The composite link between technological change and employment: A survey of the literature

The Composite Link between Technological Change and Employment: A Survey of the Literature

Jasmine Mondolo

The role played by technological change in employment trends has long been debated and investigated, but the evidence has proven to be inconclusive. This paper aims to shed light on this topic by critically reviewing a broad and heterogeneous body of literature on the employment implications of technical progress. To this purpose, it briefly discusses the main theories and models that underpin the empirical analysis and reviews the literature following two main criteria, namely, the proxy for technological change and the level of analysis. It also accounts for the effect of technical progress on both overall employment and on distinct occupational, educational and demographic groups. Particular attention is devoted to the results of some very recent studies that attempt to unfold the impact of complex automation technologies, especially robots, and to provide a preliminary account of the evolution, distribution, challenges and potential of Artificial Intelligence.

1. Introduction

Technological progress is widely regarded as a pivotal driver of economic progress, but throughout history, it has generated cultural anxiety. During the past two centuries there have been periodic warnings that new technologies may cause a widespread substitution of machines for labor, which in turn could lead to technological unemployment and a further increase in inequality in the short run, even if the long-term effects can be beneficial. The best-known early example is the Luddite movement of the early 19th century, in which a group of English textile artisans protested against the automation of textile production by seeking to destroy some of the machines (Mokyr, Vickers & Ziebarth, 2015; Autor, 2015). In the end, the fears of the workers were not realized: the mechanization of the early 19th century could only replace a limited number of human activities and increased the demand for types of labor that were complementary to the capital goods embodied in the new technologies. Importantly, technological progress also took the form of product innovation and thus created entirely new sectors for the economy, a development that was neglected in the discussions of the economists of that time (Mokyr, Vickers & Ziebarth, 2015).

However, worries about the disruptive impact of automation would periodically surface in the course of the twentieth century, especially during periods of economic slowdown and during great innovative waves, and have been recently renewed by the ongoing technological revolution, which is probably the very first one with such an accelerated pace and pervasiveness (Barbieri et al., 2019). The fears and skepticism about the latest outstanding technological advances have been amplified by anecdotal evidence in the popular press, but also by scientific publications. As an illustration, the widely discussed book, *The Second Machine Age,* by MIT scholars Erik Brynjolfsson and Andrew McAfee (Brynjolfsson & McAfee, 2014) offers a gloomy picture of the likely effects of automation on employment, and Frey & Osborne (2017) predict that almost half of total US jobs, including service/white-collar/cognitive jobs in accountancy, logistics, legal and financial services, trade and retail, could be automated over the next decade or two.

The impact of these studies on the policy debate has been significant: national policymakers, trade unions, entrepreneurs, and international economic organizations have started a lively discussion on the most appropriate actions designed to reap the benefits and to minimize the risks posed by such radical digital transformation. The discussion has also involved distinguished academic researchers, and entire issues of some high-profile academic journals (e.g., the symposium "Automation and Labor Markets" of the Journal of Economic Perspectives in 2015, and the issue "Technology and the Labour Market" of the Oxford Review of Economic Policy in 2018) have been devoted to it; however, there is still limited consensus about how and to what extent technical progress has affected and will affect labor.

The present paper aims to achieve a better understanding of the complex and multidimensional nexus between technological change and employment using a thorough survey that bridges different traditions and streams of research devoted to this topic. To this purpose, it presents the main theories and models underpinning the literature on the effect of innovation and technical change on employment and then reviews a considerable number of studies that have recently tackled the implications of disembodied technological change and/or technological change embedded in the capital inputs[1]. The literature under scrutiny, which is chiefly empirical, is reviewed following two main criteria, namely, the proxy of technological change and the level aggregation/unit of analysis.

This work adds to the extant surveys on the link between technological change and employment, in particular to the one carried out by Calvino & Virgillito (2018), from which it departs in the following main respects: it primarily focuses on the effect of the *adoption* of new technologies; it devotes particular attention to the nascent but promising strand of research that explores the latest advances in robotization and digitalization, and to the first attempts to unravel the impact and potential of breakthrough technologies related to Artificial Intelligence; it inspects the effect of technological change both on overall employment and on different categories of workers defined according to the task content of their occupation, their educational level or their demographic characteristics. In doing so, it complements and extends the review by Barbieri et al. (2019), who briefly summarize the RBTC literature and touch upon the employment implications of robots, automation and AI.

This study is organized as follows: Section 2 presents the theoretical background and briefly describes the compensation framework and the substitution framework with a focus on the RBTC hypothesis and the related task-based model; Section 3 examines the literature on the link between technological change and employment through the lens of the type of technical change and the level of aggregation; Section 4 summarizes the main considerations that emerge from the review and devotes more attention to the role played by the dimension under scrutiny (i.e., firm, sector, occupation, individual, country); Section 5 concludes.

2. Technological change and employment: the theoretical background

2.1 The compensation framework

Since its foundation, the economic discipline has stressed that the direct harmful effects of technological change on employment are counterbalanced in the long run by the indirect effects of market compensation mechanisms, which can operate at the sectoral or economy-wide level. Such mechanisms were condensed, during the first half of the nineteenth century, in a theory which Karl Marx later labelled "compensation theory**".**

During the twentieth century, the compensation theory was discussed and augmented with the contributions of different schools of thought. Freeman, Clark & Soete (1982), Vivarelli, (1995), Pianta (2005) and, more recently, Vivarelli (2014) and Calvino & Virgillito (2018) have identified

[1] This work reviews recent studies (published or made available from 2003 onwards) that employ the following proxies of technological change: R&D, computers and ICT (captured by direct or indirect measures), robots, a variety of automation and new digital technologies, and Artificial Intelligence. I also briefly recall some empirical analyses that use specific indicators of product and process innovation as key regressors, but which are out of the scope of this survey (for a comprehensive review of the recent literature on the link between innovation and employment, see Calvino & Virgillito, 2018). In order to identify the selected articles, I first explored the 'Economics, Econometrics and Finance' and the 'Business, Management and Accounting' sections of the Scopus database; then, in order to include working papers and reports released by international institutions and organizations, I scrutinized some well-known and relevant working paper series (i.e., OECD, IMF, IZA, ILO and NBER working paper series), and subsequently the 'Working Paper' section of the database EconPapers. Finally, I examined the bibliography of a considerable number of articles previously found in order to detect other suitable studies.

the following main mechanisms of compensation/job creation which are triggered by technological change, including the latest wave driven by new digital and automation technologies:

1. New machines: the introduction of new machines (e.g., robots) generates an increase of jobs in the machine-producing sector which offsets the labor displacement in the machine-using industry;

2. Decrease in prices: the increase in productivity due to the introduction of new technologies induces a reduction in the unit costs of production, which, in a competitive market, translates into decreasing prices; the latter, in turn, lead to higher demand, and therefore higher employment;

3. Decrease in wages: the workforce displacement leads to an excess of labor supply and then to a reduction in wages which, in the presence of free competition and full substitutability between labor and capital, can trigger an increase in the demand for labor;

4. New investments: in a world where competitive convergence is not instantaneous, innovative entrepreneurs can accumulate extra-profits in the gap of time between a cost decrease due to technological progress and a subsequent fall in prices generated by the former, and subsequently invest these profits in physical capital, expanding the productive capacity and hence boosting labor demand;

5. Increase in incomes: when workers manage to appropriate gains from the increase in productivity, technical progress can lead to an increase in wages and consumption, which in turn prompts labor demand and then employment;

6. New products: when technological change takes the form of the creation and commercialization of new products, new economic branches develop, stimulating consumption, and additional jobs emerge.

The first four mechanisms are attributable to the classical and neoclassical schools, which embrace an *equilibrium perspective*, whereas the fifth and the sixth ones ("increase in incomes" and "new products") have been put forward by the Keynesian-Schumpeterian tradition, which adopts a *disequilibrium perspective* (see Calvino & Virgillito, 2018 for a discussion). Additionally, mechanisms 1-5 compensate the initial labor-saving effect of process innovation (Vivarelli, 2014), most of which, as suggested by earlier prominent studies (e.g., Rosenberg, 1976; Nelson & Winter, 1982; Dosi, 1988) and confirmed by more recent microeconometric analyses (e.g., Conte & Vivarelli, 2005; Parisi, Schiantarelli & Sembenelli, 2006) is implemented through investment in new machines and equipment, also known as "embodied technological change". Conversely, mechanism 6, which is sometimes labelled "Schumpeterian mechanism", captures the job-creating effect of product innovation and is mainly related to disembodied technological change.

Some studies have provided a conceptual framework and an empirical analysis of the employment effect of ICT-induced innovations taking into account both the labor-saving effect and the compensation mechanisms. Earlier contributions include the macroeconomic analyses of Vivarelli (1995) and Simonetti, Taylor & Vivarelli, 2000 (see Vivarelli, 2014, for a review).

Recently, Dosi et al. (2021) have presented a model that, using a partial disequilibrium perspective, accounts for both the labor-creating and the labor-displacing effects of technological change and identifies the different impacts attributable to the production (product innovation) vs the adoption (process innovation) of new technologies. Specifically, the model describes a two-sector vertically integrated economy in which the upstream sector produces new machinery and equipment (product innovation), while the downstream sector is the adopter of the machines themselves (process innovation). The vertical structure of the model directly highlights the labor-friendly nature of product innovation in the upstream sector (that is the "new products" mechanism), the potential labor-saving nature of process innovation in the downstream sector (the "new investments" mechanism), and the role of the "new machines" mechanism captured by the increasing production of machines in the upstream sector. Accordingly, the net employment effect of technical change depends on either its expansionary or its replacement ("scrapping") nature, and also on the general macroeconomic conditions concerning aggregate demand, wage formation and the business climate affecting the investment decisions.

Unfortunately, the compensation arguments are subject to several limitations (see for instance Vivarelli, 2014, Calvino & Virgillito, 2018, and Dosi et al., 2021, for a review) which hinder or even neutralize their ability to counterbalance the harmful effect of technological change. In particular, many aspects intertwine, such as macroeconomic and cyclical conditions, labor market dynamics and institutional aspects, undermining the possibility of any ex-ante exhaustive prediction about their relative efficacy (Vivarelli, 2014; Calvino & Virgillito, 2018). As an illustration, both the price and income compensation mechanisms can be more or less effective depending on the degree of market competition, the demand elasticity, and the 'animal spirits' and agents' expectations, since the latter can delay the translation of additional profits and wages into effective demand (Bogliacino & Vivarelli, 2012). Conversely, the reduction of per-capita working time, the definition of social safety nets and proper union strategies would help alleviate the labor-saving effect of innovation (Pasinetti, 1981; Vivarelli, 2014).

Next, the potential 'cannibalization' effect of new products on older ones may weaken the job-creation impact of product innovations (Calvino & Virgillito, 2018; Barbieri et al., 2019). Additionally, the relationship between technical change and employment is likely to be affected by the ongoing business cycle, as changing economic conditions, such as credit constraints, the opportunity cost of investing in innovation, and the appropriability and demand conditions, shape the innovation behavior of firms, which, in turn, affects their ability to generate jobs (Peters et al., 2014; Dachs, Hud & Peters, 2020).

Ultimately, the potential labor-saving impact of process innovation, the compensation mechanisms, the hindrances to the effectiveness of such mechanisms, and the labor-friendly nature of product innovation can combine in many diverse outcomes, and economic theory does not provide a clear-cut answer about the employment effect of technological change. Therefore, empirical evidence is crucial, but applied economists face relevant empirical challenges (Vivarelli, 2014).

For instance, it is typically complicated to separate the impact of technology from the impact of other factors, whose identification also depends on the level of aggregation (Vivarelli, 2014; Barbieri et al., 2019). In particular, firm-level studies, on the one hand, allow a direct and precise firm-level mapping of innovation both in terms of innovative inputs (R&D and/or ETC) and/or output; on the other hand, they do not allow determination of the net industry-level employment effect, since selection and competitive dynamics, such as "business-stealing" (i.e., firms which are relatively more innovative, efficient and dynamic could grow in terms of market share, and plausibly also in terms of employment, at the expense of less innovative firms), firm entry and exit, and the relocation of activities, which may lead to very different employment patterns at higher levels of aggregation, cannot be identified (Calvino & Virgillito, 2018; Dosi et al., 2021).

These trends become observable at the sectoral level of aggregation: industry-level studies can identify the overall effect of technological change, accounting for both its direct impact on innovating firms and the indirect effects that operate within the industry (Mastrostefano & Pianta 2009). Notably, different sectors typically present distinct patterns of innovation and employment outcomes (Malerba, 2002; Mastrostefano & Pianta 2009; Bogliacino & Pianta, 2010[2]), and a technology that can be regarded as product innovation in one sector (e.g., telecommunications) may represent a process innovation in another (e.g., manufacturing; Dosi, 1984; Dosi et al., 2021). Sectoral analysis is thus able to capture competitive dynamics and sectoral specificities, but, at the same time, does not provide the detailed overview of firm-level innovation and adoption of technology inputs offered by microeconomic studies and overlooks intersectoral linkages and complementarities and economy-wide compensation mechanisms, which would only be captured at a macroeconomic level. As a result, analyses performed at each level of aggregation offer a different piece of the puzzle (Calvino & Virgillito, 2018).

On the whole, it can be argued that the nexus between technical progress and labor is tangled and multifaceted, and that it is difficult to predict whether the compensation mechanisms overcompensate the labor-saving effect of technological change. However, a look at different levels of aggregation can help obtain a clearer and more complete picture of this phenomenon.

2.2 The substitution framework and the bias of technological change: skills versus tasks

In light of the limitations of the compensation framework, it is unlikely that the countervailing mechanisms will always be able to offset the labor displacement attributable to the adoption of innovative technologies. The economic theories and views that focus on the displacement effect fall within the realm of what Sabadash (2013) labels the substitution framework. The latter also includes pessimistic views of a "near-workless world" (Rifkin, 1995) which, in past decades, have been mainly fueled by public activists, political advisors with various educational backgrounds, technology journalists and software executives, but which have gained new momentum during the ongoing digital revolution (see for instance the popular book by Brinjolfsson & McAfee, 2014, and Benzel et al.'s 2016 theoretical model that predicts human obsolescence and labor immiseration).

Nonetheless, an extensive strand of literature has demonstrated that technological change substitutes only certain types of skills and tasks and that in doing so, displays heterogenous effects on different types of workers. Two main theories that scrutinize the so-called qualitative effect of technical progress have been put forward. The first one, which dominated the economic debate on this topic during the eighties and the nineties and is known as the Skill-Biased Technological Change (SBTC)

[2] Bogliacino & Pianta (2010) classify manufacturing and service sectors according to a revised version of Pawitt's (1984) taxonomy (i.e., Science-based, Specialised Supplier, Scale-Intensive, Information-Intensive Suppliers Dominated) and show that each of the identified sectors mainly pursue one of the two following main innovation strategies (or trajectories): technological competitiveness, which is based on new products and new markets and then is rooted in product innovation, and cost competitiveness, which focuses on increased efficiency and is rooted in process innovation. The types of sector identified by Bogliacino & Pianta (2010) have been classified by Dosi et al. (2021) as either being "upstream'' sectors, namely the sectors that produce new machines and equipment (Science-based and Specialised Supplier) or "downstream" sectors (i.e., Scale-Intensive, Information-Intensive and Suppliers Dominated).

hypothesis, posits that Information and Communication Technologies complement high-skilled/educated workers and replace low-skilled/low-educated workers. The second theory, which was advanced at the beginning of the new millennium and is generally referred to as the Routine-Biased Technological Change (RBTC) hypothesis, focuses on workers' tasks, rather than on their education level, and postulates that ICTs substitute routine tasks and complement non-routine tasks. A brief discussion of the two aforementioned theories is provided below.

2.2.1 The Skill-Biased Technological Change (SBTC) hypothesis

The nature of technological change has changed remarkably over time. In the nineteenth century the introduction of machines in manufacturing allowed low-skilled workers to engage in the production of goods that previously required specific expertise in artisanal shops. Technology thus substituted high-skilled labor and complemented low-skilled labor. This pattern started reversing in the early twentieth century, when advances such as the electrification of factories reduced the need for large numbers of unskilled manual workers, raising the demand for relatively skilled workers. Such complementarity between technology and skills was reinforced in the second half of the twentieth century, with the widespread adoption of ICT and computer-based technologies (Goldin & Katz, 1998). Especially during the eighties, this demand for relatively skilled workers, coupled with an increase in the supply of (medium-)skilled relative to unskilled workers due to the rapid expansion of the education system, led to a process of skill upgrading in the overall economy and an increasing gap, in terms of wage and employment, between high-educated/high-skilled workers and low-educated/low-skilled workers (Katz & Murphy, 1992).

According to the Skill-Biased Technological Change (SBTC) hypothesis, these labor patterns were at least partly attributable to ICT-induced technical progress. The basic idea underlying this theory is that ICTs are "skill-biased", namely, they increase the relative productivity of high-skilled workers, who are typically more able to use new technologies, and consequently increase their relative labor demand, compared to low-skilled workers (Tinbergen, 1974, Katz & Murphy, 1992).

