UNIVERSITA' DEGLI STUDI DI PADOVA

DIPARTIMENTO DI SCIENZE ECONOMICHE ED AZIENDALI "M. FANNO"

CORSO DI LAUREA MAGISTRALE IN BUSINESS ADMINISTRATION

TESI DI LAUREA

"SLOWBALIZATION: AN ANALYSIS OF THE INVESTMENTS IN ROBOTICS AND THEIR IMPACT ON GVC"

RELATORE:

CH.MO PROF. ROBERTO ANTONIETTI

LAUREANDA: ELENA BASSETTO

MATRICOLA N. 1222708

ANNO ACCADEMICO 2021 – 2022

Dichiaro di aver preso visione del “Regolamento antiplagio” approvato dal Consiglio del Dipartimento di Scienze Economiche e Aziendali e, consapevole delle conseguenze derivanti da dichiarazioni mendaci, dichiaro che il presente lavoro non è già stato sottoposto, in tutto o in parte, per il conseguimento di un titolo accademico in altre Università italiane o straniere. Dichiaro inoltre che tutte le fonti utilizzate per la realizzazione del presente lavoro, inclusi i materiali digitali, sono state correttamente citate nel corpo del testo e nella sezione ‘Riferimenti bibliografici’.

I hereby declare that I have read and understood the “Anti-plagiarism rules and regulations” approved by the Council of the Department of Economics and Management and I am aware of the consequences of making false statements. I declare that this piece of work has not been previously submitted – either fully or partially – for fulfilling the requirements of an academic degree, whether in Italy or abroad. Furthermore, I declare that the references used for this work – including the digital materials – have been appropriately cited and acknowledged in the text and in the section ‘References’

Firma (signature) Elena Bassetto

TABLE OF CONTENTS

INTRODUCTION

Globalization over the last years has suffered a declining trend. This decrease has been emphasized during the Covid-19 pandemic. The crisis started in 2020 has caused thousands of problems all over the world, changing habits and lifestyles of every individual. The pandemic has not been indifferent to production activities either, which have suffered delays, adjustments, and transformations. In fact, as reported by Cigna et al. (2022), the coronavirus crisis, together with trade conflicts and geopolitical tensions, determined dramatic consequences, highlighting the vulnerability of complex supply chain. For decades this chain had been following a trend of expansion, favouring the phenomenon of globalization. After these abovementioned events, however, the trend is changing, recording a contraction of participation indices in global value chains, thus resulting in slowbalization. For manufacturing activities, this period is characterized by reshoring, bringing production back from those low-cost countries where activities were delocalized. The reshoring phase, beyond social and political context, is supported by another important factor: robotics. Automation and new technologies, in fact, are recording greater investments, as they result functional, more accessible, easy to implement, and cheaper than the previous year. Companies, therefore, are choosing to produce more at home and not rely on foreign countries anymore. If in the past companies were looking for those countries where labour was cheaper, now, that convenience is outweighed by the investments in robotics. Further elements that lead to the desire of relocation are fewer trade barriers, lower transport costs, and a willingness of companies to maintain greater control on their value chain, avoiding bottlenecks and costly interruption generated by external shocks.

Given the importance of automation in the value chain, this research aims at studying the relationship that exists between investments in robotics and participation in global value chains. More specifically, we will examine robotics and GVC separately, and later we will combine the two factors in order to analyse whether it exists a relationship between the two. Therefore, the paper is structured as follows: chapter one discusses robotics, its classification, the main trends of the recent years, and the major areas of use as well as major user countries. Following, the impact of automation on employment, productivity, and job positions will be analysed.

In the second chapter, global value chains will be discussed, resuming past trends, introducing the main indices used to measure participation in GVCs, focusing more on the trends of the recent decades. Finally, there will be a brief focus on the last period of slowbalization with relative consequences and impacts.

After having analysed these two phenomena individually, they will be combined, in order to study their relationship. Therefore, in the third chapter, an econometric analysis will be carried out, aimed at exploring the effects of an increase of investments in robotics on participation in global value chains. The study involves a dataset of 24 advanced and transition countries, in a range from 1993 to 2018. The research relies on the use of Panel Vector Autoregressive (PVAR) models, performing the estimation by a Generalized Method of Moments, GMM. Variables will then be tested through a Granger causality test, in order to identify a possible relationship between them.

CHAPTER 1 - ROBOTICS

Technology and digital tools are nowadays indispensable elements of day-to-day activities: in household chores, transport, communication, and in production activities. Automation represents a support for every individual, and it would be difficult to think a daily life without the help of these instruments. Thinking about productive activities, these tools represent a great help and support, aimed at simplifying routine tasks, facilitating movements, increasing the precision of operations, or even assisting every human activity.

In this chapter, therefore, we will have a look at what robots are, starting from their definition and classification. We will have a focus on industrial robots, reviewing what are the market trends that have characterised the adoption of robotics over the years, both by geographical area and by area of use. Successively, there will be analysed the main drivers behind robot adoption, to conclude with the major impacts generated by robotics. The analysis will cover the effects of robotics on employment, productivity, and the relationship between cost of robots and cost of labour.

1.1. What is a robot?

Give a definition of robot is not simple, as it can be used in many different sectors and to complete a lot of tasks, so it is complicate to identify with a unique definition the role and the characteristics of a robot. Reporting the word used by Guizzo (2018) trying to give a definition neither too general, nor too specific, "a robot is an autonomous machine capable of sensing its environment, carrying out computations to make decisions, and performing actions in the real world". Three key factors a robot has are sense, compute, and act.

The definition of a robot is vague and generic because there are many different types of robots, operating in different contexts. For instance, robots in the aerospace sector, robots for domestic use, for the entertainment of consumers, or drones, robots used by science in medicine and research, in military field and security sector, robots used in self-driving cars or those supporting telepresence, or, in the end, industrial robots. To make easier and clearer a partition of robots, they can be divided, according to Orha and Oniga (2012), into industrial and non-industrial ones. The latter is in turn divided into assistive robots and non-assistive robots. The assistive robots are those that express and perceive emotions, communicate with high level dialogue, learn, and recognize models, establish social relationships, use natural cues, exhibit distinctive personality and character, and may learn social competencies. This subgroup can be divided into non-social robots and social robots. The former is not socially interactive and concerns with physical assistive technology, while the latter is socially interactive and can communicate with users. The assistive social robots include service robots and companion robots. The first subgroup is used as functional devices that aid with basic activities and mobility. Companion robots are those devices with the aim of pet-like companionship, that give benefit to the health and wellbeing of users.

From this point forward, only industrial robots are taken into consideration. For this reason, a better explanation of what are industrial robots is required.

1.1.1. Industrial robot definition

According to the International Federation of Robotics (IFR), industrial robots are defined as *"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 application"*. It means that these machines can be changed in function of the job to be done, can be easily adapted to different purposes, can be moved, and can move toward different directions in a linear or rotary mode. The different robots are better classified and identified according to their mechanical structure. Reporting the classification by mechanical structure (International Federation of Robotics 2020), exist:

- **Articulated robot**: a robot whose arm has at least three rotary joints
- **Cartesian (linear/gantry) robot**: robot whose arm has three prismatic joints and whose axes are correlated with a cartesian coordinate system
- **Cylindrical robot**: a robot whose axes form a cylindrical coordinate system
- **Parallel/Delta robot**: a robot whose arms have concurrent prismatic or rotary joints
- **SCARA robot**: a robot, which has two parallel rotary joints to provide compliance in a plane
- **Others**: robots not covered by one of the above classes

Robots in IFR are also classified by industry and by application area. The main industry groups are agriculture, hunting, and forestry, fishing; mining and quarrying, manufacturing, electricity, gas and water supply; construction; education, research and development. The main classes for application area are handling operations/machine tending; welding and soldering; dispensing; processing; assembling and disassembling; others; unspecified.

For a better understanding of robotics studies, it is important to clarify the difference between installations and operational stocks. The former, also identified as shipments, represents the actual annual installations at the user's site. The latter, operational stock, measures the sum of robots' installations over 12 years, thus estimating an average life of 12 years.

1.2. Global trends

Having briefly analysed and understood these initial definitions and classifications, it is now possible to take a step forward and find out which countries and industrial branches have invested the most in robotics over time. In this regard, are taken into consideration data coming from World Robotics Report 2020, using data reported in the IFR industry classification in accordance with International Standard Industrial Classification of All Economic Activities (ISIC) revision 4.

1.2.1. Worldwide installation of robots

From 2004 to 2018, worldwide **installations** of robotics followed a positive trend, thanks to the desire of automation and innovation. From 2014 to 2018, annual installations increased by 17.5% on average each year (CAGR). If, however, we also take 2019 into account, this figure drops to 11%. This is probably due to two major factors: the difficulties in the leading sectors of robotics, such as automotive and electrical/electronics; and the hostile trade relations between two global players, the USA and China. An exception for this year is the installation of collaborative industrial robots or also commonly known as Cobots. According to IFR, "a collaborative industrial robot is an industrial robot that is designed in compliance with ISO 10218-1 and intended for collaborative use". Thereby, these robots are used in a shared space with workers and together they complete tasks sequentially. In 2019, the trend for these machines was upward, recording an 11% increase in the number of installations. Although this market is still in its infancy and the numbers are still low, this counter trend is a signal of market growth.

A slowdown in investments was also recorded in 2009, after the global economic and financial crisis. In one year, installations halved, falling from 113,000 units in 2008 to 60,000 units the following year. This decline, however, only delayed investment decisions, as in 2010 investments reached 120,000 units, raising the average annual investment of previous years: from 2005 to 2008, global average installations were 115 thousand units per year.

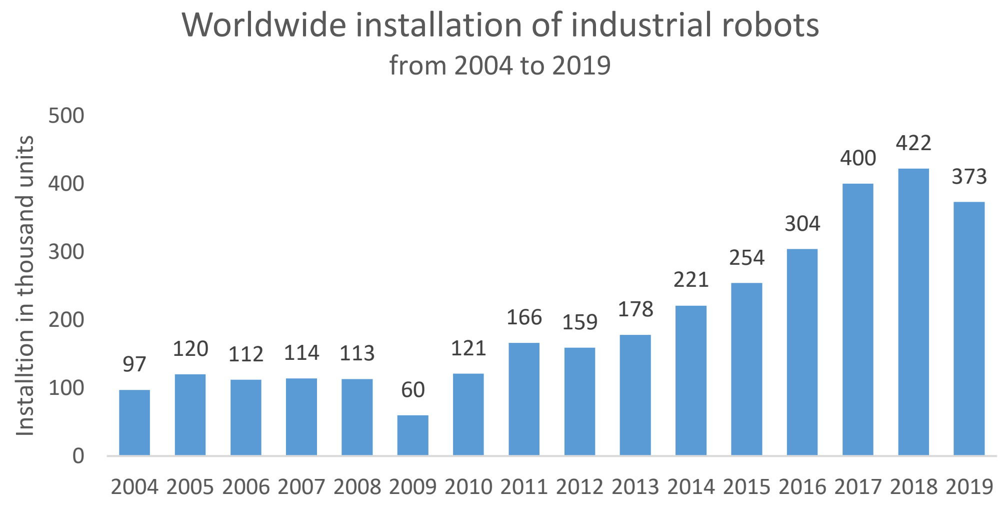


Figure 1-1 Source: Statista. Data comes from IFR (September 24, 2020b)

Proceeding with the country analysis and starting from a continent perspective, it is interesting to highlight the important role played by Asia. This, in fact, is the world's largest market for industrial robots, with a peak investment in 2018 of 283,000 units. A more detailed analysis shows that in 2010, this continent drastically increased its investments in robotics, with a percentage variation of +132% with respect to 2009, compared to +90% in the Americas and +50% in Europe. In absolute terms, the Asian continent recorded 70 thousand units of investments in robotics in 2010, 17 thousand units for the Americas, and 31 thousand units for Europe. In 2018, on the other hand, the Americas and Europe recorded 55 and 76 thousand units respectively, while the units invested in Asia reached 283,000 units, dropping to 245 the following year.

The countries with the highest investment in robotics are China, with more investments than Europe and America combined; Japan, followed by the United States, Republic of Korea and Germany. All these countries recorded a negative trend for 2019, but none recorded a negative CAGR for the period 2014-2019. The worst country in these terms was Germany, with an average annual growth rate, over the 5 years of 0% per year.

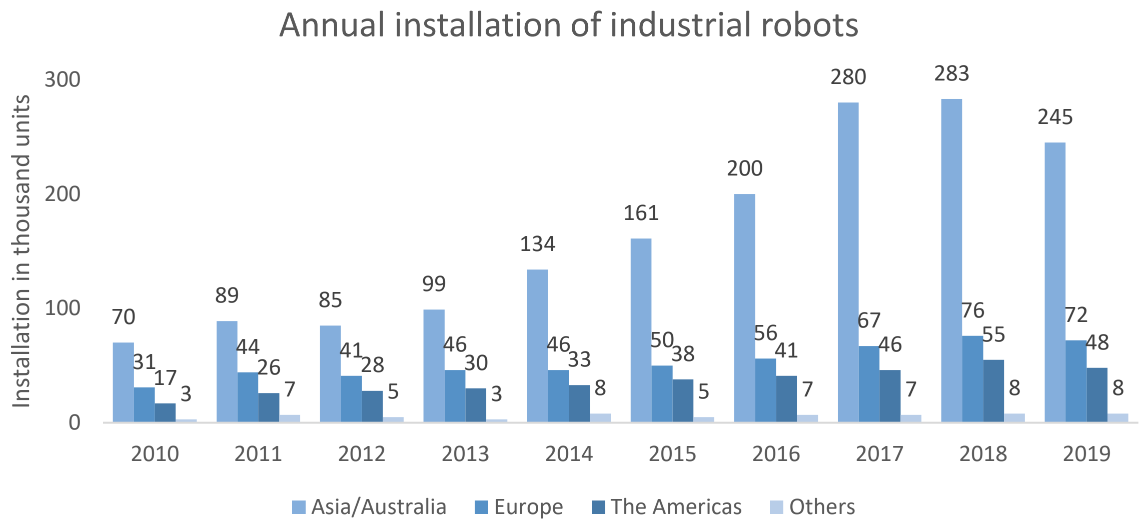


Figure 1-2 Source: Data from IFR. (September 24, 2020a). Own elaboration.

1.2.2. Worldwide operational stock of robots

From the **operational stock** perspective, the trend is quite the same as the investments. At a global glance, the trend is upward, as it was previously. The last few years have seen the strongest growth, with a CAGR in the period 2014-2019 of 13%. The average growth rate was the same in the period 2014-2018. As for investments, operational stock slowed down, although slightly, in 2009, after the financial economic crisis, decreasing the units by 38 thousand units. In 2019, unlike what happened for the same period of the previous parameter, operational stocks increase. This can be explained mainly by the fact that this is influenced by the past, as it reflects the number of robot units in use over a period of 12 years.

Figure 1-3 Source: IFR (September 24, 2020a) and Fraunhofer ISI (December, 2015)

From a countries point of view, the trend is the same as for investments. The most important players are Asian countries, with China, Japan, and Republic of Korea in the first three positions for operational stock. These three countries grow continuously over the years, and they recorded a CAGR for the period 2014-2019 of respectively +33%, +4%, and +13%, reaching, in 2019 a combined amount of 1,457,258 units of operational stocks in absolute terms. This represents more than what is reached by Europe and America combined. The fourth position is held by the United States, followed by Germany in the fifth position. The ranking of the countries with the highest number of operational stocks per year, fully reflects the ranking of annual investments, except for the trend in the numbers. In fact, the value of the operational stock of robots has grown over time, showing a positive trend even in 2019, as this value represents the number of robots in use, considering an average annual life of 12 years.

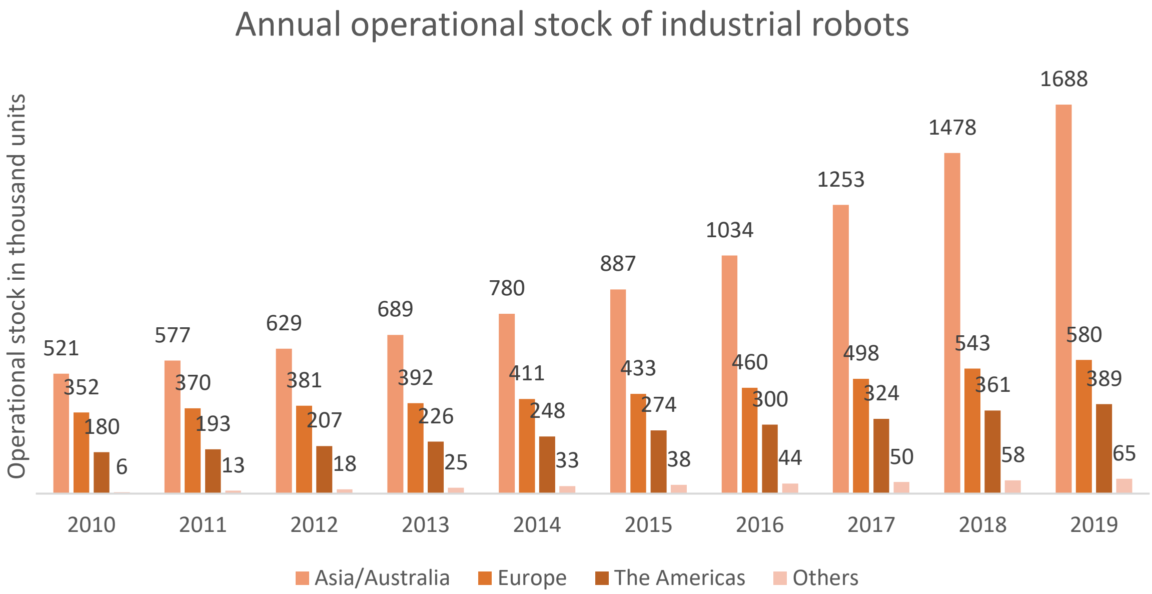


Figure 1-4 Source: Data from IFR (September 24, 2020a). Own elaboration.

In order to analyse trends in investment and operational stocks of robots by area of use in different industries, IFR adopts a measure to avoid bias when comparing different countries with different economic sizes. In fact, assuming the absolute value of units invested as parameter to compare different states, it would misinterpret data. To allow a cross-sectional comparison between countries, industries, and comparisons over time, IFR introduced the robot density. Robot density is defined by World Robotics Industrial Robot "as the number of multipurpose industrial robots in operation per 10,000 persons employed". The number of employees[1] represents the parameter that measures the economic size of a country.

1.2.3. Robots by area of use

Having introduced the robot density, it is possible to go further and examine the presence of robots for industry.

The first analysed by IFR, is manufacture, according to ISIC, rev 4: C. in 2019, after a long period of high investments, the average global robot density was 113 robots per 10,000 employees. Once again, Asia has the major density, with Singapore at first place, 918 robots per 10,000 employees, followed by Republic of Korea and Japan. Asia's robot density is growing over the years, with an average increase of 18% for the period 2014-2019 and an average of 118 robots per 10,000 employees. The growth for Europe and the Americas is a little bit lower, respectively of 6% and 9% (CAGR 2014-2019), with an average robot density of 114 and 103 robots per 10,000 employees.

Going deeply and looking at the automotive sector, within the manufacture classification, (ISIC rev 4: 29) it is possible to notice an increase in the use of robotics, also because it was one of the first sectors to invest in robotics. Here is where the major car manufacturing countries are located. In the first place there is Republic of Korea with 2,743 industrial robots per 10,000 employees in 2019, followed by Switzerland, with 2,044 robots per 10,000 employees. Switzerland is not famous for the automotive sector, but the rank is high due to the low density of employees in the industry. In the following position there are France, Belgium, and Canada with, respectively, 1,609, 1,564, and 1,475 robots per 10,000 employees. In a more general perspective, the average number of industrial robots per 10,000 employees in 2019, was equal to 722. In Asia this value is just below the global average, reaching 667 robots, while in Europe 760 and the Americas 750 the average is higher than the world average, reaching 760 and 750 robots per 10,000 employees. This sector, which is the most important for the industrial robot market, suffered a setback in 2019, with the number of robot units invested decreasing by 16% compared to the previous year. As explained by IFR, the automotive market is changing, thus switching to electric. This change of course should require major investments; however, it does not lead to an expansion of the demand for robots, due to the limited market demand. Despite this decline, the CAGR for the period 2014-2019 is positive, confirming an average annual increase of 2% in robotics in the automotive sector.

---

[1] There could be differences in the measures of employment among countries or missing data for the last years, with a time lag of at least one year. IFR estimates missing data for 2019, from 2018.

If, instead of considering robot density, we only look at the absolute value of industrial robot units installed, the ranking of countries varies slightly, but Asian countries are still in the top positions: China, Japan, the United States, Germany, and the Republic of Korea. these are, of course, the major automobile producing countries.

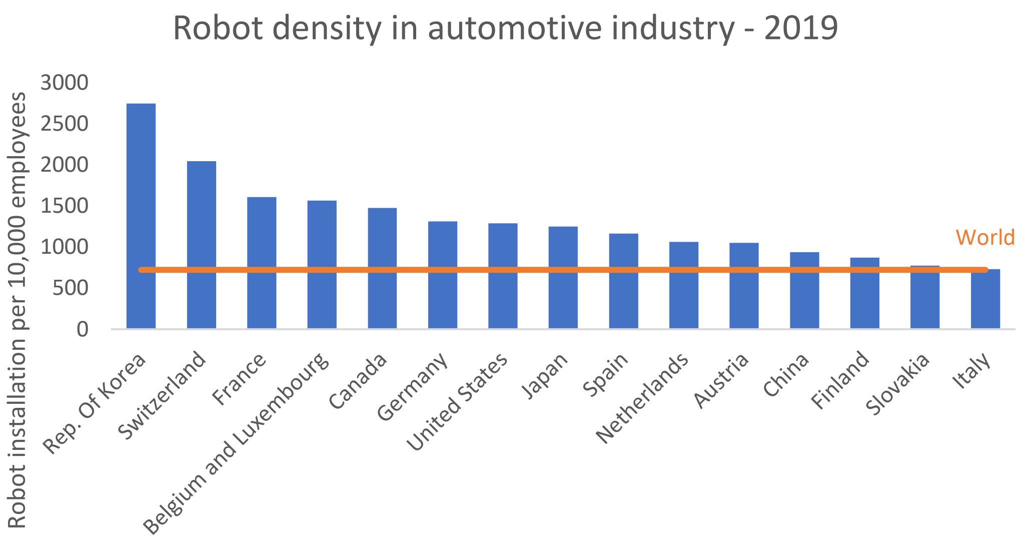


Figure 1-5 Source: IFR (September 24, 2020a)

Another important sector for industrial robots is electrical/electronics. Over time, this sector has greatly increased its investments in robotics, recording a 2014-2019 CAGR of 14%. As in the case of automotive, this sector suffered a decline in 2019, probably linked to the fall in demand for electronic devices and components, as a result of the trade conflicts between the US and China. Even for the electrical/electronic sector, the countries where the largest investments have been made, in absolute terms, are China, Japan, the Republic of Korea, the United States, and Chinese Taipei.

Next in line, as important sectors for robotics, is the metal and machinery sector, which has a CAGR 2014-2019 of 16% and increased installations by 1% from 2018 to 2019. Then comes plastics and chemical products, followed by the food industry, and ending with all the other sectors, which individually do not exceed 3% of the total share of industrial robot installations. In these remaining sectors, the countries do not vary much for annual installation, with China, Japan, and the United States in the first position and the addition of Germany and Italy in the top 5 positions for some industries.

