ARTIFICIAL INTELLIGENCE AND HUMAN CAPITAL: ARE COMPLEMENTARITIES AT RISK?

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Abstract

The employment consequences of technological innovations depend crucially on the degree of complementarity between new machines and workers. In previous episodes of technological revolutions, complementarities between technology and human labor have displayed a skill-bias, that is, they were higher for skilled workers than for unskilled ones. In this piece, facing the context of a new technological environment determined by the advances in Robotics and Artificial Intelligence, we discuss i) what are their main characteristics that may change the skill-bias observed in previous technological changes, ii) what are so far the occupations more exposed to the new technological advances brought up by Robotics and Artificial Intelligence, and iii) what kind of investment in educational is needed to fully exploit the complementarities between new technologies and human labor.

Keywords: Robotics, artificial intelligence, tasks, occupations, education.

JEL classification: I20, J24, O30.

* The views expressed are those of the authors and do not necessarily represent those of the Banco de España, European Central Bank or the Eurosystem.

I. INTRODUCTION

History of technological changes teaches us that it is the adaptation of human capital through the re-skilling of the labour force what allows to increase productivity and employment, even if technological innovations displace jobs in some occupations. Nevertheless, each wave of innovation is more likely to complement particular sets of skills. Hence, the adjustment of labor supply through investment in human capital (mostly channelled by the education system) differs with the implementation of technological innovations.

The types of technological progress we have witnessed in the past is of two types. One is skill-biased technological progress, that is, technologies that complement human labor in occupations that required high levels of educational attainments and complex manual/non-manual skills. Another is the automation of routine tasks, typically manual tasks that free human labor to more productive activities. In both cases, the adjustment of employment is through skill upgrading, so that human labor can be devoted to those productive tasks more complementary to the new technologies. Hence, the policy response should consist mainly of changes in the educational system that allow to match the skills of labour supply with those required by the new technologies.

Nowadays, a new wave of technological advances appears to have the scope of changing the production of goods and services in many dimensions. Artificial Intelligence, Machine Learning, Generative Artificial Intelligence, and Large Language Models could autonomously perform tasks that previously required the participation of human labour. This time there are great concerns that these innovations are much more disruptive since not only routine tasks, but also creative tasks can be performed autonomously by "robots" and AI algorithms without human intervention. In principle, AI is closer to be "skill-bias technological progress" than automation of routine tasks. Still, there is the possibility of AI substituting human labor in all kinds of tasks with much more job displacement, intensively and extensively, than previous technological advancements.

With these premises a key question to be addressed is: how could human capital adjust to exploit complementarities with AI? Potential productivity and employment gains, and changes in economic inequalities from the implementation of AI will crucially depend, as in previous episodes of technological revolutions, on the adjustment of labor supply. We address this question in three steps. First, we highlight what is new about the AI technological revolution, to what extent can AI provide a General Purpose Technology that affect the production of a wide variety of goods and services, and what are the human skills more likely to be performed by robots and algorithms. Secondly, we draw on our previous research (Albanesi *et al.*, 2024) to map those skills into tasks and, hence, to find which occupations are more potentially exposed to AI advancements. Thirdly, we look within occupations to find out the type of human capital (educational attainments) required to perform those occupations, Finally, we use data on educational systems across Europe to show to what extent changes in the composition of labor supply are taken place and could be complementary to AI.

II. WHAT WE TALK ABOUT WHEN TALKING ABOUT ARTIFICIAL INTELLIGENCE

AI is defined as a field of computer science that deals with the development of computer systems that can perform tasks that typically require human intelligence, such as speech recognition, natural language processing, text generation and translation, video, sound and image generation, decision making and more. The two most distinctive features of AI are the capabilities of analysing the environment and of autonomously taking actions to achieve specific goals. Its development has taken place in several waves with different techniques and instruments (from expert systems and Narrow AI to machine and deep learning and neural networks and large language models). They basically differ in two dimensions: i) degree of autonomy or need of human intervention, and ii) variety of problems/tasks that they can solve/perform. We now summarize their most relevant characteristics and their potential associations with human skills (in third Section).[1]

The first phase of AI development took place around 2010 and was based on the development of machine learning and deep learning techniques and discriminative artificial intelligence. Machine and deep learning broadly consists of applications focused on providing systems with the ability to learn and improve from experience without being explicitly programmed. Discriminative AI is built on models often used for tasks like classification or regression, sentiment analysis, and object detection, which use instruments such as logistic regressions, decision trees, and random forests.

