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Abstract

Industrial robotics is one of the technologies that, nowadays, is experiencing a remarkable and continuous progress, finding more and more applications in different industries. While this progress leads to productivity gains, it can also have an impact on employment and the labour share. Through a panel cointegration analysis on the sectoral data of nine developed countries over the period 1996-2016, we analysed the long-run relationship between the implementation of industrial robots and the labour share.

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Introduction

We are living in the period with the highest rate of innovation in the history of humanity. Every object we use in everyday life has its own technology that, although minimal, comes from discoveries, inventions, and innovations that have led to its final form, with the primary objective of enhancing its usefulness. Discoveries, inventions, and innovations are part of the history of humanity since man first appeared on Earth, just think of the discovery of fire and its first uses, or the early forms of cultivation and breeding that have allowed man to move from a nomadic lifestyle to a sedentary one. But returning to relatively more recent times and more related to the topic of this dissertation, there is a precise historical period in which technological progress has begun to grow without ever stopping, helping to improve more and more the lives of men: the First Industrial Revolution started in Britain from the fields, and expanded in the first textile factories. It is in this period that we can identify the historical moment in which machines, and so first rudimental forms of industrial automation were implemented in the productive process of the factories, increasing productivity, but also spreading among the workers the first fears of being replaced and losing their job.

Therefore, to analyse the impact of industrial automation, we started right from here, from the First Industrial Revolution, with the invention of the steam engine, coming then to the second one, with the discovery of electricity and the spread of the first cars, up to the debate around the third and the fourth revolution, with the concept of *Industry 4.0* that starts to become more and more important. It is in the years of the last two revolutions that industrial robotics – which is part of the *Industry 4.0* technologies – begins to grow, becoming a real symbol of the technological progress of recent decades and that we are experiencing today. But do advanced technologies, such as robotics, always lead to growth? There is no doubt about the positive contribution of robots on productivity both at a firm and industry level. Basically, robots can be used to perform hazardous or repetitive operations with greater precision and in less time, allowing to reduce production costs and increase the quality of the product. On the other hand, industrial robotics is expected to displace labour, by reducing the number of employees or the labour share. The literature about this topic is very wide and there are no agreed results on the direct effects of the robots' implementation on the labour component.

We tried to fit into the debate by conducting an econometric analysis on a panel dataset composed of nine developed, mostly European countries at an industry level for the period 1996-2016. We investigated the existence of a long-term relationship between robotics and some key growth indicators, such as total factor productivity and value-added, and on the main labour components, such as the employment and labour share. Data is provided by the International Federation of Robotics (IFR), the organization which collects statistics about robotics around the world, and EU KLEMS, an industry level, growth, and productivity research project, run by the Vienna Institute for International Economic Studies (wiiw). We focused our research on the manufacturing industry and particularly on the automotive sector, the one with the highest and longest tradition of industrial robots' implementation.

Chapter 1 addresses the issue of industrial automation and its evolution from a historical and geographical point of view, inspecting its diffusion with particular attention to the countries and sectors under analysis.

Chapter 2 proposes a review of the literature on robotics and its impact on productivity, employment, and the labour share, presenting the main points of view emerged in the research of different authors.

Chapter 3 shows the dataset and its construction, presenting sources, observations, and variables.

Chapter 4 describes the empirical strategy used for the analysis and comments on the results obtained.

Chapter 1. Industrial Automation: An Historical Overview

Industrial automation is an innovation process which concerns the coordinated use of technological solutions to replace part of the human work with different devices (*Enciclopedia Treccani* 2006). To better understand the concept, we may define individually the two terms "industrial" and "automation". Industrial production processes consist of procedures involving chemical, physical, electrical, or mechanical steps, through which a combination of raw material becomes a final product. According to *Encyclopaedia Britannica* (2020), the term "automation", instead, was coined in 1946 by an engineer from Ford Motor Company, to describe production systems where the human effort and intelligence were substituted with mechanical, electrical, or computerized operations.

The concept of "mechanisation" is the process through which an activity, previously carried out largely or exclusively by hand or with the help of animals, is now performed by machinery. Mechanization is included and, at the same time, overcome in the current definition of industrial automation. Now-a-days, in fact, machines can be started and function without the presence of humans and many activities as planning and supervision of the productive process that do not involve physical work are automated or can be easily automated with the current technological systems. This is a novelty compared to the past: the physical automation that, with machines and robots, replace the arms of the workers is flanked by cognitive automation that, with artificial intelligence (AI), can substitute a lot of intellectual tasks.

1.1 Innovation and Revolutions in the History of Humankind

We are living in the period with the highest rate of innovation in the history of humanity, but innovation has always accompanied mankind's history, allowing the economic progress we are experiencing today. According to Magnani (2020), the first examples of how innovation has fostered economic growth can be found in the Stone Age, with the Neolithic revolution which allowed the transition from a nomadic lifestyle, based on gathering and hunting, to a sedentary lifestyle, growing plants and raising animals.

Returning to focus on automation, to identify the historical moment in which machines were introduced for the first time in productive processes and started to support and gradually substitute the work of human operators, we need to go back to the First Industrial Revolution (1760-1840). In this period there was a process of change from an agrarian and handicraft economy to an economy characterized by industry, machine manufacturing, and technologies.

These changes introduced new ways to organize work, life, and society. This process started in Britain in the second half of the eighteenth century and then spread around the world.

1.1.1 The First Industrial Revolution

The First Industrial Revolution took place in Britain between 1760 and 1840 and it was preceded and then supported by the agricultural revolution. Instead of leaving the land uncultivated one year out of three, as was done since the Middle Ages, in the third year they began to grow forage plants, useful for feeding livestock. In this way it was possible to boost the productivity of the lands, but also improve breeding. In a short time, other countries tried to modernize their own agriculture by replicating the new English knowledge and techniques.

This increase in production was necessary to meet the demand for more products due to the increase in population occurred in those years: in 140 years the population redoubled, from 100 million in 1660 to 187 million in 1800. Given these conditions, in a short time artisans, workers, and farmers became unable to satisfy the increasing demand for goods coming from colonies and growing population. It was necessary to substitute old methods of work with new ones which allowed to produce more, in less time, and without additional costs. Thanks to the implementation of machines in the productive process and some technical innovations, the change was possible. For example, in the textile industry, spinning operations were completely mechanized and in 1833 a single worker was able to simultaneously monitor the work of four looms, producing twenty times more than one single operator working by hand.

To exploit all the potential of the machines, sources of energy different from the manual force were needed. Watt invented the steam engine in 1765, become the symbol invention of the First Industrial Revolution. The new machine was able to use the heat to produce movement, transforming thermal energy into mechanical energy, capable of operating other machines. This invention was decisive for the start in the last years of the eighteenth century of the first large textile factories which in those years was beginning to quickly mechanize.

As the machines for the production became bigger and bigger, in those years the first factories capable of containing machines and thousands of workers were born. In factories, the work could not be organized independently as the farmers did in the countryside, but it was punctuated by the rhythms of production of the machines. The working conditions in the factories and mines were very bad. Men, women, and children were employed indiscriminately, with the same heavy shifts of work of more than 12 hours per day, although the latter two were paid much less than the former. The work environments were dangerous and unhealthy and the suburbs near the factories began to be populated by the working class who lived in tiny, bleak, unhealthy, and overcrowded houses. In the first years of the industrial revolution, a lot of workers migrated from the countryside to the cities, but the flow of people was not properly controlled, and the authorities failed to immediately act to accommodate the new citizens. For this reason, the working-class neighbourhoods grew in a short time and in a disordered way, without the most basic sanitary facilities. Only during the nineteenth century, the conditions of the working class began to improve: child labour was limited, the number of skilled workers increased, and given their high specialization, they were required and paid more.

The fear of losing jobs must be added to the social and environmental problems that the industrial revolution brought. As mechanization spread in the factories, in fact, the first discontent of craftsmen and workers spread too. They feared being replaced by machines and losing their jobs, just like today many workers fear being replaced by robots and artificial intelligence. As early as 1794, English wool workers petitioned Parliament to intervene against the use of machines for combing wool. In those years, in Nottingham, the movement of the Luddites, a group of textile workers who protested the factories that used the machines, was born. Luddites became famous for their subversive actions, going so far as to destroy the machines to defend their work.

1.1.2 The Second Industrial Revolution

Between the nineteenth and twentieth centuries, the production system of the factory spread all over Europe and also outside, like in the United States, the new emerging power. Industrialization was a path a country had to take to achieve the economic development needed to compete with other countries. Productivity continued to increase worldwide, and Britain’s supremacy was gradually challenged by the growth of countries like Germany in Europe and the United States, outside Europe. The Second Industrial Revolution (1870-1914) began.

In that period, the relationship between science, technology, and industry grew stronger and stronger and this led to new discoveries, inventions, and technologies. It was the age of steel, chemistry, and oil, but the real protagonist was electricity. However, it was not until 1880 that people learned how to store, transmit, and distribute electricity over long distances, using it to enlighten, heat, start machinery, and build new ones. In fact, the incandescent filament bulb was designed by Edison in 1879. Bringing lighting in factories led to redefine working hours, allowing working day and night continuously, with no time constraints marked by sunrise and sunset, consistently augmenting labour productivity. Electricity started to be used also in the modes of transport, giving rise to mass urban transport, since steam could only be used in light railways and rural or suburbs tramways. In the United States, electric traction was introduced in 1881 and then quickly adopted in major urban centres.

New inventions and new materials discovered allowed to the revolution also in the organization of the industrial production, speeding up the process or increasing labour productivity, thanks to innovations like conveyor belts, elevators, hoists, pipe, and valve systems. The introduction of these innovations in the productive process led to a more rational and scientific use of the workers in order to reduce working costs and time. In this period, the scientific organization of work, preached by Taylor, was applied for the first time. In *The Principles of Scientific Management* (1911), Taylor explained how the *one best way* – that is the best, cheaper, and efficient method to make a product – is based on the breakdown of the production cycle in different stages and in different operations as simple as possible. Taylorism intersects with the important innovations introduced in the factories by the automobile manufacturer Ford. Ford organized his factories around the assembly line, bringing together the various stages of car assembly, transporting the necessary parts to the workers who, instead, remain stationary in their workstation, doing simple operations. The assembly line drastically reduces production time and unit costs: the price of Ford Model T, "the car for all", as written in the advertising slogans of the time, decreased from 950 dollars in 1908, when it was placed on the market, to 360 dollars in 1917, and 290 of 1927, when it ceased its production.

While in the first stages of the industrialization process, textile and metallurgical industries had required relatively modest investments, in that period, to build a chemical or steel plant, a large allocation of capital was necessary and hardly the small family businesses could afford the costs. New organizational and property's forms were necessary and, in the late 1800s, joint-stock companies and new system of raising capital through an increasingly structured financial market controlled by the banks spread. The need to reduce risks due to huge investments imposed the tendency of the enterprises to concentrate, through mergers, both vertical and horizontal, links between companies or between companies and banks, cartels, and holdings. A strong relationship of interpenetration between industries and banks started to develop. Banks and other financial institutions begun to allocate the deposits of their clients to industrial investments. The role of banks became strategic, and the phase of the financial capitalism started, underlining the key function of the financial capital directing the economy.

The revolution in the factories, from an organizational, structural, and productive point of view, was accompanied by the birth of new working figures and, in turn, of a different division of social classes. The emergence of new jobs was the natural response to the underway industrial and economic revolution requiring new needs, but the impact was varied and, in some respects, divergent. On the one hand, from 1850 to 1910, in the United States, the number of qualified workers – the so called "white collars" – increased from 3 percent to 12 percent in the manufacturing industry, and from 7 percent to 20 percent in the aggregate economy (see Table 1). On the other hand, in the nineteenth century, the technical change was mainly "de-skilling": the combination capital – unskilled labour, in fact, replaced skilled labour due to mechanization (Goldin and Sokoloff 1982; Atack et al. 2011). In the manufacturing industry, the de-skilling process is explained by the displacement of high-skilled artisans due to the quick industrialization of the factory system. Over the years, machinery became cheaper relative to output or skilled labour and, consequently, manufacturing became much more capital intensive. Sequentially implemented machines replaced certain operations related to the manual work of the artisans, but machines required anyway the presence of "operatives" to work properly. Operatives were workers with less skills with respect to craftsmen: the latter were able to manufacture a product from the beginning to the end, while the first ones could execute a limited set of operational tasks of the whole productive process with the support of the machines. This does not mean that the operatives were unskilled, indeed they started to acquire the skills necessary to properly run the machinery they had to use (Bessen 2012). In the following years, skilled workers, as engineers and mechanics, were still required to install, maintain, and design the equipment (Goldin and Katz 1998). However, the modern pattern of capital – skilled labour started emerging only between the late nineteenth century and the early twentieth century. According to Goldin and Katz (1998), the spread of electricity power and the technological shift from traditional factories to continuous-process and batch production methods had a key role in the emergence of the new combination capital – skilled labour.

Table 1. U.S. Labour Force from 1850 to 1910

	1850	1860	1870	1880	1900	1910
Manufacturing industries						
White collar	**3.1%**	**3.2%**	**4.8%**	**4.7%**	**6.8%**	**11.9%**
Professional-technical-manager	3.0%	3.1%	4.2%	4.0%	5.2%	5.6%
Clerical-sales	0.1%	0.1%	0.6%	0.7%	1.6%	6.3%
Skilled blue collar	**39.4%**	**38.5%**	**31.8%**	**29.2%**	**28.7%**	**22.8%**
Operative/unskilled	**57.5%**	**58.3%**	**63.4%**	**67.8%**	**64.5%**	**65.4%**
Aggregate economy						
White collar	**6.9%**	**8.3%**	**10.6%**	**11.6%**	**17.1%**	**19.7%**
Professional-technical	2.3%	2.6%	2.9%	3.4%	4.3%	4.6%
Manager	3.1%	3.6%	4.4%	4.3%	5.7%	5.6%
Clerical-sales	1.5%	2.1%	3.3%	3.9%	7.2%	9.5%
Skilled blue collar	**11.6%**	**11.2%**	**10.7%**	**9.1%**	**11.0%**	**11.9%**
Operative/unskilled/service	**28.7%**	**30.1%**	**32.4%**	**37.7%**	**36.4%**	**37.9%**
Agriculture	**52.7%**	**50.5%**	**46.4%**	**41.6%**	**35.3%**	**30.5%**
Operator/supervisory	23.9%	23.2%	24.8%	24.8%	20.0%	16.6%
Farm labourer	28.8%	27.3%	21.6%	16.8%	15.5%	13.9%

Source: KATZ, L. F. & MARGO, R. A., 2014. "Technical change and the relative demand for skilled labor: The United States in historical perspective". In *Human capital in history: The American record*, pp. 15-57. University of Chicago Press.

Capital and labour availability were not the only drivers of the economic development: growth was fostered by mechanisms such as increasing returns on scale, due both to the enlargement of production units that became cheaper to manage, and to increasingly specialized production. Another mechanism concerned the greater efficiency in allocating resources, by transferring manpower from low-productivity jobs to high-productivity ones (Pollard 2012).

From the late 1800s until World War I, North-Western Europe and North-Eastern United States were the main industrialized centres where modern economic growth models had already succeeded. Looking more at the global numbers of this Second Industrial Revolution, according to Pollard (2012), we can infer that in Europe, the economic growth between 1880 and 1913 had a rate of 1.5 percent per year. The United Kingdom was certainly the richest country, but the most advanced and prosperous industrial economy was represented by the United States. In 1913, the U.S. Gross National Product (GNP) per capita was five times higher than the European average, and 25 percent higher than the British GNP. The average growth rate of the U.S. economy between 1890 and 1913 can be estimated at 1.8 percent per year, higher than the one of the major advanced industrial economies. Pollard (2012) states that one of the factors which contributed to the economic expansion experienced in that period was certainly the population growth which increased because of the reduction in the death rate. There was, indeed, a sharp decrease in infant mortality, which in 1913 was particularly evident in Scandinavia and Western Europe, while in Eastern Europe the rate remained high. However, international emigration started to mitigate the effects of the natural demographic increase. From 1850 to 1914, more than 40 million people (approximately the 10 percent of the European population of the time) left Europe and moved to the "new world". In the early 1900s, departures of migratory flows mainly concerned the Mediterranean region and the Balkans in response to the demographic problem which the mainly rural societies in those areas were facing. As observed for Europe, birth and mortality rates were falling and, while for European countries the international emigration represented a dry loss of workforce, the United States were the main recipients of the migratory flows. Since most immigrants were young, the average age of the U.S. population, which was 22 years in 1890, remained low in 1910, around the age of 24. This influx of labour from abroad contributed to the expansion of the economy. International immigration was supplemented by internal emigration from rural settlements to more developed cities, as occurred in more industrialized European urban centres. Thus, the workforce employed in agriculture fell from 42 percent in 1890 to 32 percent in 1910.

Economic growth meant also higher investments in instrumental goods and specific resources such as machines and plants. Often, the necessary equipment was used to produce a single variety of product. Therefore, the specificity of the investments made the investments themselves riskier and more diversified between countries. However, in all countries with reliable data, the growth of investments was faster than the demographic growth, with the only exception of the United Kingdom which, in the first decade of the twentieth century, was more interested in investing in its overseas colonies instead of its national territory. In the United States, capital imports exceeded capital exports, increasing the already high rate of internal savings, which grew by 3.5 percent per year between 1890 and 1910 and then they slowed down for the following decade (Pollard 2012).

1.1.3 The Debate on the Third Industrial Revolution

After the Second Industrial Revolution (1870-1914), two world wars and one of the most shocking crises occurred. During the wars, factories were converted and used to produce war material and other resources useful for military operations. However, despite the period was not the best, some industries grew the same, as the automotive one which experienced in those years a real mass diffusion, especially in the United States. Moreover, a lot of military research had important developments and roles in the dissemination of technologies in the civil field, just consider nuclear energy.

The second and the subsequent Industrial Revolution are therefore years away. Indeed, the debate on the starting date of a supposed Third Industrial Revolution is very heated. According to Campa (2007), opinions are divided mainly because there are no useful preventive criteria to define a period of "revolution". Furthermore, economic and technological transformations have followed different paths in the various industrialized countries and, therefore, analyses are often flawed from an ethnocentric perspective. Some authors agree on the fact that to define a "revolution", a change in energy policy is required. In the First Industrial Revolution the key element was the steam engine that led to an economy based on coal and iron. In the Second Industrial Revolution, after the invention of the combustion and electrical engines, the economy relied on oil and electricity. After the use of nuclear weapons, a period of civilian use of nuclear energy has certainly begun, but it is also certainly true that the current economy is still based on oil and the turning point has not yet occurred. Other analysts stated that it makes no sense to compare the industrial revolutions according to the energy sources because there are other equally important aspects. The key element, among the most mentioned, is certainly the emergence of automation and artificial intelligence (AI) and their large-scale use in production processes. According to Sennholz (2006), since the early 2000s an industrial revolution has begun. Sennholz talks about an "informatic revolution" which increases the variety of marketable services. This enlargement is possible because, thanks to the new information technology, many jobs in the service sector can be shifted to workers in emerging countries. In these countries, people are equally experienced, but they are willing to accept a lower salary due to the lower cost of living in their native country. It is therefore an offshoring revolution that has important consequences on the labour market.

In the final analysis, therefore, there is no single date on which economists agree to start the beginning of this Third Industrial Revolution. Some authors think the revolution started in the fifties, others state that the revolution has started in the new millennium. But the relay could be halfway, and the symbolic starting date could be identified in the year 1974. According to Greenwood (1999), the same changes observed in the main economic parameters with the advent of the previous two revolutions occurred in 1974. In this year, in fact, there was a massive influx of new technology that had an impact comparable to the spread of the steam engine and electricity in the previous century. This input is favoured by a lower cost of the equipment, such as computers, machine calculators, and automation. Whenever a technological-industrial revolution has occurred, there has also been a consequent decline in the growth of labour productivity. The paradox is however only apparent since the decrease is consequent to the fact that the new technologies are difficult to use, and it requires time for workers to quickly adapt to the change and specialize. Greenwood pointed out that in 1974, the most technologically advanced countries experienced a reduction in the growth of labour productivity from 2 percent per year to 0.8 percent: the workers suffered the shock due to the change. Alongside, the pay gap increased, and this phenomenon can be explained by the disorientation effect: workers with useful skills to run computers and robots were rare and so they could obtain higher wages than non-skilled workers. Gradually, inequality has been redrawn thanks to the entrance in the market of more qualified workers.

