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AUTOMATION, COVID-19, AND LABOR MARKETS

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Abstract

Rapid technological progress poses challenges for labor markets. Automation can both displace and create jobs. Currently, an unprecedented digitalization of our economy is underway. Artificial intelligence has become a reality and machines are able to learn how to outperform humans in some cognitive tasks. This ongoing technological transformation of work can interact with the COVID-19 pandemic shock resulting in fewer jobs for the less educated and low-skill workers as well as further decline in the labor share of national income. This paper reviews the impact of automation and artificial intelligence on work and discusses the long-run effects of the pandemic crisis on the workforce. It also presents some thoughts on how the challenges ahead should be addressed through a multidimensional policy response.

Keywords: automation, artificial intelligence, future of work, COVID-19, labor markets

JEL Classification: J11, J21, J23, J24, J31, J38

Contents

1. AUTOMATION AND EMPLOYMENT: A BRIEF HISTORICAL PERSPECTIVE

The question of whether technological progress, machines, and innovation threaten employment is not new. Aristotle, in his *Politics*, expressed his concern that machines and inventions may replace workers, providing an alternative, more efficient way of performing job tasks:

> *"If every instrument could accomplish its own work, obeying or anticipating the will of others, like the statues of Daedalus, or the tripods of Hephaestus, which, says the poet, 'of their own accord entered the assembly of the Gods'; if, in like manner, the shuttle would weave and the plectrum touch the lyre without a hand to guide them, chief workmen would not want servants, nor masters slaves."*

The beliefs of Ancient Greek philosophers became a dominant dogma that describes the physical world until approximately the Renaissance, when a scientific revolution with the employment of experiments started questioning many of the beliefs inherited from Ancient Greece and seeking the scientific proof behind these beliefs. The initial steps of scientific developments focused on theories regarding the universe and the place of Earth in it. The law of physics and mechanics, the sun's light, and the lightning became objects of systematic study, which helped scientists to shape the principles of a new scientific approach in order to explain the world.

This critical way of thinking and the resulting experimentation led to inventions that were related to major innovations in transportation and the production process. The outcome of this was the first Industrial Revolution. One of the most important of these technologies was James Watt's steam engine (Morris 2011; Brynjolfsson and McAfee 2014). At that time, steam engines were highly inefficient as they were only able to utilize 1% of the generated energy from the combustion of coal. Watt applied revolutionary scientific methods that contributed to a significant increase in the efficiency of steam engines, which allowed their mass application in the transportation and production of goods. That led to the birth of industrial sectors such as transportation and manufacturing that shifted much of the workforce away from agriculture. During the second Industrial Revolution that followed (which started around 1870), electricity, petroleum, and steel enabled the invention of telephones, lightbulbs, the radio, and combustion engines.

Humanity had taken a new path towards the creation of big industrial structures where the new engines could overcome for the first time the limitations of human and animal muscle power. The efficient new techniques of mass production led to the mass employment of workers in industries where they had to "collaborate" with powerful engines as part of the same production chain. At the same time, the applications of these new forms of production enabled new modes of transportation and a variety of retail industries that provided products and services to final end consumers. Such vertical structures in the production chain were formed, allowing more people to be employed and more goods to be available to consumers.

Nevertheless, the concerns about employment did not cease to exist. Keynes (1930, 2–3) wrote:

> *"We are being afflicted with a new disease of which some readers may not yet have heard the name, but of which they will hear a great deal in the years to come—namely, technological unemployment. This means unemployment due to our discovery of means of economising the use of labor outrunning the pace at which we can find new uses for labor. But this is only a temporary phase of maladjustment. All this means in the long run that mankind is solving its economic problem."*

It is important to underline the temporary nature that Keynes attached to the problem of technological unemployment. While machines become more efficient due to technological progress, humans can always find a way to perform complementary tasks so that in the long run employment will not be threatened by machines and technological development.

Comparing Keynes' theory with past experience, by looking back at the impact of past big steps in automation, we conclude that Keynes' theory agrees with observation. For example:

- In agriculture, horsepower reapers, harvesters, and threshing machines replaced labor but helped the sector to grow in the long run. The resulting increase in production and the possibility of exporting agricultural products to distant countries through a well-organized and efficient transportation system helped the producers and distributors to develop a profitable network of operation, thereby increasing the opportunities for employment.
- In transportation, the introduction of automobiles in daily transportation led to a significant decline in horse-related jobs. But new jobs emerged in automobile manufacturing and repairing. At the same time, modes of transportation by air or water became possible. These technological advances resulted in minimizing the significance of distance, making it possible to travel long distances in a short time. In this way, new transportation and business markets (e.g., tourism) were created with new opportunities for employment that went far beyond horses.
- In manufacturing, machine tools replaced labor-intensive technologies, first in the artisan sense and then on the factory floor connected with the assembly line. More recently, since the 1980s we have seen industrial robots that have automated welding, machining, assembly, and packaging. Before that, we had dedicated machinery and numerically controlled machinery for such tasks.[1]

The first era of technology-oriented innovations in industrial production had a positive impact on employment in the long run and only short-run negative effects. Technological breakthroughs have transformed work to a great extent. This transformation has incorporated short-run negative effects in specific job tasks and occupations that have been wiped out because of the new technology applications. But it has also incorporated the creation of new jobs or the further development of already existing jobs, generating new labor opportunities that have counterbalanced the temporary negative effects.

[1] For further examples, see *The Economist* (2016), "Automation and Anxiety," *Special Report*, 23 June.

From the 1980s a new era of automation began with the systematic introduction of robotic systems and personal computers. That gradually shifted the attention of researchers to improving the performance of these machines through the development of artificial intelligence (AI) and machine learning (ML) technologies. In the last decade, this investment toward intelligent machines started paying off with intelligent machines that outperform humans even in specific cognitive tasks (board games such as chess, AlphaGo, and Jeopardy are characteristic examples).

New concerns about the implications of new technologies such as AI and ML for employment started emerging. These concerns often come from successful entrepreneurs that have inside knowledge about how these technologies work in practice and what their potential is. For example, the founder of Tesla, Elon Musk, expressed the opinion that these risks are real when speaking at the National Governors Association Summer Meeting[2]:

> *"There certainly will be job disruption. Because what's going to happen is robots will be able to do everything better than us. ... I mean all of us… This is really the scariest problem to me, I will tell you."*

In his talk at the World Government Summit in Dubai[3] he went one step further in identifying a potential path that could be explored in the future.