[1] A more detailed summary, with a strong focus on policies to better implement AI techniques, can be found in European Parliament (2020). More recently the OECD has updated its definition: "An AI system is a machine-based system that, for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions that [can] influence physical or virtual environments. Different AI systems vary in their levels of autonomy and adaptiveness after deployment" (https://oecd.ai/en/wonk/ai-system-definition-update).

What we are witnessing now is the development of Generative AI (Gen-AI). This is a set of algorithms capable of generating image synthesis, text, and music, using deep learning, neural networks, and large language models that detect patterns and relationships in the data to train then. Generative Adversarial Networks, Variational Autoencoders, transformer and diffusion models, and many more are specific application of Gen-AI that serve as foundational models providing basis for a wide range of tasks involving comprehension and generation of natural language (textual, mathematical, and computer programming).

III. WHICH TASKS ARE MORE POTENTIALLY EXPOSED TO AI DEVELOPMENTS?

The leading theoretical construction in Economics to analyse the labor market impact of AI technologies is the so-called "task-based framework" (Acemoglu and Restrepo, 2019). Both in the US and in Europe there are available occupational catalogues (O*NET and ESCO, respectively). These are a list of occupations classified by both the tasks that they perform and the mix of knowledge, skills, and abilities, require to perform them (see European Commission, 2020). Hence, a job post could be defined as the combination of tasks performed, and a mapping between jobs and tasks can be constructed. The connection between jobs and AI is in two dimensions: i) how much AI is making progress in the performance of tasks under each occupation ("exposure"), and ii) to what extent AI perform task substituting human labor or allowing it to be more productive ("complementarity").

As for exposure, one of the most used indicators is from Felten *et al.* (2021), based on the correspondence between 10 AI applications and 52 human skills (the so-called AI Occupational Exposure, AIOE). They use weights of importance and complexity of tasks within each occupation, and measures of AI advancements in the performance of those tasks form expert reports (taken form the Electronic Frontier Foundation) to obtain a relative measure, which Albanesi *et al.* (2024) exports to European data and normalize it to take values between 0 and 1. Similarly, Webb (2020) uses the overlap between patent descriptions (taken from Google Patent Public Data) and job descriptions (from O'NET) to construct a similar index. Both represent different aspects of AI. While the former is driven by the exposure of workers´ abilities to technological advancements, the latter highlights the availability of machine learning algorithms could perform occupations' tasks.

As for complementarity, Cazzaniga *et al.* (2023) propose to adjust the original AIOE measure with a corrected index (C-AOIE). Notice that exposure to AI does not by itself imply job displacement, as it could enhance worker´s productivity. This is more likely to happen in complex jobs, where there many tasks and most of them are "hard" (not easily codified), than in simple jobs, with only a few sets of "easy tasks". The complementarity-adjusted AIOE (C-AIOE) takes explicitly into account labor substitution. The correction is basically due to the analysis of work contexts and physical aspects of how work is conducted in each occupation. Using their own judgement, they take into account the criticality of decisions and the gravity of the consequences of errors as two main factors that we preclude full transition to AI. The construction of this index leads to conclude that exposure and complementarity are positively correlated (see Box 1 in Cazzaniga *et al.*, 2024).

An alternative approach to measure complementarity is to associate AIOE to changes in the composition of employment by occupation. In a nutshell, it is trying to see if occupations more exposed to AI gain employment shares. This is precisely what Albanesi *et al.* (2024) do using data from exposure to AI-enabled technologies and changes in employment shares by occupations in 16 European countries over the period 2011-2019. These years saw the rise of deep learning applications such as language processing, image recognition, algorithm-based recommendations, or fraud detection. Though more limited in scope than the current generative AI models such as ChatGPT, deep learning applications were nonetheless revolutionary – and still triggered concerns about the impact on jobs. As indicators of AI exposure, they use both Felten's *et al.* (2021) and Webb (2020), together with an indicator of exposure to software to gauge to what extent AI exposure is different to the implementation of digitalization. Their results show that, regardless of the exposure index used, occupations more exposed to AI indeed gained employment shares, overall, in Europe and in each country in the sample (with few exceptions). Moreover, this positive association between AI exposure and increases in employment (in relative terms) was stronger among those occupations with more young and highly educated workers. This suggests that, in principle, AI is complementary to human labor but with some "skill-bias".