The intellectual foundation of this literature, which is mainly empirical (Vivarelli, 2014), was conceptualized by Acemoglu & Autor (2011) in the so-called canonical model. This framework includes two skill groups defined according to the level of education (for instance, workers without a college degree versus workers with a college degree) performing two distinct and imperfectly substitutable task groups or producing two imperfectly substitutable goods: any given job is assigned to a certain category, and workers from the other category cannot perform it (i.e., a job is either a high or a low skill job). Thus, technology, which takes a factor-augmenting form, complements either high- or low-skilled workers. In conclusion, the canonical model predicts a positive monotonic relation between skills and employment growth. The implication is that we should observe an increase in employment for high-skilled individuals, while the low-skilled ones would suffer employment losses and, if demand shifts faster than supply, we would see also rising wage premia for higher skills. In other words, ICT complements high-skilled labor and substitutes low-skilled workers (Sebastian & Biagi, 2018).

The SBTC hypothesis has been proved empirically adequate in accounting for the trend in the skill premia and employment experienced by the United States and other OECD countries especially during the seventies and the eighties (see the influential study by Katz & Murphy, 1992, and a number of relevant contributions that summarized and extended the large subsequent literature, such as:

Autor, Katz & Krueger, 1998; Katz & Autor, 1999; Acemoglu, 2002; Goldin & Katz, 2008; Acemoglu & Autor, 2011). However, it presents several limitations.

First, the SBTC hypothesis cannot properly explain the fall in employment in middle-skilled jobs and the increase in high-skill and low-skill occupations, a phenomenon typically referred to as job polarization, observed during the nineties in the US, as well as in some European economies, including the UK (Wright & Dwyer, 2003; Autor, Katz & Kearney, 2006; Goos & Manning, 2007; Goos, Manning & Salomons, 2009).

In addition, although the SBTC argument was often used to explain rises in wage inequality, the literature has identified a range of determinants, including trade and institutional factors (in particular, labor market institutions), thus pointing to a less pronounced potential contribution of technological change to this trend compared to the one implied by the SBTC framework (e.g., Hacker & Pierson, 2011; Fortin & Lemieux, 1997; Lee, 1999; Beyer, Rojas & Vergara, 1999; Kristal & Cohen, 2017; see also the surveys on the determinants of income inequality recently conducted by Kurokawa, 2014, and by Nolan, Richiardi & Valenzuela, 2019). Besides, Kurokawa (2014) asserts that most of the empirical studies on skill-biased technological change have ignored the intersectoral linkages that operate through the use of intermediate products, and the related intersectoral technology-skill complementarity (since, as shown by Voigtländer, 2014, the skill upgrading in one sector goes hand-in-hand with increasing skill demand in many other sectors because of these linkages).

Moreover, the SBTC setting marks the correlation between technological change and labor demand, without explaining the cause or mechanism behind the relative shift in productivities and the higher demand for educated workers (Autor, Levy & Murnane, 2003; Lauder, Brown & Cheung, 2018).

Importantly, it relies on a simplistic classification of skilled and unskilled jobs where skills are identified by the level of education, while the relevance of tasks and their relationship with skills are neglected (Sebastian & Biagi, 2018). In particular, since the augmented factor, either capital or labor, becomes uniformly more productive in all tasks, potentially important changes in the task content of production are not accounted for (Acemoglu & Restrepo, 2019b; for a more exhaustive discussion on the SBTC hypothesis and its drawbacks, see Lauder, Brown & Cheung, 2018). The distinction between skills and tasks becomes particularly relevant in the ICT era, when workers of a given skill level can change the set of tasks that they perform in response to changes in technology and organization of production (Sabadash, 2013). For these reasons, from the early 2000s, a growing number of researchers have investigated how the task content of jobs helps explain the effect of technological change on labor demand.

2.2.2 The Routine-Biased Technological Change hypothesis and the task-based approach

Autor, Levy & Murnane (2003) propose a nuanced version of the SBTC hypothesis, known as the routine-biased technological change (RBTC), that relaxes the one-to-one mapping between skills and tasks and operationalizes the way technology affects the labor market through the job tasks performed. According to Acemoglu & Autor (2011, p. 1045), who refine Autor, Levy & Murnane's framework, a task is defined as a "unit of work activity that produces output (good and services)", whereas a skill is a "worker's endowment of capabilities for performing various tasks".

Autor, Levy & Murnane (2003) classify job tasks according to a two-dimensional typology, namely, routine as opposed to non-routine, and manual as opposed to cognitive; this leads to four broad categories of occupational task inputs, i.e., non-routine cognitive (in turn, subdivided into non-routine cognitive interactive and analytical), non-routine manual, routine cognitive and routine manual. The model predicts that, faced with an economic-wide decline in the price of computer capital, industries and occupations that are initially intensive in labor input of routine tasks make relatively larger investments in computer capital; subsequently, they reduce the labor input of routine tasks, for which computer capital is substituted due to the increasing ability of machines to perform routine tasks, and increase demand for non-routine task input, which computer capital complements. Accordingly, unlike the SBTC framework, this model implies that computerization has a non-linear effect on labor demand. To test these predictions, Autor, Levy & Murnane pair representative data on job task requirements from the Dictionary of Occupational Titles (DOT) with samples of employed workers from the Census and Current Population Survey to form a consistent panel of occupational task inputs over the four-decade period from 1960 to 1998.

The RBTC hypothesis may rationalize the documented patterns of polarized job growth observed in the US and other advanced countries (e.g., Autor, Katz & Kearney, 2006; Goos & Manning 2007; Goos, Manning & Salomons, 2009). Intuitively, as jobs that are intensive in either non-routine cognitive or non-routine manual tasks are generally found at opposite ends of the occupational skill spectrum, whereas jobs that are intensive in routine skills are often middle-paid, computerization may rationalize the documented patterns of polarized job growth.

2.2.3 Further developments of the task-based model

A number of subsequent contributions enrich and extend the task-based approach originally proposed by Autor, Levy & Murnane (2003). Autor, Katz and Kearny (2006) develop a model of computerization in which computers complement abstract (i.e., non-routine cognitive) tasks, substitute routine tasks and have little impact on (non-routine) manual tasks, and use it to explain the polarization patterns observed in the US labor market. Autor & Dorn (2013) build a general equilibrium model of "routine-task" replacing technological change and extend it to a spatial equilibrium setting where local labor markets have differential degrees of specialization in routine-intensive industries. Then, drawing on Autor, Katz & Kearny's task classification, they build a Routine Task Intensity (RTI) indicator and use it to estimate the degree of routinization at local labor market level, pioneering a relevant strand of literature aimed at assessing the patterns of occupational task content in local labor markets or similar constructs.

Building on Autor & Dorn (2013) and Goos, Manning & Salomons (2014), Gregory, Salomons & Zierahn (2019) elaborate and test a task-based setting that, focusing on aggregate labor outcomes rather than on relative ones, distinguishes between tradable and non-tradable goods in order to model the spatial reallocation of labor demand resulting from RBTC. It identifies three channels through which RBTC impacts aggregate labor demand: a negative substitution effect, as declining capital costs incentivize firms in the high-tech tradable sector to substitute capital for routine labor inputs and to restructure production processes towards routine tasks; a positive product demand effect, as declining capital costs reduce the price of tradables; a positive product demand spillover effect (i.e., the generation of product demand spillovers in the non-tradable sector), as the increase in product demand raises local incomes, which are partially spent on low-tech non-tradables. Hence, the final effect of RBTC on aggregate labor demand depends on the size of these three forces.

In recent years, the task-based approach has served as the starting point of a rapidly growing line of research that estimates the susceptibility to automation, or job automatability (namely, the risk or probability that an occupation is displaced by machines in the near future) of different occupations. Specifically, in their seminal study, Frey & Osborne (2017) revise Autor, Levy & Murnane's model to enable computer capital to rapidly substitute for labor also across a wide range of non-routine tasks. In so doing, they identify three sets of job tasks (i.e., creative intelligence, social intelligence, and perception and manipulation tasks) which are supposed to have a low risk of automation due to the presence of engineering bottlenecks. Then, using data from O*Net and the US Department of Labor and with the support of a Gaussian process classifier, they classify 702 detailed US occupations according to their probability of computerization, which is based on the degree to which those bottlenecks persist.

However, Arntz, Gregory & Zierahn (2016) contend that Frey & Osborne's probabilistic classification model does not account for the fact that it is typically a task, rather than a whole job, that is automated or not, and that an occupation comprises a variety of tasks. In light of these considerations, Arntz, Gregory & Zierahn (2016, 2017) and other researchers (e.g., Nedelkoska & Quintini, 2018; Dengler & Matthes, 2018; Filippi & Trento, 2019; Brussevich, 2019; Dabla-Norris & Khalid, 2019; Stephany & Lorenz, 2019; Egana del Sol, 2020) estimate the job susceptibility to automation in several countries using a task-based approach, which makes it possible to capture within-job, between-task heterogeneity, and, as a result, typically produces less pessimistic figures.

Finally, the task-based framework also underpins Acemoglu & Restrepo's (2019b) comprehensive model of the complex interactions between machines and humans, which provides a sound theoretical background to the recent but fast-growing body of literature on the labor impact of robotization. Building upon Acemoglu & Restrepo (2018a), as well as on Acemoglu & Autor (2011), Autor, Levy & Murnane (2003) and Zeira (1998), Acemoglu & Restrepo (2019b) identity three classes of technological advances: automation, which corresponds to "the development and adoption of new technologies that enable capital to be substituted for labor in a range of tasks" (Acemoglu & Restrepo, 2019b, p.30), such as robots (see Acemoglu & Restrepo, 2020); the introduction of new tasks in which labor has a comparative advantage, as automation has historically been accompanied by other technological developments that generate employment opportunities in new occupations; factor-augmenting technological improvements, which make labor or capital uniformly more productive in all tasks.

The authors illustrate how each of these classes affects labor demand. First, an increase in automation in a given sector exerts contrasting effects on aggregate labor demand: a negative displacement effect, as automation directly displaces workers in the tasks now performed by technology; a positive productivity effect, as automation causes a reduction in the cost of production and an increase in the sectoral value added, which in turn raises the demand for labor from non-automated tasks; a composition effect, which captures the reallocation of value added across sectors, and which contributes positively to aggregate labor demand if the expanding sector has a higher labor share than the contracting sector. Second, since workers are reinstated into new tasks, the introduction of new tasks is associated not only with a productivity effect, but also with *a reinstatement effect*, which has positive implications both for labor demand and labor share. Finally, in contrast to automation and new tasks, factor-augmenting technologies affect labor demand mostly via the increase in productivity, and secondly via a substitution effect that influences the labor share but does not alter the task content of production.

All in all, Acemoglu & Restrepo's (2019b) study suggests that the sign and the magnitude of the effect of technological change on labor significantly depend on the class of technological advances under study and the relative weight of different, sometimes contrasting, forces. The level of aggregation matters as well; for instance, the composition effect can be identified only in a multisector setting. The type/proxy of technological change and the level of analysis represent the two criteria through which the empirical literature is reviewed in this study.

2.2.4 The limitations of the RBTC hypothesis and the task-based approach

Even though the RBTC hypothesis and the task-based approach have helped shed light on the complex and multifaceted link between technological change and labor, they present some relevant limitations.

In their review of the RBTC literature, Sebastian & Biagi (2018) summarize some conceptual, operational and empirical challenges, some of which had been previously identified by Matthes et al. (2014), Fernández-Macías & Hurley (Eurofound, 2014) and Fernández-Macías & Hurley (2017). The first relevant conceptual issue arises when trying to capture the concept of routine tasks, which, in the RBTC model, are defined as codifiable tasks that can be performed by machines. However, what is perceived as routine for workers may not be so from the perspective of machine execution. To give an example, Matthes et al. (2014) argue that, even though it implies the repetition of the same basic activities and might be considered as routine from the worker's perspective, driving a motor vehicle is often regarded as a non-routine task because it also requires the use of some skills for which humans typically have (at least so far) a comparative advantage. Another conceptual problem lies in the fact that the RBTC framework implies that the dimensions of routine and cognitive tasks are distinct, whereas they are strongly linked both conceptually and empirically (see Fernández-Macías & Hurley, 2017 for a discussion).

An additional relevant issue is the relationship between the definitions of tasks and the operationalization of the theoretical concepts. Indeed, as the RBTC approach does not provide a unique framework for data analysis, not only is the classification of tasks into different typologies inconsistent between the original work by Autor, Levy & Murnane (2003) and following papers, but also the choice and the number of variables used to create task indices are often completely arbitrary (Sebastian & Biagi, 2018). In particular, some authors (e.g., Caines, Hoffmann & Kambourov, 2018) adopt categorizations based on the degree of task complexity (namely, the extent to which an occupation relies on tasks involving higher-order skills, such as the ability to abstract, solve problems, make decisions, or communicate effectively) rather than on the degree of routinization, or taxonomies that partly depart from the RBTC framework (for instance, Fernández-Macías & Hurley, 2017 use, together with an RBTC-related cognitive index and a routine index, an indicator of social interactions).

Moreover, Sebastian & Biagi report some misalignments in the measurement of the same category. For example, the category of "non-routine manual" is measured as "hand-eye-foot coordination" by Autor, Levy & Murnane (2003), Goos & Manning (2007) and Goos, Gregory & Salomons (2014), as "time spent performing physical activities" in Autor & Handel (2013), and as "repairing or renovating houses/apartments/machines/vehicles, restoring art/monuments, and serving and accommodating" in Spitz-Oener (2006).

With regard to data-related concerns, on the one hand, self-reported sources allow for studying the variability in task content within each occupation or job type, which cannot be studied using occupational databases based on the assessment of experts such as O*Net. On the other hand, self-reported sources are prone to introducing potential bias in the measurement, which tends to be lower in occupational databases.

Beyond the aforementioned issues, a broad limitation of the literature on routine-biased technological change is its technical and deterministic view of the economy, which is seen as a mechanical process of transforming inputs into outputs. As Fernández-Macías & Bisello (2020) point out, such a deterministic perspective, according to which a task will be performed by the cheapest factor, neglects the key role played by human agency in shaping tasks and production and service provision processes at the workplace level and lacks a proper account of the social and organizational aspects of this provision[3]. In light of these considerations, and partly drawing on the previous literature, the authors propose a taxonomy of tasks which aims at connecting the substantive content of work with its organizational context, and which classifies tasks along two axes that are conceptually different: one refers to the content of tasks, namely, the "what" of a work activity, whereas the other one refers to the methods and tools used at work, namely, the "how".

The approach proposed by Fernández-Macías & Bisello has some similarities with the perspective that comes from the evolutionary theory of technical change and the capability-based theory of the firm, according to which the space of human intervention in the production process is regulated not only by the pace of technological change, but also by organizational routines (Dosi & Nelson, 2010; Staccioli & Virgillito, 2021b). A nondeterministic perspective on technology also characterizes a number of recent fieldwork analyses, which stress the role of the interplay between technological and organizational changes in the transformation of human-machine relations (see Section 3.2.3). Finally, the role of organizational change in affecting labor demand together with technological change is the main object of a separate strand of empirical literature (see, for instance: Caroli & Van Reenen, 2001; Beckmann & Schauenberg, 2007; Aubert, Caroli & Roger, 2014; Behagel, Caroli & Roger, 2016).

3. Literature review

This section reviews a significant amount of recent empirical studies on the link between technological change and employment, grouped according to the selected proxy of technical progress. Specifically, Section 3.1 summarizes the literature on the link between disembodied technological change, proxied by Research & Development (R&D), and employment, and briefly recalls a related body of literature that, mainly drawing upon survey data, relies on specific indicators of both product

[3] Fernández-Macías & Bisello posit that the presence of human agency and social organization has four main implications for labor and tasks. First, unlike human labor, machines do not have real agency, and therefore some human labor is always required for their functioning. Second, the workers' input into the economic process requires their active cooperation; as a result, the organization of production will not only have to maximize the technical efficiency of labor inputs but also use forms of work organization that ensure the cooperation of employees. Third, work tasks very rarely exist in isolation, but are in the vast majority of cases coherently bundled into jobs, and this affects tasks in ways that are at least partly independent from technical considerations. Finally, tasks are also socially embedded because the structures of production and service provision of any economy necessarily reflect the structures of consumption of society; hence, the change in the contents and types of tasks in production will ultimately reflect how societies change in their tastes and preferences, in their institutions and organizational forms.

and process innovation. Section 3.2 covers a large and composite strand of literature that examines the employment effect of ICT and computers (3.2.1), robots (3.2.2), and a variety of automation and digital technologies (3.2.3). Section 3.3 reports preliminary evidence on the impact and potential of Artificial Intelligence. When possible, the level of aggregation and both the quantitative and qualitative effect on employment are taken into account.