1.3. Main driver behind robot adoption

Before going to analyse the consequences that automation has brought and is bringing to the labour industry, it is important to dwell on the causes that have led to this great growth of robotics.

In the first place, we can certainly say that over time the price of robots has become lower and more accessible, favouring the demand for industrial machines. The decrease in the cost of robotics is easily comprehensible if we consider that automation allows a greater and more efficient production. In fact, thanks to the introduction of robotics, industries are able to produce greater quantities, in a shorter period of time, reducing errors and waste. According to McKinsey & Company (Tiller, 2017) in the last 30 years the average robot price has fallen by half in real terms, and in relation to labour costs it decreases even more.

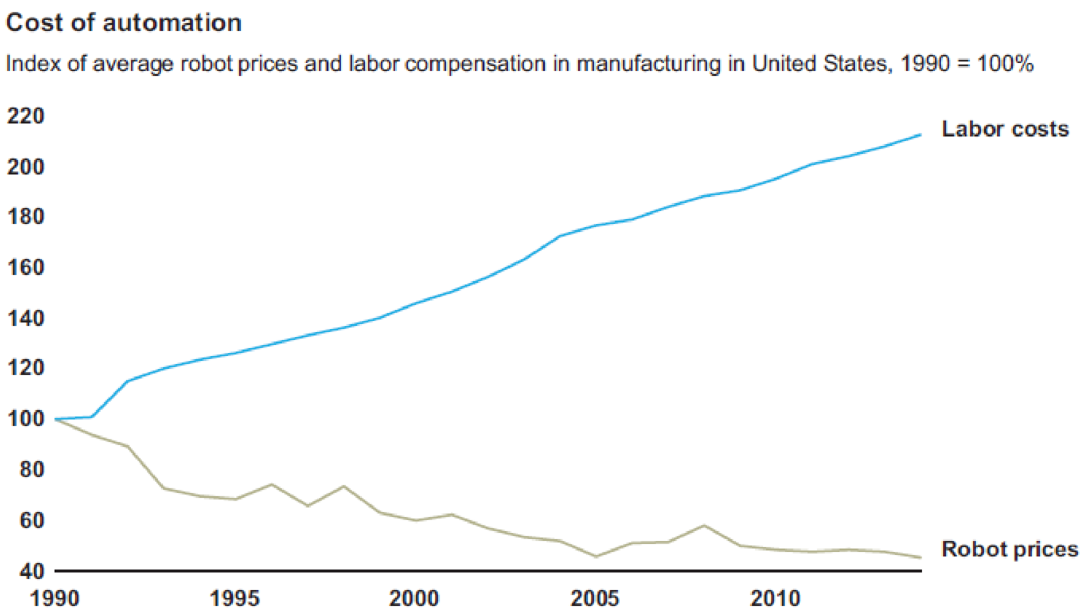


Figure 1-6 Source: McKinsey & Company (2017)

Following what Mickensey & Company reported, there are more and more people specializing in robotics, who can easily, and at a more affordable price, manage and maintain industrial robots, without necessarily having to rely on expensive experts in the field, as it could happen in the past. Moreover, technology has also evolved over time, improving, and simplifying itself. Today, thanks to the technologies network, computing power, software development techniques, it is easier and faster assemble, install, and maintain robots, which are getting smarter and integrated. Thanks to their simple programming code, robots are getting more efficient and flexible. This means that, if before they were useful only to companies that produced few products in large quantities, now they are easy to access and useful to everyone. Their flexibility allows them to quickly learn the tasks to be performed, thus being able to easily adapt to different realities, even small ones, or to increase the offer for major factories. This versatility also leads to greater variability in the tasks to be performed, which certainly turns out to be an advantage in choosing robots rather than a human operator, as with basic programming, the machine will be able to cope with obstacles, knowing how to adapt to different and complex situations.

Again, the freedom to choose which tasks automate and which ones maintain manual represents a great advantage for the economy, thus, increasing safety and precision. In addition, the combination of robots and humans and the reallocation of tasks between the two, leads to an increase in productivity, as production lines can be rebalanced as demand fluctuates. The flexibility of automation makes it possible to speed up or slow down production, while maintaining high standards, simply by a quick reprogramming. This allows a better and faster response to market fluctuations and demand seasonality.

The fact that machines are cheaper than human workers is noted also by Baldwin, in his book, *The Globotics Upheaval (2019)*, while discussing the convenience to adopt a robot rather than a human. Another point in favour of this thesis is reported by the Institute for Robotic Process Automation reported and cited by Baldwin: “software robot costs a fifth of local workers, and a third of offshore back-office workers located in, say, India”. Moreover, work is more consistent and leaves a digital trail, increasing reliability and speed of operation. Finally, robots make it possible to scale up or down production processes by intensifying or reducing the execution of software, without the need to train new and temporary personnel (Baldwin, 2019).

All these reasons, or better, a combination of them, justify the growth of adoption of robots in the last decades and define the base for the further analysis of the impacts and effects that robotics led to the market.

1.4. Impact on employment

The use of and investment in robotics has increased significantly over time, particularly in the last 10 years and this does not leave industries indifferent. The latest generation of robots is becoming increasingly sophisticated and capable of carrying out a variety of tasks, replacing entirely human labour. It can be immediately thought that robotics makes people's lives easier, facilitating movements and activities, accelerating production processes, optimizing resources, improving quality by eliminating errors and reducing variability. Automation, however, has important impacts on the labour market, and it is worthwhile analyse briefly what the major repercussions are, starting with the effects that the introduction of robotics has on employment.

To start this analysis, we consider the study conducted by Adachi et al., 2020 whose main subject of study is Japan, one of the main countries when thinking about the adoption of robots. The first result they obtained is the fact that following a decrease in prices of robots, there is an increase in the adoption of robots and, at the same time, an increase in employment. This suggests that robots and labour are grossly complementary in the production process. In this research, Adachi et al. showed how the difference in application of robots in various production processes impacts in different industries. They created a robot price index that took into account the type of task the robot would help to accomplish and related to the type of industry. For example, they noted how a decrease in the price of a robot for a specific industrial action, such as welding, in relation to the price of an assembling robot, led to greater use of robots in the automotive market (which relies more on welding robots) than in the electronics market (which relies more on assembling robots). The authors found that "robots are complementary to employment at both at the industry and regional levels" showing that at the industrial level, a 1 percent decrease in robot price leads to a 1.54 percent increase in robot adoption. Thus, 1 percent decrease in robot price, increases employment by 0.44 percent.

However, this result was in contrast with results obtained by other authors, such as the case of Acemoglu and Restrepo (2017) who found that the adoption of one robot unit per 1000 workers, generates a decrease in employment of 1.6 percent. Adechi et al., explain how this difference can be caused by the different historical periods and countries analysed. In fact, if we consider the analysis of the latter, it was about Japan, and mainly about the Japanese automotive sector between 1978 and 2017, which was in strong expansion thanks to exports and the increase of the labour demand.

Another important finding was the absence of effects on employment as a result of changes in robotics in non-manufacturing sectors. In this case, as robotics adoption increased, the total number of workers increased, but hours worked per worker decreased. Thus, "robots may have worked as work-sharing and time-saving technological changes" (Adechi et al., 2020).

According to another study conducted by Graetz and Michaels (2018) aimed at investigating the effects of industrial robots on the economy, the introduction of robots does not lead to significant effects on employment. The only effect found by the authors is a negative effect on low-skilled employment. Indeed, they noted that robotics reduces the total number of hours worked by low-skilled workers, compared to the number of hours worked by medium or high-skilled workers.

An analysis of the impacts of automation on human labour, was also carried out by Acemoglu and Restrepo (2018). The two authors want the demonstrate that machines that replace human labour might lead to lower employment and stagnant wages. From this point, they demonstrated that in the long run, employment and labour share can remain stable, even if there is an increase in automation. In fact, after the introduction of robotics, work would change, partly replaced by machines, and partly generated by new ones. But they argued that humans have a competitive advantage, which is the ability to perform more complex tasks than machines. This ability allows humans to maintain some tasks and job activities that are not replaceable by machines. More than that, automation can lead to the creation of new tasks, for example, new variants of jobs in which humans have greater productivity than machines. Automation, according to Acemoglu and Restrepo, leads to the reduction of jobs, as they are replaced by more sophisticated and automated machinery, so there could be also a reduction in wages. On the other hand, there is a new creation of jobs, which leads to an increase in productivity, an increase in wages, employment and so, also in labour share. The studied model summarises the fact that the rate of capital, necessary to invest in robotics, and the rate of labour cost, intended as wages, in the long run, will always lead to the creation of a new equilibrium that will not destroy labour. "If the long-run rental rate of capital is very low relative to the wage, there will be not sufficient incentives to create new tasks, and the long-run equilibrium involves full automation, […] otherwise, the long-run equilibrium involves balances growth based on equal advancement of the two types of technologies" (Acemoglu and Restrepo, 2018). Thereby, following the introduction of robotics, the level of automation and labour may return to its initial state, or it may lead to a decrease in employment and labour share, but without ever eliminating it. The authors themselves have stated that there will be a continuous creation of new jobs, which may be related to engineering functions rather than programming or data analysis. Jobs evolve as technology evolves, creating new tasks according to demand and needs.

In addition to the model, they introduced the distinction between low-skill labour and high-skill labour. Acemoglu and Restrepo highlight the fact that previously there was a long-term stability between automation and labour after robot introduction, later, the stability has been replaced by the concept of inequality between low-skill and high-skill labour. Thus, the automation will be directed towards those types of jobs carried out by human resources with a low skills profile, which tasks were mainly a routine, while the growth of high-skill jobs will be favoured.

1.4.1. Impact per occupation

A variety of effects can be extrapolated from the different literature. Depending on the type of study conducted and the variables analysed, for example if workers were considered by industry or by type of activities completed by the operator, the results could be more or less pessimistic or optimistic towards the introduction of automation. In fact, it was found that the impact of robot adoption could be absent or negative when analysed by industry, or it could increase the number of workers, so bringing a positive wave, considering the tasks and activities required by workers following the idea of the creation of new jobs creation previously explained. This mixed effect has been tried to clarify by the study of Caselli et al. (2021) where the different tasks and duties of workers are taken into analysis to try to give a clear answer to the impacts that automation generates. According to economic theories, robot operators, "that is workers employed in occupations clearly associated with robot installation, maintenance and use" will tend to increase along with the volume of robots used. This is because the tasks performed by the operator are complementary and, therefore, as one factor grows, so will the other. On the other hand, the jobs that are more exposed to the introduction of robots may increase or decrease, depending on the impact that automation generates for that specific case. This creates two different and opposite effects: displacement effect or reinstatement effect. The first one is realized when an increase in robots leads to a decrease in employment, while the second one, is verified and discussed in the analysis and refers to an increase by 0.27 percentage points in the local share of robot operators after an increase of 1% in robot adoption (Caselli et al. 2021).

The displacement of labour, according to Autor and Solomons (2018) could take two forms: employment displacement, when an entire group of employees is displaced, or labour-share displacement, meaning the erosion of labour's share of value-added in the economy. The causes of these displacements are to be sought on technological innovation and its direct and indirect impact in the industries where they occur. The direct effect is easier to observe and identify, while the indirect effect is more challenging to observe and quantify. The outcome of the study from Autor and Solomons (2018) reveals a general augmenting of employment in the aggregate thanks to technological progress, measured in terms of total factor productivity growth (TFP), but this is not true for labour's share of value added, in which direct labour-displacing effects dominate. The effect on employment is explainable by two steps: the direct effect of increased productivity in an industry leads to a decrease of employment in that specific sector, but this is more than fully offset by two indirect effects: the first expects an increase of labour inputs in the downstream customer industries, as the supplier industry is getting stronger; the second effect leads to a general increase in the aggregate real value-added and hence rising final demand, thus boosting the employment growth across all sectors. The effect on labour-share instead is the opposite. The growth in productivity impacts directly in a negative way labour-share, and there is not any offset by indirect effects.

Caselli et al. (2021) in their study, conclude saying that the adoption of robots and automation can generate different effects in the labour market also depending on the time and society analysed. The socio-economic situation, in fact, is a factor not to be underestimated, especially in a territory like Italy, characterized by low-skill and low-tech production, which could be negatively affected by the introduction of robotics.

1.5. Impact on productivity

The effects of automation on employment are closely linked to other aspects of the labour market. The two main factors are certainly the productivity and wages of workers. It is useful, therefore, to understand how the introduction of technology changes not only the number of workers in different industrial sectors, but also their retribution and productive efficiency.

According to Brynjolfsson and McAfee, (2011), digital technologies are "one of the most important driving forces in the economy today. They are transforming the world of work and they are key drivers of productivity and growth." For this reason, is also important to understand how the introduction of these technical machines impact on society and, especially, on productivity growth. The two authors defined productivity as "the amount of output per unit of input. In particular, labour productivity can be measured as output per worker or output per hour worked." From this point forward, we will see at the different aspects linked with robots and labour market. We begin from the analysis conducted by Richard Baldwin (2019), which in his book faced the entire process of introduction of automation into society.

Baldwin started from the first industrial revolution, when people moved from agriculture of the countryside to industries in the cities; going further with the revolution of the steam engine: a big innovation that led to important shock and changes to people. A lot of job positions have been eliminated, while new ones were created in new and different sectors. Technology, however, as Baldwin explained, leads to an increased volume of work and greater production efficiency, which fed off each other. In fact, initially, with the introduction of mechanization, the volume of work was the same with fewer workers; this obviously led to cost savings, translated into a decrease in prices; consequently, there was an increase in sales, thus having an increase in production. This, therefore, created a circle between productivity and production, causing two opposite effects. The first, the pull effect, sees technology as a "pull factor": it creates an increase in demand for production by overcoming technological efficiency and attracting the workforce back into the sector. The second effect, the push effect, sees technology prevailing over productivity, and in this case, there is an expulsion of the workforce from the sector. It is important to note, however, that technology has not eliminated occupations, but, for the most part, decreased jobs in some sectors, moving labour into new industries. Even in the period post World War II, during the Glorious Thirties (1945-1973) there was a positive trend of jobs in industries, thanks to the combination of automation and globalization there was a prosperous increase in productivity, helping people who worked with their hands (Baldwin, 2019). Subsequently, however, after the technological boost of the 1970s, there is a major push effect of technology: industries are drastically freed from the workforce, favouring jobs for more intellectual jobs, creating millions of new service-sector and professional jobs, in this area, technology caused a pull effect. There has therefore been a divisive effect of technology, favouring "head workers" over "hand workers". The introduction of ICT, with the first numerical control machines, reduced, first of all, the number of automotive workers: the share of manufacturing workers in the United States went from 30% in the 1970s to 10% in 2010. "Factories became places where workers helped machines make things, not the other way around." (Baldwin, 2019). An estimate made in 2016, by the consulting firm Forrester, predicted that in the decade 2016-2025, 16% of all U.S. jobs would be automated, this would mean losing one in six jobs. This double effect on employment, from the easy replacement of unskilled workers to the increased productivity of highly skilled workers, resulted in the phenomenon economists call "skill-biased technical change". Violante (2008) defines this effect as “a shift in the production technology that favours skilled over unskilled labour by increasing its relative productivity, and therefore its relative demand”. Industries continued to demand labour, but in different ways. Skilled workers were needed to operate the machinery, robots, and computers, which in turn replaced mass workers, and thus were no longer indispensable in the factory. In fact, low-skilled workers were still needed for cleaning and essential manual labour. Technology, therefore, granted a good situation to workers placed at the extremes, those highly and low-skilled, disfavouring those placed in the middle: it is the transformation of knowledge.

1.6. Technology and the creation of new jobs

This concept was also presented by Brynjolfsson and McAfee (2011), a few years earlier. Society often views the introduction of technology negatively because it is associated with a reduction of the human workforce. This factor is partially true, as already mentioned, for the low-skilled workforce. Digital technologies, however, are creating an extraordinary increase in jobs. Mainly in those jobs that require higher competencies and dealing with big data. The data explosion, since more and more people are connected online, requires the use and installation of new robots, which are able to manage a big amount of data in a shorter period of time and in greater security and reliability. But will still be necessary those human figures for the management of anomalous cases that a computer will not be able to interpret and maneuver. This implies an increase of work, an increase of data to be managed, and therefore requires the maintenance of human workforce, thus excluding new hires. Another reason why digital technologies can create new tasks and jobs is that robot-software are free, or almost free. In this case, it regards electrical and electronics automation, and not automotive or agriculture sectors. The unique cost is given by the low cost of the software and by the computer itself. This factor leads to hire new people for the management of the software, creating jobs in charge of management, accounting, or human resources management. A third way that generates new jobs comes from reshoring back-office jobs that had been offshored to countries where the cost of human resources is lower than the same cost in the USA or Europe. In fact, if previously the business process outsourcing was convenient because the Full-Time Equivalent worker (the total cost of the employee to that specific productive activity) was more than halved outsourcing the process, now, bringing it back to the home country and entrusting the digital technology for that action, the total production costs are drastically reduced. This favours the hiring of new employees in charge of complex cases.

1.7. Worker wages and robot prices

So far, the various impacts that automation and technology may have on employment and worker productivity have been analysed. It would be interesting to know what the subsequent effects on workers' compensation could be.

A first aspect analysed by Brynjolfsson and McAfee (2011) related to the economic effects on the market is linked with the decrease of low-skilled workforce in favour of the highly skilled. This brings to a greatest supply and specialization of the latter market segment and at the same time to an increase in the relative price of workers, expressed in terms of wages. This difference in wages leads to the creation of a large gap between the two main types of workers, making those with more knowledge, or those who are able to adapt more quickly, better off in terms of income, creating greater inequality between the population.

Another study related to the impact of industrial robotics on wages was conducted by Chiacchio, Petropoulos and Pichler (2018), who analysed six major European countries, in terms of EU industrial robots' market[2]. The authors, recall the mixed effect that automation can generate on employment: displacement effect, "by directly displacing workers from tasks they were previously performing" or productivity effect, "by increasing the demand for labour in

[2] Finland, France, Germany, Italy, Spain and Sweden, which account for 85.5 percent of the EU robots' market in 2007 (Chiacchio et al., 2018)

industries or jobs that arise or develop as a result of technological progress" (Chiacchio et al., 2018). From this point, the authors aimed to understand which effect prevails on workers as a result of the application of industrial technology. The outcome shows that "one additional robot per thousand workers reduces the employment rate by 0.16 to 0.20 percentage points." This obviously supports the fact that the effect that wins over the other is the displacement effect. The authors go on explaining that this is truer for workers of middle education, for the young and for men. However, they did not find a significant result regarding the impact of robotics on wage growth or decline in the study of European countries. However, the same authors report a study conducted by colleagues Graetz and Michaels (2015), where it is found that an increase in the use of robotics per hours worked leads to an annual increase in labour productivity of 0.37 percent, also increasing the average wages of workers[3]. In contrast, in the analyses conducted by Chiacchio et al., it does not appear significant evidence supporting an increase or decrease in wages as a result of increased robotics. In the analysis conducted by Acemoglu sand Restrepo (2017) on the other way around, they found that the U.S local labour markets suffered the exposure to industrial robots recording falls in employment and wage levels between 1990 and 2007. In conclusion, there is no fixed and constant effect of industrial automation on workers' wages. There are mixed effects that vary as other variables change.

[3] Gratez and Michaels (2015), 17 countries analysed during the period 1993-2007 (Australia, Austria, Belgium, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Netherlands, South Korea, Spain, Sweden, United Kingdom and the United States).

CHAPTER 2 - GLOBAL VALUE CHAIN

Before analysing the impacts of robotics in trade between countries, it is important to make an introduction to international trade and the different stages of globalisation, also trying to understand how the global participation of each State is assessed and measured.

To do this, it is necessary to introduce the idea of global value chains.

In this chapter, we will therefore recall the definition of global value chains, analyse the main global trends, learn about the main indices used for measuring participation in global value chains. There will be covered some effects of the participation on GVCs and finally, there will be displayed past trends with a short overview on the events of the 21st century.

2.1. Definition

According to World Bank (2019), "*a **global value chain** (GVC) is the series of stages in the production of a product or service for sale to consumers. Each stage adds value, and at least two stages are in different countries. For example, a bike assembled in Finland with parts from Italy, Japan, and Malaysia and exported to the Arab Republic of Egypt is a GVC. By this definition, a country, sector, or firm participates in a GVC if it engages in (at least) one stage in a GVC*".

The global value chains emerge because of production needs, especially when the final good is destined to be exported. Thanks to globalisation and the intensification of trade, the production process has changed over time. If, before, a country was oriented towards domestic production and the specialisation of each step of the production process, with the opening of borders, countries started to specialise in fewer tasks, demanding from the outside goods and services for which they were not competitive or able to produce. In fact, the global value chain entails the creation of more value than the value a state could create on its own internally (Baldwin, 2018). The new value comes from the combination and the exchanges from different countries. GVC can be linked to raw materials, intermediate inputs, or even tasks. The configurations that can be associated with GVC according to Baldwin and Venables (2013) are "spider-like" structures, where production takes place at different points and then converges to one central point representing the final product or component; or "snake-like" structures, where production steps follow each other, creating additional value step by step; many processes represent a mixture of the two, combining spider and snake shapes according with the step of the production. Unlike a normal international trade transaction that usually takes place between two countries, one exporting and the other importing, global value chains, as can be deduced from the definition, involve trades that often cross territorial boundaries more than once, and for more than two countries.

2.2. History of globalization

In order to fully understand the development of global value chains, it may be useful to take a historical overview on the different global stages of trade transactions, combined with the different innovations and inventions that have allowed the acceleration of globalisation.

The first date that is used to indicate the beginning of globalisation, according to Baldwin (2018), is 1820, when a fast-growing country, such as the United Kingdom, determined market prices by taking into account international supply and demand as well as national ones. At that time, a strong growth in production and trading volumes began to occur due to the steam engine, which accelerated transportation, reduced trade costs, increased industrialisation, and consequently increased incomes. The entire global economy was opening to all continents.

With the beginning of trade openings, there was a reduction or elimination of international tariff policies, which signalled a period of free trade. The first industrial districts emerged, thanks also to technological development, the concentration of factories, the stimulation of innovation and consequently a further reduction in costs. All these factors allowed the growth and establishment of advanced economies, with the direct effect of an increase in incomes per capita of the G7 countries.

This period of strong growth and international expansion has been followed by a period of stagnation between the two Great Wars, when trade suffered a setback as a result of higher customs duties and strong protectionist policies. These policies were subsequently mitigated by international trade regulations and agreements among countries. Before then, no rules and guidelines were governing international trade. After the Second World War, however, with the introduction of the GATT (General Agreement on Tariffs and Trade), countries committed themselves improving living standards and moving towards more sustainable development by reducing tariffs.

Indeed, while in the first phase of strong international expansion, the countries that became richer were those that we know to be the G7 nations; in this new phase there was an increase in industrial output in six developing countries, the Industrializing Six, I6, (China, South Korea, India, Indonesia, Thailand and Poland). Since 1990, the G7's world GDP has fallen from two-thirds to less than half. The missing shares of GDP have been gained by 11 growing countries, the so-called Rising Eleven, R11 (China, India, Brazil, Indonesia, Nigeria, South Korea, Australia, Mexico, Venezuela, Poland and Turkey). Among these, China is the country that has gained the most share (Baldwin, 2018).

The graphs below show GDP trends from 1960 to 2010 by group of countries: G7 and R11. The second graph instead highlights China's GDP alone.