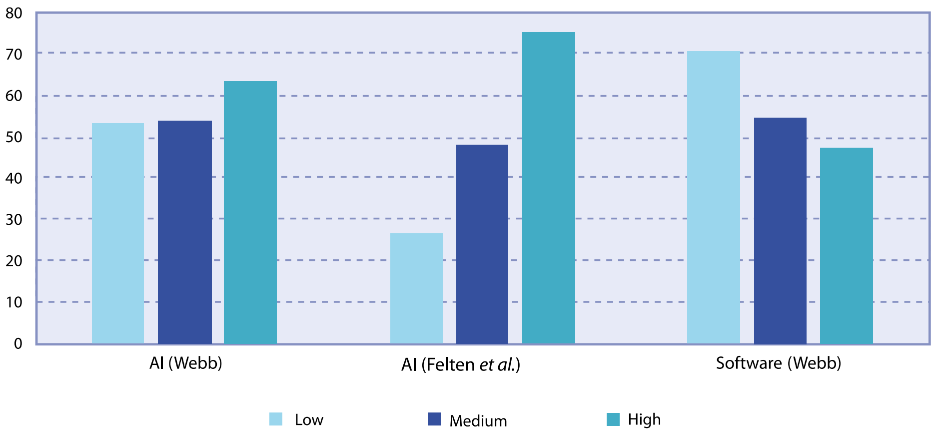
IV. WHICH EDUCATIONAL INPUTS REQUIRE THE FULFILMENT OF TASKS THAT ARE MORE POTENTIALLY EXPOSED TO AI DEVELOPMENTS?

The mapping of tasks into occupations is informative about the skills required for the performance of the tasks but does not provide detailed insights into the educational attainments that provide the skills. Which fields of study are more fit to provide skills complementary to AI technologies is an open and evolving question. The conventional wisdom is that university graduates from the so-called STEM fields (Science, Technology, Engineering and Management) will be in increasing demand. Is that what can be observed so far? If so, is labor supply adjusting to the increasing demand of skills provided by the STME fields of study?

As for the first question, figure 1 presents exposure to AI technologies by educational level, as computed by Albanesi *et al.* (2024). They group workers into cells, defined as the intersection of occupations (at the 3-digit ISCO level of aggregation) and six sectors of activity (agriculture, construction, financial services, services, manufacturing, and public services). Then, educational attainment of each cell is defined as lower/middle/upper according to the average educational attainment of its workers position in the terciles of the distribution of education levels in each country. The chart reports the exposure to AI and software by educational group. Clearly, workers with higher educational attainments are more exposed to AI, and this contrasts with the exposure to software, which goes in the opposite direction. This suggests that new AI technologies is something else than computerization or digitalization.

FIGURE 1

EXPOSURE TO TECHNOLOGY BY EDUCATION LEVEL AVERAGE PERCENTILE

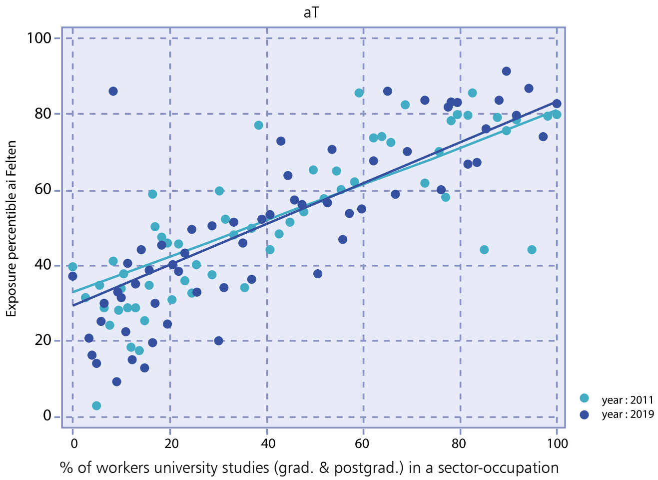


Notes: The chart reflects how exposed different "education groups" of workers are on average to the three technology measures. Education groups are defined as the subsample of occupation-sector cells whose average educational attainment is in the lower, middle, and upper third (tercile) respectively of the national education distribution.

