1). In 2017 automotive accounted for 36.81%, the largest sectoral share of industrial robots in operation.[4] Automotive has benefitted from a continuous technology push, stemming from investment in automated production technologies from major car producers since the 1970s. Automotive has always been the bedrock of manufacturing automation advances due to its high-volume production, standardization and modularization that allow the production of different parts to be assembled. The electrical and electronic industry is the other leading sector in robot's adoption (Figure 2). It has experienced a huge increase in robots' deployment mainly due to the demand-pull of new and more diverse products and components. Moreover, the production of small parts at high speed characterizing the electronic industry puts workers under enormous pressure and makes them unable to compete with machines. Manufacturing robots are in fact capable of handling screens coating circuit boards, and assembling connectors in a faultless way (IFR 2018). By 2020, the share of IRs in electronics slightly increased to 25.3%.

The other two major sectors where robots have been deployed are root industries for industrial raw materials. Metal accounts for 10.3% of operational robots, while plastic and chemical products account for another 8.14%. These industries are characterized by large capital investments, scale-intensive machinery and continuous processes involving routinized tasks which robots can perform in a highly efficient and cost-effective way. Together with automotive, electrical and electronics, these two backward industries

Table 1. Robot distribution in manufacturing sectors, 2017.

Food and beverages	Textiles	Wood and furniture	Paper	Plastic and chemical products	Glass, ceramics, stone, mineral products (non-auto)	Metal	Electrical/ electronics	Automotive	Other vehicles	All other manufacturing branches
64696	2147	4891	4156	170748	11925	216092	508629	763842	8582	72483
3.1%	0.1%	0.2%	0.2%	**8.1%**	0.6%	**10.3%**	**24.2%**	**36.4%**	0.4%	3.5%

Source: Authors based on IFR.

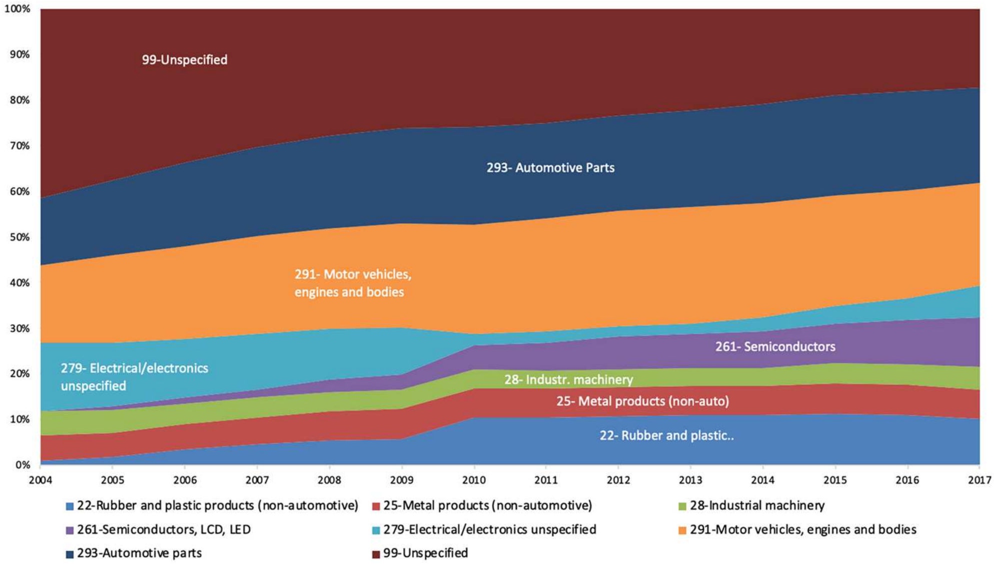

Figure 2. Robots distribution for manufacturing subsectors (operational stock), 2004–2017. Source: Authors based on IFR

account for 80% of the world's operational stock of robots (in 2020 they still accounted for 74% of the operational stock of IRs). The only other sector where robotization has found significant expansion is the food and beverages industry, through adoption in key stages of processing and packaging. Automated packaging machinery increasingly evolved with the introduction of automated intelligent systems and operational robotic arms.