> *"What to do about mass unemployment? This is going to be a massive social challenge… If there is not a need for labor… how do we ensure that the future is the one we want…? There is a potential path here that is … having some sort of merger between biological intelligence and machine intelligence."*

Another successful entrepreneur of the technology space, Bill Gates, finds it difficult to reverse the high potential of new technologies to replace human labor and suggests creating the economic incentives in order to protect employment. By taxing robots, for example, we can make their industrial use more expensive than labor, thus reducing the displacement for workers.

The rest of this paper is organized as follows. Section 2 reviews the impact of computer technologies and robots in the last three decades. It presents the main theories that deal with the impact of technology on employment as well as some relevant empirical evidence with an emphasis on Europe. Section 3 describes AI and ML and discusses their implications for the workforce. Section 4 reviews what we know so far about the impact of the COVID-19 pandemic on labor markets and evaluates how it will affect the ongoing digitalization of our economy with an emphasis on labor outcomes. Last but not least, Section 4 provides some concluding remarks about the available policy options in addressing the concerns over the new technologies and the pandemic.

2. THE IMPACT OF AUTOMATION ON EMPLOYMENT: WHAT HAVE WE LEARNED FROM THE LAST |THREE DECADES?

Prior to the rise of AI technologies that revolutionized the service sector, manufacturing was one of the sectors that had been systematically adopting automated technologies. One of these technologies that has received particular attention is the introduction of industrial robots. An industrial robot is defined as "an automatically controlled,

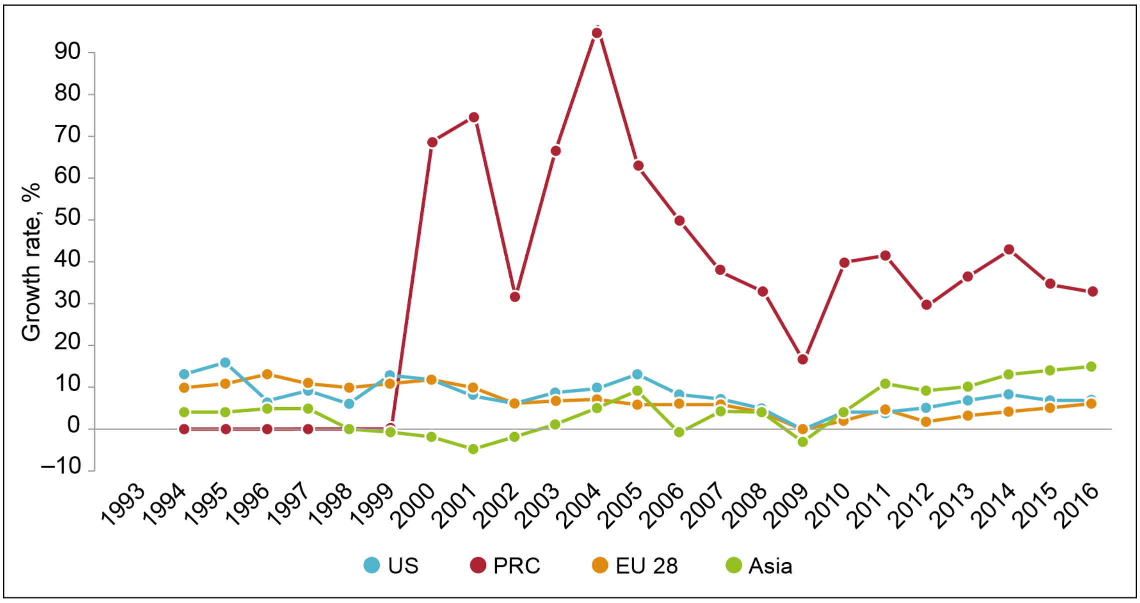
2 https://www.c-span.org/video/?431119-6/elon-musk-addresses-nga&start=5049.

3 https://www.youtube.com/watch?v=3mheJkhQeH4.

reprogrammable, multipurpose manipulator programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications" (International Federation of Robotics 2016).

The International Federation of Robotics (IFR) provides data on the number of industrial robots introduced in each industry in each country for a great number of countries. Figure 1 presents the growth rate of the adoption of industrial robots in different parts in the world. We see that the adoption of robots was the highest in Asian markets, with the People's Republic of China (PRC) being the country that adopted robots at the highest rate. One of the reasons for that is that, with the exception of Japan, the systematic adoption of robots in Asian countries started much later than in Europe and the US. So, Europe and the US are already significantly robotized, while robotization is a more recent phenomenon in Asian countries like the PRC.

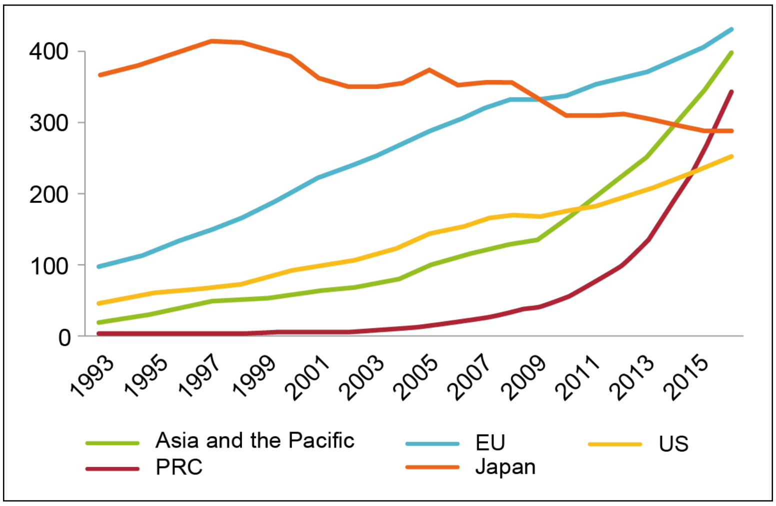
Figure 1: Growth Rate of Industrial Robots in Different Regions



Source: IFR.