Source: Albanesi *et al.* (2024).

FIGURE 2

EXPOSURE TO AI (FELTEN *ET AL.*) BY PERCENT OF WORKERS WITH UNIVERSITY STUDIES. SPAIN 2011 AND 2019



Notes: Y- axis is AI potential exposure percentile, Felten *et al.* (2021). The x-axis is the percent of workers in a sector-occupation observation with university studies (graduate and postgraduate) in 2011 and 2019.

Source: Felten *et al.* (2021).

To understand better which educational requirements are brought by the implementation of AI technologies because they are more complementary to them, we analyse data for Spain in more detail. Figure 2 plots average exposure scores, the AIOE index by Felten *et al.* (2021) for occupation-sector cells by percent of workers with university studies in 2011 and in 2019. The positive slopes, steeper in 2019 than in 2011, show that occupations whose workers predominately exhibit university education are more exposed to AI than occupations with fewer percentage of workers with university studies. In contrast, those occupations potentially more exposed to AI employ a smaller fraction of low skill workers, defined as those with primary education and less. Again, this is more pronounced in 2019 than in 2011 (figure 3).[2] This confirms the argument that AI is indeed skill-biased technological change.

More generally, Panels (a) and (b) in figure 4, borrowed from Albanesi *et al* (2024), provide evidence for 16 European countries that AI is indeed skill

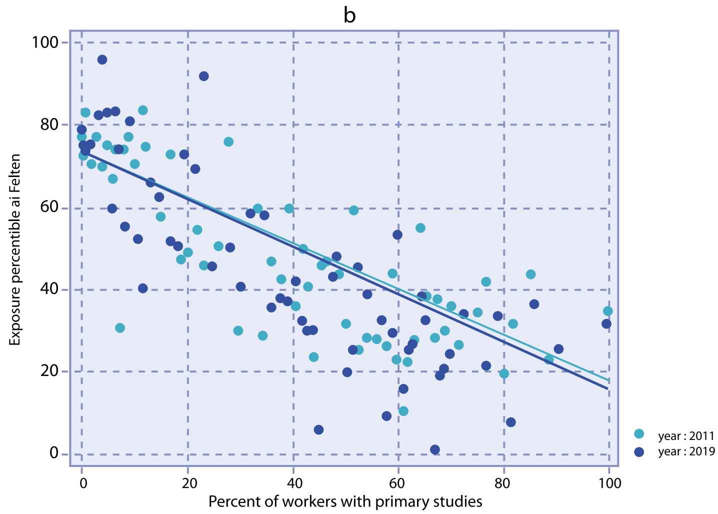
[2] Figures 2 and 3 are binned scatterplots. These provide a non-parametric way of visualizing the relationship between two variables with many observations. A scatterplot that plots every data point would become too crowded to interpret visually. These charts group the x-axis variable into equal-sized bins, computes the mean of the x-axis and y-axis variables within each bin, then creates a scatterplot of these data points.

biased. It shows the estimated coefficients of the association between changes in employment and AI-enabled automation by level of education (broken down into terciles, *i.e.* the lower, middle and upper thirds of the population). Statistically significant coefficients are plotted in dark blue. The coefficient for the whole sample is shown by the horizontal line. The bars display the coefficient estimated for the subsample of cells for average educational attainment in the lower, middle, and upper tercile respectively of the within-country education distribution. For occupations where average educational attainment is in the low and medium-skill groups, AI exposure does not seem to shake things up significantly. However, for the high-skill group we find a positive and significant association: moving 25 centiles up along the distribution of exposure to AI appears to boost the sector-occupation employment share by 3.1% using Webb's AI exposure indicator, and by 6.7% using the measure of Felten *et al.* (2021)

Admittedly, the focus in employment share neglects another important variable that shows the impact of AI technologies on the labor market, namely, wages. Did relative wages of workers more exposed to AI also increase? The

