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The empirics of technology, employment and occupations: lessons learned and challenges ahead

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The empirics of technology, employment and occupations: lessons learned and challenges ahead[1]

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Abstract

What have we learned, from the most recent years of debate and analysis, of the future of work being threatened by technology? This paper presents a critical review of the empirical literature and outlines both lessons learned and challenges ahead. Far from being fully exhaustive, the review intends to highlight common findings and main differences across economic studies. According to our reading of the literature, a few challenges—and also the common factors affecting heterogeneous outcomes across studies—still stand, including (i) the variable used as a proxy for technology, (ii) the level of aggregation of the analyses, (iii) the deep heterogeneity of different types of technologies and their adopted mix, (iv) the structural differences across adopters, and (v) the actual combination of the organisational practices in place at the establishment level in affecting net job creation/destruction and work reorganisation.

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1. Introduction

What have we learned from the most recent debates and analyses on the threat that recent technological transformations pose to the future of work? When Frey and Osborne in 2013 (published subsequently as Frey and Osborne, 2017) predicted that almost 47% of jobs would be destroyed by automation, concerns and fears of technological unemployment spread among academics and policy makers. The results were also backed by a series of studies produced by consultancy agencies, who anticipated an expulsion of massive amounts of workers (Balliester and Elsheikhi, 2018). It was also the moment in which self-driving cars and artificial intelligence were materialising, while advanced economies were still trying to recover from the 2008 crisis. Between 2012 and 2016 a number of influential books, such as Ford (2015) and Brynjolfsson and McAfee (2012, 2014), were published in the US, while European countries, and in particular Germany, were focusing on Industry 4.0 and the so-called Fourth Industrial Revolution.

At that time in the US the debate was quite polarised between techno-optimists (Bessen, 2015) and techno-pessimists (Gordon, 2015). Despite the expectations of a new disruptive paradigm, forecasts were anything but dire and some studies started instead to put into an historical perspective both the debate and the fears of technological unemployment as a recurrent theme throughout the history of capitalism (Cetrulo and Nuvolari, 2019; Staccioli and Virgillito, 2021), from Luddism onward. Empirical research has grown identifying the extent to which the content of the new technological paradigm is in fact revolutionary or not (Lee and Lee, 2021; Martinelli et al., 2021; Santarelli et al., 2022). These studies emphasise the patterns of continuity of the fourth industrial revolution in terms of knowledge bases, rather than the emergence of a discontinuity. In addition, other scholars understand Industry 4.0 as more of an implementation of strategic state-led plans to reinvigorate manufacturing positioning of some leading countries (Germany in particular) into the international production arena, rather than as a set of disruptive technological solutions toward the total Digital Factory 4.0 (Krzywdzinski, 2021).

Needless to say, the technology-employment nexus is a very important channel of transformation in labour markets, but not the only one and, possibly, not the most important. For example, the COVID-19 pandemic produced a massive drop in hours worked and deeply affected employment, unemployment, participation rates, but also inequality and reorganisation of the working activity at a global scale (ILO, 2022). In the conclusions of this survey—in line with an evolutionary approach to technology and employment—we do suggest that employment growth and income distribution are the combined results of structural change, changing demand and patterns of consumption, and organisation of labour markets in terms of institutions.

As a joint result of demand patterns and technological change, different industries react to new technologies in different ways, and this suggests potential disruptive changes for workers, as certain industries flourish while others decline. Possibly, this represents the major policy problem posed by the emerging automation technology. This paper makes the case that new productivity-improving technology will probably result in a substantial reallocation, regardless of the overall impact. For this reason, it is important to understand how technology affects the organisation of the productive process and the way work is executed. The new waves of technological change transform the nature of work and the tasks required within the different types of occupations. The pace and scope of change in the automation process may be faster than previous automation waves and extend to white-collar and professional tasks. In tracing these effects, economists need accurate data to develop fine-grained proxies for technology, able to understand the impact of different trajectories like, for example, automation, digitisation, and more standard ICT processes.

Indeed many advancements have been done in understanding the employment-technology nexus, but still challenges ahead remain. More in-depth microeconomic studies, based on carefully chosen samples (in terms of regions or technologies) analyse how changes in technology affect jobs, tasks, and the quality of

employment. However, the level of analysis should be integrated, starting from the micro business unit, going into sectors, and moving at the macro-level. Such efforts are required to provide a more conclusive evidence at the aggregate level, where other variables, such as institutional and structural changes, influence the dynamics of the labour market.

This paper advances along these lines presenting a critical review of the empirical literature and outlining both lessons learned and challenges ahead. Far from being fully exhaustive, the review intends to highlight common findings and main differences across studies. According to our reading of the literature, a few challenges—and also the common factors affecting heterogeneous outcomes across studies—still stand, including (i) the variable used as a proxy for technology, (ii) the level of aggregation of the analyses, (iii) the deep heterogeneity of different types of technologies and their adopted mix, (iv) the structural differences across adopters, and (v) the actual combination of the organisational practices in place at the establishment level in affecting net job creation/destruction and work reorganisation.

The remainder of the paper is organised as follows. First, Section 2 presents macroeconomic, sectoral-level, and firm-level studies. These latter tend to rely on more traditional notions of technological measures, including standard R&D expenses, investments in physical capital, patents, and tend to look at overall employment changes in terms of outcome variable. In Section 3, we delve into a particular type of innovation, namely automation and robotics adoption, while in Section 4 we go deeper into the effects upon workforce recomposition in terms of tasks, skills and occupations, also covering inequality beyond employment outcomes and recent advancements in AI. In Section 5 we discuss key findings and challenges ahead, while Section 6 briefly concludes.

2. Empirical evidence on the link between technological change and employment

If we include the labour market effects of previous innovation waves, such as the ICT revolution, the extant empirical literature on the link between technology and employment is vast (for recent surveys, see Vivarelli, 2014; Calvino and Virgillito, 2018; Ugur et al., 2018; Mondolo, 2022; Hötte et al., 2022a; Autor, 2022). Overall, the lesson learned from previous empirical studies is that findings vary a lot depending on the level of analysis (whether firm, sector, or macro), the proxies for technological change (whether embodied, such as investment in new physical capital, or disembodied, such as R&D expenditures), and the country and time dimensions of the analysis.

2.1 Macroeconomic studies

At the macroeconomic level, *compensation mechanisms* are the links put forward by Freeman et al. (1982) to understand the technology-employment nexus, and can be of a classical, neoclassical, or Keynesian nature. These mechanisms, acting via decreasing prices, increase in efficiency, increase in production of capital-goods etc., tend (or in principle are supposed) to compensate forthe labour-expelling effect of process innovation.
The empirical detection of their effectiveness and transmission channels, together with the opposing job-creating impact of product innovation, have been addressed by Vivarelli (1995) through a simultaneous equations model over the period 1960–1988 (three-stage least squares regressions) for Italy and the US. The author finds that the most effective compensation mechanism is the one "via decreasing prices" in both countries, while other mechanisms turned out to be less important. Moreover, the US economy emerges to be more product-oriented (and therefore emanating an overall positive relationship between technological change and employment) than the Italian economy, where the different compensation mechanisms turn out to be unable to counterbalance the direct labour-saving effect of widespread process innovation. A further test

of the macroeconomic model proposed by Vivarelli (1995), is put forward by Simonetti et al. (2000), using data from four countries (US, Italy, France and Japan) over the period 1965–1993. Their results are partially consistent with those obtained by Vivarelli (1995): in particular, the role of the mechanism "via decreasing prices" is confirmed in general, but only in France and the US a clear and significant relationship between technological change and decreasing prices emerges; consistently with Vivarelli (1995), the labour-friendly nature of product innovation clearly arise only in the US (and to a lesser extent in France).

In a more recent study, Feldmann (2013) uses as an aggregate innovation indicator the number of triadic patents—i.e. patents filed simultaneously at the European Patent Office (EPO), the United States Patent and Trademark Office (USPTO) and the Japan Patent Office (JPO)—in 21 industrial countries over the period 1985–2009, to assess the impact of innovation on the aggregate unemployment rate. Results show that technological change tends to increase unemployment, although this effect does not persist in the long run.

