

ON THE EFFECTS AND CHALLENGES OF AUTOMATION AND DIGITIZATION. PART I, AN UPDATE. / EFECTOS Y DESAFÍOS DE LA AUTOMATIZACIÓN Y LA DIGITALIZACIÓN. PARTE I, ACTUALIZACIÓN.¹

Francisco Javier Braña Pino

Instituto Complutense de Estudios Internacionales (ICEI).

fjbrana@ucm.es



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"(A) great revolution is taking place in the world today. In a sense it is a triple revolution: that is, a technological revolution, with the impact of automation and cybernation (sic); then there is a revolution in weaponry, with the emergence of atomic and nuclear weapons of warfare; then there is a human rights revolution, with the freedom explosion that is taking place all over the world. Yes, we do live in a period where changes are taking place...Through our scientific and technological genius, we have made of this world a neighbourhood and yet we have not had the ethical commitment to make of it a brotherhood. But somehow, and in some way, we have got to do this." Martin Luther King Jr. sermon delivered at the National Cathedral, Washington, D.C., on 31 March 1968. (<https://www.caribbeannationalweekly.com/caribbean-breaking-news-featured/mlk-jr-remaining-awake-revolution/> January 15, 2018)

Abstract

This contribution refers to the challenges that automation and digitization are posing, on employment and on other aspects. It relies on the results of an already published work that is intended to update, since new research and grey literature do not stop appearing. In our opinion, after analysing the information available, the two main changes that have taken place since the last third of the last century, which are profoundly affecting employment and working conditions, are the growing inequality in the distribution of income and wealth, as well as the impact of the change in the techno-economic paradigm linked to automation and digitization. The intention is to continue the debate on these changes.

Keywords: *Digital revolution; Automation; Industrial revolution; Industry 4.0; Labour, Employment and Work organization.*

JEL Classification: *O33 · O25 · L50 · J21 · J30*

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Resumen

En esta contribución se hace referencia a los retos que, la automatización y la digitalización están teniendo sobre el empleo y sobre otros aspectos. Para ello, se basa en los resultados de trabajos ya publicados que se intentan actualizar, puesto que no dejan de aparecer nuevas investigaciones, y bibliografía "gris". En nuestra opinión, tras el análisis de la información disponible, los dos cambios principales que han tenido lugar desde el último tercio del siglo pasado, que están afectando profundamente al empleo y a las condiciones de trabajo, son la creciente desigualdad en la distribución de la renta y la riqueza, así como el impacto del cambio en el paradigma tecno-económico ligado a la automatización y la digitalización. La intención es continuar el debate sobre estos cambios.

Palabras clave: *Digitalización; Automatización; Revolución industrial; Industria 4.0; Trabajo, empleo y organización del trabajo.*

JEL Clasificación: *O33 · O25 · L50 · J21 · J30*

INTRODUCTION

This contribution refers to the challenges posed by the automation and digitization of jobs, following the analysis that has been conducted in an extensive survey written by Braña (2019 and 2020), updating it with the results of several later published works. We want to expressly state that no attempt has been made to review exhaustively the articles and papers that have been published on the subject, what is offered is a selection of those that have been considered most relevant in the last five years, related to the main effects that automation and digitization are having on employment². Obviously, in terms of presenting a state of the art on the different perspectives, no primary data on those effects are offered.

The importance that has been given to the subject means that new research does not stop appearing, in addition to numerous articles in the so-called grey literature. From the analysis of the available information, it is considered that the two main changes that have been taking place since the last third of the last century, which profoundly affect the world of work, are the growing inequality in the distribution of income and wealth and the impact of change in the techno-economic paradigm linked to automation and digitization³.

We are in the middle of the fifth long wave of capitalism, which began with the decline of the techno-economic paradigm known as *Fordism*, which in turn was replaced by the so-called *Toyotism*, to be replaced in turn, after the crises of the 90s, by a new paradigm, based on information technologies and networks, the development of the knowledge-based economy, the change in the provision of collective needs and a reconfiguration of social relations⁴. In this way, digitization corresponds to the transition from an industrial capitalism to a cybernetic or digital capitalism, it is a higher level of automation in which the use of robots is paired with Artificial Intelligence (AI)⁵.

² Since the publication of Braña (2020), we have found several reviews on the effects of automation technologies on employment: Mondolo (2022); Aghion *et al.* (2022); Filippi *et al.* (2023); Hötte *et al.* (2023); and Montobbio *et al.* (2023).

³ The OECD is trying to measure in a harmonized way what is meant by *the digital economy*, developing a set of indicators of employment, skills, and their contribution to economic growth: *A roadmap toward a common framework for measuring the Digital Economy*. Report for the G20 Digital Economy Task Force. Saudi Arabia, 2020.

⁴ Braña (2020) aligns with the institutionalist theses and chooses to frame digitalization within the framework of techno-economic paradigms, so that we are in a new technological revolution, the fifth, instead of referring to a new industrial revolution, which would be the fourth, a periodification the latter behind which there is no theory. The basis of institutionalist theses, the theory of innovation, is found in the works of Freeman and Dosi. (Freeman, 1975; Dosi, 1984; Dosi *et al.*, 1988). For a recent review of technological revolutions, Knell (2021).

⁵ Nuvolari and Cetrulo (2019) consider that this supposed fourth industrial revolution would be rather an advertising hype, inasmuch as recent developments in artificial intelligence and robotics do not suppose a discontinuity in the trajectories in information and communication technologies, since the last quarter of the twentieth century, remaining constant the use of these technologies as a means of supervision of the workforce in companies, "enables a continuous control and flow of data of individual working activities".

