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Automation: impacts on labor and inequality

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SUMMARY:

INTRODUCTION

Automation consists in reducing the need for human intervention by creating machines capable of replacing one or more attributes of man in performing a job. Its application has evolved over time, from the water clock invented by the Greek engineer Ctesibius (285–222 BC) to nowadays artificial intelligence.

Automation has developed through big inventions that revolutionized technology: from its early stages, to the industrial revolution, to the age of computers, to the advent of artificial intelligence.

Automation is often associated with job destruction. By reproducing human tasks, machines can work more efficiently and, in some cases, fully substitute workers. This has been seen, e.g., in the agricultural sector: 41 percent of the US workforce was employed in agriculture in 1900: this share fell to 2 percent by 2000 (Autor 2014). However, the overall employment rate has not been significantly negative affected by automation. A first reason why is that technological change can often complement professions. The example of ATMs by Bessen (2015) illustrates this possibility. A second reason is that new technologies also create new jobs, as it can be noticed in the case of new jobs created (e.g., data scientists, social media managers, etc.), mainly because of the digitalisation.

Regarding the future of automation, many studies forecast that in the next years there will be a huge job destruction: the OECD (OECD Social, Employment and Migration Working Papers No. 202) said 14% of jobs in developed countries were highly automatable, while a further 32% of jobs were likely to experience significant changes to the way they were carried out. Estimates by The McKinsey Global Institute (2013) suggest that sophisticated algorithms could substitute for approximately 140 million full-time knowledge workers worldwide. These forecasts are not to be taken literally, however workers are starting to get worried since modern automation as well as reproducing routine tasks, is also able to automate non routine manual (e.g., health care, legal, finance and even programming activities) and cognitive (e.g., self-driving cars) tasks.

Automation also affects labor along its skill dimension: The range of high-skill and low-skill occupations tends to grow while ;the range of medium-skilled jobs tends to decrease.The main reason for this trend is that routine tasks are characteristic of middle-skilled cognitive and manual

activities, such as bookkeeping, clerical work, and repetitive production tasks; high-skill jobs grow since the technological change enhances their productivity. As for low-skill occupations, low-skill workers have reallocated their labor supply to service occupations, which are hard to automate since they rely heavily on dexterity, flexible interpersonal communication, and direct physical proximity. This phenomenon of job polarization is widely observed throughout the world with evidence in the US (Autor 2010) and also in european countries (in the UK for example, Goos and Manning 2007). The effects of the polarization of jobs on wages aren't really clear, with no evidence of wage polarization. However, automation can affect wages through other channels. As many studies show, automation is a cause of income inequality, by increasing the productivity of firms and reducing the costs of workers, capital owners tend to make more profits, while displaced workers become unemployed or start working in lower-paying jobs. This causes an inequality with the top 1% most rich people owning a 20% share of the national income, while the bottom 50% only approximately 13% (in the US, see graph). With the advent of Artificial Intelligence, the negative consequences of automation could be a serious problem and the income inequality could grow even more.
In order to tackle the consequences of automation, governments could encourage employers and educational institutions to expand apprenticeships and support displaced workers who retrain for in-demand fields.

CHAPTER ONE: AUTOMATION AND LABOR

History of automation:

The term automation identifies the technology that uses control systems (such as logic circuits or processors) to manage machines and processes, reducing the need for human intervention. It is carried out for the execution of repetitive or complex operations, but also where security or certainty of the action is required or simply for greater convenience. It is carried out for the execution of repetitive or complex operations, but also where it requires security or certainty of the action or simply for more convenience. Over the years the term "automation" gained various definitions to then draw the conclusion that automation can be understood as a phenomenon that has a technological, economic, organizational and
social nature and has as its object the management and the evolution of complex technical-organizational systems that carry out processes production of products and / or services. In Anatomy of Automation (1962), Amber and Amber, defining automation as the technology needed

to create machines capable of replacing one or more attributes of man in performing a job, propose a classification based on the attributes replaced:

Order	Attribute replaced	Example
0	None	Manual tools
1	Energy	Energy Motorized tools with manual control (hobby drill)
2	Dexterity	Single-cycle automations (parallel lathe)
3	Diligence	Repeated cycle automation (transfer machines)
4	Judgment	Closed loop control (numeric control)
5	Evaluation	Cycle optimization capacity (CNC machines with adaptive logics)
6	Learning	Limited self-programming skills
7	Reasoning	Capacity for inductive reasoning
8	Creativity	Ability to create original artifacts

In the early history, automation was at level 0: the earliest feedback mechanism was the water clock invented by Greek engineer Ctesibius (285–222 BC). Later on, in the 18th/19th century, the phenomenon of industrial revolution occurred and the level of automation increased from 0 to 3. The industrial revolution was a process of economic evolution and industrialization of the society that from an agricultural-artisan-commercial system became a modern industrial system characterized by the general use of machines driven by mechanical energy and the use of new inanimate energy sources (such as fossil fuels), all favored by a strong component of technological innovation and accompanied by phenomena of growth, economic development and profound socio-

cultural and even political changes. The biggest inventions were certainly James Watt's steam machine and Eugenio Barsanti's (and later Felice Matteucci) internal combustion engine. This type of automation is known as industrial automation.
The first machines and the first plants were designed to replace man inside the factories, so as to avoid it carrying out harmful (or only extremely repetitive) tasks that led to the alienation of the individual from the industrial world to which he belonged. Subsequently these devices were also used to speed up the work done previously by man, in order to obtain a time saving in the realization of each individual product. The 2000s and the new century have changed the basic idea of industrial automation. In fact, every single robot is now allowed to manage real information, to understand it and act accordingly.
If the birth of the first machines belonged to the First Industrial Revolution, Industry 4.0 has as its mother the Fourth Industrial Revolution, which is taking place in these years, although not everyone is really aware of it. Industrial automation has had a remarkable evolution and for this reason the Industry 4.0 has the idea to entrust to the robots, to the plants and to the industrial machineries the realization of an entire production process, which will therefore be totally interconnected between "managers" and automated. The idea of entrusting present and future production to machinery, both for speed and accuracy and, consequently, for the quality of the product produced, is based on four fundamental points.

First of all, today's technologies allow a correct use of computer and data, with a system that allows to centralize and preserve the flow of information that circulates through the robotic system. The second step to achieve a model of Industry 4.0 is to exploit the collected data. Indeed, it is estimated that only a very small percentage of industrial information, which is even around 1%, is actually used today. To be able to squeeze out the whole bag of information, to receive it correctly and to be able to use it can bring real advantages to the industry, both internally and on the market in which it operates.

It has been thought that Industry 4.0 could be the so-called 'machine learning': thanks to this system robots could even learn notions during the performance of their task, improving himself and making other machines understand the data and information he has collected, to allow a general improvement. Humans are relegated to the third phase of the Industry 4.0 process. He would deal with robotic management and the entire industrial automation, thanks to the 'touch' technology that allows to interact directly with the machine or the automated plant, influencing their activity and, as a result, improving the entire production system. The most important point however of Industry 4.0

is to switch from the system of information, data and improvement (both automatic and manual) to the real and industrial. It is therefore a question of the effective realization of the imposed tasks, but also of 3D printing, communications, interactions between machines and between robots.

Going back to Amber's classification we can say that the greatest development in the field of automation has taken place with the advent of electronics, which has made it possible to move from level 3 of pure mechanics to the possibilities offered by electronics and automatic controls (mechatronics). Today, automation has reached level 5 with some level 6 cases.
These automation levels are achieved through the interaction between pure mechanics (which replaces human attributes up to level 3) and electronic devices such as:dedicated computers called programmable logic controllers (PLCs) which with appropriate software allow the, movement of actuators or the analysis of data generated by sensors, sensors and transducers, artificial vision systems, Microcontrollers, personal computer equipped with appropriate I / O cards, generally called NC (numerical control), wired logic (now rare, as it is the ancestor of the PLC).

