DOI: 10.1111/joes.12601

JOURNAL OF ECONOMIC SURVEYS WILEY

ARTICLE

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

Fabio Montobbio[1,2,3] | **Jacopo Staccioli**[1,4] | **Maria Enrica Virgillito**[4] | **Marco Vivarelli**[1,5,6]

[1]Department of Economic Policy, Università Cattolica del Sacro Cuore, Milano, Italy

[2]BRICK, Collegio Carlo Alberto, Torino, Italy

[3]ICRIOS, Bocconi University, Milano, Italy

[4]Institute of Economics, Scuola Superiore Sant'Anna, Pisa, Italy

[5]Maastricht Economic and Social Research Institute on Innovation and Technology, UNU-MERIT, Boschstraat, Maastricht, The Netherlands

[6]Forschungsinstitut zur Zukunft der Arbeit GmbH (IZA), Bonn, Germany

Correspondence
Maria Enrica Virgillito, Institute of Economics, Scuola Superiore Sant'Anna, Piazza Martiri della Libertà 33 – 56127 Pisa, Italy.
Email: mariaenrica.virgillito@santannapisa.it

Funding information
World Bank Group

Abstract

This paper is a critical review of the empirical literature resulting from recent years of debate and analysis regarding technology and employment and the future of work as threatened by technology, outlining both lessons learned and challenges ahead. We distinguish three waves of studies and relate their heterogeneous findings to the choice of technological proxies, the level of aggregation, the adopted research methodology and to the relative focus on robots, automation and AI. The challenges ahead include the need for awareness of possible *ex-ante* biases associated with the adopted proxies for innovation; the recognition of the trade-off between microeconometric precision and a more holistic macroeconomic approach; the need for granular analysis of the reallocation and transformation of occupations and tasks brought about by different types of new technologies; the call for a closer focus on impacts on labor quality, in terms of types of jobs and working conditions.

KEYWORDS

employment, future of work, occupations, skills, tasks, technology

JEL CLASSIFICATION
O33

1 | INTRODUCTION

What has been learnt from recent debate and analysis regarding the threat that new technological transformation poses to the future of work? When Frey and Osborne predicted in 2013 (published subsequently as Frey & Osborne, 2017) that almost 47% of jobs would be lost due to automation, concerns and fears regarding technological unemployment spread among academics and policymakers. These authors' results were also backed by a series of studies produced by consultancy agencies, who anticipated a mass expulsion of workers (Balliester & Elsheikhi, 2018). This occurred at a time when self-driving cars and artificial intelligence were materializing, while advanced economies were still trying to recover from the 2008 crisis. Between 2012 and 2016 a number of influential works, 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 the so-called Fourth Industrial Revolution.

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

Needless to say, the technology-employment nexus is a very important channel of transformation in labor markets, but it is 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 and participation rates, as well as inequality and reorganization of working activity on a global scale (ILO, 2022). In the conclusions of this survey, in line with an evolutionary approach to technology and employment, we suggest that employment growth and income distribution are the combined results of structural change, changing demand and patterns of consumption, and the organization of labor markets in terms of institutions.

The combined results of demand patterns and technological change lead different industries to react to new technologies in heterogeneous ways, and this implies potential disruptive changes for workers, as certain industries flourish while others decline. This possibly 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 of labor, regardless of the overall impact. For this reason, it is important to understand how technology affects the organization of the productive process and the way work is executed. The new waves of technological change are transforming the nature of work and the tasks required within the different types of occupations. The pace and scope of change in the intelligent automation process may be faster than previous automation waves, and also extend to white-collar and professional tasks. In tracing these effects, economists need accurate data to develop fine-grained proxies for technology, able to capture the impact of distinct but interactive trajectories such as, for example, automation, digitization, and more standard ICT processes.

While our understanding of the employment-technology nexus has improved greatly, challenges still remain ahead. More in-depth microeconomic studies, based on carefully chosen samples (in terms of regions or technologies) are needed to 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, and moving to cover sectors and the macro level. Such efforts are required to provide more conclusive evidence at the aggregate level, where other variables, such as institutional and structural changes, influence the dynamics of the labor 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 the common findings and main differences across studies. Methodologically, we survey past and recent literature, mainly covering Europe and the US, drawing upon previous surveys and including new contributions such as those derived from initiatives on the future of work (e.g., Technology & Policy Research Initiative; MIT Work of the Future, UN STI Forum). In addition, we put in critical perspective and parallel analysis seminal contributions which have received academic attention, as testified by number of citations, and from which sub-streams of research have originated.

Lessons learned include the relevance of the role played by the *nature* of the technology under observation, whether embodied or disembodied, and the level of aggregation of the analysis, whether firm, sectoral, macroeconomic. These drivers help in explaining the substantial differences across studies in terms of scenarios on the future of work, when studying employment creation/destruction. More recently, the literature has been moving progressively from investigating the effects of technology on the quantity of work towards the quality of work. Shifting from quantity to quality implies new perspectives of analysis to fully embrace effects on the reorganization of the work process due to technological change. Given that the study of the transformation rather than the substitution of human work is the new realm of investigation, this requires fine grained explorations on (i) specific technological artefacts, that is, "what new technologies do and how they affect human functions," (ii) firm-level techno-organizational capabilities, that is, "how firms decide on their adopted technological mix and how they deploy the latter vis-à-vis the workforce," (iii) the role of the institutions in place, at the firm, sectoral, and country levels, in facilitating or impeding new technological adoption, that is, "how trade unions and work councils, whenever present, favor or obstruct the introduction and implementation of new technologies." These are the challenges ahead facing the future of work.

The remainder of the paper is organized as follows. First, Section 2 presents lessons learned from different levels of analysis and the nature of technological change in process versus product innovation, which we refer to as the "first wave" of innovation-employment nexus studies. These studies tend to rely on more traditional notions of technological measures, including standard R&D expenses, investments in physical capital, and number of patents, and tend to look at overall employment changes in terms of outcome variables. In Section 3, we delve into a particular type of innovation, namely automation and robotics adoption, referred to as the "second wave" of innovation-employment nexus studies. In Section 4 we present two lines of research: the first group analyses the employment impact of artificial intelligence and the second exploits

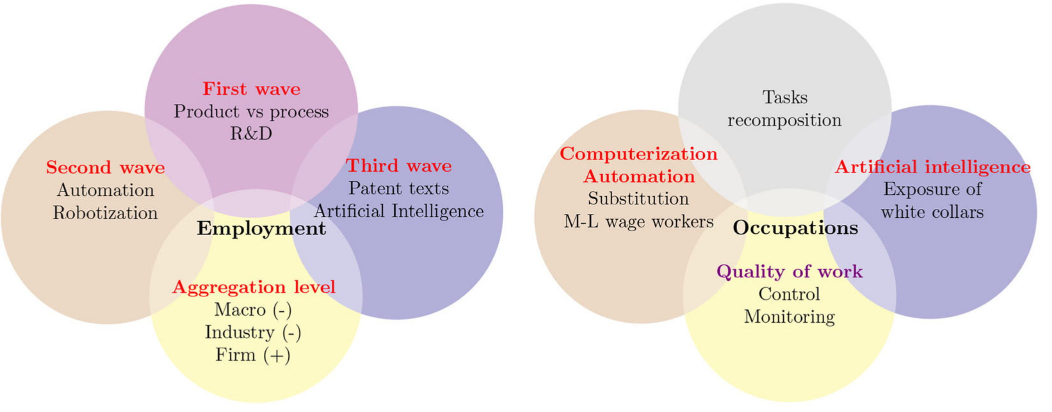

FIGURE 1 Venn diagrams conceptualizing the structure and findings of the survey: the three waves of the technology-employment nexus studies on the left; the technology-occupations nexus on the right. [Colour figure can be viewed at wileyonlinelibrary.com]

patent texts to analyse the proximity between specific innovation functions and occupations and tasks in the labor market. We call these two groups of studies the "third wave" of technological-employment nexus studies. In Section 5 we go deeper into effects on workforce recomposition in terms of tasks, skills and occupations, also covering inequality and employment outcomes. In Section 6 we discuss our key findings and the challenges ahead, while Section 7 briefly concludes.

Figure 1 is a graphical representation of the organization of the contents of the survey and the main lessons learned so far, looking at employment (left) and occupations (right).

2 | THE "FIRST WAVE" OF TECHNOLOGY-EMPLOYMENT STUDIES: THE ROLE OF PRODUCT VS. PROCESS INNOVATION ALONG DIFFERENT LEVELS OF AGGREGATION

If we include the labor market effects of previous innovation waves, such as the ICT revolution, extant empirical literature on the link between technology and employment is vast (for recent surveys, see Autor, 2022; Calvino & Virgillito, 2018; Hötte, Somers et al., 2022; Mondolo, 2022; Ugur et al., 2018; Vivarelli, 2014). Overall, the lesson learned from previous empirical studies is that findings vary widely 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 or measuring the outcome of innovative efforts, such as patents),[1] and the country and time dimensions of the analysis.

In the following, we review the main research findings deriving from the "first wave" of technology-employment studies, which vary according to the level of aggregation of the analysis (Subsections 2.1, 2.2, 2.3) and the nature of the technological change under scrutiny, whether process versus product.

2.1 | Macroeconomic studies

At the macroeconomic level, the labor-saving impact of new technologies should be compared with the possible counterbalancing effects of various market compensation mechanisms: indeed, compensation mechanisms are put forward by Freeman et al. (1982) as a way of comprehending the technology-employment nexus, and can be of a classical, neoclassical, or Keynesian nature. These market mechanisms operate through different channels. For instance, process innovation allows a decrease in average costs which in competitive markets may entail decreasing prices, increasing demand and increasing production and employment. On the other hand, in non-competitive markets, efficiency gains translate into higher profitability and possibly increasing investments, production and employment. Finally, innovation may imply an increase in the production of capital goods in upstream sectors, which may compensate the labor-expelling effect of process innovation in the downstream industries. Obviously, all these compensation mechanisms may fail (partially or totally), due to significant market failures triggered by non-competitive markets, pessimistic expectations, low values of both demand elasticity and the elasticity of substitution between capital and labor, institutional and technological rigidities, and so on (see Vivarelli, 1995 and 2015).

