END OF DREGREE PROJECT

DEGREE IN ECONOMICS

ACADEMIC YEAR 2023/24

MARCH CALL

TITLE: ECONOMETRIC ANALYSIS OF THE IMPACT OF ROBOTIZATION ON EMPLOYMENT

AUTHOR: ROMAN GUTIERREZ, LUCIA

TUTOR: ISMAEL SANZ LABRADOR

In Madrid, on 08 of February 2024

Table of contents

Table of figures

Table of tables

Table of regressions

I. Abstract

We examine the impact of robots on employment levels in Spanish manufacturing companies from 1990 to 2014. We use firm-level data from the Encuesta Sobre Estrategias Empresariales (ESEE).

The primary objective of this study is to evaluate the growing influence that automation and robotization are having on the labour market in the modern era. Robotics and artificial intelligence systems are being adopted by a number of industries as we enter the Industry 4.0 era, resulting in a significant change in the employment dynamics. Our research addresses worry about the disappearance of traditional jobs as robots and algorithms take over repetitive and routine tasks. We also look at how this technological development may lead to new job openings in fields like software development, programming, and the design, upkeep, and monitoring of automated systems.

The factors that affect workforce acceptance of and adaptation to robotics and automation are examined in the context of this study. This includes taking into account how businesses are investing in the training and skill-development of employees.

Keywords: automatization, employment, instrumental variables, robots.

II. Context of robotization and artificial intelligence

The Fourth Industrial Revolution is currently underway, brought about by the incorporation of artificial intelligence and ranging from the introduction of big data to novel forms of human-machine interaction.

Artificial intelligence (AI) and robotics have become disruptive technologies that have fundamentally and continuously changed the nature of employment around the world. Rapid advances in these fields over the past few decades have led to a number of changes in the workforce and the global economy. This phenomenon has not only sparked contentious debate but has also raised concerns about the future of work and its implications for society as a whole. We will take an in-depth look at how robotics and AI have affected and will continue to influence employment in this in-depth analysis, addressing both the opportunities and challenges they present. (Raj, M and Seamans, R. 2018)

Analyzing the development of these technologies and how they have been incorporated into different industries is essential to understanding how robotics and AI will affect employment. Robotics has advanced significantly in recent years, enabling the automation of tasks in both manufacturing and service industries. Factory production has been revolutionized by industrial robots, which have increased the accuracy and efficiency of manufacturing and, in some cases, reduced the need for labour.

For its part, AI has found use in a variety of sectors, including healthcare, customer service, human resource management and finance. Natural language processing and pattern recognition are two cognitive functions that machine learning algorithms and neural networks have proven they can perform. As a result, many processes have been optimized and routine tasks have been automated, often leading to the elimination of traditional jobs.

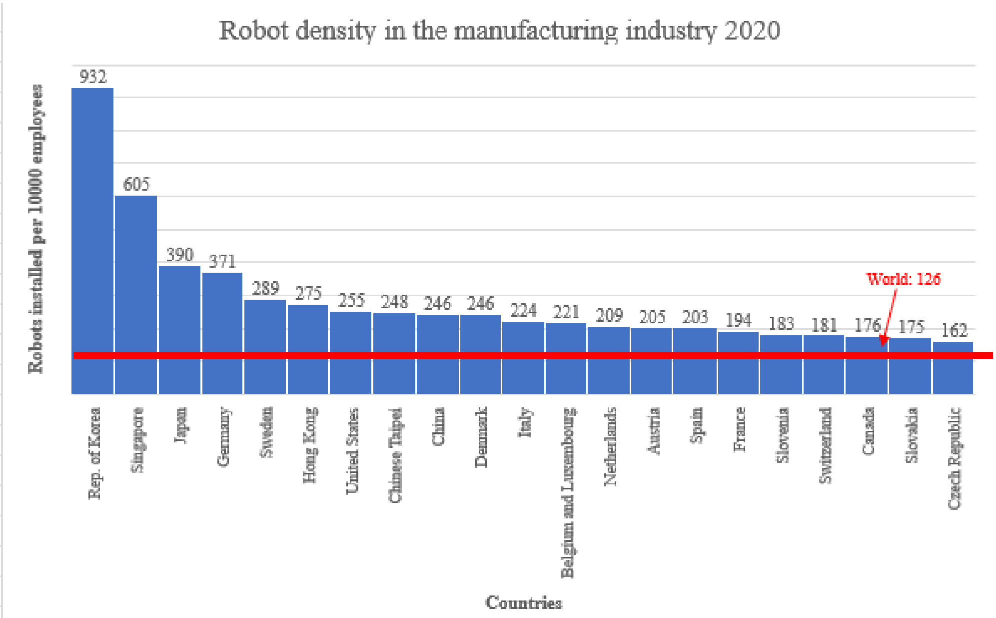


Figure 1. Number of robots per-10000 employees in the manufacturing industry 2016.

Note: Graph made by me with data from (IFR International Federation of Robotics, (2021)

Manufacturing is one of the industries that has experienced a significant impact. Robotics has increased efficiency and accuracy on production lines and, at the same time, reduced the demand for labour in the manufacturing industry. As a result, concerns have been raised about the loss of manufacturing jobs, particularly in areas where the industry is crucial to the local economy. In the above graph (Figure 1) we can see the number of installed industrial robots per 10000 employees in the manufacturing industry in 2020. As we see 126 robots per 10,000 employees is the average of global robot density in the manufacturing industries. (IFR International Federation of Robotics, 2021)

The use of chatbots and automated service systems to automate administrative and customer service tasks is becoming increasingly common in the service industry. While this can increase productivity and reduce costs for companies, it also raises concerns about the future of workers in these positions, whose tasks could be taken over by artificial intelligence systems.

Despite these difficulties, robotics and artificial intelligence have also increased job opportunities in related industries. The development of new professions and job opportunities has been driven by the growing demand for professionals with expertise in cybersecurity, data analytics, and programming. The growing demand for skilled workers is due to the advanced technical skills needed to implement and maintain robotics and artificial intelligence systems.

However, the benefits of this technological revolution are not reaching all industries and workers equally. In the age of robotics and AI, those with more specialized skills and the ability to adapt to constantly changing Industrial environments will likely thrive, while those with less specialized skills or working in highly automated industries may struggle to find employment.

Robotics and AI not only have an impact on the labour market, but also raise moral and social issues. If issues of wealth redistribution and workforce training are not adequately addressed, job automation could lead to greater economic inequality. In an increasingly AI-driven world, data security and privacy are also important issues. (Konovalov, A. 2023)

In short, robotics and artificial intelligence have brought both positive and negative changes to the employment landscape. Although these technologies have increased productivity and generated new employment opportunities, they have also presented serious problems in terms of job loss and economic inequality. Ensuring that people remain at the center of our business will require strategic planning, ongoing education, and careful ethical reflection. How we respond to these challenges will largely determine the future of employment in the age of robotics and artificial intelligence. business and society.

III. The beginning of robotization

It is necessary to mention that the first instance of automation—the steam engine, which was designed with little human involvement in mind—was what started the entire process and helped us understand the idea and roots of automation as well as the modern era to which we belong. Therefore, what may have seemed like insignificant advancements made during the first industrial revolution, which occurred in England at the end of the 18th century and began at the beginning of the 19th, are now the foundation of what we know as technology.

Considering that at the time the majority of work activity cantered around agriculture, society was able to advance in various sectors thanks to the steam engine.

However, as a result of new mechanical inventions, society develops more quickly, allowing for wider development and more significant changes. Similar to how mechanics and technology advanced around 1870, the Second Industrial Revolution was sparked by innovations like the airplane and gasoline engines, which allowed for mass production and the dawn of a new scientific era (Schwab 2020).

At the end of the 20th century the third industrial revolution arrived. The advent of mainframes and personal computers made a big difference, as the major contribution of the Third Industrial Revolution was the Internet. They also refer to this period as the "Information Age" because of the centrality of information technology in these significant changes in society and the economy.

One term used to describe the current technological revolution that is altering the way we live, work, and do business is the "Fourth Industrial Revolution", although it can also be called Industry 4.0.

The current, Fourth Industrial Revolution draws from the Third and is characterized by a fusion of technologies, blurring the lines between the physical, digital, and biological (Strategicds 2019).

