UNIVERSITÀ CATTOLICA del Sacro Cuore

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Abstract

The present technological revolution, characterized by the pervasive and growing presence of robots, automation, Artificial Intelligence and machine learning, is going to transform societies and economic systems. However, this is not the first technological revolution humankind has been facing, but it is probably the very first one with such an accelerated diffusion pace involving all the industrial sectors. Studying its mechanisms and consequences (will the world turn into a jobless society or not?), mainly considering the labor market dynamics, is a crucial matter. This paper aims at providing an updated picture of main empirical evidence on the relationship between new technologies and employment both in terms of overall consequences on the number of employees, tasks required, and wage/inequality effect.

JEL Classification: O33

Keywords: technology, innovation, employment, skill, task, routine

1. Introduction

The relationship between technology and employment has been evolving during the past century and last decades showing its complex and multifaceted nature. The fear of technological unemployment has been accompanying the great innovative waves. However, in the history of humanity, periods of intensive automation have often coincided with the emergence of new jobs, tasks, activities and industries. Indeed, the challenging question is related to the overall sign of the relationship between technological change and labor: is technology labor-friendly or is it labor-threatening? Human kind have gone through innovative cycles, starting from the very first one in the mid of the XIX century in UK when laborers became aware of the potential negative impact of machines on labor, throughout the adoption of electric power to create mass production in the mid of the XX century, up to the technological transformation associated to the extensive diffusion of ICTs at the end of the past century (see Noble 1986; Knights and Willmott 1990; Zuboff 1988).

Nowadays, the world is on the edge of a new technological revolution based on the previous one, but dramatically accelerating in the direction of automation by the pervasive diffusion of robots and Artificial Intelligence (AI) (see Acemoglu and Restrepo 2017; Brynjolfsson and McAfee 2014; Frey and Osborne 2017; Kenney and Zysman 2019). In a sense, these new technologies belong to the family of General Purpose Technologies (GPTs) which, by definition, can be applied to most sectors and can spread favoring additional applications and incremental innovations. However, if compared to ICTs (previous GPTs), this new paradigm turns out to be even more rapid in its diffusion and more flexible in its adoption. Interestingly enough, AI, self-learning algorithms and human-imitating robots can perform tasks usually requiring human beings' intelligence and physical ability/dexterity (such as speech recognition, decision-making advise, disease diagnose, complex documents translation, performance of unhealthy and dangerous tasks). Dobbs et al. (2015) from the McKinsey Global Institute estimate that, compared to the industrial revolution of the XIX century, automation and AI's disruption of society is happening 10 times faster and at 300 times the scale. This kind of potentiality might affect each job and every task, even if, in the case of AI, 'matching tasks' are the most prominent group (as, for instance, Uber, Airbnb, Linkedin, Amazon) (see Ernst et al. 2018). Indeed, automation is not confined to agriculture and manufacturing, but spreads to services. If, for instance, the regulated taxi service is considered, a 'conventional' taxi-driver is now challenged by more spread services (Uber) and, in turn, a Uber-driver might be (or will be) feat by self-driving machines making the Uber-driver job at risk. Yet, on the pros social side of a driverless vehicle, there is likely social inclusion of elderly and disabled people (see, for instance, Pettigrew et al. 2018).

This trend is involving all the developed economies, but it might also impact on emerging and developing countries (for evidence on the effect of the previous technological wave, see Conte and Vivarelli 2011; Haile et al. 2017; Vivarelli 2014). Emerging economies might catch up, but they can possibly remain in a sort of technological-trap, lagging behind unable to rapidly adjust.

This paper critically presents theories and updated evidence on the role of automation on employment and labor markets. Section 2 discusses the potential consequences of innovation on employment, under the assumption that automation introduces a process innovation aimed at reducing production cost and the use of labor. However, a number of compensation mechanisms might determine a less pessimistic result on the labor market. Section 3 examines methodological and operationalization issues related to the empirical studies. In Section 4 an updated review of existing studies on the impact of automation on employment is proposed discussing main evidence and limitations. Summary will emphasize main results from the literature and will present open issues requiring additional attention from researchers and policy-makers.

2. Technological change and employment: theoretical literature review and previous evidence

To evaluate the overall effect of technological change on employment, different mechanisms have to be taken into account. In general, the innovative effort is focused at reducing production costs as it happens in the case of process innovations. The aim is producing the same amount of output reducing the use of production inputs, such as labor. In this sense, innovation is frequently introduced to be labor-saving. In the present industrial revolution, automation (robots) is more related to the introduction of new machinery able to carry out tasks previously performed by humans, than focused on the development of more productive vintages of already existing machines (the main consequence is that the demand for labor declines – see Acemoglu and Restrepo 2018). In this scenario, the 'qualitative dimension' of workers becomes central, as some human skills/tasks are no more necessary after innovation has been introduced, while others, even new ones, become extremely relevant. The overall picture on the employment consequences is, therefore, more articulated than expected.

2.1 Theoretical models

In general, when a process innovation is introduced, there might be potential market compensation mechanisms that may counterbalance the initial labor-saving impact of innovation (see Freeman et al. 1982; Freeman and Soete 1987; Simonetti et al. 2000; Vivarelli 1995 and 2014). This happens also in the case of automation and AI. These countervailing forces, which might operate at different levels of aggregation - sectoral or economy-wide -, can be classified into Classical, Neoclassical, Keynesian and Schumpeterian.