According to Martorella (2002), the Third Industrial Revolution started around 1974 with the introduction of new production and organizational structures: the *just in time* production and the *Total Quality Management* introduced by the Japanese Toyota Motor Corporation. Martorella believes that revolutions occur in response to serious periods of economic crisis. Japan suffered more the oil shock of the 1973 due to its absolute lack of oil resources compared to the United States and the Soviet Union. For this reason, a quick and radical restructuring of the Japanese productive system was necessary. This event marked the beginning of the decline of the Fordist model, based on a rigid division of labour and focused more on the product, rather than the needs of the consumer. Toyotism, instead, implies a reversal of the logic of marketing, oriented to the elimination of returns and stock. Through the *just in time* production, in fact, companies can forsake the push-logic that finished products have to be stored in warehouses waiting to be sold and embrace the pull-logic according to which only products already sold, or which is expected to be sold in a short time can be produced. Companies do not try anymore to convince their clients to purchase a finished product, designed upstream in all its details, but agrees the characteristics of the good with potential customers and produces it to order and customizes it for the specific applicant. The new Japanese production philosophy, in a short time, achieved important results, carrying in the Eighties, Toyota from the seventh to the third place in the world ranking of motor companies, after Ford and General Motors. The new model was soon adopted by other countries, first the United States, leaving room for the post-Fordism age. Ultimately, in the opinion of Martorella (2002), the Japanese industrial revolution has transformed factories in information systems in which men are free from mechanical work and have become supervisors of the production process. This change occurred in a transition phase from the industrial society to the "post-industrial" society. With these words, the author means that the discussed Third Industrial Revolution consists in the radical transformation of the social and economic fabric that is leading the tertiary industry and the more advanced ones to dominate the secondary industry.

In this period of intensive technological and scientific revolution, United States and Japan were leader in the development of new technologies based on the application of microelectronics to computing and communications. In 1971, the tuning of the microprocessor by Intel established the transition from the electronics to the microelectronics, allowing the mass commercialization of a large set of goods (personal computers, CD and DVD players, and mobile phones) and services (e-mail and Internet) that had disrupted and continue to disrupt the habits and lifestyles of much of the population. Moving from the information technology industry to other ones, the most important discoveries and inventions concern plastics, biotechnology with studies on DNA, nanotechnology, and the conquest of space.

The fears of those who saw the new technologies as a threat to human work were accompanied by the optimism of those who were aware of the potential of this progress. Machines and computers displaced human work, but, at the same time, created new opportunities and opened the way for the tertiarization of which Martorella (2002) speaks. This totally new branch of the economy became known as *new economy* and from the Nineties, was the engine of growth, both in income and productivity terms. From 1995 to 2000, the productivity increased by 2.5 percent per year, compared to the 1.4 percent in the period 1972-1995 (Pollard 2012). Then, as we will see in the next paragraphs, the improvement in the automation procedures and the introduction of increasingly intelligent and sophisticated robots have helped to increase the labour productivity, constituting the last achievement in the path undertaken two centuries earlier with mechanization.

1.1.4 A Fourth Industrial Revolution?

Although there is no unanimous agreement on the occurrence and period of the Third Industrial Revolution, some authors speak about a Fourth Industrial Revolution. Others state that the period of high innovation we are experiencing is a second phase of the technological revolution started in the last century and described in the previous paragraph. Due to the development of information and communication technologies (ICT), such as Internet and wireless connection, industrial production has experienced significant and radical changes. As seen with the rise of Toyotism, factories have become more flexible and have started to understand the importance of vertical and horizontal integration of all participants in the production, including end customers. This integration led to a new way of thinking about the industrial production process which took the name of *Industry 4.0* (Hozdić 2015).

The term *Industry 4.0* was first adopted, in 2011, by a group of representatives belonging to difference fields – such as business, politics, and academia – as part of a proposal aiming to boost the German competitiveness in the manufacturing industry. To deal with the ambitious project, raising a smart production environment was vital and the concept of "smart factory" was soon introduced. A "smart factory" is a production solution that, in a flexible and efficient way, fulfils the integration of participants in the production process, of needed resources, both physical and digital, and between people and resources into a single cyber-physical production system. Industrial automation and ICT are the key resources in the implementation of this sophisticated system which can successfully merge real and virtual world, improving productivity, quality, and working conditions, saving costs, and avoiding errors and bottlenecks (Oztemel and Gursev 2020; Hozdić 2015).

Industry 4.0 is not a single technology, but it represents a cluster of different ones linked together due to "technological leaders, pivotal users, system integrators, and government policy makers" (Martinelli et al. 2021, p. 162). Martinelli et al. (2021) summarized the concept by providing a list of the core technologies related to *Industry 4.0*. More precisely, these technologies are:

- *Internet of Things (IoT)*. IoT concept includes all devices with self-identification capabilities – as localization, diagnosis status, data acquisition, processing, and implementation – that are connected via standard communication protocols. The scope is very wide: from manufacturing applications to other areas as housing and construction, automotive, environment, agriculture, and much more.

- *Big Data / Industrial Analytics*. This category groups methods and instruments used to process a large amount of data (which can come from IoT systems) for manufacturing, supply chain management and maintenance. The main applications of this technology relate to machine learning tools, a subset of artificial intelligence technology that creates systems able to learn or improve performance based on the data they use. This application is useful for planning and forecasting, providing predictive maintenance, and generating simulations.
- *Cloud Manufacturing*. This category entails the application in manufacturing of cloud technologies, through on-demand IT services with easy access, available to the users involved, and with the aim of supporting production processes and supplying chain management.
- *Robotics*. This cluster of technologies encompasses five subcategories, understood as five different ways to automate operations in the production process: *Articulated, Cartesian, Cylindrical, Parallel, SCARA* (see next paragraphs for precise definitions and applications). Advanced automation includes the latest developments in production systems that have improved the ability of robots to interact with the environment, self-learn, self-drive, and recognize specific patterns (the so-called co-bots).
- *Artificial Intelligence (AI)*. It refers to knowledge and techniques developed to make machines "intelligent" so that they can function in a proper way in their environment of application. Industrial AI combines computer science-based technologies with machine learning tools to generate intelligent sensors and smart production systems.
- *Additive Manufacturing*. Also known as *3D Printing*, this technology is able to produce objects by depositing layer upon layer of material in precise geometric shapes. Additive manufacturing is widely used in prototyping and manufacturing, directly producing the products, and providing maintenance and repair services.

According to Martinelli et al. (2021), the period we are living has not yet the required specifics to be considered as a Fourth Industrial Revolution because *Industry 4.0* (which is not a synonymous for Fourth Industrial Revolution, but only indicates the features of the "factory of the future" which has introduced in its productive processes the technologies described above), now-a-days, has limited scale and scope effects. The three authors, in fact, tried to understand if these technologies are *general purpose technologies* (GPTs). According to Bresnahan (Bresnahan 2010, p. 764; Bresnahan and Trajtenberg 1995 in Martinelli et al. 2021, p. 175), a GPT is a technology which:

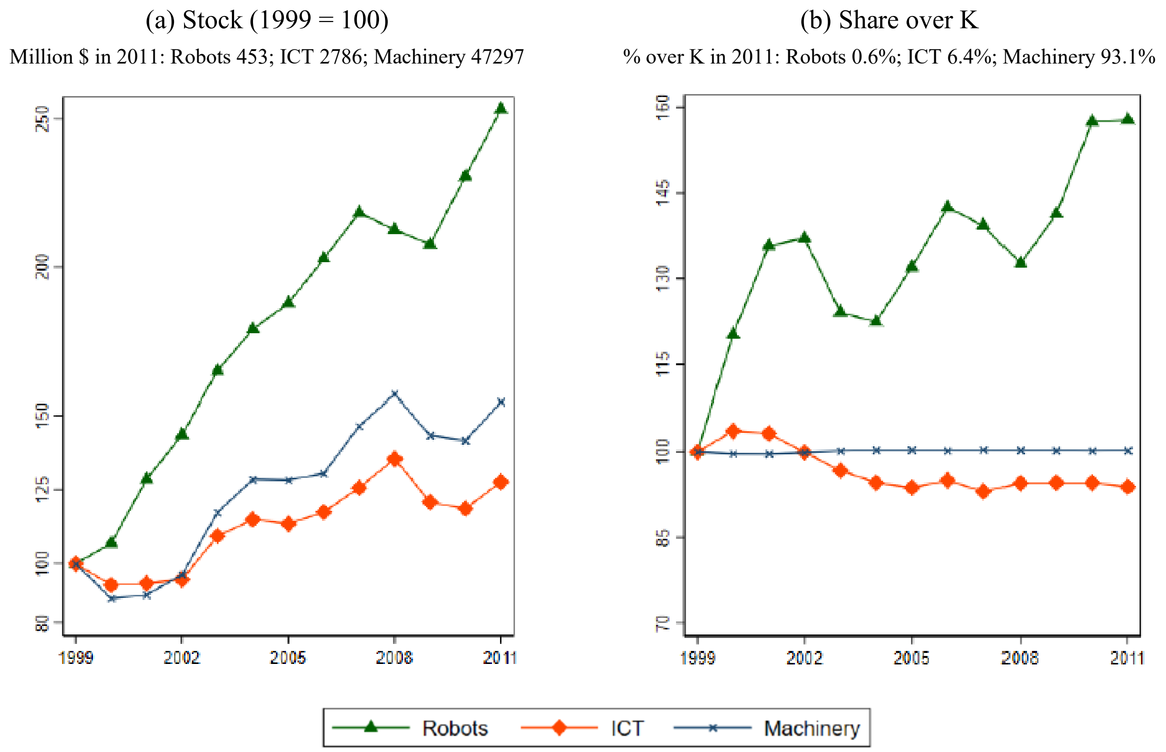
- “Is widely used” and characterised by “pervasiveness”, meaning the variety of possible application sectors.
- “Is capable of ongoing technical improvement” and characterised by “high dynamism”, meaning the ability of the technology to increase efficiency.
- “Enables innovation in application sectors” and has the ability to generate “strong complementarities”, meaning that the adoption of these technologies enhances rapid technical progress in the industries in which they are applied.

In their analysis, Martinelli et al. (2021) worked on a sample of patents related to the main *Industry 4.0* innovations: Internet of Things, big data, cloud, robotics, artificial intelligence, and additive manufacturing. Patents brings important information, as the geographical location of the innovators or the level of diffusion of the technology. In particular, the authors observed how the enabling technologies score on the basis of three indicators:

- *Generality index*. It indicates the range of later generations of inventions which have been promoted by the same patent. In other words, it refers to the technological classes that have cited the specific patent.
- *Originality index*. It refers to the backwards citations and measures the range of technological classes which are cited by the patent. A patent with high originality is characterized by the high technological dynamism which qualifies a GPT.
- *Longevity index*. It is the average lag between the year of the patent grant and the year of the latest forward citation. Therefore, patent longevity is the measure of the speed of obsolescence of a patent.

With their analysis, the three researchers observed that only big data and AI technologies can be qualified as GPTs due to their statistical significance in terms of generality, originality, and longevity of the related patents. It is difficult to make simple predictions about the other technologies, but it is certain that for the moment they do not show the same trend. They remain *enabling technologies* that are providing and can provide a substantial contribution to innovation and productivity growth in a wide range of industries. The implementation of advanced technologies remains low also according to Acemoglu et al. (2022), with only 2 percent of U.S. firms using robotics in their processes and 3.2 percent using AI in the period 2016-2018. The portions of workers dealing with these technologies, instead, are quite substantial: 15.7 percent for robotics and 12.6 percent for AI. In manufacturing industries this exposure becomes higher, with the 45 percent of U.S. workforce employed in firms using robotics and the 23 percent employed in firms using AI technologies. On the other hand, Fontagné et al. (2023) report that, even if robots represent on average only the 0.6 percent of capital stock in manufacturing industries, the share of robots grow substantially from 1999 to 2011 and at faster pace than ICT and machinery whose shares remained almost constant over these years (Figure 1).

Figure 1. Technology Adoption



Notes: The figure reports yearly weighted averages. Country-industry value-added is used as weight. Technology is expressed in volume (ref. price 2010).

Source: FONTAGNÉ, L., 2023. "Automation, Global Value Chains and Functional Specialization". *CESifo Working Papers*, No. 10281.

1.2 The Advance of Robots

Even the relatively low distribution in factories and the fact that, according to Martinelli et al. (2021), robotics can't be qualified as a *general purpose technology*, the technical progress and the always new application opportunities related to this field, especially in recent decades, can't be ignored. The use of industrial robots and their market are destined to grow and the benefits deriving from their implementation are undeniable. On the other hand, there are potential threats to human labour that cannot be ignored too. Before addressing these issues, we need to better picture the industrial robotics phenomenon from a historical and geographical perspective both at a global level and among the selected countries in our dataset.

1.2.1 Finding a Robot Definition

The idea of creating machines or beings that might perform laborious or repetitive operations instead of men extends back to ancient times. Already in the Greek-Hellenistic age, some ingenious inventors designed and tried to build devices which were defined *automata*. However, this term mainly pertains to human-like devices, whereas the word "robot" has a wider and more general meaning (Gasparetto and Scalera 2019). The term "robot" originates from *ròbot* which in turn derives from *robota* that in Czech means "work" or "hard work" and was used for the first time in 1920 by the writer Čapek, referencing to the automatons that substituted workers in his science-fiction play *R.U.R.: Rossum's Universal Robots* (Čapek 2004). It is therefore clear since the introduction of the term that robots have a function of replacement of man's work which begun with the simple mechanization of part of the human work in the First Industrial Revolution up to the advanced industrial automation of today, in which machines are also able to act alone, without the necessary human presence. Moreover, thanks to the progress in AI technology, machines are increasingly able to support and replace humans in cognitive activities, not only in those more purely mechanical. The term "robotics", instead, appeared for the first time in the novel *Runaround* (1942), then included in the famous series *I, Robot* (1950) by the writer Asimov, but the concept of "industrial robotics", as we know it today, was born about ten years later, around the 1950s.

The Robot Institute of America (1979) defined a robot as a "reprogrammable, multifunctional manipulator designed to move material, parts, tools, or specialized devices through variable programmed motions for the performance of a variety of tasks". Robotics is therefore an interdisciplinary science which involves knowledge of mechanics, biology, computer science, linguistic, psychology, and automation (Magnani 2020). According to Magnani (2020), industrial robots have three main characteristics: they operate exclusively in industrial environments, are programmable and can interact with the physical environment, relating, for example, to other production devices. Industrial robotics encompasses traditional automation, meaning entire automated production processes, integrated robotics which consists of robots inserted in particular points of the production line, and the collaborative robotics referring to collaborative robots, better known as co-bots, able to physically interact with humans in a shared environment (Martinelli et al. 2021).

The International Federation of Robotics (IFR), the organization which provides statistics about robotics in the world, as well as part of the data included in the dataset of this dissertation, identifies an "industrial robot" based on the definition provided by the Industrial Organization for Standardization (ISO 8373:2021). According to ISO (2021) and IFR (2022) an "industrial robot" is 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". This means that an industrial robot has at least three axes identifying the direction in which the robot can move in a linear or rotary mode. In addition, according to the definition, robots are:

- *Automatically controlled*. The robot is controlled by a system which operates in accordance with a set of instructions for motions and additional functions that define a specific task program. Non-automatically controlled operations are manual operations, performed by humans that use input devices, as joysticks or pushbuttons, to move the machine.
- *Reprogrammable*. Robots are designed so that the programmed motions or auxiliary functions can be changed without physical alteration of the mechanical system.
- *Multipurpose*. With physical alteration, a robot can be adapted to a different application.
- *Manipulator*. Robots are machines with the purpose of grasping and/or moving objects like pieces or tools.
- *Fixed in place or mobile*. Robots can be mounted to a stationary or non-stationary point.

This definition is quite similar to the one mentioned before by the Robot Institute of America, but here a more precise and mechanical description is present. In fact, like Martinelli et al. (2021), IFR classifies six categories of industrial robots due to their mechanical structure and kinematic configuration (see Table 2):

- *Articulated robot*. A robot whose arm has at least three rotary joints. This configuration of robot works as a human arm able to move in a spherical environment and can find application in spray painting or welding, as well as packaging or sealing.
- *Cartesian (linear/gantry) robot*. A robot whose arm has three prismatic joints and whose axes are coincident with a cartesian coordinate system. Typical uses of these robots are Pick-and-Place work or assembly operations.
- *Cylindrical robot*. A robot with axes forming a cylindrical coordinate system, allowing the robot to reach the workspace in a rotary movement. This class of robots is used for machine tool loading, forging applications, or packaging operations.
- *Parallel/Delta robot*. A robot whose arms have concurrent prismatic or rotary joints. Usually, the end effector (the device at the end of the robotic arm) is linked to the base by three or six independent arms which work parallel, meaning that they work together

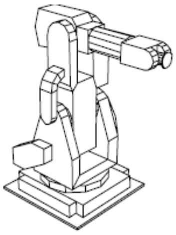
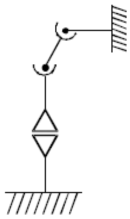
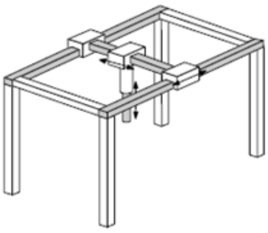
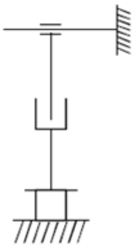
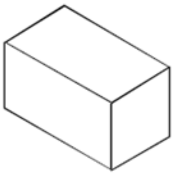
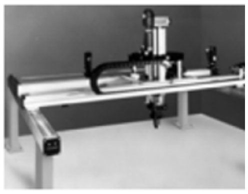
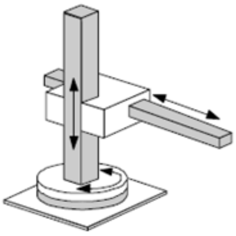
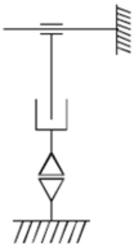
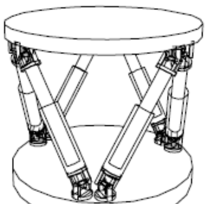
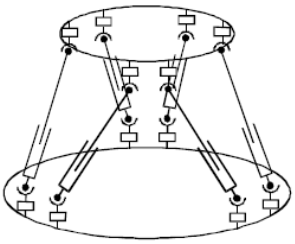
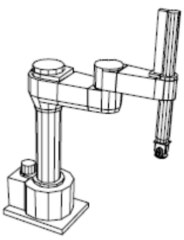
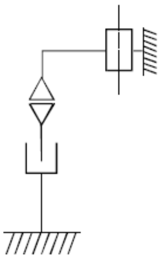
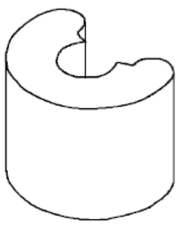
and co-ordinately, but not necessarily aligned in parallel. This configuration finds application in handling, assembly, and Pick-and-Place operations.

- *Selective Compliance Assembly Robot Arm (SCARA)*. SCARA are a type of robot with two parallel rotary joints allowing the robotic arm to move on the horizontal plane and an outlet that can rise and fall in the vertical one. This type of robots is specialized in high speed and repeatability operations in series assembly, such as Pick-and-Place from a place to another.
- *Others*. This category includes robots which do not belong to the classes described above.

The classes described above belong to the industrial robotics and particularly refer to stationary robots, the most implemented in factories. But robots are also used in the services area. The so-called service robotics, which includes professional and personal applications, is a fast-growing sector whose applications range from home use to surgery (Magnani 2020). Despite the great variety of applications, the purpose of both industrial and service robotics was always – and still is – to duplicate or improve the human function, supporting or substituting him in the more dangerous activities (Hockstein et al. 2007).