3.1. R&D and disembodied technological change

Expenditures and investments in R&D represent an innovation input and mainly capture product innovation, which has typically a job-creation effect related to the introduction of new products. All in all, the extant literature has reported evidence of a positive impact of R&D and product innovation on employment, especially when the analysis is conducted at the firm level. Examples of firm-level studies that detect such positive average effect are Stam & Wennberg, 2009 (in start-up Dutch firms), Coad & Rao, 2011 (in US high-tech manufacturing firms), Bogliacino, Piva & Vivarelli, 2014 (in publicly traded European firms), Pellegrino, Piva & Vivarelli, 2019 (in Spanish manufacturing firms), Barbieri, Piva & Vivarelli, 2019 (in innovative Italian firms), Mitra & Sharma, 2020 (in manufacturing firms operating in developing countries). However, this labor-friendly effect seems to be mainly attributable to firms with certain characteristics, such as high-tech (e.g., Stam & Wennberg, 2009; Pellegrino, Piva & Vivarelli, 2019), fast-growing (e.g., Stam & Wennberg, 2009; Coad & Rao, 2011) and large (Barbieri, Piva & Vivarelli, 2019), operating in services and high-tech manufacturing (e.g., Bogliacino, Piva & Vivarelli, 2014; Barbieri, Piva & Vivarelli, 2019).

In addition, the job-creating effect of disembodied technological change is likely to be overestimated due to the inability of firm-level studies to account for selection and competitive dynamics, such as “business-stealing” (see Section 2.1). When a multisector perspective is adopted, the results on the employment effect of technical progress are more mixed; in particular, the labor-friendly impact generally dominates in high-tech manufacturing sectors and knowledge-intensive services, namely, those sectors where product innovation prevails and the demand evolution is more dynamic; on the contrary, the labor-saving tendency is relevant especially in low- and medium-tech manufacturing, low-value-added downstream sectors. Examples of industry-level analyses are the ones conducted by Bogliacino & Vivarelli, 2012 (in manufacturing and sector services of 15 European countries), Piva & Vivarelli, 2018 (in manufacturing and service sectors of 11 European countries), Mitra & Jha, 2015 (in 11 Indian industries), Ciarli et al., 2018 (in the local labor markets of the UK), and Dosi et al. 2021 (in manufacturing and service sectors in 19 European countries).

While the abovementioned firm-level and sectoral studies investigate the quantitative effect of R&D, a number of contributions focus, instead, on the qualitative effect. Evidence that an increase in disembodied technological change is associated with a rise in the relative demand of high-skilled/high-educated workers is provided, for instance, by: Sasaki & Sakura (2005, for Japan, at industry level); Majid (2008, for a sample of advanced countries), Meschi, Taymaz & Vivarelli (2011 and 2016, in Turkish manufacturing firms); Araújo, Bogliacino & Vivarelli (2012, in Brazilian manufacturing firms). Moreover, Sharma & Mitra (2020) analyze both the quantitative and qualitative effect of technological change on employment. Some studies (i.e., Araújo, Bogliacino & Vivarelli, 2012; Mitra & Jha, 2015; Meschi, Taymaz & Vivarelli, 2011; Meschi, Taymaz & Vivarelli, 2016; Mitra & Sharma, 2020) focus on developing economies. However, the quantitative or qualitative effect of technological change in these countries is generally also (or mainly) attributable to the so-called import-related technological change (see for instance Meschi, Taymaz & Vivarelli, 2016, and Mitra & Sharma, 2020).

The adoption of R&D to proxy for technological change and innovation may imply an "optimistic bias" in terms of its employment impact, and a partial assessment of technical progress, since the latter is mainly embodied in capital investment, especially in firms and sectors that conduct very limited or null in-house R&D activity (Pellegrino, Piva & Vivarelli, 2019). Accordingly, Pellegrino, Piva & Vivarelli (2019), Piva & Vivarelli (2018), Barbieri, Piva & Vivaelli (2019) and Dosi et al. (2021) account for both R&D and embodied technological change (ETC), and find some evidence of a labor-saving effect of technological advances incorporated in capital formation.

The juxtaposition between product innovation and process innovation also emerges in a number of firm-level and sectoral studies (e.g., Harrison et al., 2014; Hall, Lotti & Mairesse, 2009; Lachenmaier & Rottmann, 2011; Peters et al., 2014), which, generally drawing upon innovation surveys, such as the Community Innovation Survey (CIS), compute an indicator of product innovation and an indicator of process innovation (or related constructs, such as the indicators of cost competitiveness and technological competitiveness proposed by Bogliacino & Pianta, 2010) and gauge the role played by each of these two macro-categories of innovation outputs in employment dynamics.

A considerable number of empirical contributions that assess the implications of innovation related to products, processes, or organizational arrangements are reviewed by Calvino & Virgillito (2018); additional related studies, published in 2019 in the Special Section "Innovation and employment" of Industrial and Corporate Change -Volume 28 (which also includes two articles covered in this survey, i.e., Breemersch, Damijan & Konings, 2019 and Barbieri, Piva & Vivarelli, 2019) are briefly summarized by Dosi & Mohnen (2019). In line with the results of the articles reviewed in the present section, this broader body of literature points to an overall positive effect of product innovation and a more ambiguous effect of process innovation.

To sum up, R&D expenditures, which are mainly associated with product innovation and the so-called disembodied technological change, generally have a positive effect on the level or growth of employment. However, this is mainly attributable to some firms (especially large, dynamic innovative firms) and to some sectors (in particular, medium-tech and high-tech sectors). In addition, the positive employment effect of disembodied technological change may be at least partially counterbalanced by the potential labor-saving behavior of embodied technological change, which, instead, is mainly related to process innovation.

3.2 Technological change embodied in the capital inputs

3.2.1 Computers and ICT

A vast strand of literature has investigated the employment consequences of the adoption of computers, or, more in general, of Information and Communication Technologies (ICTs)[4], which, since the eighties, have experienced great diffusion and advancement. As the "quality" of workers

[4] Although there is no universal definition, the term ICT generally refers to all the devices, networking components, applications and systems that enable users to access, retrieve, store transmit and manipulate information in a digital form. As an illustration, the EU-Klems sectoral variable "ICT investment" comprises the tangible assets "computing equipment" and "telecommunications equipment", and the intangible asset "software".

has turned out to be a critical variable (indeed, new technologies ask for specific skills/tasks, and then create different dynamics among different categories of workers; Barbieri et al. 2019), in the last few decades a considerable number of articles have investigated the qualitative effect of ICT-based technological change on employment.

The SBTC literature aiming to assess the skill premia (in terms of employment and especially of wages) associated with technological change mainly flourished during the nineties and the first years of the 2000s, and has already been extensively discussed and reviewed; for these reasons, it is not analyzed in this work. Rather, during the last 15 years or so, a considerable body of literature has embraced the so-called Routine Biased Technological Change (RBTC) hypothesis and has adopted a task-based approach to gauge the implications of computerization on some labor outcomes.

In line with the theory, several studies suggest that RBTC has contributed to labor market polarization in various countries and at different levels of analysis. Evidence of changes in the occupational employment shares that can rationalize this phenomenon has been reported, for instance, by: Akcomak, Kok & Rojas-Romagosa (2013) in the UK and the Netherlands; Kampelmann & Rycx (2013) in Germany; Bisello (2013) in the UK; Adermon & Gustavsson (2015) in Sweden; Sharma (2016) in India; Fonseca et al. (2018) in Portugal; Kim, Hong & Hwang (2019) in South Korea. Conversely, both Guarascio, Gualtieri & Quaranta (2018) and Basso (2019) argue that evidence of labor polarization and the role played by RBTC in driving recent labor dynamics in Italy is mixed.

Importantly, some researchers (e.g., Spitz-Oener, 2006; Ackomak, Kok & Rojas-Romagosa, 2013 and 2016; De La Rica & Cortazar, 2016; Consoli et al., 2019; Ross, 2020) resort to detailed individual-level measures of tasks to also account for within-occupation task heterogeneity and variations over time and show that RBTC has caused not only changes in employment across occupations (i.e., the extensive margin) but changes in the task content of the occupations (i.e., the intensive margin) as well.

Labor polarization has also been investigated at the within-industry and between-industry level. As an illustration, Goos, Manning & Salomons (2014) demonstrate that job polarization in 16 Western European economies in the period 1993-2010 occurred both within a certain industry and across different industries, and that the RBTC hypothesis explains both overall job polarization and its within-industry and between-industry components as well. Moreover, other contributions (e.g., Autor & Dorn, 2013; Autor, Dorn & Hanson, 2015; Moreno-Galbis & Sopraseuth, 2014; Senftleben-König & Wielandt, 2014; Dauth, 2014; Charnoz & Orand, 2017; Consoli & Sánchez-Barrioluengo, 2019) have analyzed employment trends in local labor markets or similar geographical units, which have generally experienced a reallocation of employment towards non-routine occupations, especially in the service sector.

The computer-driven shift in the skill/task content has also favored employment or the creation of new job titles in cities, especially in cities with higher shares of connected tasks (which require proximity) and with endowments of analytical and interactive skills (see Dauth et al., 2014, for Germany; Kok & ter Weel, 2014, and Berger & Frey, 2016 for the US). A few RBTC studies focus, instead, on firms, and find some evidence of employment polarization between firms and even within the same firm (e.g., Cortes & Salvatori, 2015, in the UK; Kerr, Maczulskij & Maliranta, 2020 and Böckerman, Laaksonen & Vainiomäki, 2019 in Finland).

While the aforementioned RBTC studies look at the amount of employment/labor demand of different demographic and occupation groups, other studies (e.g., Apella & Zunino, 2017; Peng, Wang & Han, 2018; Bachmann, Cim & Green, 2019; Ross, 2020) scrutinize changes in the employment status and job-to-job transitions. Their results tend to confirm that the degree of non-routine (routine) task content is related to positive (negative) employment outcomes. Interestingly, Ross (2020) also shows that the negative impact of a rise in within-occupation routine intensity is concentrated during periods of economic turmoil, stressing the fact that business cycle conditions can influence the link between technological change and employment.

Finally, some studies investigate the effect of routine-replacing technological change in developing economies, either in a single country (e.g., Sharma, 2016), or in a sample that includes both developing and advanced economies. For instance, Das & Hilgenstock (2018) argue that developing economies are on average significantly less exposed to routinization than their developed counterparts, but exposures have been steadily converging between the two, and Reijnders & de Vries (2018) assert that technological change increases the number of non-routine relative to routine occupations in all countries. All in all, evidence of RBTC is found in developing countries as well.

Most of the contributions in the RBTC literature use, as the key regressor, one or more indicators of task content, where changes are attributable to technological advances[5]. Michaels, Natraj & Van Reenen (2014), on the other hand, suggest examining ICT-based theories of job polarization by employing direct measures of ICT capital. The authors, who test the hypothesis that ICTs polarize labor in the industries of nine European countries, the US and Japan, adopt an approach that bridges the SBTC framework and the task-based perspective of the RBTC literature and find that, consistently with ICT-based polarization, industries with faster ICT growth shifted demand from middle-educated workers to highly educated workers during the period 1980-2004. A similar approach is pursued, at firm level, by Akerman, Gaarder & Mogstad (2015), who report that broadband adoption in Norwegian firms complements skilled workers in executing nonroutine abstract tasks, and substitutes for unskilled workers in performing routine tasks.

The link between computerization, proxied by a direct ICT measure, and job polarization is also explored by a number of studies that do not apply a task-based approach, such as: Massari, Naticchioni & Ragusa (2015), who find a nexus between ICT intensity and between-industry job polarization in Europe during the period 1995-2007; Breemersch, Damijan & Konings (2019), who, looking at the main determinants of between-industry and within-industry polarization, argue that, in European manufacturing industries ICT adoption explains a third of within-industry polarization (while Chinese net import competition contributed to a much smaller extent), whereas the process of between-industry polarization is driven by widespread deindustrialization and servitization in developed countries; Harrigan, Reshef & Toubal (2020), who investigate trends in labor polarization at different levels in the French private sector and proxy ICT intensity with the employment share of the ‘techies’, namely, workers with STEM (Science, Technology, Engineering and Math) skills. Indeed, “because of their central role in planning, installing and maintaining ICTs and other technologies, as well as in training and assisting other workers in the use of technology, they

[5] Exceptions are represented by the analyses conducted by Marcolin, Miroudot & Squicciarini (2016), Kerr, Maczulskij & Maliranta (2020) and Böckerman, Laaksonen & Vainiomäki (2019), who use direct indicators of ICT capital and study how the latter relate to the employment dynamics of different educational and task groups.

constitute the crucial link between economy-wide technological progress and firm-level technology adoption" (Harrigan, Reshef & Toubal, 2020, p.2). According to their results, aggregate polarization in France was driven mostly by changes in the composition of firms within industries (as firms that were intensive in middle-wage jobs grew more slowly than firms intensive in high and low wage occupations), and occurred mostly within urban areas. These findings stress the importance of accounting also for more disaggregated levels of analysis to properly study this complex phenomenon.

In addition, some researchers also investigate how ICT-driven technological change affects workers of various ages, especially older workers (e.g., Schleife, 2006; Aubert, Caroli & Roger, 2006; Beckmann & Schauenberg, 2007; Biagi, Cavapozzi & Miniaci; 2013; Behagel, Caroli & Roger, 2014; Autor, Dorn & Hanson, 2015; Peng, Anwar & Kang, 2017), or consider gender-specific employment trends (e.g., Lindley, 2012; Senftleben-König & Wielandt, 2014; Autor, Dorn & Hanson, 2015). More information on the role of age and gender in the link between technological change and employment is provided in Section 4.2.

While the aforementioned articles look at the impact of technological change on different types of workers/occupations, others investigate its net effect at different levels of aggregation. One of the most comprehensive firm-level analyses has been conducted by Pantea, Sabadash & Biagi (2017), who analyze the short-run labor substitution effects of firm-level ICT adoption in seven European countries during the period 2007-2010; the authors find no evidence that ICT substitutes labor in the short run, as its increased use within firms neither increases nor reduces the numbers of workers they employ. Some multisectoral contributions at the national level (e.gifr, Matteucci & Sterlacchini, 2003 for Italy, Gallipoli & Makridis, 2018, for the US) document an ICT-related decline in the manufacturing industries which is accompanied by an employment increase in services, especially in dynamic and innovative sectors.

Concerning country-industry studies, the extensive analysis conducted by the European Commission (2014) on the effect of ICT on employment in the EU fails to provide evidence of either a systematically positive or a systematically negative long-term effect of ICT on employment, either among sectors within a single country or across countries in a single sector, especially when labor and product market regulations are accounted for.

In a similar vein, Breemersch, Damijan & Konings (2019) posit that a large part of the overall decline in employment that occurred in Europe, especially in low-polarized industries, is not ascribable to ICT adoption or R&D intensity, but to competition with net Chinese imports. Autor & Salomons (2018) test the labor-saving effect of technological change in 28 industries of 18 OECD countries from 1970 using a broad proxy, namely TFP growth (also instrumented by foreign patents and robot adoption) and show that technical progress has lately reduced the labor share but has not been employment-displacing.

Within the task-based literature, Gregory, Salomons & Zierahn (2019) report that the substantial decrease in labor demand and employment resulting from the substitution of capital for labor over the years 1999-2010 in 238 regions across 27 European countries has been overcompensated by the positive product demand effect and its spillovers to the non-tradable sector. The authors also highlight that the distribution of the gains from technological progress is critical for the size of the overall labor demand and employment effects (indeed, in the scenario in which only wage income flows back into local product demand, whereas the rising non-wage income is not accounted for, the positive aggregate labor demand effect is only half as large), and in doing so they stress the importance of the debates about who owns the capital (Freeman, 2015).

To conclude, this heterogenous strand of literature suggests that, all in all, ICT-driven technological change has not caused a net negative effect on employment, but has led to significant changes in the occupational composition and task specialization of employment across industries, across cities, across firms operating in the same industry, and possibly within firms as well; in doing so, computerization has contributed to the increase in labor market polarization in various countries. In addition, there is some evidence that technological change is age biased.

However, most of the studies under scrutiny rely on broad or indirect proxies of technological change which are likely to capture a heterogenous array of technologies, and which do not allow us to properly understand which ones drive the employment effects under investigation. In particular, machine-based technologies are likely to have a stronger impact on workers compared to non-machined based technologies (see Balsmeier & Woerter, 2019). Besides, some complex automation technologies, such as robots, may have a more disruptive effect than more traditional technologies and the computers that featured in the "Computer Revolution" of the eighties and the nineties. The effect of robots and a variety of advanced automation and new digital technologies are illustrated in Sections 3.2.2 and 3.2.3, respectively.

3.2.2 Robots

A leading automation technology that started spreading during the nineties is represented by industrial robots. Following the definition provided by the International Federation of Robotics, which has been recording information regarding worldwide robot stock and shipment figures since 1993, an industrial robot is an automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications (IFR, 2012). Since 2010 especially, the demand for industrial robots has risen considerably and, from 2013 to 2018, annual installations of robots increased by 19% on average per year (IFR, 2019).