Classical mechanisms

- New machines. If robots are adopted widely, they might replace workers in some or all of their tasks. Nevertheless, in order to have robots available, additional production is needed. As a consequence, a sectoral shift of workers from the downstream robot-using industry towards the upstream robot-producing sectors may counterbalance the initial negative effect on employment (see Dosi et al. 2019). Still, if among machine-producers new pieces of equipment entirely cannibalize older ones, such an industry is not going to benefit from any positive effect on employment.

- Decrease in prices. The productivity increase determined by the broadly adoption of robots able to run automated tasks might induce a decline of the average production costs. This effect, just in case of highly competitive markets, is translated into a subsequent reduction of prices. Lower prices should determine a higher demand which might induce new hiring for labor in non-automated tasks (Acemoglu and Restrepo 2019a).

- Re-investment of extra-profits. The accumulated extra-profits which may emerge in non-perfectly competitive markets (where the elasticity between decreased unit costs and subsequent decreasing prices is less than one, limiting the scope of the previous mechanism) may be invested into capital formation, expanding both the productive capacity and the intermediate demand, in both cases implying an increase in employment.

Neoclassical mechanism

- Decrease in wages. With regard to the labor market, the initial workforce displacement leads to an excess of labor supply which might determine a reduction, on average, of wages or, at least if legal restrictions are at work, a limited increase. If a well-behaved production function exists, the following labor demand increase is supposed to re-equilibrate the market and absorb the initial labor supply surplus. However, lower wages might not have positive consequence on the demand side as inputs are not perfect substitutes and labor is a broad category heterogeneous in its composition (it depends on education, occupation, job and task). Indeed, the actual production processes are hardly reversible, i.e. new technologies dominate older ones irrespectively of relative prices (see Dosi and Nelson 2010 and 2013), since knowledge and technological change are characterized by path-dependence and increasing-returns (see Capone et al. 2019; David 1985; Rosenberg 1982).

Keynesian mechanism

- Increase in incomes. In every situation workers are able to appropriate gains from the productivity increase. In fact the robot adoption can lead to an increase in wages, at least for some categories of workers (those involved in non-automated tasks), and consumption. This determines higher demand and increase in employment via well-known Keynesian processes (compensating for the initial labor displacement).

Schumpeterian mechanism

- As emphasized by Schumpeter (1912), technological change cannot be reduced to the sole (potentially labor-saving) process innovation. Indeed, the introduction of new products, which might be connected to the robots' production, entails the raise of new branches of production and stimulates additional consumption. In general, in the case of AI, it can serve as a platform to create new tasks in many service industries. Higher production and enlarged consumption translate into higher demand and employment in the whole economy.

Obviously enough, employment compensation by 'decreasing prices' may be hindered by price rigidities and non-competitive practices, while additional incomes due to technical change are not necessarily invested in labor-intensive activities. Finally, even new products may displace older products and so imply a weaker impact in terms of job-creation.

Moreover, these compensation mechanisms cannot ignore the time-dimension. Therefore, the speed of this industrial revolution and the timing of the potential compensation is an additional element to consider. Berg et al. (2018) propose a general equilibrium model to study consequences of robots on output, wages and inequality. Even a small increase in the level of robot productivity can augment output enormously if robots and humans are sufficiently close substitutes. The basic mechanism discussed by the authors is that the introduction of more productive robots initially lowers wages (see also DeCanio, 2016, for a discussion on elasticity of substitution between human and robotic labor and the depressing effect on human wages due to proliferation of robots) and raises the return to both robots and traditional capital. A large amount of traditional capital has to be accumulated before a scarcity of human labor raises wages and the return on capital declines to normal levels. The whole mechanism turns out to be good for output. However, it is also bad for distribution, especially in the short-run. Authors propose a number of variants, but automation turns always out to be very good for growth and very bad for equality – according to the benchmark model real wages fall in the short-run and eventually rise, but in a worryingly long-run. Also Bessen (2019) presents a model focusing on the impact of technology on employment critically considering the time of action. His model is able to predict the actual labor demand – over a historical timeframe – reasonably well for cotton, automotive and steel. If results are extended to potential implications of robot and AI, demand is sufficiently elastic and AI does not completely replace humans, then technical change is overall able to create jobs rather than destroy them. It is a matter of speed: in this case, a faster rate of technical change will actually create faster employment growth (especially non-routine employment) rather than job losses. Indeed, Acemoglu and Restrepo (2019b) affirm that AI - since it is not just a narrow set of technologies with specific, pre-determined applications and functionalities, but it is a platform - can be deployed for much more than automation. With AI applications creating new tasks for labor (see examples in education, healthcare, augmented reality), there would be potential gains in terms of productivity and labor demand.

Overall, the economic theory does neither provide a clear-cut answer nor forecasts about the employment effect of innovation (general innovation or robots and AI), since it depends on a number of factors, assumptions, parameters, elasticities, model calibrations. Therefore, theoretical models have been integrated by empirical studies aiming at providing additional evidence.

2.2 Previous empirical evidence and job polarization

Even referring to previous innovation waves, the theoretical literature has been supplemented with empirical analysis on the possible relationship between innovation and the subsequent effects upon employment both in quantitative and qualitative (skills) terms (for recent surveys, see Calvino and Virgillito 2018; Ugur et al. 2018; Vivarelli 2014). Overall, the learning lesson from previous empirical studies is that findings vary a lot depending on level of analysis (whether firm, sector or macro), proxies for technological change (whether embodied, such as investment in new physical capital, or disembodied, such as R&D expenditures), country and time of the analysis. The general picture is quite heterogeneous. Most of the extant literature approaches the job consequences of technological change at the micro-level, from which generally emerges a job-creating effect when very innovative firms in high-tech sectors innovate by means of disembodied technological change (see, among the most recent, Bogliacino et al. 2012; Buerger et al. 2010; Coad and Rao 2011; Van Roy et al. 2018). Nevertheless, there are less univocal results when turning to the sectoral level (see Aldieri and Vinci 2018; Bogliacino and Pianta 2010; Dosi and Monhen 2019; Falk and Hagsten 2018; Piva and Vivarelli 2018). Certainly, innovations are connected among sectors, therefore the macro-level analysis is the most representative of the overall effect of innovation on employment. In this context, labor shedding effects of productivity improvements (connected to process innovation) is likely to result in sectoral job losses if they are not coupled with the introduction of product innovations. Hence, even in the most naive calculations of 'compensation effects' one ought to account for the balance between the labor-saving impact in some sectors and the labor-creating effect in some others (Dosi et al. 2019).