Empirical detection of the effectiveness of the different compensation mechanisms, together with the opposing job-creating impact of product innovation (which has to be considered an alternative form of innovation, rather than a compensation mechanism counterbalancing labor-saving process innovation), were addressed by Vivarelli (1995) through a simultaneous equations model on data from the period 1960–1988 (three-stage least squares regressions) for Italy and the US. The author found that the most effective compensation mechanism is that "via decreasing prices" in both countries, while other mechanisms turned out to be less important. Moreover, the US economy emerged as being more product-oriented (and therefore resulting in an overall positive relationship between technological change and employment) than the Italian economy, where the different compensation mechanisms turned out to be unable to counterbalance the direct labor-saving effect of widespread process innovation. A further test of the macroeconomic model proposed by Vivarelli (1995), was put forward by Simonetti et al. (2000), using data from four countries (US, Italy, France and Japan) over the period 1965–1993. Their results were partially consistent with those obtained by Vivarelli (1995): in particular, the role of the mechanism "via decreasing prices" was confirmed in general, but a clear and significant relationship between technological change and decreasing prices emerged only in France and the US; consistently with Vivarelli (1995), the labor-friendly nature of product innovation was clearly evident only in the US (and to a lesser extent in France).

In a more recent study, Feldmann (2013) used as an aggregate innovation indicator the number of triadic patents, that is, 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 showed 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 for fully investigating the link between technology and employment, considering jointly 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 somewhat controversial for different reasons: first, there are problems in measuring aggregate technological change (an attempt in this direction was made in 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 recent 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' behavior) may render the macroeconomic assessment either unreliable or meaningless. This is why nowadays sectoral and particularly microeconomic literature on the link between innovation and employment is flourishing, also thanks to the availability of new reliable longitudinal data.

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 shift from manufacturing to services. On the other hand, within manufacturing, new technologies seem to be characterized mainly by labor-saving process innovation, only partially compensated by the market mechanisms discussed above.

In this vein, Clark (1983, 1987) put forward a supply-oriented vintage model, investigating manufacturing in the UK. The author found that the expansionary effect of innovative investments (Keynesian multiplier) was dominant until the mid-1960s, after which the rationalizing effect (due to labor-saving embodied technological change incorporated in investments and scrapping) started to overtake the expansionary effect. In a later study, Pianta et al. (1996) found 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 labor-saving trajectory (restructuring sectors), with growing production and declining employment. In another contemporary study based on Italian data, Vivarelli et al. (1996) showed that in Italian manufacturing the relationship between productivity growth and employment appears to be negative. Specifically, they revealed that product and process innovation have opposite effects on the demand for labor, in line with what has been discussed above in this article.

As already mentioned, the scenario may change if service sectors are taken into account. For instance, using standardized sectoral data derived from national Community Innovation Surveys (CIS), Pianta (2000) and Antonucci and Pianta (2002) found an overall negative impact of innovation on employment in manufacturing industries across five European countries. In contrast, Evangelista (2000) and Evangelista and Savona (2002) established 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) found a positive employment impact of product innovation (which is particularly obvious in high-tech manufacturing sectors, see also Mastrostefano & Pianta, 2009). In line with this, Buerger et al. (2010), using data on four manufacturing sectors across German regions over the period 1999–2005, 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 they were not significant in the other two more traditional sectors (chemicals and transport equipment). By the same token, running GMM-SYS panel estimations covering 25 manufacturing and service sectors for 15 European countries over the period 1996–2005, Bogliacino and Vivarelli (2012) found that R&D expenditure, mainly fostering product innovation, does exhibit a job-creating effect.

More recently, Piva and Vivarelli (2018), using data covering manufacturing and service sectors over the 1998–2011 period for 11 European countries, discovered both a significant job-creation effect of R&D expenditures (albeit limited to medium and high-tech sectors) and a job-destruction impact of capital formation, suggesting a possible labor-saving effect due to the embodied technological change incorporated in gross investment (mainly related to process innovation). These outcomes are confirmed by Dosi et al. (2021), who put forward a two-sector agent-based model, able to represent the sectoral patterns of job creation and job destruction and to distinguish the alternative effects of embodied (capital formation) versus disembodied technological change (R&D expenditures). Their empirical results, based on sectoral OECD data covering 19 European countries over the period 1998–2016, reveal that R&D turns out to affect employment dynamics in the "upstream" sectors positively, while expansionary investment does so in the "downstream" industries. However, these labor-friendly effects are more than counterbalanced by the (highly significant and greater in magnitude) labor-saving impact due to the replacement of obsolete capital vintages in the downstream sectors.[2]

2.3 | Firm-level studies

Turning our attention to the wider microeconometric literature, since the late '90s studies have taken full advantage of newly available longitudinal datasets and have applied panel data econometric methodologies that take the time dimension and individual variability into account jointly. For example, Van Reenen (1997) 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 found a positive impact of innovation on employment, and this result turned out to be robust after controlling for fixed effects, dynamics, and endogeneity.

Applying a similar approach, Piva and Vivarelli (2005) also found evidence in favor of a positive effect of innovation on employment at the firm level. In particular, by applying panel methodologies to a longitudinal dataset of 575 Italian manufacturing firms over the period 1992–1997, the authors provide evidence of a significant, though small, positive link between firms' gross innovative investment and employment. Using a similar methodological approach, Lachenmaier and Rottmann (2011) 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, showed a significantly positive impact of various innovation variables on labor demand. However, Bogliacino et al. (2012), using a panel database covering 677 European manufacturing and service firms over 19 years (1990–2008), found that a positive and significant impact on employment 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 concluded that process innovation tends to displace employment (although with a weak statistical significance), while product innovation is significantly labor-friendly. The model proposed by Harrison et al. (2014) has been widely tested (see, for instance, Benavente & Lauterbach, 2008; Cirera & Sabetti, 2019; Crespi et al., 2019; Dachs et al., 2016; Hou et al., 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 correspond to the sales from innovative products (i.e. a continuous variable with a relevant variability), process innovations are merely measured by a simple dummy, that is, a discrete measure with constrained variability (in addition, this dummy just captures the "only process" innovations; therefore, process innovation combined with product innovations are not taken into account, in contrast with 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 were identified by Arenas-Díaz et al. (2020), who found a significant labor-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) again found a significant positive impact of the better measured product innovations and a non-significant (negative) effect of process innovation, although the latter becomes significant when the focus is narrowed to cover only the monopolistic sectors.

Van Roy et al. (2018) investigated the possible job creation effect of innovation activity, proxied by patents registered by almost 20,000 European companies over the period 2003–2012. The main outcome of their panel estimations is the labor-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 it is 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 closely linked to product rather than process innovation (see Section 2). Indeed, Bianchini and Pellegrino (2019) provided 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 (Small and Medium Enterprises) 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, found 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 in contrast with other studies, which may be due both to the way process innovation is measured (as a dummy) and to the so-called "business stealing" effect, namely innovative firms gaining market shares at the expense of laggards and non-innovators. However, the authors performed different robustness checks that confirmed their baseline results.

More recent studies have used longitudinal data and a more comprehensive measure of embodied technological change (see Barbieri et al., 2019; Dosi et al., 2021; Pellegrino et al., 2019). Specifically, 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 labor-friendly nature of R&D expenditures and product innovation is confirmed (consistently with the previous evidence), but a possible overall labor-saving impact of embodied technological change incorporated in process innovation is also detected.

2.4 | Wrapping up

Overall, the firm-level 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, characterized by 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 also suggests that at the aggregate (country) level, especially in the short run, technological change can have a negative effect on employment. The effect is however heterogeneous, depending on the characteristics both of markets and of the institutional framework. Innovation is more likely to enhance employment where the compensation effect in terms of price decrease is more pronounced and where product innovation is more frequent (relative to process innovation).

Technical change continuously generates a reallocation of labor across occupations, firms, sectors, and regions.[3] At the aggregate level, the overall impact depends on how firms and jobs are positioned relative to the ongoing process of transformation. It is therefore fundamental to understand the specific nature of recent waves of technical change and to determine how labor, occupations, and their related tasks are transformed. So far, discussion has suggested 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 | THE SECOND WAVE OF TECHNOLOGY-EMPLOYMENT STUDIES: THE REVIVAL OF ROBOTS AND AUTOMATION

A second wave of technology-employment studies has developed since the 2008 crisis, proposing the revival of robots and automation as the main technological artefacts of reference influencing the future of employment scenarios. In line with the organization of the previous section, these studies too can be classified according to their scope of analysis, that is, whether at the aggregate level (countries and sectors) or at the firm level.

3.1 | Automation and employment at the aggregate level

In their seminal contribution, Frey and Osborne (2017) studied computerization defined as job automation by means of computer-controlled equipment. A group of experts hand-labelled 70 occupations from the O*NET database, marking them 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 data from the US Department of Labor, they predicted that 47% of occupational categories, mostly middle- and low-skilled professions, are at high risk of being substituted by job computerization, which includes AI algorithms and robots. Occupations at risk include not only those of blue collar workers, but also a wide range of service/white-collar/cognitive tasks in areas such as accountancy, the health professions, logistics, legal work, translation, and technical writing.

Arntz et al. (2016) used information on task-content of jobs at the individual level (from the PIAAC) and showed that only 9% of US jobs are at potential risk of automation. They compared their results with those of Frey and Osborne (2017) and claimed that within the same occupation some tasks can be automatized while others cannot, and therefore the associated job can be preserved. Indeed, significant differences are found depending on whether the empirical analysis focuses on occupations or tasks. In general terms, forecasting studies which investigate occupations tend to be more pessimistic, while analyses centered 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 PIAAC data, Nedelkoska and Quintini (2018) estimated 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 of 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), bundled jobs according to their estimated risk of automation. Following Frey and Osborne (2017) and Nedelkoska and Quintini (2018), the author utilized highly disaggregated job descriptions and showed that 14% of EU adult workers are found to face a very high risk of automation. Pouliakas also found that routine professions not requiring many social and transversal abilities are particularly vulnerable. Additionally, men and individuals with lower levels of education are at a greater risk of losing their jobs to automation. The author pointed 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.