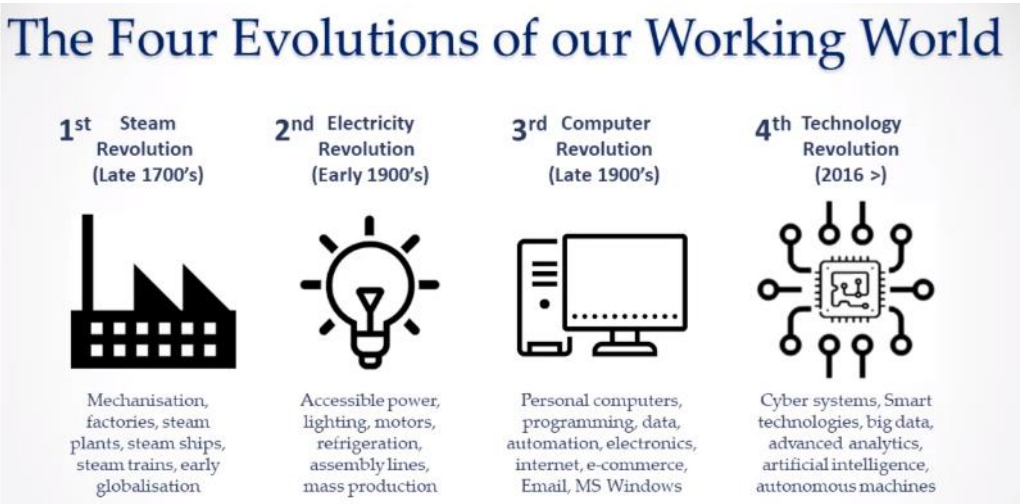


Figure 2. The four industrial revolutions.

The digital and technological revolution that began in the last decades of the 20th century is the precursor to the Fourth Industrial Revolution. The main drivers were major advances in fields such as computing, connectivity, artificial intelligence, robotics, nanotechnology and biotechnology.

Some key technologies are artificial intelligence as I explained above, big data, internet of things (IoT), 3D printing, blockchain and synthetic biology.

The Fourth Industrial Revolution may occur in three stages (PwC 2019):

- The algorithm wave, the first stage, will start in the early 2020s. It is primarily concerned with the automation of straightforward computational tasks and the analysis of structured data in fields like finance, information, and communication.
- The second stage is the augmentation wave: This phase is also in progress, but it won't fully encompass the market until the late 2020s. It focuses on automating repetitive tasks like filling out forms, communicating, and exchanging information, as well as statistical

analysis of unstructured data in environments that are only partially controlled, like robots and unmanned aerial vehicles.

- And the third stage the beginning in the 2030s, the automation of manual labour and employee activities will be a symptom of the autonomy wave. In addition, it is anticipated that the responses in dynamic, real-life situations that call for reaction and problem-solving, e. g. Robots and machines (autonomous vehicles) will take their place in production and transportation. Numerous jobs have undergone significant change as a result of Industry 4.0, and new ones have also been created.

In terms of employment, data privacy and cybersecurity, it presents significant challenges. It also provides opportunities to innovate, raise living standards and address global issues such as climate change.

Automation technologies have spread rapidly in developed countries in recent decades. The number of industrial robots per worker in the US economy increased from 0.38 to 1.8 between 1993 and 2017, and the share of information technology in total US investment increased from 3.5% to 23% between 1950 and 2020. These developments have raised fears of large-scale worker displacement and fueled debates about the future role of human labour in the economy (e.g., Mokyr et al. 2015).

IV. The fear of automation

Automation and the growing use of robots and artificial intelligence (AI) have the potential to fundamentally change the nature of work and create new jobs that complement machines and algorithms as we had said, but future automation will also threaten existing jobs. There are many employees (Acemoglu and Restrepo 2020). Labour displacement due to automation can have significant social and political consequences, as evidenced by the impact of past technological developments (Caprettini and Voth 2020). The threat of future waves of automation is therefore likely to play a key role in shaping workers' responses, public debate about economic inequality, and the role of governments in mitigating its consequences as Marta Golin and Christopher Rauth said. (Golin, M. and Rauh, C. 2023).

This study (Golin, M. and Rauh, C. 2023) discusses workers' concerns about the threat of job automation in the near future. The survey measures automation risk by asking workers how likely they are to lose or lose their jobs to automation, robots or AI in the next 10 years. About 40% of respondents believe that more than 50% of them could be replaced by cars. In particular, younger, less educated workers in the food preparation, hospitality, transport and trucking industries are more concerned, while workers in the defense service or community and social services are less concerned. We then explore the correlation between perceived risks to automation and employee preferences and behaviours. Workers can demand more redistribution from the government or reduce risks by retraining and changing jobs. The survey measures reactions to automation based on redistributive preferences, support for public spending on adult education and income support programs, employment measures such as union membership or retraining, populist attitudes and voting intentions.

The results show that the perceived risk of automation is strongly related to redistributive preferences, employment responses and populist attitudes. For example, workers who favour automation favour higher income tax rates, demand a higher universal basic income, are interested in unionization or reskilling, consider themselves anti-elite, and abstain from presidential elections.

In figure 3, the x-axis represents the expected probability of losing a job to automation in the next 10 years, compared to the average results shown in the title and y-axis. The sample is limited to controls. Thin lines represent 95% confidence intervals.

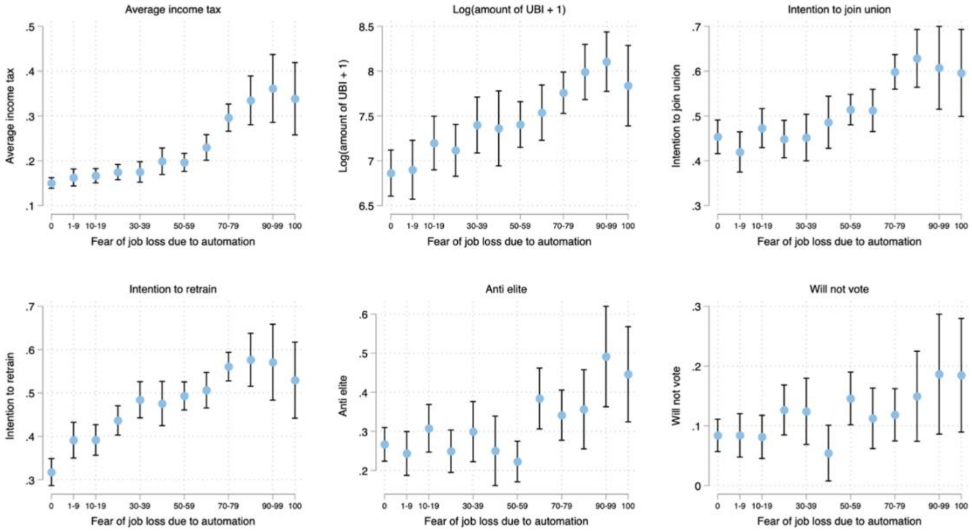


Figure 3. Fear of automation and preferences, intentions, and attitudes.

To avoid endogenous problems, experiments were included in the study to influence employees' attitudes towards the risks of automation. After inducing fear of job loss due to automation, participants are randomly assigned to a control or treatment group to obtain information on their average expectations of task automation in similar jobs. The results show that fears of automation increase the demand for a larger welfare state and influence the political landscape, reducing voting intentions and shifting ideology to the left.

Workplace responses show that higher odds of unemployment are associated with significantly higher odds of joining a union. However, no significant effects were found on intentions to change careers or to participate in retraining programmes. Furthermore, reactions to information about automation are often driven by people who perceive the potential of automation to be greater than their initial level of fear.

The study concludes by raising concerns about the potential impact of future waves of automation on public budgets due to increased demands for redistribution and a growing welfare state. It also highlights the potential for automation to fuel anti-elite sentiment, reduce voter turnout and trust in politicians, and underlines the importance of preparing workers to adapt to changes in the workplace and future challenges. (Golin, M. and Rauh, C. 2023)

V. Automation and the polarization of the labour market

Another important paper about the automatization is "*Automation and polarisation*", by the Loebbing, J. and Acemoglu, D. (2022) shows that automation polarizes labour markets, affecting jobs in the middle of the wage and skill distribution. Nevertheless, there is a lack of understanding of why automation has created such polarization.

Autor (2014) presents a main explanation of the Polany´s Paradox, suggesting that automating medium-skill tasks is easier than automating low- and high-skill tasks. This is because middle-skilled jobs are characterized by repetitive cognitive tasks that are particularly suitable for computer automation. In contrast, jobs with the lowest wages or skill ranges have a high proportion of manual tasks that people can perform intuitively without being told how to do them. Therefore, Autor suggests that the polarizing effect of automation is related to Polanyi's (1966) statement that “we know more than we can tell”. The lack of clear instructions means that the computer cannot perform these tasks.