Recent and prospective advances in robotics have renewed concerns about the potentially disruptive impacts of technological change on labor markets. Indeed, robots can perform a wide range of tasks, including welding, painting, and packaging, with very little human intervention (Graetz & Michaels, 2018). From a theoretical point of view, however, the impact of robots on employment is not clear a priori, since it involves forces moving in opposite directions, as illustrated by Acemoglu & Restrepo's (2019b) model. In addition, demand-enhancing effects may extend to other connected markets for goods and services (Dosi et al., 2021; Barbieri et al., 2019). Besides, the introduction of robots may also increase the demand for complementary non-automatable tasks, such as tasks necessary to use, run and supervise the new machines, and even boost the creation of new tasks, ranging from engineering and programming functions to those performed by audio-visual specialists, executive assistants, data administrators and analysts, meeting planners, and social workers (Autor, 2015; Acemoglu & Restrepo, 2019b).

One of the first studies to empirically examine the impact of industrial robots on labor was that conducted by Graetz & Michaels (2018). The authors develop a model of firms' decisions regarding the adoption of robot technology and the use of robots in production alongside human workers which predicts the effect of robotization on a set of economic outcomes, including employment. Using data from IFR and EUKLEMS, they estimate robot density (i.e., the stock of robots per million hours worked) in 14 industries and 17 countries from 1993 to 2007, and identify the relationship between robots and several labor variables, including employment, using both OLS and 2SLS regressions. According to their findings, robots did contribute to lower low-skilled workers' labor share, but did not significantly reduce total employment.

Other industry-level cross-country analyses on the impact of robot penetration on employment are those by: Carbonero, Ernst & Weber, 2018 (in 15 sectors and 41 countries in the years 2000-2014); Compagnucci et al., 2019 (in different manufacturing sectors of 16 OECD countries over the period 2011-2016); Blanas, Gancia & Lee, 2019 (in 10 high-income countries and 30 industries for the period 1982-2005); Klenert, Fernández-Macías & Antón, 2020 (in 14 EU countries over the years 1995-2015, with a focus on manufacturing sectors); de Vries et al., 2020 (in 19 industries in 37 countries from 2005-2015).

The results are quite mixed. Carbonero, Ernst and Weber find a negative effect of robot adoption on worldwide employment, which is small in developed countries but significant in developing economies. Compagnucci and coauthors' study, which resorts to a panel VAR approach, reveals that the increase in the number of robots reduces the growth rate of worked hours. However, the latter may not necessarily reflect a contraction in the number of employees; in this regard, Cho & Kim, 2018, who study the link between robots and employment in South Korea using robots as the dependent variable, point to a complementary relation between the number of employees and robotization and a substituting relation between the number of working hours and robotization.

Klenert, Fernández-Macías & Antón find that robot use is linked to an increase in aggregate employment. Furthermore, they argue that, contrary to what emerges from Graetz & Michaels' study, robots do not reduce the share of low-skill workers in the sample EU countries under scrutiny, and that the divergencies between their results and Graetz & Michaels' ones are mainly explained by different choices concerning the data sources, the time series, the way the robot density indicator is determined and the selection of the sectors under analysis.

Blanas, Gancia & Lee build an indicator of a country's exposure to robotization using UN COMTRADE data on robot imports, rather than IFR data, and let it interact with an industry-specific measure of exposure to automation (proxied by the routine-share index of Autor, Levy & Murnane, 2003) in order to investigate the impact of robots on individuals of different education, age, and gender in both the manufacturing and the service industries. All in all, their empirical analysis in a sample of 10 high-income countries and 30 industries for the period 1982-2005 suggests that the displacement effect dominates in manufacturing industries, where automation is already widely adopted, while the productivity effect seems to prevail in the service industries, where automation is at an earlier stage. Moreover, the manufacturing industries more exposed to robots experienced a decline in their employment of low-skill, young and female workers (but further analysis reveals that the negative effect on women is only attributable to those with low or middle education), while the service industries more exposed to robots experienced an increase in their employment of medium-skill workers, all age groups, and men. The authors also stress that their estimation strategy can only detect losses relative to other industries, and then that negative employment effects do not necessarily imply a fall in the absolute level of employment.

Finally, rather than resorting to broad occupational and educational classes, de Vries et al. (2020) focus on job tasks and classify 13 two-digit occupational groups into four task-based broad categories (i.e., routine manual, routine analytic, non-routine manual, and non-routine analytic) according to their routine-task intensity. Using a panel of 19 industries in 37 countries from 2005-2015, they demonstrate that, in high-income countries, the increased use of robots does not reduce aggregate employment, but has a qualitative effect, since it is associated with positive changes in the employment share of non-routine analytic jobs and negative changes in the share of routine manual jobs. Instead, in emerging and transition economies these relations are not significant.

Other contributions employ a different approach, sometimes known as the shift-share approach, which assigns robots to different subnational regions based on the distribution of employment, and then exploits within-country regional variation of employment dynamics and robot exposure and accounts for local employment spillover effects between sectors. In a seminal paper, Acemoglu and Restrepo (2020) create a Bartik-style (Bartik, 1991) measure of the local exposure to robot adoption in the US that combines the national penetration of robots in each industry with the local distribution of employment across industries within each US commuting zone. Building upon Acemoglu and Restrepo's (2019b) model of automation technologies and using both data from IFR and the data compiled by Leigh & Kraft, 2018 (who conducted a robotics census for the US to account for the regional variations in industry presence and the deployment of robotic capabilities), the authors show that robots negatively affected the employment level of the US local labor markets during the period 1990-2007. This prevailing displacement effect is most pronounced in manufacturing and particularly in the industries most exposed to robots and is concentrated in routine manual occupations, particularly blue-collar, namely, those that are rich in tasks that are being automated by industrial robots.

Acemoglu & Restrepo's approach was subsequently applied by: Chiacchio, Petropoulos & Pichler, 2018 (on 116 NUTS2 regions of six Western European Union countries); Dauth et al., 2017 (on German local labor markets); Dottori, 2020 (on Italian local labor market areas). Chiacchio, Petropoulos & Pichler (2018) find that robotization harms aggregate employment, but the estimated magnitude is lower than in Acemoglu and Restrepo (2020), and the authors suggest that European labor market policies could cushion the impact of industrial robots. Moreover, the negative effect, which is positive for technicians, is driven by workers of middle education and by young cohorts.

Dauth et al. (2017), who merge IMF data with detailed linked employer-employee information, conclude that robots do not cause total job losses, but they affect the composition of aggregate employment. In particular, they find a decline in manufacturing employment (which is not caused by direct destruction of existing jobs, but by a reduction of new manufacturing jobs for young people) that is fully offset, or even slightly overcompensated, by additional jobs in the service sector, and that the overall effect on total employment is neutral when employment spillovers between sectors are accounted for.

Similarly, Dottori (2020) does not find robust empirical evidence of a negative effect of robot penetration on local employment (although it has reduced new workers' likelihood of entering manufacturing). The author suggests that the analogies with Dauth et al.'s results and the departure from Acemoglu & Restrepo's main findings could partly be related to the higher similarity of the Italian economy to Germany's, compared to the US one, in terms of institutional settings (e.g., higher employment protection), economic structure (e.g., a relatively higher weight of manufacturing) and the sectoral distribution of robots (which are used more prevalently in mature sectors and less in electronics). In this respect, Aghion et al. (2020), who study the labor implications of automation technologies at different levels of aggregation (see Section 3.2.3), postulate that the heterogeneity of these studies in terms of main findings may be partly attributable to different levels of exposure to trade (for instance, Germany relies heavily on exports, while, in the US, domestic firms have a larger domestic market and are less exposed to international competition).

Caselli et al. (2021) observe that the industry shift-share approach does not account for the high degree of firms and workers' heterogeneity within an industry (as it implicitly assumes that every worker in every firm in an industry faces the same level of robot exposure and that the distribution of robots within an industry is uniform across regions conditional on the local employment shares), nor does it allow for distinguishing occupations that are complementary to robot adoption from those that are exposed (and those that are not). In their analysis of the employment consequences of robot penetration in the Italian local labor markets, Caselli et al. introduce two major novelties, namely, they match occupations and robots based on the tasks characterizing both the professions and the robots and focus on the evolution of local employment in the occupations exposed to robots, rather than resorting to broad occupational groups (e.g., skilled/unskilled, routine/non-routine, and the like). Caselli and coauthors do not detect significant changes either in the employment dynamics of the occupations exposed to robots or, like Dottori (2020), in aggregate labor market outcomes. Moreover, consistent with the view that firms hired more workers to perform activities complementary to robots (Autor, 2015; Acemoglu & Restrepo, 2019b), they find that the shares of local employment in occupations characterized by tasks that are clearly complementary to robots did expand over time.

Aggregate-level analyses do not control for heterogeneity across firms within sectors and across workers within the same firm, and do not allow to properly gauge how and to what extent robots substitute or complement labor, and which firms' characteristics favor the introduction of such automation technology (Autor & Salomons, 2018; Seamans & Raj, 2018). As advocated by Seamans & Raj (2018), some recent studies collect firm-level information on robot adoption from survey data (e.g., Koch, Manuylov & Smolka, 2019) and from fiscal and administrative data (e.g., Acemoglu, LeLarge & Restrepo, 2020), or rely on data on proxies such as robot imports (Dixon, Hong & Wu, 2019; Bonfiglioli et al., 2020).

The link between robots and labor has been assessed at the firm level by: the European Commission (2016), on 3,000 manufacturing firms in seven European countries; Koch, Manuylov & Smolka (2019), on Spanish manufacturing firms; Bonfiglioli et al. (2020) on French firms; Dixon, Hong & Wu (2019), on Canadian companies; Acemoglu, LeLarge & Restrepo (2020), on French manufacturing firms. While the European Commission's earlier analysis, which also explores the factors that increase the probability of robot adoption, but which does not control for potential endogeneity, finds that the use of industrial robots does not have any direct effect on firm-level employment, Koch, Manuylov & Smolka (2019), Dixon, Hong &Wu (2019) and Acemoglu, LeLarge & Restrepo (2020) find that robotization is beneficial to aggregate employment within the firms adopting robots. Conversely, Bonfiglioli et al. (2020) show that the positive correlation between robot imports and employment is driven by demand shocks and that, once these shocks are removed, increases in automation lead to job losses; at the same time, robot imports increase the employment share of high-skill professions.

Also, Koch, Manuylov & Smolka (2019) and Acemoglu, LeLarge & Restrepo (2020) report negative employment effects on the robot adopters' competitors that do not employ robots. In particular, Acemoglu, LeLarge & Restrepo (2020) observe that the firm-level positive effects of adopters do not translate into similar market-level impacts because of the negative externalities on their competitors, which more than offset the employment gains.

Finally, Bonfiglioli et al. (2020) note that most of the other microeconomic analyses do not use a firm-level instrument to isolate the causal effect of robot adoption, and caution is thus required when interpreting the optimistic findings.

In a nutshell, firm-level analyses tend to find a positive or negligible effect on employment, which, however, may be overestimated when endogeneity is not properly controlled for and which, at the industry level, may be more than counterbalanced by the negative employment performance displayed by the competitors that did not adopt robots. In addition, robots' impact can vary across various workers' categories within the same firm.

Further insights on robot applications come from patent analysis[6]. Focusing on industrial robots in the US, Webb (2020) shows that patents mostly describe robots as cleaning, moving, welding, and assembling various objects, whereas software (namely, computer programs which, as opposed to AI, only perform actions that have been specified in advance by a human) are described as recording, storing and producing information, and executing programs, logic, and rules. Consequently, the occupations most threatened by robots (e.g., various kinds of materials movers in factories and warehouses, and tenders of factory equipment, involving a considerable amount of easily automatable repetitive manual tasks) differ from the occupations most exposed to software (which include broadcast equipment operators, plant operators, and parking lot attendants). Additionally, and in accordance with Blanas, Gancia & Lee's findings, Webb argues that robots mostly displace individuals with less than high school education and in low-wage occupations, whereas software, consistently with the evidence of ICT-driven job polarization, mainly hinders middle-wage occupations. Finally, in line with Dauth and Chiacchio, Petropoulos & Pichler's findings, robots primarily target young male workers, who tend to engage in what Webb terms "muscle" tasks.

In conclusion, in recent years a nascent but blooming strand of research has assessed the effect of robot adoption on employment at different levels of aggregation. Even though the available evidence is quite mixed, and data limitations and different methodological choices may hinder the comparability and the reliability of the results, the review presented in this section prompts the following tentative considerations: robots differentially affect employment according to the type of skills and tasks, as they generally benefit workers who carry out tasks that complement robot applications, and negatively affect workers with low levels of education and/or performing repetitive manual tasks; the industry under scrutiny matters and, within the same industry, robots tend to have a positive effect on firm-level employment in the firms that adopt robots (which, however, may be overestimated if endogeneity is not properly controlled for) and a negative effect on the nonadopters, which sometimes more than offsets the former; the net impact on employment also depends on country-specific economic and institutional factors; the human tasks and occupations mostly exposed to robotization are different from the ones most affected by computerization.

3.2.3 Automation and new digital technologies

The ongoing technological revolution is characterized not only by widespread robotization, but also by the increasing adoption of a range of automation and new digital technologies not limited to robots. In addition, robots tend to be concentrated in specific sectors, such as the automotive one (for

[6] In the last few years, patent analysis has been used to identify the human tasks challenged by different types of technology (e.g., Montobbio et al., 2020; Webb, 2020), as well as to explore the sources and the geographical and historical patterns of adoption of automation and new enabling technologies, including AI (e.g., Montobbio et al., 2020; Van Roy, Vertesy & Damioli, 2020; Martinelli, Mina & Moggi, 2021; Staccioli & Virgillito, 2021a), and to investigate the causal link between the production or adoption of technologies and a labor variable (e.g., Dechezleprêtre et al., 2020; Mann & Püttmann, 2020).

instance, Aghion et al. 2020 report that, in France, the motor vehicle industry accounts for almost 60% of robots). As a result, the analyses focusing on robots only are likely to provide a partial picture of the ongoing digital transformation.

Firm-level data on the adoption of digital and automation technologies are only recently starting to be collected by national statistical offices and are not yet included in major innovation surveys such as the Community Innovation Survey (Balsmeier & Woerter, 2019).

As an illustration, Domini et al. (2021), who investigate how investment in automation-intensive goods impacts workers in the French manufacturing sector over the years 2002-2015, use firm-level data on imports of intermediates embedding automation technologies -which include, among others, industrial robots, dedicated machinery, numerically-controlled machines and a number of other automated capital goods identified by the taxonomy presented by Acemoglu & Restrepo (2018b), as well as 3D printers- to identify what they define as automation spikes. The authors, who account for the endogenous selection of firms into automation, show that the decision to automate has a positive impact on firms' own employment in terms of both a reduction in the separation rate and an increase in the hiring rate, probably because it improves the relative competitiveness of firms and thus enhances their expansion. Further, automation spikes do not seem to affect shares of different types of workers within firms (1- and 2-digit occupational categories, and routine-intensive vs. nonroutine-intensive), suggesting that the positive effect of technological change in the adopters is shared by various categories of labor.

Domini et al.'s results are robust to the use of an alternative definition of automation spikes, namely the one used by Bessen et al. (2019), who, looking at Dutch firms in all private non-financial industries over the period 2000-2016 and using an event study differences-in-differences design, show that automation at the firm increases the probability of workers separating from their employers and decreases the number of days worked. Older workers generally bear most of the cost of automation-driven displacement. Accordingly, in Bessen and coauthors' study the negative effect of automation prevails, but, in line with the age-biased technological change hypothesis, it is older workers that bear most of the cost of automation-driven displacement. Moreover, the authors, who also report that there are only modest differences in how male and female workers are affected by an automation event, argue that the displacement impact of automation seems mild in comparison with the effects of changing economic conditions, and does not imply net job destruction at the aggregate or firm level.

The ramifications of automation for the French manufacturing sector have also been recently scrutinized by Aghion et al. (2020), who study the effect on employment at three levels of aggregation (i.e., firm, plant and industry) using two alternative measures of automation: a broad indicator, namely the firm-level value of industrial equipment and machines, which may include also non-automation technologies, and the measure of a plant's peak capacity for electric motive power, which refers to a more specific set of automation technologies. The empirical analysis, which relies on a shift-share IV design to allow a causal interpretation, reveals that, at the firm level and plant level, automation has a beneficial effect on employment, including for low-skill industrial workers, suggesting that the productivity effect (namely, increased automation allowing the firm to expand its sales and scale, which requires hiring additional workers for production) outweighs the displacement effect. This holds also when the analysis is restricted to the automotive industry to mostly capture the effect attributable to robot adoption. Finally, the authors repeat the analysis at the industry level to account for business stealing and other equilibrium effects. Even though the industry-level relationship between employment and automation is positive on average, there is substantial heterogeneity depending on the exposure to international trade: the link is not significant in sectors with low exposure to international competition whereas it is positive and significant in sectors that face international competition. According to the authors, this fact can be explained by the business-stealing effect between national and foreign firms, which, in an open economy, compete for different varieties of the same goods.

