The evolution of technological change and its impact on workers. A survey of the literature

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The role played by technological change in the economy and in the labor markets, where it generates both winners and losers, has long been object of debate and investigation. The present paper aims to provide an updated picture of the link between technological progress and labor by surveying the recent literature on this subject. Specifically, it organizes the relevant studies according to the wave of technological change under scrutiny and the selected empirical approach, makes comparisons across articles in the same group and derives some tentative findings. Additionally, this work touches upon an emerging line of research on a related topic, namely, the link between technological change and voting choices. From the reviewed literature, it emerges that, all in all, technological change mainly hinders workers who perform routine tasks and who work in firms that did not keep pace with the digital transformation. At the same time, technological change often increases output and productivity, and can also positively affect employment, especially in the case of workers who perform non-routine tasks and of technologically advanced companies. However, the considerable heterogeneity that affects the surveyed studies makes it difficult to draw general and robust conclusions. A meta-analysis would help overcome such limitation.

Keywords: technological change, automation, robots, Artificial Intelligence, labor

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1. Introduction

Technological progress has long been a source of structural change in the economy that generates aggregate gains but also produces winners and losers (Anelli, Colantone & Stanig, 2019). The nature of technological change and then the identity of such winners and losers have changed remarkably over time. In particular, 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 IT and computer-based technologies (Goldin & Katz, 1998). This demand of 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. This process was termed 'skill-biased technological change' (SBTC), capturing the idea that technological progress results in an increase in the relative demand for medium-skilled workers (Katz & Murphy, 1992).

Starting from the eighties, the advent of computerization altered again the relation between automation and labor demand. Indeed, computers can codify and perform more efficiently routine tasks mainly done by medium-skilled workers, such as machine operators and office clerks. Rather, the tasks fulfilled by unskilled workers, such as waiters or cleaners, and by skilled workers, such as managers and computer programmers, are nonroutine in nature and cannot be easily codified and performed by computers. Accordingly, computerization is often regarded as a form of 'routine-biased technological change' (hereafter, RBTC; Acemoglu & Autor, 2011), which is consistent with the phenomenon of job polarization experienced by many countries since the end of the seventies.

In the most recent decades, the picture has changed again due to the rapid increase in the adoption of industrial robots, and even more recently, also to the advances in Artificial Intelligence (AI) and new digital technologies. These cutting-edge devices can affect wages and employment either negatively, by directly displacing workers from tasks they were previously performing, or positively, by increasing labor productivity and complementing certain tasks. Such technological advances, it should be noted, exhibit peculiar features compared to those observed in the previous decade. First, these changes favor the further slicing up of the production process and the occupation into narrower tasks that, in turn, may be negatively or positively affected by technological innovation. Second, these advances refer to tasks that are present in occupations both in the manufacturing sectors and in the service sectors, thereby extending the potential impact of technological change over an increasingly large share of the economy.

This very concise overview of the evolution of technological change illustrates well the reasons why its diverse ramifications for the economy and the labor markets have fueled a vast economic literature. Although the link between technological progress and labor has long been investigated, important advances in the empirical research on this subject have been made only in the last 15 years or so, also thanks to the increasing availability of microeconomic data and to the advent of important methodological advances. In particular, since the seminal work by Autor, Levy & Murnane (2003), a growing number of studies have addressed the effect of computerization on workers by resorting to the so-called task-based approach, whereby tasks are assessed in terms of their relationship with technological changes. In the last few years, moreover, several articles have scrutinized the impact of industrial robots and other automation technologies by looking both at the aggregate and at the micro-level. Meanwhile, the influential work by Frey & Osborne (2017) opened the way to a considerable number of studies estimating the probability that automation may displace labor in different occupations, sectors and countries. Unlike the backward-looking traditional approaches to technical change and labor, this body of literature aims to determine the susceptibility of jobs and tasks to automation and to project the prospective implications on labor markets, industries and regional economies. The impact of these studies on the policy debate has been huge: national policymakers, trade unions, entrepreneurs and international economic organizations started in a lively discussion on the most appropriate actions designed to ripe the benefits and to minimize the risks posed by such radical transformation.

The present paper aims to offer an updated and exhaustive picture of the link between technological change and labor dynamics by means of a thorough survey of the most recent contributions on the subject. To this purpose, this paper summarizes and organizes existing work according to the object of study; within each of the identified lines of the literature, by focusing on the available empirical analyses, it makes comparisons across the contributions in terms of the main variables, datasets, samples, methodologies and results. Besides highlighting the advances made in recent times by the scholarly literature, this paper also draws some tentative conclusions and proposes a promising direction for further research. Finally, the survey of the studies on the implications of technological progress for employment and wages is complemented with a review of the emerging and less known research on whether and how the perceived negative effects of automation can influence people's political preferences and voting behavior.

The structure of this work is organized as follows. Section 2 deals with the impact of computer technology on labor and is mainly devoted to the review of the empirical articles that embrace the routine-biased technological change hypothesis and then resort to a task-based approach. Section 3 presents the recent body of literature addressing the effects of the adoption of industrial robots on workers. Section 4 summarizes the preliminary empirical findings on the implications of AI and new digital technologies on economic growth and labor. Section 5 reviews the studies that estimate the probability that a certain occupation will be automated soon. Section 6 illustrates the emerging line of research on technological change and voting outcomes. Section 7 highlights the heterogeneity of the studies surveyed in Sections 2-4 and the need of performing a more systematic review in order to achieve a better understanding of the relationship under scrutiny. Section 8 concludes. Finally, Appendix 1 includes the list of the empirical articles cited in Sections 2-6, complemented with basic information on the object, the variable(s) used to capture technological progress and the major findings; Appendix 2 describes the process of selection of the articles; Appendix 3 provides a tentative classification of their dependent variables and key regressors.

2. The impact of computer technology on labor markets and the advent of the routine-biased technological change hypothesis

A vast literature has documented a pronounced increase in the relative supply of high-skilled labor coupled with rising wage skill premia in the US labor market and other advanced countries throughout the seventies and eighties. This evidence has led to the idea that technological developments have been biased towards the most skilled workers in the form of higher employment and wages, and thus to the concept of skill-biased technological change (see Katz & Murphy, 1992 and a large subsequent literature summarized and extended by Autor, Katz & Krueger, 1998; Katz & Autor, 1999; Acemoglu, 2002; Goldin & Katz, 2008; Acemoglu & Autor, 2011). The intellectual foundation of this literature is what Acemoglu & Autor (2011) refer to as the canonical model, which features two different skill groups (for instance, workers with or without a college degree) performing two distinct and imperfectly substitutable occupations or producing two imperfectly substitutable goods. Technology in the canonical model is assumed to take a factor-augmenting form, meaning that it complements either high- or low-skilled workers and thus induces either a monotone increase or decrease in wage inequality between skill groups.

While the skill-biased technological change hypothesis provides a satisfactory explanation of the aforementioned labor patterns, its ability to support more recent developments in technological change and labor market dynamics has been questioned. Autor, Katz & Kearney (2006), Goos & Manning (2007) and Goos, Manning & Salomons (2009) analyze wage and employment trends in the US, in the UK and in a sample of 16 European countries, respectively. They observe that, between the eighties and the nineties (or earlier, as in the UK), occupational employment growth shifted from monotonically increasing in wages (education) to a pattern of more rapid growth in jobs at the top and bottom relative to the middles of the wage (education) distribution, a phenomenon known as labor market or job polarization. These scholars hypothesize that one of the main drivers of this labor pattern is the decline in the price of ICT capital, coupled with the increased capability of computer technology to replicate human tasks, especially routine tasks. Technological change, the reasoning goes, has begun to substitute mainly workers performing routine tasks, who are typically medium-skilled workers, and to complement jobs involving mostly non-routine tasks. According to this more nuanced and refined version of the skill-biased technological change hypothesis, technological change is thus biased toward replacing labor in routine tasks; subsequently, this hypothesis has been labelled as routine-biased technological change (RBTC), and the approach used by the empirical studies that endorse this view is often referred to as task-based approach.

One of the first contributions to the RBTC literature is the seminal paper by Autor, Levy & Murnane (2003). The authors develop an economic model which classifies tasks according to their degree of routinization, rather than according to a simple ‘skilled’ versus ‘unskilled’ or ‘manual’ versus ‘non-manual’ distinction, and which shows that computer technology can replace human labor in routine tasks but (as yet) cannot replace human labor in non-routine tasks. Then, they 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 (i.e., non-routine analytic, non-routine interactive, routine cognitive, routine manual and non-routine manual) over the four-decade period from 1960 to 1998. When they empirically test the relation between computer adoption and task change, they find that, within industries, occupations and education groups, computerization is associated with reduced labor input of routine manual and routine cognitive tasks, and with increased labor input of non-routine cognitive tasks. Building upon Autor, Levy & Murnane’s conceptual framework, Autor, Katz & Kearney (2006) show that the observed polarization of the US labor market can be explained by a model of computerization in which computers most strongly complement the non-routine (abstract) cognitive tasks of high-wage jobs, directly substitute for the routine tasks found in many traditional middle-wage jobs, and have little direct impact on non-routine manual tasks in relatively low-wage jobs.

An in-depth analysis of job polarization in the US and an empirical assessment of its relationship with RBTC are performed by Autor & Dorn (2013). First, the authors document a hitherto unknown fact, namely that the twisting of the lower tail of the employment and earnings distributions is substantially accounted for by rising employment and wages in a single broad category of employment, namely service occupations. They hypothesize that, to avoid the negative effects of computerization, low-skilled individuals performing routine tasks tend to reallocate their labor supply to service occupations, which are difficult to automate because they rely heavily on dexterity, flexible interpersonal communication, and direct physical proximity. Then, after estimating the degree of routinization of the US local labor markets, proxied by the US Commuting Zones, they show that local labor markets specialized in routine tasks differentially adopted information technology, reallocated low-skilled labor into service occupations (employment polarization), experienced earnings growth at the tails of the distribution (wage polarization), and received inflows of skilled labor. Autor & Dorn’s estimation of local labor markets’ degree of routinization is based on an index of the degree of routinization at occupation level, defined

Routine Task Intensity (RTI), which is rising in the importance of routine tasks in each occupation and declining in the importance of manual and abstract non-routine tasks. The RTI index elaborated by Autor & Dorn and similar constructs have been subsequently used in other contributions in this stream of literature, including Autor, Dorn & Hanson (2015), Goos, Manning & Salomons (2014), Das & Hilgenstock (2018) and Guarascio, Gualtieri & Quaranta (2018; see Table A1 for more information). As an illustration, Autor, Dorn & Hanson (2015) add to Autor & Dorn's (2013) analysis by studying the simultaneous impact of both technology and import competition from China on US employment levels and job composition across local labor markets and different demographic groups[1]. The authors' empirical analysis, which resorts to two-stage-least-square regressions to account for the potential endogeneity of trade, reveals that the local labor markets more exposed to rising Chinese import competition have experienced significant falls in employment, particularly in manufacturing and among non-college workers. On the other hand, local labor markets susceptible to computerization due to specialization in routine activities experienced occupational polarization within manufacturing and non-manufacturing, but did not experience a net employment decline.

An important step forward in the estimation of occupational task content is attributable to Spitz-Oener (2006). Spitz-Oener argues that Autor, Levy & Murnane (2003) provide a comprehensive analysis of the first source of variation for measuring changes in aggregate skill requirements, i.e., employment changes between occupations (the so-called extensive margin), but are unable to accurately examine the second, namely, changes in skill requirements within occupations (the intensive margin). In this regard, Autor & Handel (2013) observe that the information from the Dictionary of Occupational Titles used by Autor, Levy & Murnane, that comes from periodic expert evaluations, is set only at occupation level, and thus it does not account for within-occupation heterogeneity in task demands (i.e., for the fact that job tasks can differ among workers within the same occupation). Spitz-Oener (2006), who focuses on West Germany's labor market from 1979 to the end of the nineties and uses individual-level measures of task inputs based on worker self-reports, shows that most of the increase in non-routine cognitive tasks and the pronounced decline in manual and cognitive routine tasks observed during the selected time frame occurred within occupations, and have been most pronounced in occupations in which computer technologies have made major headway. In turn, these changing occupational task requirements explain a significant part of the educational upgrading of recent decades.

Afterwards, other researchers, such as Ackomak, Kok & Rojas-Romagosa (2013) and Ross (2017, 2020) have measured within-occupation variation of tasks. Ackomak, Kok & Rojas-Romagosa (2013) observe that Autor & Dorn's RTI index, which draws upon time-invariant data from O*NET (i.e., the US Department of Labor's Occupational Information Network database), is assumed to remain constant over time. Then, they build an alternative measure of routine task intensity, defined as the ratio of routine tasks over two groups of non-routine tasks (services and abstract tasks), using data from the British Skill Survey.

Since these data are time-varying, the authors can decompose the changes of the importance of the three groups into changes in the intensive margin and changes in the extensive margin. Their empirical analysis reveals that technological change is one of the drivers of the significant changes in the within-occupation task content (i.e., the intensive margin) experienced by the United Kingdom between 1997 and 2006, and also of the between-occupation employment changes (i.e., the extensive margin) which, consistently with prior findings, exhibit a polarized pattern. Ross (2017, 2020) focuses on the US and shows that an increase in routine task content within occupations over time is associated with a decrease in wages and with a rise in the probability that incumbent workers would exit employment, while an increase in abstract task content is associated with an increment in wages and with a lower probability that an incumbent worker transitions out of employment or to another occupation.

While most of the studies that employ a task-based approach use task classifications mainly based on the distinction between routine and non-routine tasks, Caines, Hoffmann & Kambourov (2017) hypothesize that it is not routine intensity, but occupational task complexity (namely, the extent to which an occupation relies on tasks involving higher-order skills, such as the ability to abstract, solve problems, making decisions, or communicate effectively) the prime determinant of wages, wage growth and employment growth at the occupational level. Accordingly, they construct an index of occupational task complexity after performing Principal Component Analysis on a broad set of occupational descriptors in the O*NET data, and show that there is a positive relationship across occupations between task complexity and wage levels and between the former and wage growth, and that labor has reallocated from less complex to more complex occupations over time. Another alternative task classification is carried out by Gordo & Skirbekk (2013) in collaboration with experts in life cycle variation in cognitive and physiological abilities, and classifies tasks into three groups: tasks intense in the use of fluid abilities, tasks intense in the use of crystallized abilities and tasks that are physically demanding.