Loebbing, J. and Acemoglu, D. (2022) explain that the current polarizing nature of automation, which can be explained by Polanyi's paradox of low wages, has important implications for the future of automation. If technological advances overcome Polanyi's paradox, automation may spread to low-skilled and low-wage jobs. If low wages are a barrier, automation can spread to low-wage occupations as machine productivity increases. The framework suggests that the next phase of automation could impact low-wage jobs, moving from a polarizing effect to increasing inequality.

VI. Automation and workforce in services

In the post of Toshiaki Iizuka, Yong Suk Lee and Karen Eggleston (2021) gives data on an initial study of robots in the service sector, indicating that their incorporation has generated more employment, flexibility and solved problems of turnover in long-term care. Technologies that scare countries can also be a solution to the social and economic challenges of an ageing population.

Robots incorporate innovative technology that boosts productivity and frees workers from repetitive, strenuous and monotonous work, while helping to alleviate labour shortages resulting from ageing populations. These demographic challenges are especially important in higher-income countries that are further along in the demographic transition, such as the OECD countries, where populations in 18 of 36 countries are projected to decline by 2055. These nations face rising old-age dependency ratios, declining employment-to-population ratios and challenges in providing services to the growing number of frail older adults (Iizuka, T. et al., 2021).

Japan's experience could be instructive as demand for long-term care increases due to a shrinking population and a growing elderly population. Recognizing that robots cannot fully replace the empathy and dexterity skills needed in medicine, Japan has introduced robots to address the medical workforce shortage. By 2025, there will be a significant shortage of healthcare workers due to physical and salary challenges in the current workforce.

In addition, in Japan, the development and use of robots has been actively promoted to meet the growing demand for long-term care. The central government has implemented a "Robotics Plan" with the aim of increasing the proportion of people willing to use robots in healthcare from 60% to 80% (Iizuka, T. et al., 2021).

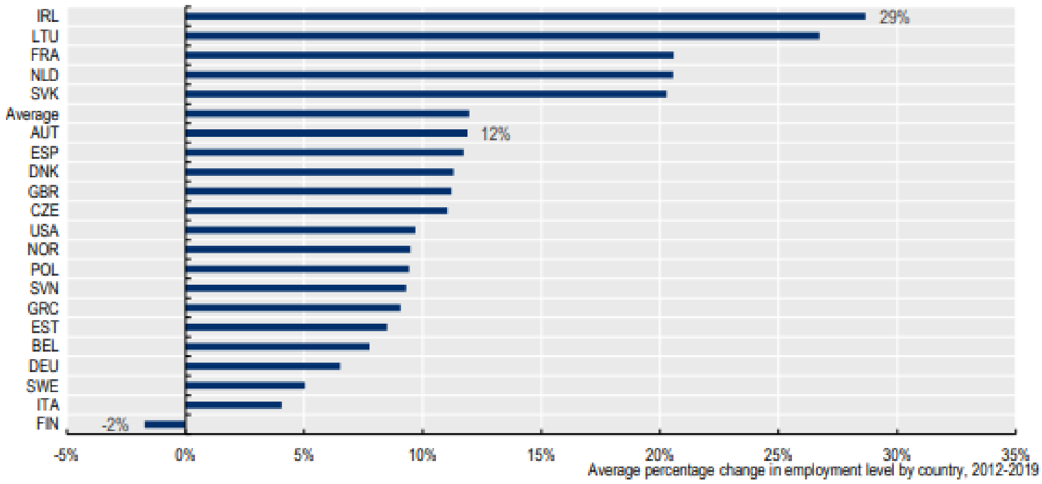
To understand the causal relationship between robots and labour, we used current subsidies as an instrumental variable for the introduction of robots. In 2017, the expected number of robots per nursing home was found to be a significant predictor of robot adoption. Despite general concerns about job cuts, the adoption of robots has increased the employment of healthcare workers and nurses.

It should be noted that the increase in the labour force occurred mainly among non-regular workers. With the introduction of robots, the number of part-time medical staff has doubled, and the number of part-time nurses has also increased significantly. However, the estimate for regular workers was negative but not statistically significant.

In Japan, where immigration has traditionally been stopped, the use of foreign workers is particularly important. But policies aimed at easing projected long-term care workforce shortages are beginning to relax. Nursing homes that adopt robots are more likely to hire foreign workers and plan to hire immigrants in the future, but this association does not appear to be causal (Iizuka, T. et al., 2021).

VII. Robots and automatization and its consequences in the OECD countries

Despite estimates that a sizeable portion of jobs worldwide were at risk of automation, this has not led to widespread unemployment. In fact, employment has grown at an average rate of 12 percent across almost all nations between 2012 and 2019 despite ongoing automation (Figure 2). The recovery from the Global Financial Crisis (GFC) can be partly blamed for this employment growth. Indeed, the nations that experienced the greatest employment losses during the crisis also saw the greatest employment growth between 2012 and 2019. (Arntz, M. et al., OECD 2016) The recovery does not, however, provide the full picture, as is covered below.



Note: Countries are ranked by percentage change in employment level. The average percentage change is calculated as the average change across occupations within a country. All averages are unweighted.
Source: Georgieff and Milanez (2020).

Figure 4. From 2012 to 2019, the average percentage change in the level of employment for each occupation was observed by country.

Since 2012, employment has increased in almost all professions, including those with a higher risk of automation, like business administration and management specialists, as accounting has recently become increasingly automated. Information and communications technology specialists experienced the greatest growth.

Despite strong global employment growth from 2012 to 2019, employment growth was slower in occupations at higher risk of automation (Figure 5). On average across all countries, employment in the top half of occupations measured by automation risk increased by 6%, compared to 18% in the bottom half. At the occupational level, these results suggest that the OECD automation risk assessment was a good predictor of subsequent employment growth. The results also show that despite automation, employment has generally increased. (Nedelkoska, L. and Quintini, G, 2018)

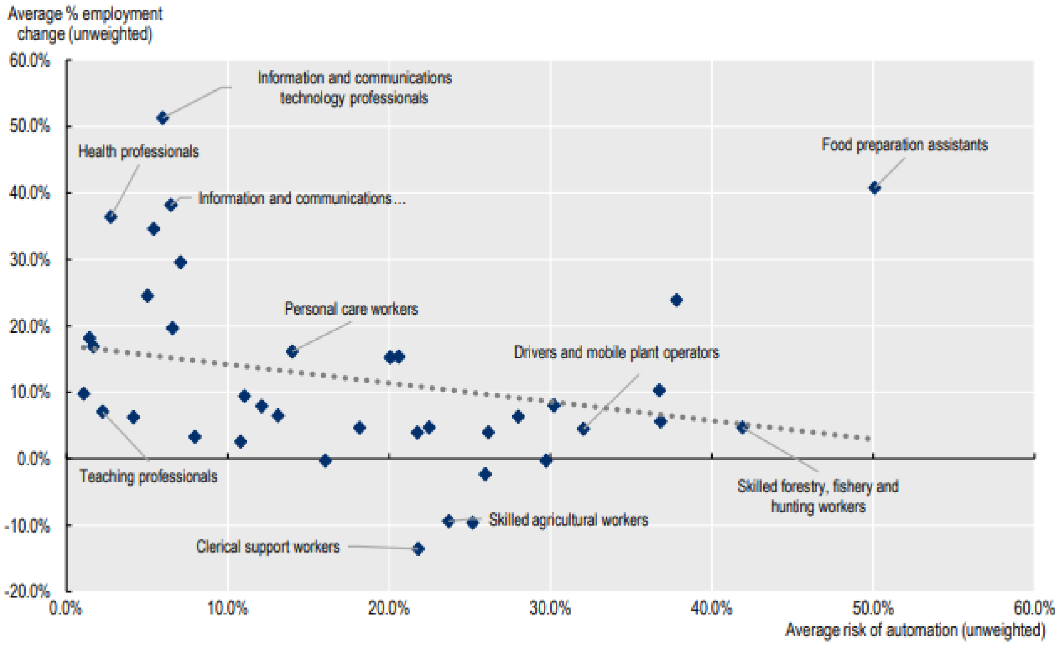


Figure 5. Employment growth was lower in occupations at higher risk of automation.

In addition, people with lower levels of education are more concentrated in high-risk occupations. In 2012, 74% of low-skilled workers were in the most hazardous occupations, compared to 53% of medium-skilled workers and 13% of high-skilled workers. However, lower employment growth in occupations at high risk of automation did not affect labour force participation among low-skilled professionals compared to other educational groups. This is because while the number of jobs for this group has fallen, so has the number of low-skilled workers in the general population. In the countries studied, the proportion of people with a low level of education in the working population decreased by an average of 4 percentage points. (Scarpetta, S and Pearson, M, 2021)

VIII. Project description: materials and methods

The primary objective of this study is to evaluate the growing influence that automation and robotization are having on the labour market in the modern era. Robotics and artificial intelligence systems are being adopted by a number of industries as we enter the Industry 4.0

era, resulting in a significant change in the employment dynamics. Our research addresses worry about the disappearance of traditional jobs as robots and algorithms take over repetitive and routine tasks. We also look at how this technological development may lead to new job openings in fields like software development, programming, and the design, upkeep, and monitoring of automated systems.