4.2. Functional applications and robotization curves

The International Federation of Robotics dataset provides data on broad and more disaggregated categories of robots' applications. If we focus on the six major groups of robot applications (Figure 3), we find that two major categories of robot applications are Handling Operations and Machine Tending (45%) and Welding and Soldering (25%).

IFR has two types of databases, one on industrial robots and one on service robots; this analysis looks at industrial robots, which are robots mostly used, by definition, in the production process.[5] There are cases in which an industrial robot is also used for training and development purposes, yet this is a negligible number. Building on an in-depth examination of the robots' applications as reported by IFR (2018), we can match robots' applications against the standard functional stages of the GVC. In particular, based on how IFR classifies industrial robots, we focus on three sub-stages of the production stage – that is, intermediate components production, components refining and pre-assembly, and assembling and product system integration (Figure 4).[6]

Welding and soldering functions account for 25% of all robot applications, primarily in the intermediate components production stage. This includes arc and spot welding, as well as laser and ultrasonic welding and soldering. These tasks have long been automated

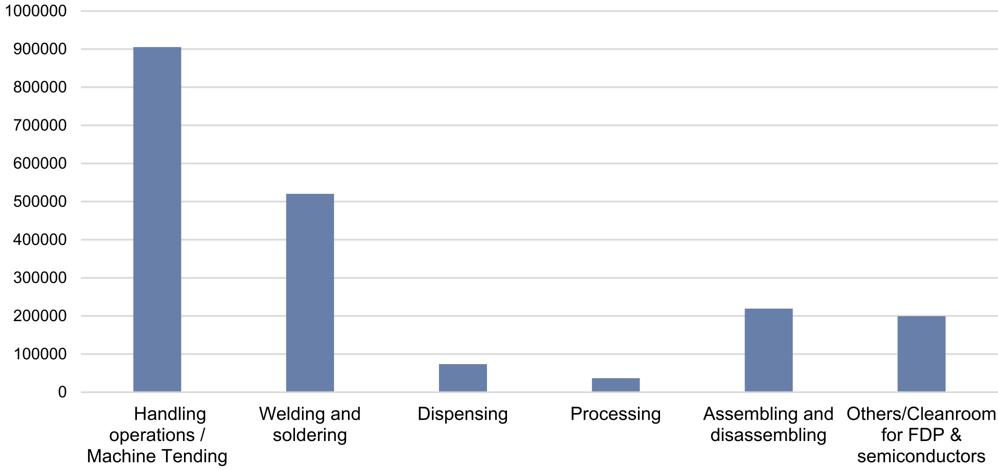

Figure 3. Robots applications: six major groups, distribution in 2017, all countries. Source: Authors based on IFR data

by robots, limiting their disruptive effects. In the components refining and pre-assembly stage, robot applications are still limited. Processing accounts for only 2% of robot applications and includes laser cutting, water jet cutting, mechanical cutting, grinding, deburring, and milling. Dispensing, which involves activities like painting, powder coating, and applying adhesives, accounts for another 4%. These tasks require extreme precision, and retrofitting these robots is a complex process. Approximately 20% of robot applications