One of the implications of the current digitalization processes is that the differences between industry and services have continued to blur, so that the relevant distinction in this fifth long wave of capitalism would be between non-routine tasks (non-repetitive, not easily codified) and routine tasks, which are associated respectively with skilled work or with a high level of education and unskilled work (distinguishing from it is not exactly the same as high-wage and low-wage jobs), regardless of the productive sector. There is also a growth in "servitization", a concept that refers to the growing importance of product-related services in the added value of manufacturing companies. Consequently, the increase in the services sector since the end of the last century would be partly associated with the outsourcing and consequent under-contracting of activities that were previously conducted within companies, activities that are statistically considered to belong to the service sector, a process that favors digitization. And we should not fail to mention another effect of digitalization on business structure and dynamics, the emergence of new transnational companies, the "multinationals of the digital economy" that value intangible (non-physical) assets more than physical assets, so that they need to a lesser extent to carry out manufacturing and service activities outside their country of origin⁶. This, in turn, had consequences for the so-called global value chains, which appeared with the current phase of globalization, since they reverse their expansion process, what has been helped by the global economic crisis unleashed in 2008, the awareness of the climate crisis and the war in Ukraine, with which processes of productive reallocation, of regionalization are taking place.

The two main effects of digitization addressed by economic research are: on the one hand, the polarization between well-paid jobs and low-paid jobs, between jobs that require high qualifications and jobs with low qualifications; and, on the other hand, the possible loss of jobs or jobs that are at risk of being lost due to automation. But there are also a few studies on the effects on working and employment conditions and on the economic and social effects⁷.

In any case, we must keep in mind that the degree and ways in which digital technologies are expected to impact on labour and jobs are much broader, diffused, and difficult to identify than in previous waves of innovation. In this sense, one working hypothesis may be that, within the framework of capitalist production, technology competes with the value of labour force, in addition to trying to increase its productivity. What occupations and jobs are going to be automated and in which places or countries, will depend above all on the value of the labour force that is to be replaced, so it seems relevant not only to know if jobs are created or lost, also the effects that technology has on the quality of those jobs.

THE ISSUE OF POLARIZATION VERSUS OCCUPATIONAL UPGRADING

Regarding the so-called *polarization*, the available empirical evidence cited in Braña (2020) seems to confirm more than reject the existence of it, although the image we find is heterogeneous, which would be an indication that polarization is not determined technologically or exogenously and that the various national specificities, and no less policies and institutions, can influence the outcome of structural change

⁶ On the importance of investing in intangibles, such as, among others, logical systems (software), databases, brands, advertising, etc., Bertani, Raberto and Teglio (2020), using computational experiments with the agent-based approach, "show the emergence of technological unemployment in the long run with a high pace of intangible digital investments". "We observe that for a moderate rate of innovation, compensation mechanisms ("via decrease in price" and via "additional employment in the capital goods sector") counteract the displacement effect caused by digital technologies in the traditional mass production system represented by consumption goods producers. Conversely, for a high rate of technological progress, the unemployment increases dramatically" (352).

⁷ Grybauskas, Stefanini and Ghobakhloo (2022) conduct an exhaustive review of academic literature and the so-called "grey documentation" on the social implications of Industry4.0. In the first case, they identify the main topics at the micro/individual and macro/regional levels, with a critical vision predominating, to the extent that the new wave of technological innovation, being focused on gains in productivity and efficiency, do not align well with social priorities. Regarding the grey documentation, the results show that most of the articles analysed, collected from news published in Google, offer a more positive than negative view of the main topics identified, which the authors attribute to the fact that this news are fed by media and lobbying organizations that pay more attention to the positive aspects of digitalization.

in the labour market ⁸. For Spain, most studies point to the existence of polarization of employment in the labour market, nonetheless without it being reflected in a polarization of wages.

Oesch and Piccitto (2019) reject, both from a theoretical view - arguing that job quality is a multidimensional concept - and from an empirical analysis, that there exists polarization. Certainly, they analyse only four countries (Germany, Spain, Sweden and the United Kingdom), for the period 1992-2015, and using four alternative indicators for good and bad occupations (earnings, education, prestige and job satisfaction), only in the UK there is polarization and only when using earnings, so the authors dare to conclude that "job polarization does not hold for Western Europe", and what happened has been instead an occupational upgrading.

Among the most recent works, we cite three studies. Breemersch, Damijan and Konings (2019) for a set of 19 countries belonging to the OECD (including Spain) for the period 1997-2010, find an outstanding heterogeneity, highlighting that polarization occurs more within the productive sectors than by the transfer of employment to sectors with better paid jobs, to the extent that it is mainly attributed to the incorporation of information and communication technologies and, to a much lesser extent, to the impact of imports from China. A similar result is from Longmuir, Schröder and Targa (2020) for 30 countries (Europe, Latin America, plus Egypt and India), to the 25th of them - including Spain with data from 1990 to 2004 - and rejects it in 5, as well as rejects the polarization in income in 23 of 25 of them, which is explained by the fact that inequality occurs fundamentally within occupations and not between different occupations. Finally, the work of Brekelmans and Petropoulos (2020), for the period 2002-2016 and 24 countries of the European Union, finds that for the whole period there has been an improvement in occupational structures instead of a polarization, although a relative polarization is detected from 2009, since occupations with medium skills have decreased substantially and occupations with high skills have had strong increases, but occupations with low skills have only increased slightly. Like other research, the evidence provided by these studies is that a large part of the skill upgrading of occupations in the EU labour market might have been driven by a substantial increase in the educational attainment of the EU labour force.

The extensive review of Martins-Neto *et al.* (2021) for a set of countries with "emerging" economies, concludes that "when we can relate labour markets outcomes to the adoption of digital technologies, the expected relation is observed" (7): an increase in the relative demand for high-skilled occupations and in some countries a reduction in jobs that are intensive in routine tasks. Although there is little evidence of labour market polarization in "developing" economies, what "could be explained by differences in the economic structures, the level of technology adoption and the interactions (sic) with other economies" (20), quoting in particular the degree of participation in global value chains and the reallocation of routine tasks to "developing" countries (offshoring).