The factors that affect workforce acceptance of and adaptation to robotics and automation are examined in the context of this study. This includes taking into account how businesses are investing in the training and skill-development of employees as well as the government policies being implemented to mitigate potentially harmful employment effects. In order to enable businesses, governments, and employees to make informed decisions in a workplace that is constantly changing, our research aims to provide a balanced view of the changes that the development of technology will bring about to the world of work.

The study also focuses on analysing the impact of robotisation for employees in different sectors and companies. We understand the impact that the implementation of automated technology can have on all types of employees, regardless of the type of company. This holistic approach seeks to identify patterns and variations in how employees in large and small companies experience and respond to the changes brought about by robotics.

By exploring the interaction between automation and employees in different business contexts, we aim to provide clear insights that address the diverse concerns and needs of employees in an era of workplace change. We believe it is important to understand how employees are affected at multiple levels and hierarchical functions, from operations to management, to provide a complete picture of the challenges and opportunities in today's workplace.

1. Participants

The study was conducted with a total sample of 4,354 Spanish manufacturing companies. It covers a broad period from 1990 to 2016, including the economic recession of 2008 and the subsequent recovery period. The high rates of investment necessary to advance companies' production technology in a new environment of international competition are captured in these data.

The research database, as I mentioned earlier, contains information on 4,354 Spanish companies, including small and medium-sized companies (74.7 percent with 3,251 companies) and large companies (25.3 percent with 1,103 companies), SMEs are companies with less than 200 employees, large companies are companies with more than 200 employees, and covers three main areas. Firstly, strategic decision-making on prices, costs, markets, and investments; secondly, the value process involving human capital (educational level, training within the company, etc.), organization, business innovation, research, and development (R&D) and ICT; and finally, the most important indicators and ratios of balance sheets and profit and loss.

In this study the companies also show us whether they always used robots, whether they used them from time to time or whether they never used them at all. One of the benefits of the ESEE (Ballestar, M. T, et al., 2020) is that it contains information on the use or adoption of robots every four years. Thus, we have data on firms' robotisation and their degree of adoption for the years 1990, 1994, 1998, 2010 and 2014.

Robotics accounted for 17:70% of manufacturing firms in 1990; SMEs made up 32.52% of this group, while large firms made up 67.58%. 2014 saw a twofold increase in robot adoption, reaching 33.27 percent. Most significantly, the makeup of robotics companies flipped; only 36.23% of manufacturing firms using robots were classified as large firms, whereas 63.77 percent of them were SMEs.

2. Variable explanation

For this study we will use data from the Encuesta Sobre Estrategias Empresariales (ESEE). The ESEE provides a representative panel of data on Spanish industrial firms, collected through an annual survey conducted by the Spanish Ministry of Finance and Public Administration,

To make variables more compatible with the Stata program, they were modified and given new names.

2.1. Variables

- PERTOT: number of employees.
- Timetrend: years, in this study 27 years (1990-2016).
- LnVAReal: real value added.
- Lnhetn: hours worked.
- Lncprealper: wage cost (when it is higher, less employees).
- NACE2: activity branch.
- Lncostesmarginales: marginal costs.
- Always_roboticstrend: dummy variable that takes value 1 when industries used robots during the 26 years of the study, and it takes value 0 when not.
- Never_roboticstrend: dummy variable that takes value 1 when industries did not use robots during the 26 years of the study and it takes value 0 when industries used them.
- Q_periods_is_robottren: data is available from 1990 to 2014. This variable measures the percentage of years in that period (24 years) that the company has had robots. For example, 50% would be 12 years. 25% would be 6 years.
- Perc_periods_is_robottrend: This is the ranking of the company by the number of years it has had robots. For example, a company that has had robots for 24 years will be at the top of the ranking (even the top) while a company that has never had robots will be at the bottom of the ranking.

- LnVAIVempresaRTyi: is an instrumental variable. It is the neperian logarithm (ln) of the value added of the companies in the same industrial sector as company “i”. In other words, to instrument for the logarithm of the value added of company “i” in year t, we use as an instrumental variable the average value of the other companies in the same industrial sector (of all the companies in the same industrial sector, except company “i” itself).
- LncostesIVempresaRTyi: is an instrumental variable. It is the neperian logarithm (ln) of the costs of the firms in the same industrial sector as company “i”. In other words, to instrument for the logarithm of the costs of company “i” in year t, we use as an instrumental variable the average value of the other companies in the same industrial sector (of all the companies in the same industrial sector, except company “i” itself).

Following with the questions answered by the industries, the analysis aims to clarify the effects of robot adoption on worker participation and employment demand by skill level when a company has started the digital transformation process. We have taken the total demand for labour at the company level from the ESEE database and used it to develop the analysis as I said before.

The adoption of robots in industries and its impact on the labour market has been a subject of intense debate. Firms that embrace robotics can expand their operations, create new job opportunities, and increase productivity. However, firms that do not adopt robots may face increased competition and potential negative effects on production and employment.

Industrial robots are machines designed to perform specific tasks automatically, replacing human workers in certain production stages. The International Federation of Robotics (IFR) reports that there are currently around two million industrial robots in use, with an expected annual growth rate of 16 percent. This rapid integration of robots into manufacturing processes has led economists and policy experts to intensively study how automation affects labour markets.

A recent study (Koch et al. 2019), using detailed data from Spanish manufacturing companies over a 27-year period from 1990 to 2016, examines which businesses employ robots and what the labour market consequences of robot adoption are. This research, based on Spain's high robot density per worker in Europe, utilizes data from the Encuesta Sobre Estrategias Empresariales (ESEE), an annual survey of approximately 1,900 Spanish manufacturing firms. The data provides comprehensive insights into various aspects of these companies, including their use of industrial robots, technology adoption, costs, pricing, employment, and more. Consequently, this study offers a valuable opportunity to understand the factors influencing robot adoption at the firm level and its broader effects.

The ESEE dataset was used to create Figure 1, which shows unequivocally that firm heterogeneity in the adoption of robots matters greatly for the effects of robot technology on the labour market. It demonstrates that companies that adopted robots between 1990 and 1998 (referred to as "robot adopters") increased the number of jobs by more than 50% between 1998 and 2016, whereas companies that did not adopt robots (referred to as "non-adopters") decreased the number of jobs by more than 20% during the same period. (“Robots and firms | CEPR”). It is impossible to recognize and investigate this striking pattern in the data using the macro-level data on robot use that is used in the existing literature.

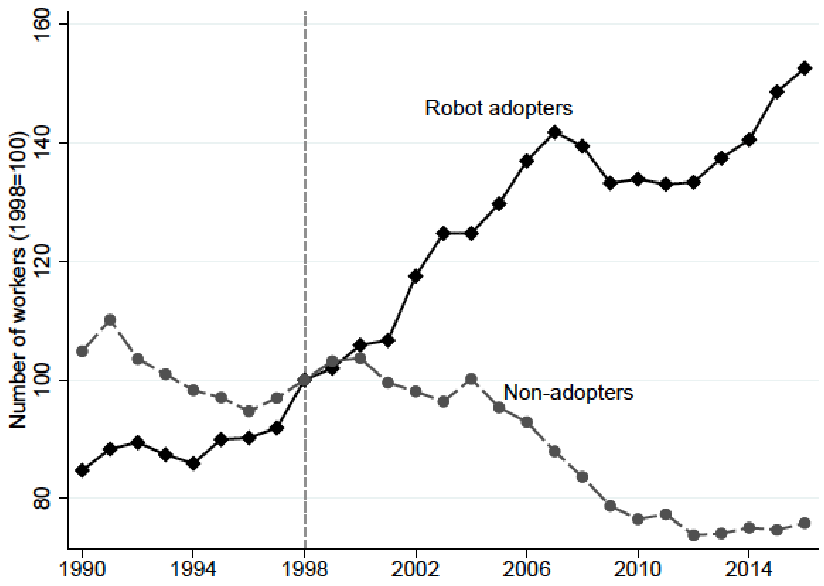


Figure 6. Evolution of firm-level employment for robot adopters versus non-adopters.

The graph shows the progression of the typical employment rate in businesses from 1990 to 2016. Firms are split into two categories: those that adopted robots (solid black line) and those that did not (dashed grey line). Also, the graph shows when compared to non-adopters, businesses that use robots in their production are already bigger and more productive.