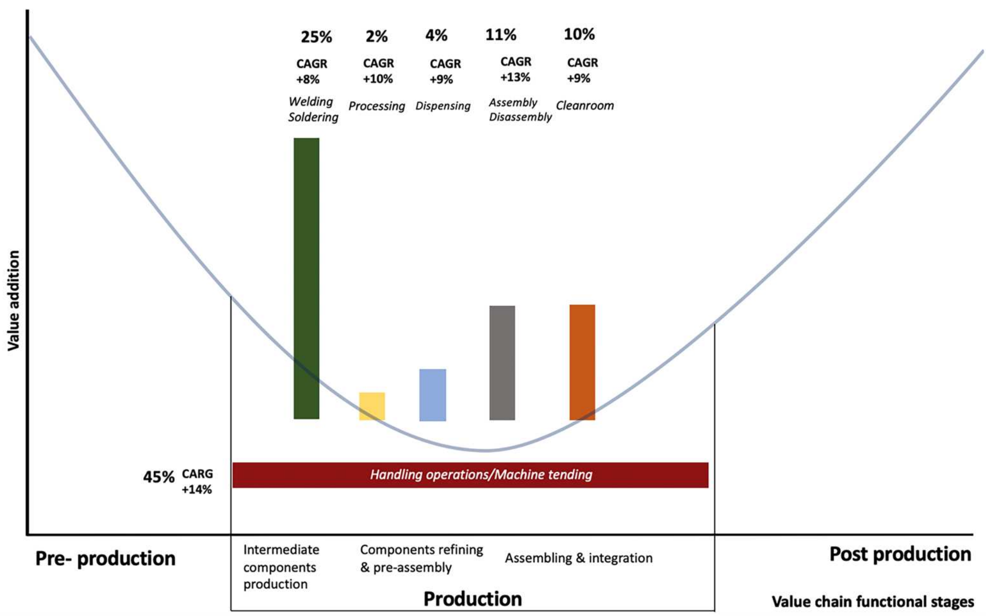

Figure 4. Functional application of robots along a general value chain. Source: Authors based on IFR data.

are found in the assembling and product system integration stage. Here, robots execute repetitive assembly procedures, yielding significant productivity gains. Activities like fixing, press-fitting, mounting/inserting, and recycling/removal are crucial in the automotive and electronics sectors. Robots in cleanrooms are essential for producing sophisticated electronics and semiconductors, as these controlled environments prevent contamination during manufacturing. Handling operations and machine tending account for nearly half of all robot applications (45%). These include various tasks distributed across different production stages. For example, plastic moulding represents 8% of applications in the intermediate components production stage. Packaging, picking, and placing, comprising 9% of applications, are primarily associated with the final stages of assembling and product system integration. Material handling, the largest subgroup, accounts for 16% of applications and involves transferring heavy and dangerous materials between machine tools. Machine tending focuses on loading and unloading tasks, often combined with part inspection, washing, deburring, and sorting. While automating these tasks does not directly add value, it improves the overall operational flow and speed of material handling.

An increase of industrial robots in production processes leads to improvements in productivity and competitiveness (Boavida and Candeias 2021; Zhao et al. 2024), while also determining process upgrading (in the case of transforming the same input into the same output more precisely and more effectively) and functional upgrading (in the likely case where a more sophisticated robot adoption entails higher skill content). Such upgrading dynamics can determine an overall long-term increase in firm's competitiveness and its functions' market value; sectoral level specificities and GVC governance shape the upgrading scenario, which ultimately determines the potential reshaping of the smiling curve. As manufacturing-related stages of production increase their value-added content, the value chain of different sectors could flatten, indicating a more even distribution of value added. Depending on which applications will become more dominant and on the governance dynamics that affect each firm in the value chain differently, the smiling curve might become bimodal or 'smirking'.

In summary, Figure 5 represents the possible outcomes of the robotization smiling curve. Robot applications enhance precision, productivity, and safety, albeit with varying degrees of sophistication and value-addition potential. The emergence of different robotization curves will be driven by the opportunities and constraints that robots offer for different production applications and the extent to which technological changes in one stage of the GVC – let's say the introduction by an OEM of new composite material in automotive or aerospace production – will induce changes in the technologies adopted along the supply chain – if, for example, a certain first tier supplier is required to introduce robots with laser welding applications.