In principle, macroeconomic empirical studies constitute an ideal setting to fully investigate the link between technology and employment, jointly considering the direct effects of process and product innovation, and all the indirect income and price compensation mechanisms. However, in practice, macroeconomic empirical exercises are very difficult to carry out and somehow controversial for different reasons: first, there are problems in measuring aggregate technological change (an attempt in this direction is a recent contribution by Christofzik et. al. 2021, where technological change is proxied by a multifaceted estimation of ICT technology shocks in the German economy over the last decades); second, the analytical complexity required to represent the various compensation mechanisms makes the interpretation of the aggregate empirical results extremely complicated; last, but not least, composition effects (in terms of sectoral belonging and single firms' behaviour) may render the macroeconomic assessment either unreliable or meaningless. This is why—also thanks to the availability of new reliable longitudinal data—nowadays the sectoral and, particularly, the microeconomic literature on the link between innovation and employment is flourishing.

2.2 Sectoral studies

The sectoral dimension is particularly important in investigating the overall employment impact of innovation; in particular, the compensation mechanism "via new product" (which in recent times generally takes the form of a compensation "via new services") may accelerate the secular shift from manufacturing to services. On the other hand, within manufacturing, new technologies seem to be characterised mainly by labour-saving process innovation, only partially compensated by the market mechanisms discussed above.

In this vein, Clark (1983, 1987) puts forward a supply-oriented vintage model, investigating manufacturing in the UK. The author finds that the expansionary effect of innovative investments (Keynesian multiplier) had been dominant until the mid-1960s, after which the rationalising effect (due to labour-saving embodied technological change incorporated in investments and scrapping) started to overcome the expansionary one.

In a later study, Pianta et al. (1996) finds an overall positive relationship between growth in value added and growth in employment. Nevertheless, especially in European countries, an important group of sectors display a markedly labour-saving trajectory (restructuring sectors), with growing production and declining employment.

In another contemporary study based on Italian data, Vivarelli et al. (1996) show that, in Italian manufacturing, the relationship between productivity growth and employment appears to be negative. In particular, they reveal that product and process innovation have opposite effects on the demand for labour, in line with what discussed in this report.

As already mentioned, the scenario may change if service sectors are taken into account. For instance, using standardised sectoral data derived from national Community Innovation Surveys (CIS), Pianta (2000) and Antonucci and Pianta (2002) find an overall negative impact of innovation on employment in manufacturing industries across five European countries. By contrast, Evangelista (2000) and Evangelista and Savona (2002) establish a positive employment effect of technological change in the most innovative and

knowledge-intensive service sectors.

Looking into manufacturing and services jointly (using CIS cross-sectional sectoral data on relevant innovations for different European countries), Bogliacino and Pianta (2010) find a positive employment impact of product innovation (which turns out particularly obvious in high-tech manufacturing sectors, see also Mastrostefano and Pianta 2009).

More recently, Buerger et al. (2010)—using data on four manufacturing sectors across German regions over the period 1999–2005—have studied the co-evolution of R&D expenditures, patents and employment through a VAR methodology. Their main result is that patents and employment turned out to be positively and significantly correlated in two high-tech sectors (medical and optical equipment and electrics and electronics), while not significant in the other two more traditional sectors (chemicals and transport equipment).

Finally, running GMM-SYS panel estimations covering 25 manufacturing and service sectors for 15 European countries over the period 1996–2005, Bogliacino and Vivarelli (2012) find that R&D expenditure, mainly fostering product innovation, does exhibit a job-creating effect.

2.3 Firm-level studies

Turning our attention to the wider microeconometric literature, since the late '90s, studies have fully taken the advantage of new available longitudinal datasets and have applied panel data econometric methodologies that jointly take into account the time dimension and individual variability.

For example, Van Reenen (1997) has matched the London Stock Exchange database of manufacturing firms with the SPRU (Science Policy Research Unit at the University of Sussex) innovation database and obtained a panel of 598 British firms over the period 1976–1982. The author finds a positive employment impact of innovation, and this result turned out to be robust after controlling for fixed effects, dynamics, and endogeneity.

Applying a similar approach, Piva and Vivarelli (2005) have also found evidence in favour of a positive effect of innovation on employment at the firm level. In particular—applying panel methodologies to a longitudinal dataset of 575 Italian manufacturing firms over the period 1992–1997—the authors provide evidence of a significant, although small in magnitude, positive link between firms' gross innovative investment and employment.

In a similar methodological fashion, Lachenmaier and Rottmann (2011) have proposed a dynamic employment equation, extended to include alternative proxies (mainly dummy variables) of current and lagged product and process innovation. Their regressions—based on a longitudinal dataset of German manufacturing firms over the period 1982–2002—show a significantly positive impact of various innovation variables on labour demand.

However, Bogliacino et al. (2012)—using a panel database covering 677 European manufacturing and service firms over 19 years (1990–2008)—have found that a positive and significant employment impact of R&D expenditures is clearly detectable only in services and high-tech manufacturing but not in the more traditional manufacturing sectors, where the employment effect of technological change is not significant.

Using firm level data (obtained from the third wave of the CIS) from four European countries (Germany, France, UK, Spain), Harrison et al. (2014) put forward a testable model able to distinguish the relative employment impact of process and product innovation. The authors conclude that process innovation tends to displace employment (although with a weak statistical significance), while product innovation is significantly labour-friendly. The model by Harrison et al. (2014) has been widely tested (see, for instance, Benavente and Lauterbach, 2008; Dachs et al., 2016; Hou et al., 2019; Crespi et al, 2019; Cirera and Sabetti, 2019), and virtually all studies have found a significant job-creating effect of product innovation and a non-significant impact of process innovation. However, an important limitation of this approach is the asymmetric way in which product and process innovation are measured; in particular, while product

innovations corresponds to the sales from innovative products (in so being, a continuous variable with a relevant variability), process innovations are merely measured by a simple dummy, i.e. a discrete measure with a constrained variability (in addition, this dummy just captures the "only process" innovations; therefore, process innovation combined with product ones are not taken into account, differently from the proxy adopted for product innovations). Given this setting, it is not surprising that process innovations generally turn out to be not significant in studies based on the Harrison et al. (2014) model. Two exceptions are Arenas-Díaz et al. (2020), who find a significant labour-saving effect of the "process only" dummy in Spanish firms over the period 2006–2014 (particularly adverse to low-skilled workers), and Lim and Lee (2019). Using data from 1999 to 2009 on more than eleven thousand manufacturing firms in Korea, Lim and Lee (2019) find again a significant positive impact of the better measured product innovations and a not significant (negative) effect of process innovation, although the latter becomes significant when the focus is narrowed to the sole monopolistic sectors.

Van Roy et al. (2018) have investigated the possible job creation effect of innovation activity, proxied by patents, by almost 20,000 European companies over the period 2003–2012. The main outcome of their panel estimations is the labour-friendly nature of innovation. However, this positive impact of innovation turns out to be statistically significant only for firms in the high-tech manufacturing sectors, while not significant in low-tech manufacturing and services. As discussed by the authors, their results may depend on the adopted proxy of innovation, since patents are much more linked to product rather than process innovation (see Section 2). Indeed, Bianchini and Pellegrino (2019) provide new evidence that persistent product innovation ensures employment growth at the firm level (Spanish firms over the 1991–2012 period), while process innovation does not.

Focusing on SMEs in emerging markets, Goel and Nelson (2022)—using the Enterprise Surveys dataset from the World Bank and covering more than 50,000 firms in 125 countries—find that both R&D expenditures and process innovation foster firms' employment growth. While the former result is consistent with most of the literature, the latter is more controversial and may be due both to the imperfect way process innovation is measured (as a dummy) and—given the cross-sectional nature of the data—to the so-called "business stealing" effect, namely innovative firms gaining market shares at the expenses of laggards and non-innovators.

Indeed, more recent studies have used longitudinal data and a more comprehensive measure of embodied technological change (see Barbieri et al., 2019; Pellegrino et al., 2019; Dosi et al., 2021). In more detail, these studies have been able to couple proxies for product innovation (such as R&D) with accurate proxies of process innovation such as investment in innovative machinery and equipment. In these works, the labour-friendly nature of R&D expenditures and product innovation is confirmed (consistently with the previous evidence), but a possible overall labour-saving impact of embodied technological change incorporated in process innovation is also detected.

2.4 Wrapping up

On the whole, the microeconometric literature offers a detailed mapping of the possible job-creating impact of innovation, revealing that it is small in magnitude and generally limited to high-tech and upstream sectors, characterised by a higher R&D intensity, and by the prevalence of product innovation. On the other hand, technological change embodied in process innovation may generate technological unemployment, particularly in downstream and more traditional sectors.