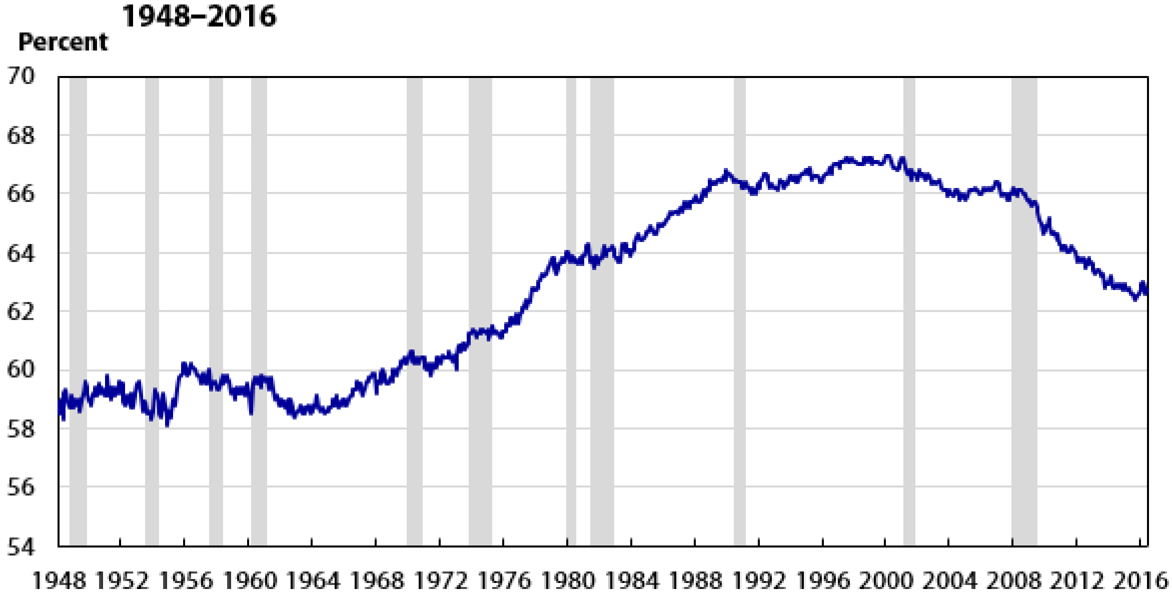
The concept of automation has therefore changed over time, from the very first invention of the water clock by the ancient Greeks to the industrial revolution, where a vast number of handwork was automated by robotics, leading up to nowadays technologies that are able to automate headwork. In fact, we can distinguish two main types of automation: handwork and headwork. Handwork automation consists in all process that mainly uses machines to perform repetitive human tasks with more precision and accuracy by using software robots; it is also known as Robotic Process Automation (RPA). RPA is ideal for those processes that do not require decision-making or human intervention. However, there are going to be plenty of situations that do require human decision-making, and when there is voluminous data involved, it can become very challenging for the human workforce to make the right decisions. Cognitive automation (the automation of headwork) mimics human behavior, which is in many ways more complex than the actions and tasks mimicked by RPA processes. RPA relies on basic technologies, such as screen scraping, macro-scripts and workflow automation. Cognitive automation, on the other hand, uses more advanced technologies, such as natural language processing (NLP), text analytics, data mining, semantic technology and machine learning, to make it easier for the human workforce to make informed business decisions. RPA does not require coding, as it depends more on the configuration and deployment of frameworks, whereas cognitive automation uses machine learning and requires the extensive use of programming knowledge. Essentially, when AI is added to an RPA, it becomes a matter of cognitive automation. In fact, the integration of different AI features with RPA helps organizations extend automation to more processes, making the most of not only structured data, but especially the growing volumes of unstructured information. Unstructured information such as customer interactions can be easily analyzed, processed and structured into data useful for the next steps of the process, such as predictive analytics, for example.

Impact on labor:

Throughout its history, automation has considerably evolved, in the sense that more and more complex skills are now perfectly reproducible by a machine. A major concern and issue with this is the fact that there can be a destruction of certain types of jobs. If a company can automate a skill that is required in their production of good (or service), it might decide to buy a machine that reproduces this skill. In order to decide whether to buy or not the machine, a company should see if it is profitable, i.e. it should look at the initial cost,eventually at the maintenance costs and at the eventual gains in productivity from the adoption of the automation technology. It must be emphasized that automation only threatens the case where the productivity gains that it allows are greater than the increase in production. Impacts of automation on employment have been seen for a long time. The industrial revolution had a big impact on labor as a whole: machineries replaced human labor since they were more productive and less costly. In 1900, 41 percent of the US workforce was employed in agriculture; by 2000, that share had fallen to 2 percent (Autor 2014), mostly due to a wide range of technologies including automated machinery. In the field of the textile industry, in the 18th century many artisans such as shearers, weavers on cotton and knitters on loom saw their jobs being replaced by machines. Many of these workers started a rebellion and destroyed a large amount of machines that were replacing them, these rebels were known as Luddites. Luddites feared that the time spent learning the skills of their craft would go to waste, as machines would replace their role in the industry. Another example can be found in China, where a company called Changying Precision Technology has automated production lines that use robotic arms to produce parts for cell phones. The number of employees before the robotization was 650, when the robots started to work, they were only 60 who were monitoring a computer control system. The results were positive: the factory has since seen fewer defects and a higher rate of production. One more example that one may not think about when talking about automation replacing jobs is the bowling ball pinsetter. Not many people know that even the bowling alley is using machines to reset the pins each time that they are knocked down. In the past, a person would sit next to the pins, clear and set the pins each time someone bowled.

With the rise in technologies and automation being more and more able to mimic tasks, many jobs were replaced by machines, with a vast amount of workers losing their jobs All these jobs are now being fully automated, so a main concern should be the rate of employment throughout these last years of industrial revolution. The following graph from the US Bureau of Labor Statistics illustrates the labor force participation rate (16years and older) from 1948 to 2016.

Figure 1. Labor force participation rate, 16 years and older, seasonally adjusted, 1948–2016



Note: Shaded areas represent recessions as determined by the National Bureau of Economic Research.
Source: U.S. Bureau of Labor Statistics, Current Population Survey.

With respect to what we just said, the results are surprising: the employment rate has overall increased over the last 60 years. Accordingly to the previous reasoning, one would expect the labor force participation rate to decrease, since our capability to automate tasks is increasing (we are able to automate much more complicated tasks than what we were capable 60 years ago). Moreover, the thought that automation makes labor redundant and our skills obsolete doesn't coincide with this graph. Which brings us to ask ourselves if automation really destroys labor.