The GVC governance is what ultimately determines the long-term effects of upgrading and whether these translate into higher value-adding processes. If, for example, a higher-tier supplier, with close interdependence with the lead firm, adopts and learns (form the lead firm) how to use a sophisticated technology (e.g. laser welding robot on new materials), this might increase the opportunity for firm's competitiveness in the market, given the new capabilities developed. This dynamic is likely to give rise to a smirking value-adding curve within the manufacturing stages. The use of industrial robots could determine a weaker supplier (especially higher tiers) position vis a vis

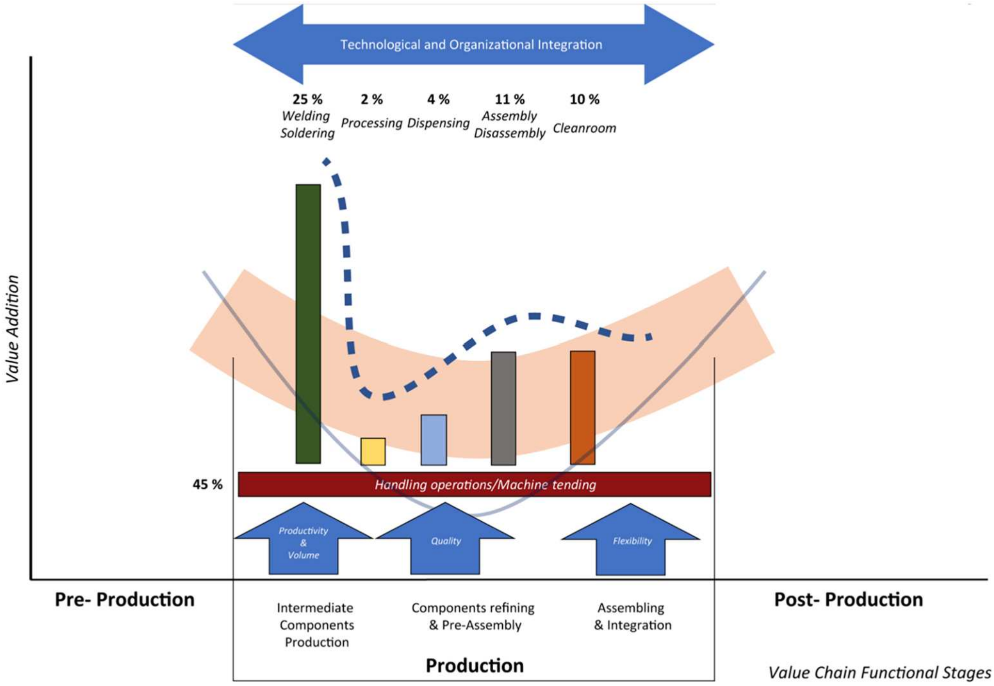

Figure 5. Robotization curve: flattening or smirking? Source: Authors based on IFR data.

lead firms that, in some cases, strictly control and dictate both product and process, thus highly limiting the space for further learning and firms' competitiveness. If this is the case, despite becoming more productive and upgrading, a supplier might have little scope for long-term learning and development, resulting in a flattening type of curve. In both cases and more generally with robot adoption, an initial upgrade might lead to narrow specialization, which can play in different directions depending on the sector and the value chain segment of the firm's operations.

5. Case study: robotization along the South African automotive value chain

5.1. Sectoral context: automotive value chain and sector-specific characteristics

The automotive industry is characterized by a complex and long value chain, which has been reshaped by significant concentration trends. In 2017, ten carmakers accounted for 66% of world vehicle production, with the top five responsible for over 40% of overall production (International Organization of Motor Vehicle Manufacturers 2018). This concentration trend at the OEM level has gone hand in hand with consolidation among first-tier suppliers; over the past four decades, component manufacturers dropped from 40.000 in 1970 to less than 3000 in 2015 (Wong 2017). More recently, with the rise of electric vehicles (EVs), the automotive sector is witnessing further disruptions. The share of EVs has increased from around 4% in 2020 to 18% in 2023, with China being by far the largest market followed by Europe (IEA 2024).