While the majority of the empirical studies reviewed in this section use, as the key regressor, one or more indicators of task content, which mediate the relation between technology and labor markets[2], some studies (e.g., Marcolin, Miroudot & Squicciarini, 2016, Böckerman, Laaksonen & Vainiomaki, 2019 and Kerr, Maczulskij & Maliranta, 2019) estimate the relationship between a direct measure of technological change and an employment or compensation-related variable for different categories of occupational task content. As an illustration, Böckerman, Laaksonen & Vainiomaki (2019), who explore the link between routinization and employment polarization using rich firm-level data on Finland, find that firm-level adoption of three categories of ICT factors (defined via PCA) are associated with increases in abstract occupation shares and decreases in routine occupation shares. Finally, a few studies employ, as regressors, both task indicators and more direct measures of technological change, either alternatively (e.g., Akcomak, Kok & Rojas-Romagosa, 2013) or simultaneously in the same regression (e.g., Antonczyk, Fitzenberger & Leuschner, 2009).

As mentioned at the beginning of this section, several researchers have adopted a task-biased approach to test the link between technological change and job polarization in one or more countries. Although the RBTC hypothesis seems to properly explain this pattern in employment and/or wages in some countries, like the US, the evidence is limited or mixed in others, such as Italy and Germany (see Gualtieri, Guarascio & Quaranta, 2018, and Basso, 2019, for Italy, and Antonczyk, Fitzenberger & Leuschner, 2009, for Germany). Moreover, Das & Hilgenstock (2018) and Mahutga, Curran & Roberts (2018) observe that developing countries are generally less exposed to routinization than developed countries. Furthermore, consistently with the view that technological change has been biased towards routine tasks especially in the last few decades, Adermon & Gustavsson (2015) find some evidence of routine-biased technological change in Sweden for the period 1990-2005, but not for the period from 1975 to 1990.

Despite the diffusion of the task-based analysis in the literature, maybe because of some conceptual problems[3] and of the operationalization difficulties related to the latter, a considerable share of empirical contributions on the link between computerization and labor dynamics released in the last 15 years or so resorts to a more traditional approach to technological change. Some of these studies use as focal regressor a direct indicator of ICT capital, such as investment in computers, internet use and adoption of IT applications like ERP, CRM, SCM, e-banking and e-government (e.g., Thewissen, Wang & Vliet, 2013; Massari, Naticchioni & Ragusa, 2015; Atasoy, Banker & Pavlou, 2016; Kristal & Cohen, 2016); others, instead, use indirect measures of technology and technological progress such as total factor productivity (e.g., Hutchinson & Persyn, 2012; European Commission, 2014; Autor & Salomons, 2018; Archanskaia, Meyermans & Vandeplas, 2019) or a reduction in the price of investment (e.g., Elsby, Hobijn & Sahin, 2013; Caselli, 2014; Dao et al., 2017).

This section has shown that, since the influential article by Autor, Levy & Murnane (2003), a growing number of empirical papers investigating the effect of technology on labor (some of which, not mentioned here, are reported in Table A1) have embraced the so-called routine-biased technological change hypothesis developed in the early 2000s. All in all, these contributions demonstrate that computer technologies tend to substitute routine tasks, and that computerization has consequently led to variations in employment across different jobs, and also to within-occupation changes in task content.

While, during the eighties and the nineties, technological change mostly consisted in the spread and improvement of computer and internet-related technologies, in recent years it has also taken the form of advances in robot technology. This will be the object of section 3.

3. The impact of robot adoption on labor markets

Due to the ongoing trend toward automation and continued technological innovations in robotics, since 2010, the demand for industrial robots[4] has risen considerably and, from 2013 to 2018, annual installations of robots increased by 19% on average per year. The five major markets for industrial robots, namely China, Japan, the United States, the Republic of Korea, and Germany, currently account for 74% of global robot installations (IFR, 2019). Recent and prospective advances in robotics have renewed concerns about the potentially disruptive impacts of technological change on labor markets. These worries have been amplified by popular books such as 'The Second Machine Age' (Brynjolfsson & McAfee, 2014), and 'the Rise of the Robots' (Ford, 2015), but a systematic analysis of the issue had not been conducted until a few years ago.

One of the first studies that empirically examine the impact of industrial robots on labor has been 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 which predicts the effect of robotization on a set of economic outcomes. Using data from IFR (which has been recording information regarding worldwide robot stock and shipment figures since 1993) and from 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 using both OLS and 2SLS regressions[5]. According to their findings, increased robot use has a positive effect on labor productivity, total factor productivity and wages. Moreover, the analysis concludes that robots did not significantly reduce total employment, but did contribute to lower low-skilled workers' labor share.

Leigh & Kraft (2018) argue that Graetz & Michaels' (2018) analysis is national in scope and fails to reflect substantial subnational variations in the use of production technologies, mainly because data on robots are still insufficient. Building on this, they conduct a robotics census for the US which accounts for the regional variations in industry presence and the deployment of robotic capabilities, and which should serve as an initial step for enabling a more robust analysis of the robotics ecosystem.

The data compiled by Leigh & Kraft (2018), together with data from IFR, have been used by Acemoglu & Restrepo (2020) to analyze the effect of the increase in industrial robot usage between 1990 and 2007 on US local labor markets. To build their empirical analysis on theory, the authors set up a model in which robots compete against human labor in the production of different tasks. Accordingly, two main forces shape labor demand: a negative displacement effect (as robots directly displace workers from tasks they were previously performing) and a positive productivity effect (as other industries and/or tasks increase their demand for labor). Indeed, robots directly substitute workers when output and prices remain constant, but there are general equilibrium effects to consider: the resulting (unit) cost reductions of labor can increase product and labor demand in the industries where the robots are installed, as well as in other industries. Whether the positive or the negative effect dominates remains an empirical issue. Thus, Acemoglu & Restrepo estimate the equilibrium impact of robots on the US local labor markets, with the latter being approximated by the 702 US Commuting Zones. To this purpose, they calculate the robot exposure of local labor markets, which is assumed to be proportional to the regional employment in the industry of the company acquiring the robot. The empirical analysis, which also resorts to IV regressions to control for possible endogeneity issues[6], points to a negative effect of robot adoption on the employment-to-population ratio and wages, and this indicates that the displacement effect prevails over the overall productivity effects. Moreover, it shows that the estimated coefficient of robot usage remains negative and significant also when a set of control variables, including imports from China and Mexico and offshoring, is added to the regression. Hence, robotization still exerts a direct effect on the labor markets after accounting for demand and supply factors such as foreign competition and delocalization of production.

Acemoglu & Restrepo's approach to measuring the degree of local labor markets' exposure to robots has been also employed by Dauth et al. (2017), Chiacchio, Petropoulos & Pichler (2018) and Aghion, Antonin & Bunel (2019) to assess the impact of robotization on labor in Germany, six Western European Union countries and France, respectively. While Chiacchio, Petropoulos & Pichler (2018) and Aghion, Antonin & Bunel (2019) find that robotization reduces aggregate employment, Dauth et al. (2017) come to the conclusion that robots do not cause total job losses, but they affect the composition of aggregate employment. In particular, the authors 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, and which is fully offset (or even slightly overcompensated) by additional jobs in the service sector. As for earnings, both Dauth et al. (2017) and Chiacchio, Petropoulos and Pichler (2018) show that the effect of robotization on wages remarkably varies across different demographic and occupation groups. Dauth and coauthors argue that robots negatively affect individual earnings mainly for the medium-skilled workers employed in machine-operating occupations, while high-skilled workers in managerial and science occupations tend to benefit both in terms of job stability and wages. Furthermore, in the aggregate, robots raise labor productivity but not wages, and thus seem to have contributed to the decline of the labor share recently experienced by several countries. Finally, the displacement effect detected by Chiacchio, Petropoulos & Pichler is particularly prominent for workers of middle education, for young cohorts and for men.

Like Graetz & Michaels (2018) and Acemoglu & Restrepo (2020), also these three studies employ IV regressions and, in some specifications, control for ICT capital. Chiacchio, Petropoulos & Pichler, who also account for the exposure to Chinese and US imports, and the exposure to routinization and offshoring, show that the growth of ICT capital has a positive impact on the employment rate, suggesting that different automated technologies can have a different impact on labor markets. This result motivates robot-specific analysis and suggests caution while generalizing findings that regard specific forms of technological advances.

Cross-country analyses on robotization and labor outcomes have been recently performed at industrial level, without using a local labor market approach, by Compagnucci et al., (2019), Blanas, Gancia & Lee (2020) and Klenert, Fernández-Macías & Antón (2020). Compagnucci et al. (2019) provide empirical evidence on the effect of robotization on labor dislocation using IFR data on the number of robots installed in the different manufacturing industries of 16 OECD countries over the period 2011-2016. By means of a panel VAR approach, they find that at, the industry level, a 1% growth in the number of robots reduces the growth rate of worked hours by 0.16, and also show that a given sector is more likely to be robotized when it is expanding both in terms of relative prices and employee compensations. Blanas, Gancia & Lee (2020) come to the conclusion that robot adoption (proxied by robot imports) reduce the demand for low and medium-skilled workers (as well as for young and for female workers) especially in manufacturing industries, while Klenert, Fernández-Macías & Antón (2020) do not find evidence that robots contribute to reducing the share of low-skilled workers across Europe.

All the articles mentioned so far resort to macro-level information by industry to construct measures of robot adoption, and do not account for heterogeneity across firms within sectors and across workers within the same firm. According to Seamans & Raj (2018), instead, this is a promising line of research. Indeed, firm-level data on the use of robotics and AI would allow researchers to address a host of interesting questions, including but not limited to: the extent to which, and under what conditions, robots and AI complement or substitute for labor; how robots and AI affect firm- or establishment-level productivity; which types of firm are more or less likely to invest in robots and AI; how market structure affects a firm's incentives to invest in robots and AI; and how adoption is effecting firm strategies. The authors, after briefly reviewing the existing literature on the labor market effects of robotics and AI and the main data sources, emphasize the lack of firm-level datasets, and consequently of firm-level studies, and the need to collect more microdata on robotic technology through surveys. The only firm-level study available at the time of Seamans & Raj's article was a European Commission's report released in 2015 and updated with more recent data in 2016 (European Commission, 2016), which examines the impact of robotization on employment using robotics data from the European Manufacturing Survey 2012 on 3,000 manufacturing firms in seven European countries. In the following years, however, a number of firm-level analyses have been performed: Koch, Manuylov & Smolka (2019) investigate differences in robot adoption across Spanish manufacturing firms and analyze the implications of these differences for the labor market effects; Bonfiglioli et al. (2020) assess the impact of robot imports on production workers of French firms; Dixon, Hong & Wu (2019) explore the consequences of robots on employment, organizational and work practices within Canadian companies; Acemoglu, LeLarge & Restrepo (2020) study the effect of firm-level robot adoption in the French manufacturing sector. While all these studies point to an increase in firm productivity, the results in terms of changes in employment are more mixed. 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. However, Acemoglu, LeLarge & Restrepo (2020) observe that such firm-level positive effects do not translate into similar market-level impacts because of the negative externalities on their competitors, which more than offset the employment gains: this leads to an overall negative impact of robots on industry employment. 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.

When analyzing the firm-level effects of robot adoption, it is important to keep in mind that the adoption decision is unlikely to be random, but it is rather driven by a number of firm characteristics. More generally, as Boniglioli et al. (2020) point out, some demand shocks can simultaneously affect both robot adoption and employment. To account for this, Koch, Manuylov & Smolka (2019), Dixon, Hong & Wu (2019) and Bonfiglioli et al. (2020) adopt an empirical strategy which addresses this potential endogeneity problem[7]. The identification of the drivers of robot adoption may not only represent an important methodological step for an unbiased estimate of the effects on labor outcomes, but it is also an interesting research topic *per se*. In this regard, the European Commission (2016) and Koch, Manuylov & Smolka (2019) also explore the determinants of the probability that firms use industrial robots, and find that ex-ante larger and more productive firms, as well as firms utilizing batch production, and export-oriented firms are more likely to adopt robots, whereas ex-ante more skill-intensive firms are less likely to do so. It remains to be clarified why this is the case. One can think of possible sunk costs in previous workers' training, threshold effects associated either with the size of production or with the level of productivity, financing constraints and the like. This represents an area of interest to be explored.

Although the extant literature on robots and labor mostly scrutinize advanced economies, some rapidly growing developing countries, especially China and the Republic of Korea, have experienced a remarkable increase in robot use. This posits some questions about the drivers of such expansion. Possible explanations pertain both to the supply and the demand sides for the markedly quick rise in robot adoption in China, which, in 2016, was the world's largest user of industrial robots. Cheng et al. (2019) find that several market- and government-related factors are associated with robot adoption, and that firms requiring more manual tasks have a greater likelihood of robot adoption. Focusing on the Republic of Korea, Cho & Kim (2019) assert that robotization occurs endogenously, and then use a robotization index based on the actual number of industrial robots currently deployed in workplaces as the dependent variable of their (OLS) multiple regressions. Hence, while most of the extant studies focus on the relationship between robotization and employment (i.e., the number of employees), Cho & Kim's study also includes the number of working hours among the regressors, as well as other variables referring to wages, the role of unions and firm size. According to their empirical analysis, robot adoption is positively associated with wages, the number of employees and firm size, while it is negatively associated with the number of working hours and with the rate of union density. These results thus point to a complementary relation between the number of employees and robotization, and to a substituting relation between the amount of working hours and robotization. The first relationship suggests that there exists the possibility of supplementing the increased human employment part with robotization; a plausible explanation for the negative link between the number of working hours and robot adoption is that firms may be motivated to boost robotization to compensate the overtime working hours that human workforce is not more willing to spend. Cho & Kim's findings suggest that the number of employees and the number of working hours should not be regarded as interchangeable employment-related variables. In particular, a reduction of working hours may either lead to a decrease in employment due to scale effects, or result in the substitution effect of replacing labor with capital. Moreover, the emerging of a significant association between robotization and labor also from regression models that use robot adoption as dependent variable implies that the link between robotization and labor market factors is likely to be bi-causal. This stresses the importance of accounting for potential reverse causality when investigating the impact of robot adoption on labor.