Apella and Zunino (2022) study the evolution of the employment profile in nine countries in Latin America and the Caribbean, based on data from the occupational information network (O*NET)⁹ and household surveys, between the mid-1990s and mid-2010s. They distinguish five types of tasks: routine manual, non-routine manual, routine cognitive, interpersonal non-routine cognitive and analytical non-routine cognitive. In eight of the countries (the exception is the Dominican Republic) the content of average employment in non-routine cognitive tasks (analytical and interpersonal) increased and the content in routine and non-routine manual tasks decreased, while the evolution of content in routine cognitive tasks

⁸ It is "apparent" because empirical research in economics, as in the rest of the social sciences, does not allow to establish causal relationships and the results of empirical studies depend on the databases, the periods analyzed, the econometric and statistical models used, etc. Nothing is further from reality than believing that economics is an exact science, even if its extreme mathematical formalization since the change that occurred with the adoption of the thesis of rational expectations may make you think otherwise.

⁹ The O*Net is a database that reports information on occupations with a specific focus on knowledge, skills, abilities, and tasks content.

is very uneven, suggesting that has gone mostly from intensive jobs in manual tasks to jobs with a higher content in cognitive tasks, in line with what has happened in "developed" countries. On the other hand, non-routine cognitive tasks are increasingly conducted in the higher deciles of the income distribution, while non-routine manual tasks are concentrated in the lower deciles, so the emergence of polarization in employment will depend on how intense the automation of routine cognitive tasks will be in each country.

Tolan *et al.* (2021) develop a methodology to know what kinds of task content and occupations are more likely to be affected by current developments of AI. They find higher impact for high-skill occupations such as medical doctors, schoolteachers, or electrotechnology engineers, but relatively low AI exposure for low-skill occupations such as drivers or cleaners, while there seems to be no clear pattern for middle-skill occupations (e.g., high exposure for general office clerks but low exposure for fishery workers and hunters). That is, high-income occupations seem more likely to be affected by AI research intensity, than low-income occupations, which leads the authors to suggest that AI will probably not have the kind of labour market polarisation effects that some people associate with the recent wave of computerisation.

A report of the European Commission's Joint Research Centre (Torrejón, *et al.*, 2023), analyses the employment structures and dynamics in eight EU countries (the Czech Republic, Germany, Spain, France, Ireland, Italy, Romania, and Sweden for the period 1997-2021). They find that there is a wide diversity of patterns of structural change across periods and countries. In the period 1997-2007 there were more countries experiencing job upgrading than job polarization. And in the periods 2008-2010 and 2011-2019 again there are diverse patterns of structural change, yet with more countries with some degree of an asymmetric job polarization, with some differences by sex.

So, as noted at the beginning of this review, the new evidence collected in this paper again seems to confirm more than reject the existence of polarization, when measured by earnings, though with several nuances.

ON THE LOSS OF JOBS DUE TO AUTOMATION AND DIGITIZATION

The second issue is the *quantification of the loss of jobs or jobs* that are at risk due to automation and digitization and whether there will be a net loss of jobs. There is also much discussion on this subject, as there was with the technological changes of the fourth long wave in the countries of the capitalist center. Today, as then, there are pessimists and optimists. CEDEFOP's (2018) forecasts that, overall, employment growth in the EU is expected to moderate over the projection period to 2030, with a large majority focused on the services sector. The review of works conducted by Braña (2020) concludes that between 45 and 50 per cent of the jobs have a high risk (more than 70 per 100) or a significant risk (between 50 and 70 per 100) of being automated and Spain is among the third of countries with the highest percentages¹⁰. In addition, the net balance of jobs that can be created and those that will be destroyed is negative, according to Eurofound estimates (2019): considering the costs of automation, net employment in manufacturing and utilities in a high-cost scenario will be 20 per 100 lower than in the baseline scenario (which forecasts moderate employment growth); and between 30 and 35 per 100 lower in two low-cost scenarios. It is well understood that these estimates do not include the effects of COVID-19 or the war in Ukraine, effects on employment that will be considerable and probably negative.

The latest available estimates, prepared by the OECD staff (Green, 2023), with a supposedly more precise methodology, based on the OECD Expert Survey on Skills and Abilities Automatability and O*NET, refer exclusively to occupations with a high risk of atomization, understood as "if they have a significant share of important skills and abilities, more than 25%, that are highly automatable." For a set of 27 OECD

¹⁰ In more detail, the OECD estimates for 2012 that, for the average of countries, 40% would have a high risk of automation, 21.7% in Spain; and 31.6% would have a significant risk of change, 30.2% in Spain.

countries and for the manufacturing sector, occupations with the highest risk of automation accounted for 27% of employment in 2019, varying between a maximum of 36% in Hungary and a minimum of 18% in Luxembourg. For total employment, the share of total employment was 9%, ranging from 18% in Hungary to less than 6% in Switzerland.

Special attention has been devoted to **the role of automation and robotization in employment** and, as is often the case in economics, the estimates collected by Braña (2020), whether macroeconomic or at the level of companies, give disparate results and some of them offer an extremely low explanatory power.

Cirillo *et al.* (2021) try to verify for the Italian case, with information for the period 2011-2016, which of the two hypotheses on the relationship between digitization and employment best fits the data obtained from an occupational survey replicating the United States O*Net, the Skill Biased Technical Change (SBTC) or the Routine Biased Technical Change (RBTC). The results show that occupations characterized by highly digitalized tasks tend to grow faster by about 2% than the rest of the workforce. Also, the joint presence of elevated levels of digitalization and routines suggest that might have a penalizing effect on employment (compared to occupations that do not present such a combination), providing support to the RBTC hypothesis in the Italian case.

It is worth citing the work of Dosi *et al.* (2021), rooted on two interrelated streams of literature, namely the evolutionary approach to technical change and the sectoral patterns of innovative activities, performing a cross-country and cross-sector panel analysis comprising 19 European countries and forty-one industries over the period 1998-2016. They employ a model with a two-sector economy, wherein the upstream sector produces new machinery - for instance robots - and equipment (product-innovation), while the downstream sector is the adopter of the machines themselves (process-innovation). Recognizing that the model does not fully take into consideration Keynesian demand creation channels, their results "weakly support the labour-friendly nature of expansionary investment, while the possible labour-saving impact of technological change embodied in scrapping turns out to be highly significant and larger in magnitude" (Dosi *et al.*, 2021; 9), questioning the labor-friendly nature of technological change and highlighting the potential weakness of the compensation mechanisms to counterbalance the labor-saving impact of process innovation.