To avoid confusion at this point of the dissertation, it is appropriate to note that where not otherwise specified (especially in the following chapters), with the terms "industrial automation", "industrial robotics", "industrial robots", "robotics", and "robots", we will refer to the industrial robots employed in factories, for which we have installation and stock data provided by IFR.

Table 2. Categories of Industrial Robots

Robot	Kinematic Structure	Workspace	Photo
Articulated			
			
Cartesian			
			
Cylindrical			
			
Parallel			
			
SCARA			
			

Source: ISO 8373:2021

1.2.2 A Brief History of Industrial Robotics

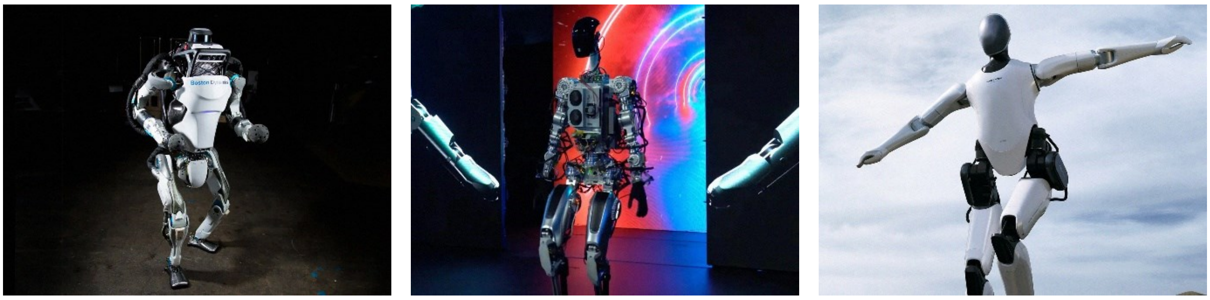
According to Zamalloa et al. (2017), four generations of robots can be identified in the history of industrial robotics. The first generation conventionally covers the period between 1950 and 1967. In these almost two decades, robots were essentially programmable devices with no ability to effectively regulate the modality of execution of their operations. From the hardware point of view, they had a low-tech apparatus and arms were not so flexible. The first digitally operated and programmable robot was designed in 1954 by the U.S. inventor and entrepreneur Devol, named the "Grandfather of Robotics". In the early 1950s, Devol developed the concept of "unimation", resulting from the merger of the terms "universal" and "automation" and, a few years later Unimate#001, the first robot, was born. Unimate#001 was designed to carry out operations potentially harmful to human and it was installed for the first time on an assembly line at General Motors' die-casting plant in Trenton (New Jersey, USA) in 1961. Since this date, other factories in the automotive industry started to adopt the new technology, innovating their productive process, mainly employing Unimates for spot-welding of cars and handling of workpieces. However, due to the difficulty to reprogram them and the rudimentary level of technology, Unimates were able to perform only a single and repetitive task.

The second generation of industrial robots ranges from 1968 to 1977. In these years, robots were programmable machines with integrated sensors and evolved control systems (microprocessors or PLC – Programmable Logic Controllers) which allowed them to interact with the external environment, perform both point-to-point motion and continuous paths (Zamalloa et al. 2017; Gasparetto and Scalera 2019). Compared to the ones of the first generation, these robots could perform more complex operations, but their versatility was not particularly high because each robot was provided with its own specific software, devoted to a specific task and difficult to reprogram. Between 1972 and 1974, the Swedish company ASEA (now ABB) developed IRB-6, the first electric industrial robot that was controlled by a microcomputer. The robotic arm could be programmed, and it was used for material handling, packing, transportation, polishing, and welding. IRB-6 was crucial for the development of robots easier to program.

The third generation of industrial robots spans from 1978 to 1999. Robots developed in these two decades were characterized by a higher level of interaction with the human operator and the surrounding environment, thanks to the implementation of complex interfaces which gave robots the ability to see and speak, for example (Gasparetto and Scalera 2019). Finally, this generation of robots could be reprogrammed, and some had even self-programming capabilities to execute different operations (Zamalloa et al. 2017). Robots could also process data from sensor readings and modify their movements to account for environmental changes. Therefore, robots of third generation were provided of some sort of "intelligence", with adaptive capabilities which enabled them to carry out more complex tasks (Gasparetto and Scalera 2019). In these years, several scientific and technical improvements fostered the spread of industrial robotics. In 1978, for example, the Japanese scientist Makino presented a new kinematic structure, giving life to SCARA robots (see Table 2), mainly employed in the assembly of small objects. In 1981, a General Motors factory implemented a new system, called *Consight*, through which three different robots could use visual sensors to pick out and sort six different auto parts as 1,400 parts per hour moved by on a conveyor belt.

Industrial robots of the fourth generation, started from 2000, are characterized by the inclusion of advanced computing capabilities that make them able to reason and to learn (Zamalloa et al 2017). In this period, the advances in field such as artificial intelligence, neural networks, logical reasoning, deep learning, and collaborative behaviour, started to be included partially or on an experimental basis, enabling robots to adjust more and more efficiently to the different circumstances they face. Improvements in the robot security systems and in the human-robot collaboration led men and robot to work together interacting with each other in the same environment, as in the case of the most recent co-bots. In an ever-closer future, thanks to the advance in collaborative robotics and related fields, robots will come out of the factories to support humans in everyday activities, simplifying and improving their life. According to Zamalloa et al. (2017), just the introduction of co-bots could identify a fifth generation of robots. The generation that will allow to move from mass customization (robots created to perform specific tasks) to mass integration, thus robots and humans peacefully coexist in society. The latest generations of robots, in addition to presenting high levels of intelligence and the ability to make decisions autonomously just like a human, increasingly resemble the human body in their set-up too, following the dream of *automata*, designed since the Hellenistic era. The recent humanoid robots presented by cutting-edge companies such as Boston Dynamics' *Atlas*, Tesla's *Optimus Bot*, or Xiaomi's *CyberOne* are examples of these advanced robots' configuration (Figure 2).

Figure 2. Examples of Humanoid Robots

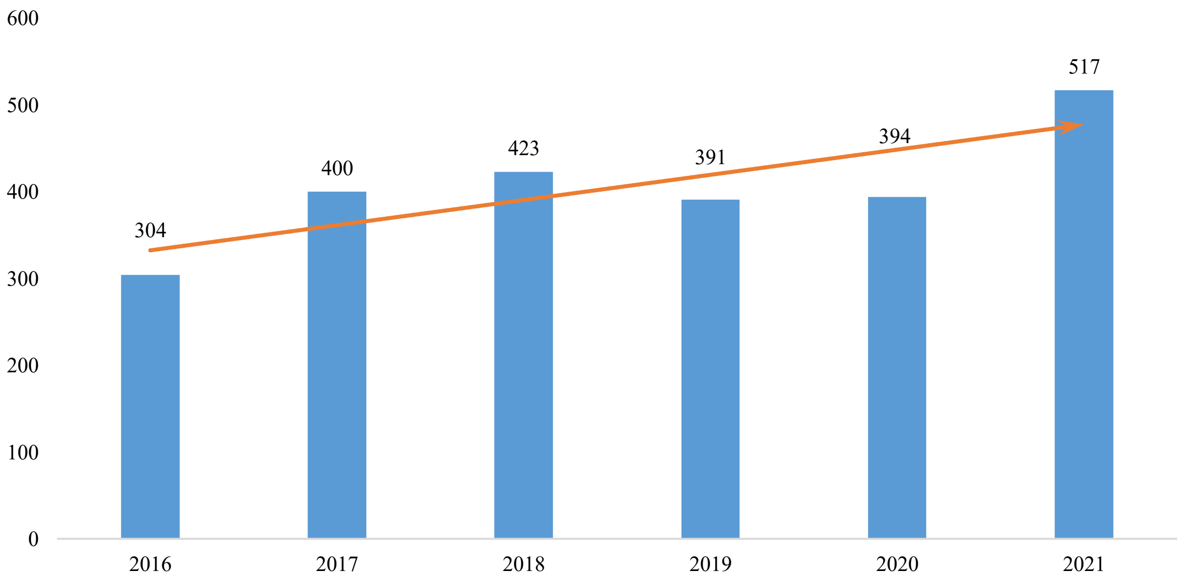


(a) Boston Dynamics' *Atlas*. (b) Tesla's *Optimus Bot*. (c) Xiaomi's *CyberOne*.

1.2.3 Robotics Around the World: A Geographical and Industry Framework

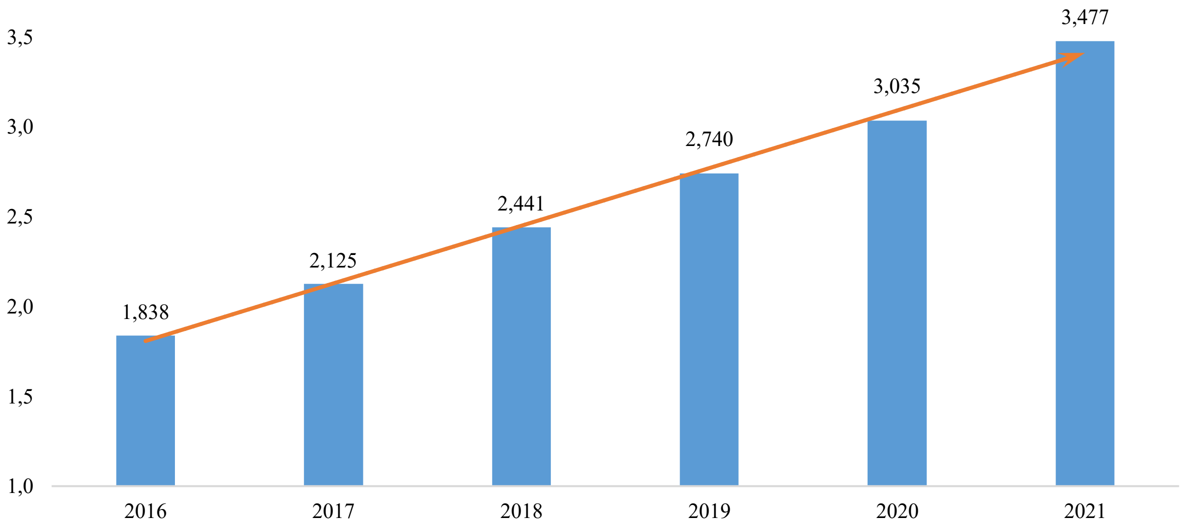
According to the latest available data provided by IFR in the *World Robotics 2022 Report*, in 2021, robots installations around the world reached a new record level, with the placement of 517,000 new units. Robots installations grew by 31 percent compared to 2020 and their stock in 2021 amounted to 3.5 million units, with a 15 percent increase compared to 2020. Although the years of Covid-19 pandemic, in the five-years period from 2016 to 2021, global new installations of industrial robots grew with an annual average of 11 percent, while the operational stock of industrial robots registered an annual increment of 14 percent on average (Figures 3 and 4).

Figure 3. Annual Installations of Industrial Robots in the World (1,000 units)



Source: Data processing on *World Robotics 2022 Report*.

Figure 4. Operational Stock of Industrial Robots in the World (1,000 units)

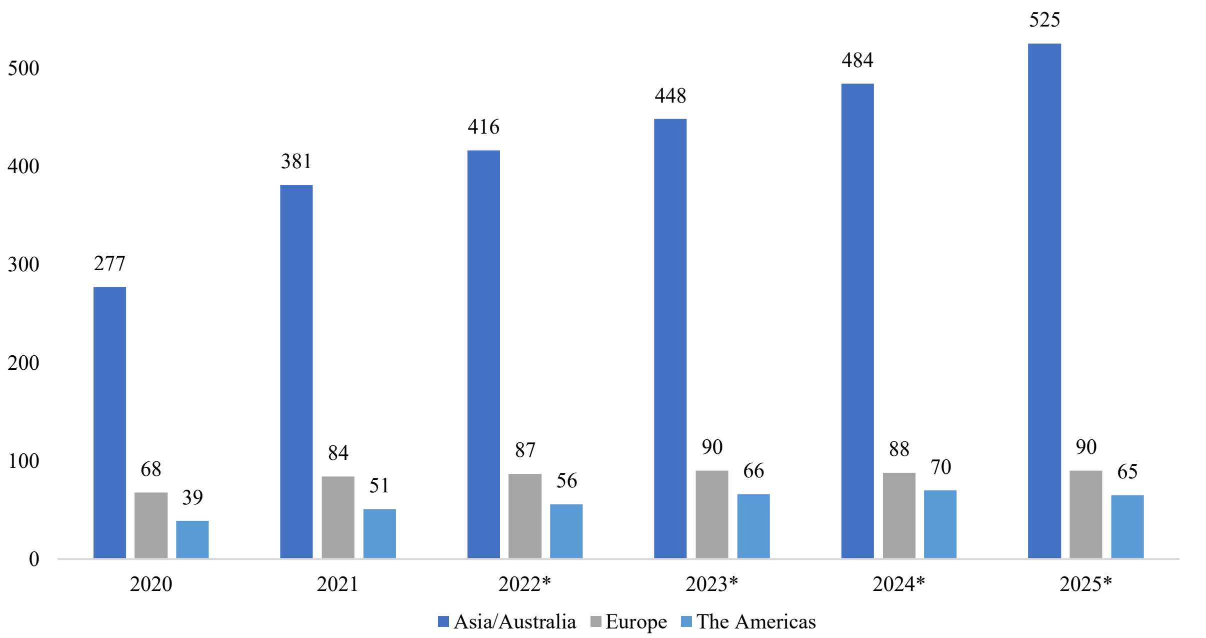


Source: Data processing on *World Robotics 2022 Report*.

From a geographical perspective, for years the American and European areas were the major adopters of industrial robotics technology, but the Asian market has grown quickly, with China and Japan that hold the record of annual installations in 2021, with respectively 268,200 of new units (+51 percent compared to 2020) and 47,200 (+22 percent). It is interesting to note that now China installs more industrial robots per year than all the countries of the rest of the world brought together, with an annual average of 23 percent in the five-years period 2016-2021.

Looking to the future, IFR (2022) estimated a global +10 percent installations growth in 2022 and then a 7 percent growth per year until 2025. According to forecasts, in the next three years, the Asian region will still be the main protagonist, with numbers ranging from 400 thousand new units in 2023 to over 500 thousand in 2025, distancing considerably from the number of annual installations that will carry out Americas and the European region, both taken separately and together (Figure 5).

Figure 5. Annual Installations of Industrial Robots 2020-2025 (1,000 units)

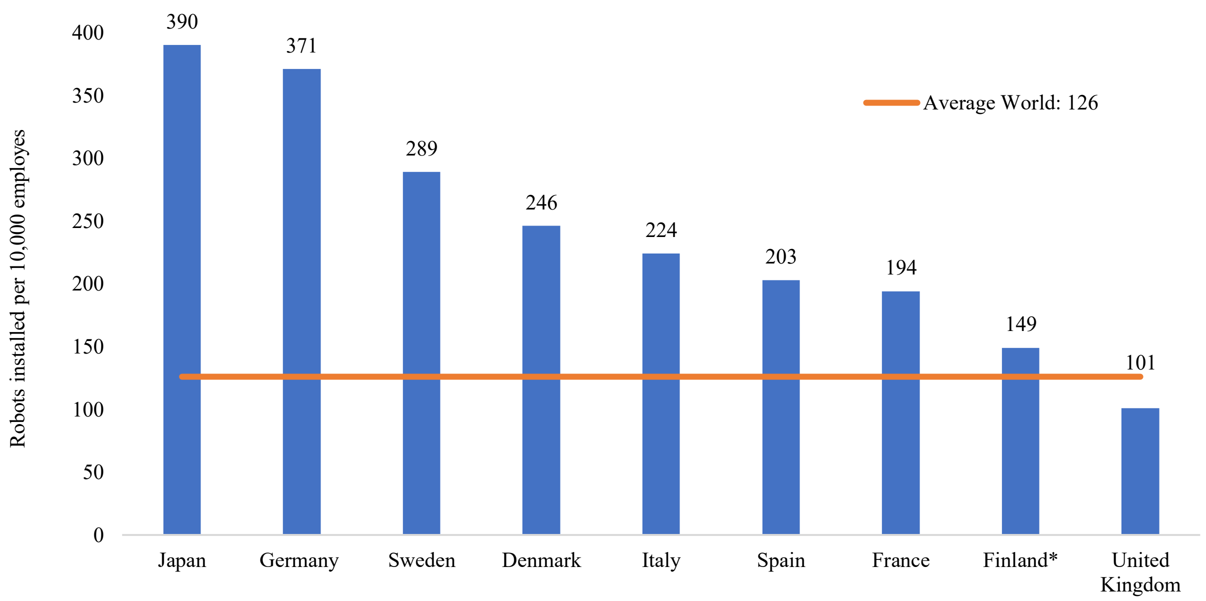


Notes: *Forecast.

Source: Data processing on World Robotics 2022 Report.

According to the *World Robotics 2021 Report* by IFR, in 2020 the world average robot density in the manufacturing industry was 126 per 10 thousand of employees. In Europe, the average was about 123 robots per 10 thousand of employees, with Germany having the highest score of 371. The American average is 111, with the United States having 255 robots per 10 thousand of employees. Lastly, the highest average in robot density in 2020, was held by Asia, with Singapore and Republic of Korea having the highest robot density in the manufacturing industry, with respectively 932 and 605 industrial robots per 10 thousand of employees, followed by Japan (390) and China (246). In Figure 6, we summarized the score of the countries in our dataset, comparing them with the European average: only United Kingdom is below average with 101 robots per 10 thousand of employees.

Figure 6. Robot Density in 2020



Notes: *Data for Finland refers to the year 2019.

Source: Data processing on *World Robotics 2020 Report* and *World Robotics 2021 Report*.

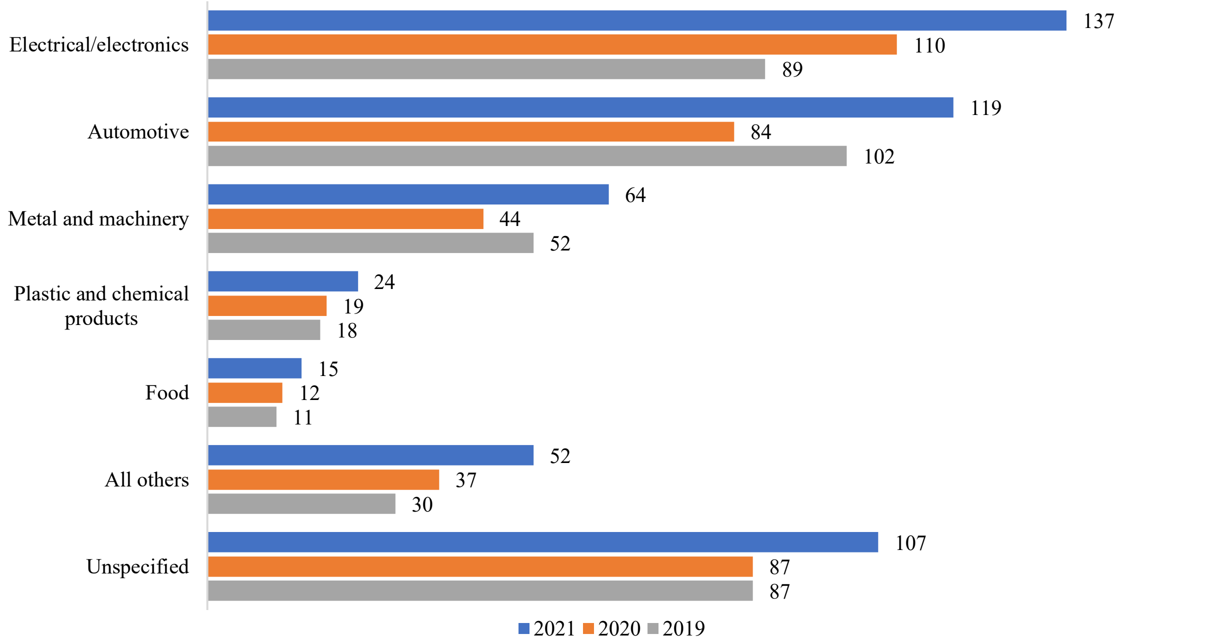
Among the countries selected in our dataset, Japan has the highest concentration of robots. Among all countries of the world, Japan also has the longest history in the implementation of industrial robots in its factories (Lynn 1983) and it is nowadays the second larger robot installer in the world after China (IFR 2022). In 2012, the population of Japanese robots per worker was 10 times that in the United States and 5 times that in Europe. Furthermore, as underlined by Dekle (2020), Japan remains an exception regarding the social impact of robots. In this country, in fact, there is no public clamour about the belief that robots can pose a threat to human labour. Indeed, robots are more seen as a source of economic survival, as the nation suffers from a serious and chronic shortage of labour force, due to the aging of the population and the decline of births. Almost certainly, Japan will be the nation to replace the largest number of jobs with robots, so much so that in 2014, Prime Minister Shinzo Abe presented a series of reforms with the goal of growing the robot market up to 21 billion dollars by 2020.