From a GVC perspective, the industry is considered a producer-driven GVC (Sturgeon et al. 2009). It is governed by large OEMs who control not only their internal assembly operations but also the distribution and sales of motor vehicles around the world and a high proportion of R&D. Most of the value-adding processes used to lie within OEMs, while today first tier suppliers highly contribute to supply chain management both directly and indirectly (Humphrey and Memedovic 2003). Control is exercised through three critical coordination decisions: (i) what is to be produced (product design), (ii) how it is to be produced (specification of processes and technologies to be used), (iii) logistic issues (how much/when to be produced) (Humphrey and Schmitz 2002).

In the South African automotive sector, value addition is concentrated among OEMs (which are all international) and Tier 1 suppliers (most of which are international), with a limited number of value-adding activities performed by Tier 2 and 3 (Barnes, Black, and Monaco 2018). Yet, Tier 1 suppliers present high heterogeneity, depending on the commodity the produce, they may exercise more or less power (Anzolin 2024). Given this distribution of value-added activities and the capital expenditure associated with robotization, including their integration and management, OEMs and, to a certain extent Tier 1 suppliers are better positioned in terms of robots' adoption. Along the supply chain, while first-tier suppliers have relatively less financial capacity than OEMs, they often have to follow OEMs in their technology decisions, tiers 2 and 3 are disadvantaged by their limited financial capacity and their relatively lower margins and operations' volume.

Figure 6 presents a three-level framework linking the robotic applications along the functional stages of a generic value chain (as discussed in section 4) with the specific functional stages and supply chain of the automotive industry. Starting from the top, a value chain by robots' application tasks is reproduced; the smiling curve is a representation of value distribution activities within the automotive manufacturing process both at the OEM and supplier levels. Such levels are introduced in the second quadrant on functional stages of the value chain emphasising that components manufacturing, and assembly can present various robotic applications. The third level, supply chain, intends to point to the existence of different components and inputs at different suppliers' levels; tasks are quite material and component-specific, so it is key to consider the type of supplier/sub-sector when discussing robotization in the automotive sector. While this mapping points to the functional stages where we expect higher levels of robotization in the automotive industry, the structural dynamics of robotization can only be captured by specific company case studies. The latter can reveal both internal robotization decisions and the potential presence of a 'cascade effect' going from OEMs to supply chain tiers. The rest of this section will discuss our case study.

5.2. Case study 1: OEM-Firm A

Firm A is a multinational corporation that serves as a final assembler of motor vehicles for both the export and South African markets. The company utilizes a substantial number of robots in its production lines, which are divided into three main areas: body shop, paint shop, and final assembly. The adoption of new industrial robots varies significantly across these areas.