Katz, Callorda and Jung (2021), study the case of Chile as an "emerging economy", that supposedly may provide evidence to anticipate the expected effects on the Latin America region. They apply different methodologies to the same data set, to compare results. First, they follow Frey and Osborne (2017) to conduct an occupational analysis, according to which, for 2017, 57,81% of jobs are facing a high automation probability within the next two decades. In an alternative approach, they conducted a task analysis, following the methodology of Nedeloska and Quintini (2018), to find that the mean percentage of automatable occupations in 2015 was 51,75%, from 55,94% with a threshold of 50% of tasks yielding a high automation likelihood to 5,22% with a threshold of 80%; and for those jobs with probabilities ranging from 50-70%, it can be expected to be restructured 33,43% and 22,51% being eliminated.

Not considered by Braña (2020), there are a few papers that use data on patents to measure automation and its effects. Mann and Püttmann (2018), classify all U.S. patents granted between 1976 and 2014 as automation or non-automation patents, documenting a strong rise in both the absolute number and the share of automation patents. They link patents to the industries that use them and, through local industry structure, to commuting zones, estimating that advances in national automation technology have a positive influence on employment in local labour markets. Manufacturing employment declines, but this is more than compensated by service sector job growth. Webb (2020) also measure automation using patent data for the U.S. between 1980 and 2010, to study the impact on employment of the introduction of industrial robots and the use of software: "Although I cannot attribute causality to the exposure scores, moving from the 25th to the 75th percentile of exposure to robots is associated with a decline in within-industry

employment shares of between 9 and 18%, and a decline in wages of between 8 and 14%, depending on the specification. For software, the magnitudes are smaller, with declines of 7-11% and 2-6%, respectively" (Webb, 2020; 3). Those individuals with less than high school education, in low-wage occupations and men under age 30 are most exposed to robots. For software, exposure is decreasing with education, but much less sharply than for robots, with individuals in middle-wage occupations most exposed.

Squicciarini and Staccioli (2022), using a novel methodology implementing a natural language approach, for one side try to detect the presence of explicit labor-saving (LS) heuristic in robotics patents published by the European Patent Office; on the other side they estimate a similarity measure associating different LS patents to one or more occupations, which allows them to identify the occupations that are more likely to be affected by LS developments, and contrast this with data about employment levels by occupation over time, for a set of 31 OECD countries over the period 2011-19. They find that, despite the steady increase in the number of robotics patents observed since 1978, and the especially fast pace characterizing the last decade, the share of LS patents has been quite stable over time and do not find an appreciable negative effect on employment shares in selected OECD countries during the past decade.

Regarding the impact of robots Reljic, Cirillo and Guarascio (2023) observe a significant country and sectoral heterogeneity in robot stock in Europe. This leads them to hypothesize the presence of robotization regimes, following the well-documented centre-periphery divide in Europe. Overall, for 21 European countries observed they find a positive effect of robotization. Yet, confirming their hypothesis, employment growth is positively affected by robot adoption in structurally stronger economies (core and service-oriented countries), pointing to a 'labour-friendly' regime, reaping the benefits from the robotization process in Europe. And, as expected, such a labour-creating effect vanishes when it comes to the periphery.

A distinct perspective is to work at the level of microeconomic analysis and using firms and plants data to assess the impact of robotization. There are several studies consulted, not included in Braña (2020) as they have been published later. Table 1 sums up the main findings. It is difficult to offer a summary of the disparate conclusions of these studies, since even those that refer to the same country (France) present quite different results, due to the heterogeneity of sources and econometric models. We can risk saying that for firms that incorporate robots, most estimates find a modest increase in employment, in many cases increasing polarization in jobs inside the firms. Nevertheless, for the industry, there may be an overall negative effect if automating firms induce a sufficiently large decline in employment for non-automating firms, and there is business stealing, partly at the cost of companies from other countries (Aghion *et al.*, 2022). Filippi *et al.* (2023), also review the impact of automation and robots on employment at firm level, concluding that the impact is not clear.

Table 1. Studies on digitalization and employment at firm level

Authors	Country	Data	Main results
Balsmeier and Woerter (2019)	Switzerland	2014-2015; firms with at least 20 employees.	A CHF 100,000 increase in investment in digitalization is associated with about 5.8 more jobs for highly educated workers, 4 less jobs for mid-skilled workers and about 2.3 less jobs for the low-skilled. In total an increase of 1.6 jobs, a small net positive impact on employment, at least in the short run. These main results are entirely driven by the group of firms that employ at least one machine-based technology.
Acemoglu, Lelarge and Restrepo (2020)	France	2010-2015; 55,388 manufacturing firms, 598 robot adopters	<i>With employment weighted specifications, robot adopters:</i> Value Added: 0.094 Δ Labour Share: -0.027 Δ Hours worked: 0.054. Δ Hourly Wage: -0.008 <i>Effect on competitors:</i> Δ Value Added: -0.209 Δ Labour Share: -0.008 Δ Hourly Wage: -0.008 Aggregating the own and the competitors' effects, robots' adoption is associated with an overall decline in industry employment: a 20-percentage point increase in robot adoption in an industry (which is approximately the average robot adoption by competitors in the sample) is associated with a 1.6% decline in employment.
Ballestar, García-Lázaro and Sainz (2020)	Spain	1990-2016. 4.354 firms.	There is a substitution effect between the most qualified workers and automation, while workers with average qualifications are complementary. This shows that the adoption of robots displaces highly skilled workers but demands technicians who can operate the robots. The impact of robotization on employment is in large companies primarily.
Bessen, Goos and Salomons (2020)	Netherlands	2000-2016; 36,490 firms.	Automating firms have 1.8 to 2 percent higher employment and 1 to 1.3 percent higher revenue growth annually, though not higher daily wage growth, compared to non-automating firms. The association between automation and firm outcomes is not significantly different for manufacturing firms compared to nonmanufacturing ones. However, around automation events themselves, employment growth slows markedly.
Bonfiglioli, Crinó, Fadinger and Gancia (2020)	France	1994-2013; 64,760 manufacturing firms, of which 746 robot adopters.	Robot adoption occurs after periods of expansion in firm size, and is followed by employment losses, improvements in firm efficiency, labour demand shifts toward high-skill workers and, possibly, increases in firm markups. The observed increase in robot intensity explains an average fall in employment equal to 3.5 percent per year among robot adopters.