In addition, the 'qualitative' dimension of labor has to be taken into account. The 'quality' of workers comes in as a critical variable due to the fact that new technologies ask for specific skills, creating different dynamics among different categories of workers. This is the 'Skill-bias technological change' (SBTC). Previous empirical literature reveals a complementarity between new technologies and skilled workers (both in terms of education – generally tertiary educated - and occupation – white-collars are usually considered the 'skilled' category), given that they are the ones able to implement effectively and efficiently those technologies. Therefore, while a positive relationship between new technologies and skilled workers is expected (and generally confirmed), a substitution effect between new technologies (especially when they determine process innovations) and unskilled workers is in general recognized (see Los et al. 2014; Machin and Van Reenen 1998).

However, the last decade has highlighted a new trend in labor market intrinsically connected to the new technological revolution. It is associated to the recent awareness of significant changes in the employment composition leading to job polarization and wage inequality together with a decreasing demand for middling occupation. This means that, if jobs are ranked by their first wage, increases in employment share are observed at the bottom and top of this distribution, while jobs in the middle have lost employment share over time. More in detail, laborers and elementary service occupations (the low-paid) are to some extent increasing and the professionals ones (the high-paid) are considerably growing, while middling occupations (such as operators of machinery/electronic equipment) are declining. Indeed, this evidence emerges from the 80s to the first decade of the XXI century showing a kind of generalized trend. Jobs are changing in terms of tasks without necessarily being related to educational and/or occupational level. This U-shaped curve represents the polarization phenomenon. Main pieces of evidence are related to flexible labor markets institutional settings, as in the case of UK and US (see Autor et al. 2006; Goos and Manning 2007; Goos et al. 2014). However, more studies present similar evidence also in other countries, such as Sweden, Germany and, recently, Portugal (see, respectively, Adermon and Gustavsson 2015; Spitz-Oener 2006; Fonseca et al. 2018).

This suggests that not only occupation and education are relevant, but indeed the 'routine dimension' comes into play. The routine-nature of jobs and tasks is the dimension that as to be considered. This evidence has induced to revise the SBTC into the new 'Task-biased Technological Change' (TBTC) or 'Routine-biased Technological Change' (RBTC) (Autor et al. 2003) or 'Routine-replacing Technological Change' (RRTC) (Gregory et al. 2019), assuming that repetitive tasks can indeed be easily replaced by recent technologies (robots, automation, AI, digitalization), while non-repetitive tasks may grasp benefits from these technologies (or, at least, not to be negatively affected: this is the case, for instance, of non-routinized unskilled tasks in personal services), determining a complementary effect.

In the next Sections this emerging literature will be discussed in detail considering, in primis, the methodological and operationalization issues.

3. Methodological issues

In order to analyze the impact of robot and AI on employment/occupation/task, two issues become relevant: 1) measures and proxies of automation; 2) operationalization of occupations in terms of tasks and routines.

