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The probability of automation of occupations in Italy

Emilia Filippi, Sandro Trento*

Abstract

There is a rising concern for technological unemployment due to the current digital revolution. In order to estimate the probability of automation of occupations we applied two methods: occupation-based approach [Frey and Osborne (2017]) and task-based approach [Nedelkoska and Quintini (2018)]. We found that occupations with a high risk of automation require many routine activities, whereas occupations at low risk require abilities like perception, manipulation, creative intelligence and social intelligence. In Italy, based on the occupation-based approach, 33.2% of workers face a high risk of replacement; this percentage decrease at 18.1% if we apply the task-based approach. Male workers appear to face a higher risk of replacement than female ones. Actual automation may be lower than expected as it depends on many factors, such as technical feasibility, economic benefits that can be obtained and job creation thanks to technology itself. Finally, we stress the importance to adopt some policies; education and training of employees seems to be the most effective one.

Key words: technological change and unemployment; automation of occupations; skills and human capital

JEL classification: E24, J24, J62, J64, O33, O39

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1. Introduction

Since the First Industrial Revolution, technology has been extremely important in fostering economic growth and improving human living standards. However, technology has also brought negative effects particularly in the work setting. This has led economists to grapple with the possible replacement of workers by machines and the so-called "technological unemployment", a term coined by Keynes (1930) and defined by him as unemployment "due to our discovery of means of economizing the use of labor outrunning the pace at which we can find new uses for labor".

The issue immediately caused a rift among economists. According to some, including Ricardo (1821) and Keynes (1930), technology could cause temporary unemployment, which was absorbed over time mainly thanks to the compensation effect: some of the workers initially displaced by one technology were re-employed to meet the increase in demand for goods created by the application of that technology, which reduced the cost of production and the price of goods. In the long run, great benefits could be achieved, such as increased productivity. According to other economists, including Rifkin (1995), technology can render workers useless and cause permanent technological unemployment. Castro Silva and Lima (2017) observe that "workers displaced by technological change… will probably fall into long-term unemployment or a sequence of short-term low-pay jobs with periods of unemployment in between".

In recent years, the fear of widespread replacement of workers by machines has returned to the fore for various reasons, reopening the debate among economists on the effects of technology on work. While until 1973 (in the United States) and 1980 (in other advanced countries), growth of labor productivity was followed by wage growth, since the 1980s there has been a growing gap between productivity growth and wage growth (Frey and Osborne, 2015). Since 1970, the share of GDP attributed to work has been decreasing (Ford, 2015; Frey and Osborne, 2015) and inequality (in terms of both income and wealth) within the populations of advanced countries is increasing (Frey and Osborne, 2015; Gordon, 2016). Job growth is slowing down since the financial crisis of 2008 and seems to relate significantly to long-term structural changes (Brynjolfsson and McAfee, 2011). From 1983-1993 to around 2010, in the United States and in many European countries, the phenomenon of "hollowing-out" of middle-skill occupations, also called "job polarization", occurred: the number of low-skill/low-wage occupations (those providing cleaning, security, or personal services) increased because their manual tasks cannot be automated (both flexibility and adaptability are required); middle-skill/middle-wage occupations (sales, administrative support, production or repair workers) have suffered a loss since the tasks they comprise are easily automatable; and the number of high-skill/high-wage occupations (professionals, managers, technicians) has grown since the cognitive tasks they comprise cannot be automated.

Finally, since 2004, technological progress has been particularly rapid and significant. Let us simply consider that in 2004 Levy and Murnane (2004) considered pattern-recognition tasks and complex communications impossible or difficult to automate because of the need to code the steps that had to be followed in their development. They argued that computers could only recognize structures in the limited situations where there were no complex perceptual problems and the requisite levels of contextual knowledge were not elevated. Rather, complex communications that could not be automated took place in complicated, emotionally engaging and ambiguous situations such as teaching, sales and management: in these cases, the possibility of communicating with a computer was remote. Recent technological advances have, however, disproved these predictions: the capabilities of the machines have in fact improved and today it is possible to automate, in addition to routine tasks, even non-routine cognitive and manual tasks. Moreover, in some cases the performance of technologies considerably exceeds that of humans, so much so that Ford (2015) does not exclude that in the future machines will be extremely intelligent (perhaps more so than humans) and able to improve themselves, starting an "explosion of intelligence". Kurzweil (2005) even believes that it will be possible to achieve so-called "Singularity", i.e. the end of the human era and the domination of machines over humans.