To sum up, in recent years a growing body of literature, fueled by the increasing availability of data on robots, including microdata, has assessed the effect of robotization at the industry, local labor market and firm level. While most of the reviewed studies point to an increase in output and labor productivity and to a decline in labor share, the results in terms of employment effects are more heterogeneous and may rely on biased estimates when endogeneity is not properly controlled for.

4. Impact and potential of Artificial Intelligence

The latest wave of the ongoing process of digital transformation is represented by the widespread of Artificial Intelligence (AI). Although this term was first used by John McCarthy in 1956, when he held the first academic conference on the advances in automation in Dartmouth, and since then it has appeared in early literature, the traditional approach to AI did not really concern independent machine learning, but intended to specify rules of logical reasoning and real-world conditions which machines could be programmed to follow and react to (Petropoulos, 2017a).

According to PwC (2018a), the term Artificial Intelligence refers to the computer systems that can sense their environment, think, in some cases learn, and take action in response to what they are sensing and their objectives. Forms of AI already in use are digital assistants, deep question and answering, machine vision and many others. PwC (2018a) groups AI systems according to the presence or not of humans in the loop, and to their adaptability or specificity. The four resulting categories are Assisted intelligence (i.e., specific/ hard-wired AI systems that assist humans in making decisions or taking actions), Augmented intelligence (i.e., adaptive AI systems that augment human decision making and continuously learn from their interactions with humans and the environment), Automation intelligence (i.e., specific AI systems that automate existing tasks -manual and cognitive tasks, both routine and non-routine), and Autonomous intelligence (i.e., AI systems that can adapt to different situations and can act autonomously without human assistance). Examples of AI technologies are Machine Learning, autonomous robotics and vehicles, computer vision, language processing, virtual agents and neural networks.

The rapid progress of AI, which is also increasing its ability in performing complex tasks in domains including voice recognition, translation and visual image recognition, has led to both excitement about its capability to boost economic growth and to concern about its potential disruption effects on human workers (Seamans & Raj, 2018). Concerning the former effect, Accenture, the McKinsey Global Institute and PwC have recently estimated the impact of AI on the global economy going forward (to 2035, 2050+ and 2030 respectively; see Table 2.1 of PwC 2018a for a comparison between the three studies). The most comprehensive analysis, conducted by PwC (2018a), employs EU and World KLEMS data on the stock of capital categorized as software, databases, computer hardware and machinery to create a variable to proxy for the stock of AI technologies, and predicts the impact of AI on global GDP exerted via both productivity gains and consumption-side product enhancements over the period 2017-2030[8]. According to the model main scenario, global GDP could be up to 14% higher in 2030 compared to its 2017 level as a result of AI. Labor productivity improvements are expected to account for over 50% of this gain, but, as new technologies are gradually adopted and consumers respond to improved products with increased demand, the share of impact from product innovation and enhancements increases over time. Drawing on the results by PwC (2018a), PwC (2018b) predicts that the job losses from automation are likely to be broadly offset by job gains arising from these new technologies. However, it is not very clear yet how and to what extent AI affects and will affect human work.

Felten, Raj & Seamans (2018) develop a method that links different advances in AI to different types of occupational abilities and which should allow other researchers, practitioners, and policymakers to model how advances in AI affect different abilities, occupations, and industries. However, as the authors remark, this methodology does suggest what occupations require abilities affected by advances in AI technology, but does not indicate whether AI serves either as a substitute or as a complement to the occupations it affects. Drawing upon several examples from the real world, and using information on several hundred artificial intelligence startups collected during their work with the Creative Destruction Lab at the University of Toronto, Agrawal, Gans & Goldfarb (2019) 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 which 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 the relative returns to labor versus capital for decision tasks. Huang & Rust (2018) use a task-based approach too for explaining the link between AI and labor: focusing on the service sector, they identify four main types of tasks, or intelligences (i.e., mechanical, analytical, intuitive, and empathetic), and develop a theory showing that AI job replacement occurs fundamentally at the task level, rather than at the job level, and that AI task replacement follows a predictable path from 'lower' (easy for AI to be performed, namely mechanical tasks) to 'higher' intelligences.

Although the above-mentioned articles provide interesting insights on this topic, and some feasibility studies also capture the effect of AI-related automation (for instance, Frey & Osborne 2017 focus on advances in fields related to Machine Learning; see section 5), empirical evidence on the equilibrium impact of AI on the labor market is still very limited. Indeed, Seamans & Raj (2018) stress the lack of public datasets[9] on the utilization or adoption of AI at either the macro or micro level. Besides, Frank et al. (2019) argue that the scientists' measurement of the effects of AI and automation on workers is hindered by the lack of high-quality data about the nature of work (e.g., the dynamic requirements of occupations), the lack of empirically informed models of key micro-level processes (e.g., skill substitution and human-machine complementarity), and the insufficient understanding of how cognitive technologies interact with broader economic dynamics and institutional mechanisms (e.g., urban migration and international trade policy).

This gap in the empirical literature is partially filled by a few studies investigating the impact of a range of advanced automation technologies, sometimes referred to as new digital technologies, on employment and wages. We recall Mann & Püttmann (2019), Balsmeier & Woerter (2019), Genz, Janser & Lehmer (2019). and Bessen et al. (2019). These articles use data on: automation patents, i.e., various devices that carry out a process independently of human intervention (Mann & Püttmann, 2019); machine-based technologies such as computerized automated control systems, programmable logistic controllers, rapid prototyping, computerized numerical control (CNC) and direct numerical control (DNC) machines, autonomous vehicles, 3D printing, and the internet of things (Balsmeier & Woerter, 2019); machines/computers that operate mostly or fully autonomously and automatically such as big data, cloud computing systems, internet platforms, cyber-physical/embedded systems or the internet of things (Genz, Janser & Lehmer 2019); automation technologies such as self-service checkouts, warehouse and storage systems, automated customer service and robotics integrator services (Bessen et al. 2019). While Mann & Püttmann (2019) use industry-level data, Balsmeier & Woerter (2019), Bessen et al. (2019) and Genz, Janser & Lehmer (2019) employ survey-based microdata (at the firm level and, in Genz, Janser & Lehmer 2019, also at the individual level). Genz, Janser & Lehmer (2019) find a positive effect of automation technologies on the individuals working in the establishment, whereas Bessen et al. (2019) observe a negative impact especially for incumbent and older workers. Finally, Mann & Püttmann (2019) and Balsmeier & Woerter (2019) discover that technology alters labor composition but have a positive aggregate effect on employment at the industry and firm level, respectively. All in all, these results suggest that the diffusion of cutting-edge technologies is mainly beneficial for the sectors, firms and workers that stay abreast of the technological developments and thus manage to take advantage of their potential.

To sum up, at present there are comparably much fewer empirical studies on the economic effects of AI than studies on the implications of robots, mainly because of the paucity of public data. However, it is likely that the increasing availability of firm-level surveys collecting information on cutting-edge technologies and the widespread interest in better understanding the challenges and opportunities posed by the latest wave of automation will foster further research on this subject.

5. The feasibility studies and the risk of automation of occupations and tasks

The literature reviewed in Sections 2-4 suggests that technological progress has been replacing workers whose tasks can be easily performed by machines, and that automation technologies have spread across countries, sectors and firms. The concerns about the negative consequences on the labor force have fueled a specific strand of literature, pioneered by Frey & Osborne (2017), aimed at estimating the susceptibility of occupations to automation. This is, in a nutshell, their probability of being automated[10]. Frey & Osborne (2017) develop a novel methodology to categorize occupations according to their susceptibility to computerization (i.e., automation by means of computer-controlled equipment); subsequently, they implement this approach to estimate the probability of computerization for 702 detailed occupations, as defined according to the US labor statistics. Specifically, they first revise the task model proposed by Autor, Levy & Murnane (2003) in order 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 have a low risk of automation due to the presence of engineering bottlenecks. Then, they classify occupations according to their probability of computerization (which is based on the degree to which these bottlenecks persist) with the support of a Gaussian process classifier. The authors' estimates suggest that around 47% of total US jobs could be automated over the next decade or two; surprisingly, this figure includes also a substantial share of employment in service occupations, where most US job growth has occurred over the past decades.

Since the working-paper version of Frey and Osborne's study has been made public in 2013, several researchers attempted to estimate the current or future job susceptibility to computerization, which is sometimes referred to as job automatability, in other countries, such as Finland (Pajarinen & Rouvinen, 2014), Singapore (Lee, 2016), the whole EU28 (Bowles, Brugels, 2014), a group of ASEAN countries (Chang & Huynh, ILO, 2016), Japan (David, 2017), 24 European countries (Lordan, European Commission, 2018), Brazil (Albuquerque, 2019) and China (Zhou, 2020). More information on these studies is condensed in Table A3. As an illustration, according to Bowles' estimates, the share of jobs that are susceptible to automation in the EU amounts to 54%.

The results in Frey & Osborne's seminal work and in the follow-up studies have raised further concerns about the threats to labor coming from technological advances. However, it has been argued, the potential for automating entire occupations and workplaces may in fact be lower than the one predicted in these contributions. In this regard, Arntz, Gregory & Zierahn (2016, 2017) observe that it is usually not an occupation, but rather a certain task that can be automated or not, and then it is the task, rather than the occupation, that is at risk of replacement. Furthermore, even within occupations, there can be a remarkable heterogeneity of tasks performed at different workplaces. Finally, the concrete substitution of humans by machines is likely to be lower than the technical possibility of doing so because of legal, ethical and/or economic obstacles, or because workers may adjust to a new division of labor between machines and humans by switching tasks. Arntz, Gregory & Zierahn estimate the automatability of jobs for 21 OECD countries (including the US) using a task-based approach, which, in contrast to the occupation-based approach adopted by Frey & Osborne, accounts for the heterogeneity of workers' tasks within occupations. Their results indicate that, on average across the 21 OECD countries under scrutiny, 9% of jobs are automatable. Although the risk of automation varies considerably across OECD countries (from 6% in South Korea and Estonia to 12% in Austria and Germany,) and across workers (being higher for low-qualified workers, compared to highly qualified workers), the threat to labor from technological advances thus seems much less pronounced compared to the one implied by the occupation-based approach. In particular, only 9% of US employees are at risk of losing their jobs to automation in the next 10 to 20 years.

A task-based estimation of the job automatability in the US has also been conducted by Brandes & Wattenhofer (2016). While, according to their results, more than half of the jobs have a probability of automation which differs by less than 20% from the one recovered by Frey & Osborne, there are jobs whose automatability is more than 80% smaller than the one reported in Frey & Osborne's paper.

In the most recent years, an increasing number of studies have estimated the risk of technology-related job displacement in one or more countries using a task-based approach: Nedelkoska & Quintini (2018), in 32 OECD countries; Dengler & Matthes (2018), in Germany; Filippi & Trento (2019), in Italy; Brussevich, Dabla-Norris & Khalid (2019), in 30 advanced and developing countries); Egana del Sol (2020), in 10 developing countries. In particular, Dengler & Matthes (2018) and Filippi & Trento (2019) calculate the probability of automation at both occupation and task level, and show that such estimate considerably lowers when assuming that only certain tasks, rather than an entire occupation, can be substituted.

A similar approach, based on the 'work activities' of a job, has been used in the research program on automation technologies and their potential effects recently conducted by the McKinsey Global Institute (MGI). Its main results are summarized in two reports (MGI 2017a and 2017c), covering the US economy (where 2,000 work activities in more than 800 occupations are scrutinized) and 46 countries comprising almost 90 percent of global GDP, respectively. Across the sample of the latter, between 5% and 26% of work activities could be displaced by 2030, with a midpoint of 15 %. When comparing the MGI (2017c) work with his study, Egana del Sol (2020) observes that there are both complementary predictions and relevant discrepancies, and that in the analysis carried out by the MGI '*there is no specific threshold defined when an employee is considered at high risk for automation based on the percentage of tasks which will be automated*' (Egana del Sol, 2020, p.12). Several recent studies of this stream of research highlight the diversity of findings regarding the degree of job automation in a certain country. Stephany & Lorenz (2019) assume that the diversity of previous estimations of job susceptibility stems to a large extent from the specification of the model. As an illustration, Frey & Osborne start with binary opinions of experts and extrapolate them via a classification model for all occupations, whereas Arntz, Gregory & Zierahn begin with discrete probabilities and then apply a fractional model. The authors notice that most of the extant studies in this line of research either employ a binary model or a fraction model; while binary models tend to yield a bimodal distribution of predicted probabilities with large high-risk groups, fractional models lead to a bell-shaped distribution of probabilities with relatively low levels of high-risk individuals. Stephany & Lorenz test this assumption by conducting a case study with local expert opinions about near-term changes in occupations in Austria. Their analysis confirms the role played by model selection in the heterogeneity of previous estimations of job susceptibility, and shows that the tasks that humans perform during their typical working day are of significant importance when determining the impact of digital technologies on the future workspace. Specifically, since today's technologies unfold their potential mainly in disciplines that require routine cognitive effort, typical computer-backed office tasks, such as in the clerical professions, are more exposed to digital transformation than manual occupations. On the other hand, jobs in which complex information is processed and that require a high level of education and training are less prone to digital change in the near future.