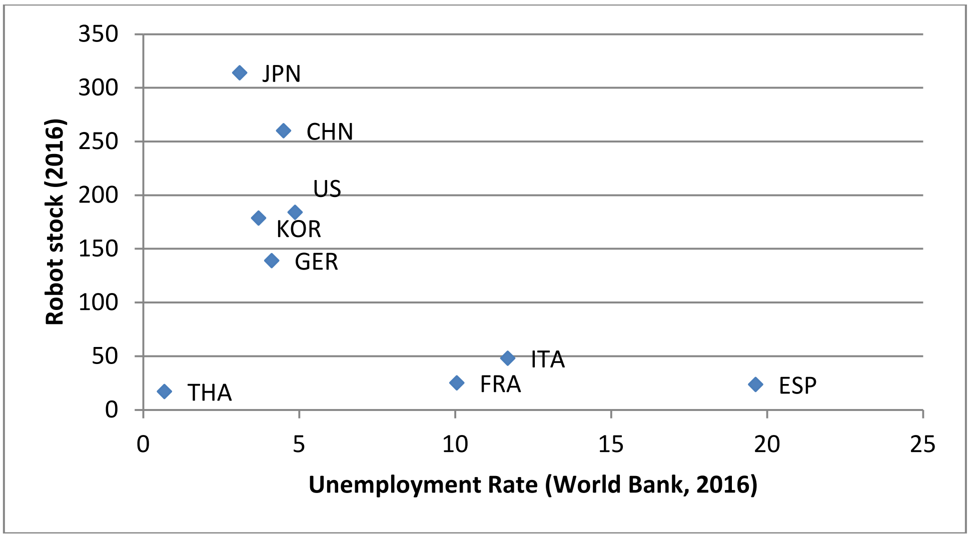
3.1 Automation, robots and AI

As stated in the Introduction, the present technological revolution is pervasive and very rapid. In addition, prices of new technologies quickly decrease making automation affordable to a large number of companies, sectors and countries (Graetz and Michaels 2018). Indeed, Boston Consulting Group (2015) estimates that price of robots will decrease by 20% and their performance will improve by around 5% annually over the 10 years. However, not a huge number of data/variables is available at all the disaggregated levels. Considering proxies for automation, at the sectoral/country-level data from the International Federation of Robotics (IFR) are the prominent source of global robotics statistics in existence (De Backer et al. 2018). The definition of industrial robot used by IFR comes from the ISO 8373:2012 "a machine that embodies the following characteristics: can be reprogrammed, is multipurpose in function, allows for physical alteration, and is mounted on an axis". IFR constructs this dataset by consolidating information on industrial robot sales from almost every industrial robot supplier in the world. The dataset therefore contains information on annual shipments (sales) and a measure of robot stock across roughly 100 geographic locations and industries (starting with a preliminary edition in 1993). Based on the latest available data, between 2011 and 2016, the average robot sales increase was, on average, 12% per year (IFR 2017). The forecasts up to 2020 are of the same percentage. Moreover, from the sectoral specialization point of view, the majority of robot use (roughly 70%) is concentrated within transport equipment, computers and electronics, chemical and mineral production and food and beverage production. The leading sector is automotive, followed by electrical/electronics with a remarkable performance in the last few years. Turning attention to the geographical specialization, almost ¾ of the global robot sales is concentrated in five countries: China, Korea, Japan, the United States, and - in Europe – Germany (see European Commission, 2016, for more data and comments on European countries).

IFR provides a measure of robot stock built on the assumption that the average service life of a robot is 12 years. However, De Backer et al. (2018) use a slightly different robot stock, based on Perpetual Inventory Method, assuming an annual depreciation rate of 10%. Authors show that US, Germany, Korea and Italy experienced considerable growth in their robot stock during the 1993-2016 period. Nevertheless, robot investments are not exclusive to OECD economies, with China, Chinese Taipei and Thailand having rapidly invested in robots and quickly catching up with main European countries. In emerging economies, the need to achieve higher quality standards is another reason for the large investments in robots.

Based on robot stock computed by De Backer et al. (2018), a scatter plot is proposed considering robot stock and unemployment rate of 9 of the top 10 users of automated machines (Taipei, due to data limitation, has been excluded) to visual inspect the possible relationship – ceteris paribus – between robot stock and unemployment rate (Figure 1).

Figure 1: *Scatter plot between Robot stock and Unemployment rate*



Source: elaboration on De Backer et al. (2018) analysis and World Bank data

While a number of variables, cyclical factors, country-specific effects might determine specific value for the two variables, there seems to be no evidence of a positive relationship between robot usage and unemployment. Obviously enough, this sketching evidence at the country level should be complemented by detailed econometric studies (see Section 4), possibly at the micro level. But unfortunately, robot penetration is available at the country and sectoral level, but not at firm-level, preventing firm-level studies.

3.2 Task and routines

Autor et al. (2003) define the RBTC, later refined by Acemoglu and Autor (2011). According to Acemoglu and Autor (2011, p.1045), a task is a “unit of work activity that produces output (good and services)” and production process is defined in terms of tasks. In this framework, job tasks are allocated to labor or to capital depending on: 1) the degree to which they are automatable (repetitive and replaceable by code and machines); 2) their separability from other tasks; 3) the relative costs of using capital versus labor (in this context, capital generally refers also to machines and robots). Acemoglu and Autor, therefore, propose a classification based on a two-dimensional typology: routine opposed to non-routine, and manual opposed to cognitive. This leads to the consideration of four broad categories: routine-manual, routine-cognitive, non-routine manual, non-routine cognitive (in turn, subdivided into non-routine cognitive interactive and analytical). 'Routine' tasks comprise those that are programmable, expressible in rules, codifiable and repetitive, i.e. a protocol. Following this approach, the expectation is that technology replaces jobs with high-routine content, while in 'non-routine' tasks there is more space for mental flexibility and/or physical adaptability.

Sebastian and Biagi (2018) discuss how task-content is measured in empirical analysis. They underline that, in general, two main options are adopted for measuring the task content of different types of jobs: 1) direct measures, drawing from occupational databases based on the assessment of experts (as in the Occupational Information Network (O*Net) case whose descriptors, based on US labor market, allow finding the task content of each occupation); 2) self-reported measures, aggregating the answers of individual workers to surveys on skills and working conditions (see Federal Institute for Vocational Training/Research Institute of the Federal Employment Service in Germany (IAB/BIBB), Programme for the International Assessment of Adult Competencies (PIAAC) in the OECD, European Working Condition Survey (EWCS) at the European level).

In general, this testifies that the RBTC approach is not characterized by a unique framework for data analysis and tasks can be classified depending on the information available in the database used. Data limitations have to be considered. In the O*Net case, for instance, one of the main problems is that it does not allow for a comparison over time (even if it is regularly updated) as it assumes that the task-content is fixed within occupations/jobs. Arntz et al. (2016 and 2017) show that narrow 'feasibility studies', by ignoring the substantial variation in job tasks within occupations, overstate the exposure of jobs to automation. On the other side, self-reported sources allow studying the variability in task content within each occupation or job type. Notwithstanding, on the minus side, self-reported sources are prone to introduce potential bias in the measurement, since workers' answers may reflect other things beside the task content in strict terms.

It is interesting to highlight that, when tasks are considered, empirical papers discuss the impact of robots on different tasks or, in some cases, consider the impact of automation on employment controlling for average tasks by means of task and routine index.

A number of recent papers, focusing on tasks, try predicting the automation risk of different occupations.