Sectoral differences in employment patterns also emerge from the patent-based study of Mann & Püttmann (2019). The authors link automation patents (i.e., those patents whose text describes a device that carries out a process independently of human intervention) granted in the US between 1976 and 2014 to the industries of their use and, through local industry structure, to commuting zones. In line with previous evidence, they demonstrate that advances in automation technologies lead to a shift from routine manufacturing jobs towards non-routine service sector jobs, with a positive average employment effect at the local labor market level.

Some redistribution of jobs across sectors associated with net positive employment also emerges from the study of Vermeulen et al. (2018), who investigate the projected impact of automation on employment in the forthcoming decade. The authors identify four types of sector affected directly or indirectly by automation, namely "applying" sectors (i.e., sectors in which the technology is applied), "making" sectors (i.e., producing, developing, supplying and supporting) complementary sectors (i.e., facilitating or inhibiting exploitation of the focal technology, such as education, legal support, and business consulting) and "spillover" or quaternary sectors (i.e., receiving local demand spillovers related to disposable income, such as leisure and traveling, entertainment and culture, sports and lifestyle). Vermeulen and coauthors show, both theoretically and empirically, that the potential job loss due to automation in the "applying" sectors is counterbalanced by job creation in the "making" sectors, as well as in the complementary and the spillover sectors, suggesting that mankind is facing "the usual structural change" rather than the "end of work".

While the aforementioned studies focus on automation, Balsmeier & Woerter (2019) account for a broader array of new digital technologies, which includes both complex machine-based digital technologies, such as computerized automated control systems, programmable logistic controllers, rapid prototyping, computerized numerical control (CNC) and direct numerical control (DNC) machines, robots, autonomous vehicles, 3D printing and the Internet of Things, and nonmachine-based digital technologies, such as ERP, social media, or e-commerce. The authors find that firms' investment in digitalization in Switzerland is associated with an increase in high-skilled workers and a decline in low-skilled workers. However, as they consider a single country and a limited dataset (covering firms with at least 20 employees in 2015), the authors recognize that it is too early to safely conclude that digitalization will have different effects on low-skilled labor to the technological developments of the past. A subsequent analysis that separately examines firms adopting complex machine-based digital technologies and firms using non-machine-based digital technologies reveals that only machine-based digital technologies are responsible for significant employment effects. Intuitively, machine-based technologies are expected to have a certain disruptive power since their implementation is often capital intensive, complex, requires high-skilled qualified labor, and is only profitable if it allows firms to produce at a much lower cost per unit or higher quality standards than otherwise possible. On the other hand, non-machine-based technologies are generally used to facilitate extant single processes rather than to disrupt or significantly change the whole production process.

Since high-skilled workers are the ones that own the technical know-how required to bring these technologies to useful usage, it is likely that these workers also play a role in the firm's decisions about the adoption of new digital technologies. This is confirmed by Cirillo and coauthors' (INAPP, 2021) study of the patterns and determinants of new technology adoption in a large representative sample of Italian firms, which highlights that workers' skills are primary determinants of the adoption of digital enabling technologies because they are necessary conditions for the extraction of productivity gains from the new assets.

Further insights into the effect of automation and new digital technologies on employment, and on the role played by social and organizational aspects that quantitative analysis is not generally able to capture, are provided by fieldwork studies (see Staccioli & Virgillito, 2021b for a discussion). To give a few examples: Pardi, Krzywdzinski & Luethje (2020) consider the current Industry 4.0 wave more of a hype than a revolution and argue that more subtle changes are taking place on the shop-floor of automotive factories that might result in deskilling and work intensification; Pfeiffer (2018), focusing on production workers in Germany, observes that in highly complex and heavily digitized production environments the significance of human labor is quantitatively decreasing, but its role in maintaining these complex production processes is becoming ever more important; Krzywdzinski (2020) argues that robot density is not a very adequate indicator of the degree of technological change in place in automotive factories (where, since the 1990s, robot adoption has tripled, but the levels of automation have remained largely the same); Cirillo et al. (2021) investigate the undergoing technological and organizational transformation in three high-tech automotive factories in Italy and posit that efforts devoted to the implementation of digitalization and interconnection of production equipment outweigh the push towards sheer automation.

To conclude, the blooming line of research on the impact of robotization on labor has been recently complemented by a few empirical contributions which, rather than looking at the employment effects of robots only, deal with a broader set of automation and new digital technologies. According to them, the adoption of such devices, which is not casual and is also fostered by high-skilled workers who are able to properly employ them, may benefit the firm in terms of increased competitiveness, productivity and production, which in turn may positively affect workers, even though it is possible that certain categories, especially low-skilled workers or older workers, are penalized. In addition, it seems that the potentially disruptive impact of new digital technologies is mainly attributable to those embedded in complex machines, such as robots and 3D-Printing. Moreover, automation and digitalization can differentially affect employment according to the characteristics (e.g., technological patterns and exposure to trade) of the sector under scrutiny. The paucity of detailed and extensive data on these breakthrough technologies still prevents empirical research from providing more systematic evidence and more comparable results. Nonetheless, judging from the rapid pace of growth of the empirical research on these topics, it is reasonable to expect that new evidence will be available soon. Finally, some complementary valuable insights may come from field research.

3.3 Impact and potential of Artificial Intelligence: preliminary findings

In recent years, three interrelated trends, namely the availability of large unstructured databases, the explosion of computing power and the rise in venture capital to finance innovative, technological projects, have boosted the development and spread of technologies based on Artificial Intelligence (AI; Ernst, Merola & Samaan, ILO, 2018).

AI refers to a broad and rapidly expanding field of technologies, so it is not surprising that there is no single, ready-made definition (Van Roy, Vertesy & Damioli, 2020). Moreover, the term is sometimes (improperly) used interchangeably with expressions that refer to more general and broader concepts, such as automation and technological change. Acemoglu & Restrepo (2019, p.1) describe Artificial

Intelligence as “the study and development of intelligent (machine) agents, which are machines, software or algorithms that act intelligently by recognizing and responding to their environment”. Even though AI includes various research areas and it is often difficult to draw precise boundaries, its core components can be identified with machine learning, deep learning, NLP (natural language processing) platforms, predictive APIs (application programming interface), image recognition and speech recognition (Martinelli, Mina & Moggi, 2021). More sophisticated applications include medical expert systems to analyze and diagnose patients’ pathologies, automated review of legal contracts to prepare litigation cases, self-driving cars or trucks, and the detection of patterns in stock markets for successful trading (Ernst, Merola & Samaan, ILO, 2018).

Artificial Intelligence can be deployed in multiple domains in the economy and is often regarded as what Bresnahan & Trajtenberg (1995) define as a general-purpose technology, namely, a technology that becomes pervasive, improves over time and generates complementary innovation. While robotic technologies often involve physical manipulation and are capable of carrying out complex manual tasks, AI technologies are largely software-based and rely on iterative learning and perception (Raj & Seamans, 2019). Importantly, unlike robots, which need to receive specific instructions, generally provided by a software, before they perform any action, an algorithm can learn for itself how to map information about the environment, such as visual and tactile data from the robot’s sensors, into instructions sent to the robot’s actuators.

AI technologies can perform tasks usually requiring specific human capacities related to visual perception, speech, sentiment recognition and decision-making, which robots are not able to do building upon traditional software methods. Consequently, Ernst, Merola & Samaan (2018, ILO, p.2) observe that “AI is replacing mental tasks rather than physical ones, which were the target of previous waves of mechanization”. However, AI does not always threaten human work. According to the authors, while AI-based applications that are focused on matching tasks (i.e., tasks that imply the matching of supply and demand, especially in markets with a heterogeneous product and services structure) tend to replace human labor, ensuring a more precise and rapid matching of supply and demand, applications involved in classification tasks (e.g., image and text recognition, X-ray image diagnosing, reading and classifying legal documents, analyzing balance sheets, fraud detecting, screening applicants) tend to complement workers performing these tasks, as they help them to concentrate on aspects requiring specific attention, while the more routine, repetitive tasks are left to a machine. Finally, AI-based applications performing process-management tasks (which concern a combination of the two previous sets of tasks, identifying patterns and bringing different suppliers and customers together along a supply chain) expand the number of tasks carried out in an economy, as they perform tasks which, due to their complexity, the human workforce was previously unable to achieve. Therefore, Ernst, Merola & Samaan believe that the effects of AI on labor will depend on the relative importance of these three different classes, and more in general also on the direction that technological change will take in the future under the influence of policies, tax incentives and public and private investment in technological research.

The ability of AI to create new job opportunities is also stressed by Acemoglu & Restrepo (2019a), who assert that AI should not be regarded as a narrow set of technologies with specific, pre-determined applications and functionalities but as a technology platform, which can be used not only to automate tasks but also to restructure the production process in a way that creates many new, high-productivity tasks for labor (in particular in the fields of education, healthcare and augmented reality), leading to societal gains both in terms of improved productivity and greater labor demand. The authors also posit, however, that because of the market failures in innovation, recent technological change in the US has been biased towards automation and to what they term "the wrong kind of AI", with insufficient focus on the creation of new tasks where labor can be productively employed.

An alternative classification of the tasks performed by AI has been proposed by Agrawal, Gans & Goldfarb (2019). Drawing on many examples from the real world, and using the information on several hundred artificial intelligence startups collected during their work with the Creative Destruction Lab at the University of Toronto, Agrawal and coauthors argue that AI directly substitutes capital for labor in performing prediction tasks -i.e., tasks based on the ability to using existing data to fill in missing information-, and may indirectly affect decision tasks -namely, tasks based on the ability to take an action based on a decision, and the judgment to evaluate the payoffs associated with different outcomes- by increasing or decreasing their relative returns to labor versus capital.

The worries concerning the possible disruptive effects of Artificial Intelligence on human work, coupled with the excitement about its great and still partly unknown potential, have fueled a vibrant discussion, inside and outside the academic arena, regarding the labor implications of AI. Nonetheless, there is very little systematic evidence: the rapid advancement in AI is indeed a nascent phenomenon, and accordingly, appropriate tools to measure its impact have not yet been developed, and public datasets on the utilization or adoption of AI are not available (Seamans & Raj, 2018; Felten, Raj & Seamans, 2019).

Frey & Osborne (2017) attempt to predict the effect of anticipated advances in technological change, which should be driven by progress in Artificial Intelligence, on labor. However, as Felten, Ray & Seamans (2019) remark, they consider the overall impact of automation, which the authors label computerization, without specifying the source (e.g., robots, AI or other types of technology) from which automation stems. Conversely, Brynjolfsson, Mitchell & Rock (2018) focus on a subfield of AI, namely machine learning, and measure the "suitability for machine learning" (SML) for labor inputs in the US economy using O*NET data on work activities, tasks, and occupations. The authors' findings suggest that machine learning technologies can transform many jobs in the economy, but also that few (if any) occupations will soon be fully automated by machine learning. Furthermore, tasks within jobs typically show considerable variability in SML, which can be interpreted as an indicator for the potential reorganization of a job (as the high and low SML tasks within a job can be separated and re-bundled), underlining the need for boosting process reengineering and task reorganization.

While Frey & Osborne (2017) and Brynjolfsson, Mitchell & Rock (2018) consider, respectively, overall automation and broad machine learning, both adopt a forward-looking perspective, and primarily focus on the extent to which labor can be displaced, Felten, Raj & Seamans (2019) assess the labor impact of advances in specific functions of AI, such as image recognition, translation, or the ability to play strategic games, on workplace abilities and occupations between 2010 and 2015 (hence, in a backward-looking view). Additionally, unlike the other two previously mentioned studies, they resort to an approach that is agnostic as to the conditions under which AI substitutes or complements human labor, and take a step forward by estimating the implications of AI for some labor outcomes. Specifically, building upon a modified version of the method described by Felten, Raj & Seamans (2018) that links specific applications of AI to different occupation-level abilities, and merging O*Net data with time-varying information on nine AI applications from the Electronic

Frontier Foundation, the authors develop a new indicator of the impact of AI on occupations, labelled the AI Occupational Impact (AIOI), which they employ to study how recent advances in AI have affected employment and wages in the US.

Felten, Raj & Seamans (2019) provide evidence that, on average, occupations impacted by AI have experienced a small but positive change in wages, but no change in employment, and that the beneficial effect on wage growth is driven primarily by occupations with higher software skill requirements. Besides, higher-income occupations have a strong positive relationship between their measure of AI and both employment and wages. These findings suggest that, although it may exacerbate labor market polarization and/or income inequality, in recent years AI has mainly complemented, rather than substituted labor. Despite some limitations (e.g., endogeneity concerns), Felten, Raj & Seamans's work represents a valuable contribution to the nascent body of literature on the link between AI and labor, and the authors reckon that the AIOI produced by their methodology may be used by other researchers to further investigate this relevant and interesting topic, for instance, by using a forward-looking perspective, or by studying how the impact varies across occupations, geographies, and backgrounds.

Meanwhile, some useful information on the patterns of origin and adoption of AI technologies and the performance of AI firms have been offered by patent analysis. Martinelli, Mina & Moggi (2021) conduct an exploratory comparative analysis of the technological bases and the emergent patterns of production and use of six major "enabling technologies", (which, according to the Commission of the European Communities, 2009, can be regarded as technologies that can contribute to innovation and productivity growth in many sectors), namely, Artificial Intelligence, Internet of Things (IoT), big data, cloud, robotics and additive manufacturing (also known as 3D printing). As far as AI is concerned, their analysis of 363,803 US patents filed between 1990 and 2014 reveals that: 1.6 % of these patents are related to AI (whereas patents related to the Internet of the Things represent 51.8% of the total number, and has increased over time); the AI field, similarly to those of the other five technologies, shows a relatively stable presence of a large number of smaller size players, coupled with a modest increase in the share of top inventors (whose group displays low stability due to high mobility); technological leaders tend to overlap across the six enabling technologies, probably due to the presence of strong complementarities in use, and IBM is the only company able to maintain the technological leadership in four out of the six technologies (i.e. AI, Big Data, Cloud, and IoT); AI and Cloud attract the largest share of entrants from related technologies, pointing to their key integrating role among the six enabling technologies.

Further information on the emergence, evolution, scale and pervasiveness of Artificial Intelligence is provided by Van Roy, Vertesy & Damioli (2020), who, unlike Martinelli, Mina & Moggi, focus specifically on AI patenting activities, which has experienced a tremendous increase since 2013. Interestingly, even though high-tech sectors such as medicine, aeronautics, and vehicles are among the main users of this emerging technology, AI patents seem to grow rapidly in traditionally less technology-intensive fields, such as agriculture, and this trend stresses the nature of AI as a transversally applicable technology. Additionally, the inventors, which are mainly concentrated in China, Japan, South Korea, and the US, display a flourishing economic performance, exhibiting on average positive employment, turnover, and labor productivity growth rates across all global competitive regions.

Patent analysis may also shed light on the degree of potential substitutability between AI and labor. In this regard, Webb (2020) resorts to patents to identify the main tasks that are executed by different types of technology, namely robots, software and AI, and uses the overlap between the text of job task descriptions and the text of patents to construct a task-based measure of the exposure of occupations to automation stemming from these three different classes. Patents describe AI -in this work referring to two kinds of machine learning algorithms, namely supervised learning and reinforcement learning algorithms- as performing tasks such as predicting prognosis and treatment, detecting cancer, identifying damage, and detecting fraud. These tasks, which can be regarded as "mental tasks", are involved in medical imaging and treatment, insurance adjusting, and fraud analysis -all areas that have been experiencing a high level of R&D in AI-, and relevantly differ from the ones identified for robots and software. Notably, even though some low-skilled jobs are potentially affected to a considerable extent (e.g., production jobs that involve inspection and quality control) as well, AI seems to mainly target high-skilled occupations, such as clinical laboratory technicians, chemical engineers, optometrists, and power plant operators, and individuals with high levels of education.

The key contribution of Webb's study is that Artificial Intelligence is qualitatively distinct from software and robots, and consequently it will probably affect different kinds of jobs and people. This result also aligns with the recent findings of Montobbio et al. (2020). The authors, unlike Webb, consider the broader category of robot-related technologies (which also includes the so-called AI-related "intelligent robots", i.e., robots that can 'sense' and communicate with their environment and operate as mobile, interactive information systems in a wider spectrum of fields, from manufacturing to service sectors) and look specifically at labor-saving innovations. They show that the latter challenge not only manual activities (e.g., in the logistics sector), which are the main target of industrial robots, but also activities entailing social intelligence (e.g., in the healthcare sector) and cognitive skills (e.g., learning and predicting), namely, tasks and skills in which human workforce has had a comparative advantage so far, but which seem to represent the major target of AI. However, Webb notes that his results on the exposure of occupations are purely descriptive, do not refer to the entire universe of AI applications, and do not allow identification of the magnitude and even the sign of the impact on labor.