First of all, automation can be seen as a complement to labor. The robots seem fully indicated to perform repetitive, dangerous or painful tasks, requiring reliability and precision in the repetition. This doesn't necessarily mean that all workers will lose their jobs. As a current example, the astonishing complementarities between information technology and employment in banking, specifically the experience with automated teller machines (ATMs) and bank tellers documented by Bessen (2015) can be considered. ATMs started to appear in the 1970's, their primarily use is automating routine cash handling task. The number of ATMs in the US almost quadrupled over the

1995-2010 time period, one would think that as a consequence, tellers have seen a replacement of their jobs by these machines. However, if we look at the number of working tellers in the US over the last 30 years we can observe that 50000 tellers were added to the workforce (although given the growth in the labor force in this time interval, these numbers do imply that bank tellers declined as a share of overall US employment). So what impact did the introduction of ATMs have on the job of tellers? ATMs surely decreased the costs of operating bank branches and the number of tellers per branch declined by more than one third (1988-2004), but we must also consider the fact that the number of urban bank branches (also encouraged by a wave of bank deregulation allowing more branches) rose by more than 40 percent. Most importantly, ATMs changed the profession of tellers as a whole: tellers shifted their main tasks from routine cash handling to less routinely tasks such as relationship banking, tellers became salespersons, forging relationships with customers and introducing them to additional bank services like credit cards, loans, and investment products. This example shows us how in some cases automation can lead to a reorganization of tasks, focusing more on less routine tasks. New technology can increase demand for a profession, offsetting presumed job losses. Other examples can be found in the labor market, as Bessen (2015) describes, during the 19th century, technology automated 98% of the labor involved in weaving cloth, but the number of weavers grew nevertheless. From the example of ATMs, we can see that in some cases automation can change the core tasks of a job: the routine and exhaustive ones being replaced, workers will focus more on those harder-to-automate cognitive-demanding tasks.

Moreover, in recent years, a new notion of automation has emerged: cobotics. The concept of collaborative (or cobotic) robotics stems from the idea of sharing the work environment between man and machine, establishing synergetic relationships between human operators and robots that take on the role of co-workers. Cobotics differs from traditional robotics in that it aims at maximizing a synergistic and equal relationship between man and machine, unlike traditional robotics which mainly aimed at developing autonomous robots. In the framework of collaborative robotics robots should therefore not replace people but assume complementary roles, in this way the tasks that are most congenial to each other would be delegated to each collaborator, maximizing efficiency. In the context of collaborative robotics, human operators would have the task of supervising production activities and performing a job of fine tune (where mastery and ability to improvise is required, as well as taking responsibility), while robots would be delegated tasks repetitive, unpleasant or dangerous. Examples of cobotics can be found in the field of medicine where it is mainly represented by medical robots (for example Da Vinci or Zeus robots), telemedicine or personal assistance and rehabilitation but also in the domain of industrial cobotics with the rising interest over powered exoskeletons. Cobotics is an interesting concept that aims to reduce the substitution effect of automation over labor by creating robots that assist humans in their jobs but without completely being able to reproduce their tasks, only the most repetitive ones.

Thus, from what we have seen with the examples of ATMs and the concept of cobotics already being applied in nowadays society, we can say that automation doesn't necessarily substitute for labor. However, the magnitude of the data that supports the thought of labor being replaced may lead to think that the cases were automation doesn't substitute for labor are not enough to offset the losses from the cases were workers saw their job being taken over from machines. Nonetheless, looking back to the graph of the employment rate the rise of labor force goes against this thought. This might be due to the fact that in the last years, a lot of new type of jobs were created.

If we look at nowadays professions many of them didn't exist 60 years ago. Social media manager, app developers, uber drivers, big data analyst, etc. all of these jobs are fairly new and yet, highly demanded. Many of these new jobs are directly related to the rise in technology. For example, with the invention of the iPhone in 2007, and Android shortly after, a whole new sector was created and now, 12 years later, almost half of the world population has a smartphone. This growth has also generated a huge appetite for apps. With an increasingly growing market for developers. Another invention that created new types of jobs is the arrival of social media. In 2006 most of the social platforms did not exist or were still in the launch phase. Today Facebook has a billion and a half users in the world, and other solutions like Twitter and Instagram have become indispensable marketing and communication tools. Advertising and the image of a brand has become a core value to firms and social media help to raise awareness and popularity of firms. Thus, a figure like the social media manager has become increasingly popular and important. At the present day, even playing video games has become a full-time paid job with gamers getting revenue from a streaming platform called Twitch and E-Sports events (tournaments). Furthermore, it goes without saying that with an increasing automation, the requests for programmers and developers are really high. Coding has become a remarkably demanded skill. As more businesses and industries assimilate digital technology into their activities, a basic understanding of computer programming as a minimum requirement is becoming more essential. The presence of computer specialists is strongly requisitioned in industries like Information technology, data analysis, design… In fact, IT, the application of computers to the use of data storage and manipulation for business processes, is crucial to more and more businesses, not just office work but also in financial, legal, medical and manufacturing sectors. Furthermore, Businesses use data analysis to forecast income and expenditure, manage production and distribution as well as, with the rise of social media and big data, analyse search and buying behaviour, discovering information about customers and significant trends. Not to mention designers who regularly use digital tools to create websites as well as products to be sold and marketed online, in jobs such as graphic design, web design and UX/UI design. The impact of coding can also be seen in the field of Science and Engineering: creating and testing products, as well as testing hypotheses and analysing the results, is made more functional by the use of digital technology, which engineers and scientists regularly work with. As digital technology becomes more important in nowadays society, demand for people skilled in coding will only increase.

The future of automation:

So, from what can be observed is that in the course of history, due to technological progress, while some works have disappeared, others have been created and the number of seconds has always exceeded that of the former. Moreover, in the transition from old to new jobs, workers' conditions have always improved, think for example of the transition from agriculture to industry and from industry to services. So what we learn from the past is that automation didn’t have a negative impact on employment since, although lots of jobs were replaced by machines, many other professions were created and some of them actually benefit from the mechanization of certain tasks that were considered exhaustive and repetitive. So why is everyone still concerned about machines taking away our jobs? Looking at how automation has affected labor in the past, we shouldn’t worry since new technologies will bring new professions and this will offset the losses of jobs that got replaced. Nonetheless, people are still worried and think that automation in the future will have a negative impact on employment, contrarily to the historical findings. A vast number of studies warns us that robots will steal a huge number of jobs in the near future. The OECD (OECD Social, Employment and Migration Working Papers No. 202) said 14% of jobs in developed countries were highly automatable, while a further 32% of jobs were likely to experience significant changes to the way they were carried out. Many are saying that there is a new era in automation, with technological changes being of increasingly relevance (meaning that there are much more changes in technology in less time) a lot of tasks that were considered “safe” from automation are now being mechanized. Particularly, a lot of concern is being brought into the non routine manual tasks and even the non routine cognitive tasks.

Regarding the latter, according to Brynjolfsson and McAfee (2011), computers increasingly challenge human labour in a wide range of cognitive tasks. Examples can be found in several fields of interest such as health care, legal, finance and even programming. As for medicine, there are new computer-based diagnostic tools that allows the computer to compare each patient's individual symptoms, genetics, family and medication history, etc., to diagnose and develop a treatment plan with the highest probability of success (Cohn, 2013). In the legal scope, law firms now rely on computers that can scan thousands of legal briefs and precedents to assist in pre-trial research. A system called Symantec's Clearwell, which uses language analysis to identify general concepts in documents, can display the results graphically, and proved capable of evaluating and sorting more than 570,000 documents in two days (Markoff, 2011). Even the work of software engineers may soon largely be computerisable. For example, advances in machine learning allow a programmer to leave complex parameter and design choices to be appropriately optimised by an algorithm (Hoos, 2012). This goes against our thoughts that since softwares are becoming crucial to our life, programmers won't be affected by automation as they are the ones programming the machines that automate the tasks. However, from this example it is clear that even this profession is at risk of being replaced. Concerning overall labor, estimates by The McKinsey Global Institute(2013) suggest that sophisticated algorithms could substitute for approximately 140 million full-time knowledge workers worldwide. The cases and predictions that are mentioned above illustrate how some cognitive tasks are already being computerised and this is getting a lot of intellective workers worried.