Although these enormous advances may not occur, it is already evident today that technologies such as the automation of cognitive work and advanced robotics are significantly changing the production of goods and the provision of services in many economic areas. While on one hand these and other recent technologies will improve the quality of life of billions of people and have a potential economic impact of $14-33 trillion per year (McKinsey Global Institute, 2013), on the other such benefits may not be equally distributed. In fact, since the automation of work affects mainly the least-qualified workers yet benefits the most highly-educated workers and capitalists, inequalities within the population in terms of wealth, income and opportunities for economic improvement could increase considerably (Brynjolfsson and McAfee, 2011, 2014; McKinsey Global Institute, 2013).

Recent changes have led economists to question what the future will be like. While "maximalist" economists (Brynjolfsson and McAfee, 2011, 2014; McKinsey Global Institute, 2013) pay close attention to recent innovations, are optimistic about the degree of technological progress and predict large increases in productivity in the face of high unemployment and growing inequality, “minimalist” experts (Gordon, 2016; Summers, 2013b, 2014, 2015) predict future change will be minimal, arguing that there will be little technological progress, that economic growth will not depend on technology, and that workers will face a reduced risk of being replaced.

More precisely, Brynjolfsson and McAfee (2011, 2014) believe that a shift is occurring from a period of slow change to a period of rapid change (referred to as the “Second Machine Age”). In the future, recent technologies will make it possible to produce a higher level of output with less input, societies will be richer and boring and repetitive jobs will decrease in favor of more creative work. However, already today technological changes are destroying jobs faster than those they are creating and contributing to phenomena such as stagnant median incomes and growing inequality in the United States and other advanced countries. In addition, the skills required to workers will differ from those currently required and there will be a struggle between technology and work training programs to fill job posts. Automation will affect more and more jobs, influencing both routine and non-cognitive tasks. As a result, few jobs will be available for “standard” workers with the most common skills and abilities. Overall, the positive aspects created by technology (the so-called “bounty”) will not be sufficient to compensate for the consequences on workers and the population (the so-called “spread”) (Brynjolfsson and McAfee, 2011, 2014).

Gordon (2016) has a different opinion. He notes that innovation in recent years has declined with respect to the past, that the Third Industrial Revolution has been revolutionary but has only affected part of the economy (that which already benefited from the internet, digitization, e-commerce and search engines) and that since 1970 only second-level improvements have taken place (by 1970 important inventions, the consequent discoveries and the basic elements of current living standards had already been achieved in many respects). In the future Gordon (2016) does not exclude changes but he believes that they will occur more slowly and that new technologies will have less impact than in the past.

Faced with the enormous changes underway, some economists have tried to estimate the probability of automation of jobs and the number of workers who could be replaced by “machines” in the future. Two approaches result as those of most interest. The occupation-based approach is based on the idea that occupations can be automated, while according to the task-based approach, it is work activity that can be automated.

2. Conceptual framework

2.1 The occupation-based approach

Frey and Osborne (2017) [F-O], in a paper widely cited, estimated the probability of automation of U.S. occupations by applying the occupation-based approach. Their study was particularly important as it was the first to deal with this aspect and gave rise to a series of studies on other countries.