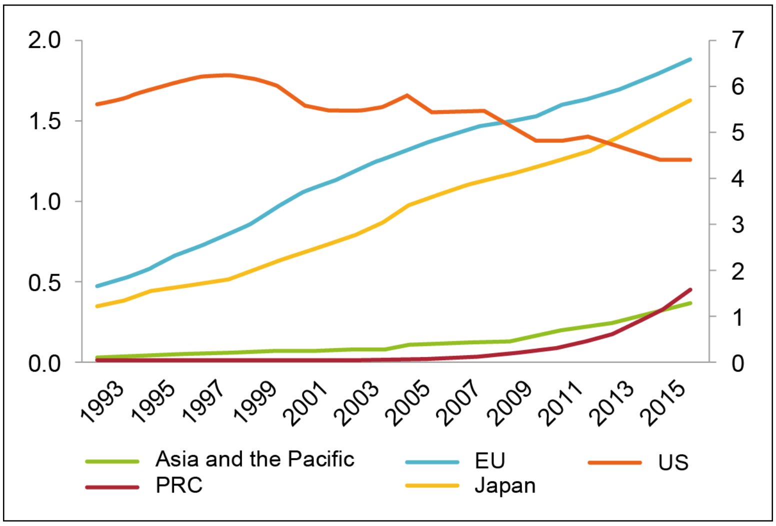
It is worthwhile reviewing the number of robots and their density (i.e., the number of robots per thousand workers) in different regions. We see that the adoption of robots is steadily increasing both in number and density over all regions except Japan. The adoption of robots in Asia has gradually shifted from Japan to other heavy industrialized countries like the PRC. The reason for this is that Japan was the first adopter of industrial robots worldwide. It had already adopted a great number of robots that are currently operating in its industries. In contrast, other Asian markets started being robotized much later, thereby explaining the observed divergence in the robot adoption trends.

Figure 2: Industrial Robots by Country (in Thousands)



Source: IFR.

Figure 3: Density of Robots by Country

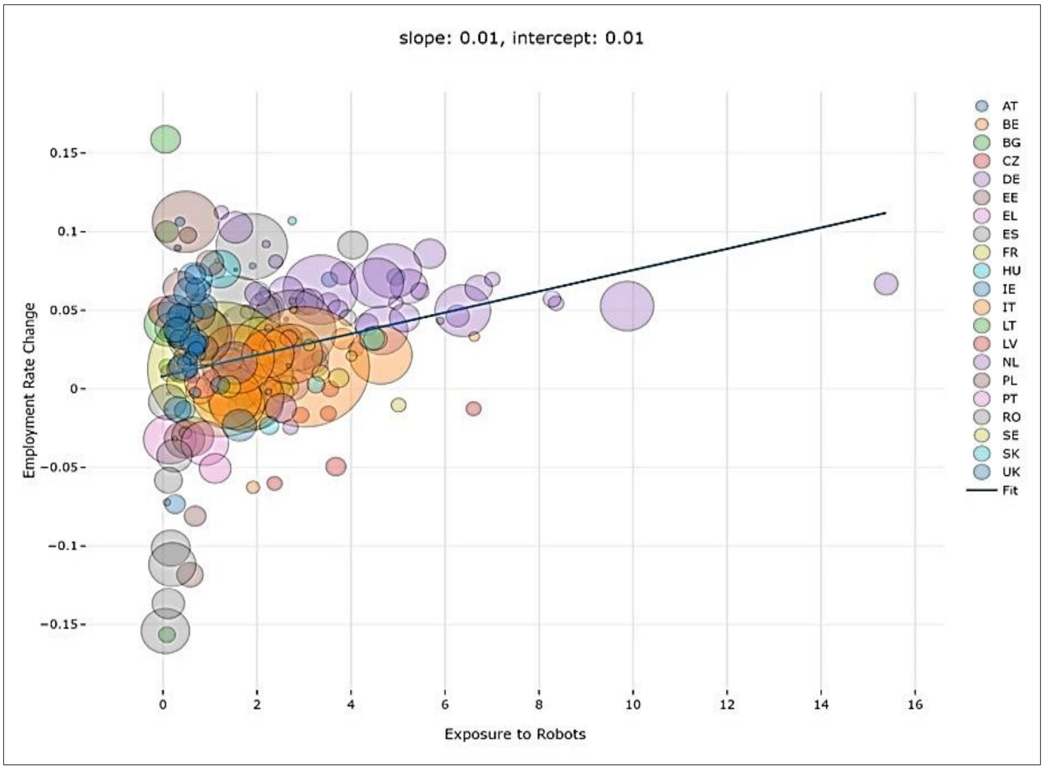


Source: IFR and ILO.

Petropoulos et al. (2019) built a data set with information about employment rates, real wages, and the density of industrial robots at regional level in the EU. They define exposure to robots as the ratio of the number of industrial robots to the number of workers in each region.

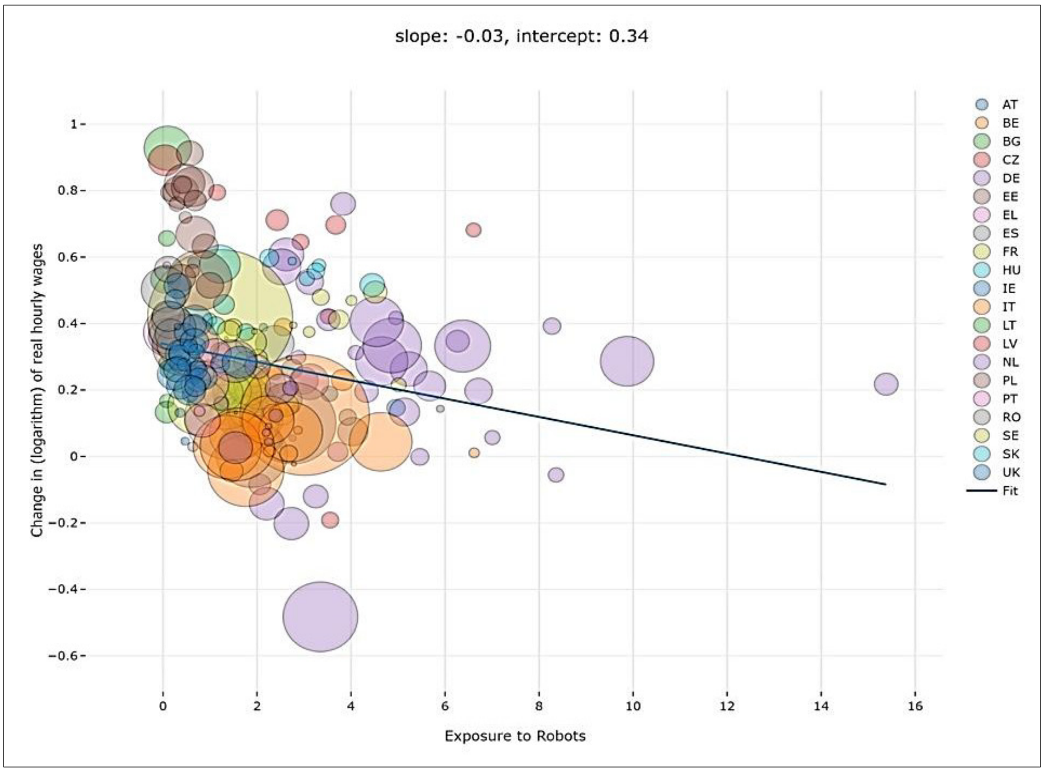
Then we can examine the relationship between the change in the regional employment rate and real wages between 1995 and 2015, and the change in the regional exposure of industrial robots.