Dixon (2020)	Canada	2000-2015; 3,981 establishments, 7,958 individual employees.	Firms are adopting robots to increase productivity. However, that does not appear to come at the expense of total employment. A 1% increase in robot investment predicts a roughly 0.015% increase in total employment within the firm. There is consistent evidence of a negative and statistically significant relationship with middle-skilled employment. There is also evidence of a positive and statistically significant relationship for both low-skilled and high-skilled employment. There is evidence of a negative and statistically significant relationship between robot adoption and managerial employment: a substantial decrease in managerial employment occurred beginning in the first year of robot adoption, suggesting that robot adoption is associated with fundamental changes in organizational design. Overall, the results suggest that robot investments are more likely to be motivated by a desire to improve the quality of production output, as opposed to a desire to improve efficiency through labour cost reductions.
Domini, Grazzi, Moschella and Treibich (2021)	France	2002-2015; max 39,058, min 34,112 manufacturing firms, depending on the year.	Automation happens in spikes, like investment in capital goods. A clear temporal pattern appears: the association between investment in automation and net firm employment growth is positive and significant before and during a spike; negative, but small and hardly significant, in the year after the spike; and negative and significant two years after the event. Yet, the study does not give information on the net effect on employment. An automation spike does not seem to be associated to a significant change in the skill composition of firms, considering 1 digit (4 categories) and 2 digit (9 categories) occupational categories, nor in the share of routine-intensive occupations. The results do not seem to support, in general, the routine-biased technical change hypothesis and the implied polarized effects of automation technologies on employment.
Humlum (2021)	Denmark	1995-2015; 3,954 firms, with more of 10 employees, 473 of which use robots.	Firms expand output by 20% but shrink their wage bill on production workers, such as assemblers and welders, by 20% when they adopt industrial robots. Firms' total wage bill increases 8% as labour demand shifts toward tech workers, such as skilled technicians, engineers, and researchers. Using a general equilibrium model (with just to sectors, manufacturing, and services), industrial robots have increased average real wages by 0.8 %, but with substantial distributional consequences. At the opposite ends of the spectrum, production workers employed in manufacturing have lost 5.4% in real wages, while tech workers have gained 3.3%. Welfare losses from robots are concentrated on old production workers. Occupational reallocation in response to industrial robots account for 26% of the fall in the employment share of production workers and 8% of the rise in the employment share of tech since 1990. The adoption of industrial robots has thus been a driver of employment polarization.

Aghion, Antonin, Bunel and Jaravel (2021)	France	1995-2017; manufacturing firms, 2,773 plants and 1,599 firms.	Firms whose international suppliers of machines become more productive increase their usage of automation technologies, and in turn their sales and their labour force. The baseline specification yields an elasticity of firm employment to automation of 0.426, with no different effects across broad skill groups within the firms. Sales increase substantially in response to increased automation, with elasticities ranging from 0.325 to 0.346 across specifications. The industry-level responses are like the firm-level responses. Automation at a firm causes a fall in competitors' employment. There is a business-stealing effect induced by automation that mainly affects foreign competitors' employment in sectors facing international competition, whereas it mainly affects domestic competitors' employment in less open sectors. In addition, it cannot be rejected that there is no impact of automation on wages, on inequality across workers, or on the labour share.
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Source: own elaboration.

Two recent papers have conducted a meta-regression analysis (MRA) to evaluate the impact of robotization on employment and wages¹¹. Jurkat el alia (2023), collect 53 papers containing 2,143 estimations. In spite that 38.6% of papers report a significantly negative effect, against 17.9% that report a positive effect (the remaining 43.5% are statistically insignificant), due to the "effect size" they conclude that the effect of industrial robots on wages (of the total population) is close to zero and both statistically and economically insignificant, with limited evidence of publication bias favouring negative results. The authors find some evidence for skill-biased technological change since wages are more positively affected in high-skilled occupations and more negatively affected in medium to low-skilled occupations. The magnitude of that effect is albeit small and less robust than it might be expected.

The MRA conducted by Guarascio *et al.* (2024) includes 36 studies, with 839 estimates, 33 studies analysing the employment effects of robots, 16 of which also analysing the wage effect, and 3 only analysing the wage effect. On average, the authors find a negative and statistically significant effects of robotization on both employment and wages, although the effects are marginal and close to zero. The authors find robust evidence for a publication bias favouring negative results, though once accounted for the bias the size of the effect remains negligible. "Factors such a country, sector and employment type matter: manufacturing sectors, medium-skilled and full-time workers are most susceptible to negative wage effects" (Guarascio *et al.* (2024; 23).

Is interesting that including pretty the same number of studies, the two MRA only share 21 studies. Summarizing, from the evidence provided for MRA studies, we can conclude that the evidence of robotization on wages shows a positive but moderate effect, yielding a greater wage growth in developed that in "emerging" countries. The evidence on the effect of robotization on employment is disparate, as being influenced by several factors, including the socioeconomic context, the nature of jobs, and the methodological rigor of the studies, because the results are sensitive to the exact specifications of the estimations.