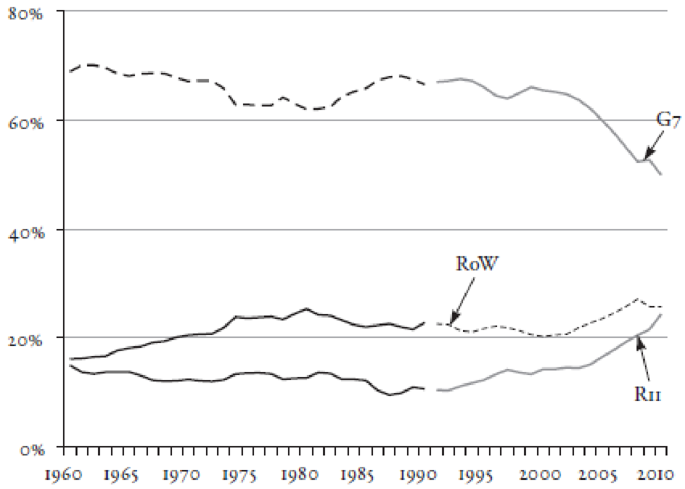


Figure 2-1. G7 and R11 global GDP share redistribution, from 1960 to 2010. Source: Baldwin (2018)

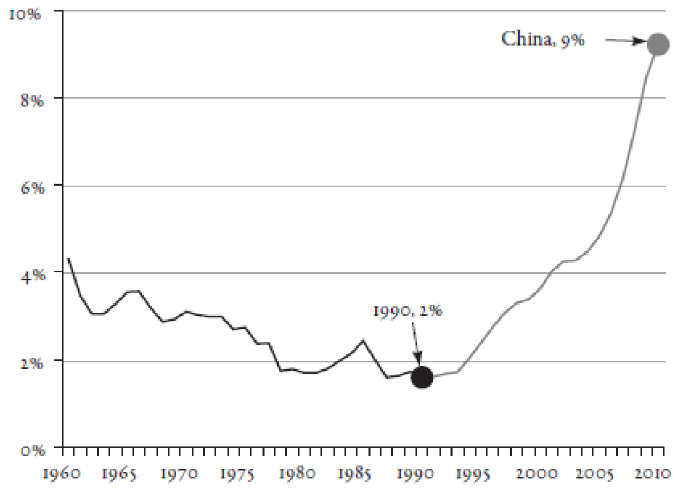


Figure 2-2.China global GDP share redistribution, 1960 to 2010. Source: Baldwin (2018)

During this phase of sharp growth for these countries, there was an improvement and evolution of information technologies that allowed them to reduce the costs of communication. During this period, the technologically advanced countries and some developing countries began to change the nature of their trade, exchanging goods of the same type across the same states: such as machinery from Germany to France and the other way around, from France to Germany. The trade could be in final or intermediate goods. These are the so called intra-industrial transactions (Baldwin, 2018).

This alternation between periods of free trade and more limited periods, due to high customs duties, obviously had consequences. In fact, as Baldwin pointed out, high customs duties do not only affect exports, but indirectly also imports. A country or a domestic company that is in favour of high tariffs will be a company that produces imported goods, because high tariffs cause the prices of imported goods to rise and thus increase their profits. Conversely, an exporting firm will prefer low tariffs from foreign countries, because otherwise they could not export and generate high profits. So, it quickly becomes clear how tariff policies are correlated between countries, and foreign ones will only decrease if domestic ones go down. The tariff policy of high customs duties could be a major problem for those developing countries that would want to enter the trade network and import goods for the creation of final goods. In fact, a component paid at a high price would also have increased the value of the final good, hampering its sale and limiting competitiveness.

Another interesting aspect to remember, when talking about global value chains, and which Baldwin mentioned (2018), is the added value of exports. This value, linked to international trade, represents the value of the final good, net of intermediates goods used in making the exports. In other words, this amount equals the value of exports minus the value of imported intermediate goods that are used to produce the exported items. Thus, in countries where global value chains are substantial, the difference between gross and net value can be substantial. In concrete terms, this is understandable with the example, given by Baldwin himself, of Chinese exports of iPhones to the US market. In 2009, the value of iPhones exported from China to the US was equivalent to USD 2 billion. However, this represents gross exports. The net export value added is only equivalent to USD 0.2 billion. The difference is due to the fact that China imported other goods from outside for the production of smartphones.

2.3. Three-Cascading-Constraints

The historical evolution of global value chains has seen the alternation of periods of greater protectionism and greater liberalism. According to Baldwin (2018), these are connected to Three-Cascading-Constraints. The three constraints are represented by the cost of trade, the cost of communication and movement of ideas and the cost related to people and their circulation. Before the beginning of globalisation, therefore before 1820, all three constraints were in place. Up to 1990, only the last two were active. Today, only the third constraint, related to the movement of people, remains. As each constraint has been removed, the exchange and movement of goods, services and people have increased, obviously leading to an increase in international trade and the enhancement of global value chains. It is, therefore, interesting to briefly analyse each constraint and the associated removal.

Before globalisation, we have already seen that the transport of goods was complex and time-consuming. Therefore, there was the constraint that linked consumption to the same place of production. This meant also low innovation and no growth, due to a dispersed production, that could not be exploited, but instead duplicated because it was required in each country and each city. It is useful to recall the simplified model of Ricardo, 1817. Ricardo took nations as the unit of analysis to conceptualize international commerce as consisting only of trade in goods. According to this model, the process of trade is determined by what is called comparative advantage, or competitive advantage, which means that certain countries are able to do certain things better than others. In this sense, therefore, there will be a specialisation of countries in the production of those goods that they can do more efficiently, limiting the production in the other countries. This leads to a greater import of those goods that the country does not produce efficiently, and a subsequent export of the other products. This trade increases productivity and incomes. In addition, trade liberalisation can reduce unit production costs, thanks also to a denser network of suppliers.

With the arrival of the steam engine, the first constraint was removed. Transport and the movement of people were faster and easier. Consumption and production were no longer bound to the same place. This allowed higher growth and innovation and enabled countries to specialise in the productions in which they were most competitive. This also boosted productivity, accelerated income growth, expanded markets, and accelerated competitiveness.

From this point arose the problem of sharing knowledge, therefore the second limit, the communication constraint, become more important. The issues of knowledge and know-how sharing were crucial in order to be able to transmit useful information to other countries and other companies for the production of goods and services. The cost of communication dropped dramatically in the late 1980s and early 1990s, thanks to the ICT revolution. From that moment on, stages of production that previously had to be contiguous could be dispersed internationally, without having to give up efficiency and timeliness. The fall of the second constraint, linked to communication costs, defines the moment when there is a rapid expansion of the GDPs of the six developing countries seen above. However, the latter, unlike the G7 countries, did not limit themselves to the creation of national know-how, but set up internal supply chains to become competitive and integrated externally into existing regional production chains. The comparative advantage mentioned before is, from this moment, denationalised (Baldwin, 2018).

Whereas previously the competition took place between goods produced in one country and goods produced in another country, now the competition takes place between transnational production chains, called, precisely, global value chains. These chains not only exchange final and intermediate goods, but also knowledge, managerial skills, services, or service inputs. The competition took a different direction: it was no longer just between sectors, but by stages of production. These important changes, however, have an impact on the labour market. The new globalisation and this new kind of competition, aggravated industries that intensively employed low-skilled workers, while it favoured industries that used high-skilled ones. The impact of globalisation had become more individual, meaning that the process of globalisation benefited the single person if the relocation enhanced the competitiveness of the productive activity in which he was engaged, on the contrary, it disincentivised him if the stage in which he was employed was relocated. Indeed, relocation was a problem for workers in the middle segment, those in the middle between the low skilled and the high skilled. The high-skilled could benefit from the competitiveness of the stage of production in which they were employed, while the low-skilled were not directly threatened by relocation because they had to carry out local activities that could not be relocated or automated, as was the case for the jobs of medium-skilled workers.

Delocalisation led to the dispersion of different stages of production, especially in countries with low labour costs. The most controlled costs are obviously those of production, with a focus on wages, depending on productivity, quality, availability, and reliability. Firms tend to relocate labour-intensive low-skilled jobs to countries where wages for low-skilled workers are lower. Conversely, jobs requiring higher qualifications tend to be retained in the "mother" country. Another aspect considered for relocation, besides labour, is the quality and excellence of the products. A company, before deciding to relocate, considers the pros and cons of the quality of the raw material, which it may or may not offset with the cost of labour. The balancing of the two factors will then contribute to the decision of whether, or not, to relocate the production stage. Moreover, a country or a company that is thinking about relocation and participation in global value chains does not decide to offshore the production for a few additional production units and the creation of a few jobs. On the contrary, the aim is to obtain and create more added value from production factors of a country, improving workers' skills, technological capabilities, overcoming internal market failures and ensuring economic progress. It is worth recognising, however, that through the specialisation of countries' production and the possibility of commercialisation, countries can concentrate more on specialising in one or a few factors: learning by doing. In this way, they can increase the quality offered by their products, intended as raw materials, parts, components, or even personnel, know-how and services. In fact, the second phase of globalisation places greater value on services. A great amount of the value added, as Baldwin (2018) reports, comes from services related to manufacturing, in those stages of production located before and after manufacturing, in support of it.

The last obstacle is the high cost of face-to-face relationships. The movement of people from one place to another has been simplified and facilitated by low transport costs, and so has the movement and sharing of knowledge, which thanks to technological developments have enabled fast information exchanges. However, the immediate presence of people from one side of the globe to the other is not yet a reality. Receiving advice from a specific person, face-to-face, first in one country and then in another, is not possible. Nowadays, Skype or Zoom calls are an important part of business meetings and make it possible to almost completely replace the need to talk to and deal with a person. Many aspects of non-verbal communication, however, cannot be interpreted through a video camera and at the same time are indispensable for a complete and trusting relationship. The costs of telepresence, at least for precision telepresence that can guarantee the transparency of all gestures, sounds and movements, replicating reality, are still very high. According to Baldwin (2018), the future will certainly be Telerobots and Holographic telepresence, but for the moment this frontier has not yet been lowered, and the costs of face-to-face remain high.

2.4. Participation indices

According to World Bank (2019), measuring the value added created through the participation of a GVC is problematic, since the standard international trade flows allow to determine *where* the transacted good or service was produced, but not *how* it was produced. Meaning that is easier to establish where the transacted good is flowing to, but not how it will be used, so whether it will be consumed in the country that imported the good, or whether it will be reexported to a third country. Therefore, in order to proceed with the analysis of global value chains and to better understand global trends in chain participation, it is important to understand how the measurements of such participation operate, and which are the main indicators used.

With the intensification of trade transactions and with the increase of interconnections between countries along the production processes, the phenomenon of outsourcing has increased. This led to the creation of the first indices aimed at measuring and quantifying the participation of countries in trade. The initial idea was that, following a production flow that involved more than one country, it was important to determine how much imported goods affected exports. Thus, to determine how much a country was able to participate in the Vertical Specialisation chain, meaning, when a country used imported inputs to produce a final output to be exported, was used the index VS, where at the numerator are placed the imported intermediates, and at the denominator the gross output. The entire ratio is then multiplied by the number of exports, in order to provide a value for the imported input content of exports (Hummels et al., 2001). A second measure, known in literature as VS1, is used to quantify the exports embodied in the second country's exports. So, briefly, the VS index measures the exports that can embody imported inputs, while VS1 is used when exports are used as inputs in foreign production and exports (Hummels et al., 1999).

Wang et al. (2017) attempted to improve the previously existing participation indices in the literature, providing additional detail, thus distinguishing value creation when there are domestic and foreign trade transactions in production activities.

Considering a basic model reported by Wang et al., a country-sector can create value-added in four different situations:

- Value-added produced and consumed domestically, that it does not involve cross border trade;
- Valued-added embodied in final product exports. This embodied domestic factor content crosses national borders for consumption only;
- Value-added embodied in exports/imports of intermediate goods and services. This is part of the cross-country production sharing activities since it is used in activities outside the home-country. Depending on the number of times the value-added crosses the borders, this third level can be divided into two subcategories:
    - Simple cross country production sharing activities
    - Complex cross country production sharing activities

  The first sub-category includes those values generated after a unique cross-national border, meaning that the value-added embodied intermediate exports/imports used by a direct importing country to produce products that end in that country. There are no indirect exports via third countries, nor re-exports/re-imports of the factors.

  The second sub-category includes domestic and/or foreign value-added embodied in intermediate exports/imports that is used by other countries to produce their exports. The difference from the previous sub-category is that in this case, it crosses the national borders at least twice.

The chart below summarizes the classification.

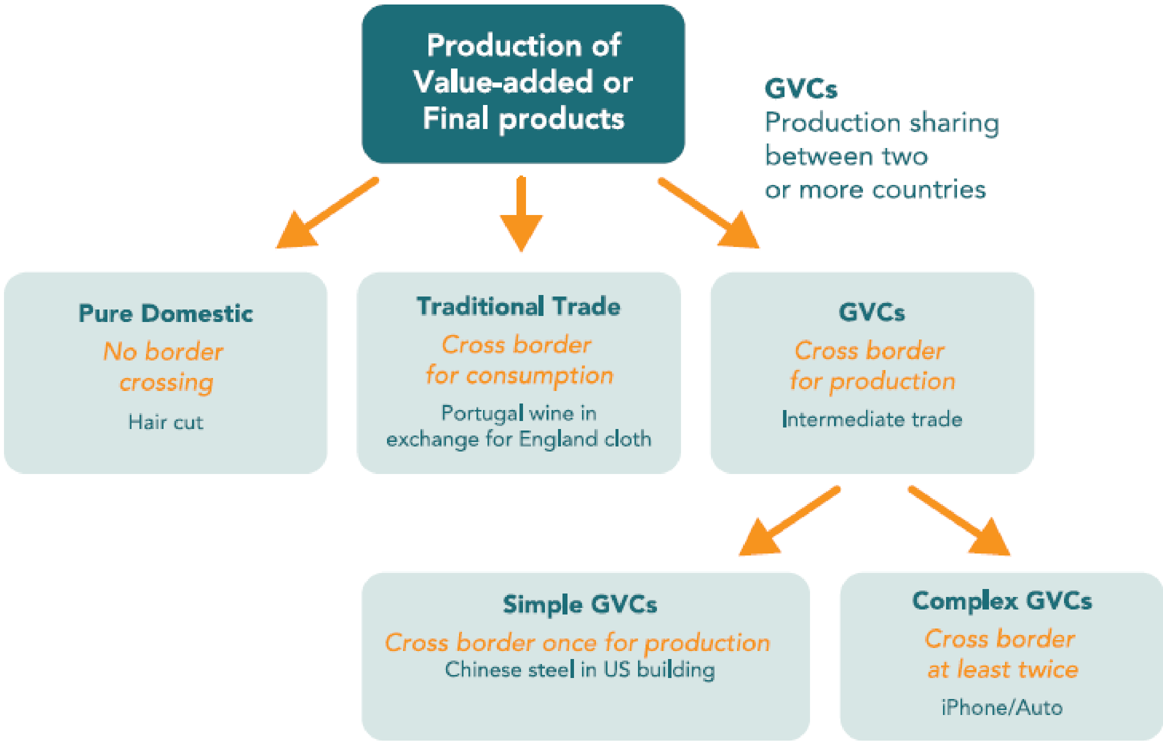


Figure 2-3. Decomposition of production activities. Source: Global Value Chain Development Report 2019.

Thanks to this classification, it is easy to compute and distinguish all the values produced and consumed domestically, what is produced to export, what is produced involving a simple international transaction and, lastly, what is produced through a more complex step, so including domestic factor content from a country-sector that is embodied in intermediate exports/imports and used by direct importing country/home country to produce exports/final product. The distinction can be used both for upstream and downstream linkages and used to identify the part of production, and final good that belongs to global value chains.

Going further with the analysis the authors noticed that a firm can participate in international production sharing in four ways:

- Exporting its domestic value-added in intermediate exports used by a direct importing country to produce for domestic consumption;
- Exporting its domestic value-added in intermediate exports used by a direct importing country to produce products for a third country;
- Using other countries' value-added to produce its gross exports;
- Using other countries' value-added to produce for domestic use.

Starting from this point, Wang et al. (2017) improved the traditional indexes used in literature and proposed by Hummels et al., seen previously. They identify and construct indexes that are able to measure the extent to which production factors used in a certain country-sector are involved in the global production process. The two GVC participation indices are the following:

The first one, also known as DVX or **Forward Participation**, is the Indirect Domestic Value added in Exports:

This index describes the "domestic value added generated from a country-sector's GVC activities through downstream firms as share of that country-sector's total value added" (Wang et al., 2017). In other words, the domestic value added generated from GVCs production and trade activities as a share of GDP. The denominator represents the total value-added generated by that specific country-sector, while the numerator equals the domestic value added embodied in the intermediate exports of that country-sector to the world. The advantage of this measure is given by the relation to the value-added rather than gross exports and that is related to production instead of trade.

The second index, known as FVA or **Backward Participation** is the Foreign Value Added in exports:

This measures "the percentage of a country-sector's total production of final goods and services that represent the value added that is involved in GVC activities through upstream firms" (Wang et al., 2017). In other words, the percentage of a country's final goods production is contributed by both domestic and foreign factors that involve cross country production sharing activities. This measure, in fact, includes, besides foreign value-added embodied in intermediate imports, also domestic factor content returned home through international trade.

These two indexes take care of both upstream and downstream perspectives. The authors, indeed, decompose the production activities into different types: the producer's perspective and a user's perspective, are considering forward and backward industrial linkages.

The two indices allow to compare a country-sector position in a global production perspective, determining its participation in the global production network. A high degree of forward participation, rather than backward participation, means that the country-sector is more committed in upstream production activities.

Therefore, in order to resume and recall the main indicators, in accordance with WTO, OECD TiVA database and UNCTAD, it is possible to classify and distinguish the indexes of participation in global value chains in domestic origin and foreign origin value added and the following are the key participation indexes:

- **DVA**: Domestic Value Added in exports. It represents the value added in exports in which the outputs are produced entirely by domestic industries.
- **FVA**: Foreign Value Added in exports. It measures the value added in exports whose outputs are produced by foreign industries. Known as backward participation.
- **DVX**: Indirect Domestic Value Added in exports. It includes the value added that is embodied in the exports of other countries, so it represents the upstream contributions of DVA of other countries. Known as forward participation.
- **GVC**: (FVA+DVX)/Gross exports. The indicator shows how the sector is involved in the Global Value Chain, through both backward and forward linkages.

2.5. Global trend of the last decades

Going deeply into detail on the historical analysis of GVC data, it is possible to see, also thanks to the graph below, how trade has intensified over the years, triggering a major growth in global value chains. From the 1990s until 2008, companies relied heavily on GVC relocating their production to low-wage countries. This period is referred to as the era of hyper-globalisation, and GVC accounted for 60% of the growth in world trade (Kilic & Marin, 2020).

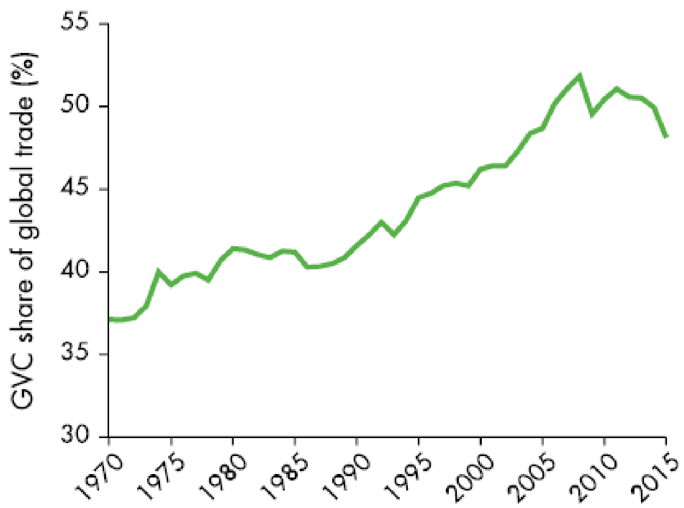


Figure 2-4. GVC participation corresponds to the share of world exports that flow through at least two borders; measured following the methodology from Borin and Mancini (2019). Source: Antràs (2020), World Bank (2019)

This prosperous era came to an end with the Global Crisis of 2008. At that time and in the following years, economic uncertainty increased and in 2012 the World Uncertainty Index increased by 200% (Kilic & Marin, 2020). Since the post-crisis period, GVCs have never resumed the increasing trends of the pre-crisis period. In fact, countries had started reshoring activities back to home countries or rich countries. Douglas (PIIE, 2020) defined the period from 2008 to 2017, "*slowbalization*", since the trade openness index, given by the sum of world exports and imports divided by world GDP, decreased, due to the erection of trade barriers on imports, mainly between USA and China. These barriers, according to the author (PIIE, 2020) disrupted the global supply chain and led to the creation of other trade barriers elsewhere. Besides the increase in risk, measured as the Uncertainty Index, another factor characterising slowbalization is the decrease in the cost of automation. The combination of increased risk and favourable investment conditions have changed the relationship between investments in automation and GVCs: before the crisis, companies used both strategies, investments in automation and offshoring; after the crisis, the two strategies were no longer complementary, and companies replaced investments in GVCs with the adoption of robots (Toschi, 2020).

Continuing with the analysis, in addition to the crisis of 2008, the trends in global value chains recorded a negative trend in 2015 and remained at a flat level in the following years, which is visible in the graph below. This is explained by a phenomenon of protectionism widespread among advanced industrial countries, in particular, it is easy to understand if we think to the policies implemented by the United States of America following Trump's inauguration or consequences related with the departure of the United Kingdom from the European Union. These protectionist policies are definitely not new and have intensified even more with the covid-19 emergency. The need for national security and protection of essential productions and frontier technologies developed within the country made protectionist policies even more relevant (Fondazione Nord Est, 2020). With the outbreak of the pandemic, these feelings of protectionism have been reinforced and new factors that affected GVCs developed. Both advanced and non-advanced economies started to adopt new technologies more and more, leading to changes in world trade as well. Thus, digital technologies lead to a reduction in GVC participation, decreasing the barriers that firms typically should face when entering in GVCs. Reducing the costs, mainly the initial fixed costs that a firm bears, facilitating the match between buyers and sellers, or facilitating the entrance in GVC to small companies, or, again, digital technologies allow easier and faster management of inventories and logistic issues improving participation also in manufacturing segments (Antràs, 2020). The high pressure of digital transformations and technological innovation has reduced the need to delocalise, allowing, instead, the development of automated systems and integrated robotics domestically. According to Fondazione Nord Est (2020), in fact, it is assumed that the new globalisation will be characterised by less international trade in final and intermediate goods, and more by information flows and knowledge sharing. In addition to this, can be mentioned also the important role played by MNEs, which have always covered a key role in GVC. Indeed, the diffusion of these large companies has driven some of the trends in GVC participation, depending on whether they choose to produce in their home-country, relocate to third countries or invest in FDI. With the diffusion of technology and the choice to produce goods themselves, together with a decrease in costs, these MNEs have led to a decrease in the last decades of GVC participation (Cigna et al., 2022).