Acemoglu and Restrepo (2020) investigated the employment effect of exposure to robots using sectoral data provided by the International Federation of Robotics (IFR), estimating national penetration rates instrumented by European data. According to their 2SLS estimates, robotization had a significant negative impact on the change in employment and wages in each US local labor market over the period 1990–2007. Specifically, they showed that one additional robot per thousand workers reduces the employment/population ratio by about 0.18-0.34%. Chiacchio et al. (2018) applied the approach outlined by Acemoglu and Restrepo (2020) to EU labor markets. They assessed the impact of industrial robots on employment and wages in 116 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) used panel data on robot adoption (IFR and EUKLEMS data to estimate robot density) within industries in 17 countries from 1993 to 2007. Dividing employees into three skill groups (namely high-, medium- and low-skilled workers), their estimated employment coefficients for the two higher-skilled groups were positive (but limited in magnitude and not always significant), while the coefficient for low-skilled workers turned out to be large and negative. However, their main finding stands at odds with the studies discussed above since they concluded that robots do not significantly reduce total employment, although they do reduce low-skilled workers' employment share.

Dauth et al. (2021) proposed an empirical exercise on Germany using IFR data over the 1994–2014 timespan, using a measure of local robot exposure for each region. They found no evidence that robots cause total job losses, although they provided 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, counterbalance the negative impact in manufacturing.

Finally, Mann and Püttmann (2023) provided a new measure of automation based on patents, and studied its employment effects. Using keywords, the authors classified all US patents granted between 1976 and 2014 as automation or non-automation patents, and they documented a strong rise in the number and share of automation patents. Interestingly, they linked patents to their industries of use (exploiting an old Canadian patent office cross-classification between patent classes and industries of use), and to commuting zones. They found that automation technology has a positive effect on employment in local labor markets, driven by job growth in the service sector.

3.2 | Robots and employment at the firm level

Domini et al. (2021), using data for French manufacturing employers over the period 2002–2015, found that robotic adoption or, alternatively, imported capital equipment, do not imply labor expulsion, but rather employment growth. However, Bonfiglioli et al. (2020), using French data over the 1994–2013 period, initially obtained a positive employment effect as a response to robot adoption, but then found a negative employment impact of robot exposure, once demand shocks were properly taken into account. Similarly, Humlum (2021), using Danish firm-level data from 1995 to 2015, found 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).

In some studies the positive employment impact at the firm level appears to be entirely due to the business stealing effect, that is, innovative adopters gaining market shares at the expense of non-innovators (Dosi & Mohnen, 2019), since negative employment impacts do emerge once non-adopters and sectoral aggregates are taken into account. Koch et al. (2021) studied robot adoption using data from Spanish manufacturing firms over the period 1990–2016 and found that within four years robot adopters raised their overall employment by around 10%. This positive impact occurs, as expected, in particular among high-skill workers, but is also found 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. Further support for the important role played by the business stealing effect is to be found in Acemoglu et al. (2020), who studied robot adoption using data for French manufacturing firms over the period 2010–2015. While the authors found that among 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 limitation common to both these studies is the simplistic way in which robots are measured, namely as a dummy in the year of adoption.

A gain in competitiveness due to the implementation of robotics may also explain the results found by Dixon et al. (2021): using data capturing imports of robots by Canadian firms over the period 1996–2017, they revealed a positive and significant employment impact of robot capital stock on total employment (although the impact is negative for medium-skilled workers and managers). Aghion et al. (2020), using firm level data for the French manufacturing sector over the time span 1994–2015, also found a positive impact of automation on employment at different levels 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 achieved 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 et al. (2021) discussed a set of interesting stylized facts about robot adoption in Germany. They showed that investment in robots is limited and highly concentrated in only a few industries (for instance, the automobile sector), that the distribution of robots is highly skewed in only a few companies in the manufacturing sectors, and that robot users are larger, have higher labor productivity, make more investments, and are more likely to export and adopt the most cutting-edge technology. Deng et al. (2021) also underlined the relevance of understanding heterogeneity in robot types, suggesting 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) emphasized that the impact of robotics has probably not been the main driver of economic transformation in recent years, and proposed that more attention should be devoted to other technologies.

With regard to the labor market, Benmelech and Zator (2022) showed that firms' adoption in Germany endogenously responds to an index of labor scarcity, measured as a binary firm assessment signaling difficulty in finding workers. In terms of labor impact, the authors found 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 from the contributions discussed above, and points again to the role played by the business stealing effect. However, identification is based on a novel strategy of combining industry-level measures of automation with local area intensity of adoption. The authors 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 above-mentioned studies) may be open to significant challenges.

Bessen et al. (2023), performing an event-study on Dutch firms, reported a higher probability of separation for workers employed in firms where an automation spike has taken place. This study has the pro of using direct automation expenditure as a proxy of technological change at the firm-level, but does not distinguish the type of automation implemented. When compared to employment losses due to plant closures, separation rates due to automation are shown to be one order of magnitude lower than in the case of massive lay-offs.

3.3 | Wrapping up

Although this evidence is not unequivocally consistent, most firm-level studies point to 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 internationalization. A substantial part of this employment growth is related to the so-called selection effect. These companies gain market shares at the expense of smaller and less innovative firms. As a consequence, at the aggregate level, results are mixed. Some papers find a negative impact of robot diffusion at the industry level. As for the results illustrated in Section 2, the negative effect on employment seems to be concentrated in the manufacturing sector and for low-skilled categories.

Some scenarios examined at the aggregate level, many of them based on the seminal work by Frey and Osborne (2017), contradict firm-level findings, and have corroborated the idea that “this time is really different” (Brynjolfsson & McAfee, 2012, 2014; Ford, 2015). A substantial share of occupations seems to be at risk of automation; however, analyses centered on tasks produce more optimistic scenarios because not all tasks in an occupation can possibly be automatized. Moreover, the occupations at risk are not restricted to those of low skilled blue collar workers in downstream manufacturing sectors but extend to a wide range of white-collar jobs in services (e.g., health and finance). Taken together, these contributions clearly indicate a significant reallocation of jobs across industries, and to a relevant transformation of how occupations are configured and tasks are allocated to different occupations. We explore this issue in more depth in Section 5.

4 | THE THIRD WAVE OF TECHNOLOGY-EMPLOYMENT STUDIES: PATENT TEXT CONTENT AND ARTIFICIAL INTELLIGENCE

In this section we present two lines of research: the first group involves analysis of the direct impact of AI on jobs, typically by the use of data on job posts or patents to assess AI exposure and study the impact of AI on employment. The second group of studies involves using patent texts to analyse the proximity between specific innovation functions and occupations and tasks in the labor market. The authors of these studies argue that the description in patent texts can be used to identify the tasks and occupations that are exposed to automation.

Very recent papers have focused on artificial intelligence, often blamed for having a strong labor-saving impact on white-collar jobs more related to service activities. For instance, Felten et al. (2021), refining the measure proposed in Felten et al. (2018), linked the Electronic Frontier Foundation dataset (EFF) within the AI Progress Measurement initiative, with O*NET abilities. They constructed 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. The matching was 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 reported higher AI exposure for white-collar workers.

Webb (2020) also found that artificial intelligence is more likely to affect skilled and older workers than previous innovation waves based on robots or software. He proposed 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 co-occurrence to verb-noun pairs carries 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 permit a distinction between labor-saving and labor-augmenting technologies.

Acemoglu, Autor et al. (2022) looked 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 were employed, namely those proposed by Brynjolfsson et al. (2018), Felten et al. (2021), and Webb (2020). Unsurprisingly, considering the still relatively niche-level nature of adoption, no clear effect at the industry and occupational level was detected, while re-composition towards AI-intensive jobs was suggested. In addition, the authors did 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 productivity enhancement after AI adoption.

Damioli et al. (2022) studied 3,500 front-runner companies who patented AI-related inventions over the period 2000–2016. They found a moderate positive employment impact of AI patenting (with a short-term elasticity of about 3–4%), and this labor-friendly effect combines with that 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.

Kogan et al. (2021) constructed 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, in accordance with the methodology described in Kelly et al. (2021). They built a measure for each (breakthrough) patent-occupation pair and observed how the exposure of an occupation varies over time. Time variability is obtained by summing the similarity with the defined breakthrough innovations in each year *t*, over the period 1850–2010, for each occupation. Breakthrough innovations, identified as the distance between backward and forward similarity of each filed patent compared to the existing stock of patents, are not ex-ante defined as being of a labor-saving nature. However, their measure singles out two types of technology: labor-saving innovations, and new technologies that while potentially complementary to labor, require skills that incumbent workers lack. This measure captures the clustering of technologies under mechanization in the first period of analysis, followed by automation and the ICT phase, and reflects the dynamics of breakthrough innovations according to their emergence during subsequent technological revolutions, quite akin to the findings of Staccioli and Virgillito (2021). They found that most exposed occupations experienced a decrease in wage and employment levels, and that over time white-collar workers become relatively more exposed compared to blue-collar workers. In particular, they found that workers are being replaced at both the top and bottom ends of the wage distribution. From this perspective, low-paid workers lose their jobs as a result of automation, while high-paid workers see slower wage growth, as some of their abilities become obsolete. However, it is not unequivocally clear whether their results reflect more long-run dynamics in technological and structural change, rather than actual similarity between patents and occupations.

The measure proposed by Kogan et al. (2021) was applied by Autor et al. (2022), who were interested in examining the entry of new work titles as revealed in the historical records of the so-called Census Alphabetical Index of Occupations (CAI), an index listing all new job-title entries. The authors defined as 'labor-augmenting' innovations those patents matched with the CAI text (new job titles), and as 'labor-automating' technologies those linked to the DOT text (existing job titles). They showed that the great majority of employment is in new jobs. The paper documents the increasing entry of white-collar middle-paid occupations in the period 1940–1980; since 1980 new jobs have been concentrated in services provided by both high-educated and low-educated workers. They also showed that 'labor-augmenting' patents and 'labor-automating' patents are correlated across occupations but have different causal effects on labor demand. The former have a positive and the latter a negative effect, with the negative effect of automation having intensified over time.

Another application of the measure proposed by Kogan et al. (2021) with reference to patents characterizing the current technologies was adopted 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. (2022) relied on textual analysis of USPTO patent applications in robotics and performed a semantic study to identify labor-saving innovations directly. They estimated a probabilistic topic model and proposed a human-machine taxonomy that describes the specific work activities and functions which are more exposed to labor-saving innovation, and found that the following activities are particularly exposed to labor-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. Montobbio et al. (2023) presented one of the first attempts at building a direct measure of occupational exposure to robotic labor-saving technologies. After identifying robotic and labor-saving robotic patents (Montobbio et al., 2023), they leveraged the 4-digit Cooperative Patent Classification (CPC) code definitions to detect functions and operations performed by technological artefacts aimed at substituting the labor input. This measure results in fine-grained information on tasks and occupations more exposed to labor-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 was then studied, complemented by investigating industry and geographical penetration rates. The authors showed that in the last two decades the occupations most exposed to robotic labor-saving technologies are associated with lower rates of employment and wage growth.