In conclusion, AI has been rapidly evolving and expanding across countries and sectors. Even though it has the potential to challenge a vast array of occupations, including some in which human labor has traditionally held a comparative advantage, it seems that, so far, it has not caused massive job losses. However, judging from the rapid advances in this field, it is very likely that AI has not unfolded its full potential yet, and, thus, it is difficult to predict how and to what extent AI will affect employment in a near future.

4. Discussion

The literature presented in Section 3 has been reviewed following two main criteria, namely the proxy of technological change, which guides the structure of the section, and the level of aggregation/unit of analysis, which has been emphasized in the various paragraphs. A summary of the main considerations prompted by the review, together with some further insights, is provided below.

4.1 Type of technological change and technological input

4.1.1 R&D and disembodied technological change

The vast academic literature on innovation has identified two broad types of technological change: disembodied technological change, which is mainly related to product innovation and thus fosters product demand and in turn labor demand and job creation, and the technological change embodied in capital inputs, which is mostly associated with process innovation and has a more ambiguous effect on employment. R&D expenditures are regarded as an indicator of disembodied technological change; the empirical literature confirms that R&D and product innovation typically exhibit a labor-friendly nature, even though their positive effect on employment is mainly driven by the more dynamic and innovative sectors and firms, namely, by those that have the "absorptive capacity" to reap the benefits of innovation. Accordingly, governments should strengthen their policies aimed at promoting innovation and R&D investments, targeting, in particular, those industries and companies that lag behind in terms of innovation efforts.

4.1.2 Computers and ICTs

A considerable number of studies have focused on the side of the adopters of technologies. Starting from the seventies, and especially during the eighties and the nineties, computers and ICTs have experienced great development and diffusion, with significant implications for labor. The introduction of these technologies in many workplaces has penalized the workers whose occupation mainly requires routine tasks that can be performed by software, and individuals with limited computer literacy; at the same time, it has been beneficial for individuals who mainly carry out tasks (e.g., both abstract tasks and complex manual tasks) that computers struggle to perform. Even though it has exerted a significant qualitative effect on labor, and has contributed to the reallocation of workers across occupations and sectors and labor market polarization, on the whole the widespread use of ICT has so far not caused massive technological unemployment, and it has also fostered the creation of new job titles. All in all, ICT has mainly benefited individuals whose tasks are complementary to the ones performed by computer technologies and those who have ICT literacy; accordingly, investments in both formal education and on-the-job training should increase such complementarity and help workers move to other jobs and sectors.

4.1.3 Robots and new digital technologies

As far as robots are concerned, some empirical analyses, especially at the aggregate level, have found a negative net effect on employment, which is typically mainly borne by more traditional manufacturing sectors and by low/ medium-skilled workers and/or young workers. However, even though "Robots' capabilities set robots apart from earlier waves of automation and more conventional ICTs, which leave flexible movement in three dimensions firmly in human hands" (Graetz & Michaels 2018, p.753), this technology mainly challenges occupations that primarily involve manual tasks. Accordingly, there are still several tasks in which human labor holds a comparative advantage, including the tasks necessary to use, run and supervise the new machines. In addition, the adoption of robots is associated with a positive productivity effect which can more than offset the negative displacement effect, especially in firms that successfully adopt these technologies. As a result, a more in-depth understanding of the capabilities and limitations of this complex technology may alleviate the fears about a possible "robocalypse" and shed light on the activities in which workers still have a comparative advantage.

Similar considerations seem to hold for a broader variety of automation technologies, even though empirical evidence is more limited. Nonmachine-based digital technologies typically have, by nature, a more labor-friendly impact compared to complex automation technologies. Besides, since March 2020, the dramatic Covid-19 pandemic has further stressed the importance of investing in digitalization for firms, and the need of mastering those digital tools that have become crucial for the employers required to work from home.

4.1.4 Artificial Intelligence

Finally, the ongoing digital revolution has been characterized by the rapid development of AI-based technologies, which, unlike computers, robots and other automation technologies, can learn for themselves how to map information about the environment and are mostly directed to "mental" tasks. Consequently, AI has the potential to challenge a considerable variety of occupations, including service occupations that are typically performed by high-skilled individuals and which have so far been regarded as difficult to automate. However, some AI tasks are still considered complementary to human tasks; moreover, at present AI algorithms still need to "learn" from existing data to improve performance, and software that can entirely think and act on its own does not exist yet. Also, we should keep in mind that AI has been fueling important advances in various scientific fields, including biomedical engineering, which can bring great benefits to humankind.

4.2 Level of aggregation and unit of analysis

4.2.1 Firm

A firm represents the main place where employment decisions are made (Harrigan, Reshef & Toubal, 2020), and firm-level analysis allows a direct and precise firm-level mapping of the innovation activities and the technological inputs. Empirical microeconomic studies tend to find a positive link between R&D/product innovation, since the firms that innovate directly benefit from the increase in market share and product demand, with positive consequences for their employers. Moreover, the gains from innovation are mainly grasped by dynamic and large firms operating in high-tech sectors, and typically do not transfer to non-innovative firms, which, on the contrary, due to the "business-stealing" effect and other competitive dynamics, may be negatively affected and experience a decline in employment.

Similar considerations hold for the adopters of complex technologies, such as robots. Even though these have an intrinsic labor-saving nature, they typically lead to an increase in the firm output, market share and competitiveness, which in turn can lead to job creation. This positive effect of technological change on the adopters can be shared either by various categories of labor (as in Domini et al., 2021) or mainly by high-skilled workers who are able to implement and control these complex new technologies (e.g., Balsmeier & Woerter, 2019). At the same time, business-stealing and negative externalities may hinder the non-adopters, which are typically less dynamic and productive firms, and this may lead to labor reallocation from the non-adopters to adopters. Accordingly, even though investing in R&D and in the adoption of new enabling technologies is generally costly, firms should consider the potential future benefits from such investments.

4.2.2 Sector

Technological change has contributed to the well-known structural shift of the economy from manufacturing to services, as it has fostered labor reallocation in service occupations that are hard to automate and the creation of new jobs. However, the manufacturing industry still represents an important share of the total economy in several countries, and also includes dynamic, high-tech sectors.

The innovation literature has shown that different sectors, including manufacturing sectors, are characterized by heterogenous patterns of innovation/technological adoption and employment, and has highlighted the juxtaposition between downstream/adopter sector, where labor-saving embodied technological change often prevails, and upstream/”making”, mainly characterized by labor-friendly disembodied technological change. However, this juxtaposition may be simplistic (for instance, the sectoral classification proposed by Vermeulen et al., 2018 includes not only the adopters and the “making” sectors, but also complementary sectors and spillover sectors), and may have been challenged by the latest wave of technological progress. Indeed, recent patent analyses have revealed that patent holders of robotics-related technologies comprise not only producers, but also adopters, with Amazon and UPS being two archetypical cases (Montobbio et al., 2020), and that AI patents are rapidly growing in traditionally less technology-intensive fields. Therefore, the opportunities stemming from the adoption of new digital technologies, in particular from those that can be applied to a variety of fields, are not limited to high-tech sectors but can be potentially grasped by the whole economy.

4.2.3 Occupation

Each occupation comprises a variety of tasks that present different degrees of routinization. In general, technological change has been detrimental for jobs that mainly involve routine tasks that can be easily displaced, whereas it has not hindered, or has even favored occupations that are rich in tasks which machines cannot carry out, or which are complementary to computer and robot applications. According to Autor & Dorn’s (2013) classification of US occupations based on the level of their Routine Task Index (RTI), the occupations with the highest degree of routinization are butchers and meat cutters, secretaries and stenographers, and payroll and timekeeping; the list of occupations with the lowest RTI scores comprises both low-skill occupations (e.g., bus drivers, taxi cab drivers and chauffeurs, and waiters) and high-skill occupations (e.g., firefighting, prevention and inspection, police, detectives and public service, and primary school teachers).

Technological change has also led to the creation of new job titles, a phenomenon that has been observed also during previous waves of technical progress and has fostered the growth of occupations that rely on ICT, which in some cases offsets the decline in occupations that are displaced by computerization (see Bessen, 2016).

In recent years, several studies have estimated the risk of automation, or job automatability, for most of the extant occupations, in the US and several other countries. They have also shown that there is significant within-occupation task heterogeneity, and that, when the latter is accounted for, the risk of automation is significantly lower compared to the predictions produced using the so-called occupation-based approach. As suggested by Brynjolfsson, Mitchell & Rock (2018), this within-job variability of tasks can be interpreted as an indicator for the potential reorganization of a job, which, if pursued and boosted, may reduce the number of jobs threatened by technical change.

4.2.4 Individual

Workers differ not only in terms of occupation but also in terms of educational level and demographic characteristics.

High-skilled workers who are able to properly use new digital technologies and can also incentivize the adoption of the latter typically benefit from technological change in terms of employment dynamics. However, as the RBTC hypothesis has stressed, the skill level is often proxied by the amount of formal education (i.e., average years of schooling or educational qualification), which can be an imprecise indicator of the competencies of an individual and the activities implied by his/her job.

The magnitude and the direction of the effect of technological change on labor can be influenced by the worker's age as well. Employment outcomes of older workers are often negatively affected by ICT-induced technological change, since they are generally less familiar with digital technologies. However, some studies (e.g., Schleife, 2006; Biagi, Cavapozzi & Miniaci, 2013; Peng, Anwar & Kang, 2017) show how high levels of education, and in particular computer literacy and the use of personal computers at work, as well as the presence of solid labor institutions, can alleviate or offset the negative impact of technological change on the older workers' employment. These results emphasize the need to invest in training programs that help workers to stay abreast of technological innovations and that strengthen the complementarity between human labor and machines.

Interestingly, in the case of robot adoption, it seems that younger individuals, especially younger males, are more exposed, as they often perform the so-called "muscle" tasks that can be easily replaced by robots. Dauth et al. (2017) show that the aggregate decline in manufacturing employment in Germany is solely driven by fewer new jobs for the young labor market entrants and suggest that, after the installation of new industrial robots, firms may tend to retain the incumbent workers but to create fewer vacancies that could be filled by young workers. The displacement effect of technological change on the most vulnerable workers may be considerably attenuated by the participation in training programs, which can both improve the technological literacy of individuals and help them transit to new career opportunities. In this respect, Nedelkoska & Quintini (2018) stress the importance of training and re-qualification and their role in reducing the risk of automation.

A few studies covered in this review also assess whether technological change differently affects male and female workers. On examining the polarization of employment in German local labor markets, Senftleben-König & Wielandt (2014) observe that most of the growth in service occupations is explained by the reallocation of female workers. Autor, Dorn & Hanson (2015) assert that while losses in routine employment among men in US local labor markets are offset by corresponding gains in occupations with abstract tasks, such offsetting gains are absent for women, thus generating a negative overall impact of technology exposure on female employment. This result may be partly ascribable to the fact that, because of their family duties, female workers can find it more difficult to transition towards a new job.

It is also possible that women tend to differ in terms of skills and tasks, as suggested by Lindley, 2012. Brussevich, Dabla-Norris & Khalid (IMF, 2019), who conduct a comprehensive analysis of the gender gap in terms of job automatability in a sample of 30 advanced and emerging economies, reporting that women, on average, perform more routine or codifiable tasks than men across all sectors and occupations; at the same time, they perform fewer tasks requiring analytical input or abstract thinking, where technological change can be complementary to human skills and improve labor productivity. This is mainly explained by women's self-selection in certain occupations (e.g., service occupations with a considerable degree of routinization), but also by the fact that, as also highlighted by Nedelkoska & Quintini (2018), women often carry out more automatable tasks than their male counterparts even within the same occupation. As a result, according to Brussevich, Dabla-Norris & Khalid's study, on average female workers are at a significantly higher risk of displacement by automation than male workers. The gender gap varies considerably across countries, however, and in line with growing educational participation, women appear to be increasingly opting into occupations that are relatively more insulated from the risk of automation, and gender differences are substantially lower or even negligeable for younger cohorts of women, suggesting that there is room for optimism about the future of work for women.

4.2.5 Country

Countries differ in terms of economic development, governance, industrial specialization, product market regulations and labor market institutions, which can be relevant moderators of the link between technological change and employment. If labor market laws and institutions are rigid and do not provide sufficient incentives for investment in skill upgrading, technology adoption may lead to job loss (Pissarides & Vallanti, 2004). Similarly, weak governance-specific institutions may motivate managers to adopt productivity-augmenting strategies at the cost of labor demand (Mitra & Sharma, 2020).

Some multi-country studies control for institutional variables (e.g., European Commission, 2014; Breemersch, Damijan & Konings, 2019), while others include country fixed effects to account for national specificities (e.g., Marcolin, Miroudot & Squicciarini, 2016). However, it is difficult to show how these factors vary across countries and, in doing so, how they moderate the technological change-employment nexus.

According to some researchers, the mixed results in terms of the employment impact of robot penetration at the aggregate level observed in different countries (e.g., the US vs European countries) are partly ascribable to differences in labor market institutions, including the level of employment protection, and also to variations in the exposure to trade (see Section 3.2.2).

Useful information on inter-country heterogeneity comes from some multi-country analyses of the risk of job displacement, even though it should be kept in mind that job automatability does not necessarily reflect the actual replacement of workers by machines. Arntz, Gregory & Zierahn (OECD, 2016) show that individuals in the same industry, occupation or even education group perform different tasks in different countries, and attribute this fact to two possible reasons, namely, to differences in the workplace organization (on average, countries which have a stronger focus on communicative tasks in their workplace organization also have a lower share of jobs at high risk) and differences in the adoption of new technologies (the automatability is lower in countries which already invest a lot in ICT).

Similar considerations are prompted by the analysis conducted by Nedelkoska & Quintini (2018) on a larger sample of countries: by means of a shift-share analysis, they show that, contrary to expectations, only 30% of the variation across countries is attributable to differences in the economic structure of economies (i.e., the mix of industries), and more than two-thirds is explained by differences in the way economies organize work within the same economic sectors, i.e., their occupational mix within industries and also the job task mix within occupations, which may reflect the extent to which automation has already taken place and jobs have adapted as a result (hence, countries where the adoption of labor-substituting technologies has not yet taken place would show a structure of job tasks that is more prone to automation).

The level of economic development of the country can matter as well. For instance, according to de Vries et al., (2020), the increased use of robots is associated with positive changes in the employment share of non-routine analytic jobs and negative changes in the share of routine manual jobs in developed countries, whereas, in emerging and transition economies, these relations are not significant. However, in recent years some dynamic, fast-growing emerging economies, such as China and India, have rapidly increased their investments in R&D, robot adoption and issue of AI patents, and their performance may deserve further investigation.

Finally, further insights on country-level specificities can be supplemented by field studies (for example, Krzywdzinski, 2020 documents the evolution of automation and digitalization, and the changes in the occupational structures that occurred in the automobile industry focusing on Germany, the United States, and Japan).

5. Concluding remarks

The present work attempts to provide a comprehensive picture of the possible implications for employment stemming from a complex and multifaceted phenomenon that has long generated both fear and excitement, namely technological change. From the review of the literature, it emerges that both the selected type/proxy for technical change and the level of aggregation/unit of analysis play an important role in determining the magnitude and the direction of the effect of technical progress on employment.

Despite the fact that the ongoing digital revolution has been displaying unprecedented pace and pervasiveness and has been affecting an increasing number of sectors and occupations, at the moment the “end of work” scenario seems remote. Technical change has contributed to the reallocation of labor across workers, occupations, firms and sectors, and in doing so it has hindered some categories, in particular the most “vulnerable” workers and the more traditional and sluggish sectors and firms that did not catch up with technical progress. However, at the same time it has benefitted the subjects that can properly use and control these new technologies. This comes to bear on policymaking, as the authorities should design interventions aimed at improving the quality of human capital and at producing skills that are complemented, rather than substituted, by technological change. In this respect, the influential work by Goos (2018) identifies a list of possible policy interventions, such as: higher investment in Science, Technology, Engineering and Mathematics (STEM) education, but also in non-routine social, motivational, and interaction skills, which are likely to remain difficult to automate at least in the short term; labor market income redistribution policies that ensure that the benefits of the Digital Revolution are broadly shared; innovation policies that can foster the creation of technologies that are complementary to workers’ skills and help mitigate the impact of technological change on economy-wide inequality. As a result, the central issue is not whether technological change is displacing labor, but how and to what extent policymakers and societies will be able (and willing) to grasp the opportunities and alleviate the potential negative effects of this complex but fascinating phenomenon.

Even though this survey may help achieve a better understanding of the composite link between technological change and employment, it is far from being exhaustive. As an illustration, it touches on some relevant topics which deserve further investigation, such as the role played by institutional factors and in particular by international openness, and the role of organizational innovation and changes in working practices.