Studies at the sectoral level confirm this evidence and show that the positive effect of technical change on employment is stronger in the knowledge-intensive service sector and in high tech manufacturing industries. Both R&D activities in manufacturing and the creation of new services (or new ways of providing old services) seem to have a positive effect on employment dynamics. This is in line with the observed process of structural change and the historical decline of employment in traditional manufacturing sectors (relative to

services) in advanced economies.

The empirical evidence suggests also that at the aggregate (country) level, in particular in the short run, there can be a negative effect of technological change on employment. The effect is however heterogeneous depending on the characteristics of markets and of the institutional framework. Innovation is more likely to enhance employment in those places where the compensation effect in terms of price decrease is more pronounced and where product innovation is more frequent (relatively to process innovation).

Technical change continuously generates a reallocation of labour across occupations, firms, sectors, and regions. At the aggregate level, the overall impact depends on how firms and job posts are positioned relatively to the ongoing process of transformation. It is therefore key to understand the specific nature of recent waves of technical change and to determine how labour, occupations, and their related tasks are transformed. The discussion so far suggests that, within advanced economies, the category of workers most affected by technical change may consist of unskilled workers in traditional manufacturing where firms tend to adopt process innovations.

The most recent empirical literature has particularly focused on robots, considered as the major drivers of automation.

3. A focus on robots and automation

The recent literature the employment impact of robot adoption can be classified according to the scope of the analysis, either at the aggregate level (countries and sectors) or at the firm level.

3.1 Robots and employment at the aggregate level

Acemoglu and Restrepo (2020a) investigate the employment effect of exposure to robots using sectoral data by the International Federation of Robotics (IFR), which provides national penetration rates instrumented by European data. According to their 2SLS estimates, robotisation has a significant negative impact on the change in employment and wages in each US local labour market over the period 1990–2007. In more detail, they show that one additional robot per thousand workers reduces the employment/population ratio by about 0.18-0.34%.

Chiacchio et al. (2018) apply the approach outlined by Acemoglu and Restrepo (2020a) to EU labour markets. In particular, they assess the impact of industrial robots on employment and wages in 116 NUTS regions within six EU countries largely representative of the European automation wave, namely Finland, France, Germany, Italy, Spain, and Sweden. Their results suggest that robot introduction is negatively associated with the employment rate (one more robot per thousand workers reducing the employment/population ratio by about 0.16-0.20%).

Graetz and Michaels (2018) use panel data on robot adoption (IFR and EUKLEMS data to estimate robot density) within industries in 17 countries from 1993 to 2007. Dividing employees in three skill groups (namely high-, medium- and low-skilled workers), their estimated employment coefficients for the two higher-skilled groups result positive (but limited in magnitude and not always significant), while the coefficient for low-skilled workers turns out to be large and negative. However, their main finding stands at odds with the studies discussed above since they conclude that robots do not significantly reduce total employment, although they do reduce low-skilled workers' employment share.

Finally, Dauth et al. (2021) propose a local empirical exercise on Germany using IFR data over the 1994–2014 time-span, using a measure of local robot exposure for every region. They find no evidence that robots cause total job losses, although they provide evidence that robots do affect the composition of aggregate employment: while industrial robots have a negative impact on employment in the manufacturing sector, there are positive and significant spillover effects as employment in non-manufacturing sectors increases and, overall, counterbalances the negative impact in manufacturing.

3.2 Robots and employment at the firm level

Domini et al. (2020)—using data for French manufacturing employers over the period 2002–2015—find that robotic adoption or, alternatively, imported capital equipment, does not imply labour expulsion, but rather employment growth. However, Bonfiglioli et al. (2020)—using French data over the 1994–2013 period—initially obtain a positive employment effect as a response to robot adoption, but then find a negative employment impact of robot exposure, once demand shocks are properly taken into account. Similarly, Humlum (2021)—using Danish firm-level data from 1995 to 2015—finds that robot adoption is harmful for both employment and wages, at least as far as production workers are concerned (while the opposite outcome holds with regard to tech workers, such as skilled technicians, engineers, and researchers).

Indeed, in some studies the positive employment impact at the firm level appears entirely due to the business stealing effect—i.e. innovative adopters gaining market shares at the expense of non-innovators (Dosi and Mohnen, 2019)—since negative employment impacts do emerge once non-adopters and sectoral aggregates are taken into account.

In more detail, Koch et al. (2021) study robot adoption using data from Spanish manufacturing firms over the period 1990–2016 and find that, within four years, robot adopters raise their overall employment by around 10%. This positive impact, as expected, takes place in particular among high-skill workers, but it is also diffused among other categories of workers (ibidem, p. 2574). However, when focusing on the industry level, robot density does have a significant negative impact on employment in companies that do not adopt robots. A further support of the important role played by the business stealing effect comes from Acemoglu et al. (2020b), who study robot adoption using data about French manufacturing firms over the period 2010–2015. While the authors find that within robot adopters employment increases by about 11% (ibidem, p. 385), at the sectoral level robot adoption by competitors negatively affects employment among non-adopters. A common limitation of both these studies is the simplistic way in which robots are measured, namely as a dummy in the year of adoption.

Indeed, a gain in competitiveness due to the implementation of robotics, may also explain the results by Dixon et al. (2021): using data capturing the import of robots by Canadian firms over the period 1996–2017, they reveal a positive and significant employment impact of robot capital stock on total employment (although a negative one on middle skills and managers). Aghion et al. (2020)—using firm level data for the French manufacturing sector over the time span 1994–2015—also find a positive employment impact of automation at different level of analysis, namely plant, firm, and industry (but only in industries open to international competition, again pointing to the possibility of exporting the business stealing effect). However, this study is affected by the way automation is measured: either through the balance sheet value of industrial equipment and machines (obviously not able to distinguish between innovative and non-innovative investment, as done by studies which use measures of embodied technological change, see above) or through electricity consumption, also an indirect and inaccurate proxy for automation.

Using firm and plant level survey data from the IAB Establishment Panel, Benmelech and Zator (2022) and Deng at al. (2021) discuss a set of interesting stylised facts about robot adoption in Germany. They show that investment in robots is small and highly concentrated in few industries (for instance, automobile), that the distribution of robots is highly skewed in few companies in the manufacturing sectors, and that robot users are larger, have higher labour productivity, make more investments, and are more likely to export and adopt the most cutting-edge technology. Deng et al. (2021) also underline that it is important to understand the heterogeneity in robot types; they suggest that is important to distinguish collaborative and less expensive robots (cobots) from the prevalent and more expensive non-collaborative robots (e.g. cage robots). Finally, Benmelech and Zator (2022) emphasise that the impact of robotics is probably not the main driver of economic transformation in recent years, and propose that more attention should be devoted to other technologies.

With regard to the labour market, Benmelech and Zator (2022) show that firms adoption in Germany endogenously responds to an index of labour scarcity, measured as a binary firm's assessment that signals difficulty in finding workers. In terms of labour impact, the authors find that robot adopters increase their employment, while, at the same time, the overall employment effect in exposed industries and regions is negative. This evidence is in line with results of the contributions discussed above, and points again to the role played by the business stealing effect. However, their identification is based on a novel strategy combining industry-level measures of automation with local area intensity of adoption. They suggest that, since robot adoption varies mostly by industry and is relatively concentrated and rare, any identification strategy that relies uniquely on industry-level data (as in some of the mentioned studies) may face significant challenges.

3.3 Wrapping up

Even if this evidence is not unequivocally coherent, the majority of firm-level studies point at a positive effect of robot adoption on employment. Adopters tend to increase their employment and are in general larger firms, with higher levels of productivity and internationalisation. A substantial part of this employment growth is related to the so-called business stealing effect. These companies gain market share at the expenses of smaller and less innovative ones. As a consequence, at the aggregate level, results are mixed. Some papers find a negative impact of robot diffusion at the industry level. Similarly to the results shown in Section 2, the negative effect on employment seems concentrated in the manufacturing sector and for low-skilled categories.

However, it is important to underline that robots are extremely heterogeneous with potential differentiated impact on tasks and occupations, and that investment in robots is not large relative to other types of investments (e.g. in digital technologies) and is limited to few industries (for instance, automobile accounts for about 50% of robot adoption). Therefore, more focus should also encompass other technologies (e.g. AI and other digital technologies), as the impact of robotics is likely not the primary driver of labour market transformations in recent years.