Germany takes second place among countries in our dataset and the fourth place in the global ranking for density per 10 thousand employees. German robots, in fact, are more than those in the United States and elsewhere except the Asian region. As reported by Dauth et al. (2017), since 1994 in Germany there were almost two industrial robots installed per thousand workers, more than twice the European average and four times as many as in the United States. Furthermore, Germany is the first major robot installer among European countries and fifth in the world. Germany continues to be one of the leading countries in terms of manufacturing output and, although the higher number of robots, it boasts a significantly high percentage of the population working in this sector. Moreover, Germany is not only a huge user, but also a large producer of industrial robots: five of the twenty largest firms have German origins.

Italy is certainly another important actor in the world of industrial robotics. Italy is, in fact, the second European country for robots installations and the sixth in the world, with 14,100 robots installed in 2021 (+65 percent than 2020) and a robot density about twice the world average (IFR 2021 and 2022). France and Spain are respectively the eighth and fourteenth country in the world ranking by number of installations, with respectively 5,900 new installations in 2021 (+11 percent than 2020) and 3,400 (+1 percent). Both countries have a robot density well above the global average. As anticipated before, United Kingdom is the only country in our dataset which has a robot density below the average, the lowest among the G7 nations, and installs few robots per years, with just two thousand new units in 2019 (IFR 2020).

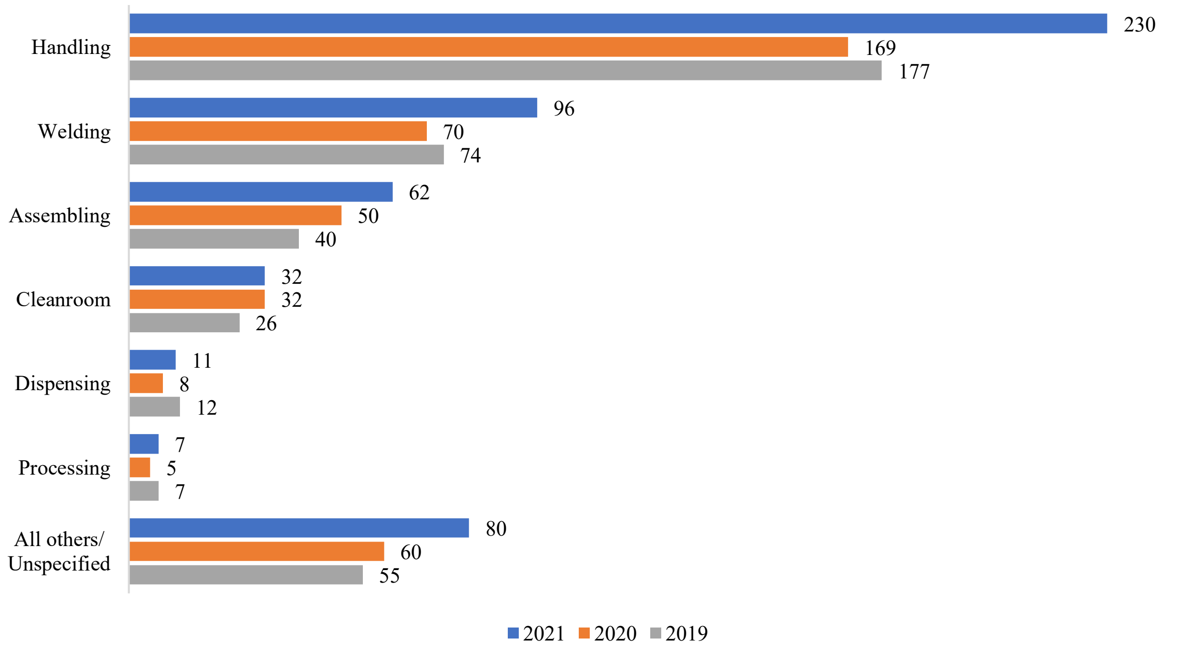
From an industry point of view, as we can see in Figure 7, globally in 2021, the sectors that make greater use of industrial robots are electrical-electronics (137,000 installations; +24 percent compared to 2020), automotive (119,000; +42 percent) and metal and machinery (64,000; +45 percent). Concerning the use (Figure 8), robots can be installed for many applications, but handling remains the major application for annual installations also in 2021, with 230,000 installations (+36 percent compared to 2020), followed by welding (96,000; +38 percent) and assembling (62,000; +24 percent). It is interesting to note that in the last two years electrical-electronics industry has overcome automotive, a sub-industry with a long tradition of installations.

Figure 7. Annual Installations of Robots by Industry – World (1,000 units)



Source: Data processing on *World Robotics 2022 Report*.

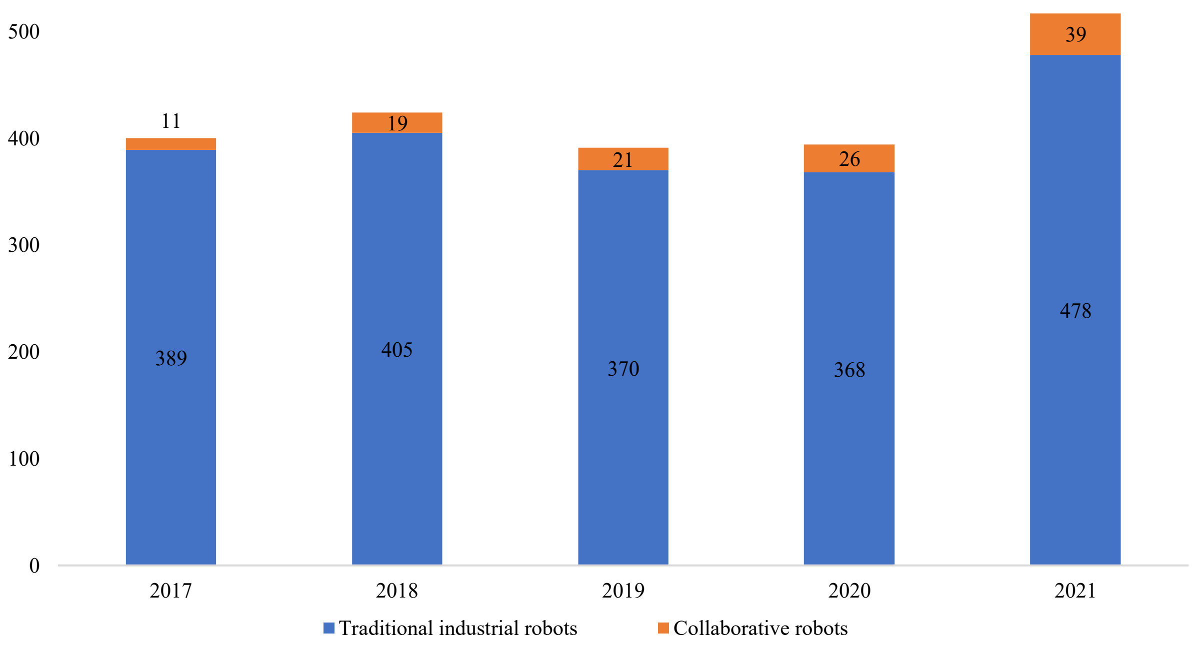
Figure 8. Annual Installations of Robots by Application – World (1,000 units)



Source: Data processing on *World Robotics 2022 Report*.

Finally, an interesting global trend to observe regarding the last three years is definitely the one that concerns the aforementioned co-bots (Table 9). The range of applications of this class of robots keeps growing, as well as the market, whose share has grown up by 50 percent in 2021. As stated in the *World Robotics 2020 Report*, although the market of collaborative robots is growing quickly, it is still in its initial phase, but it has excellent growth prospects for the future years.

Figure 9. Annual Installations: Collaborative vs. Traditional Industrial Robots (1,000)



Source: Data processing on *World Robotics 2022 Report*.

Chapter 2. Industrial Automation, Productivity, Employment, and the Labour Share: A Literature Review

Industrial automation is a process innovation involving mostly manufacturing industries and it takes a key role in global competitiveness (Mazachek 2020) and, like every "creative destruction" (Schumpeter 1942), it can undermine previous equilibria and generate new ones. But do technology and innovations always lead to growth? According to Magnani (2020), all types of innovations (technical, scientific, organizational, commercial, and financial) that occurred in the course of history brought important and disruptive changes in the economy and in the society, as described in detail in the previous chapter. Sometimes these changes broke the balance achieved previously, but there has always been a strong positive correlation between innovation and economic growth, with positive effects also on employment.

Even if with significant differences, innovation has a key role in the main growth theories. According to classicals and neoclassicals, the technological progress is an exogenous variable of the growth model, generally determined by external factors as inventions and new discoveries. For the new growth theory, instead, innovation is an endogenous variable (Romer 1990): through the accumulation of human knowledge and the development of research activities, economy can grow even without external shocks by using and improving already available factors, including existing technology.

Focusing on industrial automation, on the one hand, there are no doubts about the productivity improvements brought by the implementation of this innovation: cost reductions, quality upgrading, and the possibility to carry out tasks dangerous or impossible for human workers. Switching from the firm level to industry and country level considerations, automation is expected to increase labour productivity and boost economic growth, generate more jobs, and enhance quality of life.

On the other hand, industrial automation brings job displacement, disruptions to local economies, change in demand for skills, and inequality increases (McKay et al. 2019). Frey and Osborne (2017) and Chui et al. (2015) estimate that 45-47 percent of U.S. jobs might be automated over the near future. Acemoglu and Restrepo (2020) find evidence that robots may have reduced aggregate employment and aggregate wages in the United States. Due to the relatively limited number of robots in the U.S. economy, jobs lost would amount to a range between 360,000 and 670,000, but according to the authors the number is expected to grow over the next two decades, as predicted by Frey and Osborne too (2017). A limited impact due to a low operational stock was also observed in the UK economy, but the quick spread of robots, software, and AI could potentially increase the magnitude of the effects (Chen et al. 2022). Furthermore, according to Dauth et al. (2017), in Germany, a total loss of 275,000 manufacturing jobs due to robots occurred in the period from 1994 to 2014 and it has been estimated that one additional robot eliminates approximately two manufacturing jobs on average.

In this chapter, we review the main contributions regarding the existing literature on robotics and its impact on productivity, the labour share and employment, trying to distinguish between the different effects of this technology among the countries in our dataset, mostly for the manufacturing industry.

2.1 Industrial Automation and Productivity

In macroeconomic literature, there are various theoretical models supporting the positive perspective according to which technological progress, such as industrial automation, raises overall productivity. According to these models, an increase in total factor productivity (TFP) is associated with an increase in labour demand and salaries through four major channels (Compagnucci et al. 2019):

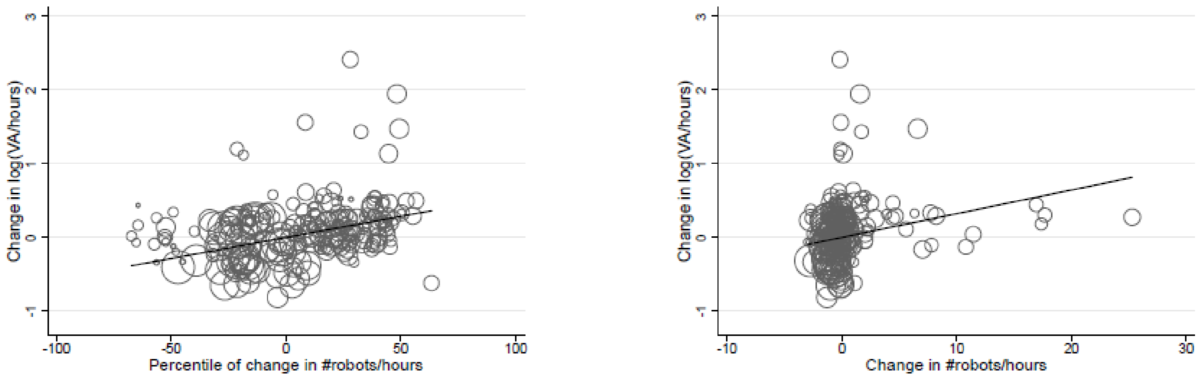
- At the intra-industry level, an increase in labour demand is observed whenever the augmented productivity is reflected in an overall growth of a sector which requires new labour force to perform non-automated tasks.
- Across industries: sectors which do not use industrial automation may benefit from the reduction of real prices in automated industries and, in turn, increase their labour demand. These effects are more visible in the particular case in which non-automated industries produce goods that are complementary to automated industries' products.
- Considering that industrial automation is capital-augmenting, the accumulation of this input alone is a boost for growth, increasing the demand for labour.
- The introduction of new tasks and jobs that cannot become automated positively affects employment, and therefore, it has positive effects on aggregate demand and growth too.

Graetz and Michaels (2018) try to bring more evidence on the implications of robotics on labour productivity, total factor productivity, and employment, both at a country and industry level. Using IFR (2012) and EU KLEMS (2007) data, they observe that the increased use of industrial robots from 1993 to 2007 augmented the annual labour productivity growth of 0.37 percent on average across the 17 analysed countries. Figure 10 plots the shift in the labour productivity log from 1993 to 2007 in comparison to the change in robot density, suggesting the existence of a relationship between productivity growth and the percentile of robot density well approximated by a linear functional form. The authors estimate that robot density (calculated as the stock of robots per million hours worked) in 14 industries in 17 countries increased by more than 150 percent, from 0.58 to 1.48, in the period from 1993 to 2007. They also find that industry-country pairs with a faster increase in robot density faced higher gains in labour productivity. On the other hand, results suggest that larger increases in robot density are associated with increasingly small gains in productivity, highlighting the presence of decreasing marginal returns from the use of industrial robotics.

Figure 10. Growth of Productivity and Robots 1993-2007

(a) Percentile of change in robot density

(b) Change in robot density



Notes: Observations are country-industry cells. The size of each circle corresponds to an industry's 1993 within country employment share. Fitted regression lines are shown. Measures of robot adoption are net of country trends. In panel (a), the estimated slope is 0:57 with a robust standard error (clustered by country and industry) of 0:27. In panel (b), the estimated slope is 0:032 and the standard error is 0:016.

Source: GRAETZ, G. & MICHAELS, G., 2018. "Robots at work". *Review of Economics and Statistics*, 100 (5), pp. 753-768.

Similar results are found in a report by SelectUSA Investment Research (Mazachek 2020) which analyses the effects of automation across industries, particularly exploring the relationship between industrial robots and the growth of productivity in the United States. In all industries, there is a positive correlation between industrial robot density and productivity: an increase in industrial robot density of one percent is associated with an increase in productivity of 0.8 percent, all else equal. An interesting point concerns the effect on slower robot adopter industries: a one percent increase in industrial robot density in these industries correlated with a 5.1 percent increase in productivity, all else equal. Mazachek (2020) proposes some reasons to explain why slower adopters experienced a higher increase in productivity than early adopters. For instance, these latter industries may have already maximised productive gains deriving from the introduction of industrial robots. Furthermore, industries which have already deployed several industrial robots may not experience the same increase in productivity deriving from an additional installation. The increase in productivity could be much larger in industries which install robots for the first time or have few robots installed. This trend could indicate different investment criteria by firms belonging to slower adopter industries. These firms may require stronger evidence that introducing industrial robots effectively leads to productivity gains to justify the investment. In other words, as pointed out by Graetz and Michaels (2018), productivity increases with the installation of industrial robots, but this may be subject to diminishing returns. By analysing the impact of robotics on the labour market, the SelectUSA researcher finds that an increase in industrial robot density correlates with a decrease in hours worked. Specifically, an increase of one percent in industrial robot density is associated with a one percent decrease in hours worked. Again, the relationship is stronger for slower robot adopter industries (2.7 times as much).

Acemoglu et al. (2022) analyse the impact of automation technologies at the firm level, by collecting data from over 300,000 U.S. firms about the implementation of five advanced technologies: AI, robotics, dedicated equipment, specialized software, and cloud computing. They report that the use of these technologies remains low, especially for AI and robotics, and varies significantly across industries. However, large, and younger firms are much more likely to introduce these technologies, and adopters experience a positive effect on labour productivity and wages, and a negative effect on the labour share. Specifically, the use of the advanced technologies listed above correlates with a 15 percent increase in labour productivity, which represents the 20-30 percent of the higher labour productivity accomplished by the largest firms in an industry. Autor et al. (2020) call this the *superstar firm* phenomenon: some large firms can reach high sales, without necessarily employing more workers than their competitors. Furthermore, as anticipated above, labour productivity decreases with the firm age, except for companies belonging to the oldest firm group observed in the research, which may experience greater effects due to their larger size achieved in the years of market presence. According to Acemoglu et al. (2022), adopters reach higher labour productivity for two reasons. First, advanced technologies used for automation lead firms to a more capital-intensive production which relies more on specialized equipment and software and less on labour. Second, advanced technologies may reduce the employment of low-skilled workers and enhance the demand for high-skilled workers. This increase from the change in the skill composition is different from a factor-neutral increase in productivity that would leave the labour share unaltered. Focusing on industrial automation, the authors find a positive and significant relationship between robotics and labour productivity: in manufacturing sectors, the presence of this technology is associated to a 11.1 percent increase in labour productivity.

2.2 Industrial Automation, Employment, and the Labour Share

Another way in which the implementation of industrial automation indirectly impacts on productivity growth is through the effects on the labour share. Industrial automation is in fact expected to reduce the labour share and, in turn for this reason, increase labour productivity.

According to multiple authors (Autor and Salomons 2018; Compagnucci et al. 2019) the displacement of labour from production, observable after the introduction of a new technology such as industrial robotics, can assume two forms. The first is the employment displacement, concerning a decrease in aggregate employment, the second one consists in the labour share displacement, concerning the erosion of the labour share of value-added in the economy. By comparing total factor productivity (TFP) growth and industry level employment growth in the period 1970-2007 for 19 OECD countries, Autor and Salomons observe that industries with faster TFP growth had experienced relative reductions in employment and in the labour share (Figure 11).