4.1 | Wrapping up

Most recent studies reported in the literature are moving towards the construction of direct measures of labor market exposure to technological change. Researchers have tried to bypass the construction of indirect proxies of technological penetration, such as the degree of routinization (discussed in the next section of this paper). This third wave mainly relies on patent data (analysed by means of natural language processing (NLPs) in their titles, abstracts and texts) overlapped with a glossary of occupation titles. Differently from the first and second waves of technology-employment studies, these papers have increased our understanding of occupation exposure to automation at a higher level of granularity and are a first attempt at tackling the issue of distinguishing whether innovations are labor displacing or complementary to existing human functions at the patent level. As regards innovations related to artificial intelligence, although work is at a very preliminary stage, results show that white-collar workers and knowledge workers could be relatively more affected. However, it is possible to argue that it is too early to detect large labor market consequences, and that at present greater effects could be observed with respect to the quality rather than the quantity of work (Berg & Gmyrek, 2023). In order to reveal the reconfiguration of the quality of work, in the following section we survey the results reached so far on the skill-biased, routine-biased and task-biased nature of technological change.

5 | 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 characterized by the simultaneous occurrence of substitution and complementary effects. The economic literature has therefore taken up the challenge of more detailed analysis of the impact of technical change on skills, occupations, and tasks.

5.1 | Skill-biased and routine biased technological change

The early literature produced in the '90s, in line with the empirical results emphasized in Sections 2 and 3, 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-collar workers usually considered the "skilled" category), given that the latter are able to implement these technologies effectively and efficiently. Therefore, while a positive relationship between new technologies and the demand for 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 generally recognized (see Bernan et al., 1994; Los et al., 2014; Machin & Van Reenen, 1998; Piva & Vivarelli, 2004).

In line with the SBTC approach, Blanas et al. (2019) analysed 30 industries across 10 high-income countries over the period 1982–2005 and found 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 digitization activities within Swiss firms in 2015, found that digitalization (and particularly the presence of robots, 3D printing and the Internet of Things) is significantly associated with job losses among mid- and low-skill workers, and with job creation among high-skill workers.

In contrast with the idea that technologies are skill biased, Hirvonen et al. (2022) used 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 looked in particular at robots and computer numerical control (CNC) machines, and exploited a large technology subsidy program, comparing proximate winners and losers using an event-study approach. They found that on average subsidy-induced technology investments drive a 23% increase in employment with no skill bias. However, their results are strongly driven by product innovations (see Section 2 on the labor-friendly nature thereof): indeed, 91% of the scrutinized firms claimed 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 measured firm-level effects of investment in automation/digitization technologies. The authors focused on the firm-level share of software developers and singled out substantial increases in the relative hiring measured as investment spikes: the latter are defined therein as increases of 1% or 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 firms 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 approach for policymakers in the fight against income inequality and pay disparity in the labor market. Researchers who believe that automation only replaces labor tend to suggest strategies for redistributing income, levying taxes to discourage excessive automation, and even encouraging engineers to forego development in the first place. However, if automation primarily complements workers, leading to higher wage disparities between firms, policy may need to be focused on minimizing gaps in firms' uneven adoption of technology.

However, during the last two decades there has also been a trend in labor markets leading to job polarization and wage inequality, together with a decreasing demand for middle-wage occupations (Autor, 2019, 2022). This means that if jobs are ranked by their wages, increases in employment share 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, laborers and elementary service providers (the low-paid) are to some extent increasing, and professionals (the high-paid) are growing, while workers in middle-wage occupations (such as operators of machinery/electronic equipment) are declining. This U-shaped curve represents the aforementioned polarization phenomenon, supported by evidence related to both flexible labor markets (as in the case of the UK and US, see Autor, 2019; Autor et al., 2006; Goos & Manning, 2007; Goos et al., 2014) and institutional settings characterized by a higher degree of employment protection (e.g., Sweden and Germany, respectively, Adermon & Gustavsson, 2015; Spitz-Oener, 2006). This suggests that not only occupation and education are relevant, but that the "routine dimension" comes into play, and attention should be paid to the actual content of 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 then 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 digitization originating a substitution effect), while non-repetitive tasks may reap benefits from these technologies (or, at least, not be negatively affected, as in the case of non-routinized unskilled tasks in personal services), determining a complementary effect.

5.2 | From skills to tasks: Measurement issues and empirical evidence

Acemoglu and Autor (2011, p. 1045) defined 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 labor 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 labor (in this context, capital generally refers to machines and robots). Acemoglu and Autor (2011), therefore, proposed a classification based on a two-dimensional typology: routine versus non-routine, and manual versus cognitive. This led 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, that is, 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 resulting in possible complementary effects.

Biagi and Sebastian (2018) discussed how task-content is measured in empirical analyses. They underlined the fact 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 assessment by experts (e.g., the O*NET—Occupational Information Network, based on the US labor market, describes the task content of each occupation); (2) self-reported measures, aggregating the answers of individual workers to surveys on skills and working conditions: see, for example, the Federal Institute for Vocational Training/Research Institute of the Federal Employment Service in Germany (IAB/BIBB), the OECD Program 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 ICP (Indagine Campionaria delle Professioni), comparable to the US O*NET, performed a data-driven dimensionality reduction factor analysis. They found that specific interaction with tools and machinery (routinization) is not what determines the variability between occupations, but rather that the latter depends on 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 the unique framework for occupational data analysis, and tasks can be classified depending on the information available in the dataset used and on the ground of other theoretical reasoning. 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) showed 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 permit study of 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.

Turning our attention to the available empirical evidence, the previously-cited seminal contribution by Autor et al. (2003) focused on the relationship between new technologies and skills/tasks, showing that innovation can replace human labor when it is largely based on routines, but it can hardly replace non-routine tasks where technology is complementary. Their analysis, covering a 1984–1997 timespan and referring to general computer use and ICTs, bridges SBTC and TBTC, as the authors considered and measured the tasks involved in each of the 450 occupations included in the Dictionary of Occupational Titles. Each occupation received a score for each of the task measures. Moreover, they measured technological change by the evolution of the share of workers in the industry who use computers 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, these seemed to be unrelated to technological change until the 1990s, when a positive and significant relationship between them emerged.

Caines et al. (2018), after formulating a model on TBTC with a special focus on complex tasks, studied 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 measured the task complexity of an occupation by performing principal component analysis on a broad set of occupational descriptors in O*NET data, and established 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, the routine-intensity of an occupation is not a significant predictor of wage growth and wage levels; labor has reallocated from less complex to more complex occupations over time; within groups of occupations with similar task complexity, labor 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 labor demand and employment effects of RRTC, proposed an empirical analysis on regional data (238 regions) across 27 European Union countries between 1999 and 2010. They showed 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 labor demand. Firstly, RRTC reduces labor demand through substitution effects, as declining capital costs push firms which are restructuring production processes towards routine tasks. Secondly, RRTC induces additional labor demand by increasing product demand, as declining capital costs reduce the prices of tradables. Thirdly, product demand spillovers also create additional labor demand: the increase in product demand raises incomes, which is partially spent on low-tech non-tradables, raising local labor demand. The first of these three forces acts to reduce labor demand, whereas the latter two work in the opposite direction (in a sort of compensation mechanism). As such, the net labor demand effect of RRTC is theoretically ambiguous.

Marcolin et al. (2019) exploited data from PIAAC merged with the United States Current Population Survey (CPS) and the European Labor 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 on 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) highlighted the fact that routine intensity is lower for more sophisticated occupations, that is, those less likely to be routinized. On average, in 2012 46% of employees in PIAAC countries were working in non-routine-intensive (18%) or low-routine-intensive (28%) occupations. The authors also provided 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 slightly related to their human capital or the job functions they are attached to through their occupational titles.

De Vries et al. (2020) combined 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.

5.3 | Wrapping up

Taken as a whole, the extant evidence supports the idea that when tasks are based on standardized processes, innovations can generally replace them. At the same time, technology can be an important complement to non-standardized 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 have been unconnected to technological advance until the 1990s, when a positive correlation started to emerge. The routine content of occupations is also associated with a lower skill intensity (see also Autor, 2022). Together with the idea that digitalization 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 routinized 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 labor market.

6 | KEY FINDINGS AND GAPS IN THE EXTANT LITERATURE

Table A1 provides a synoptic picture of the most recent and seminal works devoted to the issues investigated in this survey.

The extant literature points to the following outcomes.

(i) The employment and skill effects of technical change are heterogeneous and differ according to the level of aggregation, the adopted proxy for technology, and the unit of analysis, whether sectoral versus firm, or occupations versus tasks. In more detail, an overall positive impact of innovation on employment is detected by most previous firm-level studies, suggesting some degree of complementarity between technological change and employment (see also Hötte, Somers et al., 2022). While this complementarity is easy to comprehend at the company level, it becomes more controversial at the sectoral and aggregate levels. Moreover, it tends to be small in magnitude and limited to the most innovative firms and the most dynamic and high-tech sectors, while labor-saving effects may well arise in low-tech sectors, particularly in manufacturing (see Section 3.1). When we consider 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 in terms of both employment and wages, in particular in manufacturing (in contrast, some service sectors seem to benefit in terms of employment). On the other hand, firm-level analyses on adopting firms tend to confirm a positive employment impact after the introduction of new automation technologies, although of negligible magnitude, possibly due to selection and business stealing effects and often contrasting with an overall sectoral negative impact.

(ii) Recent developments in the literature provide interesting attempts to build direct measures of labor market exposure to technological change (Section 4). Exploiting patent texts, natural language processing (NLPs), and the glossaries of occupations and tasks, these papers provide a higher level of granularity in the analysis of the relationship between innovations, their functions, and tasks required by the labor market. They raise the issue of eliciting labor saving innovations directly, or innovations that are complementary to existing skills.