In the next figure (Figure 5) we can see the average percentage of large firms using robots among large firms and SMEs is 13.1 per 100 and 12.9 per 100 of SMEs. In contrast, non-robotic firms are found primarily among small and medium-sized firms (SMEs).

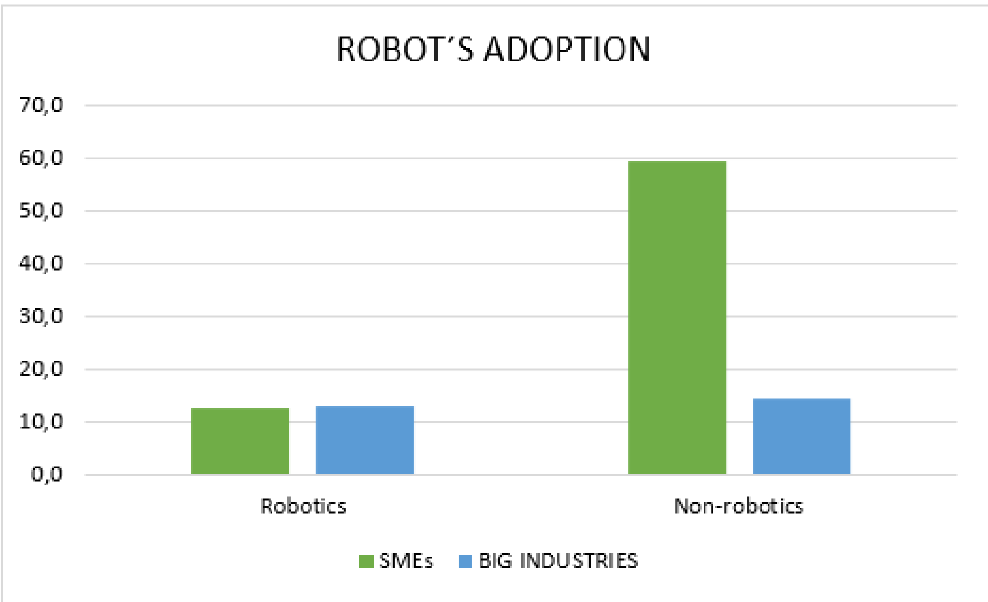


Figure 7. Robot´s adoption by firm´s size

3. Method used

For analyzing all the data, the program Stata was used, and data gathered by the Encuesta Sobre Estrategias Empresariales (ESEE) served as the foundation for our empirical analysis and made available by the SEPI foundation in Madrid. The primary feature that distinguishes the ESEE data set from other sets is what makes it ideal for our research datasets is that it contains data on the use of robots in manufacturing at the corporate level, therefore it offers a rare chance to investigate the motivations for and effects of robots' adoption within the company. We go into more detail about the data we use in the following.

Two types of regression were used in this project. The first type was the multiple regression model, a type of regression that uses some techniques to determine the relationship between a dependent variable and several independent variables. The purpose of this type of regression analysis is to find out how different independent variables affect the dependent variable. The second type of regression used was a simple linear regression model used to determine the relationship between a dependent variable and a single independent variable.

Much of the knowledge that I apply in this study has been studied in applied econometrics class with Professor Ismael Sanz Labrador.

IX. Results

Following the study of Ballestar, M. T., Díaz-Chao, Á., Sainz, J. y Torrent-Sellens, J (2021), we have 49235 employees, the biggest company has 25363 employees and the smallest one only has one employee.

Variable	Obs	Mean	Std. Dev.	Min	Max
PERTOT	49,235	240.6178	772.9188	1	25363

Table 1. Number of employees**.**

Also, in the next table we have the years using in this analysis, as we can see the minimum value of this variable is 1 year and the maximum value is 27 years.

Variable	Obs	Mean	Std. Dev.	Min	Max
timetrend	157,626	14	7.788906	1	27

Table 2. Years from 1990 to 2016.

In the following table we have the real added value of this paper, we see that the minimum value is 4.72075 and the maximum value is 21.98153.

Variable	Obs	Mean	Std. Dev.	Min	Max
lnVAreal	48,533	14.48226	1.889084	472.075	2.198153

Table 3. Description of the real added value.

In the fourth table we have the hours worked and we can see that the minimum value is 0.6931472 and the maximum value that takes this variable is 10.7056 hours worked.

Variable	Obs	Mean	Std. Dev.	Min	Max
lnhetn	46,639	4.75633	1.487267	.6931472	10.7056

Table 4. Hours worked.

In the table below we have the wage cost description, we see that the minimum value that takes this variable is 7.244744 and the maximum value is 15.86874.

Variable	Obs	Mean	Std. Dev.	Min	Max
lncprealper	48,533	14.48226	1.889084	472.075	2.198153

Table 5. Wage costs.

In the following table we have the activity branch, and we can see that the minimum value of this variable is one and the maximum value is 20.

Variable	Obs	Mean	Std. Dev.	Min	Max
NACE 2	157,626	9.858811	5.476886	1	20

Table 6. Branch activity of the study

In the table below we have the marginal costs of this study, as we can see the table show that the minimum value is -4.143307 and the maximum value is 8.938198.

Variable	Obs	Mean	Std. Dev.	Min	Max
lncostesmarginales	48,506	-.1547003	.5169332	-4.143.307	8.938198

Table 7. Marginal costs.

In the next table we see the use of robots in Spanish industries for 27 years, the variable always robotics trend, the minimum value is zero and the maximum value of this variable is 27.

Variable	Obs	Mean	Std. Dev.	Min	Max
always_robotics	148,743	2.185515	5.940668	0	27

Table 8. Always robotics trend.

In the following table we have the dummy variable never robotics trend that takes value 1 when industries did not use robots during the 26 years of the study, and it takes value 0 when industries used them. As we can see, the minimum value is zero and the maximum value of this variable is 27.

Variable	Obs	Mean	Std. Dev.	Min	Max
never_robotics	148,743	8.871665	9.161949	0	27

Table 9. Never robotics trend.

In the table below we can see the variable Q_periods_are_robot_trend which is the percentage of years in that period (1990 to 2014, 24 years in total) that the company has had robots. As seen the minimum value of this variable is zero and the variable´s maximum value is 108.

Variable	Obs	Mean	Std. Dev.	Min	Max
Q_periods_are_robots	148,743	15.08005	26.43862	0	108

Table 10. Percentage of years in 1990 to 2014.

In the following table we have the variable perc_periods_is_robottrend, which is the ranking of the company by the number of years it has had robots. The minimum value is zero and the maximum value of the variable is 2700.

Variable	Obs	Mean	Std. Dev.	Min	Max
perc_periods_is_robot	148,743	354.0207	640.1789	0	2700

Table 11. Ranking of the company by the number of years it has had robots.

In the next table we have the variable LnVAIVempresaRTyi which is an instrumental variable. It is the neperian logarithm (ln) of the value added of the companies in the same industrial sector as company "i". the minimum value of the variable is 13.34192 and the maximum value is 20.40498.

Variable	Obs	Mean	Std. Dev.	Min	Max
lnVAIVempresaRTyi	48,837	17.29943	1.37327	13.34192	20.40498

Table 12. Neperian logarithm of the value added of the companies in the same industrial sector as company.

In the following table we see the variable LncostesIVempresaRTyi, which is an instrumental variable. It is the neperian logarithm (ln) of the costs of the firms in the same industrial sector as company "i". As we see the minimum value of this variable is -9.645875 and the maximum value is 3.736459.

Variable	Obs	Mean	Std. Dev.	Min	Max
lncprealper	48,013	-.2224382	.6640022	-9.645.875	3.736459

Table 13. Instrument for the logarithm of the costs of company "i" in year t.

1. How affect robots to employees

Starting with the first regression we have the variable "pertot" as dependent variable, which is the number of employees, and the independent variables are the next ones show in this regression, but we are going to focus on "alwaysrobotictstrend," which is the dummy variable that takes value 1 when industries used robots during the 26 years of the study, so that was the first variable analysed, the industries adaptation to it:

VARIABLES	PERTOT
timetrend	-0.0037***
	(0.0004)
always_robotics	0.0016
	(0.0011)
lnVAreal	07572***
	(0.0081)
lncostesmarginales	0.6291***
	(0.0096)
lncprealper	-0.8010***
	(0.0108)
Constant	1.6398***
	(0.1498)
Observations	47,682
Number of empresa	5,495
R-Squared	0.786 [1]

Regression 1. Employees in companies that have always used robots.

[1] If the coefficient of the variable has *** means that the variable is significant at 1%.