However, according to Foster et al. (2019), theory does not give a direct linkage between the growth of productivity and labour demand at the industry level and the evolution of labour demand in the aggregate. The data in Autor and Salomons, for the period 1970-2007, seems to confirm these theoretical notes. During these years, in fact, employment increased significantly across all countries, despite a decrease in employment levels in the industries that were experiencing higher productivity growth. In contrast, during the 1970s, labour's contribution to total value added remained constant or increased. Then, it experienced a slight decline in the 1980s and 1990s, followed by a sharp decrease in the 2000s across various countries. Indeed, the effect of technological change is employment or labour share-displacing depending on two key factors:

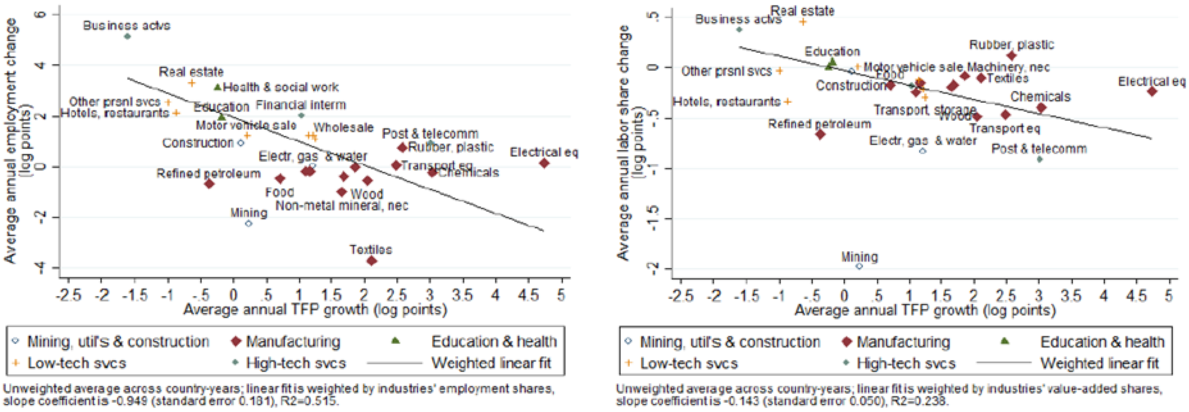
- The way in which technological innovations influence employment and the labour share *directly* in the industries where they occur.

- The way in which these direct effects are augmented or mitigated by changes in the employment and the labour share which occur elsewhere in the economy, but *indirectly* pushed by the same technological advancements.

Figure 11. Industry Level Annual Average TFP Growth 1990-2007 vs. Industry Level Annual Changes

(a) Log TFP growth versus log changes in industry employment

(b) Log TFP growth versus log changes in industry labour share



AUTOR, D. & SALOMONS, A., 2018. "Is Automation Labor-Displacing? Productivity Growth, Employment, and the Labor Share". *Brookings Papers on Economic Activity, 49* (1), pp. 1-87.

Autor and Salomons (2018) find that technological progress is broadly employment-augmenting in the aggregate, but displacing at the industry level, while for the labour share of value-added, direct labour-displacing effects prevail. These findings are consistent with a substantial part of the literature, starting with Baumol (1967), for example, which shows an employment reallocation mechanism, concerning the shift of labour from the most technologically advanced to the least advanced sector, when outputs are not perfect substitutes (Baumol cost disease). The displacement is based, in fact, on the level of substitution and complementarity of the industries which adopt robot and the industries which do not (Vivarelli 2014). If a non-adopting industry produces goods that are substitutes of the ones produced by automated industry, it suffers a decrease in the demand (automated industry's goods are cheaper due to the lower cost of production) and so in the employment. Instead, if a non-adopting industry produces goods that are complementary to a robot adopter industry, it increases its demand and employment (with the same productivity), because the demand for goods produced by the automated industry has raised due to lower prices. In terms of workers' skills, technological differences, due to the implementation of robots, could lead to labour dislocation if there is a discrepancy between skills required for new tasks and skills owned by workers substituted by robots (Vivarelli 2014).

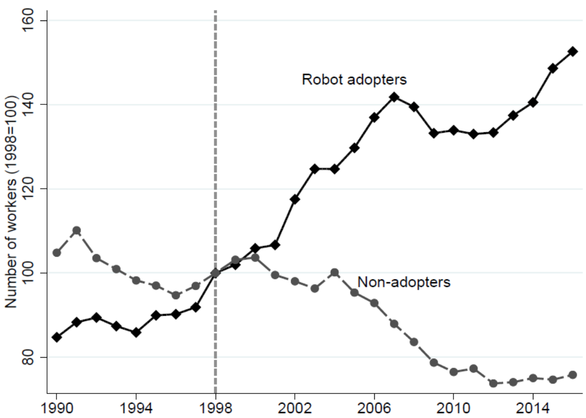
To summarise, within-sector displacement of labour demand appears to be counterweighted by the rise of labour demand in the other industries. The labour share, instead, seems to have been eroded by automation. Actually, Autor and Salomons (2018) specify that their analysis cannot directly distinguish which specific technology had caused the displacement, since TFP includes productivity growth from all different sources. Compagnucci et al. (2019) hypothesise that industrial robotics may be one of the potential causes of the emerging decoupling between wages and productivity observed by other authors (see Brynjolfsson and McAfee 2014). Workers replaced by robots, in fact, move to non-automated, low-skill, and low-pay jobs, reducing the aggregate labour share.

A similar result regarding the labour share is found in Dauth et al. (2017) who conduct a study on the effects of robotization on the careers of individual workers in the German manufacturing industry over the period 1994-2014. The German authors find no evidence that robots lead to a fall in overall employment, but that they affect its composition. According to Dauth et al. (2017), in fact, over 10 years, robots destroyed roughly 275,000 jobs in the manufacturing industry, but this damage was fully compensated by the creation of new jobs in the service sector. However, workers who are more exposed to robotization tend to stay in their initial workplace. The German researchers claim that workers remain employed, although not necessarily carrying out the same tasks. Therefore, the employment decline observed in the German manufacturing industry would not be driven by the displacement of incumbent manufacturing workers, but by the reduction of the number of new jobs offered to young entrants. In this way, incumbents achieve job stability, at the expense of lower earnings. It is, however, necessary to emphasise that this negative impact on wages is mainly associated with medium-skilled workers employed in machine-operating tasks, while high-skilled managers achieve higher incomes, benefiting from on-the-job gains. Dauth et al. (2017) suggest that the perceived threat to job losses from robots may have induced medium and low-skilled workers to accept lower wages in order to maintain their position in the original firms. This assumption is consistent with the empirical observations that robots, for these workers, negatively impact wages, but not employment.

Dottori (2021), who investigates the effects of robotization on employment in Italy, both at the local labour market and at the worker level, finds results quite similar to Germany. By analysing data from 1993 to 2017 and combining local-level and worker-level approaches, Dottori measures the likelihood of joining a sector and studied the inflows changes over time. He shows that the industries that are more exposed to robotization have consistently experienced lower relative labour inflows. This implies that the impact of robots on employment may have contributed to the redistribution of the new workforce among various sectors. Furthermore, the research shows that workers employed in the more robot exposed industries seemed to keep their jobs for longer, achieving higher lifetime earnings. Dottori (2021) associates these findings to the presence of firm-specific complementarities related to the on-the-job experience and the knowledge of workers, and the use of robots. Therefore, working in an industry which is more exposed to robots may have a positive within-firm effect on the duration of employment spells and wages.

This phenomenon of reallocation of workers from low-productive non-adopting firms to high-productive robot-adopters is also detected in Spanish firms by Koch et al. (2021), suggesting that this trend may partially explain productivity gains reported by other studies on the topic. Industrial robotics adoption, in fact, allowed Spanish firms to reach significant productivity gains, reduce the labour share, and led to net job creation. Firms adopting robots between 1990 and 1998 increased their employee count by more than 50 percent in the period 1998-2016 (Figure 12). Over the same period, firms which did not implement industrial robots experienced a loss of 20 percent of their workers. As documented by Dauth et al. (2017) for German workers, Koch et al. (2021) report particularly noticeable positive employment effects for high-skilled workers, but also for low-skilled ones, and particularly for those who were employed in the manufacturing industry, as seen for Italian workers by Dottori (2021).

Figure 12. Evolution of Firm-Level Employment in Spain (1990-2016)



Notes: The figure depicts the evolution of average firm employment (measured by the number of workers) in a balanced sample of firms from 1990-2016, separately for robot adopters (solid black line) and non-adopters (dashed grey line). Robot adopters are defined as firms that entered the sample in 1990 and had adopted robots by 1998. Non-adopters are firms that never use robots over the whole sample period.

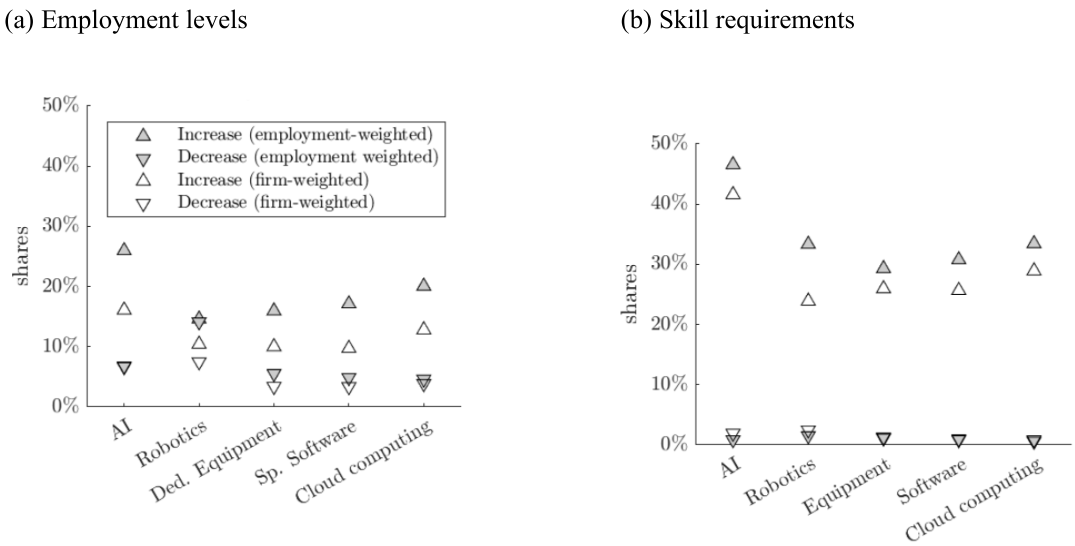
Source: KOCH, M., MANUYLOV, I. & SMOLKA, M., 2021. "Robots and firms". *The Economic Journal*, 131 (638), pp. 2553-2584.

Conversely to the results found by Dauth et al. (2017), Dottori (2021), and Koch et al. (2021) about incumbent workers, Humlum (2021) observes that in Denmark, from 1995 to 2015, welfare losses deriving from industrial robots mostly affected old production workers. Younger workers, instead, gain from the option value of changing their careers into tech and other professions whose premiums increase as robots become more prevalent in the market (see also Acemoglu et al. 2022 for the increase of labour demand for high-skilled workers deriving from robot implementation). Specifically, a quarter of the decline in the employment percentage of production employees and 8 per cent of the increase in the employment share of tech workers since 1990 may be attributed to industrial robots.

Acemoglu and Restrepo, along with LeLarge (2020), study the effects of robot adoption on French manufacturing firms over the period 2010-2015. Consistently with other research, they find that, at the firm level, the implementation of industrial robotics is associated with a reduction in the labour share and in the number of production workers, and an increase in value-added and productivity. Nevertheless, authors observe that overall employment has increased faster in firms introducing industrial robots in their productive processes. This positive effect may be explained by the fact that companies that have a greater potential for growth are more inclined to implement robotics technology. Furthermore, Acemoglu et al. (2020) suggest that this positive impact may be a result of the reallocation of output and labour towards firms that experience a reduction of costs with respect to the other competitors in the industry. In other words, the positive effect observed for industrial robotics adopters may derive from a potential for growth already present or acquired thanks to the implementation of robots itself. Conversely, competitors in the industry not adopting robot technology, suffer decreases in value-added and employment. Consequently, according to Acemoglu et al. (2020), the overall impact on manufacturing industry employment due to the implementation of robots in French firms is negative.

The effects on the skills composition are confirmed by another work of Acemoglu et al. (2022). The authors report that adopter firms experience an increase in skill requirements due to the implementation of advanced technologies, leading to higher demand for skilled labour, but there are ambiguous effects on the employment level. A large percentage of firms in the sample declared that the use of advanced technologies had not affected their employment level in recent years. However, a small share of firms documented positive or negative effects on employment due to the adoption of the technologies, indicating robotics as the technology most tightly related with a reduction in the number of workers. 14 percent of firms reported a decrease in employment resulting from the use of robots. On the other hand, approximately the same share of firms reported an increase in employment due to the use of this technology (see Figure 13).

Figure 13. Reported Changes in Employment Levels and Skill Demand by Firms Adopting Advanced Technologies, Employment-Weighted Shares from 2019 ABS



Source: ACEMOGLU, D. et al., 2022. “Automation and the Workforce: A Firm-Level View from the 2019 Annual Business Survey”. *National Bureau of Economic Research*, No. 30659.

Dekle (2020) studies the impact of robots use in Japan, a country with a long tradition of industrial robotics installations and the highest robot density among the countries mentioned in this chapter. Using long-term industry level data from 1979 to 2012, he proposes a model (like other authors, see Acemoglu and Restrepo 2020) in which he illustrates that the introduction of industrial robots has three effects on labour demand:

- Negative labour displacement effect, observable at the industry level, which refers to the substitution of tasks from labour to robots. Dekle does not find a significant effect for Japan.
- Positive industry productivity effect from the reduction of costs due to the introduction of robots. The reduction of costs increases output and employment in that specific industry.
- Positive general equilibrium effect because industrial robotics increases productivity and labour demand across all industries.

In addition, Dekle (2020) analyses the impact of robots on different disadvantaged groups such as female workers, high school graduates, and part-time workers compared to the general workforce, finding that robots raised demand for these usually marginalised categories. For instance, despite the negative displacement effect of high school graduates is higher than the one of university graduates, the overall employment of high school graduates has expanded with the use of industrial robotics.

2.3 Key Factors in Robot Adoption and Future Trends

The different perspectives analysed in the previous paragraphs highlight the difficulty to find consistent results on the impact of industrial automation across firms, industries, and countries. Therefore, the prediction of the future trends is ambiguous too, and it is also important to take into account other influencing factors that could affect the implementation and the spread of industrial robots. In a McKinsey Global Institute report (Manyika et al. 2017), the researchers indicate five determinants that could drive or slow down robotization:

- *Technical feasibility*. This element is related to the time between the invention of the new automation technology and its integration. In addition, the technology needs to be adapted into solutions for the specific uses for which they are designed, thus extending the effective implementation time. Furthermore, the variety in the tasks required by industries or firms defines the productivity and the applicability of specific types of automation technologies (Acemoglu et al. 2022), partly explaining the observed differences in the adoption of industrial robots. For instance, most of the non-manufacturing industries does not need industrial robots, while within manufacturing ones, they are required for several manual tasks involved in the heavy industry, such as welding, painting, sorting, and assembly.
- *Cost of developing and deploying automation solutions*. Both hardware and software components are required in the development of industrial automation technologies and both components represent substantial expenditure for firms which want to introduce them. As pointed out by the SelectUSA report mentioned before (2020), the existence of early and slower robot adopters may be partly explained by different investment preferences: due to the high costs of robotization, some firms may want more evidence of the gains from the implementation. The high costs could also explain why early adopters are larger or younger firms (Autor et al. 2020; Acemoglu et al. 2022). According to Acemoglu et al. (2022), the fixed costs of adopting and integrating

industrial automation rely on firm age because younger companies may face less organizational barriers, and on other firm level characteristics such as the digital expertise or the level of management information.

- *Labour market dynamics*. The supply, the demand, and the costs of human labour influence the choice to automate some activities rather than others. For example, Dauth et al. (2017) highlight how the German trade unions' strong preference for preserving elevated levels of employment and the willingness to accept flexible wages to keep jobs in case of negative shocks, could be an explanation of the overall positive performance of the employment in the German labour market. Therefore, the interaction of technology with different labour market institutions could shape the impact of the technology itself (Chen et al. 2022).
- *Economic benefits*. Industrial automation can be introduced by firms in their productive processes for different reasons, starting from the reduction of the labour cost and including improvements in productivity, precision, quality, and safety. Companies' sensitivity to these issues can play an important role in choosing to install robots.
- *Regulatory and social acceptance*. The introduction of industrial automation technology can be hindered by regulation or government policies present in the countries or promoted by organizations of States, as the European Union. The European Parliament, for instance, voted on a motion to tax the usage of robots in 2017. The goal of the robot tax was to slow down the adoption of robots so that the economy had more time to adapt to the new technology. Humlum (2021) finds that a temporary tax would be a good strategy to curb the spread of robots, but it represents an inefficient and expensive way to redistribute revenue among manufacturing production workers. On the other hand, in countries like Japan, a series of reforms with the goal of growing the robot market up to 21 billion dollars by 2020 was promoted in 2014. In addition, not only policies, but also the reactions of other stakeholders such as users and workers can be an obstacle to robotization, leading to a kind of contemporary Luddism that could push people to boycott the use of robots for fear of losing their jobs.

These influencing factors contribute to the difficulty to predict the future impacts of robotics. Nomaler and Verspagen (2019) argue that the introduction of new technologies such as machine learning, robotization, and artificial intelligence may lead to the so-called perpetual growth, concerning the rise in per capita income even in a situation in which the technology lies in a non-progressing state. At the basis of their work there is a substantial difference in the consideration of the economic impact of robots compared to most other authors. While traditional economic theories see robots as factor-enhancing technological progress, they think that robots are more factor-eliminating technical change, as described by Peretto and Seater (2013). In some cases, in fact, robotization is able to put workers out of their job with no chance of finding another one in the specific industry. The different effects on the whole economy of the two considerations can be summarised as follows:

- *Factor-enhancing technological change* needs a constant investment in human capital, research, and development. These costs are some of the reasons investigated by the McKinsey report (2017) which can slow down robotization.
- Instead, when a critical threshold in the advancement of *factor-eliminating technologies* is reached, investment is no longer required to maintain growth, leading to perpetual growth.

The authors specify a precise parameter which indicates the threshold beyond which perpetual growth arise and find that the technological change currently underway may help to reach this threshold. There are, however, three main aspects which can determine whether industrial robotics will be able to generate perpetual growth in the future:

- The degree to which technology can replace labour-intensive human tasks.
- The cost of implementation of the technology.
- How well human duties can be replaced by automated tasks in the overall manufacturing process.

Like the results from the McKinsey report (2017), technology costs and the level of replaceability of human operations with automated tasks are the major elements which can help (or hinder) the spread of robotics, leading to perpetual growth. However, Nomaler and Verspagen (2019) do not investigate the effects on employment, assuming that labour supply is infinitely elastic. In addition, factor-eliminating technological change decreases the role of labour in the production process, making employment superfluous.

2.4 Final Remarks

In conclusion, although the literature is very wide and diversified, the overall positive productivity contribution of industrial robotics, by primarily reducing the number of hours worked, is undeniable at the firm-level, as well as at the industry and cross-industries levels for papers presented in this chapter. The main used sources and their results are summarised in Table 3.

The overall impact on employment and the labour share remains ambiguous, depending on the country-industry pair considered. There are some studies which do not find significant evidence about the general effect (Acemoglu et al. 2022 at the U.S. firm level), while others find a negative impact (Acemoglu and Restrepo 2020 for United States; Acemoglu et al. 2020 for France). A consistent part of the literature (Graetz and Michaels 2018; Compagnucci et al. 2019), despite not finding statistically significant correlations between the use of robotics and total employment, show that robots may have affected the employment share from a skills composition perspective, operating through a reallocation of workers across industries (Koch et al. 2021). Also in this case, however, authors are not aligned on which employment share (high or low-skilled workers) and which sector (robot adopters or non-adopting sector) are the recipients of the migratory flow of workers. According to Compagnucci et al. (2019) workers substituted by robots move to non-automatized, low-skilled, and low-paid jobs. According to several authors (Koch et al. 2019; Acemoglu et al. 2020), firms adopting robots experience such a growth that allows them to hire workers that non-adopting firms need to fire to compete. These observed differences may depend on the existence of firm and industry complementarities (Dottori 2021), and consequently on the way in which a disruptive technological innovation, such as industrial robotics, influences employment and the labour share directly in the industry in which occur and indirectly across the other sectors (Autor and Salomons 2018). These complementarities cited by Dottori were also investigated by the McKinsey report (2017) and by Nomaler and Verspagen (2019) who found the key elements that can encourage or hinder robotization and, as a result, the effects that the introduction of this technology has on productivity growth, the labour share and employment.