FIGURE 3

EXPOSURE TO AI BY PERCENT OF WORKERS WITH ONLY PRIMARY STUDIES BY OCCUPATIONS. SPAIN 2011 AND 2019



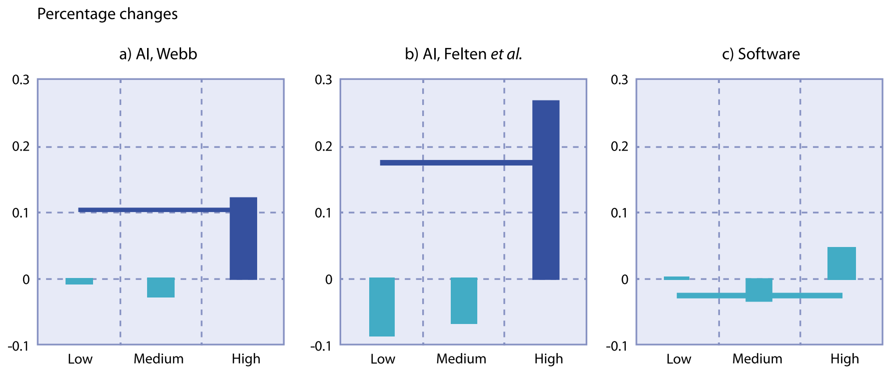
Notes: Y-axis is Ai potential exposure percentile, Felten *et al*. (2022). The x-axis is the percent of workers in a sector-occupation observation with only primary studies in 2011 and 2019.

Source: Felten *et al.* (2022).

statistical information about relative wages is more incomplete and imprecise than the statistical information about jobs. Nevertheless, Albanesi *et al.* (2024) also correlate an indicator of changes relative wages by occupations-sectors with the AIOE index.[3] In contrast with the results for employment shares, during the sample period (2011-2019) there is hardly any significant association between these two variables. Hence, so far there is no signs that AI is changing the wage distribution by occupations. This raises two interesting hypotheses. One, already formulated in the previous episodes of skill-biased technological change is that relative wages in Europe are rigid and it takes big shocks and long periods to change them. Being at its initial stage and looking only at developments during a decade might not be sufficient to detect how wages might react to the AI revolution. Another is that labor supply is already adjusting and the relative supply of workers with skill complementary to AI is also increasing. In the next section, we take this question to the available data on university graduates by fields of study.

FIGURE 4

EXPOSURE TO TECHNOLOGY AND CHANGES IN EMPLOYMENT SHARES BY SKILL LEVEL. SPAIN 2011-2019



Notes: Regression coefficients measuring the effect of exposure to technology on changes in employment share. Each observation is a ISCO 3-digit occupation times sector cell. Observations are weighted by cells' average labor supply. Sector and country dummies are included. The sample consists in data for 16 European countries, from 2011 to 2019. The coefficient for the whole sample is shown by the horizontal line. The bars display the coefficient estimated for the subsample of cells for average educational attainment in the lower, middle, and upper tercile respectively of the within-country education distribution. Coefficients that are statistically significant at least at the 10% level are plotted in dark blue.

Source: Albanesi *et al.* (2024).

[3] Changes in relative wages are proxied by changes in percentile positions along the wage distribution in 2011 and 2019. Therefore, the information is only of a "qualitative" nature, rather than fully quantitative.

V. HOW ARE EDUCATIONAL SYSTEMS ADAPTING TO AI DEVELOPMENTS AND HOW THEY SHOULD DO IT?

As noted in the Introduction, the main mechanism by which workers adapt to the labor market is by moving from displaced jobs to other jobs, either already existing or newly created by the new technologies. What kind of jobs, if any, is AI generating? In principle, if our interpretation of the data is correct, *i.e.*, there are complementarities with human skills, there will be increasing demand in the occupations where those skills are most needed. Moreover, new tasks and jobs could arise because of the implementation of AI. We have already provided some evidence on the complementarities. As for the new tasks/jobs generated by the implementation of AI, the account, so far, is pessimistic. What we are witnessing is the appearance of manipulative activities with negative social value, such as deep-fakes, misleading digital advertisements, addictive social media, or AI-powered malicious computer attacks.[4] It is difficult to see the potential increasing labor demand from these activities.

The most common view on the complementarity between AI and educational attainment hints at STEM fields. It is anticipated that working with robots and AI algorithms will require a stronger background on Science, Technology, Engineering, and Mathematics, as these fields provide a deeper understanding of how AI operates. An extremely opposite view is that technology workers are sowing their "own seeds of self-destruction" by advancing AI that will eventually take the same jobs in the future. Under this view, managerial, creative and empathetic skills, including communications, customer services and healthcare, will likely remain high in demand as they are less replaceable by technology, particularly AI.[5]

It might be too early to solve this debate. In fact, the jury will be out for some years before we see the full implementation of AI and its labor market effects. What we can see so far is to what extent labor supply is moving to some specific fields. Given the prominent role of STEM fields in the question at hand, now we provide some data on the increasing demand of STEM studies during the past decade (2013-2019) and to what extent this increasing demand of education is following the increasing labor demand in occupations that seems more complementary to AI.