(iii) 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 has not found skill-bias (Hirvonen et al., 2022), or has suggested that innovation generates a general positive impact at the firm level in terms of labor quality (Bessen et al., 2022), suggesting that the key issue is not skilled versus 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, on routinized versus non-routinized tasks and occupations, or manual versus cognitive tasks and occupations. Together with the hypothesis that job losses among mid- and low-skill employees may be significantly due to digitalization, there is evidence of a shift in employment over time to more complex, cognitive and non-routine occupations (Section 5.2). In general, occupational-level analyses tend to overstate negative labor-shedding effects, while task-based analyses are more conservative in their negative estimates. Forecasting studies point to an overall substitution effect: according to the different studies, 9% to 47% of jobs are at risk and are concentrated within more routinized 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 (see also Section 4).

Albeit extensive and diverse, the extant empirical literature is not free 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: these range from more traditional product versus process innovation at the firm level (proxied either by R&D expenditures, or patents, or embodied technological change), to the share of robots at the industry level, to imported capital-equipment, to expenditure in electricity, to the 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 labor-saving employment impact. Therefore, researchers should be cautious from a twofold perspective: on the one hand, given the data available and the perspective adopted, they should choose the most appropriate proxy for innovation;[4] on the other hand, once they have chosen a given proxy, they should take into account the aforementioned *ex-ante* biases in terms of the expected 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 disentangle in empirical analyses. With the exception of only a few aggregate studies (see Section 2.1) and some very recent contributions (see Acemoglu & Restrepo, 2022; Humlum, 2021) 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 labor-saving effect on the one hand, and on a selection of possible compensating market forces on the other (such as the "via decreasing prices" mechanism 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 shares). However, while microeconometric studies appear to be extremely precise in grasping the nature of innovation and in distilling information from very large datasets, they inevitably lose 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: while technological change is driven by science and characterized by a high degree of path-dependence, 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 expresses awareness of this issue, which is generally mitigated by means of two different strategies. Starting from Piva and Vivarelli (2005), one 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 characterized 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 Dosi et al., 2021; Lachenmaier & Rottmann, 2011; Pellegrino et al., 2019). Another strand of literature, initiated by Acemoglu and Restrepo (2020), 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 those in the US; see also Chiacchio et al., 2018 and Dauth et al., 2021).

(iii) A further gap in the current economic literature is its limited degree of granularity in dealing with different technologies. A finer analysis of the relationship between specific technological advancements, tasks, and skills becomes necessary for a detailed understanding of the impact on skills, the nature of job reallocation, the degree of obsolescence of tasks, and the possibility to learn on the job. A more granular measurement of technologies is also required to design appropriate policy interventions affecting skill supply, labor market institutions and government policies, such as 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 digitization, 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 organizational changes are more oriented towards a recombination of tasks performed by the same workforce (reallocated across different functions and departments) rather than to purely labor-saving and skill-biased strategies. In other cases, product modularity together 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 generally geographically dispersed, as additive manufacturing affects the structure of vertical relations and can be associated with reshoring. However, heterogeneity and selectivity in adoption strategies emerge as stylized facts. For instance, Cirillo et al. (2021) conducted a case study of three pivotal adopters of I4.0 artefacts and departed from the archetypal idea of a fully-fledged I4.0 factory. Indeed, they found that the introduction and use of I4.0 artefacts are scattered both between and within firms, and across different departments. In particular, not all production processes are affected to the same extent. Currently, the areas most involved 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 timely recording of the production process, the quantity produced in each phase, the errors which occurred, and possible underlying bottlenecks. Similarly, recent digitization and innovation surveys (Acemoglu, Anderson et al., 2022 for US; Costa et al., 2023 and Calvino et al., 2022 for Italy) conducted by national statistical offices through the administering of firm-level questionnaires about the level of ICT and robot adoptions reveal that implementation thereof constitutes 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 adopt selectively the most appropriate type of technology to solve specific, localized problems.

(iv) In addition, the narrow focus on robotization by the recent empirical literature should be seen as a further shortcoming. At the very least, future studies 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). Initial attempts in this direction have been made by Acemoglu et al. (2022), 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 be established 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 & Norvig, 2016). On the other hand, although 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 Giczy et al., 2022; Martínez-Plumed et al., 2020), several 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" (Damioli et al., 2022; European Commission, 2018; Fujii & Managi, 2018; WIPO, 2019). Obviously, the way in which AI technologies are singled out and measured may affect the results obtained in terms of their labor market effects (see Autor, 2022; Hötte, Tarannum et al., 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 labor-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 regarding a possible job-creation effect in the supply side, among developers of AI and robots conceived as product innovations in the upstream sectors. Initial investigations in this direction include Damioli et al. (2022).

(v) Finally, a major challenge for future research in this area should be to address the impact of technological transformation on labor quality, 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 under what conditions, workers do their jobs. To disentangle such transformations, greater granularity is needed in the analysis of different technologies to gain a precise understanding of their heterogeneous impacts on tasks, occupations, and working conditions. Some authors, focusing on highly innovative firms, have shown, 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 have found 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., Acemoglu, 2021; Hammerling, 2022). In this respect, the analysis of technological organizational capabilities at the workplace level, 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 labor market regulations) are particularly promising and interesting avenues for research.

7 | CONCLUSIONS

In this critical survey we have discussed the main technological drivers playing a role in determining the employment impact of new technologies. 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, the available empirical evidence 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 in 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 automation than non-routinised tasks, with some of the latter turning out to be complementary to the new technologies, in particular AI. Although the current standard economic conceptualization is based on the contrast between automatable and non-automatable tasks, decision choices regarding technological adoptions and firm-level techno-organizational capabilities are crucial factors in explaining across-firm heterogeneity, the mix of technology in use, and the effects on the workforce.

While more fine-grained microeconomic studies, based on selected samples (in terms of geography or technology), help to further understanding of how technological change transforms occupations, tasks, and the related quality of work and working conditions, these types of studies may not be generalized to different contexts. Indeed, more general considerations and analyses at the aggregate level help in understanding the technology-employment nexus in contexts in which other forces, such as institutional and structural change, also drive the dynamics of the labor market. Our understanding is that the issue remains at the core of the agenda of economics in general, and of classical political economics in particular; that said, both additional empirical evidence, and further efforts are required on the theoretical side. Some instances have been devised by means of macro-economic and sectoral evolutionary agent-based 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, and to address the theoretical conditions under which the labor displacing versus labor augmenting effects of technology prevail.

Finally, beyond market-based considerations concerning cost of labor and skill requirements, the role of institutions (e.g., in regulating job contracts, industrial relations, minimum wage and employment termination conditions) and of the overall macroeconomic development of a country remain among the most prominent drivers of employment dynamics and labor remuneration. These represent other future avenues of research.

ACKNOWLEDGMENTS

This paper has been developed as a background note for the report "The Future of Work: Implications for Equity and Growth in Europe" commissioned by the World Bank. The authors wish to thank the editor of the Journal and two anonymous reviewers for their helpful comments. M.V. also acknowledges the support by the Italian Ministero dell'Istruzione, dell'Università e della Ricerca (PRIN-2022, project 2022P499ZB: "Innovation and labor market dynamics").

DATA AVAILABILITY STATEMENT

Data sharing is not applicable to this article as no new data were created or analysed in this study.

ORCID

Maria Enrica Virgillito https://orcid.org/0000-0001-5958-9647

ENDNOTES

[1] There is a vast literature about the nature, limitations and *pros* and *cons* of the different variables used as proxies of innovation. For instance, R&D is an input measure, so pointing to potential innovation, driven by specific factors (being larger in big firms and high-tech sectors, for a recent survey and analysis see Goel et al., 2023),) and neglecting the embodied technological change incorporated in capital information (see *infra*). Moreover, R&D expenditures may be private, public or subsidised with relevant implications in terms of possible complementarities, substitution effects and additionality (see, for instance, Bérubé and Mohnen, 2009; Catozzella and Vivarelli, 2016; David and Hall, 2000). On the other hand, patents are an output measure but their relevance is dramatically different according to the investigated sectors, the nature of the involved technologies and the appropriability conditions in terms of institutional setting and IPRs (see, for instance, Levin et al., 1987; Hall, 2005; Goel, 2020). Although very important, these issues are beyond the scope and aims of the present study.

[2] In a similar vein, Vermeulen et al. (2018), put forward an evolutionary economic model of multisectoral structural change and discussed descriptive evidence showing how job losses due to automation in "applying" sectors may be counterbalanced by job creation in "making" sectors.

[3] Indeed, the regional dimension is explicitly taken into account in some of the articles discussed in this section (such as Buerger et al., 2010), as well as in Capello and Lenzi (2013), Moroc and Bărnutiu (2019) and Mondolo (2023); since the geographical focus is not within the scope of the present survey, we readdress the reader to the cited articles.

[4] For instance, if the investigated firms are small enterprises in traditional sectors, R&D expenditures might be a poor proxy for innovation, while the opposite might be true for large companies in high-tech industries.

REFERENCES

Acemoglu, D. (2021). *Harms of AI*. NBER Working Paper 29247.

Acemoglu, D., Anderson, G., Beede, D., Buffington, C., Childress, E., Dinlersoz, E., Foster, L., Goldschlag, N., Haltiwanger, J., Kroff, Z., Restrepo, P., & Zolas, N. (2022). *Automation and the Workforce: A Firm-Level View from the 2019 Annual Business Survey*. NBER Working Paper 30659.