Relatedly, most of the reviewed studies estimate the risk of technology-related job replacement also across different sectors, occupations and demographic groups. As an illustration, the PwC's (2018b) analysis of the projected short-run and long-run risk of automation across 29 countries reveals that transport stands out as a sector with particularly high potential for automation in the longer run, while in the short term, sectors such as financial services could be more exposed as algorithms outperform humans in an ever wider range of tasks involving pure data analysis. When individuals are considered, there are much lower potential automation rates on average for highly educated workers with graduate degrees or above, than for those with low to medium education levels. Interestingly, according to Nedelkoska & Quintini (2018), individuals employed in fully automatable jobs are more than three times less likely to have participated in on-the-job training, over a 12-month period, than workers in non-automatable jobs, and the authors' analysis of German data suggests that training is used to move to jobs at lower risk of automation. With regard to gender, the cross-country study by Brussevich, Dabla-Norris & Khalid (IMF, 2019) shows that female workers are at a significantly higher risk for displacement by automation than male workers, albeit with significant cross-country heterogeneity. Conversely, according to David (2017), in Japan there are no significant gender-based differences, while non-regular jobs (those that concern temporary and part-time workers) are more vulnerable to ICT diffusion than the others. Finally, several articles find a significant association between the degree of automatability and the degree of task-based routinization which is in line with the routine-biased technological change hypothesis.

To sum up, from the scrutiny of this growing line of research it emerges that job automation varies remarkably across countries, sectors, workers' characteristics, occupations, and sometimes also across different tasks within the same job, as highlighted by the studies that employ a task-based approach. This more disaggregated analysis of the extent of technology-related automation help to formulate appropriate policy measures aimed at supporting the adjustment to technological change. For instance, it suggests that boosting education and professional training can contribute to the contrasting of the displacing effects of technological progress. However, it is important to thoroughly understand the data, the approach and the method used to properly interpret the research findings. Additionally, as Acemoglu & Restrepo (2020) observe, these studies do not estimate the equilibrium impact of automation on employment and wages. For this reason, Acemoglu & Restrepo dub these contributions as feasibility studies. General equilibrium considerations are important to provide an assessment of the social and economic desirability of advances in automation, which should take into account also widespread productivity improvements and the emergence of new occupations.

6. Technological change and electoral outcomes

It is widely acknowledged that technological change has always produced both 'winners' and 'losers', and consequently has fueled worries and discontent among individuals. As an illustration, in 2017, according to the Eurobarometer, 72% of respondents agreed with the statement that digital technologies such as robots and artificial intelligence destroy jobs (Gallego, Kurerz & Schöll, 2018). Therefore, the potential or actual implications of technological change can influence the individuals' political preferences and, in turn, electoral outcomes.

Workers employed in occupations which are more at risk of automation are sometimes found to report preferences for more redistribution and government intervention (e.g., Cusack, Iversen & Rehm, 2006; Margalit, 2013; van Hoorn, 2018), which have been typically promoted by left parties. However, some factors can prevent these individuals to vote for them, such as the decreasing credibility of promises of redistribution and compensation of losers (especially since the financial crisis), the significant convergence between mainstream left and mainstream right in terms of redistribution and welfare state policies (which has weakened the link between social democratic parties and working class constituencies), the less prominent role of labor unions, weakened by globalization and technological change and, more in general, the less trust in the incumbent political institutions (Algan et al. 2017; Guiso et al. 2017; Anelli, Colantone & Stanig, 2019). At the same time, these persons may be attracted by nationalist, populist, and radical-right parties. Such political forces present themselves as an alternative to the traditional mainstream ones and build their appeal on nationalist rhetoric, on the promise of fighting the global economic forces that are damaging the country (including automation, for instance by means of taxes on companies adopting robots) and on the idea of defending the previous, supposedly better traditional way of life (Anelli, Colatone & Stanig, 2019).

In the last few years, a number of quantitative studies have assessed whether increasing automation influences individuals' political preferences and voting choices, and especially whether the latter has contributed to the increasing success of nationalist and radical-right parties and candidates experienced by several Western economies in the last few decades.

Building on the intuition that voters who have lost out to technology are more likely to opt for radical political change, Frey, Berger & Chen (2018) examine whether robots shaped the outcome of the 2016 US presidential election. The authors calculate the exposure to robots of the US Commuting Zones between 2011 and 2015 and, because this variable may be correlated with a variety of local economic shocks that may in turn have shaped the outcome of the election, they instrument it with two alternative instruments (i.e., a measure of robot exposure that uses CZ employment shares in 1980 rather than in 2011, and the variation in robot usage across industries in 10 European countries). , Frey, Berger & Chen's empirical analysis reveals that the support for Donald Trump was significantly higher in the local labor markets which were more exposed to robot adoption. Furthermore, a counterfactual analysis based on the authors' estimates points out that Michigan, Pennsylvania, and Wisconsin would have swung in favor of Hillary Clinton if the exposure to robots had not increased in the immediate years leading up to the election.

Local robot adoption has been used as proxy for technological change also in Anelli, Colantone & Stanig (2019) and Caselli, Fracasso & Traverso (2020). Anelli, Colantone & Stanig (2019) gauge the impact of automation on voting behavior in 14 Western European countries between 1993 and 2016 using two empirical strategies. The first strategy exploits district-level election returns and NUTS-2 regional variation in exposure to robot adoption, and, to address the endogeneity concerns, it instruments robot adoption in each country and industry by using robot adoption in the same industry but in different countries. The second strategy introduces a novel indicator of individual exposure to automation, measured as the product between individual vulnerability (whose estimation is based on individual characteristics such as age, gender, and education, and pre-sample employment patterns in the region of residence) and the national pace of robot adoption, which captures the individual exposure to automation in a way that is not contaminated by the consequences of automation itself. Anelli, Colantone and Stanig's study reveals that, at the aggregate level, automation shocks affect distinct-level election returns, leading to a tilt in favor of nationalist parties promoting an anti-cosmopolitan agenda and of radical-right parties. Consistently, the individual-level analysis shows that individuals that are more exposed to automation are substantially more likely to vote for radical-right parties, and tend to support parties with more nationalist platforms. Moreover, higher robot exposure at the individual level leads to poorer perceived economic conditions and well-being, lower satisfaction with the government and democracy, and a reduction in perceived political self-efficacy.

A positive relationship between robotization and support to far-right parties emerges also from the recent empirical study by Caselli, Fracasso and Traverso (2020). The authors, who analyze the economic forces driving the evolution of the Italian general elections occurred in 2001, 2008 and 2013 using a mixed first-difference model applied to local labor market areas (i.e., geographical units within which most people tend to live and commute to work) contribute to the prior literature in at least three major respects. Specifically, they simultaneously consider three global economic phenomena, namely technological change, immigration and foreign competition in international trade (the latter proxied by Chinese import competition), rather than focusing on technological change only; they account for spatial dependence associated with both economic spillovers (which are at least partially controlled for by using a local labor market approach) and with political spillovers across neighboring areas, by augmenting the baseline empirical specification to include the spatially-lagged dependent variable; they discuss the identification problems for the impact of robotization on voting patterns concerning the use of the shift-share IV approach. Indeed, in the case of imports and of robot adoption, the authors follow a shift-share IV design, where local industry shares are interacted with exogenous measures of shocks for trade with China and robot adoption. Subsequently, by employing state-of-the-art methodologies, they analyze the sources and the validity of the identification based on this technique. In doing so, they provide evidence on the plausibility of the identification strategy for assessing the impact of Chinese import competition on the local electoral outcome, and show that it is more difficult to identify the role of robotization and to validate the identification strategy based on shift-share IV, mainly because of the limited number of industry-related shocks available when using a two-digit sectoral classification of industrial robots.

Other three contributions in this body of literature, based on a different modelling of technological change, come from Dal Bò et al. (2019), Gallego, Kurer & Schöll (2018) and Im et al. (2019). Dal Bò et al. (2018) inspect the rise of the Sweden Democrats radical-right party between 2002 and 2014 focusing on both its politicians (the supply side) and the voters (the demand side), and show that the share of automation-vulnerable workers (i.e., individuals having an occupation with an RTI score above the median) in a municipality is robustly correlated with support for the Sweden Democrats in local elections. Rather, Gallego, Kurer & Schöll (2018) focus on the UK and resort to a direct measure of technological change, namely time-varying ICT capital stocks at the industry level. They show that digitalization favored high-skilled workers, and induced them to increase voter turnout, support for the Conservatives, and support for the incumbent. The causal interpretation of these results is supported by instrumental variable analysis, placebo tests and multiple robustness checks. Finally, Im et al. (2019) test for the effects of the risk of automation on voting behavior in 11 Western European countries by means of multinomial logit regression models, using the occupation-level probability of automation computed by Arntz, Gregory & Zierahn (2016) as the key independent variable. In line with previous literature, they demonstrate that workers in occupations at higher risk of automation are more prone to vote for radical-right parties.

The emerging strand of literature on this topic adds to the broader research on the potential economic drivers of populism, which has been recently reviewed by Margalit (2019). Margalit observes that the extant literature neglects the importance of cultural and social concerns and prejudices in driving opposition to global forces such as immigration. Moreover, he points out that such perceptions and beliefs can foster people's worries about economic change, implying a potential bi-causal relation. In the light of these considerations, the author argues that future research should attempt to refine and to test more rigorously the cultural explanations of populism, for instance through experimental surveys and study settings in which exposure to varying levels of cultural threat is exogenously determined. Although in his critical review he mainly refers to the literature on the political implications of increasing immigration and import competition, Margalit's insightful suggestions may also apply to researchers aimed at investigating the effect of technological change on voting preferences and outcomes.

To conclude the section, despite the limited amount of empirical studies on this issue, which can be partly attributable to lack of individual data and to identification issues, there is some recent evidence on the significance of the link between the advances in technological change and the rise of conservative and radical-right parties in developed countries. A direction for further research in this area may consist in accounting better for cultural and social perceptions, as advocated by Margalit (2019).

7. The heterogeneity in the empirical literature on technological change and labor and the utility of a more systematic review

From the preliminary analysis of the empirical contributions on the impact of technological change on labor reviewed in Sections 2-4, it emerges that they differ quite remarkably in terms of: choice and modelling of the dependent variable and of the key regressor (see Appendix 3); the time frame (i.e., number of years and the period); the use of either cross-sectional or longitudinal data; the level of analysis (i.e., individual, cohort of individuals based on demographic characteristics, occupation group, firm or plant, sector of activity, geographic unit - such as city, province, 'local labor market', county, state or country-); the country(s) included; the sector(s); the demographic characteristics of the workers or firms that enter the sample (e.g., highly educated vs less-educated workers, production vs non-production workers, females vs males, large vs small firms); the number and type of control variables (e.g., control for other capital-related variables or for R&D expenditure, control for trade-related indicators); the econometric model; the number of observations. Also, each contribution contains several estimates based on a different set of variables, subsamples (e.g. manufacturing vs non-manufacturing, blue collars vs white collars) and estimators (e.g., OLS vs IV), and then there could be relevant within-study heterogeneity too. Thus, the researcher's choices that might drive the significance and the sign of the effect of the technology-related regressor can be related to the way the variable of interest is measured (conceptual argument) and/or to the way the estimation is carried out (technical argument).

A useful tool which contributes to drawing more robust and general conclusions on the relationship between two variables analyzed in several empirical works is the meta-analysis. A meta-analysis can be defined as a quantitative review of empirical studies on the same issue. It helps to summarize and explain the differences across the reported results, to overcome the limitations typical of single studies (such as measurement inaccuracies, limited reliability, restricted research range, small sample size and low statistical power), and to draw more general and robust conclusions (Stanley et al., 2013; Borenstein et al., 2011). The articles included in the meta-analysis are typically known as primary studies, and the corresponding regression models provide the observations of the meta-regressions. More information on what a meta-analysis is and on how it can be performed is provided by Stanley & Doucouliagos (2012).

A meta-analytic review of 77 studies addressing the labor-market implications of technological change and/or international economic activity (i.e., international outsourcing, offshoring of intermediate goods or import competition) has been recently performed by Terzidis et al. (2019). However, the selected papers solely cover high-income countries, a relevant number of them address the effect of trade-related variables only and the majority of the studies that consider technological progress and/or trade-related indicators have been published before 2003; hence, there is still room for further investigation. In particular, only one of the papers included in this survey enters Terzidis' analysis.

It follows that the summary of the state of the art of the research on the relationship between technological change and labor dynamics offered in this paper might be of particular interest for scholars interested in carrying out an exhaustive meta-analytic review, capable of accounting for the diversity in the results found between (and also within) the existing empirical studies.

8. Concluding remarks

The role played by technological change in the societies has long been an object of debate and study. The present work provides an extensive survey of the recent literature on the labor impact of three subsequent waves of technological change, whose main feature is the spread of computer technologies, the adoption of industrial robots and the introduction of Artificial Intelligence and new digital technologies, respectively. More specifically, it organizes the reviewed studies according to the wave of technological change under scrutiny and the selected empirical approach, makes comparisons across articles in the same group and derives some tentative general findings. Additionally, although it mainly concerns the effects of technological progress and automation on employment and workers' compensation, this work touches upon an emerging line of research on a related topic, namely, the link between technological change and voting choices.

All in all, the reviewed literature suggests that technological change substitutes for labor and negatively affects the level of employment and wages especially for occupations that mainly involve routine tasks, and for firms that did not keep pace with technological innovation and are affected by the negative externalities stemming from their more technologically advanced competitors (e.g., firms that use industrial robots). At the same time, technological improvements can complement labor and increase output, productivity and employment, particularly in the case of workers who perform non-routine tasks and of firms and sectors that resort to these cutting-edge devices. Thus, the adoption of advanced technologies may represent a source of competitive advantage for the sectors and the companies that use and master them, and, also within the same firm or industry, it may differentially affect workers that differ in terms of occupation or tasks performed, age, gender, education, professional experience, etc. This bears on policy making, as the authorities could design interventions aimed at improving the quality of human capital and to produce 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 that may help to smooth the overall impact of technological change on labor, 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 in the near future; labor market income redistribution policies that ensure that the benefits of what he defines 'the Digital Revolution' are broadly shared; innovation policies that can contribute in creating technologies that are complementary to workers' skills and help mitigate the impact of technological change on economy-wide inequality.