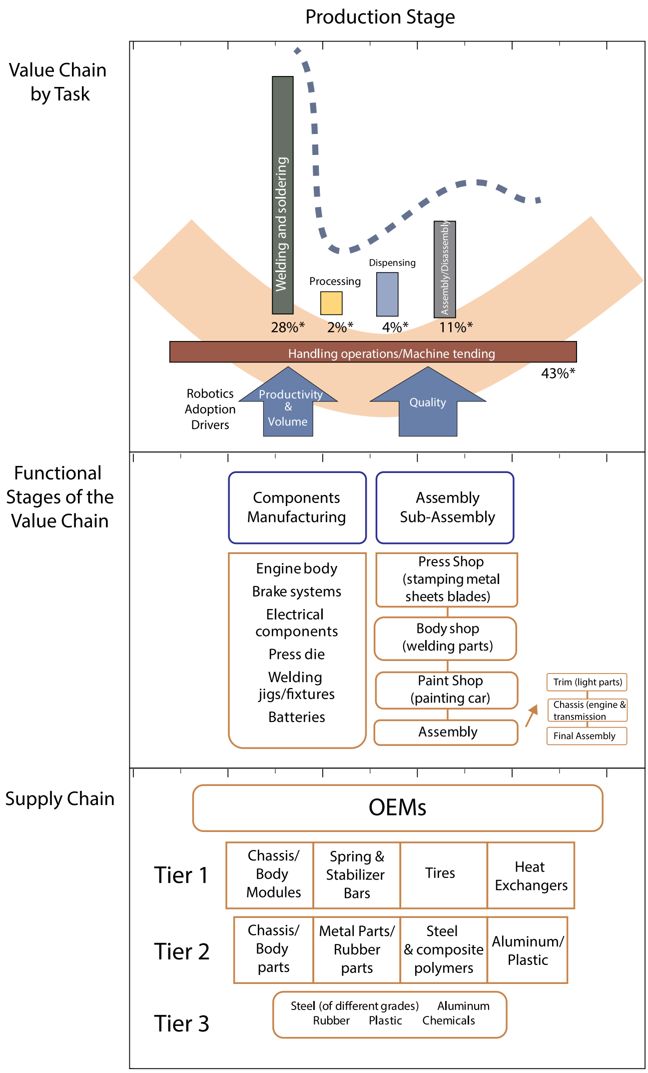

Figure 6. Three-level map: linking up value chain by task and sectoral value chain. Source: Authors.

The body shop involves numerous complex welding operations that can be performed both manually and automatically. In this area, the introduction of new robots is primarily driven by the need to increase car production volumes. Notably, Firm A plans to replace all existing robots in the body shop with the launch of a new car model, highlighting the link between robot adoption and the car model life cycle. However, this replacement does not significantly alter the value-adding distribution, as new robots perform similar tasks to the old ones. Firm A prefers a more rigid setup for robots to handle repetitive and consistent operations, minimizing variability and simplifying issue resolution. An interviewee from Firm A stated, ‘We want the robots to be rigid, with the volume and the huge amount of issues you have in a production line, the more rigidity I have, the easier [it] is for me to put my fingers on any issue … I can’t deal with variability within the variability of the machine [itself]’.

The dynamics in the paint shop differ. Over a decade ago, Firm A introduced new industrial robots for spraying and coating applications to minimize errors. These robots offer high precision for tasks like sealing and spraying. Recently, the company automated interior painting to achieve full automation in painting applications due to the high precision required and low tolerance for sub-standard work. According to an interviewee, 'Industrial robots are far more precise in the type of application such as sealing and spraying'.

In the final assembly shop, fewer industrial robots are used, mainly for safety and ergonomic reasons. The introduction of new machines here aims to facilitate workers' physical movements on the assembly line. Despite the automation, workers remain indispensable due to their flexibility in a moving line environment. The interviewee stressed that within such a setting, robots cannot replace human workers due to their adaptability.

The deployment of industrial robots at the OEM level is influenced by the predefined tasks they are intended to perform. Robots enhance the value addition of specific production stages, especially when new automated techniques are required, such as the electrostatic coating in the paint shop. Overall, the strategic use of industrial robots at Firm A improves precision, safety, and productivity across different stages of the production line.

5.3. Case study 2: Tier 1 Firm B

Firm B is a multinational corporation that operates as a Tier 1 supplier to Firm A and other OEMs. With several plants in South Africa, co-located with respective OEMs, Firm B focuses on pressing processes and welding shops, assembling specific metal components according to customer requirements. Specializing in metal commodities, Firm B produces door panels, front and back panels, and rooftops. For Firm A, which lacks an internal stamping facility, Firm B supplies metal parts with the first level of assembly. Consequently, industrial robots typically part of an OEM like Firm A are deployed within Firm B's press shop.

Firm B's decision to adopt a specific type of industrial robot is driven by the quality of the tasks performed, especially given the commodities they produce, such as steel and aluminium. However, Firm A's production lines are more manual compared to those for other OEMs, indicating a lack of flexibility between similar goods manufactured for different clients. The automation level of a line depends on two main factors: the final product cost and the cost of the robot's complexity, which includes setting up a new robotic cell, software development, jigs, fixtures, and various processing steps.