Nevertheless, for some, the pessimistic predictions about the effects of automation on employment may not have been fully realized. In an essay not collected in Braña (2020), Autor and Salomon (2018) estimate that the negative direct effect of Total Factor Productivity (TFP) on aggregate employment and hours of

¹¹ Both are working papers, not reviewed yet, and both claim to be the first attempt to use the meta-analysis methodology, however the paper of Jurkat *et al.* was published in July 2023, while the paper of Guarascio *et al.* has been published in February 2024. Dagli (2021) conducted a meta-analysis, supposedly on the impact of robots on employment, however the title of the paper is misleading, because all but one of the 21 studies included refers to R&D and innovation expenses, so is not included.

labour input, between 1970 and 2007, for a group of 17 OECD countries are more than compensated for the sum of the supplier, customer, and final demand effect, being the net effect positive. On the other side, the predicted effects of TFP growth on the aggregate labour share, direct and indirect, are all negative, being the net effect negative¹².

Georgieff and Milanez (2021) study the period between 2012 and 2019, to check if the predictions of the OECD itself derived from the work of Nedelkoska and Quintini (2018) have been fulfilled. In the 21 European countries analyzed but Finland, employment has grown between 2012 and 2019, being the average of 12%, which is not surprising, since these are the years of exit from the Great Recession. Georgieff and Milanez (2021) quote two papers for the United States, for the second decade of this century, in which a significant negative effect of automation on employment is confirmed: occupations with higher automation risk experienced slower employment growth or employment decreases over the period considered and the same result, although less clear, is obtained for the OECD countries analyzed¹³. In addition, they note that, in all but two countries, growth in employment has been accompanied by a decrease in job stability, on average a decrease of 10%, with a maximum decrease of 22% in Spain.

Another effect of automation and digitalization is that it can then be suspected that are giving rise to an increase in business (industry) concentration and the creation and strengthening of oligopolistic structures. There is enough evidence to support this view: using different methodologies: Bajgar *et al.* (2019) covering 22 European countries, Canada, and US for the period 2000-2014; and Affeldt *et al.* (2021) for the EU between 1995 and 2014. Besides, for the US firms Bessen (2020) finds that the investment in information technology (IT), specifically proprietary IT, is strongly correlated with the increase in concentration, and is occurring across all sectors, not just Big Tech; and for five European countries concentration is higher in digitally intensive industries (Koltay and Lorincz, 2021)¹⁴. An additional derivative of a greater business concentration is that it negatively affects the payment of workers, but also the quality of employment, as there is a negative impact on job security (longer temporary contracts), documented by Bassanini *et al.* (2022) for six European countries between 2010 and 2017.

One of the technologies related to digitalization, which has developed at great speed in recent years, is the so-called *Artificial Intelligence (AI)*. There is no precise definition of what AI is yet, but it presents major differences with computers, robots, and other automation technologies, with which the term is used many times interchangeably and improperly. One differential characteristic is that AI is a general-purpose technology, as it becomes pervasive, improves over time producing complementary innovation, are largely software based and can learn for itself, replacing mental tasks rather than physical ones (Mondolo, 2022; 1050).

Regarding the impact of AI on employment, "part of the promise of AI is that it actually can help lift productivity especially of low-skilled workers, while cutting demand for high- and medium-skilled professionals, quite the opposite of what has been observed in the past." (Ernst *et al.*, 2019, 12). This can be explained by the specific characteristics of AI, in comparison with former technological developments,

¹² Of course, these results are obtained from estimating a neoclassical aggregate production function, whose validity has been more than rejected for years and moreover, the most worrisome but usual in this type of work, the econometric results show a very low explanatory power.

¹³ The authors find that the lower employment growth in these occupations has not resulted in significantly lower growth in the employment rate of the low-educated compared to other education groups. This is due to the general upskilling of the workforce: there were relatively fewer jobs in risky occupations in 2019 than in 2012, but also fewer low-educated people.

¹⁴ Firooz, Liu and Wang (2022) find that in the US robot density is positively correlated with sales-based measures of industry concentration and negatively correlated with the labour share, using a panel of thirteen industries covering the years 2007-2018. An impressive work on corporate concentration in the US, covering one hundred years, is that of Kwon, Ma and Zimmermann (2023), confirming that concentration aligns with greater technological intensity. Unfortunately, there is no similar work for any European country. It should be noted that there are those who maintain that high concentration tells us nothing about levels of competition and so has no direct normative implication, because may be a sign of competition in action, with market power representing a temporary reward for innovative and efficient firms.

which has focused on three main group of tasks: (i) in those jobs matching supply and demand, tasks that substitute existing ones; (ii) classification tasks, helping workers to concentrate on non-routine tasks; and (iii) process management tasks, where AI-based applications expanded the number of tasks allowing some that the human force was not able to perform due to their complexity. And most of these tasks are mainly found in the services sectors, which have been less affected by the previous waves of automation¹⁵.

A review of studies by OCDE staff (Lane and Saint-Martin, 2021), on the specific impact of AI on employment find limited empirical evidence. The studies they quote (just three for the US) do not support the idea of an overall decline in employment and wages and some find larger increases in wages of individuals in higher wage occupations or higher educational attainment. A subsequent OECD report (Broecke, Lane and Williams, 2023), provides evidence on the impact of AI on the workplace, based on two telephone surveys to the managers of 2,053 companies (with more than twenty employees), and to 5,334 workers interested in the subject in Austria, Canada, France, Germany, Ireland, United Kingdom, and United States. From the results obtained, it is worth noting that in the financial sector 42% of the employers and 29% in the manufacturing sector said they use AI, though these data should not be interpreted as adoption rates. Combining all ways of interacting with AI, 42% of workers surveyed in the financial sector and 29% in the manufacturing sector could be considering AI users. Twenty-seven percent of employers in the finance sector, and 24% in the manufacturing sector reported decrease in employment, against 17% in finance and 21% in manufacturing that reported an increase in employment. AI users were more likely to say that they were very or extremely worried about losing their employment in the next ten years, and nearly 42% of AI users in both sectors expected a decrease in wages.