Figure 4: Industrial Robots and the Employment Rate in EU Regions



Source: Petropoulos et al. (2019). Note: Each circle depicts a distinct region. The diameter of each circle indicates the size of the working population within the region.

Figure 5: Industrial Robots Relative to Wages in EU Regions



Source: Petropoulos et al. (2019). See also note under Figure 4.

We see that exposure to industrial robots is positively correlated with employment rates. As for real wages, there is a negative correlation with exposure to industrial robots. A proper identification strategy is needed for studying the causality of these relationships. There may be contemporaneous shocks that affect both the adoption of industrial robots and labor market main indicators resulting in these particular correlations.[4]

Looking at the broad picture of these two figures, it is possible that automation increases employment but mostly in occupations that typically involve a lower wage. To examine this possibility, a natural question to ask is: Which tasks and occupations were affected by the adoption of automated systems and how?

It is precisely such second-order effects that should be our focus. Automation will not eliminate employment and its overall impact on jobs so far has been moderate. But automation can have serious implications for the content of occupational structure, income inequality, and job polarization.

The impact of technology on skills has been examined thoroughly in recent decades. The first important conclusion has been the so-called “Skill-Biased Technical Change” (SBTC) hypothesis, which supports the notion that technology directs employment from unskilled to skilled labor. This is because it increases the relative productivity of skilled work and, therefore, its relative demand. That in principle is good news. Technological progress can be translated into progress in the skills of the workforce, helping workers to become more competent and increasing the skill content of jobs.

However, the observation that wage inequality remained relatively stable in the 1990s despite the continuing advances in computer technologies (Card and DiNardo 2002) brought this hypothesis into question. Researchers started realizing that the relationship between technology and skills is non-linear and certainly more nuanced than they thought. That give rise to the routinization hypothesis where instead of the skill level, the main element for analysis is whether a job belongs to the group of routine jobs or not.

The routinization hypothesis provides an alternative explanation according to which technology leads to job polarization. It leads to a rising relative demand in well-paid skilled jobs typically requiring nonroutine cognitive skills and in low-paid less-skilled jobs requiring nonroutine manual skills. This, in turn, leads to a falling relative demand for middle-skill jobs that have typically required routine manual and cognitive skills. Autor and Dorn (2013) provide a unified theory that explains job polarization that not only involves the Routine Biased Technical Change (RBTC) hypothesis from the previous paragraph but also task offshoring (which is partially influenced itself by technological change) through the reallocation of low-skill labor to service occupations. Goos, Manning, and Salomons (2009, 2014) provide evidence of pervasive job polarization across 16 Western European advanced economies over the period 1993–2010. In Germany, Spitz-Oener (2006) has shown that greater use of ICT by workers has reduced the importance of routine work.

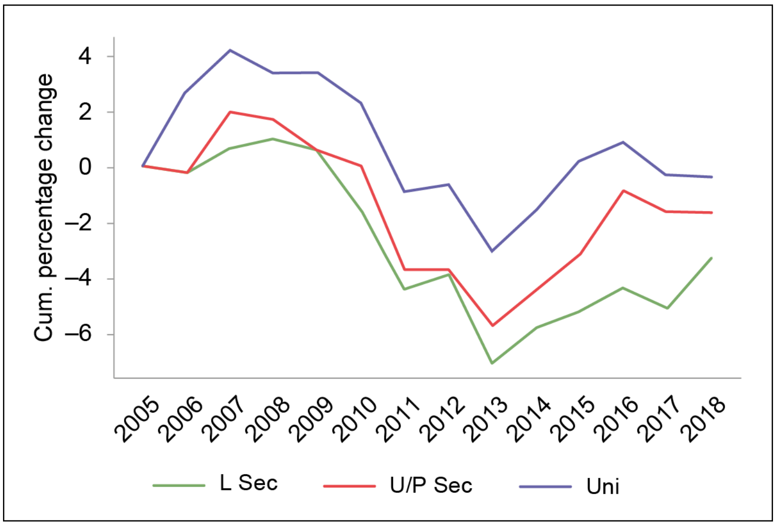
Brekelmans and Petropoulos (2020) evaluate the nature of occupational change in 24 EU countries over the period 2002–2016. They separate occupations into three skill groups following the methodology of Autor (2019), where the categorization occurs with respect to occupational wage.

[4] The development of a proper identification strategy is currently a work in progress by the author.

They find that on average, over the whole period considered, the EU countries in our sample have experienced an upskilling of their occupational structures rather than a polarization. However, this finding is more nuanced by a trend towards some polarization after 2009. Middle-skill jobs declined substantially between 2002 and 2016, and especially after 2009. The opposite trend is observed for high-skill occupations where we see sharp increases. Nevertheless, low-skill occupations have on average only slightly increased.

Another important dimension to be considered is education. Over time, EU workers have become more educated on average. But EU workers with tertiary education have experienced a relatively mild but still significant skill downgrading, which has been particularly prominent since 2009. This was not caused by a decline in the number of university graduates having high-skill jobs but rather by the relative increase in the number of them working in low-skill jobs. This finding implies that while the number of university graduates has increased, the chance that these workers will find themselves in low-skill jobs has increased as well. In other words, relative overqualification has increased for university graduates and accelerated during the Great Recession. The debt crisis led to an increase in overqualification in the EU, as the labor market's demand for skills could not keep up with the rising supply of university graduates. However, the skill downgrading experienced by university graduates was too small in size to counteract the compositional change effect of their rising number on the overall high-skill employment share.