Moreover, some recent developments have not been extensively investigated yet. For instance, more attention should be devoted to some high-growth, dynamics developing countries, especially to China, which is one of the countries that have filed the highest number of AI patents between 2000 and 2016. Further, in the last few years digitalization has led to the creation of new job profiles, connected with the new concept of “digital entrepreneur”, that rely heavily on digital technologies and especially on social media. In addition, access to digital tools and assistive technologies can improve and facilitate everyday life quality especially for people with disabilities, favoring their participation in society and increasing their employment opportunities, thus promoting social inclusion. The extant research on this topic mostly belongs to the domain of political science and law, and there is room for more empirical economic research.

On top of that, Artificial Intelligence has been experiencing a very rapid development; as an illustration, at the end of 2020 OpenAI launched GPT-3, a powerful algorithm that can create anything that has a language structure and can answer questions, write essays, summarize long texts, translate languages, take memos, and even create computer code. Future research may help to shed light on these issues, and in particular on the opportunities and challenges posed by AI.

References

Acemoglu, D. & D. H. Autor (2011). Skills, Tasks and Technologies: Implications for Employment and Earnings. In: Ashenfelter, O. & D. E. Card (ed.), Handbook of Labor Economics, Vol. 4B, Amsterdam, Elsevier, 1043-1171.

Acemoglu, D. & P. Restrepo (2018a). The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment. American Economic Review, 108(6), 1488-1542.

Acemoglu, D. & P. Restrepo (2018b). Demographics and Automation. NBER Working Paper No. 24421.

Acemoglu, D. & P. Restrepo (2019a). The Wrong Kind of AI? Artificial Intelligence and the Future of Labor Demand. NBER Working Paper No. 25682.

Acemoglu, D. & P. Restrepo (2019b). Automation and New Tasks: How Technology Displaces and Reinstates Labor. Journal of Economic Perspectives, 33(2), 3-30.

Acemoglu, D. & P. Restrepo (2020). Robots and Jobs: Evidence from US labor markets. Journal of Political Economy, 128(6), 2188-2244.

Acemoglu, D. (2002). Technical Change, Inequality, and the Labor Market. Journal of Economic Literature, 40(1), 7-72.

Acemoglu, D., LeLarge, C. & P. Restrepo (2020). Competing with Robots: Firm-Level Evidence from France. NBER Working Paper No. 26738.

Adermon, A. & M. Gustavsson (2015). Job Polarization and Task-Biased Technological Change: Evidence from Sweden, 1975–2005. Scandinavian Journal of Economics, 117(3), 878-917.

Aghion, P., Antonin, C., Bunel, S. & X. Jaravel (2020). What Are the Labor and Product Market Effects of Automation? New Evidence from France. Sciences Po-OFCE Working Paper No. 01/2020.

Agrawal, A., Gans, J.S. & A. Goldfarb (2019). Artificial Intelligence: The Ambiguous Labor Market Impact of Automating Prediction. Journal of Economic Perspectives, 33(2), 31-50.

Akcomak, S., Kok, S. & H. Rojas-Romagosa (2013). The effects of technology and offshoring on changes in employment and task-content of occupations. Technical report, CPB Netherlands Bureau for Economic Policy Analysis.

Akerman, A., Gaarder, I. & M. Mogstad (2015). The Skill Complementarity of Broadband Internet. The Quarterly Journal of Economics, 130(4), 1781-1824.

Apella, I. & G. Zunino (2017). Technological Change and the Labor Market in Argentina and Uruguay. A Task Content Analysis. Policy Research Working Paper No. 8215, World Bank group's Social Protection and Labor Global Practice Group.

Araújo, B.C., Bogliacino, F. & M. Vivarelli (1995). Technology, Trade and Skills in Brazil: Some Evidence from Microdata. CEPAL Review, 105,157-171.

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

Arntz, M., Gregory, T. & U. Zierahn (2017). Revisiting the risk of automation. Economic Letters, 159, 157-160.

Aubert, P. Caroli, E. & M. Roger (2006). New technologies, organisation and age: firm-level evidence. The Economic Journal, 116, F73-F93.

Autor, D.H (2015). Why Are There Still So Many Jobs? The History and Future of Workplace Automation. The Journal of Economic Perspectives, 29(3), 31-50.

Autor, D.H. & A. Salomons (2018). Is automation labor-displacing? Productivity growth, employment, and the labor share. Brookings Papers on Economic Activity (Spring 2018), 1-63.

Autor, D.H. & D. Dorn (2013). The Growth of Low-skilled Service Jobs and the Polarization of the U.S. Labor Market. American Economic Review, 103(5), 1553-1597.

Autor, D.H. & M. Handel (2013). Putting tasks to the test: Human capital, job tasks, and wages. Journal of Labor Economics, 31(2), 59-96.

Autor, D.H., Dorn, D. & G. H. Hanson (2015). Untangling Trade and Technology: Evidence from Local Labour Markets. The Economic Journal, 125, 621-646.

Autor, D.H., Katz, L.F. & A.B. Krueger (1998). Computing Inequality: Have Computers Changed the Labor Market? The Quarterly Journal of Economics, 13(4), 1169-1213.

Autor, D.H., Katz, L.F. & M.S. Kearney (2006). The Polarization of the U.S. Labor Market. American Economic Review, 96(2), 189-194.

Autor, D.H., Levy, F. & R.J. Murnane (2003). The skill content of recent technological change: an empirical exploration. The Quarterly Journal of Economics, 118(4), 1279-1333.

Bachmann, R., Cim, M. & C. Green (2019). Long-Run Patterns of Labour Market Polarization: Evidence from German Micro Data. British Journal of Industrial Relations, 57(2), 350-376.

Balsmeier, B. & M. Woerter (2019). Is this time different? How digitalization influences job creation and destruction. Research Policy, 48(8), 103765.

Barbieri, L., Mussida, C., Piva, M. & M. Vivarelli (2019). Testing the Employment Impact of Automation, Robots and AI: A Survey and Some Methodological Issues. IZA Discussion Paper No. 12612.

Barbieri, L., Piva, M. & M. Vivarelli (2019). R&D, embodied technological change, and employment: evidence from Italian microdata. Industrial and Corporate Change, 28(1), 203-218.

Bartik, T.J. (1991). Who Benefits from State and Local Economic Development Policies? Kalamazoo, MI: W. E. Upjohn Institute for Employment Research.

Basso, G. (2019). The evolution of the occupational structure in Italy in the last decade. Bank of Italy Occasional Paper No. 478.

Beckmann, M. & B. Schauenberg (2007). Age-Biased Technological and Organizational Change: Firm-Level Evidence and Management Implications. WWZ Discussion Paper 05/07.

Behaghel, L., Caroli, E. & M. Roger (2014). Age-biased Technical and Organizational Change, Training and Employment Prospects of Older Workers. Economica, 81, 368-389.

Benzell, S.G., Kotlikoff, L.J., LaGarda, G. & J.D. Sachs (2016). Robots Are Us: Some Economics of Human Replacement. NBER Working Paper No. 20941.

Berger, T. & C.B. Frey (2016). Did the Computer Revolution shift the fortunes of U.S. cities? Technology shocks and the geography of new jobs. Regional Science and Urban Economics, 57, 38-45.

Bessen, J. (2016). How computer automation affects occupations: Technology, jobs, and skills. Boston University School of Law & Economics Working Paper No. 15-49.

Bessen, J., Goos, M., Salomons, A. & W. van den Berge (2019). Automatic Reaction – What Happens to Workers at Firms that Automate? CPB Discussion Paper, CPB Netherlands Bureau for Economic Policy Analysis.

Beyer, H., Rojas, P. & R. Vergara (1999). Trade liberalization and wage inequality. Journal of Development Economics, 59(1), 103-123.

Biagi, F., Cavapozzi, D. & R. Miniaci (2013). Employment transitions and computer use of older workers. Applied Economics, 45(6), 687-696.

Bisello (2013). Job polarization in Britain from a task-based perspective. Evidence from the UK Skills Surveys. Dipartimento di Economia e Management-Università di Pisa Discussion Paper No. 160, Revised May 2013.

Blanas, S., Gancia, G. & S. Y. Lee (2019). Who Is Afraid of Machines? Economic Policy, 34(100), 627-690.

Böckerman, P., Laaksonen, S. & J. Vainiomäki (2019). Does ICT Usage Erode Routine Occupations at the Firm Level? Labour, 33(1), 26-47.

Bogliacino, F. & M. Pianta (2010). Innovation and employment: a reinvestigation using revised Pavitt classes. Research Policy 39(6), 799-809.

Bogliacino, F. & M. Vivarelli (2012). The Job Creation Effect of R&D Expenditures. Australian Economic Papers, 51(2), 96-113.

Bogliacino, F., Piva, M. & M. Vivarelli (2014). Technology and employment: the job creation effect of business R&D. Rivista Intemazionale di Scienze Sociali, 3, 239-264.

Bonfiglioli, A., Crinò, R., Fadinger, H. & G. Gancia (2020). Robot Imports and Firm-Level Outcomes. CEPR Discussion Paper No. 14593.

Breemersch, K., Damijan, J.P & J. Konings (2019). What drives labor market polarization in advanced countries? The role of China and technology. Industrial and Corporate Change, 28(1), 51-77.

Bresnahan, T.F. & M. Trajtenberg (1995). General purpose technologies 'Engines of growth'? Journal of Econometrics, 65(1), 83-108.

Brussevich, M., Dabla-Norris, E. & S. Khalid (2019). Is Technology Widening the Gender Gap? Automation and the Future of Female Employment. IMF Working Paper Series, WP/19/91.

Brynjolfsson, E. & A. McAfee (2014). The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies. New York: W.W. Norton & Company.

Brynjolfsson, E., Mitchell, T. & D. Rock (2018). What Can Machines Learn, and What Does It Mean for Occupations and the Economy? AEA Papers and Proceedings, 108, 43-47.

Caines, C., Hoffmann, D. & G. Kambourov (2017). Complex-task biased technological change and the labor market. Review of Economic Dynamics, 25, 298-319.

Calvino, F. & M.E. Virgillito (2018). The innovation employment nexus: A critical survey of theory and empirics. Journal of Economic Surveys, 32(1), 83-117.

Carbonero F., Ernst, E. & E. Weber (2018). Robots worldwide: the impact of automation on employment and trade. International Labour Office (ILO), Research Department Working paper No. 36.

Caroli, E. & Van Reenen, J. (2001). Skill biased organizational change? Evidence from a panel of British and French establishments. Quarterly Journal of Economics, 116, 1449-1492.

Caselli, M., Fracasso, A., Traverso, S. & E. Tundis (2021). Stop worrying and love the robot: An activity-based approach to assess the impact of robotization on employment dynamics. GLO Discussion Paper Series No. 802, Global Labor Organization (GLO).

Charnoz, P. & M. Orand (2017). Technical change and automation of routine tasks: Evidence from local labour markets in France, 1999-2011. Economie et Statistique / Economics and Statistics, 497-498, 103-122.

Chiacchio, F., Petropoulos, G. & D. Pichler (2018). The impact of industrial robots on EU employment and wages: A local labour market approach. Bruegel Working Paper, Issue 2, 18 April 2018.

Cho, J. & J. Kim (2018). Identifying Factors Reinforcing Robotization: Interactive Forces of Employment, Working Hour and Wage. Sustainability, 10(2), 1-21.

Ciarli, T., Marzucchi, A., Salgado, E. & M. Savona (2018). The Impact of R&D on Employment and Self-Employment Composition in Local Labour Markets. SPRU Working Paper Series 2018-08, SPRU - Science Policy Research Unit, University of Sussex Business School.

Cirillo V., Rinaldini, M., Staccioli, J. & M.E. Virgillito (2021). Technology vs. workers: the case of Italy's industry 4.0 factories. Structural Change and Economic Dynamics, 56, 166-183.

Cirillo, V., Fanti, L., Mina, A. & A. Ricci (2020). Digitizing firms: skills, work organization and the adoption of new enabling technologies. Inapp, WP 53 (Istituto Nazionale per l'Analisi delle Politiche Pubbliche).

Coad, A. & R. Rao (2011) The firm-level employment effects of innovations in high-tech US manufacturing industries. Journal of Evolutionary Economics, 21(2), 255-283.

Commission of the European Communities (2009). Preparing for Our Future: Developing a Common Strategy for Key Enabling Technologies in the EU. Document 52009DC0512.

Compagnucci, F., Gentili, A., Valentini, E. & M. Gallegati (2019). Robotization and labour dislocation in the manufacturing sectors of OECD countries: a panel VAR approach. Applied Economics, 51(57), 6127-6138.

Consoli, D. & M. Sánchez-Barrioluengo (2019). Polarization and the growth of low-skill service jobs in Spanish local labor markets. Journal of Regional Science, 59, 145-162.

Consoli, D., Marin, G., Rentocchini, F. & F. Vona (2019). Routinization, Within-Occupation Task Changes and Long- Run Employment Dynamics. LEM Working Paper 2019/15, LEM-Laboratory of Economics and Management, Institute of Economics Scuola Superiore Sant'Anna.

Conte, A. & M. Vivarelli (2005). One or Many Knowledge Production Functions? Mapping Innovative Activity Using Microdata. IZA Discussion Paper No. 1878.

Conte, A. & M. Vivarelli (2011). Imported skill-biased technological change in developing countries. The Developing Economies 49(1), 36-65.

Cortes, G. M. & A. Salvatori (2015). Task Specialization within Establishments and the Decline of Routine Employment. Working paper, University of Manchester, available at: https://www.frbatlanta.org/~/media/Documents/research/seminars/2016/cortes-011916.pdf (last access: 25.06.2021).

Dachs, B., Hud, M. & B. Peters (2020). Innovation, Employment, and the Business Cycle. In: Zimmermann, K.F. (ed.), Handbook of Labor, Human Resources and Population Economics, Springer Nature Switzerland.

Das, M. & B. Hilgenstock (2018). The Exposure to Routinization: Labor Market Implications for Developed and Developing Economies. IMF Working Paper No. 18/35.

Dauth, W. (2014). Job polarization on local labor markets. IAB Discussion Paper 18/2014. Institute for Employment Research, German Federal Employment Agency.

Dauth, W., Findeisen, S., Südekum, J. & N. Woessner (2017). German robots-the impact of industrial robots on workers. CEPR Discussion Paper No. 12306.

De La Rica, S. & Gortazar, L. (2016). Differences in Job De-Routinization in OECD Countries: Evidence from PIAAC. IZA Discussion Paper No. 9736.

de Vries, G.J., Gentile, E., Miroudot, S. & K.M. Wacker (2020). The rise of robots and the fall of routine jobs. Labour Economics, 66, 101885.

Dechezleprêtre, A., Hémous, D., Olsen, M. & C. Zanella (2020). Automating Labor: Evidence from Firm-level Patent Data. CEP Discussion Paper dp1679, Centre for Economic Performance, LSE.

Dengler, K. & B. Matthes (2018). The impacts of digital transformation on the labour market: Substitution potentials of occupations in Germany. Technological forecasting and Social Change, 137, 304-316.

Dixon, J., Hong, B. & L. Wu (2020). The Employment Consequences of Robots: Firm-level Evidence. NYU Stern School of Business, available at SSRN: https://ssrn.com/abstract=3422581 or http://dx.doi.org/10.2139/ssrn.3422581 (last access: 25.06.2021)

Domini, G., Grazzi, M., Moschella, D. & T. Treibich (2021). Threats and opportunities in the digital era: Automation spikes and employment dynamics. Research Policy, 50(7), 104137.

Dosi, G. & P. Mohnen (2019). Innovation and employment: an introduction. Industrial and Corporate Change, 28(1), 45-49.

Dosi, G. & R.R. Nelson (2010) Technical change and industrial dynamics as evolutionary processes. In: Hall, B.H. & N. Rosenberg (ed.), Handbook of the economics of innovation, vol 1 chapter 3, North Holland.

Dosi, G. (1984). Technology and conditions of macroeconomic development. In: Freeman, C. (ed.), Design, Innovation and Long Cycles in Economic Development (99-125). London: Design Research Publications.

Dosi, G. (1988). Source, Procedure and Microeconomic Effects of Innovation. Journal of Economic Literature 26(3), 1120-1171.

Dosi, G., Piva, M., Virgillito, M.E. & M. Vivarelli (2021). Embodied and disembodied technological change: The sectoral patterns of job-creation and job-destruction. 50(4), 104199.

Dottori, D. (2020). Robots and employment: evidence from Italy. Questioni di Economia e Finanza (Occasional Papers) 572, Bank of Italy, Economic Research and International Relations Area.

Egana del Sol, P. (2020). The Future of Work in Developing Economies: What can we learn from the South? GLO Discussion Paper No. 483, GLO- Global Labor Organization, Essen.

Ernst, E., Merola, R. & D. Samaan (2018). The economics of artificial intelligence: Implications for the future of work. ILO Future of Work Research Paper Series No. 5.

European Commission (2014). The impact of ICT on employment. Publications Office of the EU, available at: https://op.europa.eu/en/publication-detail/-/publication/2e16f508-1acc-4042-afd1-19ce3c78e841 (last access: 13.07.2021).