In order to estimate the probability of automation of occupations, F-O adopted a technological point of view taking into account the technical problems to be faced in order to automate individual occupations; the speed of diffusion and the probability of adoption of technologies capable of replacing human work were not considered. These scholars observe that although recent progress has made it possible to automate some non-routine tasks that in the past were considered exclusively human competences, there are still engineering bottlenecks that prevent the automation of a greater number of non-routine work activities. These technical limitations to total automation refer to tasks that cannot be encoded in rules and are linked to three capabilities that are still strictly "human": perception and manipulation, creative intelligence and social intelligence. As far as perception and manipulation are concerned, robots have basic identification capabilities thanks to the development of sophisticated sensors and lasers, but they lack the depth and breadth of human perception. Consequently, tasks requiring a higher level of perception and unstructured work environments present various automation difficulties. Creative intelligence tasks involve the ability to produce new and valuable ideas, theories or artifacts. If the creation of new ideas is seen as the production of new combinations of existing ideas, then this creativity is partly automatable. However, ideas must also have value and therefore a disagreement may persist as to whether or not a computer is actually creative. Finally, social intelligence tasks require the ability to respond intelligently and empathically to a human counterpart. These tasks, which are important in many occupations, can only be automated in part by computers. Given the limitations of automating perception, manipulation, creative intelligence and social intelligence, it is likely that occupations requiring these skills will not be automatable in the next twenty years. The probability of automation of an occupation could then be described as a function of these capabilities.

In order to determine the probability of automation of various occupations, F-O used the O*NET service (for the year 2010), which describes 903 U.S. occupations using a set of standardized and measurable variables.

The estimation process is as follows. In the first phase, the authors, together with some technology experts, assigned a label to certain occupations (70 out of 702) on which to build the estimation model, linking the value “1” to those that can be automated (e.g. telephone operators, accountants and delivery staff) and the value “0” to those which cannot (e.g. lawyers, doctors and cooks). They subsequently built a probabilistic classification model, where the dependent variable is given by the probability of automation and the explanatory variables are the nine O*NET variables corresponding to the three bottlenecks.

Occupations have been distinguished according to three levels of probability of automation: low (0-0.3), medium (0.3-0.7) and high (0.7-1), where, according to the authors, the high level indicates that “the associated occupation is potentially automatable over some unspecified number of years, perhaps a decade or two”. The study by F-O shows that in the United States, 47% of workers fall into the category at high risk for job replacement.

Predicting technological progress is extremely difficult. For this reason F-O acknowledged these limitations of the study: only short-term technological advances were considered and no forecasts were made of the time needed to overcome bottlenecks; the study did not capture variations within occupations resulting from the automation of certain work activities that allow workers to devote themselves to other tasks; the impact of productivity gains at work in various occupations and industries has not been examined.

The study by F-O gave rise to a series of papers on European countries and Japan. Applying the occupation-based approach to the employment data of the countries considered, it appears that on average 53.24% of European jobs are at risk of automation, with a significant difference between the various European countries (Bowles, 2014a, 2014b). Following the same procedure, it emerges that in Germany, workers at risk of replacement by machines account for 59% of the total workforce (Brzeski and Burk, 2015); in the United Kingdom, 35% of workers have a high risk of replacement (over 66%) (Haldane, 2015); while in Finland this share is 35.7% (considering a risk level of over 70%) (Pajarinen and Rouvinen, 2014). Since according to David (2017) it is not correct to apply directly to other countries the results of F-O valid for the United States because each country has its own characteristics with regard to the industrial and employment structure, the author has repeated the method of estimation used by F-O, estimating that in Japan 55% of workers have a high risk of replacement by machines.

The detailed results obtained by the mentioned authors are shown in Table 1.

Table 1 Distribution of workers by category of risk of replacement by machines

Risk of Replacement (Probability of Automation)	United States	Germany	United Kingdom	Finland	Japan
	Frey e Osborne (2017)	Brzeski e Burk (2015)	Haldane (2015)	Pajarinen e Rouvinen (2014)	David (2017)
Low Risk (0 – 0.30)	33%	59% (unspecified level of risk)	37%	-	19%
Moderate Risk (0.31 – 0.70)	10%		28%	-	25%
High Risk (0.71 - 1)	47%		35%	35,7%	55%

Source: Brzeski and Burk (2015), David (2017), Frey and Osborne (2017), Haldane (2015), Pajarinen and Rouvinen (2014)

2.2 The task-based approach

The results obtained by Frey and Osborne (2017) for the United States offer interesting insights. However, they should be considered with caution as they are based on the occupation-based approach that overestimates the percentage of the workforce at risk of replacement by "machines". This overestimation can be contained to some degree by applying a different method: the task-based approach.