Table 3. Industrial Robotics, Productivity, Employment, and the Labour Share: Literature Sources

Year	Authors	Title	Analysis	Countries	Results
2017	Dauth et al.	*German Robots – The Impact of Industrial Robots on Workers*	Local level Worker-level (1994-2014)	Germany	• Robots do not cause a fall in overall employment, but they do affect its composition. • Jobs loss is fully compensated by the creation of new jobs in the service sector. • Employment decline in manufacturing industry is not driven by the displacement of incumbent workers, but by the reduction of the number of new jobs offered to young entrants.
2018	Autor & Salomons	*Is Automation Labor-Displacing? Productivity Growth, Employment, and the Labor Share*	Country level Industry level (1979-2007)	19 countries	• Technological progress is broadly employment-augmenting in the aggregate, but employment-displacing at the industry level. • Technological progress is directly labour share-displacing.
2018	Graetz & Michaels	*Robots at Work*	Country level Industry level (1993-2007)	17 countries	• In all industries, robots contribute positively on annual labour productivity growth, raising TFP and wages and lowering output prices. • Decreasing marginal returns from the use of robots. • Robots do not significantly reduce total employment, but low-skilled workers' employment share.
2019	Compagnucci et al.	*Robotization and labour dislocation in the manufacturing sectors of OECD countries: a panel VAR approach*	Country level Industry level (2011-2016)	16 countries	• Within-sector employment displacement deriving from robots is counterweighted by the rise of labour demand in other industries. • Labour share may have been eroded by robots. • Workers replaces by robots move to non-automated, low-skill, and low-pay jobs, reducing the aggregate labour share.
2020	Acemoglu & Restrepo	*Robots and Jobs: Evidence from U.S. Labor Markets*	Local level (1990-2007)	USA	• Robots reduce aggregate employment and aggregate wages. • Response of employment and wages may be different once the number of robots exceeds a critical threshold.
2020	Acemoglu et al.	*Competing with Robots: Firm-Level Evidence from France*	Firm level (2010-2015)	France	• Robot adopters experience declines in the labour share and number of production workers and increases in value added and productivity. • Overall employment increases faster in firms adopting robots, at expense of competitors. • Overall impact of robot on manufacturing industry employment is negative.

2020	Dekle	*Robots and industrial labor: Evidence from Japan*	Industry level (1979-2012)	Japan	• No negative displacement effect of robots. • Positive industry productivity effect of robots by lowering costs. • Positive overall equilibrium effect.
2020	SelectUSA	*Robots and the Economy: The Role of Automation in Driving Productivity Growth*	Industry level (2003-2017)	USA	• Positive relationship between industrial robot density and productivity. • Negative relationship between industrial robot density and hours worked. • An additional robot leads to larger increase (decrease) in productivity (hours worked) for slower robot adopters.
2021	Dottori	*Robots and employment: evidence from Italy*	Local level Worker level (1993-2017)	Italy	• More robot exposed industries experience lower relative labour inflows. • Robots may contribute to the redistribution of new workforce among the other industries. • Workers in more robot exposed industries keep their job for longer.
2021	Humlum	*Robot Adoption and Labor Market Dynamics*	Firm level Worker level (1995-2015)	Denmark	• Robots increase average real wages, but lower real wages of manufacturing production workers. • Younger workers benefit from the option value of switching into tech and other occupations whose premiums rise as robots diffuse in the economy.
2021	Koch et al.	*Robots and firms*	Firm level (1990-2016)	Spain	• Reallocation of workers from low-productive non-adopting firms to high productive robot adopters. • Robots generate output gains, reduce the labour cost share, and lead to net job creation for robot adopters.
2022	Acemoglu et al.	*Automation and the Workforce: A Firm-Level View from the 2019 Annual Business Survey*	Firm level (2016-2018)	USA	• Use of robotics increases labour productivity and reduces labour share. • Large and younger firms are more likely to adopt robotics. • Ambiguous effects of robotics on employment.
2022	Chen et al.	*Automation or Globalization? The Impacts of Robots and Chinese Imports on Jobs in the United Kingdom*	Local level (1991-2007)	UK	• Cities more robot exposed experience significant employment declines. • Relatively large negative employment effect may depend on the small UK stock. • Due to the relatively small stock, the impact of robots on the number of jobs losses is limited.

Chapter 3. The Dataset

As seen in the previous chapter, the literature about industrial automation and its effects is very wide. In addition, the results of the analysed studies lead to different perspectives about the consequences deriving from industrial robots' implementation. In fact, even if the positive linkage between robots and productivity growth is unarguable and a common point of research, the impact on employment and the labour share does not find a unique result.

We try to make our contribution to this topic by analysing the impact of industrial robotics use in nine developed, mostly European countries at an industry level for the period 1996-2016. Particularly, we conduct a panel cointegration analysis, described in detail in the next chapter.

This chapter shows sources, observations, and variables of the used dataset and its construction.

3.1 Sources, Observations, and Variables

The nine countries and the eleven industries are summarised in Table 4 and Table 5. Although the significant importance of China and United States in the world of industrial automation, these countries are not included in the dataset because the sectoral data was not available for most of the years included in the period selected for the analysis. Industries from C1 to C8 are sub-sectors belonging to the manufacturing macro-industry, the largest robots' user. Particularly, electrical-electronics and automotive sub-industries implement annually the highest number of robots (IFR 2022). For each year and for each industry within the selected countries we have available the values of a set of variables taken from two databases: the *World Robotics 2020 Report* (2020) for data relating to robotics and *EU KLEMS Release 2019 Database* (Stehrer et al. 2019) for the industry level growth and productivity data.

Table 4. Countries in the Final Dataset

1.	DE	Germany
2.	DK	Denmark
3.	ES	Spain
4.	FI	Finland
5.	FR	France
6.	IT	Italy
7.	JP	Japan
8.	SE	Sweden
9.	UK	United Kingdom

Table 5. Industries in the Final Dataset

1.	A	Agriculture, forestry, hunting, and fishing
2.	B	Mining and quarrying
3.	C1	Food products, beverages, and tobacco
4.	C2	Textiles, wearing apparel, leather, and related products
5.	C3	Wood and paper products; printing and reproduction of recorded media
6.	C4	Plastic, chemical, and other non-metallic products
7.	C5	Metal and industrial machinery
8.	C6	Electrical-electronics
9.	C7	Automotive
10.	C8	Other manufacturing
11.	F	Construction

3.1.1 World Robotics 2020 Report

The data regarding industrial robot use is taken from the International Federation of Robotics (IFR). IFR is a non-profit organization which provides worldwide data about the annual installations and the operational stock by industry ($INST$ and $RSTOCK$ in Table 6).[1] Specifically, our data comes from the *World Robotics 2020 Report* (2020). IFR checks annual installations of industrial robots by sector and by country. Since is not always practical to track the current number of installed robots at the customer's location and the available data often pertains to the delivery of the robots, instead of their installation, shipment data is also accepted to calculate this quantity. The operational stock of robots is the measure which indicates the

[1] See more information on the IFR website.

number of robots deployed in a country's industry in a specific year. The Japanese Robot Association (JARA) directly provides this data, while for the other countries, IFR Statistical Department computes the operational stock assuming an average useful life of 12 years, followed by an immediate retirement from service. Concerning the type of robots that are the subject of the investigation, IFR collects data for industrial robots which fall within the definition provided by the Industrial Organization for Standardization (ISO 8373:2021), reported in Chapter 1.

Table 6. Variables from World Robotics 2020 Report

1.	$INST$	Industrial robot installations
2.	$RSTOCK$	Operational stock (number of robots currently deployed)

Source: INTERNATIONAL FEDERATION OF ROBOTICS, 2020. *World Robotics 2020 Report*.

3.1.2 EU KLEMS Release 2019 Database

The sectoral data regarding the national and growth accounts is provided by the *EU KLEMS Release 2019 Database* (2019). EU KLEMS is an industry level, growth, and productivity research project, run by the Vienna Institute for International Economic Studies (wiiw). The acronym EU KLEMS stands for EU level analysis of capital (K), labour (L), energy (E), materials (M) and service (S) inputs.[2] Specifically, data belongs to the "statistical database" and are fully aligned with National Accounts provided by the countries' national statistical institutes to Eurostat, the EU statistical office. Within the EU KLEMS database, growth accounting is used as a methodology to analyse the contributions of different factors to economic growth. It breaks down the overall growth rate of an economy into the contributions of various inputs, including labour, capital, energy, and technological progress. Therefore, the database includes various economic variables belonging to two categories:

- *National Accounts*. National accounts provide a comprehensive framework for measuring and analysing the overall economic activity of a country. They capture data on various macroeconomic aggregates such as GDP (Gross Domestic Product), GNI (Gross National Income), consumption, investment, government spending, imports, and exports. National accounts aim to provide a complete and consistent picture of the entire

[2] See more information on the wiiw website.

economy, enabling policymakers and researchers to monitor economic performance, assess income distribution, and analyse sectoral contributions to the economy.

- *Growth Accounts*. Growth accounts focus specifically on analysing the sources of economic growth and changes in productivity. They disaggregate the overall growth rate of an economy to identify the contributions of different factors, including labour, capital, energy, and technological progress. Growth accounts provide insights into the drivers of economic growth, allowing for a more detailed understanding of the factors shaping productivity and competitiveness.

In EU KLEMS database, the equation which highlights the contribution of the different factors to value-added growth ΔlnV_j in an industry j is the following one:

$$\Delta lnV_j = \overline{v}_{K,j}\Delta lnK_j + \overline{v}_{L,j}\left(\Delta lnLC_j + \Delta lnH_j\right) + \Delta lnT_j \qquad (1)$$

Where:

- $\overline{v}_{K,j}\Delta lnK_j$ denotes the input of capital services. Particularly, $\overline{v}_{K,j}$ is the nominal share of the asset K in the industry j. K_j is the capital stock of the asset type K in the industry j.
- $\overline{v}_{L,j}\left(\Delta lnLC_j + \Delta lnH_j\right)$ denotes the input of labour services. Particularly, $\overline{v}_{L,j}$ is the nominal share of labour in the industry j. $\Delta lnLC_j$ shows the growth contribution of the composition effect to labour service, while ΔlnH_j shows the contribution of changes in hours worked.
- ΔlnT_j represents the total factor productivity (TFP) growth in the industry j.

In this way, it is possible to calculate TFP growth as a residual from equation (1):

$$\Delta lnT_j = \Delta lnV_j - \overline{v}_{K,j}\Delta lnK_j - \overline{v}_{L,j}\left(\Delta lnLC_j + \Delta lnH_j\right) \qquad (2)$$

We include in our dataset the six EU KLEMS variables which are summarised in Table 7. Labour compensation (LAB) refers to the total amount of wages, salaries, and benefits paid to workers in exchange for their labour and it is calculated as:

$$LAB = \frac{H\_EMP}{H\_EMPE}\, COMP \qquad (3)$$

Where:

- H_EMP refers to the total hours worked by persons engaged. The value in the database is expressed in thousands (th).
- H_EMPE refers to the total hours worked by employees. The value in the database is expressed in thousands (th).
- $COMP$ is the compensation of employees. The value in database is expressed in million units of national currency in current prices (NAC mn).

Capital compensation (CAP) refers to the remuneration earned by capital owners, such as investors and shareholders, for their contribution of financial resources in the production process. It is therefore calculated as value-added minus labour compensation:

$$CAP = VA - LAB \tag{4}$$

Table 7. Variables from EU KLEMS Release 2019 Database

Labour and capital services growth (Growth Accounts)	
1. CAP	Capital compensation, NAC mn
2. LAB	Labour compensation, NAC mn
Contributions to value added growth (Growth Accounts)	
3. TFP	Total factor productivity (TFP), p.p.
Values (National Accounts)	
4. $EMPE$	Number of employees, th
5. H_EMPE	Total hours worked by employees, th
6. VA	Gross value-added (GVA), current prices, NAC mn

Source: STEHRER, R. et al., 2019. "Industry level growth and productivity data with special focus on intangible assets". *Vienna Institute for International Economic Studies Statistical Report*, 8.

3.2 Dataset Construction

Together with the variables presented above, the variables shown in Table 8 have been calculated and included in the Final Dataset. Particularly, we obtain the density of industrial robots per employees ($ROBOT$) dividing the operational stock provided by IFR ($RSTOCK$) by the number of employees ($EMPE$). Then we calculate the labour share ($LABSHARE$), the employment share ($EMPESHARE$), and the share of hours worked ($HSHARE$), simply by dividing EU KLEMS variables LAB, $EMPE$, and H_EMPE by the Gross value-added (VA in EU KLEMS database).

Table 8. Variables calculated in the Final Dataset

1.	$ROBOT$	Robot density per employees ($RSTOCK/EMPE$)
2.	$LABSHARE$	Labour share (LAB/VA)
3.	$EMPESHARE$	Employment share ($EMPE/VA$)
4.	$HSHARE$	Share of hours worked (H_EMPE/VA)

Sources: Data processing on *World Robotics 2020 Report* and *EU KLEMS Release 2019 Database.*

To summarise, all the variables included in the Final Dataset are illustrated in Table 9. For each variable we have sectoral data for each of the nine countries in the twenty-one years included in the period 1996-2016.

Table 9. Variables in the Final Dataset

Variables from *World Robotics 2020 Report*		
1.	$INST$	Industrial robot installations
2.	$RSTOCK$	Number of robots currently deployed
Variables from *EU KLEMS Release 2019 Database*		
3.	CAP	Capital compensation, NAC mn
4.	LAB	Labour compensation, NAC mn
5.	TFP	TFP, p.p.
6.	$EMPE$	Number of employees, th
7.	H_EMPE	Total hours worked by employees, th
8.	VA	Gross Value Added (GVA), current prices, NAC mn
Variables calculated in the Final Dataset		
9.	$ROBOT$	Robot density per employees
10.	$LABSHARE$	Labour share
11.	$EMPESHARE$	Employment share
12.	$HSHARE$	Share of hours worked

Sources: Data processing on *World Robotics 2020 Report* and *EU KLEMS Release 2019 Database.*

Therefore, we obtained the final dataset by merging data from *World Robotics 2020 Report* by IFR and the *EU KLEMS Release 2019 Database*, by year, country, and industry. Since the industry classification is not the same for the two, we introduce a new one for both, illustrated in Table 10. Where the industry or manufacturing sub-industry classifications were not available or not matching, we aggregate stock variables with a sum and take means of growth variables expressed as percentage points. For example, the IFR aggregate *Plastic and chemical products* (19-22) does not have a corresponding sector in the EU KLEMS dataset, so we employ aggregates (sums or averages) of each EU KLEMS corresponding item, i.e., *Chemicals; basic pharmaceutical products* (C20_C21), *Coke and refined petroleum products* (C19), etc.

Table 10. Industry Classification

IFR		EU-KLEMS		Final Dataset	
Class	**Category**	**Code**	**Description**	**Code**	**Description**
A-B	**Agriculture, hunting and forestry; fishing**	**A**	**Agriculture, forestry and fishing**	**A**	**Agriculture, forestry, hunting, and fishing**
C	**Mining and quarrying**	**B**	**Mining and quarrying**	**B**	**Mining and quarrying**
D	**Manufacturing**	**C**	**TOTAL MANUFACTURING**		
10-12	Food products and beverages; Tobacco product	C10-C12	Food products, beverages and tobacco	**C1**	**Food products, beverages, and tobacco**
13-15	Textiles, leather, wearing apparel	C13-C15	Textiles, wearing apparel, leather and related products	**C2**	**Textiles, wearing apparel, leather, and related products**
16	Wood and wood products (incl. furniture)	C16-C18	Wood and paper products; printing and reproduction of recorded media	**C3**	**Wood and paper products; printing and reproduction of recorded media**
17-18	Paper and paper products, publishing & printing	C16-C18	Wood and paper products; printing and reproduction of recorded media		
19-22	Plastic and chemical products				
		C20_C21	Chemicals; basic pharmaceutical products	**C4**	**Plastic, chemical, and other non-metallic products**
19	Chemical products, pharmaceuticals, cosmetics		C20 Chemicals and chemical products		
			C21 Basic pharmaceutical products and pharmaceutical preparations		
20-21	Unspecified chemical, petrolium products	C19	Coke and refined petroleum products		
22	Rubber and plastic products without automotive parts*	C22_C23	Rubber and plastics products, and other non-metallic mineral products		
229	Chemical products, unspecified				
23	Glass, ceramics, stone, mineral products n.e.c. (without automotive parts*)	C22_C23	Rubber and plastics products, and other non-metallic mineral products		
24-28	Metal				
24	Basic metals (iron, steel, aluminium, copper, chrome)	C24_C25	Basic metals and fabricated metal products, except machinery and equipment	**C5**	**Metal and industrial machinery**
25	Metal products (without automotive parts*), except machinery and equipment	C24_C25	Basic metals and fabricated metal products, except machinery and equipment		
28	Industrial machinery	C28	Machinery and equipment n.e.c.		
289	Metal, unspecified				
26-27	Electrical-electronics	C26_C27	Computer, electronic, optical products; electrical equipment		
275	Household/ domestic appliances		C27 Electrical equipment	**C6**	**Electrical-electronics**
271	Electrical machinery and apparatus n.e.c. (without automotive parts*)				
260	Electronic components/devices				
261	Semiconductors, LCD, LED (incl solar cells and solar thermal collectors)				
262	Computers and peripheral equipment		C26 Computer, electronic and optical products		
263	Info communication equipment domestic and professional (TV, radio, CD, DVD-Players, pagers, mobile phones, VTR etc.) without automotive parts*				
265	Medical, precision and optical instruments		C26 Computer, electronic and optical products		
279	Electrical machinery unspecified				
29	Automotive	C29_C30	Transport equipment		
291	Motor vehicles, motor vehicle engines and bodies			**C7**	**Automotive**
293	Parts and accessories for motor vehicles:				
2931	Metal products				
2932	Rubber and plastic				
2933	Electrical/electronics				
2934	Glass				
2939	Other				
2999	Parts and accessories unspecified				
299	Automotive unspecified				
30	Other transport equipment	C29_C30	Transport equipment		
91	All other manufacturing branches	C31-C33	Other manufacturing; repair and installation of machinery and equipment	**C8**	**Other manufacturing**
F	**Construction**	**F**	**Construction**	**F**	**Construction**

Sources: Data processing on *World Robotics 2020 Report* and *EU KLEMS Release 2019 Database.*

Chapter 4. Empirical Analysis

Chapter 2 illustrates the different results about the impact of industrial robotics on the economies of sectors and countries. The purpose of this analysis is to identify and quantify, in countries and industries included in our dataset, a long-run relationship between the use of industrial robots (captured by the IFR variables) and the main growth indicators from the EU KLEMS database, such as total factor productivity (TFP), value-added, employment share, the share of hours worked, and the labour share. Specifically, in accordance with part of the literature reviewed in Chapter 2, we expect to observe that an increase in the robotics variable leads to an increase in value-added and TFP, and to a reduction in the labour share.

The starting equation of our model is the following one:

$$y_{it} = \mu_i + \gamma f_t + \beta_i ROBOT_{it} + \varepsilon_{it} \tag{5}$$

Where:

- y_{it} represents the dependent variable for a specific country-industry combination i at time t. In our model y_{it} stands for each of the variables from the EU KLEMS database whose relationship with the industrial robotics variable we are investigating.
- μ_i is the term which captures unobserved country and industry-specific fixed effects.
- f_t represents unobserved year-specific common factors, like the business cycle, the economic crisis, and other macroeconomic shocks.
- β_i measures the impact of $ROBOT_{it}$ on the dependent variable y_{it}. $ROBOT_{it}$ is the independent variable and represents the industrial robot density in the country-industry combination i at time t.
- ε_{it} is the error term or residual that represents the unexplained or random component of the model for individual i at time t. It accounts for factors that are not captured by the other variables in the equation.

To achieve the aim of this study and discover the existence of a non-spurious long-run relationship between robotics and the dependent variables, we conduct a panel cointegration analysis, following the empirical strategy employed by Herzer and Donaubauer (2018) who examine the long-run effect of foreign direct investments (FDI) on TFP.