Two years later the OECD staff offers a new review of the literature on the effect of AI on labor demand and employment (Green, 2023), finding little evidence of significant negative employment effects due to AI: "Empirical studies using cross-country variation in AI exposure, or studies using within-country variation by local labour markets, do not find any statistically significant decrease in employment. Similarly, recent surveys of workers and firms, or case studies of firms adopting AI, find few employment changes. However, AI is evolving rapidly, and advances in generative in AI may disprove some of the evidence accumulated so far." (Green, 2023; 103). High-skilled occupations are those most exposed to AI, nonetheless high-skill workers have seen employment gains relative to lower-skilled workers, because AI creates new tasks with AI skills, giving rise to the "reinstatement" effect (the creation of new jobs).

Guarascio *et al.* (2023), before presenting the results of their own estimates, offer a survey of the empirical evidence on the impact of AI on employment and wages, pointing out that refers mainly to the US (with the sole exception of the paper of Albanesi *et al.* (2023) which analyses 16 European countries), finding a positive relationship between AI and employment, particularly in high-skill occupations. The fact that no strong evidence of labour substitution is found is attributed to several factors: (i) that all the available evidence relies on "potential" measures of AI exposure; (ii) that the studies did not account for the joint action of AI and other automation technologies, in particular robots; (iii) that the studies did not account for supply, demand, and structural factors. Guarascio *et al.*, like Albanesi *et al.*, find that exposure to AI increases employment (at the regional level the former, at country level the latter). But when the interaction between AI and robots is considered, given that robots can incorporate AI to increase their potential, improving their performance, the relationship between AI and employment becomes negative in

¹⁵ Just a short reference to the two main methodologies to assess the impact of AI on the labour market: Felten *et al.* (2019) and Webb (2020). Felten *et al.* made a measure that links advances in specific applications to workplace tasks and occupations, finding that those occupations affected by AI face a small but positive change in wages, pointing at white collars workers as the most exposed group, without finding any change in employment. Webb made a measure of the exposure of tasks and occupations to AI, using information from the text of patents, finding that AI will affect quite different occupations that robots and software: the most exposed are high-skill occupations and older workers. As Guarascio *et al.* (2023) point out, this literature does have limitations: first, since these are measures of technological feasibility, remain silent whether the technologies are actually employed; second, the measures lack any information about industry and firm-level technological heterogeneities.

regions with a high robot intensity, "lending support to the hypothesis of a labour-saving impact of AI when associated with automation technologies" (Guarascio *et al.*, 2023; 4).

Gmyrek *et al.* (2023), with a quite different methodological approach, use Chat GPT-4 model to estimate task-level scores of potential exposures and then estimates potential employment effects at the global level as well as by country income group, with surprising results due to modest percentage of employment that can be affected using AI. Despite representing an upper-bound estimate of exposure, they find that only the broad occupation of clerical work is highly exposed to the technology, with 24 per cent of clerical tasks considered highly exposed and an additional 58 percent with medium-level exposure. For the other occupational groups, the greatest share of highly exposed tasks fluctuates between 1 and 4 per cent, and medium exposed tasks do not exceed 25 per cent. In low-income countries, only 0.4 per cent of total employment is potentially exposed to automation effects, whereas in high-income countries the share rises to 5.5 percent. The effects are highly gendered, with more than double the share of women potentially affected by automation. The greater impact is from potential augmentation, which affect 10.4 percent of employment in low-income countries and 13.4 percent of employment in high-income countries. The authors consider the use of models like GPT will have disruptive effects on labour markets, with larger effects in high-income countries and specific occupational groups, although more jobs are affected by augmentation (AI is a complement) than by automation (AI is a substitute). However, such effects do not consider infrastructure constraints, which will impede the possibility for use in lower-income countries and likely increase the productivity gap.

Pizzinelli *et al.* (2023) offer a more nuanced look at the effects of AI on employment, adjusting the measure of AI occupational exposure to capture the potential to complement or substitute for labour in each occupation, applying the new measure to two advanced economies (AEs) and four "emerging" ones (EMs). When the complementarity of AI is taken in account, the workers exposure is almost the same amongst AEs (UK and the US) y EMs (Brazil, Colombia, and South Africa, been India an exception due to the high proportion of workers in agriculture). The total of workers with high exposure is 52% in the UK and 50% in the US; and the percentage with high exposure and low complementarity, those in a higher risk of losing their jobs, is 32% in the UK and 30% in the US. This means that in these countries there can be a great possibility of polarisation in employment, with a high percentage of workers enduring the most of labour displacement, and a high, but smaller, percentage of workers in occupations where AI is going to be a complement. In the EMs, 40% of workers are in high exposure occupations, of which half have low complementarity, India standing apart, with percentages of 26% and 12%, so these countries face less short-term disruption probability.

CONCLUDING REMARKS

The picture that appears from reading all these studies on the impact of digitization and automatization is rather dark. The following paragraph, from the review of studies conducted by Filippi *et al.* (2023) summarizes it concisely and largely coincides with the conclusions reached by the reviews that have been conducted by Mondolo (2022), Hötte *et al.* (2023) and Montobbio *et al.* (2023):

"it emerges that the literature investigating how automation technologies affect employment is extremely complex, uncertain and immature. The complexity is because publications investigate many levels of analysis, apply different approaches to assessing the impact and consider different automation technologies and because the results are extremely detailed. Moreover, the results are often inconsistent, creating uncertainty in the literature. Even publications that are similar in approach, level of analysis and technology produce opposite results and clear and irrefutable results are few" (Filippi *et al.*, 2023; 11)

Besides that, there some important shortcomings of the empirical research, as highlighted by Montobbio *et al.* (2023), what is worth collecting here two of them here.

- . There are many alternative "proxies" for technology at distinct levels of aggregation, yet adopting alternative measures of technological change is not neutral.
- . Empirical analysis conducted at sectorial or firm level only focus on the direct labor-saving effect on the one hand, and on a selection of possible compensating market forces on the other. Microeconomic studies could grasp the nature of innovation, however, are not able to assess the overall impact of technological change and must deal with its intrinsic endogeneity.