An increase in parts supplied to Firm A could lead to greater use of robotics, but the robots would be used rigidly to lower complexity and maximize productivity gains. As the interviewee from Firm B stated, 'When the cell is producing, we don't touch it from beginning to the end'. Although Firm A did not directly influence Firm B's robotization decisions, it indirectly affected them by setting the volume of parts to be produced.

The relationship between OEMs and first-tier suppliers can vary significantly. Firm B reported that, in collaboration with another OEM, they were required to install a new laser welding machine to weld aluminium parts. This investment was made to respond to a product and process change at the OEM level, with Firm B taking on the risk for the order, installation, and maintenance of the new machine; yet the risk also allowed broader learning effects, which are represented by Firm B having a second laser welding robot for development and training purposes. The decision to robotize welding operations in a more sophisticated manner reflects broader changes in the automotive industry, specifically the adoption of new and lighter materials for more fuel-efficient cars. In this case, the use of advanced industrial robots was driven by higher quality requirements in welding processes rather than a complete disruption within the production line.

Overall, the use of industrial robots at Firm B is determined by task quality and production needs, with a focus on rigid automation to maintain consistency and productivity. The relationship with different lead firms (OEMs) influences the extent and sophistication of robot adoption, thus determining the space for the developmental returns to upgrading.

5.4. Case study 3: Tier 2 Firm C

Firm C is a supplier of some input materials that Firm B uses to produce components for Firm A. Specifically, Firm C supplies metal sheets of different steel grades; its manufacturing process is characterized by a continuous process that starts with the steel coil sourced from the mill. Along the production lines, there is a lack of industrial robots' applications, and this is mainly because an industrial robot is not suitable to perform those types of continuous operations happening in sequence (e.g. oiling, cutting, etc.). The process is characterized by some buffers that consist of deeper conveyor belt stages that are set up to compensate for variations in the production process. Within this process, the only type of operation that could be performed by industrial robots is related to handling & picking operations, but the costs and time to set up an entire robotic cell make robots' adoption not a viable solution. In fact, according to our interviewee in Firm C, 'there is no business case, and it would be too complex to install and to maintain a robotic cell just for handling/picking operations'. Firm C's example points to the fact that materials and production process characteristics are crucial elements that determine the introduction of new technologies and the consequent space to increase value addition.

5.5. Discussion

The case study analysis revealed how the structural dynamics of robotization are driven by different factors along the value chain and depend on specific features of production processes and supply chain tiers. Four general results can be highlighted.

First, the introduction of industrial robots in the automotive sector is still incremental, and robot cells are configured in a much more rigid way, as often reported in the literature on flexible automation. Our interviews suggest that flexible robot deployment is still relatively rare and this might be mainly related to the complexity associated with the flexible use of robots, within stations and along the entire production process (Anzolin and Andreoni 2023). Welding and soldering are the applications whose tasks are automated more often, and such applications present a strong quality advantage when they are performed automatically.

Second, and relatedly, the adoption of industrial robots is process and materials-specific. Processes associated with metal components are more likely to adopt industrial robots. In this respect, we also find that the introduction of new materials (e.g. aluminium) leads to the introduction and adoption of new technologies through a structural learning dynamic.

Third, the robotization decision is linked to an increase in the quantity produced, either at the level of OEMs or supply chain lower tiers (Anzolin, Andreoni, and Zanfei 2020; Barnes, Black, and Monaco 2018). This production volume consideration raises a series of political economy type of questions on the role of demand-side policies at the national and regional levels. While this is beyond the scope of this paper, the relevance of volume for further technology adoption in sectors where economies of scale matter considerably is a critical field for future research.