4.1 Empirical Strategy

Figures 14-19 represent the natural logarithm of the analysed variables by industry over the period 1996-2016. These figures illustrate that the individual time series of the analysed variables graphically present a trend, suggesting that they are non-stationary. The first step of the empirical analysis concerns precisely the identification of the variables that are non-stationary. In its most basic form, stationarity refers to the absence of changes over time in the statistical characteristics of a process producing a time series. This does not mean that the series does not show variations during the observed years, but that the way it changes over time remains constant. Conversely, a non-stationary time series is one whose statistical characteristics change over time. Therefore, a time series containing a trend or seasonality is non-stationary. This is because trends and seasonality will always have an impact on the mean, variance, and other statistical properties of the series. To verify if it is correct to reasonably assume that the variables in our dataset are non-stationary, it is necessary to test the presence of a unit root. A unit root refers to a characteristic of time series data that exhibits a stochastic trend, implying that the variable does not revert to a stable mean over time. Therefore, the existence of a unit root suggests that the series has a long-term dependence on its past values and lacks stationarity, making it difficult to predict or analyse using traditional statistical methods.

Once the assumptions concerning the non-stationarity of our variables are confirmed by the panel unit root tests (described in more detail in the next paragraphs), we need to demonstrate that the detected relationship is not spurious. In other words, we must establish that the correlation is not coincidental or unrelated. For this purpose, we need to check if the variables share a common unit root and thus, a common stochastic trend. This second step of our investigation is carried out by a panel cointegration analysis, useful to examine the long-term equilibrium relationship between the variables in the panel dataset. Specifically, a panel cointegration analysis allows for the investigation of common trends and co-movements among variables across multiple individuals or entities (such as the nine countries and the eleven industries in our dataset) over time. If we have one or more cointegrated variables, the error term in the regression is stationary, implying that no relevant non-stationary variables are omitted from the model. In fact, if a relevant non-stationary variable is omitted from the regression, it would introduce a spurious relationship, leading to a non-stationary error term. In this case, cointegration would not be found. Therefore, the estimates obtained through cointegrating regressions remain robust even if there are variables omitted from the cointegrating relationship.

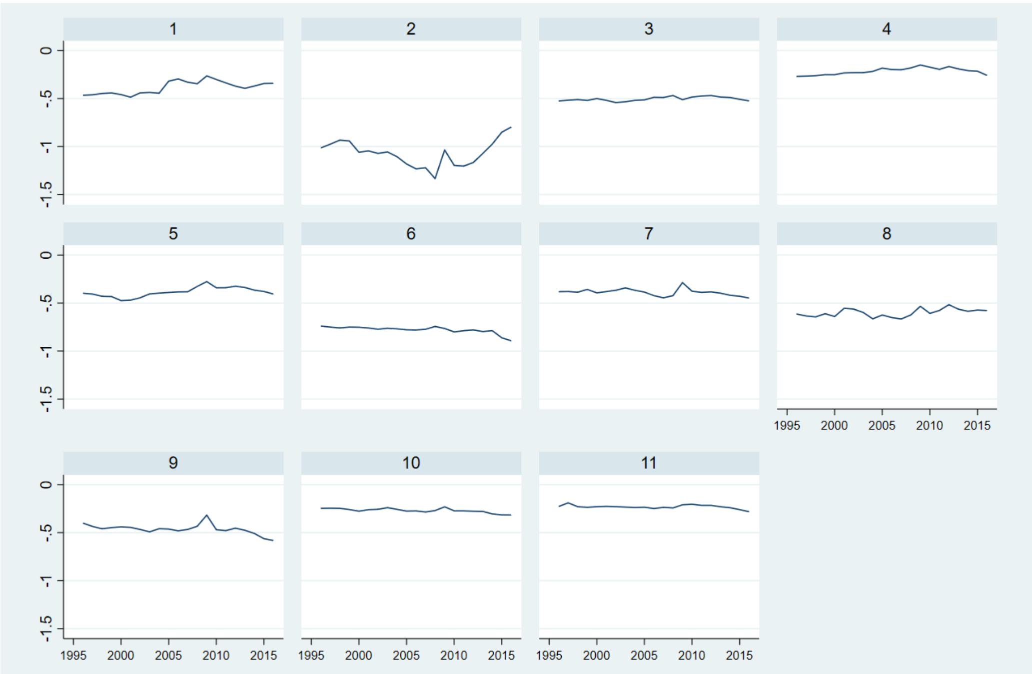
To estimate the coefficients consistently and efficiently, in the case of cointegrated variables, we use the Dynamic Ordinary Least Squares (DOLS) which helps mitigate the problems associated with spurious regression and provides more reliable and meaningful results. One of the main properties of the DOLS estimator is that it is super-consistent and asymptotically unbiased, meaning that any endogeneity between the dependent and independent variables does not influence the estimated long-term coefficients.

Although the presence of cointegration implies long-run causality in at least one direction, the estimation by DOLS does not give us any guarantee on this identified direction of causality. This means that, for example, a significant cointegrating relationship between the operational stock of robots and the labour share does not automatically imply that, in the long run, changes in the number of robots deployed cause changes in the labour share. The direction of causality can be reversed or operate in both directions at the same time. It is, therefore, necessary to conduct tests of causality and exogeneity, employing an Error Correction Model (ECM) and Granger causality tests. The ECM incorporates both the short-term dynamics and the long-term equilibrium properties of the variables and estimates the speed at which the variables adjust to deviations from their long-term relationship, capturing the error correction mechanism. In this way, the estimation of the ECM allows us to define the direction of the long-run causality. Granger causality is an approach which explores whether one time series can predict or provide relevant information about the dynamics of another time series. It is based on the idea that if a variable x "Granger-causes" a variable y, the past values of x should contain useful information for predicting future values of y beyond what can be predicted using the past values of y only (see Granger 1988).

Figure 14. Natural Logarithm of ROBOT by Industry over the Period 1996-2016

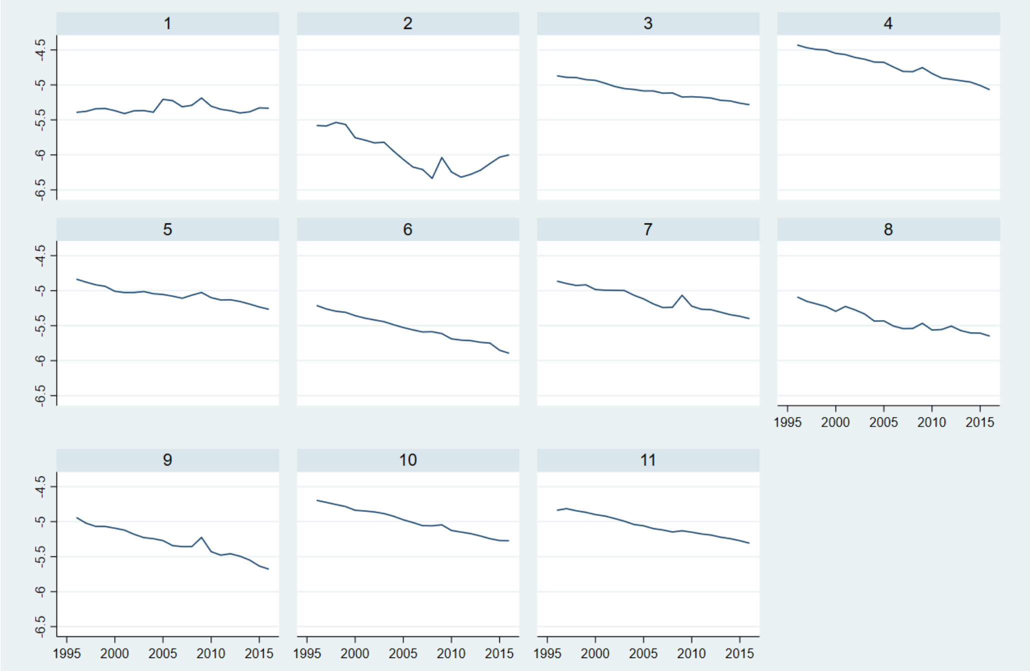
Notes: The industries from left to the rights are: (1) Agriculture, forestry, hunting, and fishing; (2) Mining and quarrying; (3) Food products, beverages, and tobacco; (4) Textiles, wearing apparel, leather, and related products; (5) Wood and paper products; printing and reproduction of recorded media; (6) Plastic, chemical, and other non-metallic products (7) Metal and industrial machinery; (8) Electrical-electronics; (9) Automotive; (10) Other manufacturing; (11) Construction.

Figure 15. Natural Logarithm of LABSHARE by Industry over the Period 1996-2016



Notes: The industries from left to the rights are: (1) Agriculture, forestry, hunting, and fishing; (2) Mining and quarrying; (3) Food products, beverages, and tobacco; (4) Textiles, wearing apparel, leather, and related products; (5) Wood and paper products; printing and reproduction of recorded media; (6) Plastic, chemical, and other non-metallic products (7) Metal and industrial machinery; (8) Electrical-electronics; (9) Automotive; (10) Other manufacturing; (11) Construction.

Figure 16. Natural Logarithm of EMPESHARE by Industry over the Period 1996-2016



Notes: The industries from left to the rights are: (1) Agriculture, forestry, hunting, and fishing; (2) Mining and quarrying; (3) Food products, beverages, and tobacco; (4) Textiles, wearing apparel, leather, and related products; (5) Wood and paper products; printing and reproduction of recorded media; (6) Plastic, chemical, and other non-metallic products (7) Metal and industrial machinery; (8) Electrical-electronics; (9) Automotive; (10) Other manufacturing; (11) Construction.

Figure 17. Natural Logarithm of HSHARE by Industry over the Period 1996-2016

Notes: The industries from left to the rights are: (1) Agriculture, forestry, hunting, and fishing; (2) Mining and quarrying; (3) Food products, beverages, and tobacco; (4) Textiles, wearing apparel, leather, and related products; (5) Wood and paper products; printing and reproduction of recorded media; (6) Plastic, chemical, and other non-metallic products (7) Metal and industrial machinery; (8) Electrical-electronics; (9) Automotive; (10) Other manufacturing; (11) Construction.

Figure 18. Natural Logarithm of TFP by Industry over the Period 1996-2016

Notes: The industries from left to the rights are: (1) Agriculture, forestry, hunting, and fishing; (2) Mining and quarrying; (3) Food products, beverages, and tobacco; (4) Textiles, wearing apparel, leather, and related products; (5) Wood and paper products; printing and reproduction of recorded media; (6) Plastic, chemical, and other non-metallic products (7) Metal and industrial machinery; (8) Electrical-electronics; (9) Automotive; (10) Other manufacturing; (11) Construction.

Figure 19. Natural Logarithm of VA by Industry over the Period 1996-2016

Notes: The industries from left to the rights are: (1) Agriculture, forestry, hunting, and fishing; (2) Mining and quarrying; (3) Food products, beverages, and tobacco; (4) Textiles, wearing apparel, leather, and related products; (5) Wood and paper products; printing and reproduction of recorded media; (6) Plastic, chemical, and other non-metallic products (7) Metal and industrial machinery; (8) Electrical-electronics; (9) Automotive; (10) Other manufacturing; (11) Construction.

4.2 Empirical Analysis

The methodology described above can be recapped in the following four major steps:

- First, we need to verify if our variables show a long-run trend and thus, if they are non-stationary, through the presence of a unit root.
- Once established the non-stationarity of our variables, we test whether they share a common unit root, through a panel cointegration analysis. If our variables are cointegrated, we can detect a long run-relationship which is not spurious.
- Then, we estimate the coefficients consistently and efficiently through Dynamic Ordinary Least Squares (DOLS).
- To detect the direction of causality, we estimate the Error Correction Model (ECM) and assess the directional influences between variables through weak and strong exogeneity and Granger causality tests.

4.2.1 Unit Root Tests

The first step of the analysis consists in testing the presence of unit roots in the variables of interest. To deal with the issue of potential cross-sectional dependence because of omitted common factors, we employ a second-generation panel unit root test. Particularly, the test at stake is the cross-sectionally augmented panel unit test, known as CIPS (Cross-sectional Im, Pesaran, and Shin) test, proposed by Pesaran (2007). This test is developed to rule out the cross-sectional dependence which occurs when the observations from different individuals or entities in the dataset are not independent but rather exhibit some form of mutual influence or correlation. To deal with this issue, the procedure is to increase the individual Augmented Dickey-Fuller (ADF)[3] regressions with the cross-sectional averages of lagged levels and first differences of the individual series as proxies for the unnoticed common factors. The general equation to be estimated for each of our variables is the following one:

$$\Delta y_{it} = \alpha_i + \beta_i \, y_{it-1} + \gamma_i \, \overline{\Delta y_{it}} + \delta_i \, \overline{y_{it-1}} + \varepsilon_{it} \qquad (6)$$

Where:

[3] The Augmented Dickey-Fuller (ADF) regression is a statistical test used to assess the presence of a unit root in a time series variable. It extends the traditional Dickey-Fuller test by including lagged differences of the variable as additional explanatory variables in the regression model.

- Δy_{it} is the first difference of the dependent variable for a specific country-industry combination i at time t. In other words, it represents the change in the variable y from one period to the next.
- α_i is the intercept and it captures the baseline value of the first difference Δy_{it} for country-industry combination i when all the other variables are zero.
- β_i is the coefficient which measures the effect of y_{it-1} on the current first difference Δy_{it} for country-industry combination i. y_{it-1} is the lagged level of the dependent variable y. In other words, β_i indicates how much the previous value of the variable y influences the change in y.
- γ_i is the coefficient which measures the impact of $\overline{\Delta y_{it}}$ on the first difference Δy_{it} for country-industry combination i. $\overline{\Delta y_{it}}$ is the average of the first difference across the sample.
- δ_i is the coefficient that captures the effect of $\overline{y_{it-1}}$ on the first difference Δy_{it} for individual i. $\overline{y_{it-1}}$ represents the cross-sectional average of the lagged levels of the dependent variable y across the sample.
- ε_{it} is the error term or residual that represents the unexplained or random component of the model for individual i at time t. It accounts for factors that are not captured by the other variables in the equation.

Following this statistical approach (Pesaran 2007; Burdisso and Sangiacomo 2016), we test the null hypothesis of the presence of a unit root in the panel data (and therefore the non-stationarity of the variable across both individual units and time) against the alternative hypothesis that the panel data does not have a unit root (and therefore the stationarity of the variable across both individual units and time). The two hypotheses can be expressed analytically in this form:

$H_0: \beta_i = 0$ for all i, versus the alternatives

$H_1: \beta_i < 0$ for $i = 1, \dots, N_1$,

$\beta_i = 0$ for $i = N_1 + 1, N_1 + 2 \dots, N,$ with $0 < N_1 \leq N$

We first test the presence of a unit root in our variables in levels and then in their first differences. To state that our variables are non-stationary, the test should not reject H_0 when variables are in levels, while it has to reject it when variables are in first differences. In this case we can point out that our variables are integrated of order 1 and non-stationary.

Table 11 reports the results of the CIPS tests for the levels and first differences of the series of our variables using one lag[4]. Comparing the values resulting from the test with the critical values at 1, 5, and 10 percent levels of significance, we reject H_0 at all thresholds when variables are in levels. On the contrary, when we analyse the test results of the variables in first difference, we reject H_0. Ultimately, we can state that all our selected variables have a unit root, so they are integrated of order 1, non-stationary, and exhibit a long-term trend.

Table 11. Pesaran (2007) Panel Unit Root Tests

	Variables	CIPS	Non-stationarity
Levels	$lnMAROBOT$	-2.267	✓
First difference	$\Delta lnMAROBOT$	-4.702 ***	✗
Levels	$lnEMPE$	-1.683	✓
First difference	$\Delta lnEMPE$	-3.567 ***	✗
Levels	lnH_EMPE	-1.907	✓
First difference	ΔlnH_EMPE	-3.639 ***	✗
Levels	$lnVA$	-2.083	✓
First difference	$\Delta lnVA$	-3.945 ***	✗
Levels	$lnEMPESHARE$	-2.048	✓
First difference	$\Delta lnEMPESHARE$	-4.068 ***	✗
Levels	$lnHSHARE$	-2.363	✓
First difference	$\Delta lnHSHARE$	-4.172 ***	✗
Levels	$lnTFP$	-2.483	✓
First difference	$\Delta lnTFP$	-4.615 ***	✗
Levels	$lnLABSHARE$	-2.098	✓
First difference	$\Delta lnLABSHARE$	-4.232 ***	✗
Levels	LAB	-1.458	✓
First difference	ΔLAB	-3.904 ***	✗
Levels	CAP	-2.094	✓
First difference	ΔCAP	-3.904 ***	✗

Notes: The panel has N = 99 observations (9 countries x 11 industries) and T = 21 (levels), T = 20 (first difference).
*** Indicate the rejection of the null hypothesis of a unit root at the 1% level.

[4] Some variables are taken in natural logarithm. The industrial robotics variable $ROBOT$ is substituted by the natural logarithm of its moving average to three years ($lnMAROBOT$) to smooth out fluctuations.

4.2.2 Cointegration Tests

Now that we know that the variables of our interest are non-stationary, we check if they share a common unit root, i.e., whether they are cointegrated. The presence of cointegration indicates that there exists a non-spurious long-term relationship between the variable under investigation. Specifically, we want to investigate the long-run relationship between the variable $lnMAROBOT$, our industrial robotics diffusion level indicator, and the other variables. To deal with this purpose, we need to conduct a panel cointegration test, useful to assess common trends and co-movements among our variables, across countries and industries in the panel dataset. The test at hand is the bootstrap approach developed by Westerlund (2007) which provides a more accurate and robust inference for panel cointegration tests because it considers potential issues such as heterogeneity, dependence, and non-normality that may be present in the data. Westerlund (2007) test consists of a second-generation approach composed, in turn, of two group of two tests. The first ones (G_τ and G_α, using the nomenclature in Westerlund 2007) are designed to test the null hypothesis of no cointegration between the selected variables versus the alternative hypothesis that the panel is cointegrated as whole. The other two tests (P_τ and P_α) test the alternative that at least one cross-sectional unit in the panel dataset is cointegrated. Therefore, to conclude that we are in presence of a shared unit root and assess that our variables are cointegrated, we need to reject the null hypotheses of no cointegration in both the groups.

We first conduct the Westerlund (2007) tests on the whole panel, but we do not find any evidence of panel cointegration between the robotics variable $lnMAROBOT$ and the other ones included in the panel dataset. Therefore, we choose to focus our investigation at the industry-level, following the approach of several authors reviewed in this dissertation (see Table 3 from Chapter 2 for a summary) who conduct the analysis among the different sectors. Particularly, we decide to include in our industry level analysis only manufacturing sub-sectors, excluding *Agriculture*, *Mining*, and *Construction* industries. Moreover, as shown by IFR (2022), the manufacturing industry is one of the sectors with the longest and highest tradition of implementation of industrial robots and several authors find significative results focusing on this industry in their works (e.g., Dauth et al. 2017, Acemoglu et al. 2020, Humlum 2021, and Dottori 2021). Therefore, conducting the analysis at a manufacturing sub-sector level may lead to more interesting outcomes.

With the new adjustments, we find some significative evidence of cointegration between $lnMAROBOT$ and some other variables in the automotive sub-industry. Specifically, Table 12 reports results of the Westerlund (2007) tests for this sector. When we test the presence of cointegration between $lnMAROBOT$ and variables $lnLABSHARE$, $lnEMPESHARE$, $lnHSHARE$, $lnVA$, and $lnTFP$, G_τ and P_τ tests strongly reject the null hypothesis of no cointegration at 1 and 5 percent levels of significance. At this point, we can state that a long-term relationship, which is not spurious, among $lnMAROBOT$ and the variables listed above exists. Indeed, it could also be true the opposite ($lnMAROBOT$ may be influenced by the other variables) or we can be in the presence of mutual influence ($lnMAROBOT$ and the other variables explain each other). In fact, as mentioned above, the panel cointegration tests proposed by Westerlund (2007) do not provide any information about the direction of causality. In the next paragraphs, to deal with this issue, first, we estimate the cointegration relationship through Dynamic OLS (DOLS), and an Error Correction Model (ECM) followed by a series of Granger causality tests.