In light of these patterns, a more comprehensive framework is needed to examine how recent changes in employment in advanced economies are influenced by the interplay between workers abilities, job tasks, and developing technologies. The latest wave of technological progress is based on a deepening process of automation, artificial intelligence, and widespread digital transformation, and might impact different categories of workers. A substantial amount of literature has therefore tried to disentangle this phenomenon and to understand how skills, occupations, and tasks are affected. In doing so, this literature analyses not only the determinants of employment dynamics, but also which complementary skills, occupations, and tasks are expanding and, on the other hand, those expected to decline.

4. Occupations, skills, and tasks

The different forms of automation (in particular, AI and robots) observed in recent years are more related to the introduction of hardware and software able to carry out tasks previously performed by humans, rather than to the development of more productive vintages of already existing machines. In this scenario, the quality aspect of the workforce assumes a crucial role because, as a result of innovation, some human abilities/tasks become superfluous, while others become relatively more important. The overall picture is therefore characterised by the simultaneous occurrence of substitution and complementary effects. The economic literature has therefore taken up the challenge of analysing at a finer level the impact of technical change on skills, occupations, and tasks.

4.1 Skill-biased and routine biased technological change

The early literature in the '90s, in line with the empirical results emphasised in Sections 2 and 3, has focused on the so-called "skill-biased technological change" (SBTC), revealing a complementarity between new technologies and skilled workers (both in terms of education—generally tertiary education—and occupation, with white-collars usually considered the "skilled" category), given that the latter are able to implement effectively and efficiently those technologies. Therefore, while a positive relationship between new technologies and skilled workers is expected (and generally confirmed by available empirical evidence, see below), a substitution effect between new technologies (especially when they originate from process innovation, see above) and unskilled workers is in general recognised (see Berman et al., 1994; Machin and Van Reenen 1998; Piva and Vivarelli, 2004; Los et al., 2014).

Still in line with the SBTC approach, Blanas et al. (2019) analyse 30 industries across 10 high-income countries over the period 1982–2005 and find that ICTs and robots (measured on the basis of bilateral trade data) negatively affect the demand for low- and medium-skill workers (especially in manufacturing) and increase the demand for high-skill workers (especially in services). By the same token, Balsmeier and Woerter (2019), using a representative survey on digitisation activities within Swiss firms in 2015, find that digitalisation (and particularly the presence of robots, 3D printing and Internet of Things) is significantly associated with job losses among mid- and low-skill workers, and with job creation among high-skill ones.

In contrast with the idea that technologies are skill biased, Hirvonen et al. (2022) use a new approach based on large-scale data and quasi-experimental research designs to study the effects of advanced technologies on employment and skill demand in Finland (1994–2018). They look, in particular, at new production technologies, such as robots and computer numerical control (CNC) machines, and exploit a large technology subsidy program, comparing close winners and losers using an event-study approach. They find that, on average, subsidy-induced technology investments drive a 23% increase in employment with no skill bias. However, their results are heavily driven by product innovations (see Section 2 about the labour-friendly nature thereof): indeed, 91% of the scrutinised firms claim that their technology investments were motivated by new products and increasing demand.

Complementarity of investments in automation/ICT/AI is stressed in Bessen et al. (2022). Using Burning Glass Technologies data, they measure firm-level investment in automation/digitisation technologies in companies who make major investments in their internal information technology. The authors use the firm-level share of software developers and single out substantial increases in their relative hiring (investment spikes are defined therein as increases of 1% of more in the share of software developers, relative to the mean share over the previous four quarters). According to their DiD results, spiky firms, when compared to non-spiky ones, hire a greater number of workers, with more diverse skills, and also pay higher wages, making a case for the complementary attributes of technologies which tend to reverberate beyond the specific complementary group (software engineers) affecting other workers at the firm-level. Such an approach highlights the role of innovating firm hiring strategies.

This offers an alternative discourse for policy in the fight against income inequality and pay disparity in the labour market. Researchers who believe that automation only replaces labour tend to suggest strategies to redistribute income, levy tax to discourage excessive automation, and even encourage engineers to forego its development in the first place. However, if automation primarily complements workers, leading to higher wage disparities between firms, policy may need to focus on minimising gaps in firms' uneven adoption of technology.

However, the last two decades have also highlighted a trend in labour markets, leading to job polarisation and wage inequality, together with a decreasing demand for middling occupations (Autor, 2019, 2022). This means that, if jobs are ranked by their wage, increases in employment shares are observed at the bottom and the top of this distribution, while jobs in the middle tend to lose employment share over time. More in detail, labourers and elementary service occupations (the low-paid) are to some extent increasing and professionals (the high-paid) are considerably growing, while middling occupations (such as operators of

machinery/electronic equipment) are declining. This U-shaped curve represents the aforementioned polarisation phenomenon, supported by pieces of evidence related to both flexible labour markets and institutional settings (as in the case of UK and US, see Autor et al., 2006; Goos and Manning, 2007; Goos et al., 2014; Autor, 2019) characterised by a higher degree of employment protection (e.g. Sweden, Germany and Portugal, respectively, Adermon and Gustavsson, 2015; Spitz-Oener, 2006; Fonseca et al., 2018).

This suggests that not only occupation and education are relevant, but that indeed the "routine dimension" comes into play, and attention should be paid to the actual content of the different jobs, namely the tasks performed by workers. This line of reasoning has induced a revision of the SBTC approach, first into the so-called "Routine-biased Technological Change" (RBTC) interpretative framework (Autor et al., 2003), and ultimately into the new "Task-Biased Technological Change" (TBTC) or "Routine-replacing Technological Change" (RRTC) (Gregory et al., 2019) vision. This approach assumes that repetitive tasks can indeed be easily replaced by recent technologies (particularly robots, automation, AI, and digitisation originating a substitution effect), while non-repetitive tasks may grasp benefits from these technologies (or, at least, not be negatively affected, as in the case of non-routinised unskilled tasks in personal services), determining a complementary effect.

4.2 From skills to tasks: measurement issues and empirical evidence

Acemoglu and Autor (2011, p. 1045) define a task as a "unit of work activity that produces output (goods and services)", and a production process as a set of tasks. In this framework, job tasks are allocated to either labour or capital depending on: 1) the degree to which they are automatable (repetitive and replaceable by code and machines); 2) their separability from other tasks; 3) the relative cost of using capital versus labour (in this context, capital generally refers to machines and robots). Acemoglu and Autor (2011), therefore, propose a classification based on a two-dimensional typology: routine vs. non-routine, and manual vs. cognitive. This leads to the consideration of four broad categories: routine-manual, routine-cognitive, non-routine manual, and non-routine cognitive (in turn, subdivided into non-routine cognitive interactive or analytical). Routine tasks comprise those that are programmable, expressible in rules, codifiable and repetitive, i.e. a protocol. Following this approach, the expectation is that technology replaces tasks with high-routine content, while in non-routine tasks there is more space for mental flexibility and/or physical adaptability to the new technologies, therefore originating possible complementary effects.

Biagi and Sebastian (2018) discuss how task-content is measured in empirical analyses. They underline that, in general, the task content of different types of jobs is measured in two ways: 1) direct measures, drawing from occupational databases based on the assessment of experts (e.g. the O*NET – Occupational Information Network, based on the US labour market, describes the task content of each occupation); 2) self-reported measures, aggregating answers of individual workers to surveys on skills and working conditions— see e.g. the Federal Institute for Vocational Training/Research Institute of the Federal Employment Service in Germany (IAB/BIBB), the OECD Programme for the International Assessment of Adult Competencies (PIAAC), and the European Working Condition Survey (EWCS – Eurofound).

However, Cetrulo et al. (2020), working on the Italian IPC (Indagine Campionaria delle Professioni) perform a data-driven dimensionality reduction factor analysis comparable to the US O*NET. They find that the specific interaction with tools and machinery is not what determines the variability between occupations, but rather traits of power, meant as hierarchical positioning of the occupation and the knowledge required to accomplish the task.

In general terms, this testifies that the RBTC approach is not characterised by a unique framework for data analysis, and tasks can be classified depending on the information available in the used databset. However, there are important data limitations. In the O*NET case, for instance, it is difficult to study the evolution of tasks within occupations over time (although the database is regularly updated), since it is assumed that the task-content of a given occupation is time-invariant. Indeed, Arntz et al. (2016, 2017) show that narrow

feasibility studies, by ignoring the substantial variation in job tasks within occupations, may overstate the exposure of jobs to automation. On the other hand, self-reported sources allow to study the variability in task content within each occupation or job type. However, on the minus side, self-reported sources are prone to introduce potential measurement bias, since workers' answers may reflect other things beside the task content in strict terms.