Although some general considerations can be made, this paper warns that there exists a remarkable heterogeneity between (and within) the results produced by the empirical contributions reviewed in this work. This suggests using care in drawing definitive conclusions and carrying out further research undertakings in order to clarify the sources of such heterogeneous and often contrasting findings. Despite its inevitable limitations, this qualitative survey may represent the starting point for future meta-analytical studies that intend to achieve a better understanding of the factors underpinning the relationship between technological change and labor.

Notes

[1] Another important globalization-related phenomenon which can have relevant ramifications for labor markets is the increasing international openness. Consequently, several studies reviewed in this work (e.g., Caselli, 2014; Goos, Manning & Salomons, 2014; Meschi, Taymaz & Vivarelli, 2011; Acemoglu & Restrepo, 2020), as well as some earlier influential contributions (see for instance Berman, Bound & Griliches, 1994 and Feenstra & Hanson, 1999), analyse the joint impact of international economic activity (i.e., trade, international outsourcing and/or offshoring) and technological change on labor indicators. Interestingly, the task-based approach can help explain also the link between international openness and labor: according to the so-called offshoring theory by Blinder (2006, 2009), routine tasks and abstract tasks that do not require personal delivery to customers are considerably more vulnerable to international outsourcing than interactive tasks. Although empirical evidence suggests that both technological progress and trade are important to explain recent labor market developments in many OECD countries, the relative contribution of each of these causes is less clear. In order to shed light on the link between these three variables, Terzidis, Brakman & Ortega-Argiles (2019) conduct a meta-analysis of 77 studies that scrutinize the labor market effects of technological change and/or international economic activity (i.e., international outsourcing, offshoring of intermediate goods or import competition) in high- income countries. The main results of their ordered probit model indicate that, in general, both technological change and international economic activity are important. More specifically, the former is beneficial at the firm level, and is more likely to displace low-skilled employment, while the latter is more likely to benefit high-skilled employment and affects industry negatively.

[2] While in some papers, including the seminal contributions by Autor, Katz & Levy (2003) and by Spitz-Oener (2006), the task content of an occupation represents the dependent variable of the main regression model, and the key regressor is a direct measure of technological change (typically computer use), other studies make a step forward and, after building one or more indicators of occupational task content, they use them as technology-related regressors. See also table A1.

[3] A relevant conceptual problem is that what is perceived as routine from a worker's point of view may not be so from the perspective of machine execution. This poses a further challenge to the operationalisation of the concept, as highlighted

by Matthes et al. (2014). To give an example, the authors assert that driving a motor vehicle is often considered as a non-routine task because, even though it implies the repetition of the same basic activities and might be considered as monotonous (i.e. routine from the workers perspective), it also requires the use of some skills for which humans typically have a comparative advantage. In addition, while the concept of routine is quite precisely defined (at least in theory), the cognitive dimension is vaguer (Sebastian & Biagi, 2018).

[4] The International Federation of Robotics (IFR) defines an industrial robot as 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).

[5] In order to mitigate concerns about the possibility of reverse causality from productivity growth to increased robot adoption, Graetz & Michaels (2018) also run 2SLS regressions using two different instruments. The first instrument, labelled 'replaceability index', consists in the fraction of each industry's hours worked in 1980 (namely, before robots became ubiquitous) performed by US occupations that by 2012 became prone to replacement by robots. The second instrument, defined 'reaching and handling', consists in the extent to which industries used occupations requiring reaching-and-handling tasks compared to other physical tasks in 1980.

[6] Since some industries may be adopting robots in response to other changes that they are undergoing, which could directly impact their labor demand, and since any shock to labor demand in a commuting zone affects the decisions of local businesses, including robot adoption, the OLS estimates are likely to be biased. Accordingly, to identify the component of robot penetration driven by exogenous changes in technology, the authors instrument the US exposure to robots using an analogous measure constructed from the penetration of robots in European countries that are more advanced than the US in robotics technology, which captures the variation in robot adoption originating from the technological frontier.

[7] Koch, Manuylov & Smolka (2019) use a difference-in-differences approach combined with a suitable propensity score reweighting estimator, while Bonfiglioli et al. (2020) and Dixon Hong &Wu (2019) run IV regressions (although Dixon, Hong & Wu do that as a robustness check and do not report the results). The instrument employed by Bonfiglioli et al. (2020) is obtained by interacting a proxy for how suitable production is for automation in a given industry, with a proxy for the ease with which robots can replace worker activities within each firm. Rather, Dixon, Hong & Wu (2019) instrument for robot adoption by multiplying the percentage of workers in each 4-digit NAICS code in occupations with high 'manual dexterity' and relatively low 'verbal ability' in 2000 by the inverse of the median price per robot in Canada for each year.

[8] PwC (2018a) examines the impact of all the AI technologies that fit the broad definition of AI reported at the beginning of this section and that either have been adopted already, are in the process of development for future adoption or have been conceived of and are likely to be adopted to some extent before 2030. The PwC's experts in AI, together with Fraunhofer, identified and rated nearly 300 use cases of potential AI applications across the value chain of 8 different industry sectors. Next, they condensed them in the so-called AI Impact Index, which assigns a score to different sectors, subsectors and product lines according to five key criteria (i.e., the potential that AI has to improve the quality of products, the potential for products in an industry to be more personalized, the amount of time that consumers could save from using AI, the consistency of products as AI technologies 'level the playing field', and the improvements to data availability enabling producers to react to new consumer preferences). Then, they estimated the relationship between AI and labor productivity in six macro-regions by means of a LSDV estimator applied to panel-data, and finally, they employed a dynamic, global S-CGE (Spatial Computable General Equilibrium) model to assess the net impact of AI on the economy worldwide.

[9] As Raj & Seamans (2018) mention, the McKinsey Global Institute (MGI) has conducted an investigation on trends in investment in artificial intelligences and on the companies' uses of AI technologies using a multi-faceted approach based on surveys to executives at over 3,000 international firms, interviews to industry experts, and analysis of investment flows using third-party venture capital, private equity, and mergers & acquisitions data. Relying on the information collected in these ways, MGI attempts to answer questions regarding AI adoption by sector, size and geography, to look at performance implications of adoption and to examine potential impacts on the labor market in a report published in June 2017 (MGI, 2017b). Although the findings are presented at an aggregate level, much of the data, particularly the survey of executives, were collected at the firm level, allowing for further investigation. Unfortunately, these data are proprietary and inaccessible to the general public or the academic community.

[10] Expressions such as susceptibility/probability of automation/computerization and automatability are used interchangeably in this section.

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Data Availability Statement

The data that support the findings of this study, namely, relevant information on the articles that are the object of the survey, is contained in the tables included in Appendix 1. Further information is available upon request.

Appendix 1

This Appendix presents a set of tables that condense information on several empirical studies reviewed in Sections 2-5 (and also some additional studies using a task-based approach). Another version of these tables that also contain information on the dependent variable and some additional details is available upon request.

Table A1. Empirical studies which investigate the effect of computerization on labor using a task-based approach.

Author	year	object of the study	variable(s) capturing technological change	main findings
Antonczyk, Fitzenberger & Leuschner	2009	This paper investigates the changes in the German wage structure for full-time working males from 1999 to 2006 using a task-based approach	the five task measures suggested by Autor et al. 2003 (i.e., non-routine analytic tasks, non-routine interactive tasks, routine cognitive tasks, routine manual tasks, and non-routine manual tasks) but based on direct worker-level information, and PC use	Altogether, the task-based approach cannot explain the recent increase of wage inequality in Germany.
Autor & Dorn	2013	This study offers a unified analysis of the growth of low-skill service occupations between 1980 and 2005 and the concurrent polarization of US employment and wages, and assesses whether the later stems from the interaction between consumer preferences, which favor variety over specialization, and the falling cost of automating routine, codifiable job tasks	Commuting Zones' shares of routine occupations based on the RTI index	Local labor markets that specialized in routine tasks differentially adopted information technology, reallocated low- skill labor into service occupations (employment polarization), experienced earnings growth at the tails of the distribution (wage polarization), and received inflows of skilled labor.
Autor & Handel	2013	The authors analyze job content and wage determination using task indicators at both occupational and personal level, and then accounting for possible within-occupation heterogeneity in task demands	task content (abstract, routine, manual) at personal and occupational level	An increase in the abstract task scale is associated with a wage premium, while increases in routine and manual tasks are associated with wage penalties.

Akcomak, Kok & Rojas-Romagosa	2013	The authors analyze both the changes in employment between occupations and in the task content of occupations (thus, both the extensive and the intensive margin) in the United Kingdom and in the Netherlands between 1997 and 2006	RTI index (calculated by the authors) and computer use index (extent of PC use in occupations, estimated using PCA), used alternatively	The task-content of occupations (i.e., the intensive margin) has experienced significant changes in the United Kingdom between 1997 and 2006, which can be mainly explained by technological improvements and unionization levels, while offshoring didn't play a relevant role. Analyzing changes at the extensive margin, there has been job polarization for both the UK and the Netherlands, and this job polarization can be explained by both technological change and offshoring, though technological change seems to be a more influential factor.
Gordo & Skirbekk	2013	Using a task-based approach, the authors study how technological progress in Germany contributed to the changes in the distribution of tasks performed by the men and the relative wages they received for the 1986-2006 period	three task categories, namely: tasks with intense use of fluid abilities, tasks with intense use of crystallized abilities and physically demanding tasks	All cohorts, also when education was controlled for, experienced a rapid increase in fluid task use by the 2000s. Further, the relative earnings of those in their 50s compared to younger age groups increased – possibly as result of a shift towards cognitively based work tasks where age-earnings curves are relatively steep.
Böckerman, Laaksonen & Vainiomäki	2013	The authors perform decompositions and regression analyses in order to test for the routinization hypothesis and for job polarization at the firm level in the Finnish private sector	firm-level change in R&D intensity (+ change in capital intensity)	Although all in all there is weak evidence for labor polarization in the educational and occupational employment structures in Finland, the results for the intermediate education group and the routine occupation group are consistent with polarization at the firm level.
Kampelmann & Rycx	2013	This article uses detailed German household panel data to assess the relation between occupational task content and relative employment and wage changes	initial task content of occupation (based on Autor, Levy & Murnane's classification)	The task composition of occupations in 1985 is significantly associated with relative employment changes and accounts at least partially for the job polarization that occurred during the period 1985-2008. By contrast, initial task content is not related to observed trends in remuneration.
Bisello	2013	This paper analyzes occupational changes in Britain between 1997 and 2006 from a task-based perspective using data from the UK Skills Surveys	initial level of routine intensity of the occupation	Changes in employment shares are negatively related to the initial level of routine intensity.

Goos, Manning & Salomons	2014	This paper documents the pervasiveness of job polarization in 16 Western European countries over the period 1993-2010. It then develops and estimates a framework to explain job polarization using routine-biased technological change and offshoring	occupational routine intensity (based on the RTI index by Autor & Dorn, 2013), multiplied by a time trend	Job polarization is pervasive across European economies in the period 1993-2010 and has within-industry and between-industry components that are both important. The routine-biased technological change hypothesis explains overall job polarization and also its within-industry and between-industry components.
Moreno-Galbis & Sopraseuth	2014	This paper investigates the impact of aging and technological change on recent labor market dynamics using a panel of 96 French departments for the period 1993-2010	share of routine jobs (interacted with age variable in four out of five specifications)	The combined effect of population aging and technological diffusion has increased demand for personal services and, thus, demand for labor in these positions.
Senftleben-König & Wielandt	2014	This paper analyzes the polarization of employment and wages in Germany between 1979 and 2006, focusing on the role of technological progress	the share of initial employment in routine-intensive occupations (based on Autor &Dorn's RTI) in a region	The occupational structure of labor markets that were particularly susceptible to computerization has polarized, as employment shifted from middle-skilled, routine clerical and production occupations to less-skilled non-routine manual and service occupations. Occupational shifts are gender-specific, with gains in service employment being exclusively realized by female employees. Moreover, employment gains in services are accompanied by significant wage losses.
Dauth	2014	The author proposes a straightforward way to measure the actual magnitude of job polarization and investigates the latter in the German local labor markets (LLMs)	LLM share of routine share tasks relative to all tasks / share of routine-cognitive and of routine-manual tasks in 1980	While RBTC caused the decline of routine work, the complementary growth of high-skilled jobs is not uniform among local labor markets. Since interactive tasks benefit most from agglomeration forces, high paid jobs tend to concentrate in cities. Job polarization is thus predominantly an urban phenomenon.
Adermon & Gustavsson	2015	This study assesses whether the hypothesis of task-biased technological change (TBTC) explains the increase of job polarization in Sweden between 1975 and 2005	occupational task content: routine, abstract and service (dummies equal to 1 for occupations with the relative task score above the overall mean)	The estimates do not support the TBTC explanation for the 1970s and 1980s. Stronger evidence for routine-biased technological change, albeit not conclusive, is found for the 1990s and 2000s. In particular, there is both a statistically and economically significant growth of non-routine jobs and a decline of routine jobs. However, results for wages are mixed.