About non routine manual tasks, the enduring technological development of robotic hardware is having a distinguished impact upon employment: over the past decades, industrial robots have taken on the routine tasks of most operatives in manufacturing. However, in recent years, improvements in the advanced sensors helped robots to start reproducing non routine manual tasks. As an illustration, we can look at General Electric who has recently developed robots to climb and maintain wind turbines, and more flexible surgical robots with a greater range of motion will soon perform more types of operations (Robotics-VO, 2013). Another example is the mechanization of driving with the so-called self-driving cars, although full self-driving versions haven't yet appeared on their market, companies like Tesla are offering car models that can take control over the car in order to guarantee the safety of the driver and the passengers, there is also a sort of "flight mode" that can be set and lets the car drive it self, as long as the vehicle goes slowly and stays in lane. Jobs related to driving cars such as taxi or uber drivers are starting to get concerned about these new technologies.

Therefore, automation has started to affect also jobs that involve non routine manual and even cognitive tasks. Furthermore, The McKinsey Global Institute (2013) says that robot prices are dropping, placing them within reach of more users. Another aspect of automation that explains how machines can work better than humans is the fact that robots hold two comparative advantages over human labor: scalability and their absence of some human bias. In software engineering, telecommunications, computer science and other disciplines, scalability generally denotes the ability of a system to increase or decrease in scale according to needs and availability. With respect to human bias, an algorithm can be designed to ruthlessly satisfy the small range of tasks it is given. Humans, in contrast, must accomplish a variety of tasks unrelated to their occupation, such as sleeping, necessitating occasional sacrifices in their occupational performance. A robot can work as long as the owner wants it to, it doesn't need any sleep or any lunch break.

There is a major concern among workers of whether their job will be computerized or not, and some should definitely be anxious, however there are still some type of tasks that will hardly be automated, as in the near future. As Osborne and Frey (2013) state, there are three types of skills that can be observed: perception and manipulation, creative intelligence and social intelligence. These types of tasks aren't really threatened by automation. In fact, the main challenges to robotic computerisation, perception and manipulation, largely remain and are unlikely to be fully resolved in the next decade or two (Robotics-VO, 2013). Robots are still unable to match the extent and broadness of human perception. While basic geometric identification is fairly mature, enabled by the rapid advancement of sophisticated sensors and lasers, important challenges remain for more complex perception tasks, such as identifying objects and their properties in a cluttered field of view. The difficulty of perception resides in the handling of irregular objects, for which robots still struggle to reach human levels of aptitude in manipulations. As for creative tasks, the principal obstacle to computerising creativity is stating our creative values sufficiently clearly that they can be encoded in a program (Boden, 2003). Creativity is a very complex concept that humans have problems to give a proper definition, it would be even harder to express that definition into the language of a program. Regarding social intelligence tasks, human social intelligence is important in a wide range of work tasks, such as those involving negotiation, persuasion and care. While algorithms and robots can now emulate some aspects of human social communication, the real time recognition of natural human emotion remains a challenging problem, and the ability to respond rationally to such inputs is even more difficult. Thus, in the decades to come, workers who have a job that involves perception and manipulation, creative intelligence and social intelligence tasks don't have to worry about robots replacing them. Examples of these jobs can be teachers, as their tasks do not simply limit to give information on a subject: they have to make sure that each student understand the lesson and is able to achieve the requirements of the course, which requires a lot of social intelligence skills. Also writers can rest assured, although some computers have been designed to write journalistic articles, it is unlikely that a machine can imitate human creativity in inventing stories. Looking at the bigger picture, the future of employment is going to the direction where a vast number of tasks will be mechanized, these tasks, diversely to what happened in the past, also involve non routine manual and cognitive tasks. This is why a lot of people are saying that this time is different: because of the increase in research and implementation of Artificial Intelligence, humans are becoming capable to automate a tremendous amount of tasks and in the future this will only increase. The new jobs that will be created (technological change being an important factor of this creation) may not offset the losses of automated labor. Workers that are replaced, in order to find a job, will have to make a choice, either completely change their type of job (if all the tasks that involve their job are automated) or focus on the non automatable tasks of their profession and try to improve them, making them the core tasks, thus reshaping the skillset of their work.

Overall, automation has affected labor through different patterns. The course of history shows us that machines can reproduce a task in a more efficient and productive way than humans, and thus it is usually preferred by companies to human labor. This can be seen by the destruction of certain types of jobs (farmers, production workers…). However, automation only replaced a fraction of the whole working population, some workers had to change their core tasks in order to keep working (but they kept working, for example tellers). Furthermore, lots of jobs were created, this gave more working opportunities and the losses of jobs being automated were compensated by the new types of jobs. Despite the non negative signs of automation in the past, its relationship with labor is changing, mainly because of the research and implementation of Artificial Intelligence, which made it possible to start automating non routine cognitive and manual tasks. Many workers are getting worried that their job is going to be replaced and that they will have nowhere to go after that. Regarding overall employment there has been signs that automation has also affected the distribution of employment, with some repercussion on wages.

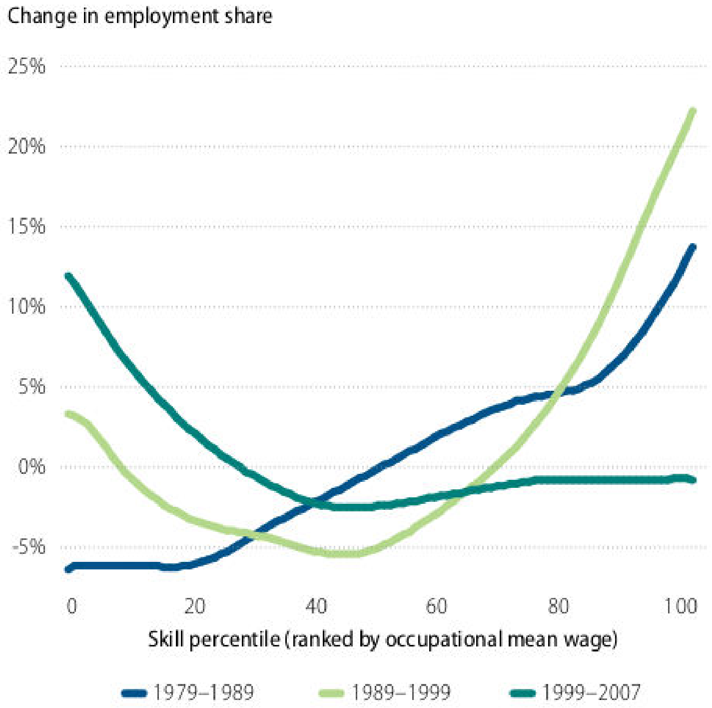
CHAPTER TWO: IMPACT ON WAGES AND INEQUALITIES

Job polarization:

Economists addressing about the repercussions of technology on the labor market in recent years have tended to emphasize the role played by skill-biased technical change (SBTC), the idea that technology is biased in favor of skilled workers and against unskilled workers (see Katz and Autor [1999] for a survey of a very large literature). The idea behind the concept of skill-biased technical change (SBTC) is that there is a shift in the production technology that favors skilled over unskilled labor by increasing its relative productivity and, therefore, its relative demand. This approach would mean that jobs that require high skills are growing more than those who require less skill. However, Autor (2010) analyzes changes in employment by occupational skill percentile and observes that SBTC does not hold true with the data. The following graph plots the change in the share of U.S. employment in each of the last three decades for 326 detailed occupations encompassing all of U.S. employment.