The task-based approach is based on the assumption that it is the work activities that can be automated, rather than the occupations. As a result, it takes into account the following aspects: work activities that constitute an occupation have different potentials for automation and not all of them are easily automated; tasks that are currently non-routine and therefore non-automatable may become routine in the future; sometimes technology is complementary with workers. The probability of automation obtained by applying the task-based approach is lower than that obtained with the occupation-based approach because even occupations that according to the occupation-based approach have a high probability of automation are composed of work activities that are difficult to automate. The estimate of the probability of automation of occupations is derived from the probability of automation of work activities and from the time dedicated to their performance.

Following the task-based approach, Chui *et al.* (2015, 2016) and McKinsey Global Institute (2017a, 2017b, 2017c) estimated the probability of automation of U.S. occupations based on the estimate of the probability of automation of work activities and the time devoted to their performance. Their analysis shows that both routine activities and those that require experience and tacit knowledge can be automated, even if the probability of automation is different. For example, the probability of automation is high in the case of physical activities performed or related to the operation of machines in predictable environments (81%) and for data and information collection and analysis activities (64% and 69%), while it is low in the case of interaction with stakeholders (20%), the application of skills in decision-making, planning or creative work (18%) and activities of personnel management and training (9%). In terms of occupations, all have a potential for automation that is more or less high, as in more than 60% of occupations the activities that can be automated exceed 30% of the total, while only 5% of occupations are fully automatable (Chui *et al.*, 2015, 2016; McKinsey Global Institute, 2017a, 2017b, 2017c).

Arntz *et al.* (2016, 2017) also applied the task-based approach and estimated a more modest impact on occupations. These authors criticize the approach followed by Frey and Osborne (2017) [F-O], noting that the expert assessments regarding the potential for automation of an occupation are based on valid information but consider representative occupations and do not take into account the fact that tasks vary substantially between occupations and adapt to computerization. According to Arntz *et al.* (2017), this leads to an overestimation of the risk of employment automation. For example, also occupations that according to F-O are at high risk of automation require activities that are very difficult to automate.

In order to correct and avoid the resulting overestimation, Arntz *et al.* (2016, 2017) have considered information regarding the content of the activities of each job. In particular, the authors estimated the relation for the United States linking the tasks performed by the workers employed in the individual occupations and the characteristics of the jobs to the probability of automation calculated by F-O. This relation was then applied to the other OECD countries considered in the study.

To this end, the authors have combined the results of F-O with the observations contained in the dataset of the PIAAC (Programme for the International Assessment of Adult Competencies) referring to the United States. Since the classification of occupations used by F-O is more specific than that used in the PIAAC dataset, Arntz *et al.* (2016) assigned multiple values of the probability of automation to each individual in the PIAAC dataset and followed a multiple imputation approach. For each individual in the PIAAC data the automation result with the highest probability according to this method was assigned.

Subsequently, the authors followed a two-step process. In the first phase, the authors made a regression between the probability of automation and a series of explanatory variables including those contained in the PIAAC dataset, the employee's gender, education level, skills, income, sector, enterprise size and other auxiliary variables. In the second phase they calculated the probability of automation on the basis of the results obtained in the previous phase in order to improve the model.

The resulting model and the estimated parameters show how the explanatory variables used affect the probability of automation in the United States. In order to estimate the probability of automation for other OECD countries, Arntz *et al.* (2016) applied this model to the PIAAC datasets for the countries considered.

Following the task-based approach, Arntz *et al.* (2016) are able to consider the set of work activities that people actually perform at their workplace and the differences that exist between the various workers. Moreover, workers with the same structure of work activities are subject to the same risk of replacement in all OECD countries; the differences in the probability of automation between the various countries derive from differences in the structure of work activities or from the other explanatory variables (Arntz *et al.,* 2016).