Turning our attention to the available empirical evidence, the already cited seminal contribution by Autor et al. (2003) has zoomed into the relationship between new technologies and skills/tasks, showing that innovation can replace human labour when it is largely based on routines, but it can hardly replace non-routine tasks where technology is complement. Their analysis, covering the 1984–1997 time-span and referring to general computer use and ICTs, bridges SBTC and TBTC, as the authors consider and measure the tasks involved in each of the 450 occupations included in the Dictionary of Occupational Titles. Each occupation receives a score for each of the task measures. Moreover, they measure technological change by the evolution of the share of workers in the industry who use computer on the job. Regressing the change in task involvement on the change in computer use reveals that technological change is positively related to the increased use of non-routine cognitive tasks. On the other hand, routine tasks (both cognitive and manual) turn out to be negatively related to technological change. As far as non-routine manual tasks are concerned, they seem to be unrelated to technological change until the 1990s, when a positive and significant relationship between them emerges.

Caines et al. (2018), after formulating a model on TBTC with a special focus on complex tasks, study the relationship between task complexity connected to automation and the occupational wage/employment structure in the US market. Complex tasks are defined as those requiring higher-order skills, such as the ability to abstract, solve problems, make decisions, or communicate effectively. They measure the task complexity of an occupation by performing principal component analysis on a broad set of occupational descriptors in O*NET data. They establish four main empirical facts over the 1980–2005 time period: there is a positive relationship across occupations between task complexity and wages and wage growth; conditional on task complexity, routine-intensity of an occupation is not a significant predictor of wage growth and wage levels; labour has reallocated from less complex to more complex occupations over time; within groups of occupations with similar task complexity, labour has reallocated to non-routine occupations over time.

In a similar fashion, Gregory et al. (2019), after developing a task-based framework to estimate the aggregate labour demand and employment effects of RRTC, propose an empirical analysis on regional data (238 regions) across 27 European Union countries between 1999 and 2010. They show that while RRTC has indeed triggered strong displacement effects in Europe, it has simultaneously created new jobs through increased product demand, outweighing displacement effects and eventually resulting in net employment growth. This task-based framework builds on Autor and Dorn (2013) and Goos et al. (2014), and incorporates three main channels through which RRTC affects labour demand. Firstly, RRTC reduces labour demand through substitution effects, as declining capital costs push firms restructuring production processes towards routine tasks. Secondly, RRTC induces additional labour demand by increasing product demand, as declining capital costs reduce the prices of tradables. Thirdly, product demand spillovers also create additional labour demand: the increase in product demand raises incomes, which is partially spent on low-tech non-tradables, raising local labour demand. The first of these three forces acts to reduce labour demand, whereas the latter two go in the opposite direction (in a sort of compensation mechanisms at work). As such, the net labour demand effect of RRTC is theoretically ambiguous.

Marcolin et al. (2019) exploit data from PIAAC merged with the United States Current Population Survey (CPS) and the European Labour Force Survey (EULFS) to construct a novel measure of the routine content of occupations for 20 OECD countries. This measure is built on information about the extent to which workers can modify the sequence in which they carry out their tasks and decide the type of tasks to be performed on the job. This study sheds light on the relationship existing between the routine content of occupations and the skills of the workforce, intended as both the skills that workers are endowed with and

those that they use on the job. Marcolin et al. (2019) highlight that the routine intensity of occupations is lower for more sophisticated occupations, i.e. those less likely to be routinised. On average, in 2012, 46% of employees in PIAAC countries are working in non-routine-intensive (18%) or low-routine-intensive (28%) occupations. They also provide evidence of a negative but weak correlation between skill intensity and the routine content of occupations. The more routine-intensive occupations thus tend to require fewer skills, but while non-routine- and low routine-intensive occupations appear to be monotonically increasing in skill intensity, the same is not true for medium- and high-routine-intensive occupations, which are mostly intensive in medium skills. This strengthens the evidence that workers perform a bundle of tasks only barely related to workers' human capital or the job functions they are attached to through their occupational titles.

De Vries et al. (2020) combine data on robot adoption (proxied by the sectoral penetration rates provided by the International Federation of Robotics) and occupations in 19 industries and 37 countries over the period 2005–2015. As in the previous study, occupations are ranked using the Routine Task Intensity (RTI) index. Their results show that robot adoption is associated with significant positive changes in the employment share of non-routine analytical jobs and with significant negative changes in the employment share of routine manual jobs.

Kogan et al. (2021) construct a similarity measure between the textual description of tasks in the fourth edition of the Dictionary of Occupation Titles (DOT) and that of so-called breakthrough innovations, according to the methodology devised in Kelly et al. (2021). The measure is constructed to allow for time variability by keeping constant the textual content similarity while summing it for each defined breakthrough innovation at each time step, exploiting patent information over the period 1850–2010. Breakthrough innovations, identified as the distance between backward and forward similarity of each filed patent compared to the existing stock of patents, are by no means ex-ante defined as being of a labour-saving nature. In addition, the way the measure is built reflects more the dynamics of breakthrough innovations according to their emergence along subsequent technological revolutions, quite akin to the findings of Staccioli and Virgillito (2021), rather than their actual penetration in the labour market. Therefore, the measure captures the clustering of technologies under mechanisation in the first period of analysis, followed by automation and the ICT phase. They find that most exposed occupations experienced a decrease in wage and employment level, and that over time white-collar workers become relatively more exposed compared to blue-collar ones. In particular they find that workers are being replaced at both the top and bottom of the wage distribution. According to their perspective, low-paid people lose their jobs as a result of automation, and high-paid workers see slower wage growth, as some of their abilities become obsolete. However, it is not clear whether the results are reflecting more long-run dynamics in technological and structural change, rather than actual similarity between patents and occupations. Indeed, the within patent-occupation text-similarity is kept constant over time.

The Kogan et al. (2021)'s measure has been applied by Autor et al. (2020), interested in devising the entry of new work titles along the historical records of the so-called Census Alphabetical Index of Occupations (CAI), an index listing all new work-title entries. The authors define as complementary technologies those patents matched with the CAI text (new job titles), and as labour-saving technologies the ones linked to the DOT text (existing job titles). The paper documents the increasing entry of white-collar middle-paid occupations in the period 1940–1980; since 1980 new jobs have been concentrating in both high-educated and low-educated services. Another application of the Kogan et al. (2021)'s measure has been used with reference to Industry 4.0 (I4.0) patents by Meindl et al. (2021), matching in this case the patent text corpus with the "detailed work activities" (DWAs) section of the O*NET. According to their results, financial and professional occupations are more exposed to I4.0 patents compared to non I4.0 patents.

Montobbio et al. (2021) presents one of the first attempts at building a direct measure of occupational exposure to robotic labour-saving technologies. After identifying robotic and labour-saving robotic patents (Montobbio et al., 2022), they leverage on the 4-digit Cooperative Patent Classification (CPC) code definitions to detect functions and operations performed by technological artefacts directed to substituting the labour input. This measure allows to obtain fine-grained information on tasks and occupations more

exposed to labour-saving robotic technologies (according to text-similarity rankings between patents CPC codes and tasks). Occupational exposure by wage and employment dynamics in the United States is then studied, complemented by investigating industry and geographical penetration rates. The authors show that, in the last two decades, occupations most exposed to robotic labour-saving technologies are associated to lower rates of employment and wage growth.

4.2.1 Wrapping up

Taken together, the extant evidence supports the idea that when tasks are based on standardised processes, innovations can generally replace them. At the same time, technology can be an important complement to non-standardised tasks; indeed, this literature shows that technological change is positively related to the increased use of non-routine cognitive tasks. On the other hand, non-routine manual tasks appear to be unconnected to technological advancement until the 1990s, when a positive correlation starts to emerge. The routine content of occupations is also associated to a lower skill intensity (see also Autor, 2022). Together with the idea that digitalisation can be significantly associated with job losses among the mid- and low-skill workers, some evidence emerges of a reallocation from less complex to more complex and non-routine occupations over time. In parallel, new jobs are created through increased product demand that can outweigh the displacement effects on routinised jobs, eventually resulting in net employment growth. Long-run studies suggest that both direct job loss due to exposure to automation and skill obsolescence play an important role in the transformation of the occupational structure of the labour market.

While the studies discussed so far are retrospective, a number of recent papers, focussing on tasks, try to predict the risk of automation risk for different specific occupations.