FIGURE 1

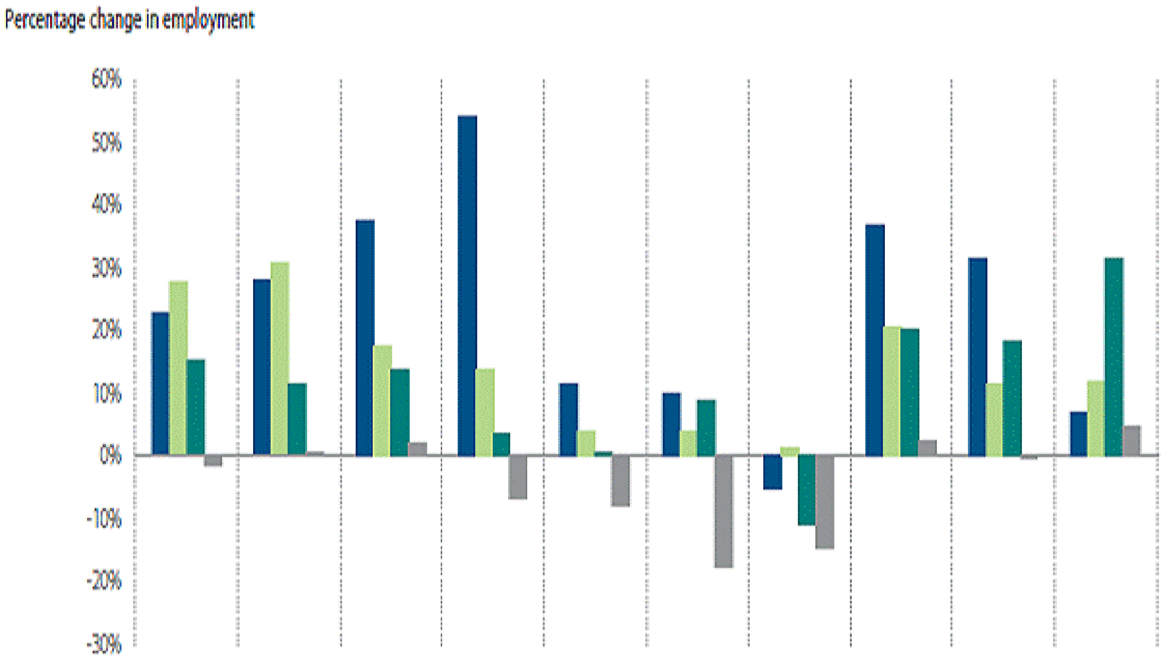
Smoothed changes in employment by occupational skill percentile, 1979–2007



Source: Autor (2010)

These occupations are arranged on the x-axis by their degree of skillness from lowest to highest, where a profession's skill rank is approximated by the average wage of workers in the occupation in 1980. The y-axis of the figure corresponds to the change in employment at each occupational percentile as a share of total U.S. employment during the decade. The graph shows that there is a change of distribution of employment across professions over the three time periods presented, which becomes more noticeable in each decade. In fact, occupations that are considered to have a low skill rank grow in terms of employment share throughout the years, while the medium skill ranked jobs decrease each decade and high skill professions employment share increase the first two decades ant then flattens in the third one.

By rejecting the hypothesis of the skill-biased technological change, Autor introduces the notion of job polarization. The job polarization is the process by which the job growth is increasingly concentrated at the tails of occupational skill distribution, in both high-education, high-wage occupations and low-education, low-wage occupations. To illustrate better this phenomenon, Autor (2010) uses the following figure, which plots changes in employment by decade for 1979 through 2009 for 10 major occupational groups.



	Managers	Professionals	Technicians	Sales	Office and admin	Production, craft, and repair	Operators, fabricators, and laborers	Protective services	Food prep, building and grounds cleaning	Personal care and personal services
1979–1989	22%	28%	37%	54%	11%	10%	-5%	36%	31%	7%
1989–1999	27%	30%	17%	14%	3%	4%	1%	20%	11%	12%
1999–2007	15%	11%	14%	4%	1%	8%	-11%	20%	18%	31%
2007–2009	-1%	0%	2%	-7%	-8%	-17%	-15%	2%	0%	5%

Source: Autor (2010)

Three categories of professions can be distinguished: high-skill (managers, professionals and technicians), medium-skill (sales, office and administrative, production, craft and repair and operators, fabricators, and laborers) and low-skill (protective services, food preparation, building and grounds cleaning and personal care and personal services). This bar chart gives further insight on the polarization of the employment, indeed, it is clear that in the first three periods high-skill and low-skill occupations increased and the medium-skilled decreased. During the period of 2007-2009, which is associated with the Great Recession, medium-skilled jobs had a tremendous negative change in employment, ranging from -7% to -17%, while high-skill and low-skill occupations absorbed the shock without showing any significant negative percentage change in employment.

The two graphs and the analysis presented by Autor (2010) only accounts for the U.S. labour market. However, there are many studies that show how job polarization is manifesting throughout the whole global economy. In the UK, Goos and Manning (2007) classified jobs, according to the

Labor Force Survey, on their wages and then by arranging these in decile where decile 1 expresses the 10% of jobs paying the lowest wage. The results show that the largest increase in employment share has been depicted by decile 10 followed by decile 9, so that, the largest growth in jobs was related to the high-level jobs. Also low-skilled jobs experienced a growth with an increase in shares of decile 1 and 2. The decile in the middle, instead, have all seen a decrease in their employment share over all the period studied. Holmes and Mayhew (2012) also replicated the results of Goods and Mannings, by analyzing a longer period that goes from 1981 to 2008. They ranked jobs again by mean average pay and then divided into decile. The findings highlight an employment share growth in decile 1,9 and 10. In Germany, Spitz-Oener (2006) created her own skill index, based on levels of education, and ranked occupations in Germany into decile as Autor and Goos. She then plotted the change of employment shares for each decile over the period 1979-1999, and obtained similar results to those in the UK and US.

Job polarization has been observed in various countries and most of the data supports this concept that medium-skilled occupations are declining and high-skill and low-skill jobs are increasing. One interesting issue are the causes of these trends in employment. Autor (2010) describes four possible causes: a routine task-replacing technological change, international trade and offshoring of good and services, declining private sector labor union penetration and the declining real value of the federal minimum wage. Even if the causes are four, the main cause to be considered is the routine task replacing technological change. In point of fact, Goos and Manning (2010) show how RBTC (routine biased technological change) is much more important than offshoring in explaining job polarization.