According to the model obtained from Arntz *et al.* (2016), the probability of automation is low when the level of education required is high or the worker must train, interact, or collaborate with other people (interactive or cognitive activities); on the other hand, the probability of automation is high when employment involves the frequent performance of work activities related to the exchange of information, sales and use of hands (routine activities). These results are partly consistent with the engineering bottlenecks identified by F-O.

Arntz *et al.* (2016, 2017) show that the results obtained with the occupation-based approach have a bipolar structure: many occupations have a high or low probability of automation, while few fit into the intermediate category. According to this approach, 38% of workers in the United States have a replacement risk of more than 70% (Arntz *et al.,* 2017). On the other hand, the results obtained with the task-based approach show less extreme values at the two poles: fewer occupations have a low or high probability of automation, and most have an average level of probability of automation. Following this approach, the share of workers with a replacement risk of more than 70% in the United States is 9% (Arntz *et al.,* 2016, 2017).

Arntz *et al.* (2017) explain the reasons for the difference between the results obtained with the two approaches: most occupations involve a greater frequency of non-automated work than the representative employment used in the occupation-based approach, since workers in the same occupation specialize in non-automated work or work that is complementary to technology.

As far as the main OECD countries are concerned, the percentage of workers at high risk of replacement (more than 70%) is 12% in Germany and Austria and only 6% in Korea and Estonia; in Italy it is about 9.5% (Arntz *et al.*, 2016).

Arntz *et al.* (2016) have identified the reasons that lead to different percentages of workers at high risk of replacement by machines in different countries. The results of Arntz *et al.* (2016) show that in different countries workers employed in the same industry, in the same job or with the same level of education carry out work that can be automated to different extents. The authors attribute this fact to two possible reasons: jobs are organized differently; new technologies are adopted at a different level.

As far as work organization is concerned, two countries with comparable technologies may have a different percentage of workers at high risk of replacement because the work carried out in the country with the lowest percentage may include a higher percentage of non-automatable work activities. The relationship between the incidence of communicative work activities (face-to-face interaction or group work) and the percentage of workers at high risk of replacement is negative (Arntz *et al.*, 2016). As a result, in countries such as the United States and the United Kingdom where more attention is paid to communication activities, the percentage of workers at high risk for replacement is lower (Arntz *et al.*, 2016).

As far as the adoption of technologies is concerned, even if two countries do not have significant differences in the organization of the workplace, the percentage of workers at high risk of replacement may be lower in a country if it invests or has already invested heavily in automation technologies and therefore has already replaced work with capital for carrying out automatable work activities (Arntz *et al.*, 2016). On the other hand, countries such as Slovakia and Ireland with a high percentage of workers at high risk of replacement have invested little in automation technologies in the past and have untapped automation potential (Arntz *et al.*, 2016). The relationship between previous investment in automation technologies and the proportion of workers at high risk of replacement is negative (Arntz *et al.*, 2016).

Once the differences between countries in terms of job organization and adoption of technology have been isolated, one aspect common to all the countries considered is the negative relationship between the level of education and income and the percentage of workers at high risk of replacement (Arntz *et al.*, 2016). Low-skilled and low-income workers present a higher risk of replacement.

Bessen (2016) shares the view expressed by Arntz *et al.* (2017) and notes that the overestimation of the percentage of workers at risk of replacement according to Frey and Osborne (2017) is linked to the fact that the automation of a task is often confused with the automation of a job. In particular, Bessen (2016) criticizes the assumption of Frey and Osborne (2017) regarding the assignment of a label to certain occupations, pointing out that none of the occupations considered automatable by the authors have actually been fully automated at this point. In support of his claim, Bessen (2016) notes that in the last 60 years automation has been high but has almost always been partial (and not total) automation; in fact, technology rarely automates entire occupations. However, Bessen (2016) does not rule out the possibility that, in the future, the technology related to artificial intelligence may be capable of automating entire occupations.
The difference between the concepts of partial automation and total automation is also relevant when the effects are considered: while total automation implies a net loss of jobs in a certain occupation, this does not necessarily occur in the case of partial automation. Automation in fact reduces the price of goods, increasing the (elastic) demand for goods and the demand for the labor necessary to produce them (the so-called compensation effect); only when demand is inelastic to price reduction it does not result in an increase in demand for goods and for labor, causing a decrease in employment (Bessen, 2016).