[4] See Acemoglu (2024) for a quantification of the effects of these activities on productivity and GDP growth.

[5] This, for example, is the view of Nobel Prize Laureate Chris Pissarides.

FIGURE 5

UNIVERSITY GRADUATES IN STEM FIELDS, 2013-2019

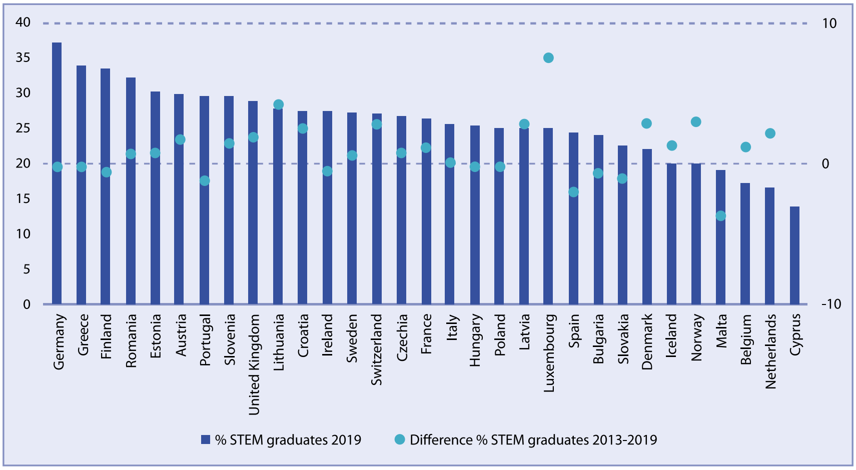
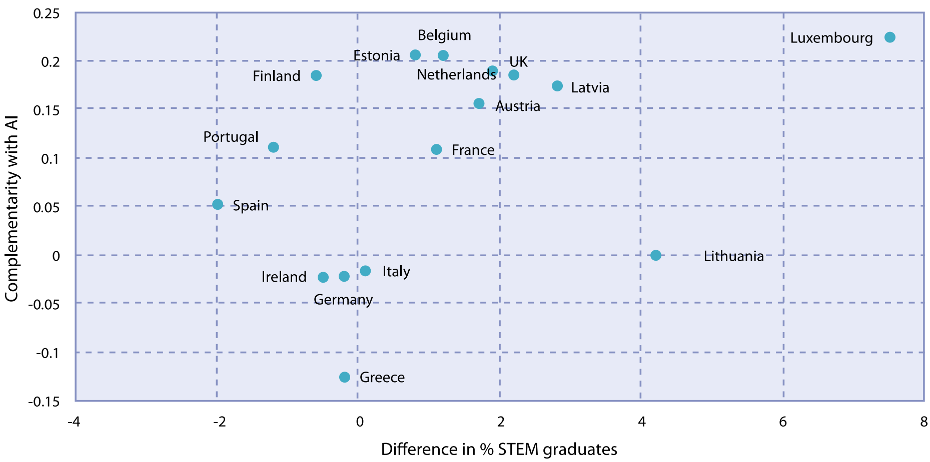


FIGURE 6

INCREASE IN UNIVERSITY GRADUATES IN STEM FIELDS, 2013-2019, AND COMPLEMENTARITY WITH AI



Notes: Complementarity with AI is the statistical association between the AIOE index and changes in employment shares across occupations-sectors, 2011-2019, from Albanesi *et al.* (2024).

Source: Albanesi *et al.* (2024).

Figure 5 plots data from Eurostat Education attainment statistics on the proportion of university graduates in STEM fields in 2013 and 2019.[6] There are wide differences across European countries, with Germany, Greece, and Finland at the top, and Belgium, the Netherlands, and Cyprus at the bottom. Moreover, although the proportion of STEM university graduates has increased in most countries during the last decade, there are a few countries where this proportion diminished. Spain is among the countries with a lower proportion of STEM university graduates and among the few where it decreased between 2013 and 2019.