Finally, a worsening of the global economy can also be seen from another factor, the FDIs, often taken into account when talking about global value chains because it is closely related to international trade transactions and the decision to offshore production. Openness to FDI is often linked to increases in GVC, as companies, observing productivity and cost differentials across countries, determine where and how to produce. In fact, a first decision made by companies when it is not convenient to produce a product internally, is whether to outsource that activity or to do it through FDI. In the latter case, GVCs, and in particular backward participation, are increased (Cigna et al., 2022). However, from the World Investment Report 2021 (UNCTAD, 2021) it is possible to observe how Covid-19 generated a 35% drop in foreign direct investments in 2020, compared to the previous year, leading to a monetary decrease from \$1.5 trillion in 2019 to less than \$1 trillion in 2020. Most of the decline is recorded in developed countries. Douglas (PIIE, 2020) argues that the global pandemic only adds "further momentum to the retreat of globalization", started in 2008 and continued with the trade barriers. In addition, Cigna et al. (2022), states that during the pandemic GVCs only registered a decrease in the first period of 2020, with a quick recovering in the second half of 2020. This is mainly due to trends related to China: when the Asian country recovered in the second quarter, trade in intermediate goods also increased, generating a positive trend globally.

Today, almost 50% of global trades involve GVCs, and in the last decades, global value chains powered an economic revolution, including growth accelerated and income rose. Even if today the trend is not as positive as before the financial crises of 2008, GVCs can still represent a force for sustainable and inclusive development for both developing countries and advanced economies (World Bank, 2019).

In the graphs below, it is possible to see how the trend of GVCs has changed over time at a global level, from 1990 to 2018. In particular, it is interesting to note that developing countries, such as China, have grown the most both in terms of forward participation and backward participation. On the contrary, developed economies, such as European countries or the United States increase mainly in terms of backward participation, thus increasing foreign value added.

Moreover, according to Cigna et al. (2022), supply chains have strengthened their regional structure over time, thus requiring raw materials and intermediate goods in their own production area, especially for European and Asian countries. Latin American countries, on the other hand, have strengthened their GVCs, as the graphs show, by increasing their participation in international trade. The authors also point out that the level of economic development, measured by GDP, and the degree of the economy has a positive relationship with backward linkages, while it is negative with labour costs. In fact, labour costs represent an important factor taken into consideration when companies decide to offshore the production. The positive link with backward participation is also given by sound institutions, investments in education and tax burden.

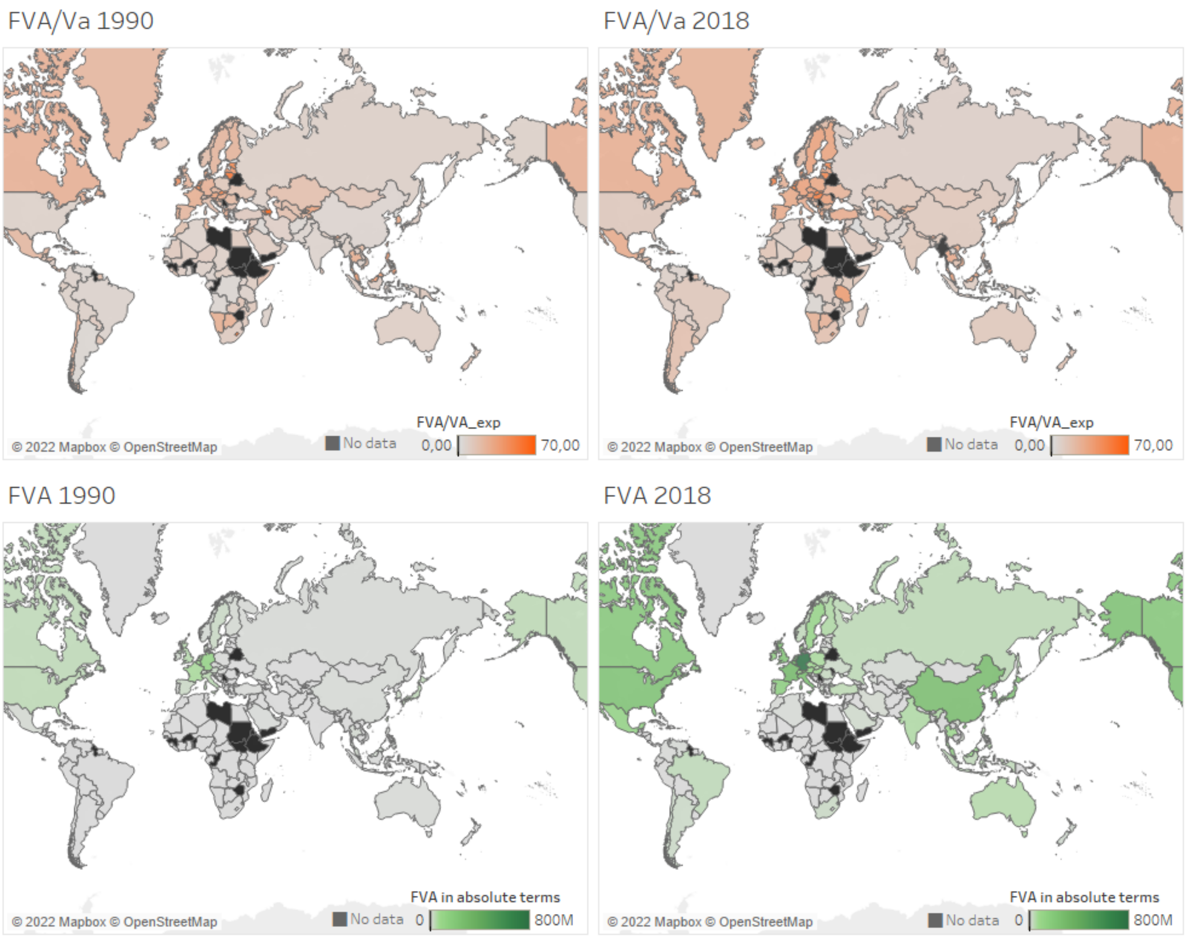


Figure 2-5. Backward Participation. Data source: Eora database. Own Elaboration

This first set of graphs, show the change over time of backward participation. In the upper area there is the variation in % terms of the index. It does not show important variation, but a general increase of the participation of all the countries. China and Latin America increase, as well as

European countries. In the lower part, Figure 2-6 returns data in absolute terms, showing, again a general increase of all the countries from 1990 and 2018. The graphs highlight also that the most important players are represented by advanced economies, with Germany covering the first place.

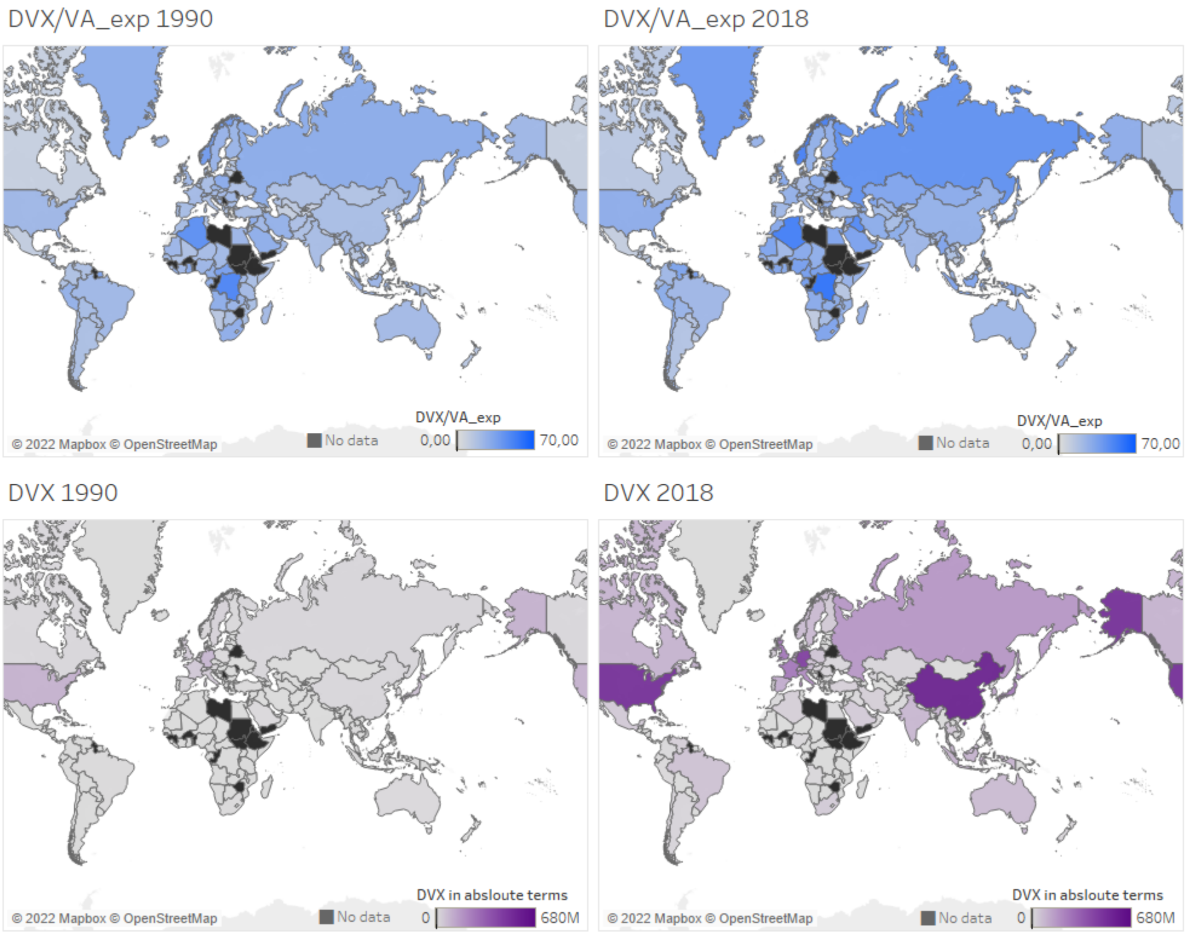


Figure 2-6. Forward Participation. Data source: Eora database. Own elaboration

In the second set of graphs are plotted forward participation measures. From 1990 to 2018, even in this case is recorded a general increase of participation, as demonstrated by the first part of the figure. The two maps on the bottom, instead, reveal important increases, in absolute terms of domestic value for exports of other countries mainly in China, Germany, United States.

The following charts, Figure 2-7, in fact, point out the main players in GVC. In both cases, the intensity of colours represents the participation in GVC, in absolute terms for the countries. The dimension of circles, instead returns the participation, forward and backward, for the countries, where the higher the participation, the greater will be the circle. The relevant points that emerge are the major players of the global value chain participation.

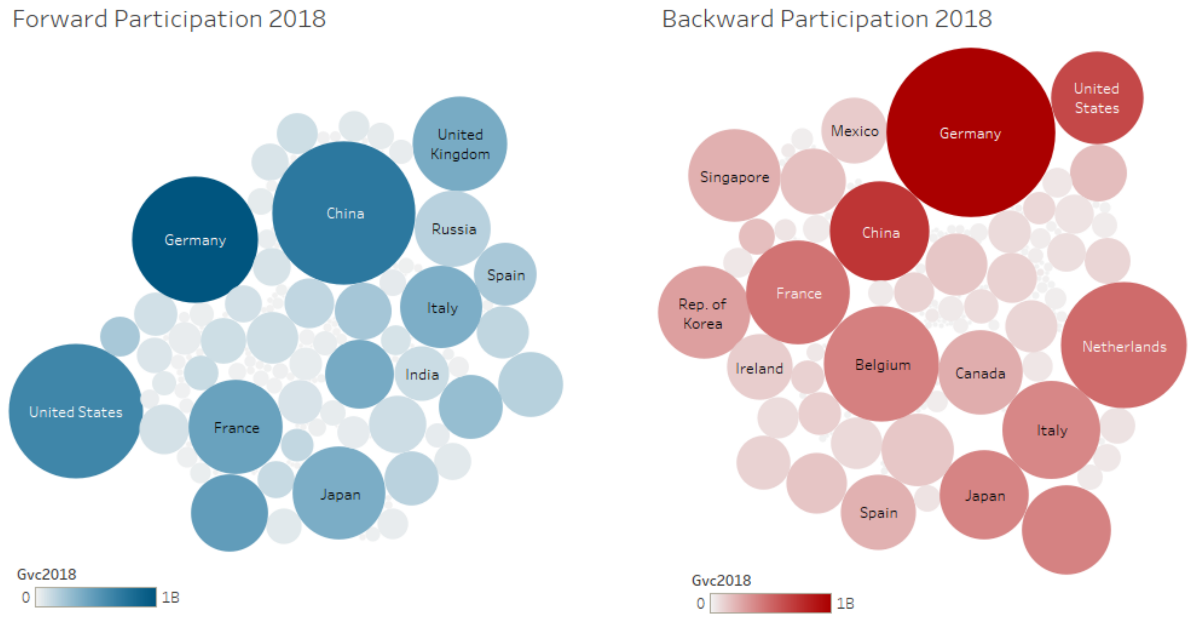


Figure 2-7. Relationship between GVC, DVX and FVA in 2018. Data source: Eora database. Own elaboration

Figure 2-8 resumes the index GVC/VA, grouping countries per continent.

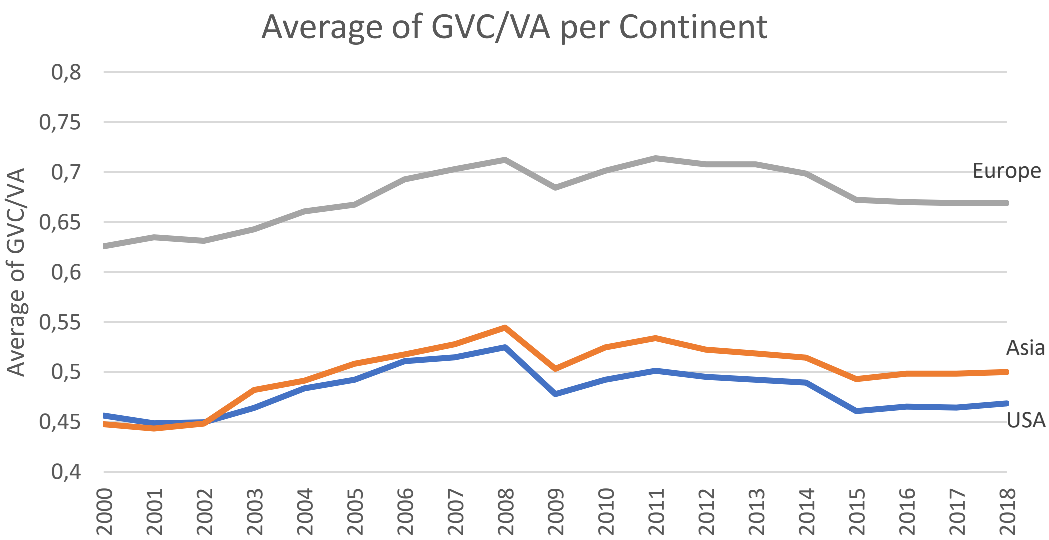


Figure 2-8. GVC per continent. Data source: Eora database. Own elaboration[4]

[4]The chart takes into consideration 24 countries. Asia includes China, Japan and Republic of Korea; Europe includes Austria, Belgium, Czech Republic, Denmark, Finland, France, Germany, Italy, Norway, Netherlands, Poland, Portugal, United Kingdom, Romania, Slovakia, Spain, Sweden, Switzerland, Turkey and Hungary.

2.6. Consequences of participation in GVC

The increase in global value chains and its participation over time inevitably generates consequences and changes for companies and countries. In the past, international trade was mainly characterised by the exchange of finished goods. Over the years, however, this aspect has changed: considering the presence of fixed costs, it is easy to understand how companies have increased their participation in global value chains by including raw materials, intermediate goods and also services, in trade transactions. More specifically, by importing goods at a lower cost, companies enjoy cost advantages, and they will be more efficient thanks to the creation of economies of scale in production, increasing the benefits they can receive from participating in GVCs. In addition, the improved efficiency that results will mean that less productive firms would exit GVCs. The efficiency resulting from the specialisation of one or few production steps, within a larger production, allows smaller countries and companies, which otherwise would not have been able to do, to enter global value chains (World Bank, 2019) Small and developing countries, thanks to the new globalisation, have the opportunity to embed themselves in a production stage, learn the know-how, specialise, but most importantly compete globally without having to specialise in the whole sector (Baldwin, 2018) The general idea is that participating in GVC bring "positive and significant gains in productivity and technology spillover […] thus improving the economic growth" (Wang et al., 2017). The positive effects are a consequence, as already mentioned, of a finer division of labour and task specialization, leading to the development of a competitive advantage. Antràs (2020) adds that larger firms, or those that are efficient enough to amortize the costs associated with importing inputs, will also be able to export successfully, and will be associated with high backward GVC participation. In contrast, firms that export raw materials and semi-finished goods are associated with high forward GVC participation.

Antràs (2020) points to further consequences and aspects of increased participation in value chains. Indeed, countries with high levels of skilled workers benefit from a comparative advantage in producing goods that require high levels of specialisation and knowledge, while they have an advantage in importing low-skill-labour-intensive goods from countries where low-skilled labour abounds. The factors that a country possesses and benefits from, are of crucial importance in determining its participation in global value chains. Indeed, a country with a high rate of natural resources will be more likely to have high levels of forward participation in GVCs, as it will export its raw materials to other countries and companies in the downstream production process.

In conclusion, this increase in participation in GVCs over time has been confirmed to be linked to several benefits, both for the participating companies and the host countries (OECD, 2013). By specialising in a single stage of operation or a single product, as just mentioned, companies can become more efficient and productive and can import, from other countries, those goods that they cannot produce internally as efficiently as others do. In this way, it is obtained a direct advantage: the reduction of production costs. Furthermore, an indirect effect is achieved: participating in global value chains, companies can reach a wider field, so that they can boost efficiency and income, increasing the scale of operation of firms engaged in GVC, thereby average costs are reduced, and productivity enhanced (Antràs, 2020).

On the other hand, of course, there are also risks involved in participating in GVCs. By linking up in a chain and thus increasing the level of interconnections with others, countries or companies, there is a risk that the partner will suffer shocks that may have negative effects. According to OECD (2020), however, this exposure to risk is not necessarily linked to higher economic losses. In fact, thanks to this network, companies are able to create greater diversification, which then leads to a mitigation of risks, both direct and indirect, which are those related to partners. To cope with this problem, some argue that a more localised production is desirable, thus favouring a process of reshoring, limiting the effects of external shocks. However, this would not be beneficial if the shock occurred internally within the country. The study conducted and presented by OECD (2020) reveals how "localised regime, where economies are less interconnected via GVCs due to a combination of higher import tariffs, subsidies to domestic production and less flexible sourcing possibilities in GVCs, has significantly lower levels of economic activity and lower incomes". Furthermore, it seems that these regimes are more vulnerable to shock. The research shows that, typically, interconnected countries are better off, both in terms of level and stability of economic activity.

Another negative factor that emerges from the Antràs study (2020) related to the participation of countries in GVCs is the disequilibrium that emerges between wages of skilled and unskilled workers. Thus, in economies with a high rate of skilled workers, the relative wages of skilled workers appear to be higher than those of unskilled workers, while wage inequality decreases in countries with few skilled workers, generating inequality in the distribution of income.

2.7. Slowbalization and reshoring

As we have seen so far, the period following the financial crisis is characterised by an opposite trend to hyper-globalisation: Slowbalization. The downward trend of global value chains and international trades changed also due to political choices, such as those dictated by Trump and translated by the slogan "America first", aimed at protecting American jobs, or the departure of the UK from the European Union. But these are not the only causes: Covid-19 pandemic, large-scale cyber-attacks, geographical events, heat stress, flooding and trade disputes are also impacting global value chains. All these phenomena generate important consequences in international trade. Uncertainty and increased risk change the perception of companies, consumers, but also of governments themselves, increasing costs and generating changes in trends. More specifically, Brakman and van Marrewijk (2022) highlighted how global value chains were often too long and vulnerable, therefore not able to deal with shocks like a crisis. Recovery times would be too long and production inefficient. "Practices such as just-in-time production, sourcing from a single supplier or relying on customized inputs with few substitutes amplify the disruption of external shocks and lengthen companies' recovery times" (McKinsey, 2020) from Brakman and van Marrewijk (2022). From the literature review emerged that the more companies are involved in global value chains, the more susceptible they are to shocks. In fact, the two authors reported "the stronger the involvement in global supply chains, the slower the recovery of countries to recessions". Being too dependent on value chains, leads governments, firms and consumers to re-evaluate the total benefits offered by long supply chains. Cigna et al. (2022), also report in their paper how, due to the country connections that exist for GVCs, a problem arising in one country can generate problems in the imports or exports of other countries, even indirectly linked to the first country. This could be seen especially from the problems generated as a result of COVID concerning the supply of goods and bottlenecks created. In fact, the failure of one single supplier causes problems for the whole production chain, leading to increased costs for downstream firms, which have to search for other suppliers or produce by themselves. The authors came to the conclusion that interconnected countries that produce substitutable items are better positioned to face GVC shocks.

To cope with this problem, therefore, the main solution suggested is to stop relying on foreign production, making global value chains shorter. This is embodied in the phenomenon of reshoring. The solution leads to a reduction in the costs that firms and states would have born as a consequence of the shocks and, at the same time, to the rise of slowbalization. At the same time, however, there does not seem to be a cohesive point of view. In fact, if on the one hand the pandemic, and thus a shock, led to the reshoring of production, on the other hand, it generated a reduction in the length of GVC. By shortening the supply chain, the risk is not mitigated, and countries would face higher problems caused by shocks generated internally (Cigna et al., 2022).

According to Brakman and van Marrewijk (2022), it is not only gross exports (in % of GDP) that have fallen, but also GVC shares (% of total trade), demonstrating a shift of activities from third countries to home countries, thus shortening supply chains.

It will therefore be interesting to find out whether there is any real empirical evidence of the development of slowbalization, and reshoring, supported by investments in robotics.

According to Cigna et al. (2022), the impact generated by automation does not seem to be clear and well defined. Indeed, on the one hand technology and robotics lead to higher productivity, thus making firms, especially MNEs, choose to relocate from low-cost countries back to advanced economies, bringing production back home. On the other hand, however, the same new-generation technologies have the advantage of shortening communication and knowledge transfer times, thus leading to a further unbundling of production. The overall effect and impact are not well defined. Therefore, we are going to analyse if there exists empirical evidence between investments in robotics and GVC indexes participation.

CHAPTER 3 - EMPIRICAL ANALYSIS

Now that the concepts of robotics and global value chain have been introduced, and the trends and effects of the individual phenomena have been explained, we can go further analysing how they are connected and interlinked. We are going to observe which are the main effects that robotics creates on employment, an effect already introduced, but in this chapter, we will consider an international perspective, thus taking into account productivity and employment generated at the level of different industries through the global value chain network.

In this chapter, therefore, the relationship between robotics and global value chains will be analysed and will be introduced the main purpose of this thesis. It will be presented the relationship that exists between the cost of investment and the cost of personnel in order to understand its convenience and to try to explain the market trends associated. Then following with the consequence this cost rate causes to GVCs, and in particular to backward and forward participation. For the last part of the thesis, it will be presented an econometric strategy with the analysis performed adopting the PVAR model and testing the variables through a Granger causality test. There will be then discussed the main results obtained by the research.