Brandes and Wattenhofer (2016) express a different opinion with regard to the seminal study by Frey and Osborne [F-O] first published in 2013. While acknowledging that the authors have done an excellent job in opening a debate on such an important issue, they criticize their findings as "opaque".
In their study, Brandes and Wattenhofer (2016) set the goal of estimating the probability of automation of work activities, starting from the frequency with which they are carried out within an occupation. In particular, since the weighted average of the probabilities of automation of work activities is equal to the probability of automation of occupations and similar work activities (even if carried out in different occupations) must have the same probability of automation, the authors used the probabilities of automation of occupations to estimate the probability of automation of all the work activities that make up such occupations.
The analysis of Brandes and Wattenhofer (2016) yields additional information as compared to the first results of F-O. In addition to the probability of automation of a job, it is possible to understand which of the job activities that make up the job can be automated and what their

probability of automation is. The analysis shows that for most work activities the probability of automation is very high or very low.

The automation probabilities of the occupations obtained by Brandes and Wattenhofer (2016) differ by less than 20% from those of F-O for the majority of occupations. In cases where the probability of automation of occupations obtained by Brandes and Wattenhofer (2016) differs significantly from that initially estimated by F-O, the detailed analysis of the work activities that make up these occupations and their probability of automation allows us to understand which result is most reliable.

The approach used by Brandes and Wattenhofer (2016) allows to identify possible outliers in the first estimates of Frey and Osborne and to deepen the analysis of the probabilities of automation of these occupations, thus allowing the prediction of better estimates.

Nedelkoska and Quintini (2018) also tried to make corrections to the Frey and Osborne (2017) [F-O] method. The authors faithfully replicated the F-O method using PIAAC data and applying the method to job characteristics rather than occupations. This implied two steps: to identify a match between the 70 occupations labelled by F-O and the 440 ISCO-08 occupancy classes in the PIAAC database; to select the variables in this database corresponding to the "bottlenecks" identified by F-O.

The study by Nedelkoska and Quintini (2018) shows that for the 32 countries studied, 14.0% of occupations have a high probability of automation (higher than 70%), 31.6% an intermediate probability (between 50% and 70%), 54.4% a low probability (lower than 50%).

There are considerable differences between the countries considered: while the share of high-risk occupations is about 7% in Norway, Finland and Sweden, this share reaches about 24% in Slovenia and Greece and 33% in Slovakia; only 10% of U.S. occupations are at high risk (Nedelkoska and Quintini, 2018).

The results obtained by the authors for the main countries are shown in Table 2.

Table 2 Distribution of workers by category of risk of replacement by machines

Risk of Replacement (Probability of Automation)	Average OECD	Norway	Finland	United States	United Kingdom	Denmark	Canada
Low Risk (0 - 0.50)	54.4%	68.6%	66.4%	62.8%	62.3%	61.7%	57.9%
Medium Risk (0.51 - 0.70)	31.6%	25.7%	26.4%	27.0%	26.0%	27.6%	28.6%
High Risk (0.71 - 1)	14.0%	5.7%	7.2%	10.2%	11.7%	10.7%	13.5%

Risk of Replacement (Probability of Automation)	Korea	France	Italy	Spain	Germany	Japan	Slovakia
Low Risk (0 - 0.50)	56.8%	50.8%	49.3%	48.1%	45.8%	45.7%	35.6%
Medium Risk (0.51 - 0.70)	32.8%	32.8%	35.5%	30.2%	35.8%	39.2%	30.8%
High Risk (0.71 - 1)	10.4%	16.4%	15.2%	21.7%	18.4%	15.1%	33.6%

Source: Nedelkoska and Quintini (2018)

Approximately 70% of the variance in the probability of automation between countries is linked to differences in the way that jobs are organized within the same economic sector, while 30% is due to differences in the sectoral structure of the economy (Nedelkoska and Quintini, 2018).