Starting from a seminal paper, Frey and Osborne (2017), using a Gaussian process classifier applied to data from O*Net and US Department of Labor, predict that 47% of the occupational categories, mostly middle- and low-skilled professions, are at high risk of being automated, due to the routine-nature of their tasks (including a wide range of service/white-collar/cognitive tasks such as accountancy, logistics, legal works, translation and technical writing). However, Arntz et al. (2016 and 2017), proposing the same exercise, but using also information on task-content of jobs at individual-level, conclude that only 9% of US jobs are at potential risk of automation.

Extending the analysis to a multi-country approach, Nedelkoska and Quintini (2018) estimate the risk of automation for individual jobs based on PIAAC in 32 OECD countries. Evidence shows that about 14% of jobs are highly automatable (probability of automation over 70%), while another 32% of jobs have a risk of between 50 and 70% pointing to the possibility of significant change in the way these jobs are carried out as a result of automation (a significant, but limited, share of tasks could be automated, changing the skill requirements for these jobs). Moreover, the risk of automation is not distributed equally among workers: the findings in this study suggest a rather monotonic decrease in the risk of automation as a function of educational attainment and skill levels. Conversely, Marcolin et al. (2019) exploit data from PIAAC merged to EULFS and US CPS to construct a novel measure of the routine content of occupations for 20 OECD countries. This measure is built on information about the extent to which workers can modify the sequence in which they carry out their tasks and decide the type of tasks to be performed on the job. This study sheds light on the relationship existing between the routine content of occupations and the skills of the workforce, intended as both the skills that workers are endowed with and those that they use on the job. Marcolin et al. highlight that the routine intensity of occupations is lower for more sophisticated occupations, i.e. such occupations are less likely to be routinized. On average, in 2012, 46% of employed persons in PIAAC countries are working in non-routine-intensive (18%) or low-routine-intensive (28%) occupations. They also provide evidence of a negative but weak correlation between skill intensity and the routine content of occupations. The more routine-intensive occupations thus tend to require fewer skills, but while non-routine- and low routine-intensive occupations appear to be monotonically increasing in skill intensity, the same is not true for medium- and high-routine-intensive occupations, which are mostly intensive in medium skills. This strengthens the evidence that workers perform a bundle of tasks only barely related to workers' human capital or the job functions they are attached to through their occupational titles.

At the European level, Pouliakas (2018), using data on tasks and skill needs in jobs collected by the European Skills and Jobs Survey (ESJS), bundles jobs according to their estimated risk of automation. With respect to PIAAC, ESJES collects information on the frequency of engaging in routine, autonomous or learning tasks at work. Following Frey and Osborne (2017) and Nedelkoska and Quintini (2018), the author utilises highly disaggregated job descriptions and shows that 14% of EU adult workers are found to face a very high risk of automation. The distribution of high risk of automation across industries and occupations is also found to be skewed towards routine jobs with low demand for transversal and social skills. In addition, the risk of job displacement by machines is higher among males and lower-skilled workers.

All in all, studies on routine-content of tasks and how they evolve together with skills and occupations is something that should be taken into account as employment is more and more multidimensional and heterogeneous.

4. Automation and employment: recent empirical evidence

The most updated studies linking automation/robotization to employment/tasks are developed at the country/industry-level, while firm-level studies are generally not available due to the lack of these data/information at micro-level (Raj and Seamans, 2019, underline how a more systematic collection of data on the use of these technologies at the firm level should be pursued).

An additional caveat is that these works tend to cover time-spans in which the 'robotic' wave has not been fully at work. Therefore, even if they are updated in terms of publication year, evidence is generally based on periods ahead of 2007. Omitting post-2007 data from the analysis is a sort of cleaning process to avoid influences by the large cyclical fluctuations of the Great Recession and the subsequent recovery. However, in doing so, the most relevant robot adoption wave is not considered. Furthermore, in terms of sectoral composition, in the pre-2007 era industrial robots were the relevant ones, while service robots were still in their infancy.

Two main streams of empirical analyses can be considered:

- studies analyzing the impact of robots and new technologies of employment and controlling for routinization of tasks
- studies focusing on the change of employment due to task complexity and evolution

With reference to studies belonging to the first group, Acemoglu and Restrepo (2017) analyze the effect of the increase of industrial robot usage (IFR data, see Section 3.1) between 1990 and 2007 in the US local labor markets. Using a model in which robots compete against human labor in the production of different tasks, they provide evidence of how robots may reduce employment and wages, regressing the change in employment and wages on the exposure to robots in each local labor market. However, the exposure to robots is not specific (IFR data do not measure robot use by subnational geography), but it is proxied using the national penetration of robots into each industry and the local distribution of employment across industries. Adopting this approach, authors reveal the existence of negative effects of robots on employment and wages across commuting zones. The effect is isolated from other possible explanations connected to globalization and routine dimension. Indeed, they control for imports from China and Mexico, the decline of routine jobs, offshoring, other types of IT capital, and the total capital stock not correlated with robots. According to their 2SLS estimates, one more robot per thousand workers has a significant impact in terms of magnitude as it reduces the employment to population ratio by approx. 0.18-0.34% and wages by 0.25-0.5.