Acemoglu, D., & Autor, D. H. (2011). Skills, tasks and technologies: Implications for employment and earnings. In (D Card and O Ashenfelter Eds.), *Handbook of labor economics* (4(B), pp. 1043–1171). Elsevier. https://doi.org/10.1016/S0169-7218(11)02410-5

Acemoglu, D., Autor, D. H., Hazell, J., & Restrepo, P. (2022). AI and jobs: Evidence from online vacancies. *Journal of Labor Economics*, *40*(S1), S293–S340. https://doi.org/10.1086/718327

Acemoglu, D., Lelarge, C., & Restrepo, P. (2020). Competing with Robots: Firm-level evidence from France. *AEA Papers and Proceedings*, *110*, 383–388. https://doi.org/10.1257/pandp.20201003

Acemoglu, D., & Restrepo, P. (2018). The race between man and machine: Implications of technology for growth, factor shares, and employment. *American Economic Review*, *108*(6), 1488–1542. https://doi.org/10.1257/aer.20160696

Acemoglu, D., & Restrepo, P. (2019). Automation and new tasks: How technology displaces and reinstates labor. *Journal of Economic Perspectives*, *33*(2), 3–30. https://doi.org/10.1257/jep.33.2.3

Acemoglu, D., & Restrepo, P. (2020). Robots and jobs: Evidence from US labor markets. *Journal of Political Economy*, *128*(6), 2188–2244. https://doi.org/10.1086/705716

Acemoglu, D., & Restrepo, P. (2022). Tasks, automation, and the rise in U.S. wage inequality. *Econometrica*, *90*(5), 1973–2016. https://doi.org/10.3982/ECTA19815

Adermon, A., & Gustavsson, M. (2015). Job polarization and task-biased technological change: Evidence from Sweden, 1975–2005. *Scandinavian Journal of Economics*, *117*(3), 878–917. https://doi.org/10.1111/sjoe.12109

Aghion, P., Antonin, C., Jaravel, X., & Bunel, S. (2020). *What are the labor and product market effects of automation? New evidence from France*. CEPR discussion paper DP14443.

Antonucci, T., & Pianta, M. (2002). Employment effects of product and process innovation in Europe. *International Review of Applied Economics*, *16*(3), 295–307. https://doi.org/10.1080/02692170210136127

Arenas-Díaz, G., Barge-Gil, A., & Heijs, J. (2020). The effect of innovation on skilled and unskilled workers during bad times. *Structural Change and Economic Dynamics*, *52*, 141–158. https://doi.org/10.1016/j.strueco.2019.09.012

Arntz, M., Gregory, T., & Zierahn, U. (2016). *The Risk of Automation for Jobs in OECD Countries: A Comparative Analysis*. OECD Social, Employment and Migration Working Papers No. 189.

Arntz, M., Gregory, T., & Zierahn, U. (2017). Revisiting the risk of automation. *Economics Letters*, *159*, 157–160. https://doi.org/10.1016/j.econlet.2017.07.001

Autor, D. H. (2019). Work of the past, work of the future. *AEA Papers and Proceedings*, *109*, 1–32. https://doi.org/10.1257/pandp.20191110

Autor, D. H. (2022). *The labor market impacts of technological change: from unbridled enthusiasm to qualified optimism to vast uncertainty*. NBER Working Paper 30074.

Autor, D. H., & Dorn, D. (2013). The growth of low-skill service jobs and the polarization of the US labor market. *American Economic Review*, *103*(5), 1553–1597. https://doi.org/10.1257/aer.103.5.1553

Autor, D. H., Katz, L. F., & Kearney, M. S. (2006). The polarization of U.S. labor market. *American Economic Review*, *96*(2), 189–194. https://doi.org/10.1257/000282806777212620

Autor, D. H., Levy, F., & Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *Quarterly Journal of Economics*, *118*(4), 1279–1333. https://doi.org/10.1162/003355303322552801

Autor, D. H., Salomons, A., & Seegmiller, B. (2022). *New Frontiers: The Origins and Content of New Work, 1940–2018*. NBER Working paper 30389.

Balliester, T., & Elsheikhi, A. (2018). *The future of work: a literature review*. ILO Research Department Working Paper 29.

Balsmeier, B., & Woerter, M. (2019). Is this time different? How digitalization influences job creation and destruction. *Research Policy*, *48*(8), 103765. https://doi.org/10.1016/j.respol.2019.03.010

Barbieri, L., Piva, M., & Vivarelli, M. (2019). R&D, embodied technological change, and employment: evidence from Italian microdata. *Industrial and Corporate Change*, *28*(1), 203–218. https://doi.org/10.1093/icc/dty001

Benavente, J. M., & Lauterbach, R. (2008). Technological innovation and employment: Complements or substitutes? *European Journal of Development Research*, *20*, 318–329. https://doi.org/10.1080/09578810802060744

Benmelech, E., & Zator, M. (2022). Robots and Firm Investment. NBER Working Paper 29676.

Berg, J., & Gmyrek, P. (2023). Automation hits the knowledge worker: ChatGPT and the future of work. In *UN Multi-Stakeholder Forum on Science, Technology and Innovation for the SDGs (STI Forum)*.

Bernan, E., Bound, J., & Griliches, Z. (1994). Changes in the demand for skilled labor within US manufacturing industries: Evidence from the Annual Survey of Manufacturing. *Quarterly Journal of Economics*, *109*(2), 367–397. https://doi.org/10.2307/2118467

Bérubé, C., & Mohnen, P. (2009). Are firms that receive R&D subsidies more innovative? *Canadian Journal of Economics*, *42*, 206–225.

Bessen, J. (2015). *Learning by doing: The real connection between innovation, wages, and wealth*. Yale University Press.

Bessen, J., Denk, E., & Meng, C. (2022). *The Remainder Effect: How Automation Complements Labor Quality*. Boston University School of Law Research Paper No. 22–3.

Bessen, J., Goos, M., Salomons, A., & van den Berge, W. (2023). What happens to workers at firms that automate? *The Review of Economics and Statistics*, 1–45.

Biagi, F., & Sebastian, R. (2018). *The Routine Biased Technical Change hypothesis: A critical review*. Publications Office of the European Commission, catalogue number KJ-NA-29364-EN-N. https://doi.org/10.2760/986914

Bianchini, S., & Pellegrino, G. (2019). Innovation persistence and employment dynamics. *Research Policy*, *48*(5), 1171–1186. https://doi.org/10.1016/j.respol.2018.12.008

Blanas, S., Gancia, G., & Lee, S. J. (Tim) (2019). Who is afraid of machines? *Economic Policy*, *34*(100), 627–690. https://doi.org/10.1093/epolic/eiaa005

Bogliacino, F., & Pianta, M. (2010). Innovation and employment. A reinvestigation using revised Pavitt classes. *Research Policy*, *39*(6), 799–809. https://doi.org/10.1016/j.respol.2010.02.017

Bogliacino, F., Piva, M., & Vivarelli, M. (2012). R&D and employment: An application of the LSDVC estimator using European data. *Economics Letters*, *116*(1), 56–59. https://doi.org/10.1016/j.econlet.2012.01.010

Bogliacino, F., & Vivarelli, M. (2012). The job creation effect of R&D expenditures. *Australian Economic Papers*, *51*(1), 96–113. https://doi.org/10.1111/j.1467-8454.2012.00425.x

Bonfiglioli, A., Crinò, R., Fadinger, H., & Gancia, G. (2020). *Robot Imports and Firm-Level Outcomes*. CEPR Discussion Paper No. DP14593.

Brynjolfsson, E., & McAfee, A. (2012). *Race against the machine: How the digital revolution is accelerating innovation, driving productivity, and irreversibly transforming employment and the economy*. Digital Frontier Press.

Brynjolfsson, E., & McAfee, A. (2014). *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*. W. W. Norton & Company.

Brynjolfsson, E., Mitchell, T., & Rock, D. (2018). What can machines learn, and what does it mean for occupations and the economy? *AEA Papers and Proceedings*, *108*, 43–47. https://doi.org/10.1257/pandp.20181019

Buerger, M., Broekel, T., & Coad, A. (2010). Regional dynamics of innovation: Investigating the co-evolution of patents, research and development (R&D), and employment. *Regional Studies*, *46*(5), 565–582. https://doi.org/10.1080/00343404.2010.520693

Caines, C., Hoffmann, F., & Kambourov, G. (2018). Complex-task biased technological change and the labor market. *Review of Economic Dynamics*, *25*, 298–319. https://doi.org/10.1016/j.red.2017.01.008

Calvino, F., DeSantis, S., Desnoyers-James, I., Formai, S., Goretti, I., Lombardi, S., Manaresi, F., & Perani, G. (2022). *Closing the Italian digital gap: The role of skills, intangibles and policies*. OECD Science, Technology and Industry Policy Papers No. 126.

Calvino, F., & Virgillito, M. E. (2018). The innovation employment nexus: A critical survey of theory and empirics. *Journal of Economic Surveys*, *32*(1), 83–117. https://doi.org/10.1111/joes.12190

Capello, R., & Lenzi, C. (2013). Innovation and employment dynamics in European Regions. *International Regional Science Review*, *36*(3), 322–353. https://doi.org/10.1177/0160017612462874

Catozzella, A., & Vivarelli, M. (2016). The possible adverse impact of innovation subsidies: Some evidence from Italy. *International Entrepreneurship and Management Journal*, *12*, 351–368. https://doi.org/10.1007/s11365-014-0342-3

Cetrulo, A., & Nuvolari, A. (2019). Industry 4.0: revolution or hype? Reassessing recent technological trends and their impact on labor. *Journal of Industrial and Business Economics*, *46*(3), 391–402. https://doi.org/10.1007/s40812-019-00132-y

Cetrulo, A., Guarascio, D., & Virgillito, M. E. (2020). Anatomy of the Italian occupational structure: Concentrated power and distributed knowledge. *Industrial and Corporate Change*, *29*(6), 1345–1379. https://doi.org/10.1093/icc/dtaa050

Chiacchio, F., Petropoulos, G., & Pichler, D. (2018). *The impact of industrial robots on EU employment and wages: A local labor market approach*. Bruegel Working Paper 2018/02.

Cirera, X., & Sabetti, L. (2019). The effects of innovation on employment in developing countries: Evidence from enterprise surveys. *Industrial and Corporate Change*, *28*(1), 161–176. https://doi.org/10.1093/icc/dty061

Cirillo, V., Rinaldini, M., Staccioli, J., & Virgillito, M. E. (2021). Technology vs. workers: The case of Italy's Industry 4.0 factories. *Structural Change and Economic Dynamics*, *56*, 166–183. https://doi.org/10.1016/j.strueco.2020.09.007

Clark, J. (1983). Employment projections and technological change. In (D. L. Bosworth Ed.), *The employment consequences of technical change* (pp. 110–125). Palgrave Macmillan.

Clark, J. (1987). A vintage-capital simulation model. In (C. Freeman & L. Soete Eds.), *Technical change and full employment* (pp. 86–98). Basil Blackwell.

Christofzik, D., Elstner, S., Feld, L. P., & Schmidt, C. M. (2021). *Unraveling the Productivity Paradox: Evidence for Germany*. CEPR Discussion Paper No. DP16187.