In any case, most studies on the effects of digitalization and automation and on the future of work forget about historical experiences, about what happened in earlier technological revolutions. And when they include a chapter or a reference to history, the discussion usually ends on an optimistic note, suggesting that technology will not lead to significant unemployment, no permanent technological unemployment, if anything it would be a transitory effect, "without considering the adaptation process or lasting impacts of these shocks on workers, families, or places. It bases expectations of the future on a misunderstanding of the past: there may be some disruption, but innovation will proceed and improve wellbeing across the globe" (Schneider and Vipond, 2023; 10). And experiences of the past are not used to inform policy recommendations.

Regarding to AI, we must be very careful with the econometric predictions that are made with a technology as potentially disruptive as this one, given that what may happen in the future will also depend on institutional factors, including public policies, as well as the reaction of workers, particularly where trade unions have bargaining power.

The rather simple recipes that almost all "experts" propose to combat the expected negative effects of automation and digitization focus on the need for more education, lifelong learning and "active" employment policies, to the extent that some econometric estimates find that a higher spending on active labour market programs and education is associated with a lower likelihood that a person previously employed in a routinizable sector or occupation drops out of the labour force (Grigoli, Koczan, Topalova, 2020), without acknowledging that these policies have seen relatively little success, as stated by the MIT Work of the Future group (Autor, *et al.*; 2020).

Some go further and unload the weight of the dramatic effects on workers, appealing to their personal responsibility to maintain lifelong learning and to voluntarily undergo regular skills updating. This is striking when it is known that workers with less education and lower skills are concentrated in occupations with a high risk of automation, without being able to move to occupations with a lower risk, to the extent that they are the ones who have more difficulties to achieve opportunities for improvement. And what seems to be happening is that when they find a new job, "often come with less favourable working conditions, little job stability, too long or inadequate working hours as they are shaped in an environment where increasing job offshoring, outsourcing, use of home-offices, platforms and crowdsourcing become the order of the day" (Özkiziltan and Hassel, 2020; 18). And middle-skill workers, those most affected by the polarization of employment, are increasingly working in low-skill jobs, which comes with a significant decline in the job quality, less job stability, more prevalent fixed-term contracts and more likely part-time, in addition to lower wages. (Green, 2019).

For Spain it is often forgotten that it has the highest percentage of over-qualification or educational mismatch in the European Union, 35,9 per 100 of the graduates according to the CYD Foundation Report of 2023, the highest figure in the EU, around 20 per 100 of them permanently, growing uninterruptedly the number of graduates over the jobs that are created, although the mismatch is not the same by degrees and is very influenced by social origin (Ramos, 2017). And in this mismatch the productive structure is

fundamental: with a country strongly oriented towards services, with a predominance of tourism and hospitality, it is difficult to offer jobs for graduates, even less for the STEM professions (science, technology, engineering, and mathematics). In Martín, Rodríguez and Suso (2020) some recommendations are made, in line with reaching a great digital social pact, yet without too much specificity.

To deal with the challenges of the automation and digitization on labour markets, Goos (2018) is one of the few that pays attention to other policies. For instance, as far as education and training policies, they should include not only to solve the shortage of highly educated technical workers, but also to the increasing demand for workers with skills difficult to automate and less educated workers in low paid jobs¹⁶. Goos also digs into the labour market policies to improve intermediation, on the need of redistribution policies, and on the need to better regulate the design and implementation of digital technologies, in particular Artificial Intelligence, about what we discuss in the second part of this work.

Regarding the acquisition and improvement of digital skills (DS), Caravella *et al.* (2023), show that in the same way that the innovation opportunities are concentrated in key hubs benefiting from self-reinforcing mechanisms, digital skills are also unevenly distributed across regions, and such differences are persistent, due to a process of structural divergence and polarization in the diffusion of digital skills. Based on this evidence, they investigate how the European structural and regional funds shape the diffusion and accumulation of digital skills, showing that amount spent by three specific funds, "appear to be not particularly effective in shaping a process of convergence between core and periphery regions in terms of DS accumulation." They propose that, in addition to the aim of national Recovery and Resilience Plans (RRPs), focused on the development of broadband infrastructure, action also be taken on the demand side, especially on firms. Plans to promote digital investments are based on fiscal expenditures, of recognized inefficiency, which benefit large companies and, therefore, the distribution of public resources reproduces the spatial location of the productive base. This means that the least developed areas are not provided, in quantitative and qualitative terms, with the conditions to conduct the digital transformation. Therefore, industrial policies are necessary that increase and enhance the local productive base and complement the actions on broadband infrastructure.

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¹⁶ Lassébie (2023) points out the importance of public policies to promote training provision by employers, and to ensure an integrated approach to skills for the development of AI strategies, from initial education to lifelong learning, nevertheless few propose sufficient measures to develop them: "In general, while several existing programmes focus on digital or AI skills, few recognise the importance of complementary skills such as transversal competences, and a minority develop an integrated approach to AI skills development" (Lassébie, 2023; 171).

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SOBRE EL AUTOR / ABOUT THE AUTHOR

Francisco Javier Braña Pino es Doctor en Ciencias Económicas y Empresariales por la Universidad Complutense de Madrid. Profesor Titular de Universidad, Universidad Complutense, área de Economía Aplicada. Asesor del presidente de una de las grandes empresas públicas españolas. Jefe de Relaciones Institucionales de la afiliada española de una empresa transnacional. Catedrático de Universidad, Universidad de Salamanca, hasta la jubilación. Actualmente es Investigador Asociado en el Instituto Complutense de Estudios Internacionales (Grupo de Economía Política de la Innovación). Ha publicado 44 artículos, 41 libros y 33 capítulos de libros de economía en editoriales españolas e internacionales, habiendo presentado comunicaciones y ponencias en más de 50 congresos nacionales e internacionales. Sus actuales líneas de investigación se centran en la política industrial, en particular en el impacto de la automatización y la digitalización y en las políticas públicas, en particular en los efectos de la descentralización.