If the coefficient of the variable has ** means that the variable is significant at 5%.

If the coefficient of the variable has * means that the variable is significant at 10%.

In this first regression we have four significant variables which really affected employees and industries. as we see in Regression 1 (table above) (Ballestar, M. T, et al., 2021). The first variable that must be considering is time trend with a significant level of 1%. The regression shows a negative effect that is easy to explain, there is a general trend in employment not related to robotization which is making Spanish industrial companies reduce employment, this general trend may be that Spanish industries are specialising in other services than industry. The timetrend variable is included because we want the always robot's variable to be uncontrollable.

If the time variable had not been included, then a negative effect would have been attributed to the incorporation of robots because firms are adopting more and more robots and there is a tendency to reduce employment, and this would have been wrongly attributed to the adoption of robots. But as the time variable is included, we see that the robot adoption variable does not have a positive or negative effect on employment, as we can see the coefficient 0.00016 is positive but not significant, so in conclusion always_robots does not have a negative or positive effect on employment.

The second significant variable with a significance level of 1% is the real added value, this regression shows the importance in the assessment of the efficiency and productivity of enterprises especially when robots and automation are introduced into the production line as in this case. When companies introduce robots, automation is expected to reduce labour costs and improve production efficiency, thereby increasing real value added.

More specifically, companies are trying to increase production efficiency while reducing labour costs when introducing robots and automation. These efficiency gains lead to an increase in real value added, an important measure of a company's economic contribution. In conclusion, this regression analysis quantifies how the introduction of technologies such as robots and automation positively affect a company's efficiency and productivity, as well as real value added as a key indicator of economic performance.

The third variable with a 1% significance level is lncostesmarginales Gregory et al. (2022), which are the marginal costs of this study. We can see that marginal costs in this regression have a positive effect, meaning that a decrease in marginal costs is related to an increase in real value added. This could imply that the introduction of robots has led to efficiencies in production, reducing marginal costs and improving the profitability of the company.

The fourth significant variable is Lncprealper. This variable is the wage costs, and it has a 1% significance level too. This regression shows a negative effect, which means that higher wage costs could be associated with higher labour costs, which could result in financial pressure on firms. This leads to the implementation of efficiency measures, such as automation, to reduce total labour costs. This can lead to an increase in the labour force, which in turn can have positive effects on real value added. More employees could translate into higher production capacity, greater operational efficiency and, potentially, an increase in the overall productivity of the company.

It is important to note that this phenomenon may depend on the type of industry and the level of automation involved. In environments where labour is essential to production and where automation has not completely replaced workers, lower wage costs could facilitate the expansion of the workforce and thus increase real value added.

Now we must discuss a problem. As you can see, there are some insignificant variables in the model, but that does not mean they are not informative. However, non-significant variables can be important for several reasons as I studied during the last courses:

- Marginal Effects and Economic Significance: Even if a variable is not statistically significant, its marginal effect on an outcome may be economically significant. There may be cases where a variable has a significant effect on the phenomenon under study despite its lack of statistical significance.
- Collinearity: Collinearity between variables can affect the significance of individual estimates. Even if a particular variable is not important, it may be correlated with other important variables.
- Specification issues: Model misspecification can make some variables appear insignificant, but they are important under the right circumstances.

The non-significant variable that must be consider is always robots which is the time that industries used robots in this case 26 years using robots. If the variable is not significant, it means that regardless of the use of robots by Spanish manufacturing firms, unemployment will not be affected. As mentioned before, unemployment in the Spanish industries in this study could be caused by a general trend such as specialisation in other industry services. The regression shows us that adding robots in industries has a positive effect as it increases work because robots do the routine tasks and employees can spend their time on other tasks. This means that implementing robots does not affect the workforce of employees in Spanish sample industries.

Robotization requires a good deal of complementarities related to the knowledge and skills of workers, both in new companies and in those already established. Automatization creates a 'virtuous circle' that improves well-being and growth by improving the organization. In spite of that many companies are eager to adopt these technologies as a way to increase the productivity, some concerns have been raised about the cost impact of transformation and its effect on the workforce due to training and new forms of work organization (Acemoglu et al., 2019).

In the second regression (table below) we have the number of employees ("pertot") as dependent variable again and as independent variable the following ones shows in the table above, but as I said before this paper is focus on the effect of robotization on general employment, so in this regression we focus on the variable "never_roboticstrend" which is a dummy variable that takes value 1 when industries did not use robots during the 26 years of the study and it takes value 0 when industries used them, in this take this variable takes value 1.

VARIABLES	PERTOT
timetrend	-0.0030***
	(0.0005)
lnVAreal	07569***
	(0.0081)
lncostesmarginales	0.6290***
	(0.0096)
lncprealper	-0.8008***
	(0.0108)
never_robotics	-0.0014*
	(0.0007)
Constant	1.6430***
	(0.1498)
Observations	47,682
Number of empresa	5,495
R-Squared	0.786

Regression 2. Employees in companies that have never used robots.

In this second regression we have five significant variables which really affected employees and industries, as we find out in Regression 2 (table above). The first variable that must be considering is the time of this study (timetrend) with a significant level of 1% (Ballestar, M. T, et al., 2021). As shown this variable has a negative effect, this negative effect can be explained as it is possible that there is a general trend in employment not related to robotization which is making Spanish industrial companies reduce employment, I said before in the previous regression. This general trend may be because Spanish industries are specialising in other services than industry.

The second variable is the added value, and it has a significant level of 1%. This regression result highlights the importance of assessing the efficiency and productivity of firms, especially when robots and automation are introduced in the production line but is not the case here. By incorporating robots, automation is expected to lower labour costs and optimise production efficiency, thereby generating an increase in real value added.

The third significant variable is the marginal costs of the study following Gregory et al. (2022), with a significance level of 1%. If the marginal cost variable is significant at the 1% level, it means that it has a large impact on the overall economic performance of the company. A positive correlation indicates that efforts to optimize and reduce additional costs incurred during the production process contribute significantly to increasing real value added. This is an important insight for companies that want to optimize their cost structure and improve economic performance. Essentially, regression analysis provides quantitative evidence to support the idea that controlling and reducing marginal costs can have a real, positive impact on a company's economic value.

The fourth significant variable is Lncprealper. With a 1% significance level. This variable is the wage costs, and it has a 1% significance level too. This regression analyses show a negative effect. In other words, higher labour costs mean that higher labour costs can put financial pressure on businesses. This leads to the implementation of efficiency measures such as automation to reduce overall labour costs. This could lead to an increase in the working population, which in turn could have a positive impact on real value added. More employees improve production capacity, increase operational efficiency and improve overall company productivity.

Surprising, the last significant variable with a significance level of 10% is “never_roboticstrend” which is the no use of robots in the Spanish industries during 1990 to 2016. The regression shows a negative effect, there is an explanation for this negative effect, which is that long-term non-use of robotics is associated with a reduction in employment. This suggests that the introduction and use of robots during this period can positively contribute to the creation or maintenance of jobs.

In this regression we can see how the lack of the use of robots negatively affects employment in the Spanish industries in this study. These firms may find it difficult to compete in the market. Firms that are at the cutting edge of technology may be competitive, which may have a negative impact on less innovative firms in terms of rapid growth and ultimately employment. This may also be related to the impact of the introduction of automation and robotics on production efficiency. If firms that do not use robots fall behind in efficiency, their demand for labour may fall because automation allows them to perform certain tasks more efficiently.

The third regression shows us as dependent variable the number of employees again, and as independent variables the ones below, but we are focus on the variable q_periods_is_robottrend which is the percentage of years in that period (data from 1990 to 2014) that the company has had robots.

VARIABLES	PERTOT
timetrend	-0.0041***
	(0.0005)
lnVAreal	07570***
	(0.0081)
lncostesmarginales	0.6290***
	(0.0096)
lncprealper	-0.8007***
	(0.0108)
q_periods_is_robottrend	0.0004*
	(0.0002)
Constant	1.6429***
	(0.1501)
Observations	47,682
Number of empresa	5,495
R-Squared	0.786

Regression 3. Percentage of the use of robots that affect employees**.**

In the third regression analysis, we identified five noteworthy variables that had a considerable impact on employees, as revealed in Regression 3. The initial factor warranting attention is the duration of this study, attaining statistical significance at the 1% level. As mentioned earlier, this factor exhibits a negative result, which may be exposed by the presence of an overarching employment trend unrelated to automation. As previously indicated in the preceding regression analysis, this overall trend could stem from Spanish industrial firms shifting their focus towards services distinct from traditional industrial activities.