Following the labor market equilibrium approach adopted by Acemoglu and Restrepo, Chiacchio et al. (2018) apply it in the context of the EU labor market. They assess the impact of industrial robots on employment and wages in six EU countries: Finland, France, Germany, Italy, Spain and Sweden. These six countries are largely representative of the European automation as they account for 85.5% of the EU robots market in 2007. However, there are significant differences between countries in terms of penetration of robots revealing heterogeneity even within Europe. While Germany, due to its strong automobile specialization, employed around 4.5 industrial robots per 1000 workers in 2007, the exposure of the French labor force was about half that rate in the same year. The sample includes 116 NUTS regions further disaggregated by gender, age and education to derive the employment rate and wage for each demographic group for a total of 2,088 possible observations. As Acemoglu and Restrepo (2017), authors assume that the distribution of robots within an industry is uniform across all regions within a country conditional on employment shares in each region-industry, the regional exposure of robots in each industry is proportional to the regional employment in that industry. Authors also control for regional routinization and offshoring index. The routinization indicator quantifies the degree of routine tasks within an occupation and the 'offshorability' indicator is based on actual offshoring events registered by European companies. Results show that one additional robot per thousand workers reduces the employment rate by 0.16-0.20%. The displacement effect seems particularly evident for workers of middle education and for young cohorts, while men are more affected than women. Their estimates, however, do not point to significant results of the impact of robots on wage growth.

Graetz and Michaels (2018) extend and integrate previous analysis, using novel panel data on robot adoption (IFR and EUKLEMS data to estimate robot density, i.e. the stock of robots per million hours worked) within industries in 17 countries from 1993 to 2007. The time-span is limited also because coverage in the EUKLEMS data becomes uneven after 2007. While the first aim is to measure the impact of robotization on productivity, authors extend their analysis to the employment consequences. In addition to the robot adoption variable, as robustness checks, authors compute two instruments. The first one, based on classifying tasks performed by robots, considers data on US occupations in 1980, before robots became ubiquitous, and defined occupations as 'replaceable' if by 2012, their work could have been replaced by robots. Then they estimate the fraction of each industry's hours worked. The second instrument is a measure of how prevalent the reaching and handling tasks were in each industry prior to robot adoption (to check for the widespread use of robotic arms). Dividing employees in three groups (high, medium and low-skilled), the OLS and 2SLS estimates for the two higher-skilled groups are positive (in terms of hours worked), but limited in magnitude and not always significant, while estimates for low-skilled workers are large and negative, and, in almost all cases, statistically significant.

At a country-level, Dauth et al. (2017) propose the local empirical exercise in the German-case using IFR data over the 1994-2014 time-span. They construct a measure of local robot exposure for every region. They find no evidence that robots cause total job losses, but they do affect the composition of aggregate employment. While industrial robots have a negative impact on employment in the manufacturing sector, there is a positive and significant spillover effect as employment in the non-manufacturing sectors increases and, overall, counterbalances the negative effect. They estimate that every robot destroys two manufacturing jobs. This accounts for almost 23% of the overall decline of manufacturing employment in Germany over 20 year till the 2014. This loss was fully offset by additional jobs in the service sector. With respect to wages, the negative impact of robots on individual earnings arises mainly for medium-skilled workers in machine-operating occupations, while high-skilled managers gain. In the aggregate, robots raise labor productivity but not wages. Thereby they contribute to the decline of the labor income share.

In general, as already discussed, most of the papers studying the role of automation on employment consider developed countries. However, also developing economies might be involved in the direct adoption of robots or in an indirect effect connected to re-shoring of some production process phases back to developed countries (for this reason, from the developed world perspective, many papers control for offshoring and trade). Indeed, much of the work available in developing countries is relatively unskilled and routine, repetitive and predictable in nature. These works are at high risks of being automated. In this regard, firms in developed countries may find it cheaper to automate certain processes instead of running the production abroad. The implication would be a further detrimental effect on employment in middle- and low-income countries. For this reason, UNCTAD (2017) recommends that developing countries invest in digital technologies, if not the risk of lagging further behind might increase. Automation could lead the developing world into a low or middle-income trap, and even, according to Rodrik (2016), to a ‘premature de-industrialisation’ in many of those countries.
With this global perspective in mind, Carbonero et al. (2018) provide evidence on the effects of robots on worldwide employment and trade, including emerging economies. This is a very interesting extension as developing countries are usually not included and they might be significantly affected by robotization and automation. In particular, they document that the use of robots is rapidly increasing in both developed and emerging countries. Given the globalization of the supply chain, they also look at whether robots influence the trend in off-shoring in developed countries and, by that, the change in employment in emerging countries. In other words, they analyze whether firms in developed countries may find it more profitable to bring production back home after having it previously off-shored to low-cost, emerging economies. They use IFR data at sectoral/country level merged with data on employment and value added available from the Socio Economic Accounts of the World Input-Output Database. After the merge 41 countries and 15 sectors survive in the 2005-2014 period. To instrument the use of robots, they introduce an index of technical progress, defined as the ability of robots to carry out different tasks. Robots turn out to have a statistically significant negative impact on worldwide employment. However, this effect is heterogeneous among countries. While it is small in developed countries, for emerging economies it is -14% in the 2005-2014 period (results for developed countries are in line with preliminary evidence provided by De Backer et al., 2018, who study the relationship between offshoring and automation in 30 developed economies for a longer period 2000-2014).

The second group of studies begins with the seminal contribution of Autor et al. (2003) (and extensions, see Section 3.2). It has zoomed into the relationship between new technologies (mainly computers and ICT) and skills, sustaining indeed that innovations can replace human labor when it is largely based on routines, but they can hardly replace non-routine tasks where technologies are complements. This analysis, covering, in particular, the 1984-1997 time-span and referring to general computer use and ICTs, bridges the SBTC and the TBTC as authors define the tasks involved in each of the 450 occupations included the Dictionary of Occupational Titles. Each occupation receives a score for each of the task measures. Moreover, they measure technological change by the evolution in the fraction of workers in the industry who use computer in their jobs. Regressing the change in task involvement on the change in computer use reveals that technological change is positively related to the increased use of non-routine cognitive tasks. On the other hand, routine tasks (both cognitive and manual) turn out to be negatively related to technological change. As far as non-routine manual tasks are concerned, they seem to be unrelated to technological change until the 1990s when a positive and significant relationship between them emerges.