3.1. Robots and GVC: the current state of the literature

In order to start the analysis with the relation between robot adoption and global value chains, we begin from the effects that robotics generates in the labour market, and in particular, we recall the effects on employment, TFP and real value added. Now, however, the analysis is supported by an international perspective, differentiating the impacts by industries, countries, and also by origin and destination industries across global value chains. In fact, the increase of robotics in one sector may not affect the sector itself, but it may generate important variations on other neighbouring sectors, through backward or forward linkages. The example given by Ghodsi et al. (2020) helps to better understand this situation: a service industry will not adopt robots, because by definition, it will never need them, and therefore cannot benefit from any direct effect from robotics. However, it may receive some indirect effects from the use of technology by related industries, such as a manufacturing industry that adopts robots for computers or electronics and enjoys better productivity, offering higher quality products at a lower price. Consequently, non-manufacturing industries could also adopt these types of products, which are more efficient and could increase productivity in service industries as well. This, therefore, generates an increase in productivity in sectors that are different from the original one, and potentially it also generates an increase in employees.

According to a study conducted by Autors and Salomons (2018), where they try to explain the effects of technological progress on employment, there exists a positive impact on it. The authors studied the effects on four different labour market outputs: own-industry effects, upstream-industry effects, downstream-effects and final demand effects. This is precisely because if an industry becomes more productive, for instance, by automating a number of processes, downstream industries might also benefit since the price could be lower, thus representing a positive effect in forward linkages. In the same way, suppliers in upstream industries may take advantage of this higher productivity, for an expansion of the industry and a consequential increase in demand of inputs from the upstream firms. The latter will be a positive backward linkage. They concluded that automation offers a negative direct impact on employment, but positive indirect effects, and overall, the positive results outweigh the negative ones. The study carried out by Autors and Salomons (2018) considers total factor productivity (TFP) as the instrument to measure the effects of automation and technological progress and treats a range of advanced countries within the model.

In the more detailed study conducted by Ghodsi et al. (2020), however, the range of countries is widened to include emerging and transition economies; the impact of the change in the stock of industrial robots is considered; and finally, the important aspect of the consequences generated in foreign countries along the GVC is analysed, so considering international linkages, in addition to domestic linkages.

The first investigation (Autors and Salomons, 2018) concluded that there are positive effects on employment due to a change in TFP at domestic backward linkages level, while there appeared to be no significant effects for domestic forward linkages. Ghodsi et al. (2020), in addition, emphasised the importance of global chains, showing that there is a significant correlation for employment and international forward linkages. Indeed, "real and nominal value-added growth is positively affected by own-industry TFP growth, backward linkages - both domestic and international- and international forward linkages" (Ghodsi et al. (2020).

Improving the research, and taking into account robotics, it was also found that the growth of robots has positive and direct impacts on employment growth, growth in hours worked and value added. On the other hand, no significant effects were found with respect to the labour share. Regarding the effects of robotics on the value chain industries, positive effects are found for domestic backward linkages, but only for hours worked, while for international chains positive effects are found both for hours worked and nominal value-added growth. In the case of forward linkages, on the other hand, again from the study conducted by Ghodsi et al. (2020), it can be seen that a variation in the stock of robots determines significant negative effects on the outcome variables, with the exception of labour share and real value-added growth. If, for example, companies downstream in an industry are thought to be more efficient and digitalised, they will consequently have less need to have certain tasks carried out by other companies further down the chain. Consequently, upstream companies will be negatively affected, thus producing a negative impact along the domestic forward linkages.

To sum up, there is a positive direct effect on backward linkages, both domestic and international, and a negative direct effect for domestic forward linkages, while the effect for international forward linkages is positive. Overall, the positive effect is stronger, yielding a positive effect of 0.3% per year on employment[5] (Ghodsi et al. (2020). Figure 3-1 summarises these generated effects on employment, also breaking down the categories by type of market analysed. The major effects come from emerging economies, as they are characterized by high growth rate in stock of robots, they started from a low number of technological machines, and they have greater opportunity of growth.

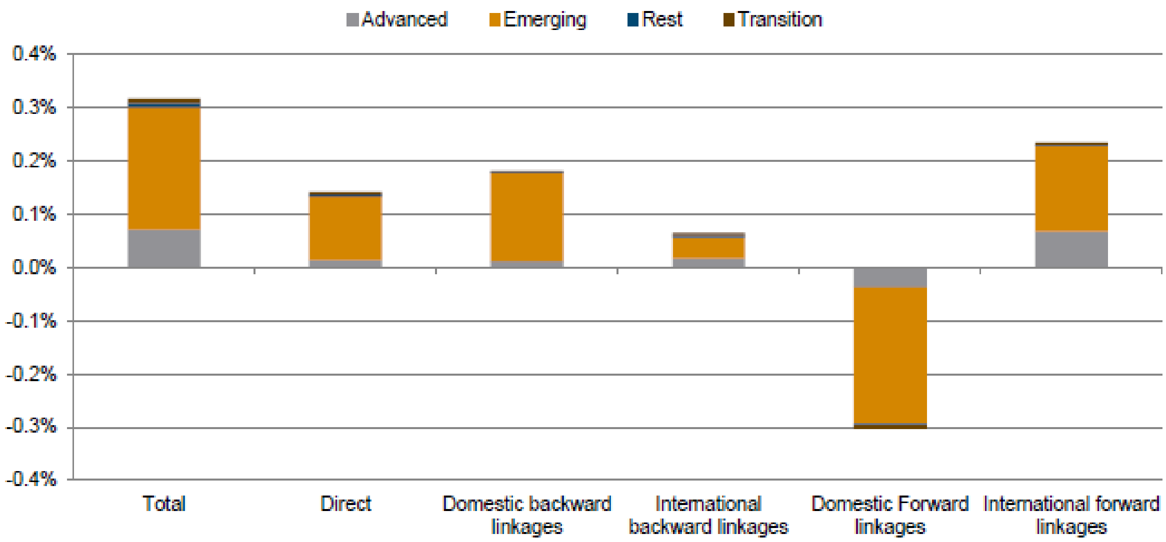


Figure 3-1. Predicted effects of the growth of robots on economy-wide employment, World Input-Output Database average. Source: Ghodsi et al. (2020)

The effects generated by a variation of robotics have also been analysed in terms of real value added. Here again, the international relationship is not indifferent; indeed, the greatest impact is generated at the level of international forward linkages. In this case, the main impact is

[5] Statistically significant at 10 per cent level, according to Ghodsi et al. (2020).

generated by the advanced economies, due to their higher share of value added in the world economy.

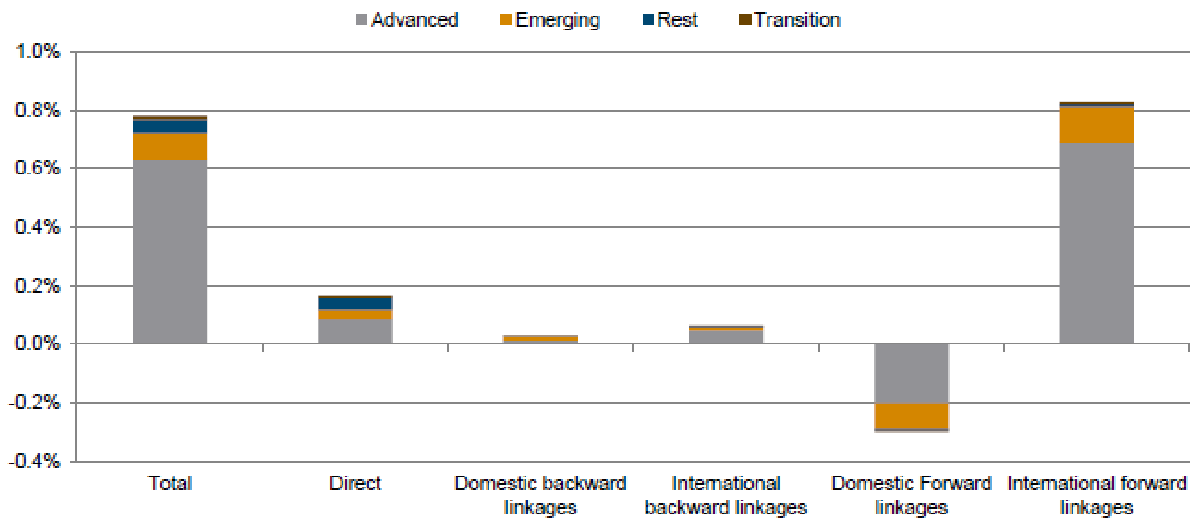


Figure 3-2. Predicted effects of the growth of robots on economy-wide real value added, World Input-Output Database average. Source: Ghodsi et al. (2020)

A last analysis carried out by Ghodsi et al. (2020) was aimed at understanding which are the major industries with the greatest impact on employment of other industries. Obviously, the manufacturing sector has the most direct impact, according to the origin perspective, considering that it is the sector that adopts robotics the most. On the contrary, services industries not using robots have a direct effect, following the origin perspective, equal to 0. This, since the industry does not adopt robotics, then it is not responsible for any change, in employment, in other industries and countries. On the contrary, the manufacturing sector, by implementing robotics, creates positive impacts in other industries and countries.

3.2. The research question

Having introduced this relationship between robotics and global value chains, we can introduce the problem that we want to investigate in this thesis. To do so, we make also use of the study conducted by Faber (2018), aimed at knowing what the consequences in an emerging and offshoring country are, such as Mexico, after an increased use of robotics by an advanced country, the United States. Faber tried to analyse the impact of the increase of robotics in advanced countries, in the employment rate in countries where previously there was offshoring, therefore how robotics impacts the reshoring process. Reshoring, according to Faber, "describes the reverse process of offshoring, where manufacturing is moved to another country where labour is cheaper". A driver that leads to reshore a process for companies can be the reduction of costs of production, due to an advance in robotic automation. Therefore, robots can fuel reshoring, as they increase the relative attractiveness of domestic production, as compared to offshoring. Research has shown that increased adoption of robotics in the US has a negative impact on employment in Mexico, by reducing the exports to the US. Two groups of workers appear to be most affected: low-educated machine operators and technicians in manufacturing, and highly-educated service workers in managerial and professional occupations. In fact, the estimate predicts that the Mexican labour market, if exposed to US robotics, would be negatively impacted by 2.9 percentage points of lower growth in the employment-to-population ratio. This determines that "one US robot roughly replaces 11 Mexican workers" (Faber, 2018).

In this thesis, we will therefore attempt to analyse and understand the effects of investments in robotics on global value chains. More specifically, considering the argue that robots seem to be the driver for the revival of manufacturing rich countries, we are going to study how the main indices of participation in global value chains vary over time, and if they are in line with the slowbalization phenomenon. We will try to understand whether an increase in investments in robotics in advanced economies leads to a decrease in forward participation while increasing backward participation.

To do so, we will also consider the years of Global Crisis, taking 2008 as a reference point, a year that characterises important changes in trends of indices of value chains, but also in the change of the cost of robots relative to hourly wages. By retrieving a graph highlighting the global trend of GVCs, from the years 2000 to 2014, and focusing on 2008, the steep decline in the evolution of global value chains, already analysed above, immediately appears.

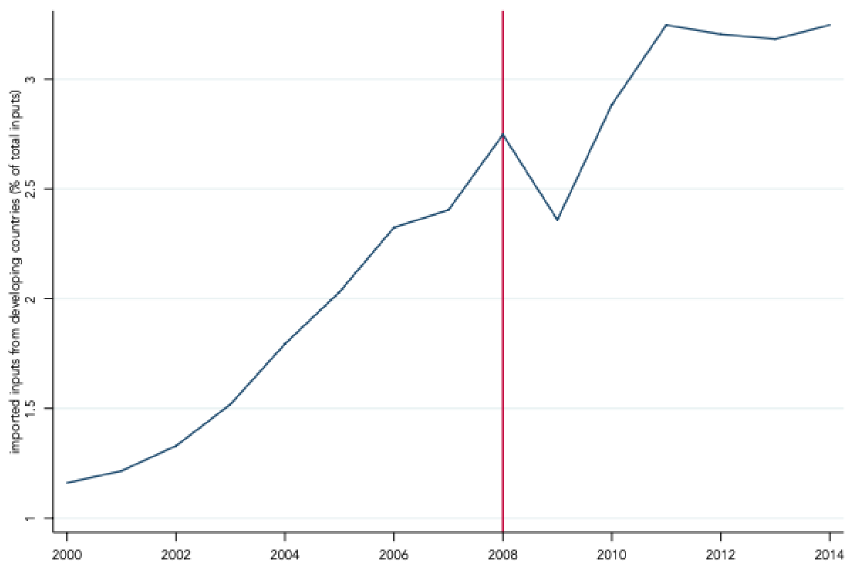


Figure 3-3. The evolution of global value chains, 2000–2014. Source: Kilic & Marin, 2020

Now, it is interesting to add into the analysis two variables, which are the wages and the interest rate. This measure, given by $\frac{r}{w}$, represents the convenience for investments in automation in relation to adopt employees for production. After the global financial crisis, companies started to compare the difference between wages in low wage countries, where they used to offshore the production, and wages in their home countries, with the saving in cost achieved using robots. The global crisis made the cost of global supply chain more expensive, with the additional risk of non-delivery of goods. Moreover, after 2008 firms expected higher tariff rates, thus a higher price for inputs as they need to cross several times country boundaries. During this phase, a reduction in the cost of robot adoption is also recorded, therefore encouraging the investment in automation. The mix of these two characteristics is observable in a reshoring of production back to home markets with an increase of investment (Kilic & Marin, 2020). It can be concluded that before the Crisis, GVC and use of robots were complementary strategies, while after the global crisis, they became substitutes.

The graphs below show the relation of investment rate to hourly wages of some advanced economies. All the rates decreased after the Crisis, even if for the US the negative slope became few years earlier.

Figure 3-4. The cost of a robot declined relative to hourly wages. Source: Kilic & Marin (2020)

At the same time is useful visualize the increase in robot adoption, with the threshold in 2008. The graph shows the two main industries adopting robots, which are automotive and electrical/electronics sectors, as well as the general trend for all industries.

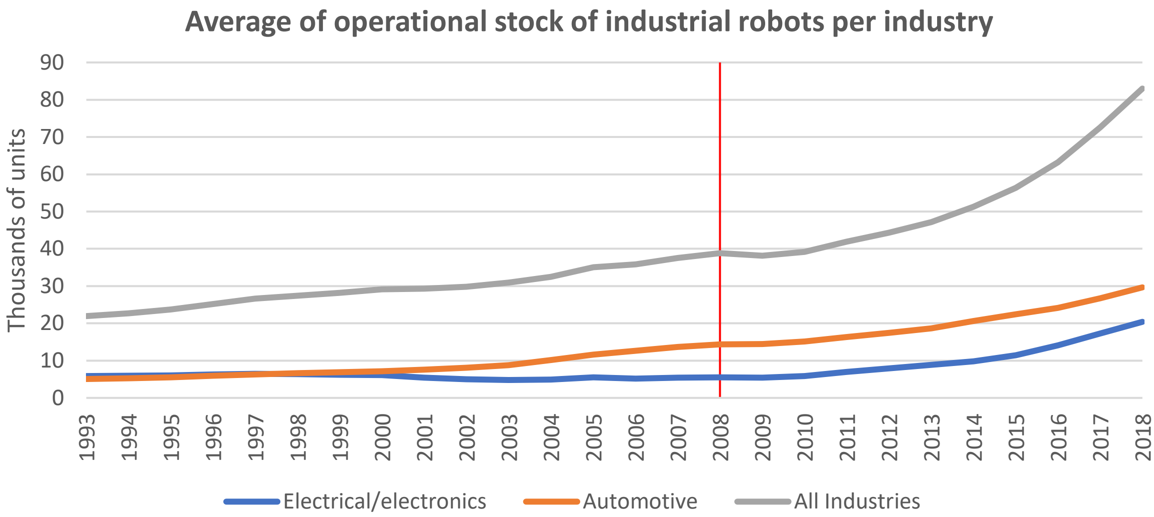


Figure 3-5. The average operational stock calculated for 24 countries.
Source: data come from IFR (2021); industries respect ISIC rev. 4. Own elaboration

It has already been said, therefore, that GVCs have declined since 2008 and here below it is possible to observe changes in the trends of the main indices of participation in global value chains.

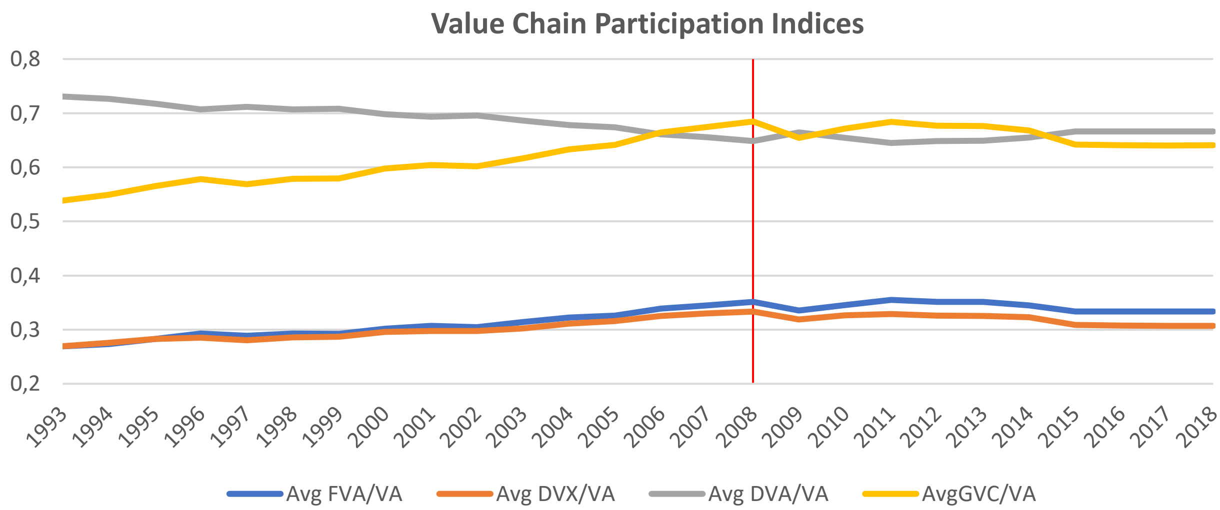


Figure 3-6. Value chain main participation indices. Average of indices calculated for 24 countries.
Source: EORA Database. Own elaboration

From this point forward we want to start to pursue the research of this thesis. We want to investigate whether there is a significant relationship between an increase in investment in robotics and a change in forward and backward participation. In particular, the research is aimed at knowing whether, and in which terms, robotics is a driver of the slowbalization phenomenon.

3.3. Data

The data used for the research came from three major sources: EORA Database, IFR (International Federation of Robotics), and WorldBank.

For the analysis we took into consideration a panel of 24 countries for 26 years, from 1993 to 2018, for a total amount of 624 observations. The choice of years was constrained by the availability of data in the different sources. The countries analysed are advanced or developing countries and the list of them, with their respective geographical area, and continent is the follow. In the Table 3-1 are also included statistical information related to the econometric analysis:

Country	**Area**	**Continent**	**Freq.**	**%**	**Cum.**
Austria	Western and Nordic Europe	Europe	26	4,17	4,17
Belgium	Western and Nordic Europe	Europe	26	4,17	8,33
China	South East Asia	Asia	26	4,17	12,50
Czech Republic	Central and Eastern Europe	Europe	26	4,17	16,67
Denmark	Western and Nordic Europe	Europe	26	4,17	20,83
Finland	Western and Nordic Europe	Europe	26	4,17	25,00
France	Western and Nordic Europe	Europe	26	4,17	29,17
Germany	Western and Nordic Europe	Europe	26	4,17	33,33
Hungary	Central and Eastern Europe	Europe	26	4,17	37,50
Italy	Western and Nordic Europe	Europe	26	4,17	41,67
Japan	South East Asia	Asia	26	4,17	45,83
Netherlands	Western and Nordic Europe	Europe	26	4,17	50,00
Norway	Western and Nordic Europe	Europe	26	4,17	54,17
Poland	Central and Eastern Europe	Europe	26	4,17	58,33
Portugal	Western and Nordic Europe	Europe	26	4,17	62,50
Rep. of Korea	South East Asia	Asia	26	4,17	66,67
Romania	Central and Eastern Europe	Europe	26	4,17	70,83
Slovakia	Central and Eastern Europe	Europe	26	4,17	75,00

Spain	Western and Nordic Europe	Europe	26	4,17	79,17
Sweden	Western and Nordic Europe	Europe	26	4,17	83,33
Switzerland	Western and Nordic Europe	Europe	26	4,17	87,50
Turkey	Central and Eastern Europe	Europe	26	4,17	91,67
United Kingdom	Western and Nordic Europe	Europe	26	4,17	95,83
United States	North America	America	26	4,17	100,00

Table 3-1. List of countries

3.3.1. IFR

A database containing information about the investment is retrieved by International Federation of Robotics, in which the use of robots is distinguished on the base of country, industry, installation and operational stock. The database returns data as number of units of robots. From this source we retrieved information for a primary analysis mainly about operational stock of robots, thus considering the average installation of robots over 12 years. This choice reflects the need to take a longer period into account and to have more accurate estimates and studies. For the econometric analysis, that follows, all the data equals to 0, have been replaced by 0,1 in order to obtain valid results from the estimation, and to be able to transform data in natural logarithm. Through this replacement, the robot density is not affected, and it is almost the same[6].

The industry categories respect the classification of economic activities ISIC, rev. 4, and for the purpose of the research Electrical/Electronics and Automotive categories are considered. Class 26-27, Electrical and electronics, includes the subcategories explained below.

26-27	Electrical/electronics
275	Household/domestic appliances
262	Computers and peripheral equipment
271	Electrical machinery n.e.c. (non-automotive)
263	Info communication equipment, domestic and professional
260	Electronic components/devices
261	Semiconductors, LCD, LED
265	Medical, precision and optical instruments
279	Electrical/electronics unspecified

Table 3-2. IFR Class 26-27. Source: IFR (2021)

[6] Kernel density test confirms that there is not a loss in information and distribution of data after the replacement

The Automotive category, IFR class 29, includes:

29	Automotive
291	Motor vehicles, motor vehicle engines and bodies
299	Automotive unspecified
293	Parts and accessories for motor vehicles

Table 3-3. IFR Class 29. Source: IFR (2021)

Moreover, a general data, including all the industries was taken. Table 3-4 reports all the macro sectors summarized in the item *All Industries*:

000	All Industries
A-B	Agriculture, forestry, fishing
C	Mining and quarrying
D	Manufacturing
E	Electricity, gas, water supply
F	Construction
P	Education/research/development
90	All other non-manufacturing branches
99	Unspecified

Table 3-4. IFR Class 000. Source: IFR

The two categories Electrical/Electronics and Automotive, seen above, fit in class IFR D, Manufacturing.

For more precise estimates, the data were then converted into an index, thus obtaining robot density, measured by the number of operational robot stocks per thousand inhabitants. Thanks to the data collected from IFR, it was in fact possible to create the following graphs, which clearly show how there is a strong upward trend in investments in robotics, both for the general industries and for the two main sectors adopting automation.