The second factor under consideration is the added value (Gregory et al. (2022)), with a significance level of 1%. This finding emphasizes the critical need for evaluating the effectiveness and productivity of enterprises, particularly in the context of the integration of robots and automation into the production process. The introduction of automation is anticipated to have a pronounced impact on reducing labour costs and enhancing overall production efficiency. Consequently, this is poised to contribute to a tangible rise in the actual value added by the firms. It underscores the importance of closely monitoring how the adoption of robotics technology not only influences cost dynamics but also plays a pivotal role in optimizing the value generated in the production ecosystem. In essence, the strategic implementation of automation holds the potential to deliver substantial improvements in operational outcomes, ultimately shaping the landscape of added value in the business domain.

The third variable with a significance level of 1% is the marginal cost of this study. In this regression, we can see that marginal cost is positively affected. This means that a decrease in marginal cost is associated with an increase in real value added. This could mean that the introduction of robots improves production efficiency, lowers marginal costs, and improves company profitability.

This fourth significant variable represents wage costs and shares the same 1% significance level. The results of this regression reveal a negative impact. In other words, an increase in labour costs can put financial pressure on firms. This scenario drives the adoption of efficient measures, such as automation, to reduce total labour costs. This strategy could result in an increase in the labour force, generating, in turn, a positive impact on real value added.

Increasing the number of employees has the potential to boost production capacity, improve operational efficiency and raise the overall productivity of the firm. The correlation between wage costs and the implementation of automated technologies highlights the need to closely examine how companies balance cost management with the drive for efficiency. Ultimately, understanding these linkages is crucial to addressing financial challenges and exploring strategic opportunities to maximise added value in today's business environment.

The fifth significant variable is q_periods_is_robottrend which is the percentage of years from 1990 to 2014 that the company has had robots. This variable has a significance level of 10%. This variable has a positive effect in the regression analysis of employment growth, indicating that the introduction of robots in firms is associated with an increase in the number of employees. This may be because the introduction of robots can increase the efficiency and productivity of a firm, leading to higher output and a greater need for workers. It may also be because the automation of routine tasks can free employees to take on more specialised and creative roles, creating additional demand for staff. And it may also be that the adoption of robots may be associated with overall business growth, requiring the hiring of more workers to meet the increased demand.

In this analysis of the fourth regression, we have the number of employees as dependent variables once again and the variables timetrend, lnVAreal, lncostesmarginales, lncprealper and perc_periods_is_robottrend as independent variables. In this regression we are focus on the perc_periods_is_robottrend variable, which is the ranking of the company by the number of years it has had robots.

VARIABLES	PERTOT
timetrend	-0.0042***
	(0.0005)
lnVAreal	07570***
	(0.0081)
lncostesmarginales	0.6289***
	(0.0096)
lncprealper	-0.8008***
	(0.0108)
perc_periods_is_robottrend	0.0000*
	(0.0000)
Constant	1.6438***
	(0.1501)
Observations	47,682
Number of empresa	5,495
R-Squared	0.786

Regression 4. How can affect the ranking of the company by the number of years it has had robots to employees.

In the fourth regression analysis, we identified five significant variables that had a considerable impact on employees. The initial factor warranting attention is the duration of this study, attaining statistical significance at the 1% level. As mentioned earlier, this variable has a negative result, which suggests that there is a general employment trend unrelated to automation. As seen in the previous regression analysis, this general trend can be attributed to the fact that Spanish industrial companies are shifting their focus from traditional to non-traditional industrial activities.

The second most important variable is value added with a significance level of 1%. These results highlight the critical need to assess the efficiency and productivity of companies, especially in the context of the integration of robots and automation in production processes. The introduction of automation is expected to have a significant impact on reducing labour costs and improving overall production efficiency. As a result, it contributes to the significant increase in the real added value of the company. This underscores the importance of carefully monitoring how the adoption of robotic technologies not only impacts cost dynamics, but also plays a key role in optimizing the value generated in the manufacturing ecosystem. Essentially, the strategic implementation of automation can significantly improve operational results, ultimately forming a value-added environment for your business. The third variable with a significance level of 1% is the marginal cost of this study. This regression shows that marginal cost has a positive effect. This means that as marginal cost falls, real value added rises. This could mean that the introduction of robots improves production efficiency, lowers marginal costs and improves company profitability.

This fourth significant variable represents labour costs and has the same 1% significance level following a similar study of Gregory et al. (2022). The results of this regression analysis indicate a negative impact. In other words, rising labour costs can put financial pressure on companies. This scenario recommends introducing effective measures such as automation to reduce overall labour costs. This strategy could lead to an increase in the workforce, which in turn could have a positive impact on real value added.

Increasing the number of employees can increase production capacity, increase operational efficiency and increase the overall productivity of the company. The correlation between labour costs and the adoption of automation technology highlights the need to carefully examine how companies balance cost management and the pursuit of efficiency. Ultimately, understanding these connections is critical to solving financial challenges and exploring strategic opportunities that increase value in today's business environment.

The fifth significant variable is the ranking of the company by the number of years it has had robots (perc_periods_is_robottrend). This variable has a significance level of a 1%. In this regression the significance of perc_periods_is_robottrend can be for several reasons: the duration and experience effect because the variable "perc_periods_is_robottrend" may reflect the accumulated experience or robotisation effect of the firm. A significant positive coefficient indicates that a higher ranking of a firm (indicating a longer period of robot availability) has a corresponding positive effect on employment. This may be due to the cumulative benefits and learning curve associated with the long-term impact of robotic technology.

Another reason can be the operational efficiency: by adopting robotics, companies can optimise their operations more effectively. These improvements in operational efficiency can have a positive impact on increasing production and employment. The more a company uses robots, the more complex its processes become and the more productive it becomes.

An alternative reason is the technological advances: companies that score high in the use of robots are likely to have made technological advances over the years. Upgrading robotic systems, increasing functionality, and improving integration with existing processes can have a positive impact on overall productivity and employment.

An additional reason is the market competitiveness. Companies that adopt robotics early can gain a competitive advantage in their industry. This competitive advantage may generate greater demand for their products or services, which may require more labour to meet market demand.

And the last reason is the skills development and training: companies that have been using robots for a long time are likely to have invested more in employee training and skills development to effectively integrate and manage these technologies. These investments in human capital can have a positive impact on the workforce as a whole and increase employment.

2. How affect robots to the hours worked

In this first regression we have as dependent variable “hetn” which is the employee´s hours worked and as independent variables timetrend, lnVAreal, lncostesmarginales, lncprealper and always_roboticstrend.

VARIABLES	hetn
timetrend	-0.0073***
	(0.0005)
always_robotics	0.0012
	(0.0013)
lnVAreal	07133***
	(0.0089)
lncostesmarginales	0.5838***
	(0.0100)
lncprealper	-0.4100***
	(0.0131)
Constant	-1.2397***
	(0.1814)
Observations	45,502
Number of empresa	5,477
R-Squared	0.706

Regression 5. Employee´s hours worked affected by the use of robots from 1990 to 2016.

If we look at Regression 5, we can see that we have four significant variables. The first significant variable is timetrend with a significant level of 1%. The regression shows a negative outcome that is easy to clarify, there is a general time trend unrelated to robotisation, which is reducing hours in Spanish industrial companies. This general trend may be the specialization of Spanish industry in service sectors other than manufacturing. As we said before, since robot variables cannot always be controlled, a time trend variable was included.

The second significant variable with a significance level of 1% is real value added (Gregory et al. 2022). This regression analysis highlights the importance of assessing the efficiency and productivity of a company, especially when robots and automation are introduced in the production line, as in this case, so we can deduce that the hours that were spent by employees on routine tasks are now spent on other tasks as the routine tasks are done by robots. When a company introduces robots, automation reduces labour costs, increases production efficiency and increases real added value.

The third important variable is the marginal cost of the study with a significance level of 1%. The fact that the marginal cost variable is significant at the 1% level means that it has a significant impact on the overall economic performance of the company. A positive correlation indicates that efforts to optimize and reduce additional costs incurred during the production process contribute significantly to increasing real value added. This is an important insight for companies that want to optimize their cost structure and improve economic performance. Essentially, regression analysis provides quantitative evidence to support the idea that controlling and reducing marginal costs can have a real, positive impact on a company's economic value.

This fourth important variable represents labour costs and has the same 1% significance level. The results of this regression analysis showed a negative impact. In other words, rising labour costs can put financial pressure on companies and can reduce employees' hours worked. This scenario can introduce effective measures, such as automation to reduce total labour costs. This strategy can increase the labour force and, consequently, has a positive effect on the real value.