4.3 Scenarios on jobs exposure to automation

Frey and Osborne (2017) studied computerisation defined as job automation by means of computer-controlled equipment. A group of experts hand-labelled 70 occupations from the O*NET database, marking 1 if automatable, and 0 if not, and developed an algorithm (using a Gaussian process classifier applied to the full O*NET data) to extend the assessment of automatability to 702 occupations. Using also data from the US Department of Labor, they predict that 47% of the occupational categories, mostly middle- and low-skilled professions, are at high risk of being substituted by job computerisation, which includes AI algorithms and robots. Occupations at risk include not only blue collars, but also a wide range of service/white-collar/cognitive tasks such as accountancy, health professions, logistics, legal works, translation, and technical writing.

Arntz et al. (2016) use information on task-content of jobs at the individual-level (from the PIAAC) and show that only 9% of US jobs are at potential risk of automation. They compare their results with Frey and Osborne (2017) and claim that, within the same occupation, some tasks can be automatised while others cannot, and therefore the associated job can be preserved. Indeed, it makes a big difference whether the empirical analysis focuses on occupations or tasks. In general terms, forecasting studies which investigate occupations tends to be more pessimistic, while analyses centred on tasks generally produce more optimistic scenarios. For instance, in the case of a radiologist doctor, X-ray screenings can be performed more efficiently by a robot, but other diagnostic tasks are still based on the doctor's competences and experience; in this case, an occupation-based empirical analysis would conclude that the occupation is at risk, while a task-based one would conclude that the job is likely to be preserved.

Building on Frey and Osborne (2017) but leveraging on PIAAC data, Nedelkoska and Quintini (2018) estimate the risk of automation for individual jobs in 32 OECD countries. Their evidence shows that about 14% of jobs are highly automatable (probability of automation over 70%), while another 32% of jobs present a risk of replacement between 50 and 70%, pointing to the possibility of significant changes in the way these

jobs will be carried out as a result of automation.

At the European level, Pouliakas (2018)—using data on tasks and skill needs collected by the European Skills and Jobs Survey (ESJS)—bundles jobs according to their estimated risk of automation. Following Frey and Osborne (2017) and Nedelkoska and Quintini (2018), the author utilises highly disaggregated job descriptions and shows that 14% of EU adult workers are found to face a very high risk of automation. They also find that routine professions that don't require a lot of social and transversal abilities are particularly vulnerable. Additionally, men and individuals with lower levels of education are at a larger risk of losing their jobs to automation. They point out that the risk of automation is not distributed equally among workers: the findings in this study suggest a rather monotonic decrease in the risk of automation as a function of educational attainment and skill levels.

Montobbio et al. (2022) rely on textual analysis of USPTO patent applications in robotics and perform a semantic study to directly identify labour-saving innovations. They estimate a probabilistic topic model and propose a human-machine taxonomy that describes the specific work activities and functions that are more exposed to labour-saving innovation. They find that the following activities are particularly exposed to labour-saving robotic patents: (i) transport, storage, and packaging, (ii) diagnosis and therapy, (iii) transmission of digital information, (iv) optical elements, (v) chemical and physical laboratory apparatus (measuring and testing in chemistry), and (vi) moving parts.

These scenarios, many of them based on the seminal work of Frey and Osborne (2017), have corroborated the idea that "this time is really different" (Brynjolfsson and McAfee, 2012, 2014; Ford, 2015). A substantial share of occupations seems at risk of automation; however, analyses centred on tasks produce more optimistic scenarios because not all tasks in an occupation can possibly be automatised. Moreover, the occupations at risk are not restricted to low skilled blue collars in downstream manufacturing sectors but extend to a wide range of white-collar jobs in services (e.g. health and finance). Eventually—beyond exposure to automation—taken together these contributions clearly point at a substantial reallocation of jobs across industries and to a relevant transformation of how occupations are performed and tasks are allocated to different occupations.

4.4 Artificial intelligence

Very recent papers have focused on artificial intelligence, often blamed to have a strong labour-saving impact on white-collar jobs, more related to service activities. For instance, Felten et al. (2021), who refine the measure proposed in Felten et al. (2018), link the Electronic Frontier Foundation dataset (EFF), within the AI Progress Measurement initiative, with O*NET abilities. A direct matching between 10 AI selected scopes of application (abstract strategy games, real-time video games, image recognition, visual question answering, image generation, reading comprehension, language modelling, translation, and speech recognition) and human abilities is constructed. The matching is performed by crowd-sourcing a questionnaire to gig workers at Amazon's Mechanical Turk (mTurk) web service. 2,000 mTurkers residing in the United States were asked whether, for each of the 52 abilities listed in the O*NET, they believe that the AI application is related or could be used in their place. The study reports higher AI exposure for white-collar workers. However, the measure is silent about any direct replacement or complementarity effect.

Webb (2020) also finds that artificial intelligence is more likely to affect skilled and older workers than previous innovation waves based on robots or software. He proposes a direct measure of exposure via co-occurrence of verb-noun pairs in the title of AI patents and O*NET tasks. One potential limitation is that titles of patents do not contain a full description of the underlying functions executed by the technological artefact and, in addition, restricting to verb-noun pairs bears a high likelihood of false positives. The measure of exposure is not constructed in terms of overall similarity of the two text corpora but rather in terms of the relative frequency of occurrence of the elicited pairs in AI titles versus the remaining titles of non-AI patents. Moreover, the proposed methodology does not allow to distinguish labour-saving from labour-augmenting

technologies.

Acemoglu et al. (2020a) look at AI exposed establishments and their job posts using Burning Glass Technologies data, which provide wide coverage of firm-level online job postings, linked to SOC occupational codes. In order to account for the degree of firm-level AI exposure, three alternative measures are employed, namely the ones put forth by Brynjolfsson et al. (2018), Felten et al. (2021), and Webb (2020). Unsurprisingly, considering the still relatively niche adoption, no clear effect at the industry and occupational level is detected, while re-composition toward AI-intensive jobs is suggested. In addition, the authors do not find evidence of any direct complementarity between AI job posts and non-AI jobs, hinting at a prevalent substitution effect and workforce re-composition, rather than a productivity enhancement after AI adoption.

Damioli et al. (2021, 2022), study 3,500 front-runner companies who patented AI-related inventions over the period 2000–2016. They find a moderate positive employment impact of AI patenting (with a short-term elasticity of about 3-4%), and this labour-friendly effect combineswith the one triggered by other (non-AI) firm innovation activities. These findings confirm the employment-friendly nature of product innovation in general (see Section 2), and provide novel specific evidence for emerging AI technologies.

5. Key findings and gaps in the extant literature

Table 1 provides a synoptic picture of the most recent and seminal works devoted to the issues investigated in this survey.

[Table 1 about here]

The extant literature points at the following outcomes.

i. The employment and skill effects of technical change are indeed heterogeneous and differ according to the level of aggregation, the adopted proxy for technology, and the unit of analysis, whether sectoral vs. firm, or occupations vs. tasks. In more detail, an overall positive impact of innovation on employment is detected by most of previous firm-level studies, suggesting some degree of complementarity between technological change and employment (see also Hötte et al., 2022a). While this complementarity is easy to understand at the company level, it gets more controversial at the sectoral and aggregate level. Moreover, it tends to be small in magnitude and limited to the most innovative firms and the most dynamic and high-tech sectors, while labour-saving effects may well arise in low-tech sectors, particularly in manufacturing (see Section 3.1). When we move to recent automation technologies (Section 3.2), sectoral studies (generally limited to studying the impact of robot adoption) tend to highlight a significant substitution effect, with negative implications both in terms of employment and wages. In contrast, firm-level analyses on adopting firms tend to confirm a positive employment impact after the introduction of new automation technologies, although of negligible magnitude, and often contrasted with an overall sectoral negative impact (business stealing effect).

ii. Turning our attention to the impact of innovation on workers' skills, the literature on SBTC has underlined a substitution effect between new technologies and unskilled workers, and a positive relationship between new technologies and skilled (white-collar) workers. At the same time, some recent literature either do not find the skill-bias (Hirvonen et al., 2022) or suggest that innovation generates a general positive impact at the firm level in terms of labour quality (Bessen et al., 2022), suggesting that the key issue is not skilled vs. unskilled, but rather the difference across firms in terms of innovativeness and across jobs in terms of task content. In parallel, the empirical literature has focused on different categories of exposed workers, focussing on routinised vs. non-routinised tasks and occupations, or manual vs. cognitive tasks and occupations. Along with the hypothesis that

job losses among mid- and low-skill employees may be significantly attributed to digitalisation, there is evidence of a shift in employment over time to more complex, cognitive and non-routine occupations (Section 4.2). In general, occupational level analyses tend to overstate the negative labour-shedding effects, while task-based analyses are more conservative in their negative estimates. Forecasting studies points to an overall substitution effect: according to the different studies, jobs at risk range from 9% to 47% and are concentrated within more routinised tasks and occupations. In contrast, a very recent focus on AI technologies has so far produced rather mixed evidence, pointing to a higher degree of exposure for white-collar and service jobs, without clearly showing whether the substitution or the complementary effect is dominant.