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

In addition, Gregory et al. (2019), after developing a task-based framework to estimate the aggregate labor demand and employment effects of RRTC, propose an empirical analysis on regional data (238 regions) across 27 European Union countries between 1999 and 2010. Authors show that while RRTC has indeed had strong displacement effects in Europe, it has simultaneously created new jobs through increased product demand, outweighing displacement effects and resulting in net employment growth. This task-based framework builds on Autor and Dorn (2013) and Goos et al. (2014), and incorporates three main channels through which RRTC affects labor demand considering trade and spillover, moving from a local-market perspective. Occupations are coded by one-digit (ISCO-1988) codes: for each of these, they obtain a Routine Task Intensity (RTI) index. Firstly, RRTC reduces labor demand through substitution effects, as declining capital costs push firms restructuring production processes towards routine tasks. Secondly, RRTC induces additional labor demand by increasing product demand, as declining capital costs reduce the prices of tradables. Thirdly, product demand spillovers also create additional labor demand: the increase in product demand raises incomes, which is partially spent on low-tech non-tradables, raising local labor demand. The first of these three forces acts to reduce labor demand, whereas the latter two go in the opposite direction (in a sort of compensation mechanisms at work). As such, the net labor demand effect of RRTC is theoretically ambiguous. For each of these three labor demand channels, authors model the resulting labor supply responses to obtain predictions for changes in employment. Empirical evidence, however, as previously declared, is overall positive.

Overall, previous contributions have shown that empirical analyses are flourishing and, even if some of them adopt the same methodology, results are not homogeneous. Acemoglu and Restrepo (2017) reveal a negative and significant impact of robots on employment and wages in the US, while evidence from Chiacchio et al. (2018) for European countries is less detrimental for employment (with no effect on wages). Indeed, the displacement effect is especially significant for middle-skilled works in line with the ‘job polarization’ evidence. In the case of Graetz and Michaels (2018), the evidence is less pessimistic for overall employment, while negative consequences affect low-skilled workers. Moreover, the results proposed by Dauth et al. (2017) for the German case put in an additional tile to the puzzle discussing an industrial composition effect where decline in manufacturing employment has been counterbalanced by employment in service sector. Carbonero et al. (2018) consider a worldwide approach showing that developing countries are more at risk than developed ones in terms of negative impact (direct or indirect) from automation. From a different perspective, additional works (Autor et al. 2003; Caines et al. 2018; Gregory et al. 2019) discuss the nature of tasks connected to automation and complexity providing interesting, even if partially contradictory, evidence on the overall effect of employment and wages. Table 1 presents a synoptical analysis.

5. Summary

The link between technological change and employment has been evolving during the past century and last decades showing its complex and multifaceted nature. On the one hand, the fear of technological unemployment has always been increasing during great innovative waves, such as the present one; on the other hand, economists have always been optimistic about the long-term employment impact of innovation. Is this time different?

Indeed, the economic theory does not provide a clear-cut answer about the employment impact of new technologies, since it depends on a number of factors, assumptions, parameters, elasticities and model calibrations. Therefore, empirical evidence is crucial.

Overall, the learning lesson from previous empirical studies on the impact of computers and ICT is that findings vary a lot depending on the level of analysis (whether firm, sector or macro), proxies for technological change (whether embodied, such as investment in new physical capital, or disembodied, such as R&D expenditures), country and time of the analysis. However, most of the extant literature points to a job-creating effect, although this impact is very small and limited to R&D intensive firms in high-tech manufacturing and service sectors.

Turning our attention to the recent technological wave characterized by the spread of robots and AI applications, some methodological caveats have to be pointed out. Firstly, there seems to be no evidence of a positive relationship between robot usage and unemployment at the national level. Obviously enough, this preliminary evidence at the country level should be complemented by detailed econometric studies at the micro level, but this is impossible since robot penetration is available at the country and sectoral level, but not at the firm-level. Secondly, even the available country/sector evidence is mainly based on periods ahead of 2007, so omitting the post-2007 period when the most relevant robot adoption has taken place, also spreading beyond manufacturing and involving service sectors and cognitive skills.

Having these limitations in mind, different studies on the employment impact of the current automation are generally predicting a reduction of employment, ranging from 9% to 47% of present jobs. In this regard, estimations are very different since tasks within the same occupations are at different risk of automation; indeed, when studies account for a detailed task classifications, forecasts become dramatically less pessimistic (in fact, within the same occupation, some tasks may be run by a robot, but the worker implied may shift to other tasks less automatable or even complementary to the new technologies).

Looking at skills, while previous literature on ICT has first underlined the skill-biased nature of technological progress and later the polarization impact of innovation (making the routinized middle skilled jobs more redundant), the available evidence on the impact of robots and AI seems to work in the same direction. According to the different studies, on the one hand high-skilled and non-routinized jobs seem to be relatively safe (or even expanding along robot diffusion), while on the other hand routinized low and middle skills seem to be the more at risk.

Finally, so far developing countries are usually not included in the empirical analyses. Yet, the few available studies reveal that emerging economies are significantly affected by robotization and automation, and that the labor-saving impact of these new technologies might be even more pronounced than in the developed economies.