Autor, Dorn & Hanson	2015	The aim of this study is to analyze the simultaneous impacts of technology and trade on US employment levels and job composition, juxtaposing their effects across local labor markets, over time, between sectors and occupations, and among workers of different education, age and sex categories	routine employment share of a Commuting Zone (based on Autor & Dorn's RTI)	Local labor markets whose initial industry composition exposes them to rising Chinese import competition experience significant falls in employment, particularly in manufacturing and among non-college workers. With regard to the effect of technology, local labor markets susceptible to computerization due to specialization in routine task-intensive activities experienced occupational polarization within manufacturing and non-manufacturing but did not experience a net employment decline. The effect of technology appears to shift from automation of production activities in manufacturing towards computerization of information processing tasks in non-manufacturing.
Cortes & Salvatori	2015	This study explores firm-level occupational changes in the UK using a task-based approach	workplace-level task specialization indicators (i.e., RC, RM, NRM and NRC) / whether a workplace has adopted a new technology	Interestingly, the recent adoption of new technologies is correlated with very little subsequent change in the share of employment in non-routine cognitive occupations within the establishment. Surprisingly, the adoption of new technology is associated with an increase in the use of routine tasks within the establishment, although the effect is not significant in the case of routine manual task.
Sharma	2016	This paper analyzes the employment and wage trends for Indian workers for the period 2005-2012 using a task-based approach	occupational group's share of non-routine cognitive and routine cognitive occupations in 2005 multiplied by different years	The analysis reveals evidence of job polarization for India -middle skilled jobs that are most likely to be routine cognitive, have the lowest share in employment, whereas routine manual jobs have much higher shares in employment. Further, the share of non-routine cognitive jobs has been increasing over the period under consideration at the expense of routine manual jobs. Finally, returns to workers specializing in routine cognitive tasks and nonroutine cognitive tasks increase more than workers specializing in routine manual tasks, especially for males.
Consoli, Vona & Rentocchini	2016	The authors analyze changes in the skill content of occupations in US four-digit manufacturing industries between 1999 and 2010 using a task-based approach	industry shares of non-routine skill intensity	Both technology and trade with low-wage countries are associated with mild cross-industry convergence in skill intensity, while trade with high- and medium-wage countries are at the root of persistent heterogeneity across occupational groups. Moreover, higher non-routine skill intensity has had, at best, a modest effect on productivity and wages, except in high-skill occupations.
Cortes	2016	This paper presents a theoretical and empirical analysis of the effects of routine-biased technical change on occupational transition patterns and wage changes of individual workers	individual occupation dummies: nonroutine cognitive (equal to 1 if the individual is employed in a nonroutine cognitive occupation at time t) and routine	There is strong evidence of selection on ability in the occupational mobility patterns of routine workers, a significant fall in the wage premium in routine occupations, and faster wage growth over long-run horizons for workers switching out of routine jobs relative to those who stay.

Marcolin, Miroudot & Squicciarini	2016	This work addresses the role of global value chains, workforce skills, ICT, innovation and industry structure in explaining employment levels of routine and non-routine occupations in 28 OECD countries over the period 2000-2011	ICT intensity (the proportion of ICT-related employment in the industry over total industry employment) + number of patents	Employment in all types of occupations positively relate to innovation, and a positive correlation is observed between the offshoring of inputs and domestic outsourcing with more routine-intensive jobs.
Ross	2017	This analysis explores changes in the premium for abstract relative to routine task both across and within occupations over time in the US	occupation-level abstract and routine indexes in 2004, also interacted with a linear time trend in some specifications	An increase in routine task content corresponds with a decrease in wages, while an increase in abstract content lead to an increase.
Charnoz & Orand	2017	The authors test one of the main hypotheses put forward to explain the shift in labor demand occurred in the past three decades in France, namely a skill-biased technical change driven by the dissemination of ICT and the automation of routine tasks, leading to their disappearance in favor of high-skilled and service jobs	local labor market share of routine occupations in 1982	With the development of ICT, low-skilled workers switch from routine tasks to service occupations (manual tasks), or to unemployment. Moreover, high-skilled jobs concentrated in zones where the share of high-skilled occupations was initially higher, and where support routine jobs were also over-represented.
Caines, Hoffmann & Kambourov	2017	This paper studies the relationship between task complexity and the occupational wage-and employment structure in the US for the period 1980-2005	index capturing the task complexity of an occupation (namely, the extent to which they rely on complex tasks), and in some specifications, also the routine index	There is a positive relationship across occupations between task complexity and wages and wage growth. Conditional on task complexity, the routine intensity of an occupation is not a significant predictor of wage growth and wage levels. Labor has reallocated from less complex to more complex occupations over time. Within groups of occupations with similar task complexity, labor has reallocated to non-routine occupations over time.
Apella & Zunino	2017	This paper aims to analyze the employment profile trends in Argentina and Uruguay according to the task content performed by the workers in their jobs	individual-level index of intensity of four task (routine-cognitive, routine-manual, nonroutine-cognitive and nonroutine-manual)	A greater insertion of new technologies of automated production has two direct effects on the market. On one hand, the increase in probability of unemployment among those workers in occupations intensive in routine manual tasks. On the other hand, a reduction in the level of income for those who work in occupations which are intensive in manual tasks, and an increase in income for those workers in occupations intensive in cognitive tasks, especially non-routine.
Fonseca, Lima & Pereira	2018	This paper studies labor market polarization in Portugal using firm census data for 1986-2007, using a task approach	initial employment share in abstract, routine cognitive and routine manual tasks for each demographic cell, interacted with each year of the two periods	There is a sharp increase of both employment and wage premium for abstract tasks relative to routine tasks, and also a sharp decline in routine manual employment, while the decline in routine cognitive employment is modest and coupled with an increased wage premium.

Roy & Consoli	2018	This paper employs a task-based approach in order to analyze structural changes in regional employment within a rich vocational education setting in West Germany during 1979 and 2012	district-level initial share of routine employment	In Germany, regional employment districts with high initial share of routine occupations have experienced larger decline in routine occupations, greater growth of low-skilled service job and of non-routine high-skilled occupations in subsequent periods. Exposure to global imports in goods and services has reduced overall employment in routine-intensive occupations, but the magnitude is notably smaller as compared to technology.
Peng, Wang & Han	2018	This study examines worker displacement in the US using a job task framework in which tasks performed by workers interact with information technology in different ways and therefore can potentially lead to worker displacement. It also investigates what kinds of skills are more helpful for reemployment in today's increasingly computerized workplaces	abstract, routine and service tasks + IT investment in the industry in which the employee worked before displacement	Employees performing routine tasks at workplaces are more likely to be displaced, while those performing abstract and service tasks are less likely to be displaced. Moreover, information technology can be both upskilling and deskilling, depending on the kinds of jobs performed by workers.
Das & Hilgenstock	2018	This study explores the exposure to routinization, namely, the risk of the displacement of labor by information technology, and its relationship with labor market polarization, in 85 countries since 1990	exposure to routinization (based on routine task intensity score) of a certain occupation category in a certain industry and country + change in the price of investment	Developing economies are significantly less exposed to routinization than their developed counterparts; the initial exposure to routinization is a strong predictor of the long-run exposure; among countries with high initial exposures to routinization, polarization dynamics have been strong and subsequent exposures have fallen, while among those with low initial exposure, the globalization of trade and structural transformation have prevailed and routine exposures have risen.
Mahutga, Curran & Roberts	2018	The authors calculate individual-level RTI and offshorability scores for 38 countries and analyze their association with work hours and labor incomes in the global North and South	occupational RTI, also interacted with year	Both the degree of routinization and offshorability have an increasingly negative association with work hours in the global North, but not in the global South. RTI has a negative association with labor incomes in both the North and South, but has an increasingly large labor income penalty over time in the North and no trend in the South.
Guarascio, Gualtieri & Quaranta	2018	This work analyzes empirically if and to what extent employment patterns in Italian occupations are affected by task characteristics in terms of 'relative routinarity'	RTI dummy (whether the occupation-sector falls in the 4th or 5th quintile of the RTI distribution and 0 otherwise)	Occupations characterized by relatively large shares of routinary tasks are penalized in terms of employment dynamics. However, while in services the negative relationship between routine task and employment is verified, in manufacturing the same relationship becomes statistically weak. Moreover, Italian occupations with high level of routinary tasks seems to get 'younger' rather than 'older', and highly routinary occupations youth employment tends to grow rather than shrink. Finally, being in highly routinary occupations seems to be less an issue for workers with college degree.

Bachmann, Cim & Green	2019	Using an administrative panel dataset for Germany, the authors follow workers over an extended period of time and provide evidence of both the short-term adjustment process and medium-run effects of routine task-intensive job loss at an individual level	occupation-level RTI index based on Antonczyk, Fitzenberger & Leuschner' s (2009) approach	There is a marked, and steady, shift in employment away from routine, middle-skill, occupations. Exposure to jobs with higher routine task content is associated with a reduced likelihood of being in employment in both the short term (i.e., after one year) and the medium term (i.e., after five years).
Kim, Hong & Hwang	2019	This article analyzes changes in employment structures in Korea from 1993 to 2015 and the relationship between the 'routineness' of an occupation and changes in employment share and wages	Autor & Dorn's (2013) RTI index / the three components of the RTI	There is evidence of polarization of the Korean labor market, which seems to be driven by routine-biased technological change.
Consoli & Sánchez-Barrioluengo	2019	This paper empirically studies the evolution of the Spanish local labor markets over the period 1981-2011	province's share of routine employment at the beginning of each decade based on an RTI index similar to Autor & Dorn's (2013) one	There is a strong association between the decline of 'routine' mid-skill jobs and the expansion of low-skill service employment as well as differential labor market outcomes by levels of formal education.
Kerr, Maczulskij & Maliranta	2019	The authors analyze occupational polarization within and across firms using a census of matched employer–employee panel data from Finland in the period of 2000-2014, focusing on the role of globalization and on technological change	firm-level percentage of workers (level and change) using ICT/ firm's R&D expenditure	Both the increase in high-level abstract jobs and the decrease in routine occupations are predominantly a within-firm phenomenon. The former is mainly explained by outsourcing and greater ICT and R&D intensity, while the latter is linked to decreased international trade, the outsourcing of production functions abroad and the replacement of routine jobs with computers.
Böckerman, Laaksonen & Vainiomaki	2019	This paper examines the routinization hypothesis and employment polarization using rich firm-level data on Finland	firm's adoption of three ICT factors (defined via PCA) related to: internet access + usage of EDI (electronic data interchange) + share of SCM (supply chain management)	ICT factors are associated with increases in the demand for highly educated workers and reductions in the demand for the low educated, whereas the intermediate education group is independent of ICT. In addition, ICT factors are associated with increases in abstract occupation shares and decreases in routine occupation shares. These occupational patterns support the routinization hypothesis at the firm level. Since routinization is the main mechanism producing polarization, these results are also consistent with job polarization.
Consoli et al.	2019	This study analyses within-occupation task changes in the US over the period 1980-2010 and their relationship with educational upgrading and employment growth	initial value/ change in the occupation-level RTI + non-routine manual intensity	Conditional on the initial routine task intensity, a task reorientation towards non-routine tasks allows one to escape employment decline, especially in 1990-2000 and among Clerical occupations.

Basso	2019	This study explores whether the Italian labor market in the period 2007-2017 is polarized and, if so, whether this pattern is the consequence of a pure technology-driven shock	RTI index / two groups of occupation task contents, in which each task is interacted with a linear trend	In Italy, it seems that cross-sector reallocation, which favored the low value added service sector, and the rise of low-skilled migrant and college graduate labor supply explain most of the observed occupational changes, while evidence of the role played by routine-biased technological change is mixed.
Ross	2020	The author investigates how changes to task content affect incumbent workers in terms of their likelihood of transitioning to non-employment or changing occupations	changes in routine task intensity + change in abstract task intensity within an occupation (also interacted with a binary variable indicating whether state-level unemployment was at or above 7%)	An increase in routine task content within occupations over time was associated with an increase in the probability that incumbent workers would exit employment, while an increase in abstract task content was associated with a decrease in the probability that an incumbent worker transitioned out of employment or to another occupations.

Table A2. Empirical studies assessing the effect of robots and new digital technologies on labor.

Author	year	main object	variable(s) capturing technological change	Main results
European Commission	2016	This study provides empirical evidence on the impact of development and diffusion of industrial robot systems on growth, productivity and employment in the European manufacturing industry using firm-level data from the European Manufacturing Survey 2012	firm-level intensive robot use (dummy variable)	The use of industrial robots has neither a negative nor a positive direct effect on firm-level employment. Instead, companies using industrial robots obtain significantly higher levels of productivity in their manufacturing processes.
Dauth et al.	2017	This work studies the impact of rising robot exposure on the careers of individual manufacturing workers, and the equilibrium impact across industries and local labor markets in Germany	change in industry-level robot adoption + change in ICT equipment per worker in some specifications	Robots do not cause total job losses, but affect the composition of aggregate employment: they lead to a decline of manufacturing employment, which is totally offset by the rise of service jobs. Robots negatively affect individual earnings mainly for medium-skilled workers in machine-operating occupations, while high-skilled workers in managerial and science occupations tend to benefit both in terms of job stability and wages. Finally, in the aggregate, robots raise labor productivity but not wages, and then seem to have contributed to the decline of the labor income share.
Graetz & Michaels	2018	This work aims to investigate the industrial robots' contribution to the US economy in terms of labor productivity, TFP, employment and wages	industry-level robot adoption (i.e., change in the number of robots per million hours worked) + change in IT capital	Robots did not significantly reduce total employment, although they did reduce low-skilled workers' employment share. Moreover, increased robot usage positively contributed to increases in annual TFP and labor productivity growth and to the lowering of output prices.
Chiacchio, Petropoulos & Pichler	2018	The authors assess the impact of industrial robots on employment and wages in six EU countries, namely, Finland, France, Germany, Italy, Spain and Sweden	change in robot exposure (i.e., change in the number of robots per 1000 workers) in a given region + change in ICT capital exposure and routinization as controls	One additional robot per thousand workers reduces the employment rate by 0.16-0.20 percentage points. Hence, the significant displacement effect dominates. This displacement effect is particularly prominent for workers of middle education, for young cohorts and for men. Rather, the results for the impact of industrial robots on wage growth are mixed.