Costa, S., De Santis, S., Dosi, G., Monducci, R., Sbardella, A., & Virgillito, M. E. (2023). From organizational capabilities to corporate performances: at the roots of productivity slowdown. *Industrial and Corporate Change*, *32*, 1217–1244. https://doi.org/10.1093/icc/dtad030

Crespi, G., Tacsir, E., & Pereira, M. (2019). Effects of innovation on employment in Latin America. *Industrial and Corporate Change*, *28*(1), 139–159. https://doi.org/10.1093/icc/dty062

Dachs, B., Hud, M., Koehler, C., & Peters, B. (2016). Innovation, creative destruction and structural change: Firm-Level evidence from European countries. *Industry and Innovation*, *24*(4), 346–381. https://doi.org/10.1080/13662716.2016.1261695

Damioli, G., Van Roy, V., & Vertesy, D. (2021). The impact of artificial intelligence on labor productivity. *Eurasian Business Review*, *11*, 1–25. https://doi.org/10.1007/s40821-020-00172-8

Damioli, G., Van Roy, V., Vertesy, D., & Vivarelli, M. (2022). AI technologies and employment. Micro evidence from the supply side. *Applied Economics Letters*, *30*(6), 816–821. https://doi.org/10.1080/13504851.2021.2024129

David, P. A., & Hall, B H. (2000). Heart of darkness: Modeling public-private funding interactions inside the R&D black box. *Research Policy*, *29*(9), 1165–1183.

Dauth, W., Findeisen, S., Südekum, J., & Woessner, N. (2021). The adjustment of labor markets to robots. *Journal of the European Economic Association*, *19*(6), 3104–3153. https://doi.org/10.1093/jeea/jvab012

Deng, L., Plümpe, V., & Stegmaier, J. (2021). *Robot adoption at German plants*. IWH Discussion Papers 19/2020.

de Vries, G J., Gentile, E., Miroudot, S., & Wacker, K M. (2020). The rise of robots and the fall of routine jobs. *Labor Economics*, *66*, 101885. https://doi.org/10.1016/j.labeco.2020.101885

Dixon, J., Hong, B., & Wu, L. (2021). The Robot revolution: Managerial and employment consequences for firms. *Management Science*, *67*(9), 5586–5605. https://doi.org/10.1287/mnsc.2020.3812

Domini, G., Grazzi, M., Moschella, D., & Treibich, T. (2021). Threats and opportunities in the digital era: Automation spikes and employment dynamics. *Research Policy*, *50*(7), 104137. https://doi.org/10.1016/j.respol.2020.104137

Dosi, G., & Mohnen, P. (2019). Innovation and employment: An introduction. *Industrial and Corporate Change*, *28*(1), 45–49. https://doi.org/10.1093/icc/dty064

Dosi, G., Pereira, M. C., Roventini, A., & Virgillito, M. E. (2022). Technological paradigms, labor creation and destruction in a multi-sector agent-based model. *Research Policy*, *51*(10), 104565. https://doi.org/10.1016/j.respol.2022.104565

Dosi, G., Piva, M., Virgillito, M. E., & Vivarelli, M. (2021). Embodied and disembodied technological change: The sectoral patterns of job-creation and job-destruction. *Research Policy*, *50*(4), 104199. https://doi.org/10.1016/j.respol.2021.104199

Ertel, W. (2018). *Introduction to artificial intelligence: Undergraduate topics in computer science*. Springer.

European Commission. (2018). *Artificial Intelligence: A European Perspective*. European Commission Joint Research Centre, Seville. https://doi.org/10.2760/936974

Evangelista, R. (2000). Innovation and employment in services. In (M Vivarelli and M Pianta Eds.), *The Employment Impact of Innovation: Evidence and Policy* (pp. 121–148). Routledge.

Evangelista, R., & Savona, M. (2002). The impact of innovation on employment in services: Evidence from Italy. *International Review of Applied Economics*, *16*(3), 309–318. https://doi.org/10.1080/02692170210136136

Feldmann, H. (2013). Technological unemployment in industrial countries. *Journal of Evolutionary Economics*, *23*, 1099–1126. https://doi.org/10.1007/s00191-013-0308-6

Felten, E. W., Raj, M., & Seamans, R. (2018). A method to link advances in artificial intelligence to occupational abilities. *AEA Papers and Proceedings*, *108*, 54–57. https://doi.org/10.1257/pandp.20181021

Felten, E. W., Raj, M., & Seamans, R. (2021). Occupational, industry, and geographic exposure to artificial intelligence: A novel dataset and its potential uses. *Strategic Management Journal*, *42*(12), 2195–2217. https://doi.org/10.1002/smj.3286

Ford, M. (2015). *The rise of the robots: Technology and the threat of mass unemployment*. Basic Books, a member of the Pereus Books Group.

Freeman, C., Clark, J., & Soete, L. (1982). *Unemployment and technical innovation*. Pinter.

Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation?' *Technological Forecasting and Social Change*, *114*, 254–280. https://doi.org/10.1016/j.techfore.2016.08.019

Fujii, H., & Managi, S. (2018). Trends and priority shifts in artificial intelligence technology invention: A global patent analysis. *Economic Analysis and Policy*, *58*, 60–69. https://doi.org/10.1016/j.eap.2017.12.006

Giczy, A. V., Pairolero, N. A., & Toole, A. A. (2022). Identifying artificial intelligence (AI) invention: A novel AI patent dataset. *Journal of Technology Transfer*, *47*, 476–505. https://doi.org/10.1007/s10961-021-09900-2

Goel, R. K. (2020). IPR infringement in the United States: Impacts on the input and output of R&D. *Journal of Technology Transfer*, *45*(2), 481–493. https://doi.org/10.1007/s10961-018-9708-y

Goel, R. K., Göktepe-Hultén, D., & Nelson, M. A. (2023). Drivers of international research spending. *Annals of Science and Technology Policy*, *7*(1), 1–80.

Goel, R. K., & Nelson, M. A. (2022). Employment effects of R&D and process innovation: Evidence from small and medium-sized firms in emerging markets. *Eurasian Business Review*, *12*, 97–123. https://doi.org/10.1007/s40821-022-00203-6

Goos, M., & Manning, A. (2007). Lousy and lovely jobs. The rising polarization of work in Britain. *Review of Economics and Statistics*, *89*(1), 118–133. https://doi.org/10.1162/rest.89.1.118

Goos, M., Manning, A., & Salomons, A. (2014). Explaining job polarization: Routine-biased technological change and offshoring. *American Economic Review*, *104*(8), 2509–2526. https://doi.org/10.1257/aer.104.8.2509

Gordon, R. J. (2015). 'Secular stagnation: A supply-side view. *American Economic Review*, *105*(5), 54–59. https://doi.org/10.1257/aer.p20151102

Graetz, G., & Michaels, G. (2018). Robots at Work. *Review of Economics and Statistics*, *100*(5), 753–768. https://doi.org/10.1162/rest_a_00754

Gregory, T., Salomons, A., & Zierahn, U. (2019). *Racing with or against the machine? Evidence from Europe*. IZA Discussion Paper No. 12063.

Hall, B. (2005). Exploring the patent explosion. *Journal of Technology Transfer*, *30*, 35–48.

Hammerling, J. H. F. (2022). *Technological change in five industries: Threats to jobs, wages, and working conditions*. UC Berkeley Labor Center. URL: https://laborcenter.berkeley.edu/technological-change-in-five-industries/

Harrison, R., Jaumandreu, J., Mairesse, J., & Peters, B. (2014). Does innovation stimulate employment? A firm-level analysis using comparable micro-data from four European countries. *International Journal of Industrial Organization*, *35*, 29–43. https://doi.org/10.1016/j.ijindorg.2014.06.001

Hirvonen, J., Stenhammar, A., & Tuhkuri, J. (2022). *New Evidence on the Effect of Technology on Employment and Skill Demand*. ETLA Working Papers No 93.

Hötte, K., Somers, M., & Theodorakopoulos, A. (2022). *Technology and jobs: A systematic literature review*. arXiv preprint arXiv:2204.01296.

Hötte, K., Tarannum, T., Verendel, V., & Bennet, L. (2022). *Exploring artificial intelligence as a general purpose technology with patent data: A systematic comparison of four classification approaches*. arXiv preprint arXiv:2204.10304.

Hou, J., Huang, C., Licht, G., Mairesse, J., Mohnen, P., Mulkay, B., Peters, B., Wu, Y., Zhao, Y., & Zhen, F. (2019). Does innovation stimulate employment? Evidence from China, France, Germany, and The Netherlands. *Industrial and Corporate Change*, *28*(1), 109–121. https://doi.org/10.1093/icc/dty065

Humlum, A. (2021). *Robot Adoption and Labor Market Dynamics*. Mimeo. URL: https://andershumlum.com/s/humlumJMP.pdf

ILO. (2022). *World Employment and Social Outlook: Trends 2022*. International Labor Office. URL: https://www.ilo.org/global/research/global-reports/weso/trends2022/WCMS_834081/

Kelly, B., Papanikolaou, D., Seru, A., & Taddy, M. (2021). Measuring technological innovation over the long run. *American Economic Review: Insights*, *3*(3), 303–320. https://doi.org/10.1257/aeri.20190499

Koch, M., Manuylov, I., & Smolka, M. (2021). Robots and firms. *Economic Journal*, *131*(638), 553–2584. https://doi.org/10.1093/ej/ueab009

Kogan, L., Papanikolaou, D., Schmidt, L. D. W., & Seegmiller, B. (2021). *Technology-Skill Complementarity and Labor Displacement: Evidence from Linking Two Centuries of Patents with Occupations*. NBER Working Paper 29552.

Krzywdzinski, M. (2021). Automation, digitalization, and changes in occupational structures in the automobile industry in Germany, Japan, and the United States: A brief history from the early 1990s until 2018. *Industrial and Corporate Change*, *30*(3), 499–535. https://doi.org/10.1093/icc/dtab019

Lee, J., & Lee, K. (2021). Is the fourth industrial revolution a continuation of the third industrial revolution or something new under the sun? Analyzing technological regimes using US patent data. *Industrial and Corporate Change*, *30*(1), 137–159. https://doi.org/10.1093/icc/dtaa059

Lachenmaier, S., & Rottmann, H. (2011). Effects of innovation on employment: A dynamic panel analysis. *International Journal of Industrial Organization*, *29*(2), 210–220. https://doi.org/10.1016/j.ijindorg.2010.05.004

Levin, R., Klevorick, A., Nelson, R., & Winter, S. (1987). Appropriating the Returns from Industrial R & D. *Brookings Papers on Economic Activity*, *3*, 783–820.