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Table 1

Authors	Country	Period	Unit of observation	Model	Dependent vars	Indipendent vars	Results
Acemoglu and Restrepo (2017)	USA	1990-2007	Local labor markets (722 commuting zones)	2SLS (cross-section)	- change in Census private employment to population ratio - change in employment to population ratio from the County Business Patterns - change in the log hourly and weekly wage	- change in exposure to robots - change in number of computers	- Robots may reduce employment and wages (one more robot per thousand workers reduces the employment to population ratio by about 0.18-0.34% and wages by 0.25-0.5%)
Autor et al. (2003)	USA	1984-1997 (1960-1998)	Employed workers	OLS (cross-section) with clustering std error	- within-industry change in task input - change in quantile of task measure - within-occupation change in quantile task measure	- change in computer adoption - log of computer investment per FTE - log of capital investment per FTE - change in log capital/FTE - Computer use, college graduate, high school graduate, and female employment shares	- Within industries, occupations, and education groups, computerization is associated with reduced labor input of routine manual and routine cognitive tasks and increased labor input of nonroutine cognitive tasks - Translating task shifts into education demand, the model can explain 60% of the estimated relative demand shift favoring college labor - Task changes within nominally identical occupations account for almost half of this impact
Caines et al. (2018)	USA	1980-2005	Non-farm workers	OLS (cross-section) with std errors clustered at occupation level	- log wages (in 1980 and 2005) - change in log wages - change in employment share	- task complexity index/indicator - routine task intensity index/indicator (control variables: female share, college share, high school share, non-white share, married share, mean age, mean # children)	- Positive relationship across occupations between task complexity and wages and wage growth - Conditional on task complexity, routine-intensity of an occupation is not a significant predictor of wage growth and wage levels - 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. - Workers in non-routine occupations with low ability of solving complex tasks are not shielded from the labor market effects of automatization.
Carbonero et al. (2018)	41 countries (developed and emerging)	2005-2014	Sectoral-level	OLS and IV (cross-section)	- employment - off-shoring (share of imported non-energy inputs from emerging countries in total non-energy inputs)	- robots (also weighted for trade) - labour intensity - plus interaction (- country FE, - industry FE; control variables: VA, wage, domestic robots also interacted with labor intensity)	- New index of technical progress (=ability of robots to carry out different tasks) - Robots have a statistically significant negative impact on worldwide employment (small in developed countries, -14% between 2005 and 2014 in emerging economies) - Robots in developed countries decrease off-shoring just as employment in emerging economies
Chiacchio et al. (2018)	EU countries (Finland, France, Germany, Italy, Spain	1995-2007	116 NUTS2 regions and 18 demographic groups (2,088 obs)	OLS (cross-section) clustering std err, wild cluster bootstrap	- change in employment rate - change in wage	- change in robot exposure (control variables: dummy regions, total population, share of working age pop, 1995 share of employed completed high school level, share of employment in manufacturing,	- One additional robot per thousand workers reduces the employment rate by 0.16-0.20%: significant displacement effect particularly evident for middle education workers and for young cohorts; men more affected than women - No robust and significant results on the impact of

	and Sweden)					exposure to Chinese and US import, routine jobs and offshoring baseline, ICT growth)	robots on wage growth, even after accounting for possible offsetting effects across different populations and sectoral groups
Dauth et al. (2017)	Germany	1994-2014	402 local labor markets (=EU NUTS3)	OLS (cross-section) or IV cluster std errors	- cumulated individual labour market outcome - total local employment growth (change in log total employment in region 1994-2014, manufacturing employment, employment-to-pop ratio, output per worker, …)	- increase in number of installed robots (control variables: gender, foreign nationality, 3 skill categories, 3 tenure categories, 2 age group, 6 plant size group) - industry-level exposures to net exports (vs China and Eastern EU) - ICT	- No evidence that robots cause total job losses, but they do affect the composition of aggregate employment; - Every robot destroys two manufacturing jobs: this loss is fully offset by additional jobs in the service sector. - Robots have not raised the displacement risk for incumbent manufacturing workers: more robot exposed workers are even more likely to remain employed in their original workplace, though not necessarily performing the same tasks, and the aggregate manufacturing decline is solely driven by fewer new jobs for young labour market entrants. This enhanced job stability for insiders comes at the cost of lower wages. - The negative impact of robots on individual earnings arises mainly for medium-skilled workers in machine-operating occupations, while high-skilled managers gain. - In the aggregate, robots raise labour productivity but not wages. Thereby they contribute to the decline of the labour income share.
Graetz and Michaels (2018)	17 developed countries (US, 14 EU, South Korea, Australia)	1993-2007	Sectoral-level	- OLS and 2SLS (cross-section) robust standard errors, two-way clustered by country and industry - Regressions weighted by 1993 within-country employment shares	- change in the outcome (VA, hours worked, TFP, output prices, hourly wages also by different skill group's)	- change in the use of robots/labour input (control variables: FE, initial 1993 wages, capital-labour ratios, changes in other inputs, industry FE)	- Increased robot use contributed approximately 0.36% to annual labor productivity growth, raising total factor productivity and lowering output prices - Robots apparently did not significantly reduce total employment, although they did reduce low-skilled workers' employment share
Gregory et al (2019)	27 EU countries	1999-2010	Regional (NUTS1-2) tradable sectors	OLS with std error clustered by region	- log employment - log regional production	- routine task intensity index - log regional gross production - log regional marginal cost index - log regional wages (control variables: region-occupation FE, region-year FE, linear time-trend)	- routine-replacing technologies (RRTC) had strong displacement effects in the EU between 1999 and 2010 - RRTC has simultaneously created new jobs through product price reduction and growing local income that increased product demand - The aggregate labor market effects depend on the distribution of gains from technological progress

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