Figure 6: Cumulative Percentage Changes in Real Yearly Wages by Education Attainment in Selected EU Countries, 2005–2018



Source: Brekelmans and Petropoulos (2020).

Over the period 2005–2016, Brekelmans and Petropoulos observe that overall, for all educational groups, the post-2009 period was one of real wage decline initially, followed by a mild recovery from 2013 onwards. Looking at the whole period, from 2005 to 2016, we notice that real wages tended to stagnate for EU countries. Differentiating by educational attainment groups, we observe that workers with different levels of educational attainment faced unalike real wage dynamics over the studied period. Notably, more highly educated workers (with tertiary education, university) experienced positive real wage growth between 2005 and 2018, with a 1.9% increase. Upper and post-secondary educated workers (U/P Sec) saw their real wages increase less, by 1.5% over the same period to be precise, and finally lower secondary educated workers' (L Sec) real wages were constant. A common characteristic in each educational group is that during the recovery from the crisis, the cumulative growth of real wages did not reach pre-crisis levels (with the peak in 2007).

Such trends suggest an increasing wage inequality in the EU. This is consistent with the US experience where reliable data are available for a considerably longer period of time. Autor (2019) reports that before the late 1970s we observe a pattern of growth of shared prosperity where the real wages of all demographic groups increase by approximately 2% per year. But then, from the late 1970s, and especially the early 1980s, we see a major divergence in the real wage patterns of different demographic groups, with a sharp decline among less education workers. In particular, high school dropouts and graduates received significantly lower wages in the 1990s and 2000s than those with at least some college education.

It is also insightful to look at modern theory on the impact of automation on labor markets (Acemoglu and Restrepo 2018, 2019, 2020). To do that we need first to define a useful unit for further analysis. This unit is the job task. Each occupation incorporates a variety of tasks, some of which can be easily automated while some others are very hard to automate. The automation of a task refers to the situation in which an automated system can perform this task more efficiently than human labor and at an affordable price.

These technological advances, then, can be modeled as the increase in the range and number of tasks that can be automated. But the nature of each occupation is also important for understanding the potential of automation to expand to more tasks within the given occupation.

In theory, there are three major effects of automation on employment. The first is that it displaces labor. When automated systems become more capable of performing job tasks, the risk that they will replace workers in these tasks increases. However, this may also mean that automated systems make workers more productive in complementary tasks that are not easy to automate. Through close coordination between humans and machines, we can increase the efficiency in the provision of tasks, raising in this way the demand for labor in tasks that are not automated. This is the so-called "productivity effect." Third, new automated technologies have the potential to create a new product market and services, generating demand for new jobs in the ecosystems that are created due to such technological advances. So, assessing the overall impact of automation on employment requires estimation of the overall impact of automation or, in other words, how these three effects compare to each other. An underlying important question is how we can adjust public policy in order to influence the signs of each of these three effects, promoting productivity and new job creation effects and minimizing potential displacement of workers.

One important implication of automation is that capital becomes a more important factor of the production function. So, it is natural to ask whether labor exhibits a diminishing return in income because of automation. Looking at US sectoral data, Acemoglu and Restrepo (2019) find that for the period 1947–1987, the labor share in value added in six aggregate sectors is fairly constant (except for mining and agriculture, which are relatively small sectors). However, the picture changes somewhat in the period 1987–2017. A lot of the sectors where we think monopoly power has increased, such as services and transport, are fairly constant in terms of their labor share. The decline in labor share is mostly a manufacturing phenomenon. Manufacturing exhibits almost a 20 percentage point decline in labor share over the course of about 20 years. In mining the drop is even bigger, but as mining is a smaller sector, its overall effect is more moderate.

There is a potential risk if firms adopt an excessive investment strategy in automation, ignoring the fact that in many cases it is the interaction between labor and machines that brings greater benefits. For this reason, Elon Musk has admitted that the excessive automation investment strategy of Tesla was a mistake.[5]

A related concern is the so-so technologies, which have just enough efficiencies to be adopted with a large displacement effect but only small productivity gains. Such automation is in fact the real enemy of labor. So, the fact that we observe a modest productivity growth does not necessarily signal a slowdown of automation. It may signal a lot of marginal automation.

3. LOOKING AHEAD: WHAT ARE THE IMPLICATIONS OF AI FOR WORK?

AI systems are based on algorithmic systems that perform well-defined tasks based on ML techniques. The usual structure involves an artificial neural network where relevant (training) data are introduced through an input layer. The network incorporates weighting functions that introduce the input in the main area of computation, the hidden layers of the ML algorithm. Finally, the output of the algorithmic process is observed in the final layer of the neural network (which is often called the "output layer"). This process is repeated over time, helping the AI system to be able to improve itself over time and provide a more accurate output in relation to its well-defined objective.[6]

Such AI systems have become very popular in a wide range of tasks, from the classification of alternatives to the matching of individuals that wish to supply or demand products and services. These technologies gave rise to platform ecosystems that helped e-commerce to grow at a significant rate all over the world.

AI systems appeared mostly in the last decade because three preconditions were satisfied:

- Availability of data: Data storage and sharing have grown exponentially in the last few decades. Since data are the input of AI algorithmic systems, data availability allowed these systems to develop many different applications for which suitable data sets already exist.
- Computing power: Computer hardware has advanced drastically, thereby improving the computing power needed to perform algorithmic computations. This improvement was a necessary prerequisite for these systems to deliver a high-quality output in a time-efficient manner.
- Costs associated with digital technologies and data storage have drastically declined. This made it possible to make AI systems commercially profitable.

5 https://techcrunch.com/2018/04/13/elon-musk-says-humans-are-underrated-calls-teslas-excessive-automation-a-mistake/.

6 Deep learning systems are an example of ML and represent a form of "narrow AI," which is AI that can be tailored to a specific task but that is difficult to repurpose to a new task, even one with superficial similarities. Deep learning systems are particularly good at recognition or matching tasks, especially where there are large volumes of learning data available. Consequentially, a lot of successful applications of deep learning have come in the data analytics/big data area.