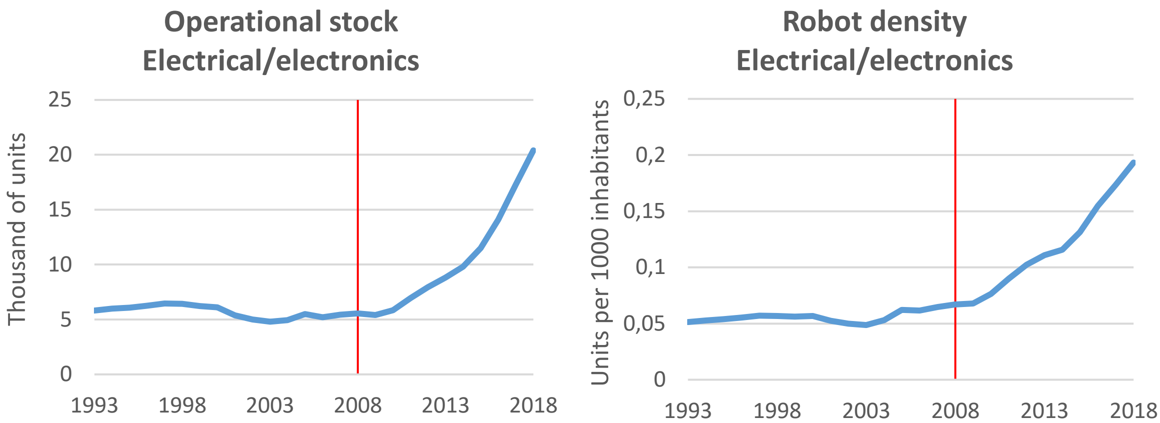


Figure 3-7. Operational stock for electrical/electronics sector in absolute terms and per capita. Average calculated for 24 countries. Source: IFR (2021); industries respect ISIC rev. 4. Own elaboration

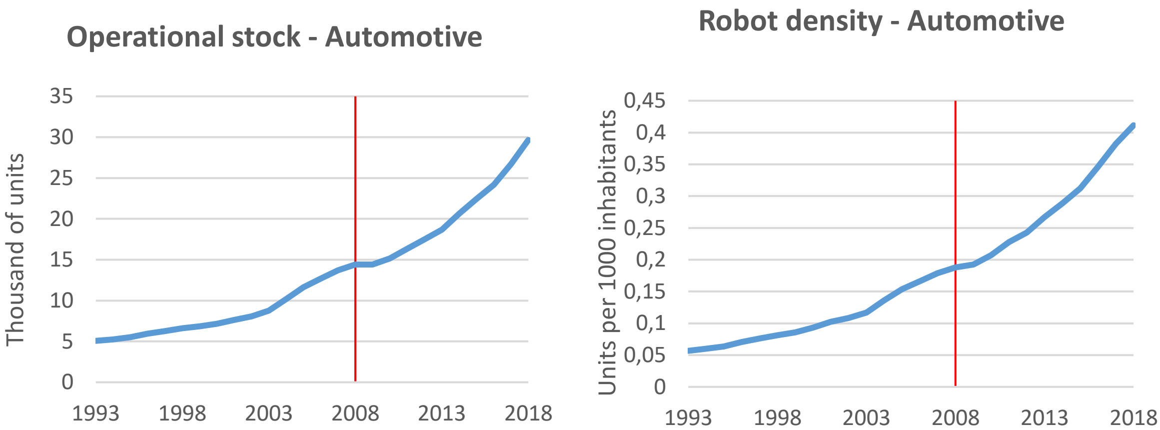


Figure 3-8. Operational stock for automotive sector in absolute terms and per capita. Average calculated for 24 countries. Source: IFR (2021); industries respect ISIC rev. 4. Own elaboration

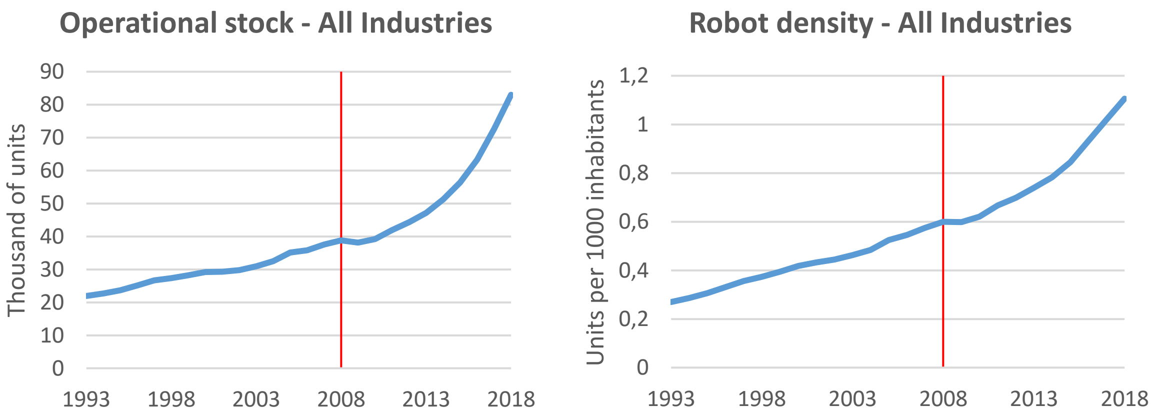


Figure 3-9. Operational stock of all industries in absolute terms and per capita. Average calculated for 24 countries. Source: IFR (2021); industries respect ISIC rev. 4. Own elaboration

A deeper qualitative analysis can be done by observing the trend by industries for geographical area of countries.

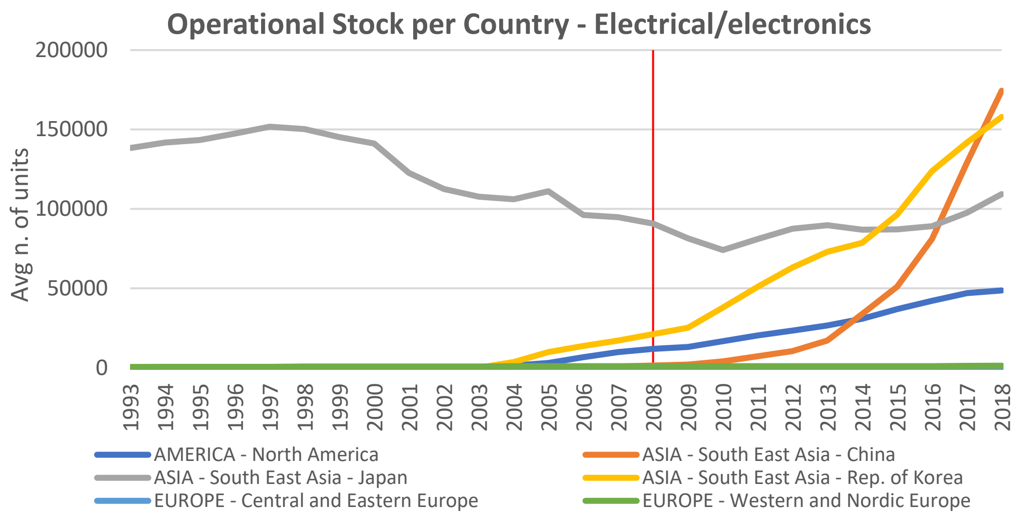


Figure 3-10. Operational stock for electrical/electronics sector by geographical area. Source: IFR (2021); industries respect ISIC rev. 4. Own elaboration

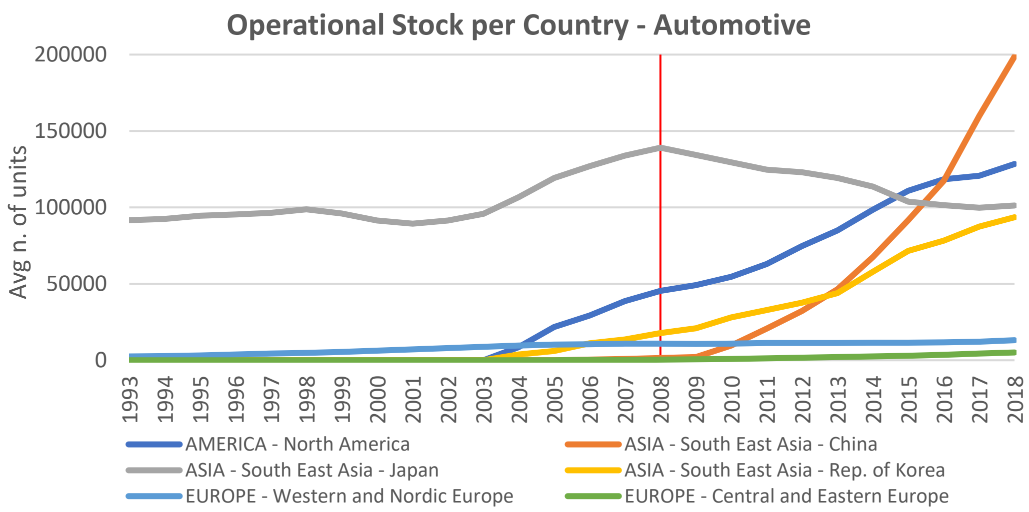
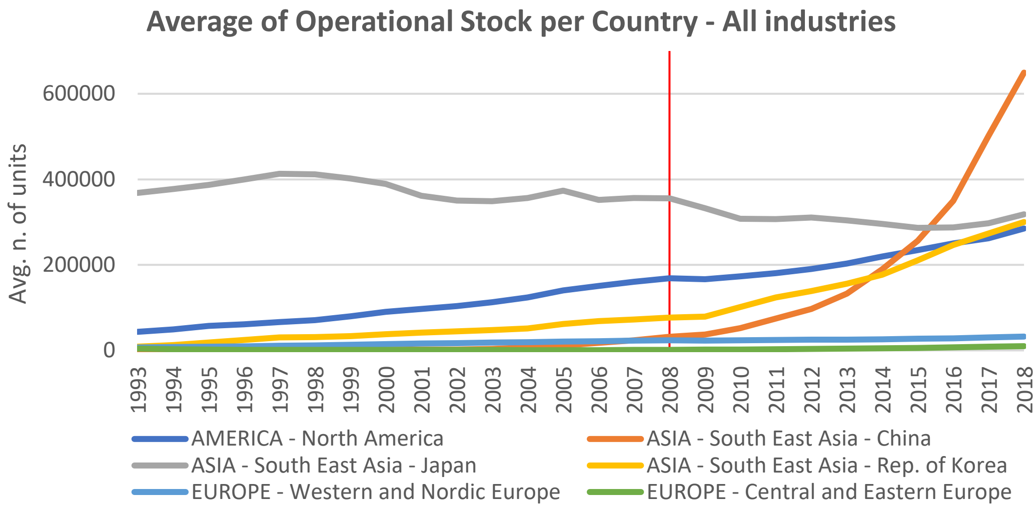


Figure 3-11. Operational stock for automotive sector by geographical area. Source: IFR (2021); industries respect ISIC rev. 4. Own elaboration

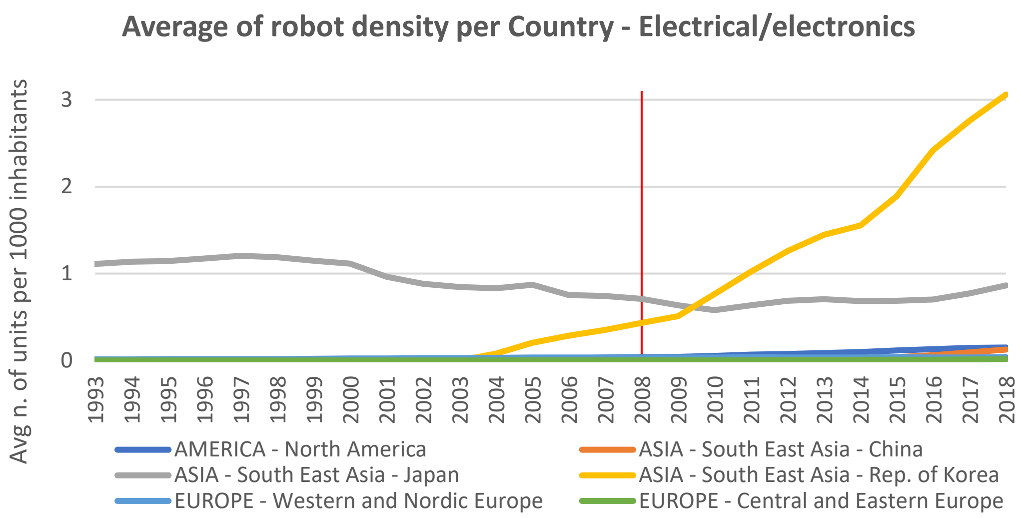


3-12. Operational stock for all industries sector by geographical area.
Source: IFR (2021); industries respect ISIC rev. 4. Own elaboration

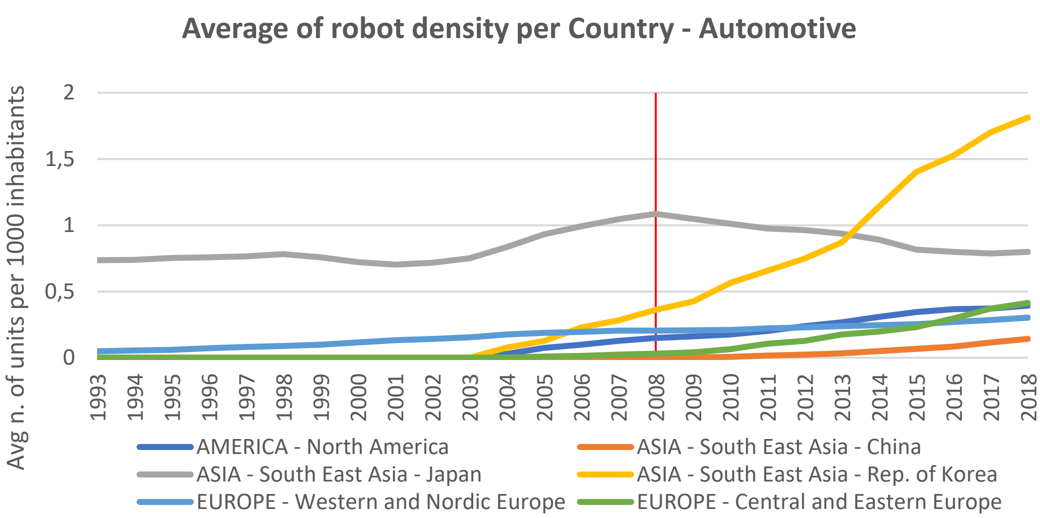
From these graphs, it is interesting to note how Japan has anomalous trends compared to the average trends of the other countries analysed. Especially in the automotive sector, where Japan plays a fundamental role, it is curious how there is a change of direction for the operational stock of robotics followed by a continuous decreasing trend.

On the contrary, a country in strong development, which has rapidly reached and surpassed the robotics numbers of its competitors, is China. In fact, in just a few years, China has become the leader in the three sectors analysed.

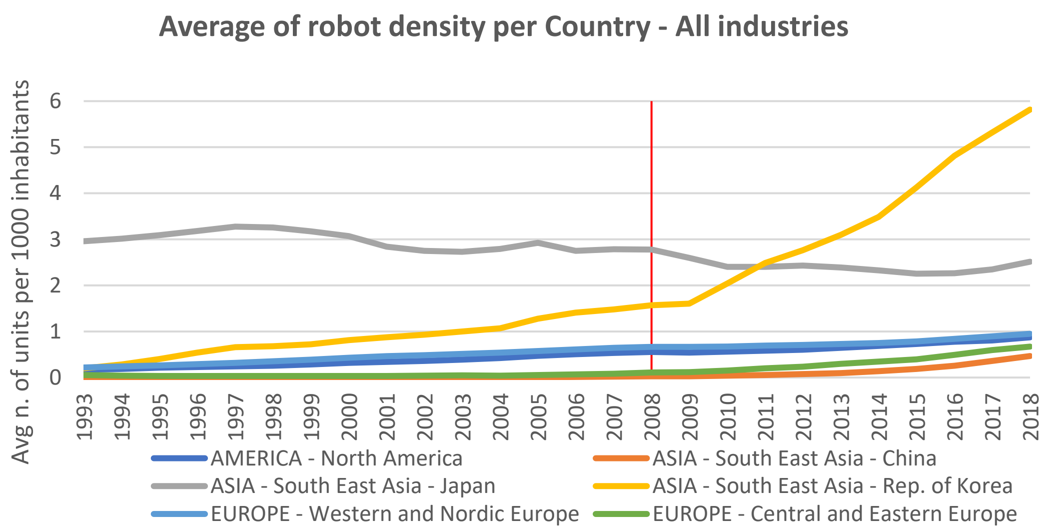
But, if we take into consideration the data per capita, thereby, considering the number of robots per 1000 inhabitants we can note, how the trend changes for China, following now the average of the European and American states. The country that stands out the most, is Republic of Korea, reaching an average of more than 3 robots per 1000 inhabitants in the automotive sector for 2018, against a European average that does not even reach 0.5 robots per 1000 inhabitants. Considering all industries together, this data almost doubles, counting nearly 6 robots per 1000 inhabitants, while in Europe the figure remains below the unit.



3-13.Operational stock by country per thousand inhabitants for electrical/electronics sector. Source: IFR (2021); industries respect ISIC rev. 4. Own elaboration



3-14. Operational stock by country per thousand inhabitants for automotive sector. Source: IFR (2021); industries respect ISIC rev. 4. Own elaboration



3-15.Operational stock by country per thousand inhabitants for all industries. Source: IFR (2021); industries respect ISIC rev. 4. Own elaboration

Since we did not have information by sector on the global value chains data, it was not possible to proceed with the empirical analysis by industry sector. In fact, the analysis continues only at a general level, with the data incorporating all sectors, IFR class 000. However, it is possible to conclude that the trends of the two groups, automotive and electrical/electronics, as well as all industries, are very similar, as can be seen from the graphs above, and the growth is notable, mainly for the Asian countries considered. The general increase, moreover, is particularly significant after 2008, when as already noticed, a drastic drop in the price of robotics, encouraged investments in automation.

3.3.2. WorldBank

The second source for data of the analysis is the WorldBank. From this source, country-specific data were retrieved, in particular the population data, which have been used to determine indices and data per capita, as already shown.

3.3.3. EORA Database

The last main source was EORA Database (UNCTAD – Eora Global Value Chain Database) which contains all the main GVC indicators by country from 1990 to 2018. All the values are in current year '000 USD. It includes:

- DVX: domestic value for export of other countries, meaning the amount of input supplied to other states for their exports
- VA_exp: value added trade, that equals to DVA + FVA
- FVA: foreign value added, the amount supplied by other countries for own exports
- GVC: global value chain, that equals to FVA + DVX
- DVA: domestic value added, the amount produced internally to a country

For missing values in the dataset, they were filled in by approximating the missing data with the average of the values for the year before and the year after of the one of interest[7].

Knowing the participation indices to global value chains, it was possible to create graphs similar to the previous ones, always keeping 2008 as a threshold parameter. In this way, it is easier analyse data and obtain first answers to the research question. In particular, the following graphs show a general drop in GVCs after the financial crisis. This change in trend had already been noted in the previous paragraph and now is confirmed for all countries. Similarly, we had seen a slight growth in domestic value added, which also in this case is confirmed for all groups of countries. In the previous graph, finally, we noted a decrease in forward and backward

[7] Missing value for Domestic Value Added (DVA) of Republic of Korea in 1997.

participation. Once again, the graphs by country show a general trend in line with what we saw previously for the two indices.

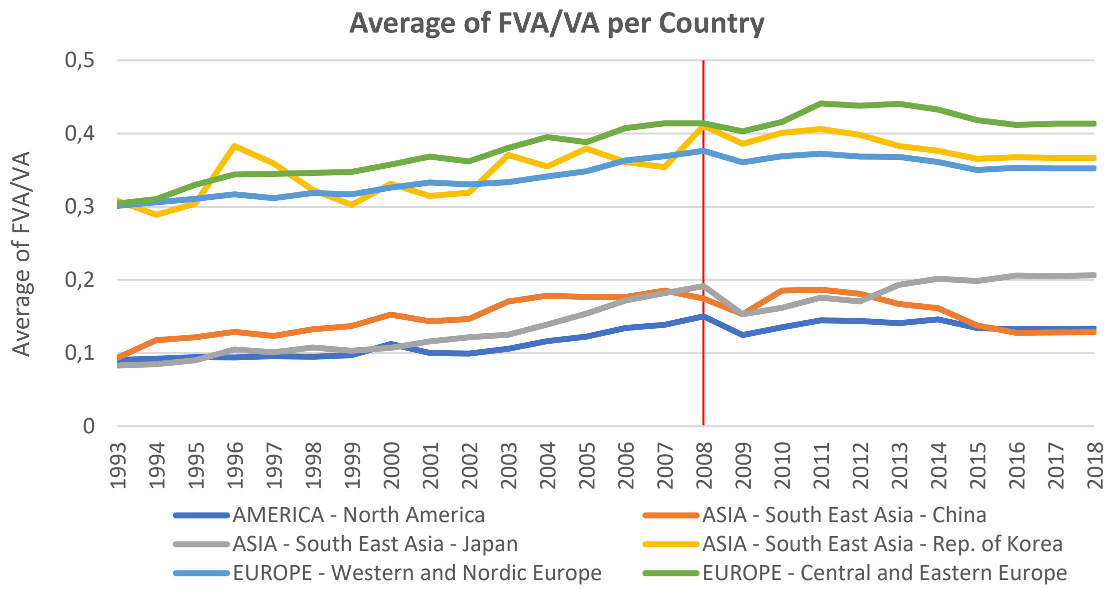


Figure 3-16. Backward Participation per geographical area.
Source:EORA Database. Own elaboration

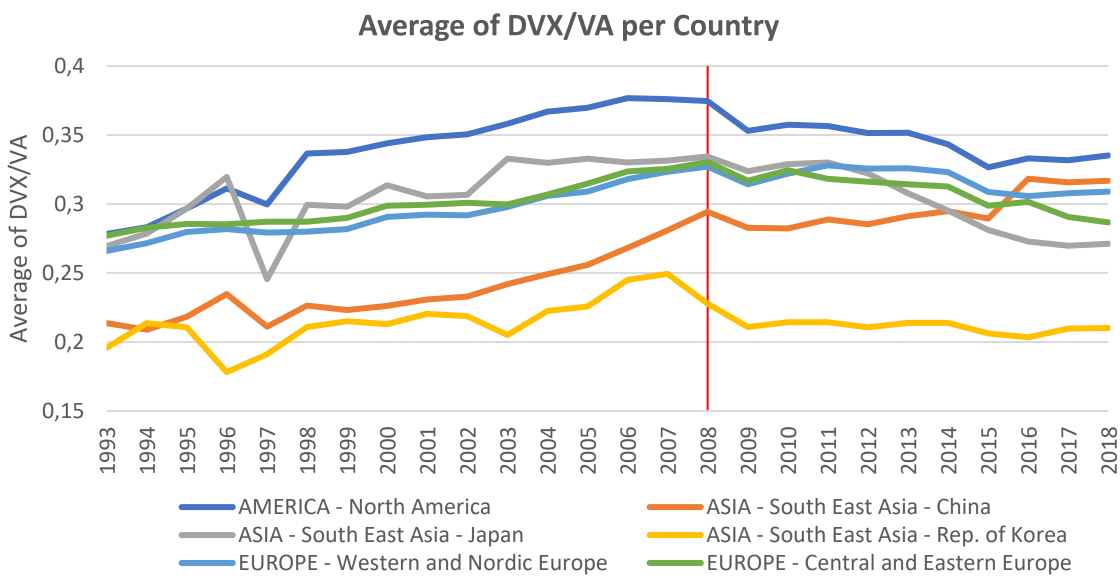


Figure 3-17. Forward Participation per geographical area
Source: EORA Database. Own elaboration