Compagnucci et al.	2019	This paper assesses the effect of robotization on labor dislocation in the different manufacturing sectors of 16 OECD countries over the period 2011-2016	sectoral-level growth rate of the number of robots, also used as dependent variable (panel VAR approach)	At the industry level, a 1% growth in the number of robots reduces the growth rate of worked hours by 0.16, as well as the selling prices and the real values of the compensations of employees. Moreover, a given sector is more likely to be robotized when it is expanding both in terms of relative prices and employee compensations.
Balsmeier & Woerter	2019	The present paper addresses the impact of emerging digitalization on the labor market with econometric analyses based on unique firm-level microdata from Switzerland, one of the technological leaders of the world	firm-level change in investment in digitalization between 2014 and 2015, also divided in fairly complex machine-based digital technologies and other non-machine-based technologies + change in investment in R&D	Increased investment in digitalization is associated with increased employment of high-skilled workers and reduced employment of low-skilled workers, with a slightly positive net effect. The main effects are almost entirely driven by firms that employ machine-based digital technologies, e.g. robots, 3D printing or the Internet of Things.
Aghion, Antonin & Bunel	2019	The authors explore the effect of robotization on employment in France over the 1994-2014 period	change in exposure to robots in a French employment zone between 1994 and 2014 + ICT capital stock in industry	Robotization reduces aggregate employment at the employment zone level, and non-educated workers are more negatively affected by robotization than educated workers.
Genz, Janser & Lehmer	2019	Using a novel linked employer-employee data set that contains detailed information on establishments' technological upgrading between 2011 and 2016, this study investigates the impact of investment in digital technology on the wage growth of employees within German establishments	being employed in a peloton (/ pioneer) establishment relative to being employed in a latecomer establishment + individual share of digital tools and of different types of tasks	Investments in new digital technologies at the establishment level positively affect the wages of the establishments' workers. Sector-specific results show that investments in new digital technologies increase wages in knowledge intensive production establishments and non-knowledge intensive services. The wage growth effects of employees in digital pioneer establishments relative to the specific reference group of workers in digital latecomer establishments are most pronounced for low- and medium-skilled workers.
Dixon, Hong & Wu	2019	The authors explore the employment consequences of robots within firms and how organizational and work practices are changing in response to robot adoption in Canada in the period 2000-2015	firm's investment in robots (+ ICT capital in one robustness check)	Investments in robotics are associated with increased employee turnover, but also with an increase in total employment within the firm. Examining changes in labor composition, manager headcount has decreased but non-managerial employee headcount has increased, suggesting that robots displace managerial work that in prior waves of technology adoption was considered more difficult replace.

Acemoglu & Restrepo	2020	This paper analyzes the effect of the increase in industrial robot usage between 1990 and 2007 on US local labor markets	A Commuting Zone's exposure to robots + exposure to IT capital	An increase in robot adoption in the US leads to a reduction in employment to population ratio and wages. Moreover, the impact of robots is distinct from and only weakly correlated with the impact of imports from China and Mexico, the decline of routine jobs, offshoring, other types of IT capital, and the total capital stock.
Koch, Manuylov & Smolka	2019	Focusing on Spain, the authors attempt to understand which firms adopt robots, the labor market effects of robot adoption at the firm level and how firm heterogeneity in robot adoption affects the industry equilibrium	firm-level robot adoption (i.e., dummy variable equal to one if the firm uses robots and zero otherwise) in year t + robot adoption in year t-4 (+ deflated R&D intensity and capital intensity) / robot density (i.e., industry-level share of sales attributable to robot-using firms in total industry sales) + robot density*firm-level robot use (i.e., dummy equal to one if the firm uses robots at least once during our sample period)	Ex-ante larger and more productive firms are more likely to adopt robots, while ex-ante more skill-intensive firms are less likely to do so. Robot adoption generates substantial output gains in the vicinity of 20-25% within four years, reduces the labor cost share by 5-7%-points, and leads to net job creation at a rate of 10%. Finally, there is productivity-enhancing reallocation of labor across firms, from non-adopters to adopters.
Bessen et al.	2019	The authors estimate the impact of automation on individual workers by combining Dutch micro-data with a direct measure of automation expenditures covering firms in all private non-financial industries over 2000-2016	treatment indicator of a worker-level event study DiD specification, equal to 1 if the firm experienced spikes in automation cost shares in a year	Automation at the firm increases the probability of workers separating from their employers and decreases days worked, leading to a 5-year cumulative wage income loss of about 8% of one year's earnings for incumbent workers. There is little change in wage rates. Further, lost wage earnings are only partially offset by various benefits systems and are disproportionately borne by older workers and workers with longer firm tenure.

Blanas, Gancia & Lee	2019	The authors study how information and communication technologies, software, and especially industrial robots affect the demand for workers of different education, age, and gender in 10 high-income countries and 30 industries for the period 1982-2005	industry-level ratios of ICT net of software + software capital stocks to real gross value-added, also interacted by industry-level index measuring the prevalence in routine tasks in 1980/ robot intensity interacted with the routine task index	Software and robots reduced the demand for low and medium-skill workers, the young, and women, especially in manufacturing industries; but raised the demand for high-skill workers, older workers and men, especially in the service industries.
Bonfiglioli et al.	2020	Using French data over the period 1994-2013, the authors study how imports of industrial robots affect firm-level outcomes	firm-level robot adoption (i.e., dummy variable equal to one if the firm start importing robots over the sample period) / robot intensity (i.e., ratio between the stock of robot capital and the total capital stock of the firm) / change in robot adoption	While demand shocks generate a positive correlation between robot imports and employment, exogenous changes in automation lead to job losses. Moreover, robot imports increase sales per worker and the employment share of high-skill professions, but have a weak effect on total sales, suggesting that productivity gains from automation may not be entirely passed on to consumers in the form of lower prices.
Acemoglu, LeLarge & Restrepo	2020	This paper studies the firm-level implications of robot adoption using a large sample of French manufacturing firms (about 20% of which are robot adopters)	firm-level robot adoption (i.e., dummy variable equal to one if the firm adopted robots in the period 2010-2015) / robot adoption + competitor's robot adoption	Consistent with theory, robot adopters experience significant declines in labor share and the share of production workers in employment, and increases in value added, productivity and employment. However, this expansion comes at the expense of their competitors, and the overall impact of robot adoption on industry employment is negative.

Klenert et al.	2020	This paper assesses the impact of robot adoption on employment in Europe	robot adoption, i.e: robot stock/ robot density/ percentile of robot density (+ ICT capital, capital formation and capital-labor ratio as controls in some specifications)	Robot use is linked to an increase in aggregate employment. Contrary to some previous studies, evidence of robots reducing the share of low-skill workers across Europe is not found.

Table A3. Empirical studies estimating the susceptibility of automation of occupations.

Author	year	object of the study	main findings
Bowel	2014	In a Bruegel Blogpost, the author briefly describes the results of his estimation of job automatability in the EU	In the EU, 54% of jobs are susceptible to automation.
Pajarinen & Rouvinen	2014	This work estimates the probability of automation of occupations in Finland and compares it with the US one	One third of Finnish employment is highly susceptible to computerization in the next decade or two. While this share is large, it is ten percentage points less than the corresponding share in the United States, which reflects cross-country differences in occupational structures. Low wage and low-skill occupations appear more threatened. Service jobs are relatively more sheltered than manufacturing jobs.
Chang & Huynh	2016	The study assesses what types of occupations in five ASEAN countries (i.e., Cambodia, Indonesia, the Philippines, Thailand and Viet Nam) have a high probability of being automated	The key findings in this study are: approximately 56 % of all employment in the ASEAN-5 is at high risk of displacement due to technology over the next decade or two; across the ASEAN-5 countries, prominent industries with high capacity for automation are hotels and restaurants, wholesale and retail trade, and construction and manufacturing; industries with low automation risk across the ASEAN-5 include education and training, as well as human health and social work; prominent occupations in certain countries face extreme risks of automation; in each of the ASEAN-5, women are more likely than men to be employed in an occupation at high risk of automation. Moreover, less educated workers and employees earning lower wages face higher automation risk.

Lee	2016	This paper aims to provide an estimate of the susceptibility of jobs in Singapore to computerization and automation over the next ten to fifteen years	About one-quarter of Singaporean employment is at high risk of computerization. This places the country as having one of the lowest proportion of jobs under high risk internationally. Within this high-risk category of workers, a significant number of them have non-tertiary educational qualifications and tend to be older adults, making them less likely to be re-employed if they lose their jobs.
Arntz, Gregory & Zierahn	2016	The main purpose of this work is to estimate the automatability of jobs for 21 OECD countries (including the US) using a task-based approach	On average across the 21 OECD countries under scrutiny, 9 % of jobs are automatable. The threat from technological advances thus seems much less pronounced compared to the occupation-based approach. However, low qualified workers are likely to bear the brunt of the adjustment costs as the automatability of their jobs is higher compared to highly qualified workers. Moreover, there are considerable differences across OECD countries.
Brandes & Wattenhofer	2016	The authors estimate the probability of automation of US occupations at task level	While, according to the authors' results, more than half of the jobs have a probability of automation which differs by less than 20% from the one reported in Frey & Osborne (2017), there are jobs where the probability calculated by the authors is more than 80% smaller than the one found by Frey & Osborne.
Frey & Osborne	2017 (WP version made public in 2013)	The authors implement a novel methodology to estimate the probability of computerization for 702 detailed occupations, using a Gaussian process classifier	According to the authors' estimates of the probability of computerization of occupations, around 47% of total US jobs could be automated relatively soon, perhaps over the next decade or two. Their model predicts that most workers in transportation and logistics occupations, together with the bulk of office and administrative support workers, and labor in production occupations, are at risk. More surprisingly, a substantial share of employment in service occupations, where most US job growth has occurred over the past decades, are highly susceptible to computerization.
David	2017	This paper evaluates the risk of job destructions induced by computer technology in Japan	Approximatively 55% of jobs are susceptible to be carried by computer capital in the next years. Moreover, there is no significant difference on the basis of gender. On the contrary, non-regular jobs (those that concern temporary and part-time workers) are more vulnerable to computer technology diffusion than the others

McKinsey Global Institute	2017a	This report summarizes the main findings of a research program on automation technologies and their potential effects conducted by the Institute over the past two years. In particular, this analysis enabled to estimate the technical automation potential of more than 2,000 work activities in more than 800 occupations across the US economy	About 49 % of the activities that people are paid to do in the global economy have the potential to be automated by adapting currently demonstrated technology. While less than 5 % of occupations can be fully automated, about 60 % have at least 30 percent of activities that can technically be automated by 2055.
McKinsey Global Institute	2017b	The authors estimate the probability of automation of jobs by 2030 in 46 countries that comprise almost 90 percent of global GDP	Across the countries under scrutiny, between 5% and 26% of work activities could be displaced by 2030, with a midpoint of 15 %. The proportion varies widely across countries, with advanced economies more affected by automation than developing ones, reflecting higher wage rates and thus economic incentives to automate.
Nedelkoska & Quintini	2018	This paper aims to estimate the risk of automation for individual jobs for the 32 OECD countries that have participated in the Survey of Adult Skills (PIAAC) so far, using a task-based approach	The main findings are as follows: across the 32 countries, close to one in two jobs are likely to be significantly affected by automation, based on the tasks they involve, but the degree of risk varies (for instance, about 14 % of jobs in OECD countries participating in PIAAC are highly automatable); the variance in automatability across countries is large (in jobs in Anglo-Saxon, Nordic countries and the Netherlands are less automatable than jobs in Eastern European countries, South European countries, Germany, Chile and Japan); about 30% of the cross-country variance of automatability is explained by cross-country differences in the structure of economic sectors and 70% is explained by the fact that, within these sectors, countries employ different occupational mixes; the risk of automation is not distributed equally among workers (automation is found to mainly affect jobs in the manufacturing industry and agriculture, although a number of service sectors, such as postal and courier services, land transport and food services are also found to be highly automatable); the risk of automation is the highest among teenage jobs; although adult learning is a crucial policy instrument for the re-training and up-skilling of workers whose jobs are being affected by technology , workers in fully automatable jobs are more than three times less likely to have participated in on-the-job training, over a 12-months period, than workers in non-automatable jobs; the analysis on Germany shows that participants already use requalification the participation in a training course that provides a new qualification – as a mechanism to transition from more to less automatable occupations.

Dengler & Matthes	2018	The authors calculate automation probabilities, labelled as substitution potentials, for occupations in Germany, assuming that only certain tasks in an occupation, rather than entire occupations, can be substituted	When assuming that entire occupations are replaceable, the authors find that approximately 47% of German employees work in a substitutable occupation in 2013. However, when assuming that only certain tasks can be substituted, they find that only 15% of German employees are at risk.
Lordan	2018	This work documents the shares of non-automatable and automatable jobs in 24 European countries over the last three decades using two definitions of automatable work (capturing jobs that were automatable in the last three decades and jobs that are recently automatable, respectively)	Many more jobs can now be automated, and the shares of these recently automatable jobs vary greatly from country to country, from 37% of the total jobs being recently automatable for Norway, to 69% for the Czech Republic. When distinguishing between fully automatable and polarized jobs, the authors find that the former range from 21% (Ireland) to 45% (Italy), while the share of polarized automatable job ranges from 13 % (Norway) to 35% (Belgium).
PwC	2018b	This PWC report explores the automation patterns across 29 countries (27 OECD countries, Singapore and Russia) and also predicts the proportion of existing jobs that might be of high risk of automation by the 2030s for different countries, different industry sectors, occupations within industries, and workers of different genders, ages and education levels	The estimated proportion of existing jobs at high risk of automation by the early 2030s varies significantly by country. These estimates range from only around 20-25% in some East Asian and Nordic economies with relatively high average education levels, to over 40% in Eastern European economies. Transport stands out as a sector with particularly high potential for automation in the longer run, while in the shorter term, sectors such as financial services could be more exposed as algorithms outperform humans in an even wider range of tasks involving pure data analysis. When individuals are considered, there are much lower potential automation rates on average for highly educated workers with graduate degrees or above, than for those with low to medium education levels. Differences are less marked by age group, although some older workers could find it relatively harder to adapt and retrain than younger cohorts.
Albuquerque	2019	In this paper, the authors replicate the method applied by Frey & Osborne to investigate the automation probability of jobs in Brazil, using data from Brazilian labor market administrative records between 1986 and 2017	In 2017, 55% of all formally employed workers in Brazil are in jobs with high or very high risk of automation.