One new form of employment emerged out of this process, the so-called "platform work." This is probably the most prominent example of new forms of work created by the application of these technologies. While the legal status of platform workers is currently under debate, in economic terms, workers supply services in exchange for an enumeration that depends on the time they choose to spend on the platform. Research on platform work relies mostly on surveys as in most countries it is not captured by official statistics.

Brekelmans and Petropoulos (2020) compute the exposure to AI per skill group of European occupations for the year 2016, based on the methodology of Frey and Osborne (2017). They find that this exposure is particularly prominent for the middle- and low-skill groups and it is quite low for the high-skill group. Higher exposure to AI and machine learning technologies of mid-skill and low-skill workers reflects that some tasks in such occupations may be easier to replace or at least change because machine learning technologies are adopted. Indeed, such occupations involve performing a relatively high share of cognitive and/or manual tasks that can be accomplished by following explicit rules and can thus be affected by AI technologies. However, low-skill tasks also involve some manual tasks that require less precision but more human dexterity or presence, so their overall SML score is somewhat lower. High-skill occupations involve nonroutine problem-solving skills and advanced communication skills that are difficult to automate, making these jobs consequently less exposed to such developments, as shown by their SML score.

These results deviate from the routinization hypothesis in that they show that low-skill occupations are also expected to be affected by AI and machine learning. That may suggest that we are entering a new era of technological development related to machine learning, which might have a different impact on skills than the development and adoption of computer technologies that started in the early 80s. The division of tasks into routine ones and nonroutine ones will not be sufficient for addressing the implications of AI. AI, due to its continuous adaptability and improvement, is much more able to perform tasks that are not routine ones than previous automation technologies.

This implies that responding to the challenges of labor markets in the AI era requires a new toolbox of policy options. Of particular importance is the ability to identify the new jobs that are created thanks to AI technologies. We also need to introduce some flexibility and further adjustments to institutions that are important for labor relationships.

One important dimension is how AI will affect the employer-employee relationship. AI systems can provide the opportunity for the employer to monitor the employees closely. That may not only violate fundamental privacy rights but it can also create a work environment where emotional and sociological pressure affects the productivity of workers. Clear rules should be established to protect workers from pervasive surveillance.

In addition, workers working on online platforms face a paradoxical challenge. While digital means allow them to communicate with each other easily without any geographical restrictions, so far they have found it very difficult to be organized in bodies that will allow them to exercise collective bargaining actions. Collective bargaining can be an important parameter for shifting the benefits of AI technologies towards workers. Legislation should be carefully designed in order to help workers in the platform ecosystem to organize themselves in unions in order to increase their bargaining power when they have to negotiate the terms of work with the platform.

However, this should be done in a way that does not decrease flexibility in these ecosystems.

One of the big puzzles related to AI is why we do not capture its efficiencies in productivity statistics. Current methodologies are not appropriate to capture contributions by intangible capital. The example presented by Hal Varian helps in understanding the root of the problem in accounting for these contributions[7]:

"In 2000, there were 80 billion photos produced. We know that because there were only three companies that produced film. And fast-forward to 2015, there are about 1.6 trillion photos produced. Back in 2000, photos cost about 50 cents apiece. Now they cost zero a piece essentially. So any ordinary person would say, wow, what a fantastic increase in productivity, because we've got a huge amount more output and we've got a much, much lower cost. But if we go look at that through the GDP lens, it doesn't show up in GDP for the most part because those photos are typically traded among friends and put in albums and things like that. They're not sold on the market. GDP is the market value of transactions out there, and anything that's not sold or has a zero price isn't going to show up in GDP."

Brynjolfsson, Rock, and Syverson (2017) provide an alternative explanation for why AI has not boosted productivity statistics yet. AI as a general-purpose technology requires some complementary innovations to be in place in order to derive the expected productivity benefits. Hence, we still lack these complementary innovations in order to observe the impact of AI on productivity. So, when these innovations arrive, it is likely that a greater productivity effect associated with employment will be observed with a resulting increase in labor demand or the creation of new jobs.

The developments in the field of artificial intelligence in industrial applications are expected to progress significantly. There are two main reasons for this:

- technological progress in the field of AI and the fact that the best algorithms are now available open-source and everyone can use and improve them;
- the ongoing general digitalization of industrial processes leads to a significant increase of data assets that can be used as input for AI applications.

One important driver for the emerging AI business opportunities is the Internet of Things (IoT), meaning that "things" are networked together and produce data, and data are the food for AI. IoT applications will yield a vast quantity of data that will have to be analyzed. By relying on the recent advances in computing power available today, more and more data can be analyzed, and AI is making great strides. These technical advances are ready to address industrial challenges and thus intelligent application for industry can be developed in a shorter time and with higher performance. AI will very soon be ready to be extensively used in the business-to-business arena.

4. THE COVID-19 SHOCK: HOW DOES IT AFFECT THE RELATIONSHIP BETWEEN AUTOMATION AND EMPLOYMENT?

The COVID-19 pandemic is an unprecedented shock that has significantly affected labor markets across the globe. It has completely changed the conditions and the nature of work in many occupations. Many people are confined to their homes while a

7 https://www.aei.org/economics/googlenomics-a-long-read-qa-with-chief-economist-hal-varian/.

large number of businesses have been forced to close, contributing to an increase in the unemployment rate as well as in the number of applications for unemployment insurance (UI) claims.

Early observations of the short-run effects of the pandemic suggest that we face a major economic shock with direct implications for labor markets and work. OECD data[8] show that the US unemployment rate increased to 14.7% in April 2020 (as opposed to 3.5% in February 2020). However, it has been declining since then, reaching 7.90% in September 2020. Japan's unemployment rate had a milder response to the COVID-19 pandemic but it was also more persistent, increasing from 2.4% in February 2020 to 3% in August 2020.

Goldsmith-Pinkham and Sojourner (2020) developed a model that predicts the number of UI claims in the US with the help of Google Trends and they conclude that in the week of 22 March to 28 March there were 6.3 million UI claims (seasonally adjusted). They also predict large variations across states.

Bai et al. (2020) underline the importance of firms' ability to have their employees working from home for their financial viability during the current troublesome market conditions. Specifically, they developed a firm-level index that assesses each company's suitability for working from home. They find that firms with a high work-from-home index enjoy higher stock returns, lower stock volatility, and better financial performance.