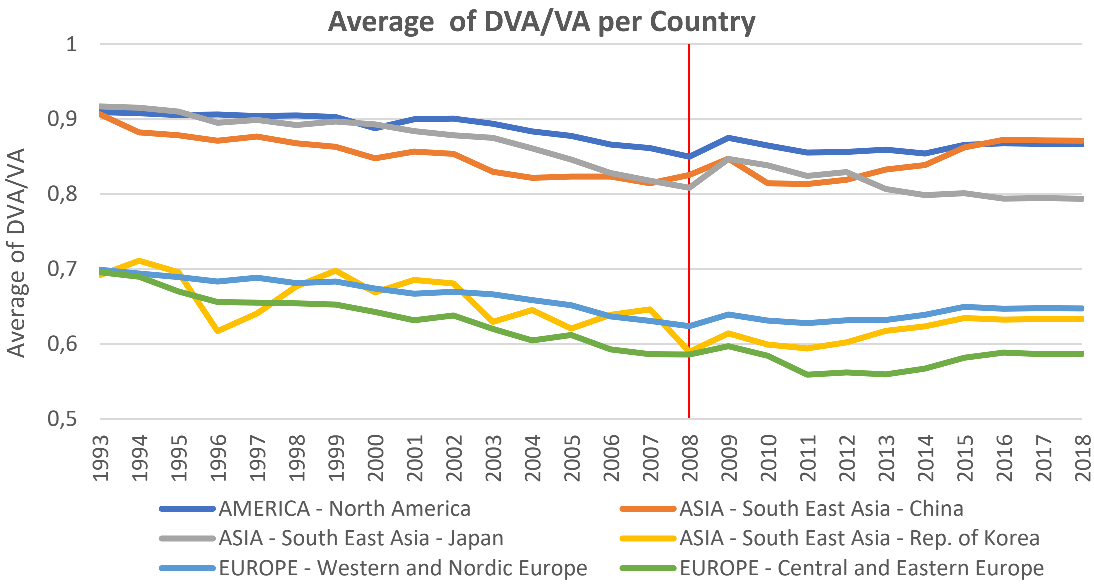


Figure 3-18. Domestic value added per geographical area.
Source: EORA Database. Own elaboration

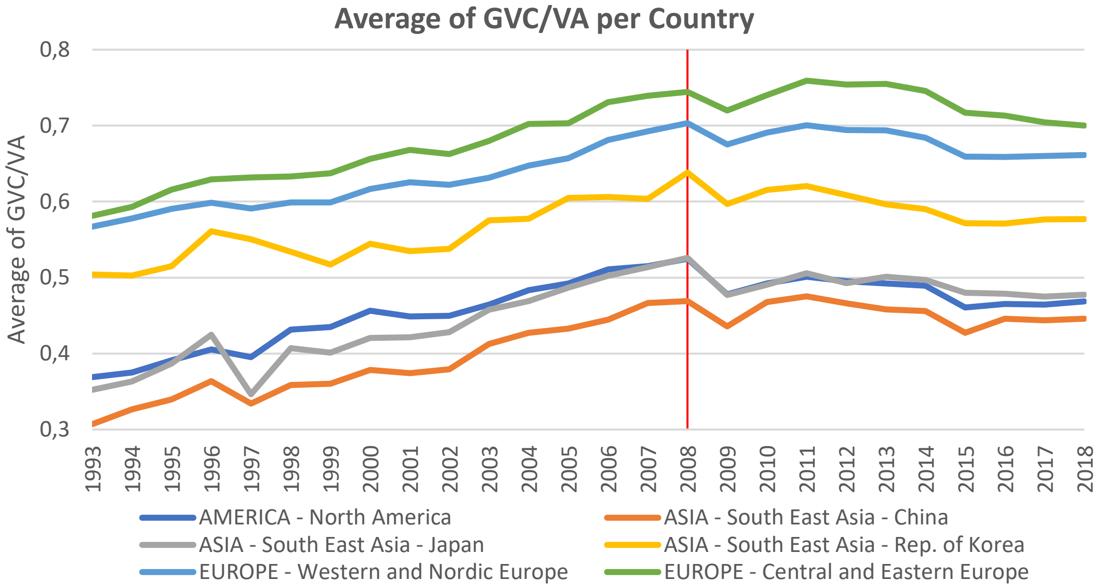


Figure 3-19. Global Value Chain participation index per geographical area.
Source: EORA Database. Own elaboration

Thanks to the matching of these three main datasets, it was possible to make a preliminary qualitative analysis and a graph analysis. This allowed us to obtain the first results that will be useful for a more detailed and in-depth study. Thus, consequently to the financial crisis of 2008, there has been a strong increase in investments in robotics and, at the same time, a decrease in participation in global value chains. Now, to obtain a more reliable outcome, all the data will be object of econometric study, in order to better understand if these two factors correlate and to what extent.

Table 3-5 provides a summary of all the variables of the panel, consisting of 24 countries and 26 years, used in the econometric strategy[8].

Variable	Obs	Mean	Std.dev.	Min.	Max.
Rob_den	624	0.5919014	0.7473813	0	5.817024
GVCVA	624	0.6276646	0.1126681	0.3070231	0.8523991
FVAVA	624	0.3287707	0.120382	0.08298	0.5964555
DVXVA	624	0.298894	0.0684317	0.1781261	0.5851178
DVAVA	624	0.6712293	0.120382	0.4035445	0.9170199

Table 3-5. Summary Statistics

3.4. Econometric strategy

In the statistical analysis we want to investigate the relationship between investments in robotics and their impact in the long run on GVC. Our goal is to look at the data from 1993 to 2018 to find the relationship between automation investments and GVC participation indices. If such a correlation is found, we would then be able to forecast a trend for the future of the GVC. Therefore, in this research, we rely on the use of Panel Vector Autoregressive (PVAR) models, a multivariate panel regression of each variable on lags of itself, lags of all other dependent variables and lags of exogenous variables. The estimation is performed by a Generalized Method of Moments, GMM. The variables of the model are then examined by a Granger causality test, purposed at discovering a prediction among factors. The Granger causality concept studies if a x variable Granger causes the y variable, indeed, if past values of x contain information about the prediction of variable y, above and behind the information provided by past values of y alone (Granger, 1969). In our case, the independent variable is robot density, and the different dependent variables are the GVC participation indicators. The idea behind the investigation is to estimate a forecast, based on the times series of robotics, able to determine changes in participation to Global Value Chain.

[8] All variables are transformed in natural logarithm

The first step of the analysis is to test whether there is a unit root in the variables of interest, which means testing for the presence of a trend in the time series. If a variable is characterized by the presence of a unit root, then it is not-stationary, or integrated of order one, (denoted by I(1)). If, on the contrary, the variable does not have a unit root, then, we define it as stationary, or I(0). The presence of a unit root is important to assess the Granger causality in the short or in the long run. In case of two I(1) variables, then a cointegration analysis could help assessing whether they are also linked by a long-run, non-spurious, relationship. In case of one, or two, I(0) variables, a PVAR approach can be used instead, which is particularly useful when assuming all variables to be endogenous and interdependent.

Panel VAR

The PVAR model is used in multiple applications across fields and, as the title clearly suggests, is used to analyse panel data. This model can capture the heterogeneity of the agents' socioeconomic performance against both cross-section and time-series models. Panel data entails with a series of units over time and multiple observations for each unit. Therefore, a panel consists of N units, over a number of periods T. In our case *N* is the number of countries (*N=24)*, and we observe annual data for 26 years (*T=26).* Panel-data can be distinguished into two sub-categories. When we talk about micro panel, the number of T is from 2 observations to a maximum of 10/20, while the number of N is very large and could be equal to hundreds or thousands of units. In macro panel, instead, the number of T is greater, recording annual or quarterly data, in a range that goes from 20 to 60 years; N can be small or large. Macro-panel data are also known in literature as "panel time series" (Burdisso and Sangiácomo, 2016). In our research the database consists of macro-panels.

The application of panels to VAR models represents an alternative to multivariate simultaneous equation models, and the Time-series vector autoregression models are used in different applications across fields (Abrigo and Love, 2016). A PVAR follows the same logic of a Vector Autoregressive model, with the addition of a cross sectional dimension. The adoption of a VAR allows to focus on the relationship between multiple variables and their lags, analysing their change over time.

A panel VAR considers a system of linear equations like the follow:

$$Y_{it} = Y_{it-1}A_1 + Y_{it-2}A_2 + \cdots + Y_{it-p+1}A_{p-1} + Y_{it-p}A_p + X_{it}B + u_i + e_{it}$$

$$i \in \{1, 2, \dots, N\}, \qquad t \in \{1, 2, \dots, T_i\}$$

Where Y_{it} is a (1 x k) vector of dependent variables, X_{it} is a (1 x l) vector of exogenous covariates. u_i and e_{it} are respectively, the vector or dependent variable-specific panel fixed-effects and the error terms. The (k x k) matrices A_1, A_2, … A_{p-1}, A_p and the (l x k) matrix B are parameters to be estimated (Abrigo and Love, 2016).

In the following sections, we will conduct a stationarity test for each variable of the Panel VAR, using a unit root test Panel VAR. Later, a Panel VAR analysis of the optimal number of instruments to adopt will be determined through Hansens's *J* test of overidentifying restrictions.

3.4.1. Unit root test

Taking into consideration the fact that we are analysing a panel of several countries over the years, we must pay attention on not having a biased estimation due to the stationarity of the time series. This could be the case if we include in the model variables that are biased by the presence of shock common only to some countries. For example, if we think to some commercial agreement or incentive that only a group of countries can receive, as the European Union countries; the policy would change the trend of only few nations, distorting the entire stationary test. In fact, the first-generation panel unit root tests are sensitive to the cross-sectional dependence that emerges because of shock common to group of countries, or because of spillovers across countries. To be reliable, the first-generation test, should assume all the units of the panel independent in the case of cross-sectional dependence. To avoid this problem, the test used is the second-generation panel unit root test developed by Pesaran (2007), based on the Im, Pesaran and Shin (2003) unit root test. (Antonietti and Franco, 2021).

The equation estimated to detect the presence of a unit root is the follow:

$$\Delta y_{it} = \beta_i y_{it-1} + \gamma_i \overline{\Delta y_{\iota t}} + \delta_i \overline{y_{\iota t-1}} + \mu_i + \varepsilon_{it}$$

Where Δy_{it} represents the change in the dependent variable *y*; $\beta_i y_{it-1}$ is the lag of y with its coefficient; $\gamma_i \overline{\Delta y_{\iota t}}$ and $\delta_i \overline{y_{\iota t-1}}$ are, respectively, the means of the lagged levels and the mean of the first difference of the individual regressor *y*. μ identifies the fixed effect, ε is the error term; *i* refers to the country and *t* to the year.

This extends the individual augmented Dickey-Fuller (ADF) regressions with the cross-sectional means of the lagged levels and first differences of the individual regressor *y* (i.e. *lnROBDEN*, *ln*GVCVA, *ln*FVAVA, *ln*DVXVA and lnDVAVA respectively) that are used as proxy for the unobserved common factors.

$$\begin{cases} H_0: \beta_i = 0 \quad \text{for } i = 1, \dots, \mathrm{N}_i & \rightarrow \ non\ stationarity \\ \\ H_1: \begin{matrix} \beta_i < 0 \quad \text{for } i = 1, \dots, \mathrm{M}_i \\ \beta_i = 0 \quad \text{for } i = \mathrm{M}_1 + 1, \mathrm{M}_1 + 2 \dots, \mathrm{N} \end{matrix} & \rightarrow stationarity \end{cases}$$

β_i=0, represents the null hypothesis which is tested by averaging the t_i statistics corresponding to β_i in the equation above (Pesaran, 2007; Burdisso and Sangiacomo, 2016). If the condition is accepted, thus β_i=0, it means that the variable has a unit root, and it is non-stationary. The alternative hypothesis, instead, is that β_i<0 for i=1,2,…,M and β_i=0 for i=M+1, M+2,…, N (with M<N). The test is called the cross-sectional Im, Pesaran and Shin (CIPS) test and is based on the null hypothesis that the variable has a unit root. The idea behind the test is that if the process is stationary, by definition, it will revert to the mean. Therefore, the first lag of y will inform us about its future change, that is its first difference Δy_{it}. On the contrary, if the process presents a unit root, the first lag level of the series will not give any information about the future changes, and an estimated regression of Δy_{it} on y_{it-1}will have a null coefficient. Additionally, in the CIPS test, the means of the lagged level and first differences of the individual regressor y, had been added as controls to the simple regression.

We examine the unit root in all the variables and the results are observable in Table 3-6. The statistic takes into consideration a maximum lag of 5 years, and a minimum lag of 1, deserving the criteria to decide for the right number of lags to adopt to the Portmanteau test (Q).

We start by analyzing the stationarity of the robot density variable (*lnROBDEN*) in log levels, and in first difference.

Pesaran (2007) panel unit root test	
	lnROBDEN
CIPS	-2.319
	ΔlnROBDEN
CIPS	-2.910 ***

Table 3-6. Unit root test for robotics variable

Figure 3-20. Evolution of lnROBDEN across countries

The CIPS test for the variable *ln*ROBDEN equals to -2.319. The critical value at 10%, 5% and 1%, are respectively, -2.58, -2.66 and -2.81. Therefore, the CIPS test does not reject the null hypothesis for *ln*ROBDEN, so we accept the non-stationary hypothesis when the variable is in level. The results are also confirmed by simply looking at the graphs in Figures 3-7, 3-8 and 3-9 where the operational stocks for the different industries are shown, at level and in density. The trend of the investment in robotics was increasing, and the line did not simply fluctuate around the mean. This is clearly visible also in the plots above, which show the *ln*ROBDEN for each country and confirms the presence of a unitary root. From the graph emerges the interesting increasing trend of mainly west European countries, as Czech Republic, Hungary, Poland, Slovakia, and, as already mentioned before, the Asian country, China, and South Korea.

Successively, we go further with the analysis, and we investigate the stationarity for the first difference of the variable. In the second row of the table, we can note the unit root test of the first difference. In this case CIPS is -2.910, we can affirm that the test is rejected, and the variable in first difference is stationary, integrated of order 1.

We completed the first root test for the variable related to GVC. Since the cointegration analysis requires stationarity for both the variables, we proceed with the CIPS test for the other factors related to GVC. As before, we start with the statistic in which rejecting the null hypothesis of β_i=0, means that we reject the presence of unit root, thus the variable is stationary, or I(0).

Pesaran (2007) panel unit root test				
	*ln*GVCVA	*ln*FVAVA	*ln*DVXVA	*ln*DVAVA
CIPS	-3.012^{***}	-2.902^{***}	-2.745^{**}	-2.835^{***}
	Δ*ln*GVCVA	Δ*ln*FDIPOP	Δ*ln*DVXVA	Δ*ln*DVAVA
CIPS	-5.023^{***}	-4.894^{***}	-4.897^{***}	-4.934^{***}

Table 3-7. Unit root test for GVC variables

In Table 3-7, we always reject the null hypothesis, both for the variables in level and for the variables in first difference. Therefore, we conclude that they are stationary or integrated of order 0, I(0).

Figures 3-21, 3-22, and 3-23 show the evolution of, respectively, *ln*GVCVA, *ln*FVAVA and *ln*DVXVA, across the 24 available countries.

Figure 3-21. Evolution of lnGVCVA across countries

Figure 3-22. Evolution of lnFVAVA across countries

Figure 3-23. Evolution of lnDVXVA across countries

3.4.2. Panel VAR - GVC and Robot density

To assess the Granger causality between robot density and GVC participation in the short-run, we proceed by selecting only stationary variables: to do so, following the results of our unit root tests, we consider all our variables in first difference. In this way, we can estimate the short run relationship between robot density and GVC participation of countries, using a GMM estimator for the PVAR models, as suggested by Holtz-Eakin et al. (1988). The equation estimated is the follow:

$$lnGVCVA_{it} = \sum_{k=1}^{K} \beta_k lnGVCVA_{it-k} + \sum_{k=1}^{K} \gamma_k lnRobden_{it-k} + \mu_i + \varepsilon_{it}$$

where i refers to the country, t refers to the year, ε is the vector of idiosyncratic errors, μ_i represents the vector of country-specific fixed effect. Due to the limited number of years available, we set k =1.

The fixed effect μ_i included in the model can correlate with robotics, thus biasing the estimates of the coefficients. For this reason, by first differentiating each variable in the equation, we remove such an unobserved country-specific component. Moreover, since GVC and robots can be endogenous variables, we apply the Generalized Method of Moments (GMM) approach, using lagged values of the variables as instruments, in order to obtain consistent estimates of the coefficients (Holtz-Eakin et al., 1988). Through this approach, therefore, we use the history of the variables to instrument the same variables. In our case, the *lnGVCVA* and *lnROBDEN*, are instrumented with their levels at times t-1, t-2 and t-3. In the instrumental variable approach, the instruments must correlate with its endogenous variable, but not with the dependent variable.

Thanks to the PVAR, we can estimate causality in both directions, from robotics to GVC, and vice-versa. This can be tested performing a Granger causality test. Our PVAR regression provides, as dependent variable *y*, *lnGVCVA*, and as independent variable *x*, *lnROBDEN*, including up to three-time lags of the variables in levels as instruments for the corresponding variables in first differences. The errors in the model are clustered at country level to avoid unobserved arbitrary within-group correlation across observations.

Table 3-8 below shows the results of the PVAR regression.

PVAR estimates					
	Coefficient	**z**	**P>|z|**	**[95% conf. interval]**	
lnGVCVA					
$lnGVCVA_{t-1}$	-0.0353211 (0.1262407)	-0.28	0.780	-0.2827484	0.2121062
$lnROBDEN_{t-1}$	-0.0030084*** (0.0005059)	-5.95	0.000	-0.0039999	-0.002169
lnROBDEN					
$lnGVCVA_{t-1}$	16.05287*** (4.167224)	3.85	0.000	7.885256	24.22048
$lnROBDEN_{t-1}$	-0.0437916 (0.0284782)	-1.54	0.124	-0.0996078	0.0120247
N. of obs	552				
N. of panels	24				
Ave. n. of T	23				

Table 3-8. PVAR estimates for lnGVCVA and lnROBDEN

From Table 3-8 it is possible to obtain information on the impacts that one variable generates on the other and vice versa. In the upper part of the table, we notice how the variable *lnGVAVA* lagged by one year, correlates with its own variable at year t. Subsequently, how the variable *lnROBDEN* correlates with *lnGVCVA*. In the second part of the table, we observe exactly the opposite. In fact, the advantage of panel VAR is exactly this, to be able to also monitor the opposite direction. Thus, we can see how robotics at time t-1 impacts on robotics in the following year and how global value chains impact on robotics. The last part of Table 3-8 shows the total observations, with years and countries. The number of years in this case is lower due to differences in computed years. In the PVAR considered, the instruments are the levels of *lnGVCVA* and *lnROBDEN*, from time t-1 to time t-3.

We also use the Hansen's *J* test[9] to check for overidentification. In the test, the null hypothesis is that the overidentifying restrictions are valid and the model is correctly specified. In the regression we use one endogenous variable for each equation with three instrumental variables for each. The statistic is 14.65, and is not, or weakly, statistically significant (p-value= 0.07), meaning that the number of instruments is adequate.

[9] The statistic is distributed as a chi-square with (m-k) degrees of freedom, where m equals the number of instruments and k the number of endogenous variables

The next step is the panel Granger causality test, which verifies if the independent variables do not Granger cause the dependent variable. So, in the top row of Table 3-9, we analyse whether robot density Granger causes the GVC participation of countries and, in the bottom part, if the GVC Granger causes robot density.

PVAR Granger causality			
Equation / Excluded	**Chi2**	**Df**	**Prob>chi2**
lnGVCVA			
lnROBDEN	35.366	1	0.000
ALL	35.366	1	0.000
lnROBDEN			
lnGVCVA	14.839	1	0.000
ALL	14.839	1	0.000

Table 3-9. PVAR Granger causality lnGVCVA and lnROBDEN

The null hypothesis therefore assumes that there is no Granger causality between the two variables, in either direction. The Wald statistic rejects the null hypothesis at the 1% level, meaning that the Granger causality runs in both directions. This result, however, could be predicted also following the analysis of Table 3-8. In fact, the test on the impact of robotics on GVCs and the one generated by GVCs on robotics are respectively -5.95 and 3.85. Both results have a high absolute value and therefore the estimates are statistically significant, implying that each variable Granger causes the other one. In other words, the panel VAR suggests that, in the short term, the two variables have a strong influence on each other: a higher growth rate in GVC participation stimulates greater investment in robotics, and at the same time, investment in robotics stimulates participation in global value chains. By looking more closely, it is evident that the two estimated coefficients reveal two different and opposite causal effects. The coefficient of GVC on robotics is positive, while the one of robotics on GVCs is negative. Therefore, the impact of robotics is to reduce the participation of countries to GVC. On the other side, a higher GVC participation induces an increase in automation.

So far, we have analysed the general participation of GVCs. Now, we can go to the next step to better understand how robotics has an impact in forward and backward participation. Following the same procedure of GVC and robot density, we perform a Panel Vector Autoregressive analysis and then move on to the panel VAR Granger causality test.

3.4.3. Panel VAR - DVX and Robot density

We now analyse forward participation and resubmit the panel VAR, this time focusing on what are the impacts of DVX (the proxy for forward participation) of year t-1 and the robotic density of year t-1, on the DVX of year t. Conversely, how the two variables at year t-1 impact the robotic at year t. The number of observations has not changed compared to the previous one, thus keeping 552 total observations.

$$lnDVXVA_{it} = \sum_{k=1}^{K} \beta_k lnDVXVA_{it-1} + \sum_{k=1}^{K} \gamma_k lnRobden_{it-1} + \mu_i + \varepsilon_{it}$$

Again, as before, the instruments are the levels of *lnDVXVA* and *lnROBDEN*, from time t-1 to time t-3, *i* represents the countries, ε is the vector of errors, μ_i refers to the vector of country-specific fixed effect.

	PVAR estimates				
	Coefficient	**z**	**P>|z|**	**[95% conf. interval]**	
lnDVXVA					
$lnDVXVA_{t-1}$	-0.1278424 (0.0879866)	-1.45	0.146	-0.3002929	0.0446082
$lnROBDEN_{t-1}$	0.0033521*** (0.0010835)	3.09	0.002	0.0012284	0.0054758
lnROBDEN					
$lnDVXVA_{t-1}$	2.576278 (3.941734)	0.65	0.513	-5.149379	10.30194
$lnROBDEN_{t-1}$	-0.0638147** (0.0314891)	-2.03	0.043	-0.1255321	-0.0020972
N. of obs	552				
N. of panels	24				
Ave. n. of T	23				

Table 3-10. PVAR estimates for lnDVXVA and lnROBDEN

The Hansen's *J* statistic equals 2.86 (p-value = 0.9) and does not reject the null hypothesis of no overidentification.

Next, the PVAR granger causality tests were performed, to find out whether the two variables impacted one other. The null hypothesis, as before, states that the independent variable does not Granger-cause the dependent one.

PVAR Granger casuality			
Equation / Excluded	**Chi2**	**Df**	**Prob>chi2**
lnDVXVA			
lnROBDEN	9.570	1	0.002
ALL	9.570	1	0.002
lnROBDEN			
lnDVXVA	0.427	1	0.513
ALL	0.427	1	0.513

Table 3-11. PVAR Granger causality lnDVXVA and lnROBDEN

The results on Table 3-11 determine that the direction of causality only goes from robotics to DVX, not the other way around. The P-value of the lower part of the table, 0.513 is very high, so the null hypothesis is not rejected. There is no return effect from forward participation to investments in robotics, but only from robotics to forward participation. This impact is positive, that is it creates a higher rate of forward participation.