Brussevich, Dabla-Norris & Khalid	2019	Using individual-level data on workers, including task composition at work, for 30 advanced and emerging economies, the authors derive probabilities of automation at the individual level based on worker and task characteristics, evaluate differences in the probability of automation across different demographic groups and estimate the proportion of the female working population that is at risk of being displaced by automation given the current state of technology	Female workers are at a significantly higher risk for displacement by automation than male workers, with 11 % of the female workforce at high risk of being automated given the current state of technology, albeit with significant cross-country heterogeneity. The probability of automation is lower for younger cohorts of women, and for those in managerial positions.
Filippi & Trento	2019	The authors estimate the probability of automation of occupations in Italy by applying both an occupation-based approach and a task-based approach	In Italy, based on the occupation-based approach, 33.2% of workers face a high risk of replacement; this percentage decrease at 18.1% when the task-based approach is applied. Male workers appear to face a higher risk of replacement than female ones. In general, occupations with a high probability of automation require a large number of routine (automatable) tasks to be performed. These occupations concern the following sectors: transport and logistics (e.g., taxi drivers, delivery personnel), office and administrative support (e.g., accountants), and production.
Stephany & Lorenz	2019	The authors aim to estimate the probability of automation of occupations in Austria and to demonstrate that the diversity of previous findings regarding the degree of job automation is, to a large extent, driven by model selection and not by controlling for personal characteristics or tasks	While clerical computer-based routine jobs are likely to change in the next decade, professional activities, such as the processing of complex information, are less prone to digital change.
Egana del Sol	2020	The authors examine job automatability in10 developing countries throughout Latin America, Africa and Asia, using a task-based approach	The developing countries under scrutiny range in their level of highly automatable jobs (i.e., jobs consisting of more than 70% automatable tasks) from the lowest of the Chinese province of Yunnan, with 7.7%, to the highest of Ghana, with 42.4%. In addition, occupations containing relatively more routine tasks are more likely to be automated, while workers with a higher level of education reduce their risks.
Zhou	2020	This research calculates the actual substitution probability by AI for various occupations in China in 2017, and then predicts the number of employed people that would be replaced by AI in each industry by 2049	About 35.8% of the current employment in China will be replaced by AI technology by 2049. Moreover, AI has larger substitution impacts on female, old age, low-education and low-income workers.

Table A4. Empirical studies addressing the influence of technological change on electoral outcomes.

Author	year	object of the study	variable(s) capturing technological change	main findings
Frey, Benedikt, Berger & Chen	2018	Building on the intuition that voters who have lost out to technology are more likely to opt for radical political change, this study examines if robots shaped the outcome of the 2016 US presidential election using a local labor market approach	a Commuting Zone (proxy for local labor market)'s exposure to robots between 2011 and 2015	The support for Donald Trump was significantly higher in local labor markets more exposed to the adoption of robots. Moreover, according to a counterfactual analysis based on the authors' estimates, Michigan, Pennsylvania, and Wisconsin would have swung in favor of Hillary Clinton if the exposure to robots had not increased in the immediate years leading up to the election.
Gallego, Kurer & Schöll	2018	This work examines whether digitalization causes divergence in political preferences focusing on the UK	industry-level ICT capital stock over employment	In the UK, digitalization favored high-skilled workers, and induced them to increase voter turnout, support for the Conservatives, and support for the incumbent.
Dal Bó et al.	2019	This work studies the rise of the Sweden Democrats party and attempts to understand whether the so-called economic losers contributed to it	whether an individual has an occupation with an RTI index score above the median (‘vulnerable insider status’)	The groups which faced relative-income decline and higher job insecurity (including workers threaten by automation) are over-represented among the politicians and voters of the Swedish radical right.
Im, Mayer, Palier & Rovny	2019	This paper studies the association between the risk of automation and vote choice in 11 Western European countries	probability of automation of occupations (calculated by Arntz, Gregory & Zierahn, 2016)	Individuals who perceive themselves as ‘coping on present income’ are significantly more likely to vote for radical right parties as risk of automation increases. They are also less likely to vote for major right parties.
Anelli, Colantone & Stanig	2019	The authors investigate the impact of robot adoption on electoral outcomes in 14 Western European countries, between 1993 and 2016	regional exposure to robots (based on the change in the operational stock of industrial robots between two years in a given industry and country); in the individual-level specification: individual exposure to robot adoption	Automation shocks have political effects on aggregate election returns at the district-level, leading to a tilt in favor of nationalist parties promoting an anti-cosmopolitan agenda, and in favor of radical-right parties. Consistently, the individual-level findings show that individuals that are more exposed to automation are substantially more likely to vote for radical-right parties, and tend to support parties with more nationalist platforms. Moreover, higher robot exposure at the individual level leads to poorer perceived economic conditions and well-being, lower satisfaction with the government and democracy, and a reduction in perceived political self-efficacy.
Caselli, Fracasso & Traverso	2020	The authors analyze the impact of robotization, immigration and import competition on the outcome of Italian general elections occurred in 2001, 2008 and 2013, using a mixed first-difference model applied to local labor market areas (LLMAs)	Local labor market area exposure to robots (based on changes in the number of robots per worker at the LLMA level)	All three factors (i.e., robotization, immigration and import competition) are associated with increases in votes for far-right parties in the period 2001-2008, only robotization continues to have such an impact in the following period.

Appendix 2

This Appendix briefly illustrates the selection process of the literature reviewed in this work.

In order to conduct this survey, we first searched for relevant studies in the 'Economics, Econometrics and Finance' and in the 'Business, Management and Accounting' sections of the database Scopus (last access: 24 April 2020) through several search algorithms that matched a set of keywords (i.e., 'labor' AND: 'technological change'/ 'robot'/ 'automation'/ 'computer'/ 'artificial intelligence' / 'technology AND routine'). Next, in order to also include working papers and reports released by international institutions and organizations, we scrutinized some well-known and relevant working paper series (i.e., OECD, IMF, IZA, ILO e NBER working paper series), and subsequently the 'Working Paper' section of the database EconPapers (last access: 24 April 2020). Since the latter also stores the working paper version of articles that were subsequently published, it allowed us to recover additional publications which we had not found in Scopus. Finally, we inspected the bibliography of a considerable number of previously selected articles in order to find other suitable studies.

We selected empirical papers written in English, that resort to robust econometric analysis to study the effect of technological change (captured by different variables, see Appendix 3) on one or more indicators of employment and compensation (e.g., number of employees or hours worked, labor share, absolute wage, wage skill premium) during a time frame that starts from the second half of the nineties or the early 2000s, and which were released from year 2003 onwards. We excluded papers which cover a very specific and restricted sector or labor market, as well as papers which simply proxy technological change with a general indicator of capital intensity at firm or industry-level or with a time trend. Moreover, the 'focal regressor' has to refer to domestic technological change, and not to the so-called import or trade-related technological change or technological transfer, namely technological progress driven by imports or inward FDI from other countries, which has been mainly observed in developing countries (see for instance Mitra, 2009; Conte & Vivarelli, 2011; Mrabet & Lanouar, 2013; Lee & Wie, 2015). Indeed, in the case of technological transfer, the effect of technological change overlaps with that of another important phenomenon, i.e. international economic activity. At the same time, we also identified some interesting qualitative contributions.

We ended up with about 170 studies, most of which are empirical papers that can represent the starting point of a meta-analysis.

Appendix 3

Appendix 3 aims to show the relevant between-study and within-study heterogeneity in the conceptual and modelling choices concerning the dependent variable and the key regressor made by the researchers who investigate the effect of technological change on labor. Due to their peculiarities, the so-called feasibility studies, which aim to estimate the susceptibility of occupations to automation and are reviewed in section 5, are excluded from the tentative classification of the main variables reported below.

A.3.1 The dependent variable

The dependent variable of a regression model can be either in level or in differences (long difference o annual change), sometimes in real terms and/or gross; it is often expressed in logarithm, sometimes multiplied or divided by a certain number (e.g., 100 or 1000) to make the interpretation of the regression results more intuitive. A preliminary classification of the dependent variables used in the selected studies is reported below.

Employment-related variables

-total employment: number of employees or number of hours worked, sometimes of a certain category only (occupation, sector, demographic, task content, education group etc…);

-total employment divided by total or working age population (e.g., Autor, Dorn & Hanson, 2015; Acemoglu & Restrepo, 2020), or by another variable, such as unemployment (Ciarli et al. 2018); in some papers, a note below the regression tables specifies that the whole regressions are weighted by a certain variable;

- share of employment of a specific group, such as: occupation group (e.g., Aksoy, 2009; Kampelmann Rycx, 2013; Autor, Dorn & Hanson, 2015; Das & Hilgenstock, 2018); sector (e.g., Moreno-Galbis & Sopraseuth, 2014; Koch et al., 2019; Acemoglu, LaLarge & Restrepo, 2020); demographic group (e.g., Beckmann & Schauenberg 2007; Behaghel, Caroli & Roger, 2014; Peng, Anwar & Kang, 2017); education/skill group (e.g., Falk & Biagi, 2017, Charnoz & Orand 2018; Das & Hilgenstock 2018; Graetz & Michaels, 2018), gender (e.g., Autor & Dorn, 2013);

-other employment-related variables, such as: risk of involuntary job loss (Givord & Maurin, 2004); employment flows (Behaghel, Caroli & Roger, 2014); probability of increasing employment between two different years (e.g., Cortes & Salvatori, 2015); employment transitions, like transitions to non-employment, job-to-job transitions, transition to employment, entry and re-entry into employment (e.g., Behaghel & Moschion, 2016; Dauth et al., 2017; Peng, Wang & Han, 2018; Bachmann, Cim & Green, 2019; Ross 2020); probability of being unemployed (e.g., Apella & Zunino, 2017).

Compensation-related variables

-Total wages, total wages of a specific group, such as skill/education group (e.g., Hijzen, 2007; Caselli, 2014), sometimes divided by another variable, such as employment (e.g., Rasekhi & Cheratian, 2019);

-wage share of a certain demographic group (e.g., Behaghel, Caroli & Roger, 2014; Peng, Anwar & Kang, 2017) or education/skill group (Hur, Seo & Lee, 2005; Xu & Li, 2008);

-labor/wage-bill share (i.e., labor compensation over value of production), also by occupation, sector, age, education etc (e.g., Sommer, 2009; Meschi, Taymaz & Vivarelli, 2011; Böckerman, Laaksonen & Vainiomäki, 2013; Elsby, Hobijn & Sahin, 2013; Michaels, Natraj & Van Reenen, 2014);

-earning/wage inequality, measured by: standard deviation of wages (Borghans & ter Weel 2006); Gini coefficient (e.g., Perugini & Pompei, 2009); mean log deviation (Thewissen, Wang & Vliet, 2013); top nth / bottom nth decile/percentile or ratio between them (e.g., Kristal & Cohen, 2016; Bessen, 2016);

-direct measure of polarization, namely: 'polarization index' (Dauth, 2014; Kerr, Maczulskij & Maliranta, 2019) and industry-level share of workers in high-paid relative to middle-paid occupations ('top') and share of workers in low-paid occupations to middle-paid ('bottom': Breemersch et al., 2019). However, the presence of labor market polarization is more often inferred from certain trends in the labor market, such the change in share of noncollege employment in service occupations in a commuting zone in Autor & Dorn (2013), the occupation-level change in employment or employment share between two different years in Akcomak, Kok & Rojas-Romagosa (2013), Bisello (2013) and Adermon & Gustavsson (2015), and the change in wage bill shares by education group and by task content of occupations in Böckerman, Laaksonen & Vainiomäki (2013). Furthermore, the studies mainly aimed at investigating job polarization typically conduct a decomposition analysis too.

-gender wage gap, i.e. the ratio between the wages of men and women (e.g., Lup Tick & Oaxaca 2005; Beaudry & Lewis, 2014).

-wage skill premium, i.e. the ratio between the wages of two different education/skill group (e.g., Corsini, 2012; Caselli, 2014; Mallick & Sousa, 2017; Nogueira, Afonso & Soukiazis, 2018). Sometimes the wage skill premium is indirectly measured by running a regression for each category of workers. In this regard, Srour, Taymaz & Vivarelli (2014, p.13) posit that '(…) *one-equation setting does not permit the researcher to go a step further into investigating the relative versus absolute skill bias*'. Some authors (e.g., Caselli, 2014) use both these methods. Finally, in some articles, wage differentials across different education/skill groups are captured by interactions between the key regressor on technological change and dummy variables referring to different education/skill groups. Similar considerations hold for the variable 'gender wage gap'.

A.3.2 The key regressor

Like the dependent variable, the key regressor of a regression model can either be in level or in differences (long-difference o annual change), sometimes in log, sometimes multiplied/divided by a certain number (e.g., 100 or 1000) to make the interpretation of the regression results more intuitive. In some cases (generally to indicate whether a worker or firm adopts a certain technology) it is a dummy variable. A tentative classification in macro-groups is provided below. Some studies employ, in the same regression or separately, different technology-related regressors that fall into at least two different categories.

- direct measures of ICT (e.g, computers, internet and computer-related and internet related technologies; see section 2);

-TFP (see section 2);

-reduction in the price of investments (see section 2);

-indices of occupational task content, which indirectly captures technological change (see section 2);

-robots (see section 3);

-advanced automation technologies different from robots (see section 4);

- R&D activity: several studies, most of which partly draw on innovation economics, use R&D expenditures or R&D intensity as proxy of technological change (e.g., Bogliacino & Vivarelli, 2012; Böckerman, Laaksonen &Vainiomäki, 2013; Mishra & Smyth, 2014; Bogliacino, Piva & Vivarelli, 2014).

A table which summarizes the main information contained in the aforementioned papers and in additional ones using direct measures of ICT, R&D activities, decrease in investment price and TFP to account for technological change is available upon request.

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