Concerning the first (and main) cause, it can be said that a leading explanation for job polarization focuses on the changing demand for job tasks spurred by the advent of workplace computerization. There are some studies that show how prices in robots have been significantly decreasing in the last years: as stated in the first chapter, The McKinsey Global Institute (2013) says that robot prices are dropping, placing them within reach of more users. Furthermore, a recent paper by Yale economist William Nordhaus (Nordhaus, William D. 2007) estimates that the real cost of performing a standardized set of computational tasks using information technology fell by roughly one-third to one-half annually over the past six decades, leading to a cumulative decline of at least a trillion-fold in the cost of computing. Processing tasks that were unthinkably expensive 30 years ago (such as searching the full text of a university's library for a single quotation) are now trivially cheap. This fast, secular price fall creates gigantic economic incentives for employers to substitute information technology for costly labor in performing workplace tasks. At the same time, it creates important advantages for workers whose skills become more and more productive as the price of computing falls. As stated in the first chapter, the jobs that are currently not replaceable by any machines are those who involve perception and manipulation, creative intelligence and social intelligence tasks, and those who experience a replacement of their job by a machine are jobs that involve routine tasks and even some jobs that involve non routine tasks (chapter 1 illustrates both cases). Routine tasks are characteristic of many middle-skilled cognitive and manual activities, such as bookkeeping, clerical work, and repetitive production tasks. Because the core job tasks of these occupations follow precise, well-understood procedures, they are progressively codified in computer software and executed by machines. Such tasks are core components of the medium-skilled jobs described in the previous bar chart. The bar chart also shows how jobs that are less susceptible to replacement are found at the opposite end of the occupational spectrum. As for high skill jobs, the concept of skill-biased technological change (SBTC) can hold true, since high-skill jobs are composed of tasks that are hard to automate due to their social and creative nature. However, SBTC holds true only for high-skill professions since medium-skilled occupations are decreasing and low-skill jobs jobs are increasing. As for low-skill occupations, it is not intuitive that their share in employment is increasing due to automation, one might think that since they don't require an intensive training, they are easy to automate. However, as the studies on job polarization show, there has been an increase in this lower end of the spectrum of occupations. This is also stated by Autor and Dorn (2013), where they show that between 1980 and 2005, the share of hours worked in service occupations among non college workers rose by more than 50 percent. Furthermore, they illustrate how a rising employment in service occupations account for a substantial share of aggregate polarization and growth of the lower tail of the US employment earnings distribution between 1980-2005. Recent automation has replaced for low-skill workers in performing routine tasks while complementing the abstract, creative, problem-solving, and coordination tasks performed by highly-educated workers. As the falling price of computer technology has driven down the wage paid to routine tasks, low-skill workers have reallocated their labor supply to service occupations, which are hard to automate since they rely heavily on dexterity, flexible interpersonal communication, and direct physical proximity. Autor and Dorn's (2013) model shows that if the demand for these service outputs does not admit close substitutes, then the replacement of machines that operate on the basis of information technology for routine tasks used in goods production can induce rising wages and employment in low-skill service occupations. This concept builds on Baumol's (1967) model of unbalanced technological progress by broadening it to

the study of skill demands and wage structure (in addition to Baumol's focus on sectoral composition).
Interestingly, employment projections from the U.S. Bureau of Labor Statistics also support the concept that low-education service jobs are expected to be a major contributor to U.S. employment growth in the future. The BLS forecasts that employment in service occupations will increase by 4.1 million, or 14 percent, between 2008 and 2018. The only major occupational category with greater projected growth is professional occupations, which are predicted to add 5.2 million jobs, or 17 percent. (U.S. Bureau of Labor Statistics. 2010, Occupational Outlook Handbook).

Thus, technological change and automation are a major cause to job polarization. However they are not the only cause: Autor (2010) also presents international trade and offshoring of good and services as a potential explanation. Routine tasks that are typical from the medium-skilled workers are found to be very susceptible of being offshored and, thus, replaced by foreign workers (usually paid less). This leads to a polarization of jobs, however, as Goos et al (2014) state, RBTC (routine-biased technological change) is much more important than offshoring in explaining job polarization. Indeed, the main belief of many economists is that the principal cause of job polarization is automation and technological change. There are also other smaller, less important explanations as to why jobs are polarizing such as declining private sector labor union penetration and the declining real value of the federal minimum wage. These are not considered to be a major driving factor of job polarization, however Autor (2010) describes how they can have some sort of influence on the labor distribution. Overall, regarding job polarization, it can be said that automation has a major impact on the distribution of labor causing a decrease in the growth of employment share of medium-skilled occupations and an increase in the share of low-skill and high-skill workers; thus polarizing labor.

The question that rises from this phenomenon of job polarization is: is there an impact on wages? Would this polarization explain the rise in wage inequality?
As stated previously, job polarization is the process by which the job growth is increasingly concentrated at the tails of occupational skill distribution, in both high-education, high-wage occupations and low-education, low-wage occupations. If the high wages and the low wages increase, there is an inequality among wages since they are not allocated smoothly among people, meaning that the high-skilled workers will be paid more and the low-skill workers less. Concerning wage inequality, job polarization may not be the only factor causing it. However, Goos and Manning (2003), show how increased job polarization can explain 33% of the increase in the

log(50/10) differential between 1976 and 1995 and 54% of the increase in the log(90/50) wage differential. They also note that this process of polarization seems relatively smooth throughout the period: one cannot readily identify sub periods in which all the change occurred. Many researchers have documented increasing wage inequality in industrialized countries (see the surveys by Acemoglu and Autor 2011; Katz and Autor 1999). Since the late 1970s, and continuing through the mid-2000s, wage inequality has been increasing in the U.S. (Autor 2014; Autor et al. 2008; Lemieux 2006) and also in other countries such as Germany (Biewen et al. 2017; Card et al. 2013; Dustmann et al. 2009). Moreover, rising wage inequality has been identified as a key driver of the rise in income inequality (OECD 2016; Piketty and Saez 2014). According to the theory of supply and demand, a decrease in the relative demand for workers in middle-skill occupations results in a decline in the relative wage for those workers. Similarly, an increase in the relative demand for workers in low- and high-skill occupations leads to higher relative wages for these workers (Tüzemen, 2013). Intuitively, one might think that a polarization of jobs would have effects on the wages in a similar way, as some studies suggest. However, some other studies done on the impact of job polarization on wages, looking for a possible wage polarization, show no evidence of job polarization having consequences on the wages. For example, Machin (2009) and Mieske (2009) both analysed the growth rate in wages at each decile of the initial wage distribution over the period 1979-2008. What Miseke found was no evidences for wage polarization as the growth rates of real wages were highest in the middle of the distribution with a single exception of decile 6. Similar results were found by Machin (2009) who analyzed the growth in wages at specific percentiles instead of decile as in Mieske. For every decade starting from the 1980s, he found that the growth rate of wages has raised in the 10th, 25th, 50th, 75th and 90th percentiles, thus, with no evidence of wage polarization.

Frey and Osborne (2013) suggest a truncation in the current trend towards labour market polarization, with growing employment in high and low-wage occupations, followed by a hollowing-out of middle-income jobs. Rather than reducing the demand for middle-income occupations, which has been the pattern over the past decades, their model predicts that computerisation will mainly substitute for low-skill and low-wage jobs in the near future. By contrast, high-skill and high-wage occupations were found to be the least susceptible to computer capital. Frey and Osborne's results thus disagree on this phenomenon of job polarization because they found that new technologies are being capable of reproducing much more complicated tasks than before and that these tasks now include also non-routine cognitive and manual tasks, explaining that machines can substitute for some low-skill jobs that were previously considered to be irreplaceable by technology, as previously discussed in the first chapter. These conflicting results may indicate that the effect of job polarization on wages is ambiguous, Dirk Antonczyk, Thomas DeLeire, Bernd Fitzenberger (2018) suggest that these conflicting results may be driven by the fact that some of them were done in different countries, and thus the context may be different. They show how Autor and Dorn (2013) found that employment and wages in low-skill service jobs, which involve non-routine manual tasks and which pay low wages, have grown considerably since the early 1990s and in contrast, Dustmann et al. (2009) for Germany and Goos et al. (2014) for 16 EU countries found no evidence for this. Hence, despite similar employment changes, wage inequality has been changing differently in the U.S. compared to European countries.

Overall, the impact of job polarization on wages is ambiguous, some studies suggest that from a theory demand and supply point of view there might be some changes in wages due to job polarization, others continually find evidences of the rapid growth of real wages at the top end of the distribution, but show no evidences to illustrate faster wage growth at the bottom relative to the middle part of the wage distribution.

As stated previously, technological change and automation are a major cause of job polarization. Nonetheless, job polarization fails at properly describing a wage polarization and, thus, an impact on wage inequality. Hence, one might think that automation itself fails at explaining wage inequality. As the studies on the impact of job polarization on wages show, technological change doesn’t appear to be a main cause of wage inequality. this holds true but only through the job polarization channel, wage inequalities can be explained by automation and technological change in other ways, through different channels.