Albeit huge and articulated, the extant empirical literature is not immune from important shortcomings; the main research drawbacks and gaps appear to be the following.

i. There are currently many alternative proxies for "technology" at different levels of aggregation: they range from more classic product vs. process innovation at the firm level (proxied by either R&D expenditures, patents, or embodied technological change), to share of robots at the industry level, to imported capital-equipment, to expenditure in electricity, to share of newly hired software engineers. However, adopting alternative measures of technological change is not neutral. On the one hand, some technological variables—such as R&D expenditures and patents—are more linked to product innovation and often drive an overall positive employment impact (complementarity). On the other hand, other technological variables—such as scrapping or robot adoption—are more related to process innovation, often involving an overall labour-saving employment impact.

ii. Some methodological limitations and trade-offs affect the available empirical/econometric analysis. On the one hand, the relationship between technological change and employment triggers both partial equilibrium re-adjustments and general-equilibrium compensation forces which are particularly difficult to be disentangled in empirical analyses. With the exception of few aggregate studies (see Section 2.1) and some very recent analyses (see Humlum, 2021; Acemoglu and Restrepo, 2022) able to combine partial and general equilibrium settings, empirical analyses conducted at the sectoral or, a fortiori, at the firm level, only focus on the direct labour-saving effect on the one hand, and on a selection of possible compensating market forces on the other (such as the mechanism "via decreasing prices" confined to a specific market). This prevailing partial-equilibrium setting in empirical firm-level analyses needs to be admitted and mitigated: for instance, the "business stealing" effect discussed above should be taken into account with the inclusion of proper controls in the preferred econometric specification (through regressors such as firm's value added, sales, or market share). However, while microeconometric studies appear to be extremely precise in grasping the very nature of innovation and in distilling information from very large datasets, they inevitably loose something in terms of assessing the overall employment impact of technological change. On the other hand, empirical studies have to deal with an intrinsic endogeneity issue: indeed, technological change is driven by science and characterised by a high degree of path-dependence; however, it is also affected by economic determinants such as cumulated profits, cash-flow, demand expectations, etc. This means that the technological impact variable (proxied by R&D or other measures) should be cautiously considered endogenous and possibly instrumented. Indeed, most of the empirical literature appears to be aware of this issue, which is generally mitigated by means of two different strategies. Starting from Piva and Vivarelli (2005), a strand of studies makes use of GMM methodologies (generally GMM-SYS given the highly autocorrelated nature of the employment series and the availability of panel data characterised by a dominant cross-sectional nature) to instrument both the lagged employment variable and most of the regressors, including the proxy for innovation when necessary (see also Lachenmaier and Rottmann, 2011; Pellegrino et. al., 2019; Dosi et al., 2021). Another strand of literature—initiated by Acemoglu and Restrepo (2020a) —instruments the key impact variable (for instance the robot sectoral penetration taken from the

International Federation of Robotics dataset) using data related to different geographical locations (for instance, European robot penetration rates instrumenting US ones; see also Chiacchio et al., 2018 and Dauth et al., 2021).

iii. A further gap in the current economic literature is its rough degree of granularity in dealing with different technologies. A finer analysis of the relationship between specific technological advancements, tasks, and skills becomes necessary to understand in detail the impact on skills, the nature of the job reallocation, the degree of obsolescence of tasks, and the possibility to learn on the job. A more granular measurement of technologies is required also to design appropriate policy interventions affecting skills supply and labour market institutions and government policies, like taxes, R%D subsidies, and regional policies for innovative clusters. Indeed, even within the automation domain, specific technologies, devices and algorithms might exert different impacts in terms of affected jobs, skills, and tasks. For instance, while robotics might be aimed at substituting human functions, other forms of automation targeted to ergonomic improvements and digitisation— such as the adoption of Enterprise Resource Planning or Manufacturing Execution Systems—are more directed at improving control monitoring, rather than automating tasks and making jobs redundant. In this respect, technological and organisational changes are more oriented toward a recombination of tasks performed by the same workforce (reallocated across different functions and departments) rather than to purely labour-saving and skill-biased strategies. In other cases, product modularity with the use of additive manufacturing jointly provide new products and processes, reshaping and reallocating tasks along the vertical supply chain. Employment effects can be largely geographically dispersed, as additive manufacturing affects the structure of vertical relations and can be associated with reshoring (first attempts to discuss these aspects can be found in the managerial and/or sociological and/or organisational literature, which are beyond the scope of this paper). However, heterogeneity and selection in adoption strategies emerge as stylised facts. For instance, Cirillo et al. (2021) conduct a case study of three pivotal adopters of I4.0 artefacts and depart from the archetypal idea of a fully-fledged I4.0 factory. Indeed, they find that the introduction and use of I4.0 artefacts are scattered both between and within firms, and across different departments. In particular, not allproduction processes are affected to the same extent. Currently, the most involved areas are not assembly lines (as suggested by common wisdom), which are already equipped with intelligent robots, but rather communication and monitoring systems, and interconnected machines which allow to timely record the production process, the quantity produced in each phase, the errors occurred, and possible underlying bottlenecks. By the same token, recent digitisation and innovation surveys (Acemoglu et al., 2022 for US; Costa et al., 2021 and Calvino et al., 2022 for Italy) conducted by national statistical offices by administering firm-level questionnaires about the level of ICT and robots adoptions, reveal that implementations thereof constitute a very selective process, both in terms of sectors and across firms within the same sector. In addition, the multiple technology approach, which involves the simultaneous adoption of robots, software, AI, cloud computing, etc. does not represent the rule but rather the exception across firms. In other words, firms tend to selectively adopt the most appropriate type of technology to solve specific, localised problems.

iv. By the same token, the narrow focus on robotisation by the recent empirical literature should be seen as a further shortcoming. At the very least, future analyses should encompass the entire AI domain (including robots, but extended to other applications of AI in manufacturing, and particularly in services, ranging from software algorithms to platforms). First attempts in this direction are Acemoglu et al. (2020a), Webb (2020), Felten et al. (2021), all discussed in the previous section. However, there are at least two important limitations in this nascent literature. On the one hand, there are multiple ways of unpacking AI sectors and firms, since a clear definition of AI technologies has yet to beestablished in the scientific debate. In fact, conceptual definitions of AI typically insist on the ability of a system to perform human-like cognitive functions (learning, understanding, reasoning and interacting) aimed at obtaining rational outcomes (Ertel, 2018; Russell and Norvig, 2016). On

the other hand, albeit AI technologies focus on a core of digital technologies including knowledge processing, speech recognition, computer vision, evolutionary computation, natural language processing, and machine learning (see Martínez-Plumed et al., 2020; Giczy et al., 2022), various studies consider a broader definition of AI which includes a combination of software and hardware components, as well as functional applications such as robots and "big data" (European Commission, 2018; Fujii and Managi, 2018; WIPO, 2019; Damioli et al., 2021). Obviously enough, the way in which AI technologies are singled out and measured may affect the results obtained in terms of their labour market effects (see Hötte et al., 2022b; Autor, 2022). Moreover, the extant literature devoted to the employment impact of AI technologies has so far dealt only with the demand side, by looking at the potential labour-saving effect that may take place among users of AI and robotics technologies conceived as process innovations in downstream sectors. However, an obvious gap exists about the possible job-creation effect in the supply side, among developers of AI and robots conceived as product innovations in the upstream sectors. First attempts in this direction include Damioli et al. (2021, 2022).

v. Finally, the impact of technological transformation on labour *quality* should be addressed as a major challenge in this literature, not only in terms of wages (e.g. Vannutelli et al., 2022), but also in terms of types of jobs and working conditions. While the aggregate quantitative employment impact of different forms of technological change (from robots to AI) is still unclear, what is becoming increasingly evident is that technology transforms how, and in which conditions, workers do their jobs. To disentangle such transformations, it is needed again a greater granularity in the analysis of different technologies to understand precisely the heterogeneous impact on tasks, occupations, and working conditions. Some authors, focussing on high innovative firms, show, for example, that the adoption of ICT increases demand for a variety of skills and tasks and raises wages (e.g. Bessen et al. 2022). However, other authors find that, particularly in low wage industries, the quality of jobs, wage levels, and equal treatment of disadvantaged workers can be seriously threatened by new technological advancements (e.g. Hammerling 2022; Acemoglu, 2021). In this respect, the analysis of technological organisational capabilities at the workplace level (and their impact on the way technology is implemented and on the nature of the work process) and the institutional setting (e.g. trade unions and labour market regulations) are particularly promising and interesting avenues for research.