3.4.4. Panel VAR - FVA and Robot density

We now turn to the backward participation side, analysing the relationship between robotics and FVA (backward participation). In this case too, we proceed with the abovementioned steps, starting from the PVAR, which maintains the same structure as the previous ones, and analysing the following equation:

$$lnFVAVA_{it} = \sum_{k=1}^{K} \beta_k lnFVAVA_{it-1} + \sum_{k=1}^{K} \gamma_k lnRobden_{it-1} + \mu_i + \varepsilon_{it}$$

Again, the Hansen J statistic equals 12.49 (p-value = 0.13) does not reject the null hypothesis of no overidentification.

PVAR estimates					
	Coefficient	**z**	**P>|z|**	**[95% conf. interval]**	
lnFVAVA					
$lnFVAVA_{t-1}$	-0.0273439 (0.0380065)	-0.72	0.472	-0.1018353	0.0471475
$lnROBDEN_{t-1}$	-0.0139915^{***} (0.0027751)	-5.04	0.000	-0.0194306	-0.0085524
lnROBDEN					
$lnFVAVA_{t-1}$	-0.1330768 (0.3655167)	-0.36	0.716	-0.8494764	0.5833228
$lnROBDEN_{t-1}$	0.5650335^{***} (0.0626001)	9.03	0.000	0.4423395	0.6877275
N. of obs	552				
N. of panels	24				
Ave. n. of T	23				

Table 3-12. PVAR estimates for lnFVAVA and lnROBDEN

We now continue with the PVAR Granger causality, where we can see that even in this case, the causality effect only exists between robotics and FVA and not vice versa, as it was the case for forward particpation. FVA does not Granger-cause robotics. The p-value is high enough to reject the null hypothesis.

PVAR Granger causality			
Equation / Excluded	**Chi2**	**Df**	**Prob>chi2**
lnFVAVA			
lnROBDEN	25.420	1	0.000
ALL	25.420	1	0.000
lnROBDEN			
lnFVAVA	0.133	1	0.716
ALL	0.133	1	0.716

Table 3-13. PVAR Granger causality lnFVAVA and lnROBDEN

3.4.5. Panel VAR - DVA and Robot density

As a final indicator of global value chains, we check the relationship between domestic value added and robotics. The estimated equation follows:

$$lnDVAVA_{it} = \sum_{k=1}^{K} \beta_k lnDVAVA_{it-1} + \sum_{k=1}^{K} \gamma_k lnRobden_{it-1} + \mu_i + \varepsilon_{it}$$

PVAR estimates					
	Coefficient	**z**	**P>|z|**	**[95% conf. interval]**	
lnDVAVA					
$lnDVAVA_{t-1}$	-0.0337601 (0.0453078)	-0.75	0.456	-0.1225618	0.0550416
$lnROBDEN_{t-1}$	0.0021616^{**} (0.0009529)	2.27	0.023	-0.000294	-0.0040293
lnROBDEN					
$lnDVAVA_{t-1}$	-3.713706^{*} (2.19928)	-1.96	0.091	-8.024215	0.5968029
$lnROBDEN_{t-1}$	-0.0132674 (0.0281981)	-0.47	0.638	-0.0685347	0.0419999
N. of obs	552				
N. of panels	24				
Ave. n. of T	23				

Table 3-14. PVAR estimates for lnDVAVA and lnROBDEN

As usual, we performed the Hansen's *J* test obtaining a statistic of 2.88 which does not reject the null hypothesis of no overidentification (p-value = 0.94).

Table 3-15 shows the outcome of the Granger causality test:

PVAR Granger causality			
Equation / Excluded	**Chi2**	**Df**	**Prob>chi2**
lnDVAVA			
lnROBDEN	5.146	1	0.023
ALL	5.146	1	0.023
lnROBDEN			
lnDVAVA	2.851	1	0.091
ALL	2.851	1	0.091

Table 3-15. PVAR Granger causality lnDVAVA and lnROBDEN

Differently from before, the statistics are less statistically significant. Robotics, once again, has an impact on DVA, generating a positive but small effect, while the other way around is not rejected. A variation on DVA does not generate a statistically significant effect on robotics. In this case, however, the relation between robotics on DVA is not so strong as it was before in forward and backward participation. Even if we observe the PVAR estimates, we can notice how the statistics test for *lnDVAVA* accepts the null hypothesis only at a 10% level, while is rejected when the significance level is reduced to 5%.

3.4.6. Impulse response function

Once the PVAR has been estimated, we can proceed with the analysis of the impulse response functions. In the previous sections, we have estimated the direction of causality between variables. Now, we can proceed by observing what is the effect of an exogenous shock of one standard deviation in the variable of interest x, on the value of y. In our case, we are giving an exogenous impulse to robotics, generating an exogenous increase in robotic investments, and analysing its effects over a 5 years horizon. The confidence interval taken into analysis is the 95% one and is represented by the grey area in the graphs.

The graph obtained thanks to the impulse depicts the same story of the previous analysis. In fact, we have seen that an increase in robotics leads to an increase in forward participation (DVX) of about 0.3%. In Figure 3-24 this trend is observable in the first period only. After one year, the curve slows down, to remain almost flat the subsequent years. So, this tells us once again that the effect is valid only for the short run. On the other hand, the effect for the backward participation (FVA) is negative for the first period, decreasing by 1%, and returning back to 0 after the first year. For domestic value added (DVA), we mentioned before how the test was not so strong as the others. This is translated in the graph in a very large confidence interval, denoted by the grey area, indicating a low level of precision in the estimate. For the graph related to GVC, the output combines the two effects given from forward participation and backward participation. Overall, the short-run effect for the GVC is negative for the first year, suggesting that the negative trend of the backward participation prevails. In the subsequent horizons, the curve goes back to zero.

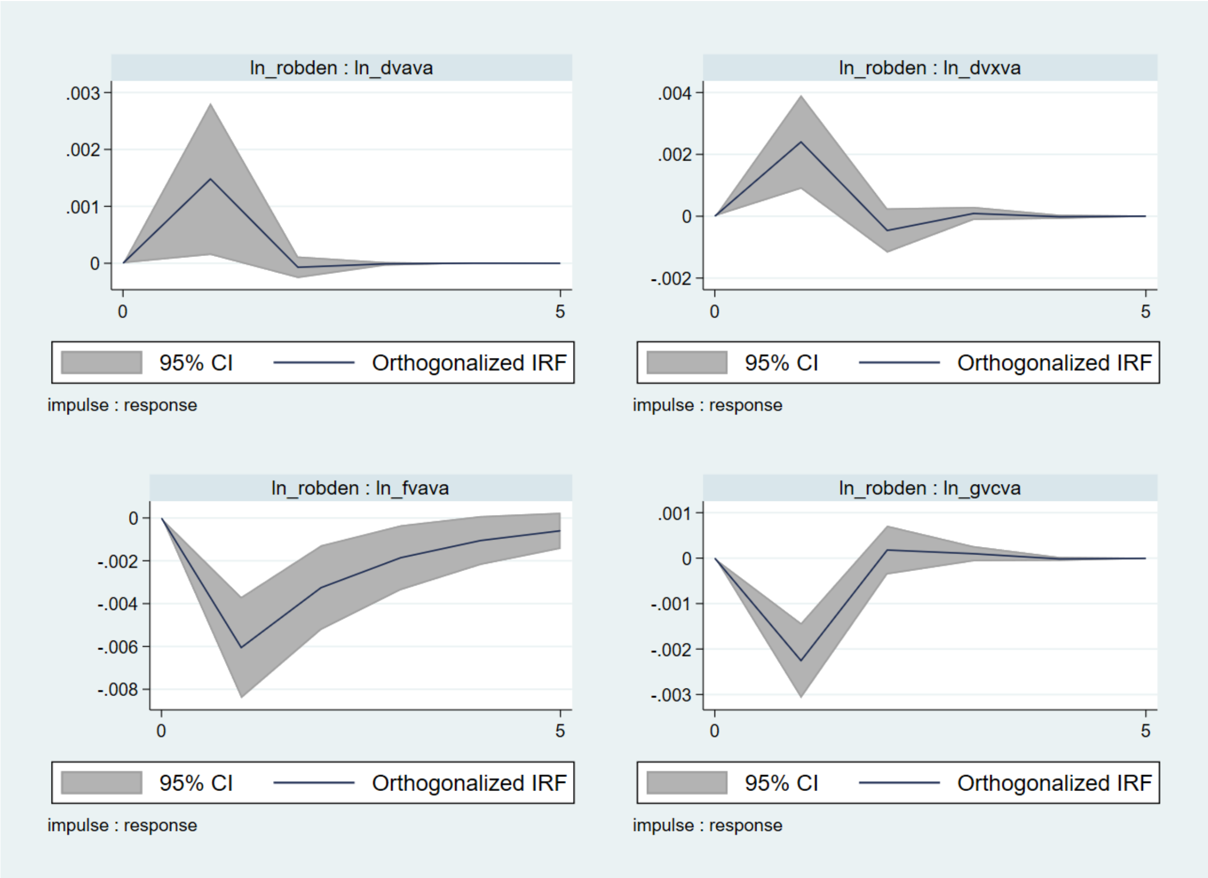


Figure 3-24. Impulse response function of robotics on GVC indicators

3.4.7. Results and discussion

In the previous sections, we began our econometric analysis by testing the stationarity of the variables. *lnROBDEN* appears to be non-stationary when analysed in level, while it is stationary in the first difference. The variables related to global value chain possess all a unit root, that is they present a stationary process, both in level and in first difference. We then decided to operate with all variables in first difference to be able to apply PVAR models which require stationary variables. So, we proceed with the creation of panel VAR models, adopting all the variables in first difference level. Thanks to this step, it is automatically implied that all the fixed effects are removed, generating estimates robust to endogeneity. In fact, by definition, fixed effects are time-invariant and by looking at the first differences we are able to get rid of them. We instrumented the variables with their own lags, and we checked the effect they generated on both directions with a PVAR Granger causality test, from robotics to GVC and the other way around.

The results obtained, are that greater investments on robotics and automation leads to a general decrease in the growth of participation in global value chains. But an increase in GVC participation has a significant impact also on investments in robotics. Robotics favour also greater domestic production, even if in this case the results are less significant. The most important and interesting results are related to forward and backward participation. In fact, thanks to the PVAR Granger causality test, we could notice that for both indices, it is only robotics that seems to have an impact on DVX and FVA, and not vice versa. In the case of forward participation, the impact generated is positive, while it is negative for backward participation.

This overall result leads to the suggestion of a reshoring mechanism from foreign countries to the home country. Automating the process seems to require less need and demand for low-cost goods produced by other countries, and consequently, there is less backward participation. At the same time, by creating greater productive efficiency, countries can become more competitive offering also inputs and intermediate goods at more competitive and lower prices. These goods can then be placed on the market, thus resulting in greater export of goods to third countries and an increase in forward participation.

It should also be noted that the effect analysed is focused only on the short run, by taking the variables in first difference we automatically implied an analysis on a short-term basis. Moreover, the results obtained are mild effects, and do not predict drastic decreases or sudden increases in the curves. Despite these mild effects, thanks to the Granger causality analysis, we can affirm that robotics does have a real impact on participation in global value chains. In fact, our PVAR model analyses macro phenomena that have developed over time. It would be therefore difficult to identify an immediate effect generated by investments in robotics on other variables. On the other hand, the fact that our approach depicts significant trends over time gives us greater confidence in the results. Thus, robotics has the ability to predict and forecast participation in GVCs. This is because robotics has a significant impact on GVCs, in addition to the impact dictated by the history of GVCs themselves. In other words, in addition to the impacts generated by the past of the GVCs themselves, robotics defines a persistent impact over time, which thus generates consequences in the participation in value chains.

In the model, however, some variables that correlate with robotics and GVC, were not included, and they would have required more detailed research. Given these limitations, however, we can say that the results obtained from PVAR in our analysis are robust and significant.

CONCLUSION

Slowbalization is a current phenomenon that is influenced by different factors. In our research, we have examined this phenomenon through the perspective of production reshoring. In particular, after a brief literature review and an analysis of robotics and global value chain individually, we studied how these two variables are related to each other. Through panel VAR models we investigated how robot density impacts on the variables GVC (Global value chain), DVX (Forward participation), FVA (Backward participation), and DVA (Domestic value added). Furthermore, by performing a Granger causality test, we were also able to investigate the opposite effect, that is whether GVC participation variables had an impact on the increased rate of robotics investment. The results show that an increase in automation leads to a decrease in participation in GVCs in the short term and then it is stabilised the years later. On the contrary, a growth in GVCs leads to more investment in robotics. Robotics, moreover, determine greater forward participation and lower backward participation. This relationship does not find any statistically significant effect in the opposite direction. On the other hand, domestic value added is positively affected by higher investment in robotics, although the effect is not statistically significant at 5% but only at 10%. In other words, the augmented automation and the adoption of new industrial technologies establish a higher rate of production in home-countries, diminishing the reliance on inputs from third countries. Indeed, there is statistical evidence that backward participation decreases as the use of robots increases. At the same time, the greater productivity and efficiency of local companies means that they can be more competitive in global markets, supplying goods at a lower cost and increasing benefits. These dynamics, therefore, represent a reshoring phenomenon. Observing the trend of the last period of GVCs, the results obtained were expected. Indeed, companies would tend to decrease delocalization, favouring domestic production, with inevitable consequences also at backward and forward levels.

It should be noted that our analysis was conducted only on advanced and transition economies, over a period of 26 years, from 1993 to 2018. In these years there have been several events that generated both positive and negative impacts on slowbalization. Among others there are the US-China trade war, the UK's departure from Europe, and the financial crisis of 2008. It would have been very interesting to analyse the trends before and after the 2008 financial crisis, to observe whether there is a statistical significance on the impact before and after a crisis, but in order to maintain meaningful estimates, all the 26 years were necessary for the panel of data. Moreover, we have seen that there are several factors impacting participation in global value chains, and we could have considered different variables in the econometric analysis.

Nevertheless, we wanted to investigate the impact of automation, thus the relationship between investments in robotics and indices of participation in GVCs. What can be said, therefore, is that we did not analyse a policy or a single event that generates an immediate impact, but rather, we analysed a macro factor, a structured phenomenon that developed over time. We were able to estimate, thanks to the Granger causality test, how the history of the trends in robotics has impacted on the participation indices of GVCs, regardless its own history. Reaching statistically significant results, regardless of the other elements impacting on GVCs, strengthens our results. In other words, if we had not obtained relevant results, then we would have concluded that other predominant factors are impacting on GVCs.

Undoubtedly, after the financial crisis, as Cigna et al. (2022) reported, uncertainty, instability, and insecurity increased, both at political and market levels. Consumers, governments, and businesses have preferred to have more internal control over production, trying to limit external shocks. This search for greater security and stability, together with a decrease in the cost of robotics, has certainly favoured reshoring. This new trend of reshoring, different from the previous common desire for offshore production, contributed to the phenomenon of slowbalization.

To conclude, we can therefore say that by examining past trends in robotics investments, we have obtained important results for short-term forecasts in global value chain participation indices. In fact, as one might expect, higher investment in automation within home-country leads to lower participation in GVCs, decreasing, in the short run, also the backward participation, but increasing the forward one.

Into the analysis, however, Covid-19 is not included, but we can suppose that, given the results obtained from our research, these will be even more emphasised. In fact, after Covid pandemic a greater desire for stability and security among consumers, governments, and firms will be required, thus leading to a lower degree of GVC participation, higher domestic production, greater forward participation, and lower backward participation. Cigna et al. (2022), in their paper, stated how new Industry 4.0 technologies could discourage offshoring and shorten value chains, enforcing regionalization. However, this is not yet entirely certain, especially in the long run. Nevertheless, the authors go on saying that the coronavirus pandemic may exacerbate these trends. In fact, during the pandemic, many productions stopped and encountered problems along the supply chain, but robotics has the great advantage of being able to shorten distances, limiting even the physical proximity between workers, thus ensuring greater safety. So, Covid-19 pandemic could accentuate investment in robotics even more, encouraging reshoring and increasing the slowbalization phenomenon.

REFERENCES

Abrigo, M. R., Love, I. (2016). Estimation of panel vector autoregression in Stata. The Stata Journal, 16(3), 778-804.

Acemoglu, D., Restrepo, P. (2017). Robots and Jobs: Evidence from U.S. Labor Markets. NBER Working Paper No. 23285, March.

Acemoglu, D., Restrepo, P. (2018). The race between man and machine: Implications of technology for growth, factor shares, and employment. American Economic Review, 108(6), 1488-1542.

Adachi, D., Kawaguchi, D., Saito, Y. (2020). Robots and Employment: Evidence from Japan, 1978-2017. Discussion papers, 20051.

Antonietti, R., Franco, C. (2021). From FDI to economic complexity: a panel Granger causality analysis. Structural Change and Economic Dynamics, 56, 225-239.

Antràs, P. (2020). Conceptual aspects of global value chains. The World Bank Economic Review, 34(3), 551-574.

Autor, D., Salomons, A. (2018) Is Automation Labor-Displacing? Productivity Growth, Employment, and the Labor Share, NBER Working Paper No. 24871, July 2018

Baldwin, R. (2018). The great convergence: information technology and the new globalization. Harvard University Press.

Baldwin, R. (2019). The Globotics Upheaval: Globalisation, Robotics, and the Future of Work. Oxford University Press.

Baldwin, R., Venables, A. J. (2013). Spiders and snakes: Offshoring and agglomeration in the global economy. Journal of International Economics, 90(2), 245-254.

Brakman, S., van Marrewijk, C. (2022). Tasks, Occupations, and Slowbalization: On the Limits of Fragmentation. CESifo Working Paper No. 9514.

Brynjolfsson, E., McAfee, A. (2011). Race against the machine: How the digital revolution is accelerating innovation, driving productivity, and irreversibly transforming employment and the economy. Brynjolfsson and McAfee.

Burdisso, T., Sangiácomo, M. (2016). Panel time series: Review of the methodological evolution. The Stata Journal, 16(2), 424-442.

Caselli, M., Fracasso, A., Scicchitano, S., Traverso, S., Tundis, E. (2021). Stop worrying and love the robot: An activity-based approach to assess the impact of robotization on employment dynamics (No. 802). GLO Discussion Paper.

Chiacchio, F., Petropoulos, G., Pichler, D. (2018). The impact of industrial robots on EU employment and wages: A local labour market approach (No. 2018/02). Bruegel working paper.

Cigna, S., Gunnella, V., Quaglietti, L. (2022). Global value chains: measurement, trends and drivers. ECB Occasional Paper, (2022/289).

Douglas, A. I. (2020). Globalization is in retreat for the first time since the Second World War. PIIE, 23 April.

EORA, (2018). UNCTAD-Eora Global Value Chain Database.

Faber, M. (2020). Robots and reshoring: Evidence from Mexican labor markets. Journal of International Economics, 127, 103384.

Fondazione Nord Est, (2020). La ripartenza: Studi e analisi per un nuovo sviluppo delle regioni del Nordest. Report 2020 Fondazione Nord Est. February, 2020.

Ghodsi, M., Reiter, O., Stehrer, R., Stöllinger, R. (2020). Robotisation, employment and industrial growth intertwined across global value chains (No. 177). WIIW Working Paper.

Graetz, G., Michaels, G. (2018). Robots at work. Review of Economics and Statistics, 100(5), 753-768.

Graetz, G., Michaels, G. (2015). Robots at work. CEP Discussion Paper No 1335

Granger, C. W. J. (1969). Investigating Causal Relations by Econometric Models and Cross-spectral Methods. Econometrica 37 (3): 424–438.

Guizzo E. (2018) Robots your guide to the world of robotics. IEEE. Retrieved November 29, 2021, from https://robots.ieee.org/learn/what-is-a-robot/

Holtz-Eakin, D., Newey, W., Rosen, H.S., (1988). Estimating vector autoregressions with panel data. Econometrica 56, 1371–1395.

Hummels, D. L., Ishii, J., Yi, K.M. (March 1999). The Nature and Growth of Vertical Specialization in World Trade. FRB of New York Staff Report No. 72

Hummels, D., Ishii, J., Yi, K.M. (2001). The Nature and Growth of Vertical Specialization in World Trade. Journal of International Economics, 2001, 54(1): 75-96.

IFR (2021). International Federation of Robotics. Industrial Robotics Database

IFR (September 24, 2020b). Worldwide installations of industrial robots from 2004 to 2019 (in 1,000 units) [Graph]. In Statista. Retrieved August 26, 2021, from https://www.statista.com/statistics/264084/worldwide-sales-of-industrial-robots/

IFR (Septemebr 24, 2020a). IFR Press Conference. Frankfrut. Presentation_WR_2020

Im, K.S., Pesaran, M.H., Shin, Y. (2003), Testing for unit roots in heterogeneous panels, Journal of Econometrics, 115(1), 53–74.

Jäger, A. & Moll, Cornelius & Som, O. & Zanker, Christoph & Kinkel, Steffen & Lichtner, Ralph. (December, 2015). Analysis of the impact of robotic systems on employment in the European Union. Fraunhofer Institute for Systems and Innovation Research ISI; Karlsruhe University of Applied Sciences

Kilic, K. Marin, D. (2020). How COVID-19 is transforming the world economy. VoxEU.org, 10 may

Li, X., Meng, B., Wang, Z. (2019). Recent patterns of global production and GVC participation. Global Value Chain Development Report 2019, 9.

OECD (2013), Interconnected Economies: Benefiting from Global Value Chains, OECD Publishing, Paris.

OECD (2020). Efficiency and risks in global value chains in the context of COVID-19. 16 Dec 2020. Arriola C., Guilloux-Nefussi S., Koh S., Kowalski P., Rusticelli E., Van Tongeren F. OECD Economics Department Working Papers

OECD database. Trade in Value Added database. Retrieved December 29, 2021, from https://www.oecd.org/sti/ind/measuring-trade-in-value-added.htm

Orha, I., Oniga, S. (2012). Assistance and telepresence robots: a solution for elderly people. Carpathian Journal of Electronic and Computer Engineering, 5, 87.

Palandrani, P. (September 11, 2020). Global Supply Chain Disruptions Driving Robotics Adoption. Robotics business review.

Pesaran, M.H. (2007), A simple panel unit root test in the presence of cross-section dependence, Journal of Applied Econometrics, 22(2), 265-312.

The World Bank. Data Catalog. World Development Indicators. Dataset

Tilley J. (2017) Automation, robotics, and the factory of the future. McKinsey & Company

Toschi, G. (2021). Tecnologia (informatica) e nuova globalizzazione. Lecture notes. Economia Internazionale. University of Padova. Delivered March 2021.

UNCTAD, (2019). Yedan, A. Measuring value chains: Introduction of quantitative instrument based on input-output tables. Bijilo, Gambia

UNCTAD, (2021). World Investment Report. Investing in sustainable recovery. New York: United Nations.

Violante G.L. (2008) Skill-Biased Technical Change. In: Palgrave Macmillan (eds) The New Palgrave Dictionary of Economics. Palgrave Macmillan, London. Retrieved from: https://doi.org/10.1057/978-1-349-95121-5_2388-1

Wang, Z., Wei, S. J., Yu, X., Zhu, K. (2017). Measures of participation in global value chains and global business cycles (No. w23222). National Bureau of Economic Research.

World Bank (2019). "World Development Report 2020: Trading for Development in the Age of Global Value Chains", World Development Report

WTO (2021). Trade in Value-Added and Global Value Chains: statistical profiles. Explanatory notes. Retrieved December 29, 2021, from https://www.wto.org/english/res_e/statis_e/miwi_e/countryprofiles_e.htm