European Commission (2016). Analysis of the Impact of Robotic Systems on Employment in the European Union – 2012 Data Update. Publications Office of the EU, available at:

https://www.researchgate.net/publication/311718924_Analysis_of_the_Impact_of_robotic_systems_on_employment_in_the_European_Union_-_Update (last access: 25.06.2021)

Felten, E.W., Raj, M. & R. Seamans (2018). A Method to Link Advances in Artificial Intelligence to Occupational Abilities. AEA Papers and Proceedings, 108, 54-57.

Felten, E.W., Raj, M. & R. Seamans (2019). The Occupational Impact of Artificial Intelligence: Labor, Skills, and Polarization. NYU Stern School of Business, Available at SSRN: https://ssrn.com/abstract=3368605 (last access: 25.06.2021).

Fernández-Macías, E. & Bisello, M. (2020). A Taxonomy of Tasks for Assessing the Impact of New Technologies on Work. JRC Technical Report No. 120618, Joint Research Centre (European Commission).

Fernández-Macías, E. & J. Hurley (2014). Drivers of recent job polarisation and upgrading in Europe. European Jobs Monitor 2014, Publications Office of the European Union, Luxembourg.

Fernández-Macías, E. & J. Hurley (2017). Routine-biased technical change and job polarization in Europe. Socio-Economic Review, 15(3), 563-585.

Filippi, E. & S. Trento (2019). The probability of automation of occupations in Italy. DEM Working Paper N. 2019/17, DEM-Department of Economics and Management, University of Trento.

Fonseca, T., Lima, F. & S.C. Pereira (2018). Job polarization, technological change and routinization: Evidence for Portugal. Labour Economics, 51, 317-339.

Ford, M. (2015). The Rise of the Robots. Basic Books, New York: Basic Books.

Fortin, N. & T. Lemieux (1997). Institutional Change and Rising Wage Inequality: Is There a Linkage? Journal of Economic Perspectives, 11, 75-96.

Freeman, C., Clark, J. & L. Soete (1982) Unemployment and Technical Innovation. London and New York: Pinter Publisher.

Freeman, R. (2015). Who Owns the Robots Rules the World. IZA World of Labor, 5, 1-10.

Frey, C.B. & M.A. Osborne (2017). The future of employment: how susceptible are jobs to computerisation? Technological Forecasting & Social Change, 114, 254-280.

Gallipoli, G. & C.A. Makridis (2018). Structural transformation and the rise of information technology. Journal of Monetary Economics, 97, 91-110.

Goldin, C. & L.F. Katz (1998). The Origins of Technology-Skill Complementarity. Quarterly Journal of Economics 113(3), 693-732.

Goldin, C. & L.F. Katz (2008). The race between education and technology. Cambridge, MA: Harvard University Press, Belknap.

Goos, M. & A. Manning (2007). Lousy and Lovely Jobs: The Rising Polarization of Work in Britain. The Review of Economics and Statistics, 89(1), 118-133.

Goos, M. (2018). The impact of technological progress on labour markets: policy challenges. Oxford Review of Economic Policy, 34(3), 349-361.

Goos, M., Manning, A. & A. Salomons (2009). Job polarization in Europe. American Economic Review, 99(2), Papers and Proceedings of the One Hundred Twenty-First Meeting of the American Economic Association (May 2009), 58-63.

Goos, M., Manning, A. & A. Salomons (2014). Explaining job polarization: routine-biased technological change and offshoring. American Economic Review, 104(8), 2509-2526.

Graetz, G., & G. Michaels (2018). Robots at work. Review of Economics and Statistics 100(5), 753-768.

Gregory, T., Salomons, A. & U. Zierahn (2019). Racing With or Against the Machine? Evidence from Europe. IZA Discussion Paper No. 12063.

Guarascio, D., Gualtieri V. & R. Quaranta (2018). Does routinization affect occupation dynamics? Evidence from the 'Italian O*Net' data. INAPP WP No.3, INAPP (Istituto Nazionale per l'Analisi delle Politiche Pubbliche).

Hacker, J.S. & P. Pierson (2010). Winner-Take-All Politics: Public Policy, Political Organization, and the Precipitous Rise of Top Incomes in the United States. Politics & Society, 38(2),152-204.

Hall, B.H., Lotti, F. & J. Mairesse (2009) Innovation and productivity in SMEs: empirical evidence for Italy. Small Business Economics, 33(1), 13-33.

Harrigan, J., Reshef, A. & F. Toubal (2020). The march of the techies: job polarization within and between firms. Research Policy (article in press).

Harrison, R., Jaumandreu, J., Mairesse, J. & B. Peters (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.

IFR (2012). World Robotics. Industrial Robots 2012.

IFR (2019). World Robotics Industrial Robots 2019.

Kampelmann, S. & F. Rycx (2013). Dynamics Of Task-Biased Technological Change: The Case Of Occupations. Brussels Economic Review, 56(2), 113-142.

Katz, L.F. & D.H. Autor (1999). Changes in the Wage Structure and Earnings Inequality. In: Ashenfelter, O. & D.E. Card (ed.), Handbook of Labor Economics, Vol. 3A, 1463-1555.

Katz, L.F. & K.M. Murphy (1992). Changes in Relative Wages, 1963–1987: Supply and Demand Factors. The Quarterly Journal of Economics, 107(1), 35-78.

Kerr, S., Maczulskij, T. & M. Maliranta (2020). Within and between firm trends in job polarization: the roles of globalization and technology. Journal of Economic Geography, 20(4), 1003-1039.

Kim, E., Hong, A. & J. Hwang (2019). Polarized labor demand owing to routine-biased technological change: The case of Korea from 1993 to 2015. Telematics and Informatics, 39, 1-10.

Klenert, D., Fernández-Macías, E. & J.-I. Antón (2020). Do robots really destroy jobs? Evidence from Europe. JRC Working Papers Series on Labour, Education and Technology 2020/01, Joint Research Centre (European Commission).

Koch, M., Manuylov, I. & M. Smolka (2019). Robots and firms. CESifo Working Papers No. 7608.

Kristal, T. & Y. Cohen (2017). The causes of rising wage inequality: the race between institutions and technology. Socio-Economic Review, 15(1), 187-212

Krzywdzinski, M. (2020). Automation, Digitalization, and Changes in Occupational Structures in the Automobile Industry in Germany, the United States, and Japan: A Brief History from the Early 1990s Until 2018. Weizenbaum Series #10, Weizenbaum Institute for the Networked Society, Berlin.

Kurokawa, Y. (2014). A Survey Of Trade And Wage Inequality: Anomalies, Resolutions And New Trends. Journal of Economic Surveys, 28(1), 169-193.

Lachenmaier, S. & H. Rottmann (2011). Effects of innovation on employment: a dynamic panel analysis. International Journal of Industrial Organization, 29(2), 210-220.

Lauder, H., Brown, P. &, S.-Y. Cheung (2018). Fractures in the education-economy relationship: The end of the skill bias technological change research programme? Oxford Review of Economic Policy, 34(3), 495-515.

Lee, D.S. (1999). Wage inequality in the United States during the 1980s: Rising dispersion or falling minimum wage? The Quarterly Journal of Economics 114.3 (1999), 977-1023.

Leigh, N.G. & B. R. Kraft (2018). Local Economic Development and the Geography of the Robotics Industry. Regional Studies, 52(6), 804-815.

Lindley, J. (2012). The gender dimension of technical change and the role of task inputs. Labour Economics,19, 516-526.

Malerba, F. (2002). Sectoral systems of innovation and production. Research Policy 31(2), 247-264.

Mann, K. & L. Püttmann (2020). Effects of Automation: New Evidence From Patent Texts. Available at: https://www.diw.de/sixcms/media.php/17/Mann_BAMS_Nov2020.pdf (last access: 25.06.2021).

Marcolin, L., Miroudot, S. & M. Squicciarini (2016). GVCs, Jobs And Routine Content Of Occupations. OECD Trade Policy Paper No. 187, OECD Publishing, Paris.

Martinelli, A., Mina, A. & M. Moggi (2021). The Enabling Technologies of Industry 4.0: Examining the Seeds of the Fourth Industrial Revolution. Industrial and Corporate Change, 2021, 1-28.

Massari, R., Naticchioni, P. & G. Ragusa (2015). Unconditional and conditional wage polarization in Europe. CeLEG Working Paper No. 04/15, Dipartimento di Economia e Finanza, LUISS Guido Carli.

Mastrostefano, V. & M. Pianta (2009) Technology and jobs. Economics of Innovation and New Technology, 18(8), 729-741.

Matteucci, N. & A. Sterlacchini (2003). ICT and Employment Growth in Italian Industries. Quaderni di Ricerca No.193, Università Politecnica delle Marche, Dipartimento di Scienze Economiche e Sociali.

Matthes, B., Christoph, B., Janik, F. & M. Ruland (2014). Collecting information on job tasks - an instrument to measure tasks required at the workplace in a multi-topic survey. Journal for Labor Market Research, 47(4), 273-297.

Meschi, E., Taymaz, E. & M. Vivarelli (2011). Trade, technology and skills: Evidence from Turkish microdata. Labour Economics, 18, S60-S70.

Meschi, E.., Taymaz, E. & M. Vivarelli (2016). Globalization, technological change and labor demand: a firm-level analysis for Turkey. Review of World Economics 152(4), 655-680.

Michaels, G., Natraj, A. & J. Van Reenen (2014). Has ICT polarized skill demand? Evidence from eleven countries over 25 years. Review of Economics and Statistics, 96 (1), 60-77.

Mitra, A. & A. J. Jha (2015). Innovation and employment: a firm level study of Indian industries. Eurasian Business Review, 5, 45-71.

Mitra, A. & C. Sharma (2020). Employment Impact of Technologies in the Developing World. In: Zimmermann, K.F. (ed.), Handbook of Labor, Human Resources and Population Economics, Springer Nature Switzerland.

Mokyr, J., Vickers, C. & N. L. Ziebarth (2015). The History of Technological Anxiety and the Future of Economic Growth: Is This Time Different? The Journal of Economic Perspectives, 29(3), 31-50.

Montobbio, F., Staccioli, J., Virgillito, M.E. & M. Vivarelli (2020). Robots and the origin of their labour-saving impact. LEM Working Paper Series 2020/03, LEM-Laboratory of Economics and Management, Institute of Economics Scuola Superiore Sant'Anna.

Moreno-Galbis, E. & T. Sopraseuth (2014). Job polarization in aging economies. Labour Economics, 27,44-55.

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

Nelson, R.R. & S.G. Winter (1982). An Evolutionary Theory of Economic Change. Cambridge, MA: Harvard University Press.

Nolan, B., Richiardi, M.G. & L. Valenzuela (2019). The Drivers of Inequality in Rich Countries. Journal of Economic Surveys, 33(4), 1285-1324.

Pantea, S. Sabadash, A. & F. Biagi (2017). Are ICT displacing workers in the short run? Evidence from seven European countries. Information Economics and Policy, 39, 36-44.

Pardi T., Krzywdzinski, M. & B. Lüthje (2020). Digital manufacturing revolutions as political projects and hypes: evidences from the auto sector. ILO Working Paper No.3, April 2020.

Parisi, M.L., Schiantarelli, F. & A. Sembenelli (2006). Productivity, Innovation and R&D: Micro Evidence for Italy. European Economic Review, 50(8), 2037-2061.

Pasinetti, L. (1981). Structural Change and Economic Growth. Cambridge: Cambridge University Press.

Pavitt, K. (1984) Sectoral patterns of technical change: towards a taxonomy and a theory. Research Policy, 13(6), 343-373.

Pellegrino, G., Piva, M. & M. Vivarelli (2019). Beyond R&D: the role of embodied technological change in affecting employment. Journal of Evolutionary Economics, 29, 1151-1171.

Peng, F., Anwarc, S. & L. Kang (2017). New technology and old institutions: An empirical analysis of the skill-biased demand for older workers in Europe. Economic Modelling, 64, 1-19.

Peng, G., Wang, Y. & G. Han (2018). Information technology and employment: The impact of job tasks and worker skills. Journal of Industrial Relations, 60(2), 201-223.

Peters, B., Dachs, B., Dünser, M., Hud, M., Köhler, C. & C. Rammer (2014). Firm Growth, Innovation and the Business Cycle. Background report for the 2014 Competitiveness Report, ZEW - Center for European Economic Research, Manheim.

Pfeiffer, S. (2018). The 'Future of Employment' on the Shop Floor: Why Production Jobs are Less Susceptible to Computerization than Assumed. International journal for research in vocational education and training, 5(3), 208-225.

Pianta, M. (2005). Innovation and employment. In: Fagerberg, D.M.J. & R.R. Nelson (ed.), The Oxford Handbook of Innovation (568-598). Oxford: Oxford University Press.

Piva, M. & M. Vivarelli (2018). Technological change and employment: is Europe ready for the challenge? Eurasian Business Review, 8, 13-32.

Raj, M. & R. Seamans (2019) Primer on artificial intelligence and robotics. Journal of Organization Design, 8(1), 1-14.

Reijnders, L.S.M & G.J. de Vries (2018). Technology, offshoring and the rise of non-routine jobs. Journal of Development Economics, 135, 412-432.

Rifkin, J. (1995). The End of Work - The Decline of the Global Labour Force and the Dawn of the Post-Market Era, New York: Tarcher/Putnam.

Rosenberg, N. (1976). Perspectives on Technology. Cambridge: Cambridge University Press.

Ross, M.B. (2020). The Effect of Intensive Margin Changes to Task Content on Employment Dynamics over the Business Cycle. Industrial and Labor Relations Review, DOI: 10.1177/0019793920910747

Sabadash, A. (2013). ICT-induced technological progress and employment: a happy marriage or a dangerous liaison? a literature review. JRC Technical Reports 2013/07, Institute for Prospective and Technological Studies, Joint Research Centre (European Commission).

Sasaki, H. & K. Sakura (2005). Changes in the Demand for Skilled Labor within Japan's Manufacturing Sector: Effects of Skill-Biased Technological Change and Globalization. Bank of Japan Working Paper Series No.05-E-12.

Schleife, K. (2006). Computer Use and Employment Status of Older Workers — An Analysis Based on Individual Data. Labour, 20(2), 325-348.

Seamans, R. & M. Raj (2018). AI, Labor, Productivity and the Need for Firm-Level Data. NBER Working Paper No. 24239.

Sebastian, R. & F. Biagi (2018). The Routine Biased Technical Change hypothesis: a critical review. JRC Working Paper No. 113174, Joint Research Centre (Seville site).

Senftleben-König, C. & H. Wielandt (2014). Spatial Wage Inequality and Technological Change. BDPEMS Working Paper 2014-08, BDPEMS-Berlin Doctoral Program in Economics and Management Science.

Sharma, S. (2016). Employment, Wages and Inequality in India: An Occupations and Tasks Based Approach. Indian Journal of Labour Economics, 59, 471-487.

Simonetti, R., Karl, T. & M. Vivarelli (2000). Modeling the Employment Impact of Innovation. In: Vivarelli, M. & M. Pianta (ed.), The Employment Impact of Innovation: Evidence and Policy (26-43) London: 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.

Staccioli, J. & M.E. Virgillito (2021a). Back to the past: the historical roots of labour-saving automation. Eurasian Business Review, 11, 27-57.

Staccioli, J. & M.E. Virgillito (2021b). In: Zimmermann, K.F. (ed.), Handbook of Labor, Human Resources and Population Economics. Springer Nature Switzerland.

Stam, E. & K. Wennberg (2009). The roles of R&D in new firm growth. Small Business Economics 33(1), 77-89.

Stephany, F. & H. Lorenz (2019). Back to the Future-Changing Job Profiles in the Digital Age. EconStor Preprints 202035, ZBW - Leibniz Information Centre for Economics.

Tinbergen, J. (1974). Substitution of graduate by other labor. International Review for Social Sciences, 27(2), 217-226.

Van Roy, V., Vertesy, D. & G. Damioli (2020). AI and Robotics Innovation. In: Zimmermann, K.F. (ed.), Handbook of Labor, Human Resources and Population Economics, Springer Nature Switzerland.

Vermeulen, B., Kesselhut, J., Pyka, A. & P.P. Saviotti (2018). The Impact of Automation on Employment: Just the Usual Structural Change? Sustainability, 10(5), 1-27.

Vivarelli, M. (1995). The Economics of Technology and Employment: Theory and Empirical Evidence. Aldershot: Edward 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.

Voigtländer, N. (2014). Skill Bias Magnified: Intersectoral Linkages and White-Collar Labor Demand in US Manufacturing. Review of Economics and Statistics, 96(3), 495-513.

Webb (2020). The Impact of Artificial Intelligence on the Labor Market. Available at SSRN and at: https://www.michaelwebb.co/webb_ai.pdf (last access: 25.06.2021).

Wright, E.O & R.E. Dwyer (2003). The patterns of job expansions in the USA: a comparison of the 1960s and 1990s. Socio-Economic Review, 1(3), 289-325.

Zeira, J. (1998). Workers, Machines, and Economic Growth. Quarterly Journal of Economics, 113(4), 1091-1117.