6. Conclusions

In this critical survey we have discussed the main technological drivers which play a role in determining the eventual employment impact of new technologies. Indeed, since economic theory does not have a definitive answer to the overall employment effect of innovation, the role of empirical analyses is pivotal. In general terms, taking stock of the available empirical evidence, the literature supports a positive (although small in magnitude) link between technology and employment, especially when R&D and/or product innovation are adopted as proxies of technological change, and when the focus is on high-tech sectors. On the other hand, job losses may occur the downstream and more traditional economic sectors.

However, three decades of literature have shown that the employment impact of innovation is different across tasks and occupations, and not only across firms and sectors. So-called routinised tasks are more prone to be automatable than non-routinised ones, with some of the latter which turn out to be complementary to the new technologies, in particular AI. However, albeit the current standard economic conceptualisation is based on the contrast between automatable and non-automatable tasks, decision choices of technological adoptions and firm-level techno-organisational capabilities are crucial factors to explain across-firm heterogeneity, the mix of technology in use, and the effects on the workforce.

Indeed, in spite of the lessons learned, some challenges still remain ahead. First and foremost, the nature and

the type of technology measure employed as a proxy of technical change, whether embodied or disembodied, department or firm specific; second, the level of aggregation of the analysis, whether firm, sectoral, or macroeconomic; third, the distinction between developers and adopters and the different employment patterns they create as net job creators/destroyers; fourth, the type of techno-organisational capabilities at the workplace level which affect both the way in which technology is deployed and the work process in itself; fifth, the type of institutions operating, including trade unions, regulations of hiring and firing, hours of work, and more generally internal HR practices at work at the firm level.

While more fine grained microeconomic studies—based on selected samples (in terms of geography or technology)—help understanding how technological change transforms occupations, tasks, and the related quality of work and working conditions, these types of studies may not be generalised to different contexts. Indeed, more general considerations and analyses at the aggregate level help understanding the technology-employment nexus in contexts in which also other forces, like institutional and structural change, drive the dynamics of the labour market. Our understanding is that the issue remains at the core of the agenda of economics in general, and of classical political economy in particular; that said, together with additional empirical evidence, it requires further efforts on the theoretical side. Some instances have been devised by means of macro-economic and sectoral evolutionary models addressing the topic from a multi-level, integrated perspective (see Dosi et al., 2021, 2022). However, more research in these directions is very much needed in order to escape the trap of partial analysis consideration, and to be able to address the theoretical conditions according to which labour displacing vs. labour augmenting effects of technology prevail.

Finally, the role of institutions (e.g. job contracts, industrial relations, minimum wage and firing regulations) and of the overall macroeconomic development of a country remain among the most prominent—beyond market-based considerations on cost of labour and skills requirements—drivers of employment dynamics and labour remuneration. These represent other future avenues of research.

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Appendix

Table 1: a synoptic summary of most recent and seminal studies

TECHNICAL CHANGE AND EMPLOYMENT			
Paper	**Coverage/Methods**	**Effect**	**Level of analysis**
Simonetti et al. (2000)	four countries (US, Italy, France and Japan) over the period 1965-1993	positive effects on employment via decrease in prices	macro level
Clark (1983,1987)	UK, manufacturing sector, since the sixties	expansionary effects of innovative investment had been dominant until the mid-1960s, when the rationalizing effect started to overcome the expansionary one	sectoral level
Vivarelli et al. (1996)	Italy, manufacturing sector since the eighties	negative employment vs productivity growth relationship	sectoral level
Bogliacino and Pianta (2010)	CIS cross-sectional sectoral data on relevant innovations for different European countries	positive employment impact of product innovation, particularly in high-tech sectors	sectoral level
Van Reneen (1997)	598 British firms over the period 1976–1982	positive employment impact of innovation robust after controlling for fixed effects, dynamics and endogeneity	firm-level
Piva and Vivarelli (2005)	longitudinal dataset of 575 Italian manufacturing firms over the period 1992–1997	evidence in favour of a positive effect of innovation on employment at the firm level	firm-level
Harrison et al.	the third wave of the CIS from four	significant job-creating effect of product	firm-level

(2014)	European countries (Germany, France, UK, Spain)	innovation and a non-significant impact of process innovation	
Barbieri et al., 2018; Pellegrino et al., 2019; Dosi et al. (2021)	Italy, Spain and EU countries	labour-friendly nature of R&D expenditures and product innovation is confirmed, but a possible overall labour-saving impact of embodied technological change incorporated in process innovation is also detected	firm- and sectoral-level

AUTOMATION			
Paper	**Coverage/Methods**	**Effect**	**Level of analysis**
Acemoglu and Restrepo (2018, 2019, 2020a)	share of robot adoption using IFR data for the US	displacement effects on low-wage workers	industry level
Chiacchio et al 2018	AR framework adopted for six EU countries	robot introduction is negatively associated with the employment rate	industry level
Graetz and Michaels (2018)	robot adoption (IFR and EUKLEMS data to estimate robot density) in 17 countries from 1993 to 2007	robots do not significantly reduce total employment, although they do reduce the low-skilled workers' employment share	industry level
Dauth et al. (2021)	German industry adopting IFR data over the 1994-2014 time-span, using a measure of local robot exposure for every region	no evidence that robots cause total job losses and there are positive and significant spillover effects in services	industry level
Domini et al. (2020)	French manufacturing employers over the period 2002–2015	robotic adoption or, alternatively, imported capital equipment, do not limply labour expulsion, but rather employment growth	firm-level
Bonfiglioli et al. (2020)	French data over the 1994-2013 period	initial positive employment effect as a response to robot adoption but then turning into a negative one	firm-level
Koch et al. (2021)	robot adoption using data from Spanish manufacturing firms over the period 1990-2016	within four years robot adopters raise their overall employment by around 10 percent, particularly for high-skilled workers	firm-level
Deng at al. (2020)	IAB Establishment Panel, Germany	investment in robots is small and highly concentrated in few industries, the distribution of robots is highly skewed in few companies in the manufacturing sectors, size of robot users are larger, have higher labour productivity, make more investments, and are more likely to export and adopt the most updated technology	firm-level
Benmelech and Zator (2022)	IAB Establishment Panel, Germany	robot adopters increase their employment, while—at the same time—the overall employment effects in exposed industries and regions are negative	firm-level

OCCUPATIONS, SKILLS AND TASKS			
Paper	**Coverage/Methods**	**Effect**	**Level of analysis**
Arntz et al.	technological bottlenecks identified in	low-skilled occupations are the most exposed,	tasks level

(2016) and Nedelkoska and Quintini (2018)	Frey and Osborne (2017) applied at the task level covering OECD countries.	with figures much lower than FO	
Felten et al. (2018) and Felten et al. (2021)	questionnaire on 10 AI selected scopes of application crowd-sourced to mTurk workers. US labour market.	most exposed occupations are white-collar workers	jobs which refer to tasks aggregated at the occupational levels
Webb (2020)	co-occurrence of verb-noun pairs in the title of AI/robot patents and O*NET tasks. US labour market	low-wage occupations most exposed to robot. Medium-wage occupations most exposed to software. High-wage occupations most exposed to AI	job levels
Kogan et al. (2021)	term frequency-inverse document frequency matrix of patent text of breakthrough innovations and DOT. US labour market (long run)	time varying exposure of occupations reflecting waves of technological change	job levels
Montobbio et al. (2021)	term frequency-inverse document frequency matrix of CPCs and O*NET tasks	low-wage occupations concentrated in production, installation and maintenance segments but also affecting service based activities (e.g. healthcare practitioners), geographically located in the ex-industrial areas and in the South of US	job levels