Table 12. Westerlund (2007) Cointegration Tests in the Automotive Industry

	$lnLABSHARE$	$lnEMPESHARE$	$lnHSHARE$	$lnVA$	$lnTFP$
G_τ	-3.770 *** (0.000)	-3.815 *** (0.000)	-3.252 *** (0.001)	-3.485 *** (0.000)	-3.529 *** (0.000)
G_α	-9.008 (0.908)	-8.979 (0.910)	-9.137 (0.898)	-7.409 (0.979)	-9.580 (0.858)
P_τ	-9.322 *** (0.000)	-10.425 *** (0.000)	-8.413 *** (0.009)	-9.045 *** (0.001)	-9.233 *** (0.001)
P_α	-8.900 (0.506)	-9.422 (0.405)	-8.653 (0.554)	-7.382 (0.776)	-4.951 (0.974)

Notes: Bootstrap *p* values (based on 100 replications) in parentheses.
*** Indicate the rejection of the null hypothesis of no cointegration at the 1% level.

4.2.3 Long-Run Relationship

Considering that in the previous step, we found significant evidence of cointegration only in the automotive sector, we opt to continue the analysis focusing only on this industry. Therefore, as a third step, we estimate the long-run cointegration relationship between $lnMAROBOT$ and the other variables, through the Dynamic Ordinary Least Squares (DOLS), following the approach developed by Kao and Chiang (2000). This estimator is super-consistent and, unlike the standard OLS approach, is asymptotically unbiased and normally distributed, even if we are in presence of endogenous regressors. DOLS estimator accounts for potential autocorrelation and endogeneity, by augmenting the cointegrating regression with lead (future values of the independent variable), lag, and current values of the first differences. Therefore, in analytical terms, the specification of the DOLS regression estimated in the analysis is as follows:

$$lny_{it} = \mu_i + \gamma f_t + \beta_i lnMAROBOT_{it} + \sum_{j=-k}^{k} \lambda_{ij} \Delta lnMAROBOT_{it} + \varepsilon_{it} \qquad (7)$$

Where:

- lny_{it} represents the dependent variable whose relationship with the robotic variable we are investigating (e.g., $lnLABSHARE$, $lnEMPESHARE$, etc.).
- μ_i represents country-specific fixed effects or unobserved factors that are unique to each country i, but remain constant over time. These effects capture country-specific characteristics that may affect the dependent variable lny_{it}.
- f_t represents time-specific fixed effects or unobserved factors that are unique to each time t but are the same across countries. These effects capture time-specific factors that may influence the dependent variable lny_{it}.
- β_i is the coefficient which measures the impact of $lnMAROBOT_{it}$ on the investigated dependent variable.
- $\sum_{j=-k}^{k} \lambda_{ij} \Delta lnMAROBOT_{it}$ represents the sum of lagged changes in $lnMAROBOT_{it}$ for a range of k periods. It captures the potential lagged effects of changes in $lnMAROBOT_{it}$ on lny_{it}. The coefficient λ_{ij} measures the magnitude and direction of these effects.
- ε_{it} is the error term or residual that represents the unexplained or random component of the model for individual i at time t. It accounts for factors that are not captured by the other variables in the equation.

Table 13 reports the coefficients estimated with the DOLS approach. In row (1) the lag order for the dependent variables is set to 2 using automatic lag selection, meaning that the DOLS model is considering two lagged values of the dependent variable in the estimation. Moreover, in row (1), the number of leads is set to 1, meaning that no future values of the independent variable are included. In row (2), both the lag order and the number of leads are set to 1. These options allow the DOLS specification to automatically ascertain the appropriate lag order for the dependent variable and exclude future values of the independent variable, helping to avoid potential endogeneity issues and improve the model's reliability.

As shown by the data, the p value in the model specifications of the dependent variables $lnEMPESHARE$, $lnHSHARE$, and $lnVA$ is lower than the common significance level of 5 percent and suggests that the coefficients of $lnMAROBOT_{it}$ are highly statistically significant. In the model specification for $lnLABSHARE$ the coefficient of $lnMAROBOT_{it}$ is not statistically significant. Nevertheless, we can still comment on the results, bearing in mind that the coefficient is representative of all nine countries and could therefore have distortive effects which would not arise if the countries were taken individually. Therefore, we can state that almost all variables have a significant long-term relationship with $lnMAROBOT_{it}$. Particularly, considering row (2), a one percent increase in $lnMAROBOT_{it}$ leads to a 0.008, 0.464 and 0.465 percentage decrease respectively in $lnLABSHARE$, $lnEMPESHARE$, and $lnHSHARE$, and to a 0.245 and 0.089 percentage increase respectively in $lnVA$ and $lnTFP$. Consequently, we can observe how the effects on quantitative labour variables, such as the number of employees ($lnEMPESHARE$) and the number of hours worked ($lnHSHARE$), are more evident than the impact on the labour share, a variable that takes into account a quality aspect of the labour such as the salaries of the employees. This lower decrease in the labour share can be partly explained by trade unions polices who may mitigate the direct effects on salaries by requesting wage adjustments (see Dauth et al. 2017 and Dottori 2021).

Table 13. The Long-Run Relationship: DOLS Estimates

	Dependent variables				
	$lnLABSHARE$	$lnEMPESHARE$	$lnHSHARE$	$lnVA$	$lnTFP$
(1) $lnMAROBOT$	-0.097 (0.180)	-0.480 *** (0.000)	-0.480 *** (0.000)	0.253 *** (0.000)	0.098 ** (0.028)
No. of countries	9	9	9	9	9
No. of observations	153	153	153	153	153
(2) $lnMAROBOT$	-0.008 (0.267)	-0.464 *** (0.000)	-0.465 *** (0.000)	0.245 *** (0.000)	0.089 ** (0.035)
No. of countries	9	9	9	9	9
No. of observations	162	162	162	162	162

Notes: p values in parentheses. *** (**) Indicate significance at the 1% (5%) level.

4.2.4 Long-Run Causality

Even if cointegration implies Granger causality in at least one direction, the DOLS coefficients estimated in the previous paragraph do not tell us anything about this direction of causality. This means that, at this point of the empirical analysis, we cannot yet determine whether the variables are influenced by $lnMAROBOT_{it}$ or vice versa, or whether both affect each other. Moreover, we don't know if a short-run relationship exists too. Therefore, we must proceed with next and final step, using the Error Correction Model (ECM). The ECM is able to describe the dependent variable and the independent variable changes in the short run consistently with a long-term cointegrating relationship.

As a preliminary first step, we need to reduce as much as possible the issue of cross-sectional dependence, that is unobserved effects or country-industry common shocks that could make endogenous the relationship between the variables. To control for cross-sectional dependence, we use an econometrics technique concerning the demeaning of the dependent set of variables in the panel dataset (Pedroni 1999). In this way, we calculate six new variables (Δlny_{it}) simply subtracting cross-section averages ($\overline{y_t}$) from the observations (y_{it}) of each of the variables analysed so far ($lnMA\_ROBOT$, $lnLABSHARE$, $lnEMPESHARE$, $lnHSHARE$, $lnVA$, and $lnTFP$). As a second preliminary step, we take the new variables in their first differences to control for year-fixed common factors specific for countries and industries.

To test for causality, we employ the Pooled Mean Group (PMG) regression developed by Pesaran, Shin, and Smith (1997, 1999). PMG consists of a Panel Vector Error Correction Model (PVCEM), that is an econometrics technique which employs the long-term cointegrating regression coefficient estimated with the DOLS to compute the lagged Error Correction (EC) term. The EC term corresponds to the error-correcting speed of adjustment to the long-run equilibrium. We obtain it from the long-run relationship equation estimated with the DOLS coefficient of each variable (see Table 12):

$$ec_{it} = lny_{it} - (\beta_i lnx_{it} + \mu_i) \tag{8}$$

To establish the long-run causality between our variables we need now to estimate two equations in which we incorporate the lagged EC term.

$$\Delta lny_{it} = \mu_{1i} + a_1 ec_{it-1} + \sum_{j=1}^{k} \beta_{11j} \Delta lny_{it-j} + \sum_{j=1}^{k} \beta_{12j} \Delta lnMAROBOT_{it-j} + e_{it}^{y} \tag{9.1}$$

$$\Delta lnMAROBOT_{it} = \mu_{2i} + a_2 ec_{it-1} + \sum_{j=1}^{k} \beta_{21j} \Delta lnMAROBOT_{it-j} + \sum_{j=1}^{k} \beta_{22j} \Delta lny_{it-j} + e_{it}^{MAROBOT} \tag{9.2}$$

In the first one, Δlny_{it} represents one of the demeaned dependent variables taken in first difference, while $\Delta lnMAROBOT_{it}$ is the main regressor, demeaned as well. In the second one, on the contrary, $\Delta lnMAROBOT_{it}$ is the demeaned dependent variable, while Δlny_{it} is the main regressor, demeaned as well. At this point we need to check the significance of the two coefficients β_{12j} and β_{22j}.

As a second step, we need to look at the estimated coefficient of the lagged EC terms in all the equations:

- If the coefficient is not significant, it means that the regressor is weakly exogenous in the considered equation and therefore, there is no long-run Granger causality between the two variables.
- If the coefficient is statistically different from zero and negative in one equation, there is Granger causality between the two variables in the direction indicated by the coefficient of the independent variable in the regression.
- If the coefficient is statistically different from zero and negative in both the equations, the long-run Granger causality operates in both directions, so there is mutual causality.

Table 14 reports the PVECM estimates and the results of the short-run Granger causality, and weak and strong exogeneity tests (explained in detail below). Specifically, in the upper part of the table, we summarise parameters and test results of equation (9.1), that is when $\Delta lnMAROBOT$ is used as the independent explanatory variable and the other ones are the dependent variables. The lower part of the table, instead, reports the estimates and results of equation (9.2), that is when $\Delta lnMAROBOT$ is the dependent variable, while the other ones are used as explanatory variables. First, we need to check if the coefficients of our variables are significant. Looking at β_{12j} and β_{22j}, we observe that they are statistically different from zero in both the equations for $\Delta lnMA\_ROBOT$, $\Delta lnLABSHARE$, $\Delta lnEMPESHARE$, and $\Delta lnHSHARE$. For $\Delta lnVA$ and $\Delta lnTFP$, instead, the coefficients are significant only in the second specification when $\Delta lnMAROBOT$ is the dependent variable.

Following the instructions summarised above, we now compare the EC terms of the two equations. As data shows, for $\Delta lnLABSHARE$, $\Delta lnEMPESHARE$, and $\Delta lnHSHARE$ variables, EC terms are statistically different from zero and negative in both the equations. Therefore, we can state that long-run Granger causality operates in both directions for these three variables. Particularly, looking at the β_{12j} and β_{22j} coefficients, a one percent increase in $\Delta lnMAROBOT$ leads to a percentage decrease of 0.282 in $\Delta lnLABSHARE$, and of 0.208 for both

$\Delta lnEMPESHARE$ and $\Delta lnHSHARE$. Conversely, the one percent increase contribution to $\Delta lnMAROBOT$ of these three variables when they are taken as independent variables is respectively 15.41 percent, -2.168 percent, and -2.612 percent. Concerning $\Delta lnEMPESHARE$ and $\Delta lnHSHARE$ variables, there is a long-run reciprocal relationship: a higher exposition to industrial robotics reduces the weight of labour on value-added and vice versa. This means that as the weight of labour decreases, automotive firms increasingly invest in industrial robotics which in turn reduce this weight. It is interesting to note, instead, that an increase in $\Delta lnLABSHARE$ leads to an increase in the industrial robotics variable $\Delta lnMAROBOT$. Therefore, on one side, robotics causes a decrease in the labour compensation, but, on the other side, a higher labour compensation induces automotive firms to invest more in robotics. With regard to the variables $\Delta lnVA$ and $\Delta lnTFP$ we find a negative long-run causality between $\Delta lnMAROBOT$ and these variables. Particularly, a one percent increase in $\Delta lnVA$ and $\Delta lnTFP$ leads to a decrease in $\Delta lnMAROBOT$ of respectively 9.848 percent and 46.161 percent. These last results suggest that lower productivity may enhance investments in industrial robotics.

Moreover, we perform three additional tests to check for weak exogeneity, short-run Granger causality, and for strong exogeneity. For the weak exogeneity, we use a χ^2 statistics to test the null hypothesis that the EC term's adjustment coefficients (a_1 and a_2 in equations (9.1) and (9.2)) are equal to zero. If the adjustment coefficient is not significant in equation (9.1) – which investigates the relationship in the direction $\Delta lnMAROBOT \rightarrow \Delta lny$ – it means that lny is weakly exogenous and $lnMAROBOT$ has no long-term causal effect on the dependent variable. Hence, the long-run causality runs from lny to $lnMAROBOT$. The same findings apply to equation (9.2) in which the relationship goes in the direction $\Delta lny \rightarrow \Delta lnMAROBOT$: if the coefficient is not significant, $lnMAROBOT$ is weakly exogenous and lny has no long-term causal effect on $lnMAROBOT$. If both coefficients are different from zero, the long run Granger causality runs in both directions. Looking at the results reported in Table 14, we observe that all coefficients are strongly different from zero, rejecting the null hypothesis of exogeneity and bringing further evidence of the presence of a non-spurious long-run relationship between the variables which runs in both directions.

To test for the presence of short-run Granger causality, we use a χ^2 statistics in which the null hypothesis is that the coefficient of the demeaned independent variable is equal to zero. If we reject the null hypothesis, therefore, we are in presence of Granger causality also in the short run. Results show that none of the coefficients are statistically significant, meaning that Granger causality in the short run is not observable and it requires more time to see the impact of the variables. Since a relatively short number of years is included in our panel, we set a lag of a single year.

Finally, to test for strong exogeneity, we employ a χ^2 statistics in which the null hypothesis tests that adjustment coefficient and the coefficient of the demeaned variable are both equal to zero. This test does not distinguish between short-run and long-run causality, but as reported in Table 14, we observe that we strongly reject the null hypothesis for all variables and both the specifications, getting proof again that Granger causality runs in both directions.

Table 14. PVECM Estimates and Causality Tests

$\Delta lnMAROBOT \rightarrow \Delta lny$	$\Delta lnLABSHARE$	$\Delta lnEMPESHARE$	$\Delta lnHSHARE$	$\Delta lnVA$	$\Delta lnTFP$
β_{12j}	-0.282 *** (0.000)	-0.208 ** (0.037)	-0.208** (0.011)	-0.001 (0.941)	-0.0003 (0.759)
EC	-0.432 *** (0.000)	-0.447 *** (0.000)	-0.407 *** (0.000)	-0.280 *** (0.001)	-0.550 *** (0.000)
Demeaned data	Yes	Yes	Yes	Yes	Yes
No. of countries	9	9	9	9	9
No. of observations	180	180	180	180	180
Weak exogeneity test	21.18 *** (0.000)	24.80 *** (0.000)	17.03 *** (0.000)	12.11 *** (0.001)	55.34 *** (0.000)
Short run Granger causality test	0.89 (0.344)	0.89 (0.346)	0.55 (0.459)	1.01 (0.315)	0.98 (0.323)
Strong exogeneity test	21.31 *** (0.000)	24.87 *** (0.000)	17.07 *** (0.000)	12.11 *** (0.002)	63.35 *** (0.000)

$\Delta lny \rightarrow \Delta lnMAROBOT$	$\Delta lnLABSHARE$	$\Delta lnEMPESHARE$	$\Delta lnHSHARE$	$\Delta lnVA$	$\Delta lnTFP$
β_{22j}	15.410 *** (0.000)	-2.168 ** (0.017)	-2.612 *** (0.001)	-9.848 *** (0.000)	-46.161 *** (0.000)
EC	-0.224 *** (0.001)	-0.267 *** (0.001)	-0.275 *** (0.001)	-0.242 *** (0.000)	-0.183 *** (0.007)
Demeaned data	Yes	Yes	Yes	Yes	Yes
No. of countries	9	9	9	9	9
No. of observations	180	180	180	180	180
Weak exogeneity test	11.25 *** (0.001)	19.12 *** (0.000)	16.85 *** (0.000)	15.40 *** (0.000)	7.30 *** (0.007)
Short run Granger causality test	1.90 (0.169)	0.02 (0.886)	0.000 (0.970)	0.51 (0.475)	0.25 (0.615)
Strong exogeneity test	12.16 *** (0.002)	20.44 *** (0.000)	18.06 *** (0.000)	17.19 *** (0.000)	7.49 ** (0.024)

Notes: *p* values in parentheses. *** (*) Indicate significance at the 1% (5%) level. Short run Granger causality, weak and strong exogeneity tests are computed as a χ^2 statistics.

Conclusions

The implementation of advanced technologies, such as industrial robotics, has changed the world from different points of view. Like every disruptive innovation, it brought benefits, but also broke balances previously achieved and reached new ones. On the one side, industrial robots positively contribute to the productive process by enhancing productivity, precision, and quality of the product, by reducing costs of production and hours worked, and by relieving man from difficult, dangerous, or repetitive operations. On the other side, industrial robots are expected to displace the labour component by reducing the employment and the labour share depending on direct effects that robots adoption has on the industry which implements them and indirect effects across the other industries (Author and Salomons 2018). As evidenced by the literature reviewed in Chapter 2, there are no unique results about the impact of robotics on this aspect. There are some studies which do not find significant evidence about the general effect (Acemoglu et al. 2022 at the U.S. firm level), while others find a negative impact (Acemoglu and Restrepo 2020 for the United States; Acemoglu et al. 2020 for France). Furthermore, the impact can be augmented or mitigated according to country or industry-specific complementarities (Dottori 2021).

We investigate the existence of a long-run relationship between industrial robotics and other growth indicators such as total factor productivity and value-added, and other variables such as the labour share, the employment share, and the share of hours worked. More precisely, we conduct a panel cointegration analysis at an industry level among nine developed, mostly European countries, particularly focusing on the manufacturing industry's sub-sectors. As shown by IFR (2022), the manufacturing industry is one of the sectors with the longest and highest tradition of implementation of industrial robots and several authors find significative results focusing on this industry in their works (e.g., Dauth et al. 2017, Acemoglu et al. 2020, Humlum 2021, and Dottori 2021). We find evidence of the effectiveness of this procedure from the results of our panel cointegration analysis because when it is conducted on the whole panel it does not generate significant coefficients. Conducting the analysis at the sectoral level, instead, brings us statistically significant results for the automotive industry. It is not a coincidence: automotive is the industry which, until 2020, adopted the largest stock of industrial robots, surpassed in recent years only by the electrical-electronics industry (IFR 2022).

Talking about the outcomes of the analysis, through the Dynamic Ordinary Least Squares (DOLS), we found that there is a non-spurious long-run relationship between the industrial robot density and the labour share, the employment share, the share of hours worked, TFP, and value-added. Specifically, an increase in industrial robot density leads to a decrease in the labour share, the employment share, and the share of hours worked, and to an increase in value-added and total factor productivity (TFP). Additionally, we test for presence of short-run and long-run Granger causality. We found no evidence of a short-run relationship among our variables, suggesting that it requires more time to see the impact of industrial robotics on growth and labour components. Conversely, the weak and strong exogeneity tests brought us further evidence of the presence of a non-spurious long-run mutual relationship between the variables.

An aspect we do not consider in the analysis concerns the skills composition of the labour components among the industries. Consistent part of the reviewed literature (Graetz and Michaels 2018; Compagnucci et al. 2019; etc.), show that robots may have affected the employment share from a skills composition perspective, operating through a reallocation of workers across industries (Koch et al. 2021), but also in this case authors are not aligned on which employment share (high or low-skilled workers) and which sector (robot adopters or non-adopting sector) are the recipients of the migratory flow of workers. Therefore, conducting an analysis at a worker level could give us a more precise explanation of the effects of industrial robots on the labour share.

In addition, it is important to underline that, despite the quick growth in the last decades of industrial robotics, this technology has a lower weight relatively to the whole capital stock of manufacturing industries which is composed for a major part of traditional machinery (Acemoglu et al. 2022; Fontagné 2023). Therefore, the long-run relationship could become more evident when the stock of industrial robots reaches a certain threshold, as reported by Acemoglu et al. (2022).

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