The only non-critical variable to consider is always robots. The length of time that robots have been used in the industry (in this case, 26 years of using robots). If the variable is not significant, it means that the Spanish manufacturer has no effect on the working schedule of its employees, regardless of whether it uses robots or not. As noted above, unemployment in Hispanic industries in this study may be due to general trends such as specialization in other industrial services. The regression analysis shows that the integration of robots in the industry has a positive effect because it increases the workload because robots perform routine tasks and employees can spend their time on other tasks. This means that the introduction of robots does not affect the labor force or working hours of workers in the sample industries in Spain.

X. Conclusion

Based on the various regression analyses and the data derived from them, several conclusions can be drawn. The first conclusion is that people with lower educational attainment occupy jobs with a higher risk of automation. Low employment growth in these sectors has not disproportionately affected labour market participation compared to other educational groups. This is because the share of low-skilled workers in the total labour force is decreasing due to the decline in jobs for low-skilled workers. In conclusion, automation may affect workers differently depending on their level of education, but other factors, such as demographic dynamics and the composition of the labour force, also influence how automation affects employment.

Following this conclusion, I must add that in my opinion automation has uneven effects depending on the educational level of the workers. Tasks that require routine and repetitive skills tend to be automated. These may be low-skilled jobs that involve repetitive and predictable tasks, such as manufacturing or operating machinery.

Another important conclusion is that the research into the introduction of robots into the service sector has helped increase employment opportunities for casual healthcare workers, reduce turnover in nursing homes and provide flexibility to workers. This evidence suggests that technology can help address the social and economic challenges of an aging population, even as it exacerbates fears. Governments can intervene to regulate the negative social and economic impact of new technologies. Given that the adoption of robots in the service sector is still in its infancy, researchers and policymakers should consider how robots will complement or replace different types of work, as well as their impact on wages, quality of life, services and society in general.

I think this conclusion the positive potential of technology is demonstrated by the introduction of robots in the service sector to solve social and economic problems such as the ageing population. Some of the benefits identified include increased employment of respite care workers, reduced turnover of nursing home staff and the provision of labour flexibility. However, technology is known to cause fear and anxiety, especially when it comes to job loss or job quality. This therefore highlights the importance of government intervention to regulate the negative social and economic impacts of new technologies.

As we have seen in this paper, another important conclusion to note is that despite estimates indicating significant risks related to job automation, employment increased significantly in many countries between 2012 and 2019. This increase in employment was a key factor in overcoming the global financial crisis.

It is also added that employment increased in all occupations, but employment growth was slower in occupations with higher automation risk. This suggests that the OECD's assessment of automation risks was a good predictor of subsequent employment growth.

In addition, occupations with high automation risk have a high concentration of low-skilled workers. Employment growth in these occupations is slower than in other industries but does not disproportionately affect the labour force participation of low-skilled workers compared to other education groups. This is due to the simultaneous decline in the share of the low-skilled in the total labour force.

And last but not least, a conclusion to highlight is that as we have seen in the results, the companies that used robots during the 26 years of the study did not affect unemployment, on the contrary, the robots adopted the routine tasks thus freeing up workers' time to focus on other tasks. In contrast, the study of companies that did not adopt any type of robots in any year during those 26 years can be seen to affect unemployment, for example because companies become outdated and cannot keep up with the competition.

In conclusion, robots and automation have not led to an increase in unemployment, but have had a positive impact on employment. This is due to several factors, such as the creation of new jobs, as automation may eliminate some jobs, but it may also create new jobs in technology, engineering and automated systems services. Another factor is the increase in productivity. This is because robots and automation can increase productivity in many industries, leading to increased demand for products and services. This increased demand will create more jobs in various sectors of the economy. Another important factor is cost savings. Automation reduces production costs, which allows companies to invest in expansion and growth, creating more jobs. Finally, the complementarity between humans and robots. In many cases, robots and humans can work together in a complementary way and leverage each other's strengths. This can drive job growth by increasing efficiency and productivity in the workplace.

XI. References

- Acemoglu, D. and Restrepo, P. (2019). "*Automation and New Tasks: How Technology Displaces and Reinstates Labour*". Cambridge, MA. Available at: doi: 10.3386/w25684.
- Acemoglu, D and P Restrepo (2020), "*Robots and jobs: Evidence from US labour markets*", Journal of Political Economy 128(6): 2188-2244
- Arntz, M., T. Gregory, and U. Zierahn (2016), "*The Risk of Automation for Jobs in OECD Countries: A Comparative Analysis*", OECD Social, Employment and Migration Working Papers, No. 189, OECD Publishing, Paris. Available at: http://dx.doi.org/10.1787/5jlz9h56dvq7-en
- Autor, D (2014), "*Polanyi's Paradox and the Shape of Employment Growth*," NBER Working Paper 20485.
- Ballestar, M. T., Díaz-Chao, Á., Sainz, J. y Torrent-Sellens, J. (2020). "*Knowledge, robots and productivity in SMEs: Explaining the second digital wave*". Journal of Business Research, 108, pp. 119-131. Available at: https://doi.org/10.1016/j. jbusres.2019.11.017
- Ballestar, M. T., Díaz-Chao, Á., Sainz, J. y Torrent-Sellens, J (2021) "*Impact of robotics on manufacturing: A longitudinal machine learning perspective*". Technological Forecasting and Social Change, 162, 120348. Available at: https://doi.org/10.1016/j. techfore.2020.120348
- Caprettini, B and H-J Voth (2020), "*Rage against the machines: Labour-saving technology and unrest in industrializing England*," American Economic Review: Insights 2(3): 305–20
- Golin, M. and Rauh, C. (2023) *Workers' responses to the threat of automation*, *CEPR*. Available at: https://cepr.org/voxeu/columns/workers-responses-threat-automation
- Gregory, T. Salomons, A. Zierahn, U. (2022) "*Racing With or Against the Machine? Evidence on the Role of Trade in Europe*", Journal of the European Economic Association, 20 (2), 869–906, Available at: https://doi.org/10.1093/jeea/jvab040
- IFR International Federation of Robotics (2021) "*Robot density nearly doubled globally"*, IFR International Federation of Robotics. Available at: https://ifr.org/ifr-press-releases/news/robot-density-nearly-doubled-globally.
- Iizuka, T., Lee, Y.S. and Eggleston, K. (2021) *Robots and labour in the service sector*, *CEPR*. Available at: https://cepr.org/voxeu/columns/robots-and-labour-service-sector
- Kelkar, A. and Shao, E. (2023) "*Unlocking the industrial potential of Robotics and Automation"*, McKinsey & Company. Available at: https://www.mckinsey.com/industries/industrials-and-electronics/our-insights/unlocking-the-industrial-potential-of-robotics-and-automation)

- Konovalov, A. (2023) "*Council post: Ai will impact the labour market, but workers should embrace the technology, not fear It"*, Forbes. Available at: https://www.forbes.com/sites/forbestechcouncil/2022/10/31/ai-will-impact-the-labour-market-but-workers-should-embrace-the-technology-not-fear-it/
- Loebbing, J. and Acemoglu, D. (2022) "*Automation and polarisation"*, CEPR. Available at: https://cepr.org/voxeu/columns/automation-and-polarisation
- Manuylov, I, Smolka, M, Koch, M, (2019), "*Robots and firms*", CESifo Working Paper 7608. Available at: https://cepr.org/voxeu/columns/robots-and-firms
- Nedelkoska, L. and Quintini, G (2018), "*Automation, skills use and training*", OECD Social, Employment and Migration Working Papers, No. 202, OECD Publishing, Paris, Available at: https://dx.doi.org/10.1787/2e2f4eea-en.
- Polanyi, M (1966), "*The Tacit Dimension*", Doubleday.
- PwC (2019), "*Will robots really steal our jobs? An international analysis of the potential long-term impact of automation*", Available at: https://www.pwc.com/hu/hu/kiadvanyok/assets/pdf/impact_of_automation_on_jobs.pdf
- Raj, M and Seamans, R (2018), "*AI, labour, productivity, and the need for firm-level data*", in The Economics of Artificial Intelligence: An Agenda, University of Chicago Press.
- Scarpetta, S and Pearson, M (2021) "*What happened to jobs at high risk of automation? - OECD*. Available at: https://www.oecd.org/future-of-work/reports-and-data/what-happened-to-jobs-at-high-risk-of-automation-2021.pdf .
- Schwab, K. P.Gayozzo and F. López de Pomar Trad. (2020). *"La Cuarta Revolución Industrial"*. FuturoHoy.1(1). Pp. 6-10, Available at: https://doi.org/10.52749/fh.v1i1.1
- Strategicds (2019) "*How the fourth industrial revolution will reshape risk management"*, Strategic Decision Solutions. Available at: https://strategicdecisionsolutions.com/fourth-industrial-revolution-risk-management/