Figure 6 displays the association between changes in the proportion of STEM university graduates and complementarity with AI, measured by Albanesi *et al.* (2024).

In principle, there is a positive correlation, so that labor supply with STEM educational requirements is increasing by more in those countries where the complementarity with AI is higher. Nevertheless, the changes in the proportion of STEM university graduates seem, overall, small in relation to the big changes in the composition of labor demand that AI might bring. Better and more detailed educational statistics and a closer follow-up of the employment prospects of university graduates by fields of study will be needed, both for understanding the consequences of AI and for preparing sound policy responses.

Nevertheless, the consequences of the Robotics and AI for human capital accumulation go beyond the composition of university graduates by fields. Being a General-Purpose Technology, their implementation is bound to affect all kinds of occupations and activities, regardless of their educational contents, by levels and by fields. Thus, the curricula of both vocational training and of university education across all fields will need to be adapted to the requirements of the new technologies for complementarities with human labor to be fully exploited. Moreover, reforms should also consider changing the style of educating and training workers in the new technological scenario, where knowledge and creativity will also be provided by machines. Admittedly, there is a high degree of uncertainty about how new technologies will evolve and how they will be implemented in the production of goods and services. And because uncertainty may bring the need of rapid adjustment it is urgent to start providing to the educational sector with the instruments and flexibility needed for rapid adaptation.

[6] We take as university studies those under levels 5-8 of the International Standard Classification of Education (ISCED, 2011). In STEM fields we include: i) Natural sciences, mathematics and statistics, ii) Information and Communication Technologies, and iii) Engineering, manufacturing and construction.

VI. CONCLUDING REMARKS

During the deep learning boom of the 2010s, occupations potentially more exposed to AI-enabled technologies increased their employment share in Europe. Occupations with a relatively higher proportion of younger and skilled workers gained the most. For wages, the evidence is less clear and suggests neutral to slightly negative impacts. These results do not amount to an acquittal: AI-enabled technologies continue to be developed and adopted. Most of their impact on employment and wages –and therefore on growth and equality– has yet to be seen. There are reasons to expect that Generative-AI is more significant as a General-Purpose Technology and more disruptive for labor markets than earlier versions of AI technologies. Although may conjecture on either catastrophic or fortunate effects of future developments in AI, it is too early to see them in hard data.

In any case, educational systems will need to adapt. Keeping an eye on data to observe rapid changes and guaranteed sufficient flexibility in educational systems to respond as quickly as changes are observed, would be of paramount importance to exploit the full potential and AI and mitigate its negative consequences

BIBLIOGRAPHY

Acemoglu, D. (2024). *The Simple Macroeconomics of AI*. MANUSCRIPT.

Acemoglu, D., and Restrepo, P. (2019). Automation and New Tasks: How Technology Displaces and Reinstates Labor. *Journal of Economic Perspectives, 33*(2), 3-30. DOI: 10.1257/jep.33.2.3

Albanesi, S., Dias Da Silva, A., Jimeno, J. F., Lamo, A., and Wabitsch, A. (2024). New technologies and Jobs in Europe. *Economic Policy.* Forthcoming.

Cazzaniga, M., Jaumotte, F. Li, L., Melina, G., Panton, A. J., Pizinelli, C., Rockall, E. J., and Mendes Tavares, M. (2024). Generative AI and the Future of Work. *Staff Discusion Notes, 2024(001).* International Monetary Fund. https://doi.org/10.5089/9798400262548.006

European Commission. (2022). The crosswalk between ESCO and O*Net. *Technical Report. Employment, Social Affairs and Inclusion.* https://esco.ec.europa.eu/system/files/2022-12/ONET%20ESCO%20Technical%20Report.pdf

European Parliament. (2020). Artificial intelligence: How does it work, why does it matter, and what can we do about it? European Parliament Research Service, June 2020. https://www.europarl.europa.eu/RegData/etudes/STUD/2020/641547/EPRS_STU(2020)641547_EN.pdf

Felten, E., Raj, M., and Seamans, R. (2021). Occupational, Industry, and Geographic Exposure to Artificial Intelligence: A Novel Dataset and Its Potential Uses. *Strategic Management Journal, 42*(12), 2195– 217.

Webb, M. (2020). The Impact of Artificial Intelligence on the Labor Market. *Stanford University Working Paper.* Stanford, CA.