Fourth, we also found evidence of a robotization cascade effect. The final customer OEM has a specific role in industrial robots' adoption, not only because it is the single most important adopter of industrial robots (333.804 out of a total of 763.842[7] – almost 44%) in the automotive industry but also because it has the power to direct its closest suppliers to the introduction of specific robots; this can happen either as a consequence of an increased volume of vehicles produced by the OEM and the higher number of robots that are required to respond to an increase in product demand (Firm B with Firm A), or by prescribing a specific robot for a task application that has to be carried out in a specific way (Firm B with a different OEM in the example of the laser welding robot). The governance mode of lead firms such as Firm A along the value chain determines the learning associated with it, which can either be more encompassing as with Firm B (which can then in turn be constrained by a broader use of the capabilities acquired in the relation with other lead firms) or, absent as in Firm C where the lack of financial and organizational resources restrict robotization related opportunities for upgrade and productivity. As for Firm B, it is also to note that by influencing first-tier suppliers in robot adoption, OEMs engage in a risk-shifting process (Jacobides, MacDuffie, and Tae 2016; Kang, Mahoney, and Tan 2009) whereby risk moves from the OEM to the supplier who is responsible for both the robot's financial investment and its complex technological and organizational integration. If the supplier has enough capabilities to respond to such changes, it might turn into a greater increase in capabilities.

6. Conclusions

The paper sheds new light on the structural dynamics of robotization, and its diffusion along GVCs. The empirical analysis based on the International Federation of Robotics (IFR) dataset highlights the disproportional distribution of robotization across sectors and along different stages and production functions of global value chains (GVCs). The sectoral case study analysis has also complemented the empirical evidence by showing how the dynamics of robotization in the automotive sector affect supply chain tiers differently. We have also indicated preliminary evidence of the existence of a robotization 'cascade effect' from OEMs to supply chain tiers that produce metal-related commodities.

Robotization has been and will continue to be affected by disproportional and heterogeneous dynamics. Within the intermediate components production stage of the value chain and for the basic handling and tending operations, the productivity and cost-reduction driver of robotization emerged as the key factor to look at. As for the more complex processes of processing and dispensing, robotization will be driven by the increasing higher quality product standards and the increasing complexity of interdependent processes integrated through new automated technologies. This is critical for countries that have specialized in manufacturing stages with high potential for robotization; opportunities to upgrade and increase learning spillovers through the use of new robots require further analysis in the context of powerful MNCs that can often determine the conditions at which technologies are adopted, thus restricting the space for broader developmental impact (Anzolin and Andreoni 2023; Fu, Pietrobelli, and Soete 2011).

Our paper contributes to the fields of innovation technologies and development in two ways. First, we provide evidence that research questions about robotization require the combination of both quantitative and qualitative methods; indeed, it is in the space of a mixed methods approach that the multiple levels of complexity of technological change can be tackled. Second, at the policy level, our analysis reveals that any type of policy that would aim at encouraging technology adoption for productivity increases has to consider the micro-level technical details that are at the core of, as per our case, industrial robotics and their application. Future studies in this space will be key to understanding the different dynamics at play across other commodities in the same automotive sector, across other sectors and concerning other automation and digital technologies.

Notes

1. The paper uses 2017 as reference year for the value chain analysis for two main reasons. First, at the time when the firm-level case study analysis was conducted, 2017 was the most updated data point available (IFR 2018). While some updated data points were reviewed in 2020 (IFR 2022) and are referenced in the paper, there was no major changes to justify a new analysis. Second, the automotive sector went through a major contraction during the 2020–2022 due to COVID, with global sales of passenger cars of 2019 (64.8 million) reaching this level again only in 2023 (65.2 million) (OICA 2023). Given the life cycle of investments in the automotive industry and the contraction phase recorded, we are confident the analysis from 2017 remains valid.
2. Original Equipment Manufacturer. In the automotive sector final assemblers are called OEMs.
3. Although it has been diminishing over time, the unspecified sectoral category is relatively large and accounts for 11% of the total operational robots.
4. In 2020, IRs in automotive accounted for 32.2% of all robots in manufacturing (IFR 2022).
5. The definition states that they are 'for use in industrial automation applications' (IFR 2018).
6. For a similar approach see Rehnberg and Ponte 2018.
7. Operational stock value in the world at the end of 2017. This number is referring to class 291 of IFR dataset, which is related to the assembly of motor vehicle engines and bodies.

Disclosure statement

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