Analysis of US job vacancy postings during the pandemic illustrates that job postings had declined by 40% by late April 2020 (Forsythe et al. 2020). The decline was observed in nearly all states and industries. The contraction in job postings was the most significant for leisure and hospitality services and nonessential retail, while essential retail exhibited smaller declines.

Brynjolfsson et al. (2020) ran a survey on a representative sample of the US population between 1 and 5 April 2020 and study how they are adapting to the COVID-19 pandemic. Their focus is on the impact on employment and the ability of the working population to work from home. They find that approximately 34% of the respondents that are in an employment relationship have shifted from commuting to working from home. In addition, 11.8% report being laid-off. The probability of working remotely increases with the number of reported COVID-19 cases in a given region.

The fact that the pandemic leads to remote work can have several implications that are related to digital technologies and automation. Technology can facilitate remote work but not to the same degree for all occupations. Dingel and Neiman (2020) shed light on which occupations can be done easily from home: computer and mathematical occupations, education, training and library occupations, legal occupations, and other managerial and professional jobs. So, remote work applies primarily to the top quartile of higher-educated or high-skill workers, those that face the fewest risks from automation and artificial intelligence.

Indeed, Stevenson (2020) indicates that workers without an undergraduate degree experienced a greater increase in unemployment and a steeper fall in US labor force participation. The biggest disparity occurred in April when nearly three in ten workers without a bachelor's degree who had been employed in February were not employed anymore.

[8] http://www.oecd.org/sdd/labour-stats/unemployment-rates-oecd-update-november-2020.htm.

The implications for youth employment are depressing as well. US youth unemployment was more than twice as high in July 2020 compared to July 2019. In Europe, youth unemployment has increased less, but still increased from 15% to 17% between February and September 2020. Based on these pictures, it is possible that the increase in youth unemployment will take a long time to heal. That can in turn create further damage: Workers who were unemployed when young tend to earn significantly less over their lifetimes. This implies that the young unemployed look at the future less optimistically. They also tend to leave the parental home later and start families later.

The long-run effects of the COVID-19 pandemic on how work is organized in the long run may be significant. Altig et al. (2020) report that firms expect the share of working days delivered from home to triple after the pandemic has passed. The proportion of people working from home at least one day a week is expected to jump in the construction, real estate, mining, healthcare, education, leisure and hospitality, and utilities sectors.

Digital technologies have made remote work more efficient and productive. But, if remote work displaces office time and business travel, that can have several implications for occupations of the service sector that are closely related to these activities and are difficult to fully replicate with automated systems and artificial intelligence. Autor and Reynolds (2020) discuss this possibility underlying the important long-run impact of the pandemic on low-skill workers: We can see steep declines in demand for building, cleaning, security, and maintenance services; hotel workers and restaurant staff; urban transportation service (taxi and ride-hailing drivers); and many other workers who participate in food preparation, transportation, clothing, entertainment, and other occupations that are relevant to people that spend a considerable fraction of their time outside the home for business reasons. Collectively, these services account for one in four US jobs. So, a substantial, long-run demand contraction in these services will mean significant job losses and substantial transformation of labor markets.

Remote work can reduce the need for business travel and personal interaction that once seemed to be indispensable. Due to the pandemic, this trend has expanded to sectors for which physical contact had been the normal way to deliver services. Telemedicine for delivering the subset of medical services from distance has become a popular option during the pandemic: "Rather than expect all outpatient practices to keep up with rapidly evolving recommendations regarding COVID-19, health systems have developed automated logic flows (bots) that refer moderate-to-high-risk patients to nurse triage lines but also permit patients to schedule video visits with established or on-demand providers, to avoid travel to in-person care sites" (Hollander and Carr 2020). Telemedicine is likely to remain an attractive option in the longer run, reducing office time among both providers and patients.

If indeed demand for personal and business services is permanently diminished in the post-pandemic labor market, that will essentially mean that many noncollege-educated low-paid low-skill workers will be driven out of the market. So, the COVID-19 shock will complement the impact of technology in removing middle-skill routine jobs and extend this trend to the lowest bar of skill distribution. Workers who remain in these jobs may face even lower wages. Those displaced will find it difficult to find new jobs, and if they do manage to find one, it will potentially be in an occupation where they do not have any experience or training.

One of the fundamental changes due to COVID-19 has to do with workers' preferences over safety. Workers might choose to be away from certain workplace environments in favor of those that allow for more personal space at the work site or through work-from-home policies. That could have serious implications for labor demand and wages of specific occupations that are considered unsafe through the lens of the pandemic. The resulting reallocation of workers will incentivize firms to invest in new technologies and automation that can "fill the gap" in unsafe occupations. New technologies can also be directed toward making the work environment safer, limiting the changes in workers' preferences.

The pandemic experience is very likely to accelerate the automation and digitalization wave across different sectors of our economy (Giordani and Rullani 2020). On the supply side, the experience with the applications of automation during the pandemic has been very positive and helpful: Disinfecting robotic systems have been introduced in warehouses to reduce the infection risk, and drones have been used for the delivery of products and services in different parts of the world. Firms have invested in establishing an efficient virtual network of interactions among colleagues, which works well in many cases. The realization that the digital channel can provide a productive and sometimes cheaper alternative for work will lead to an increase in investments in the digital direction that will further contribute to the decline in low- and middle-skill jobs.

On the demand side, even reluctant consumers have been forced to invest in digital literacy and participate in their daily interactions and transactions through the digital channel due to the social distancing restrictions. They have become more proficient in using these technologies for their needs and preferences. Having paid the fixed cost of the learning curve, they are likely to continue relying on the digital channel for an increased number of their activities in the longer run. There are two fundamental forces that can contribute substantially to this shift: the network externalities of digital ecosystems, both on the supply and the demand side, and the investments of firms to provide a more user-friendly online experience can result in a fundamental shift of consumers toward digitally enabled options.

The pandemic can also create new jobs through accelerating investments in digital infrastructure. Some countries, such as the PRC, are promoting the construction of new types of infrastructure such as 5G and alternative energy generation and consumption, to match the development of the digital economy. They are also investing in smart city solutions for the development of new applications of robotics and drones.

The fundamental transformation of work in the post-pandemic era can also give rise to offshoring practices as well as self-employment. Since physical presence will be a less favorable requirement in post-pandemic work, firms can explore further the opportunities of the global labor market for remote work that is not subject to the legal and administrative costs associated with immigration. Digital platforms can be instrumental in this process in matching supply and demand.