Lim, J., & Lee, K. (2019). Employment effect of innovation under different market structures: Findings from Korean manufacturing firms. *Technological Forecasting and Social Change*, *146*, 606–615. https://doi.org/10.1016/j.techfore.2018.04.022

Los, B., Timmer, M. P., & de Vries, G. J. (2014). *The demand for skills 1995–2008. A global supply chain perspective*. OECD Economics Department Working Papers 114.

Machin, S., & Van Reenen, J. (1998). Technology and changes in skill structure: Evidence from seven OECD countries. *Quarterly Journal of Economics*, *113*(4), 1215–1244. https://doi.org/10.1162/003355398555883

Mann, K., & Püttmann, L. (2023). Benign effects of automation: New evidence from patent texts. *Review of Economics and Statistics*, *105*(3), 562–579. https://doi.org/10.1162/rest_a_01083

Marcolin, L., Miroudot, S., & Squicciarini, M. (2019). To be (routine) or not to be (routine), that is the question: A cross-country task-based answer. *Industrial and Corporate Change*, *28*(3), 477–501. https://doi.org/10.1093/icc/dty020

Martinelli, A., Mina, A., & Moggi, M. (2021). The enabling technologies of industry 4.0: Examining the seeds of the fourth industrial revolution. *Industrial and Corporate Change*, *30*(1), 161–188. https://doi.org/10.1093/icc/dtaa060

Martínez-Plumed, F., Tolan, S., Pesole, A., Hernández-Orallo, J., Fernández-Macías, E., & Gómez, E. (2020). Does AI qualify for the job? A bidirectional model mapping labor and AI intensities. *Proceedings of the AAAI/ACM Conference on AI, Ethics, and Society, February 2020*, 94–100. https://doi.org/10.1145/3375627.3375831

Mastrostefano, V., & Pianta, M. (2009). Technology and jobs. *Economics of Innovation and New Technology*, *18*(8), 729–741. https://doi.org/10.1080/10438590802469552

Meindl, B., Frank, M. R., & Mendonça, J. (2021). *Exposure of occupations to technologies of the fourth industrial revolution*. arXiv preprint arXiv:2110.13317.

Mondolo, J. (2022). The composite link between technological change and employment: A survey of the literature. *Journal of Economic Surveys*, *36*(4), 1027–1068. https://doi.org/10.1111/joes.12469

Mondolo, J. (2023). The interplay between R&D intensity, institutional quality and employment. Evidence from the Italian NUTS-3 regions. *Scienze Regionali-The Italian Journal of Regional Science*, forthcoming. https://doi.org/10.14650/107318

Montobbio, F., Staccioli, J., Virgillito, M. E., & Vivarelli, M. (2022). Robots and the origin of their labor-saving impact. *Technological Forecasting and Social Change*, *174*, 121122. https://doi.org/10.1016/j.techfore.2021.121122

Montobbio, F., Staccioli, J., Virgillito, M. E., & Vivarelli, M. (2023). Labour-saving automation: A direct measure of occupational exposure. *The World Economy*, forthcoming. https://doi.org/10.1111/twec.13522

Moroc, A., & Bărnuțiu, O. (2019). Job quality, innovation and employment—A structural equation modeling on regional level. *International Journal of Innovation and Economic Development*, *5*(1), 54–65.

Nedelkoska, L., & Quintini, G. (2018). *Automation, skills use and training*. OECD Social, Employment and Migration Working Papers No. 202.

Pellegrino, G., Piva, M., & Vivarelli, M. (2019). Beyond R&D: The role of embodied technological change in affecting employment. *Journal of Evolutionary Economics*, *29*, 1151–1171. https://doi.org/10.1007/s00191-019-00635-w

Pianta, M. (2000). The employment impact of product and process innovations. In (M. Vivarelli & M. Pianta Eds.), *The employment impact of innovation: Evidence and policy* (pp. 77–95). Routledge.

Pianta, M., Evangelista, R., & Perani, G. (1996). The dynamics of innovation and employment: An international comparison. *STI Review*, *18*, 67–93.

Piva, M., & Vivarelli, M. (2004). The determinants of the skill bias in Italy: R&D, organisation or globalisation? *Economics of Innovation and New Technology*, *13*(4), 329–347. https://doi.org/10.1080/10438590410001629025

Piva, M., & Vivarelli, M. (2005). Innovation and employment: Evidence from Italian microdata. *Journal of Economics*, *86*, 65–83. https://doi.org/10.1007/s00712-005-0140-z

Piva, M., & Vivarelli, M. (2018). Technological change and employment: Is Europe ready for the challenge? *Eurasian Business Review*, *8*, 13–32. https://doi.org/10.1007/s40821-017-0100-x

Pouliakas, K. (2018). *Determinants of Automation Risk in the EU Labor Market: A Skills-Needs Approach*. IZA Discussion Paper 11829.

Russell, S., & Norvig, P. (2016). *Artificial intelligence: A modern approach*. Pearson Education Limited.

Santarelli, E., Staccioli, J., & Vivarelli, M. (2022). Automation and related technologies: A mapping of the new knowledge base. *Journal of Technology Transfer*, *48*(2), 779–813. https://doi.org/10.1007/s10961-021-09914-w

Simonetti, R., Taylor, K., & Vivarelli, M. (2000). Modelling the employment impact of innovation. In (M. Pianta & M. Vivarelli Eds.), *The employment impact of innovation* (ch., 3, pp. 26–43). Routledge.

Spitz-Oener, A. (2006). Technical change, job tasks and rising educational demands: Looking outside the wage structure. *Journal of Labor Economics*, *24*(2), 235–270. https://doi.org/10.1086/499972

Staccioli, J., & Virgillito, M. E. (2021). Back to the past: The historical roots of labor-saving automation. *Eurasian Business Review*, *11*, 27–57. https://doi.org/10.1007/s40821-020-00179-1

Ugur, M., Sefa, A. C., & Solomon, E. (2018). Technological innovation and employment in derived labor demand models: A hierarchical meta-regression analysis. *Journal of Economic Surveys*, *32*(1), 50–82. https://doi.org/10.1111/joes.12187

Vannutelli, S., Scicchitano, S., & Biagetti, M. (2022). Routine-biased technological change and wage inequality: Do workers' perceptions matter? *Eurasian Business Review*, *12*, 409–450. https://doi.org/10.1007/s40821-022-00222-3

Van Reenen, J. (1997). Employment and technological innovation: Evidence from U.K. Manufacturing Firms. *Journal of Labor Economics*, *15*(2), 255–284. https://doi.org/10.1086/209833

Van Roy, V., Vértesy, D., & Vivarelli, M. (2018). Technology and employment: Mass unemployment or job creation? Empirical evidence from European patenting firms. *Research Policy*, *47*(9), 1762–1776. https://doi.org/10.1016/j.respol.2018.06.008

Vermeulen, B., Kesselhut, J., Pyka, A., & Saviotti, P. P. (2018). The impact of automation on employment: Just the usual structural change? *Sustainability*, *10*(5), 1–27. https://doi.org/10.3390/su10051661

Vivarelli, M. (1995). *The economics of technology and employment: Theory and empirical evidence*. Elgar.

Vivarelli, M. (2014). Innovation, employment, and skills in advanced and developing countries: A survey of economic literature. *Journal of Economic Issues*, *48*(1), 123–154. https://doi.org/10.2753/JEI0021-3624480106

Vivarelli, M. (2015). *Innovation and employment*. IZA World of Labor. URL: https://wol.iza.org/articles/innovation-and-employment

Vivarelli, M., Evangelista, R., & Pianta, M. (1996). Innovation and employment in Italian manufacturing industry. *Research Policy*, *25*(7), 1013–1026.

Webb, M. (2020). *The Impact of Artificial Intelligence on the Labor Market*. Available at SSRN. https://ssrn.com/abstract=3482150

WIPO. (2019). *WIPO Technology Trends 2019: Artificial Intelligence*. World Intellectual Property Organization.

How to cite this article: Montobbio, F., Staccioli, J., Virgillito, M. E., & Vivarelli, M. (2024). The empirics of technology, employment and occupations: Lessons learned and challenges ahead. *Journal of Economic Surveys*, *38,* 1622–1655. https://doi.org/10.1111/joes.12601

APPENDIX

TABLE A1 A synoptic summary of the 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 rationalizing effect started to overcome expansionary effects	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 favor of a positive effect of innovation on employment at the firm level	firm-level
Harrison et al. (2014)	the third wave of the CIS from four European countries (Germany, France, UK, Spain)	significant job-creating effect of product innovation and a non-significant impact of process innovation	firm-level
Barbieri et al. (2019); Pellegrino et al. (2019); Dosi et al. (2021)	Italy, Spain and EU countries	labor-friendly nature of R&D expenditures and product innovation is confirmed, but a possible overall labor-saving impact of embodied technological change incorporated in process innovation is also detected	firm- and sectoral-level

(Continues)

TABLE A1 (Continued)

Automation Paper	Coverage/Methods	Effect	Level of analysis
Acemoglu and Restrepo (2018, 2019, 2020)	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 timespan, using a measure of local robot exposure for each region	no evidence that robots cause total job losses and there are positive and significant spillover effects in services	industry level
Domini et al. (2021)	French manufacturing employers over the period 2002—2015	robotic adoption or, alternatively, imported capital equipment, do not imply labor 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 becoming negative	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 et al. (2021)	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 is greater, firms have higher labor 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

(Continues)

TABLE A1 (Continued)

Occupations, skills and tasks Paper	Coverage/Methods	Effect	Level of analysis
Arntz et al. (2016) and Nedelkoska and Quintini (2018)	technological bottlenecks identified in Frey and Osborne (2017) applied at the task level covering OECD countries.	low-skilled occupations are the most exposed, with figures much lower than FO	tasks level
Felten et al. (2018) and Felten et al. (2021)	questionnaire on 10 AI selected scopes of application crowd-sourced to mTurk workers. US labor 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 titles of AI/robot/software patents and O*NET tasks. US labor 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 labor market (long run)	time varying exposure of occupations reflecting waves of technological change	job levels
Montobbio et al. (2023)	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