Automation as a cause of income inequality:

Economic inequality (also known as the gap between rich and poor, income inequality, wealth inequality, or differences in wealth and income) includes disparities in the distribution of economic assets (wealth) and income among individuals in a population. As it can be seen on the following graph, which shows how the share of national income of the top 1% richest part of the population and the 50% bottom one have evolved over time, inequality has been increasing in the recent years.

Source: WID.world (2017). See wir2018.wid.world for data series and notes.

The graph indicates that in 2015, the top 1% most rich people owned a 20% share of the national income, while the bottom 50% had only approximately 13%. It can also be seen that prior to 1995, the distribution of national income was different, the bottom 50% held more share than the top 1%. Shortly after the year 1995, the top 1% started to earn more share of the national income than the bottom 50%, this points out that the rich are becoming richer and that the poor are becoming poorer, thus creating inequalities.

There are many causes as to why inequality might take place. One of them seems to be technological change and, thus, automation. Several studies were done in order to understand whether automation has an impact on inequalities or not. One key insight for understanding these possible effects of technological change is the replacing nature of robots: as seen in the first chapter, machines can either substitute a profession or complement it (it can also reshape the core tasks of the occupation). By automating tasks, usually the productivity raises and in the case where workers are fully substituted, the costs are decreased because there are no more workers that need to be paid. The higher productivity should make firms more efficient and thus leading to possible higher profits. However, these profits don't seem to be equally distributed: capital owners tend to earn more profits while some workers experience a negative impact on their wages, as machines substitute for them. As a matter of fact, Dauth et al. (2017) recall that robots cause, on average, more stable jobs but lower wages for individual manufacturing workers in Germany. The positive effect on accumulated days in employment does not differ strongly across different groups, but the wage and earnings effects do. High-skilled workers in non-routine occupations tend to benefit both in terms of job stability and wages. Medium-skilled workers who mainly perform routine and manual tasks, however, face significant earnings losses from increasing robot exposure. Those losses do not come from displacements or interruptions in work biographies, but they mainly arise on existing jobs through lower wages. In other words, they find that the increase in labor productivity caused by robots is not reflected in higher average wages. This suggests that the rents created by this technology are not captured by labor at large, but mostly by the owners of other factors, such as capital, or by residual profit claimants. They conclude by stating that robots seem to have contributed to the declining labor income share. Furthermore, Acemoglu and Restrepo (2017) estimate the impact of industrial robots on employment and wages in the United States between 1990 and 2007 on US local labor markets. They start with a simple task-based model in which robots compete against human labor in the production of different tasks. In this model, robots may have a positive or negative effect on employment and wages. Their positive impact comes from the productivity effect, while their negative impact is due to the direct displacement of workers by robots. Acemoglu and Restrepo (2017) also state that one additional robot per thousand workers now reduces aggregate employment to population ratio by 0.34 percentage points and aggregate wages by 0.5 percent. There are also other studies that show how automation can have an impact on inequality. For example,Dauth et al (2017) find that robot exposure causes notable on-the-job earnings gains for high-skilled workers, especially in scientific and management positions. But for low- and especially for medium-skilled manufacturing workers they find sizable negative impacts, particularly in machine-operating occupations. it seems plausible that those workers (or unions and work councils on their behalf) have accepted, in view of the threat posed by robots, lower wages in return for maintained job security. The focus is thus to whether a worker is considered to be high, medium or low skilled. High skilled workers tend to gain from automation, as they are complemented by the efficiency of the machines, most of medium skilled professions are being replaced by machines and as a consequence, their wages seem to decrease as they either lose their job (they can also accept lower wages and keep working). For low-skilled labor, some types of jobs can be considered to be at risk of automation and thus experiencing a wage loss, others, such as service occupations, seem to be not threatened by automation due to their requirements in social skills, which are yet difficult to automate. However, Frey and Osborne (2013) find that the next generation of automating technologies are much more likely to be able to complete all the tasks of lower-skills jobs, relative to higher skill ones. This outcome is different from previous waves of automation in which mid-skilled jobs were affected more than low-skill jobs, because increasingly new technologies are able to perform manual tasks that previously were not technologically feasible. Thus, regarding the future of automation, an important share of low-skilled tasks might get replaced by machines, even though other low-skill professions are likely not to be replaced. If these non-automatable low-skilled professions are put aside, the effect of automation on inequality are much more clear. Lankisch et al. analyse the effects of automation in a model with low-skilled and high-skilled workers in which low-skilled workers are easier to replace by robots than high-skilled workers. They show that there is the possibility for perpetual economic growth despite the absence of technological progress, automation decreases the real wages of low skilled workers and has the potential to even decrease the wages of high-skilled workers, and automation raises the skill premium. All three results are consistent with the experience of the United States over the past decades and help to explain why the less well-educated did not benefit from economic growth. This example, by considering low-skill jobs easier to substitute than high-skill occupations, shows how automation is an important aspect in the explanation of the evolution of income inequality. Further evidence of this relationship between automation and income inequality has been studied by Prettner et al. (2019): they propose a model of endogenous technological progress and economic growth according to which R&D-based innovations in machine technology lead to more automation, a higher skill premium, and more inequality in terms of income and wealth. The model predicts that more sophisticated technology induces more education but only to a certain degree because, eventually, some individuals who do not manage to obtain a college degree due to ability constraints will be left behind. The feature that low-skilled labor does not benefit from automation creates rising inequality because the wages of high-skilled individuals increase at the rate of technological progress. They have also shown that it is difficult to improve income of low-skilled individuals as long as both technology and education are endogenous.

Overall, new information technology has led to improvements in productivity and well-being by leaps and bounds, but has also played a central role in driving up the skill premium, resulting in increased labor income inequality. Many studies have shown the effects of automation on inequality, almost all of the studies mentioned above analyse the impact of automation by first ascertaining that automation can either benefit or substitute workers, depending on their skills and on the nature of these tasks (routine or non-routine). Those who benefit are usually the capital owners, and by improving the productivity of their firms, they increase the profits. High-skilled workers also see their income rising, since the automation of certain tasks allow them to work even better since they are complementary to automation, hule medium-skilled and even some low-skilled workers are being substituted by machines and, as a consequence, they either lose their job or accept professions that are paid less. This mechanism causes a big division in terms of income, creating an increase in income inequality. However, automation isn't the only driver of income inequality. Education can play an important role in income inequality, as it determines occupational choice, access to jobs, and the level of pay, and plays a pivotal role as a signal of ability and productivity in the job market. Also offshoring has been detected as a cause of income inequality:

when rich countries trade with poor countries, unskilled workers in rich countries can see their wages cut as a result of competition, while workers' wages in poor countries should increase. Market economist Paul Krugman (2007) believes that market liberalization has had a measurable effect on the growth of inequality in the United States.