The long-run effects of COVID-19 on market structures may also be important. The pandemic shock is likely to negatively affect small firms that lack the liquidity and preferential access to credit markets needed to survive many months of inactivity (Walsh 2020). The wave of business closures will accelerate the current trend of the rising dominance of large firms across numerous industries (Rose 2020), which will have negative consequences for workers (Autor and Reynolds 2020). This is because large firms tend to pay a smaller share of earnings to workers and a larger share to owners and investors.

The reallocation of economic activity from small and medium-size firms to large firms will also lead to a reduction in the share of national income paid to wages and salaries (Autor et al. 2020; De Loecker Eeckhout, and Unger (2020). This reduction will reinforce the sharp fall in the labor share of national income that has been discussed above. That will lead to a rise in inequality, due to the fact that ownership of capital is far more concentrated than ownership of labor, and a contraction in labor's slice of the economic pie means rising aggregate income concentration and inequality.

So, the long-run effects of the pandemic are expected both to accelerate the automation process and to reinforce many of the effects that automation contributes: inequality, contraction of labor share, differential impact on workers of different skill groups by mostly favoring the high-skill workers, and increasing income inequality across skill groups.

But there is also a positive side of future possibilities. The acceleration of digitalization of our economy and life due to the pandemic can incorporate benefits. Investing in a better-quality digital infrastructure can help to create a better ecosystem of opportunities that is all-inclusive. Building our human capital with a focus on digital capabilities can open a horizon of new opportunities for work. The pandemic helped us realize the potential of communication through digital means, which has had important implications for minimizing physical distance restrictions in doing business efficiently. We have seen the creation of scientific consortia with common objectives that are efficiently working together while enjoying the luxury of being at home. It is striking that the number of submissions in scientific journals has increased during the pandemic as coauthors found digital means to be an efficient way to exchange notes and coordinate.

A new tribe of digital nomads was created for whom the places of living and work do not coincide. Countries realized that attracting such people can be beneficial for their national economy and started a "race" of legislative measures to ensure the work flexibility and tax privileges to attract these (high-skill) workers.

New technologies have also played a role in contact tracing and in fighting the pandemic so that workers can return to their job's location as soon as possible. Asian countries have been quite successful in introducing contact tracing applications that have allowed the authorities to monitor the spread of the virus in real time and intervene when necessary to avoid mass contagion. Thus, they managed to restrict the spread and the effects of the virus, thereby reducing significantly the length of the lockdown restrictions.[9]

The global pandemic is without doubt a big shock with direct effects and challenges for the labor markets. But this time the digitalization of our economy incorporates opportunities to overcome these challenges. A crucial point is to make sure, through well-designed policies, that these opportunities are all-inclusive and do not concern only the high-skill working population.

9 Other measures were also needed in order to reduce the length of the lockdown restrictions, such as a comprehensive testing strategy and individual responsibility for respecting social distancing measures and basic hygiene rules.

5. CONCLUDING REMARKS

The impact of automation on employment and the COVID-19 shock require the design of careful policies that should focus primarily on low-skill low-wage workers. Priority should be given to the adoption of proper public stimulus packages that support businesses' adoption of digital solutions as well as providing the necessary fiscal incentives for investments. The adoption of new technologies and robotic systems can help firms to overcome more quickly the negative effects of the pandemic shock while keeping their workforce safe. It is also important to incentivize the allocation of resources to forms of remote work, where it enables the continuation of business activities. Japan, for example, introduced a subsidy covering up to 50% of the cost of installing telework facilities.

At the same time, adequate social protection schemes should be used and extended to all workers, both employed and self-employed. Some countries, such as Australia and the US, have already expanded entitlement to unemployment benefits to the self-employed. Some countries have also adjusted the duration and the amount of the unemployment benefit accordingly, in response to the pandemic.

In the short run, the use of short-time work schemes can be beneficial. These are programs under which employers can temporarily reduce or suspend working activities for all or some workers without dismissing them. Workers still receive part of their salaries from the state. In the case of the COVID-19 crisis, many countries have funded such programs through their public finance accounts.

They incorporate benefits both for the employees and the employers. In the former case, they provide some security against dismissal by allowing workers to have a minimum source of income during the crisis. Employers, on the other hand, through this scheme can rely on their employees when they restart their production and other business activities without having to bear the cost of searching for new workers.

In the longer run, particular attention should be paid to education and training programs. It is necessary to educate young generations with an emphasis on the types of skills they will need to interact with intelligent machines in the work environment with a focus on the complementary types of tasks that are more difficult to automate. At the same time, it is important to convince workers to engage in lifelong learning activities, in the area of specialization. For this it is necessary to create training programs for the unemployed in order to increase their chances of finding a new job.

At the same time, we need to adjust employment contracts so that they incorporate opportunities for retraining. Different occupations have different needs in terms of training in order to remain up to date with relevant technological developments. So, the opportunity for training while in an employment relationship should be designed taking into consideration the occupation characteristics and how dynamically these characteristics evolve due to technology.

The results of Deming and Noray (2020) are striking. They study the impact of changing job skills on career earnings dynamics for US college graduates. They find that college graduates in all fields experience rapid earnings growth. Yet the relative earnings advantage for graduates majoring in applied subjects such as computer science, engineering, and business is highest at labor market entry and declines rapidly over time. A flatter wage growth for technology-intensive majors coincides with their faster exit from career-specific occupations. This implies that in order to prolong careers in technology-intensive majors, investments in human capital should not stop when we enter the labor market. We should instead continue investing in lifelong learning and training. As digital technologies penetrate more and more sectors and occupations, the majors for which we observe such rapid declines in earnings growth have the potential to expand in the future.

Longer-run priorities for social security involve the design of a sustainable work protection system where both employees and self-employed workers (such as platform workers) can derive benefits throughout their life and can be protected against poverty. This will require rethinking how we can finance such general systems through state and private funds. Applying a pay-as-you-go scheme may not be sufficient if we consider the demographic changes and the fact that the working class is shrinking over time in many countries. A more funded system, on the other hand, should also incorporate safety controls over the associated financial risks (which may become quite significant at the time of a pandemic).

Artificial intelligence and new technologies in general can offer great potential for the future of work. It is important to understand correctly their implications and design policies that are all-inclusive when they distribute the associated benefits.

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