CHAPTER THREE: POSSIBLE POLICIES

Focusing more on automation, the question that arises from the evidence of its effects on income inequality is: what can be done in order to limit these effects?
A possible proposition for containing the substitution of labor through machines is training. Workers who are likely to see their job automated should be worried and, in order not to be negatively affected by the substitution, learn new tasks that are considered to be non automatable. Nedelkoska and Quintini (2018) finds that the relationship between the risk of substitution and training participation will depend on several factors: the skill level and interest of workers at risk of automation when it comes to obtaining training, the opportunities to relocate workers within the same organisation following re-training, the level of mismatch between their skills and the job requirements of the available jobs, and the availability of training outside the job through government-sponsored or private sector programmes. They also suggest that the relationship may differ for on-the-job training and training that is undertaken to improve the chances of finding a new job, workers at high risk of automation may receive less on-the-job training, but may be more likely to invest in training that helps them find a new job. Moreover, the Aspen Institute (2019) presents many possible policies in order to reduce the negative effects of automation, one of them is to encourage employers and educational institutions to expand apprenticeships. With technology changing, the tasks required to perform many jobs change as well, as does the occupational composition of the economy, workers need to adapt to these changes. They can do that by accessing to programs that provide in-demand skills that lead to better professions. The institute suggests that the most effective strategies incorporate work based learning models, programs designed through partnerships between employers and educational institutions that pair classroom learning with on-the-job learning. It also states that apprenticeships are well suited programs that can help workers to acquire these new skills and that there are four critical elements to apprenticeship programs' success: the program content should be supervised by local employers who are supposed to make sure that it is aligned with the needs of the labor market, the opportunity cost of training should be compensated, the program should be closely related to work, thus avoiding possible difficulties with

traditional classroom learning, employment should also be incorporated into the program. The White House (2015) has shown how apprenticeships succeed in placing workers in higher-paying jobs, in fact, close to 90 percent of apprentices are employed after completing their programs with an average starting wage of over fifty thousand dollars. However, the number of apprenticeships in the US has been shown to be small (Lerman 2014), the reasons are various, but Roespe (2017) indicates that the small number occurs because there is a lack of awareness of the program among workers and that the US government doesn't really promote them. Moreover, Lerman (2014) gives further insight as to why there is a small number of apprenticeships in the US by showing that there are cost and administrative burdens. The government should play an active role in increasing apprenticeships, since they can help workers to find a new, higher-paying, job.

Another suggestion made by the Aspen Institute (2019) is to support displaced workers who consider to retrain for in-demand fields. The institute explains how there are barriers to retraining, indeed, finding time and money to enroll in a training program can be difficult, especially for the workers who lost their job because of automation. One barrier consists in the fact that community college and vocational training programs can have costly tuition and fees. Workers who become displaced have an urgent need for retraining and they might need an additional financial support There are also other type of barriers to retraining that might occur such as child or elderly care. In fact, the Aspen Institute (2018) states that individuals raising preschool-age children have half as much time available for academics, sleeping, eating, and leisure activities compared to a childless person. This might cause a problem for retraining programs that require a long time period of course work. There is also another factor to consider to understand better why retraining can be difficult, that is the important opportunity cost of enrolling in a retraining program. Workers consider returning to work as an alternative, since they need to pay bills. By taking low-paying jobs, workers will also find less time to engage in training (Conway 2018). The suggestion of the Aspen Institute (2018) consists in the fact that policymakers should introduce vouchers and stipends: training benefits provided to displaced workers. Vouchers up to ten thousand dollars, enough of what is required for most two-year community college and vocational training programs, destined for programs that qualify the worker for high-growth, high-demand occupations as determined by workforce boards. Stipends would be given on a weekly basis, for up to two years, while workers are enrolled in training programs. They would help the workers to face basic living expenses and additional costs that derive from the attendance of the programs, such as child care and transportation (the institute suggests that the stipend would be an amount equal to a portion of the worker's pre-displacement wages consistent with the state's UI wage-replacement rate plus an additional $150 per week). Nonetheless, as the number of displaced jobs increases, this will indicate that the additional financial support that the Aspen Institute (2019) suggests would require a vast amount of money. And it is not clear and questionable on how will the government find the necessary funds for this support. However, if displaced workers don't invest in retraining, they will either become unemployed or find a lower-paying job (which is not sure to happen). Nevertheless, retraining will create more high-skilled workforce and will satisfy the growing demand of high-skilled workers.

These suggestions focus on the current workers, by retraining them, destruction of jobs can be reduced, however there are also upcoming workers that need to adapt to the new skills being demanded, thus, interventions in the educational system might be required. The younger generations are still in time to adapt to the technological changes, in order to adapt, they should be trained relatively more in the skills that are not affected by automation and that are increasing in importance. These are perception and manipulation, creative intelligence and social intelligence tasks. Governments should ensure that the primary and secondary school system imparts foundational technology skills and sets up incentives to encourage effective retraining and lifelong learning. Moreover, it is important that the future labour force is comfortable with machines and can communicate effectively with them, since most jobs will evolve to require significant interaction with machines. Today, that means that more graduates should possess computer programming skills, regardless of whether their degree is in a scientific subject or in arts. Understanding how computers operate, their strengths and their limitations, will be an important asset. Education should also focus on adaptable skills such as problem solving, critical reasoning, creative thinking, social skills and emotional intelligence. These skills are not yet threatened by automation and can be important for future jobs. Thus, education can play an important role in the attempt of limiting the destruction of labor by automation. It is then obvious that obtaining an undergraduate or even postgraduate education is mostly necessary: as it has been shown in the first and second chapter, the jobs that are less susceptible of being replaced by robots are professions such as managers, engineers and technicians, doctors, programmers… all of these professions require a higher education. With only a secondary education, one will find it hard to find a job, since machines are now able to do a vast amount of tasks that were usually done by workers with a low education (no higher education) such as occupations that involve manufacturing.

Overall, education and training programs can play an essential role in containing the damaging effects of automation on workers. By encouraging retraining programs, workers can upgrade their skills, face the new demands of the labor market and find a better paying job. These training programs will prevent workers from being unemployed or from finding another less-paid job, in order to pay the bills. Primary and secondary education can also be important, the new generations should be more than ever adapted to the technological changes by gaining computer knowledge and practical skills, and also focusing on problem solving, critical reasoning, creative thinking, social skills and emotional intelligence.

CONCLUSION:

Technological progress is the application of scientific discoveries to production. Technological progress allows companies to reduce production costs or create new markets or market segments in which to operate. It has brought to many inventions, such as innovative machines and robots, and it is usually seen as an evolution of the human being, meaning that humans expand their knowledge by creating new machines. Nonetheless, technological progress is often regarded as a threat. The mechanical loom, introduced during the industrial revolution, was was considered to be a cause of low wages and unemployment. Luddism, a workers' protest movement developed in the early nineteenth century in England, promoted sabotage of industrial production. The concern about technological progress is also gained popularity thanks to movies and books (e.g., The Terminator by James Cameron, Wall-e by Andrew Stanton, I, Robot by Isaac Asimov) presenting a scenario in which robots take over humans. Stephen Hawking, in an interview with the BBC in December 2014 stated: “the development of full artificial intelligence could spell the end of the human race…. It would take off on its own, and re-design itself at an ever-increasing rate. Humans, who are limited by slow biological evolution, couldn’t compete and would be superseded”. In January 2015, Stephen Hawking, Elon Musk and dozens of experts in artificial intelligence signed an open letter calling on researchers to study the societal impacts of artificial intelligence.

As a core element of technology (i.e., creating machines and robots that can replicate human tasks), also automation is debated: many people feel threatened by an increasing automation of tasks. Over the last decades, and now more than ever, there has been a major concern over labor-replacing automation . : many workers (one example can be seen in the case of luddites) see their job automated, and even more are likely to see their job automated in the next future. This study presents a literature review focused on automation and its impact on labor. The first part asks how automation has affected the labour market in the course of history and how it is expected to affect it in the future. The second part concentrates on whether automation can actually exacerbate the extent of (wage and income) inequality over the next decades. Finally, the literature suggestions on how to deal with the possible consequences of automation are considered.

The key message is that there is actually no clear-cut evidence of a negative impact of automation on overall employment. However, the future might be different, as a negative impact on income inequality is already documented by several authors.

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