In this study we will apply the methods proposed by Frey and Osborne (2017) and by Nedelkoska and Quintini (2018) to the data concerning Italian occupations. At the end of the article we will offer our ideas regarding economic policy.

3. Data and methods

3.1 Occupation-based approach

We, first, estimated the probability of automation of Italian occupations, following the occupation-based approach.

In the first phase a label was assigned to some Italian occupations on the basis of which the estimation model was built. The labels consist of a value of “1” for automatable occupations and a value of “0” for those that are not. The labelled Italian occupations are those corresponding to the U.S. occupations considered by Frey and Osborne (2017) [F-O]: the conversion of the labels between U.S. and international occupations is that proposed by Nedelkoska and Quintini (2018) [N-Q]; the conversion between international and Italian occupations is that provided by ISTAT (Istituto nazionale di statistica - National Institute of Statistics).
Subsequently, the database called “Informative System regarding Professions” for the year 2012 was used. It is a database promoted jointly by ISFOL (Istituto per lo sviluppo della formazione professionale dei lavoratori - Institute for improvement of vocational training for workers) and ISTAT and it provides information on the 800 professional units identified in Italy. The professions are described with more than 300 variables, grouped in the following categories: knowledge, skills, attitudes, values, working styles, generalized (working) activities and working conditions. The information contained in the database is provided directly by the workers through interviews.
The variables of this database concerning activities generally corresponding to bottlenecks (perception and manipulation, creative intelligence and social intelligence) were then identified since they affect the level of future automation.
Subsequently a probabilistic classification model was built, where the dependent variable is given by the probability of automation and the explanatory variables are the nine variables of the database that were selected. In order to assign an automation probability to all occupations, a model was built on the basis of the labels assigned to the occupations of the training set; this model was then used to estimate the automation probability of all occupations.
The automation probabilities obtained were then applied to the data concerning the number of workers employed in each occupation. The data are those provided by ISTAT (Continuous Labour Force Survey Section) and consist of the average for the period from 2014 to 2016. In cases where ISTAT does not provide employment data, these have been obtained from other sources, including sector studies, websites of professional associations and articles available on the Internet.

3.2 Task-based approach

We then applied the task-based approach using the PIAAC (Programme for the International Assessment of Adult Competencies) data for Italy. PIAAC is an OECD programme of assessment and analysis of adult skills, which also examines the education and employment status of individuals.

Since for each international occupation, this database contains multiple observations and each international occupation corresponds to multiple Italian occupations, for each international occupation contained in the database a representative observation has been constructed calculating the average of the observations of each variable. The task-based method was applied to the occupations thus obtained.

In the first phase, a label was assigned to some international occupations on the basis of which the estimation model was built. The labels consist of the value "1" for the automatable occupations and the value "0" for those that are not. The international occupations labelled are those used by Nedelkoska and Quintini (2018).

Subsequently, the variables of the database corresponding to the engineering bottlenecks were identified.

A probabilistic classification model was then constructed, following the same procedure adopted for the occupation-based case.

Finally, the automation probabilities obtained for international occupations were assigned to the corresponding Italian occupations and applied to the employment data for Italy.

4. Results

The probability of automation of the Italian occupations, obtained by applying the occupation-based approach [Frey and Osborne (2017)] and the task-based approach [Nedelkoska and Quintini (2018)], are shown in Table 3.

Table 3 Probability of Automation of Italian occupations

Occupation	Estimated probability of automation	
	O-B approach	T-B approach
Pre-primary school teachers	0.0076	0.2073
Social workers	0.0151	0.2173
Dentists and Oral surgeons	0.0186	0.2159
Medical doctors, general practitioners	0.0460	0.2142
Business managers administrators of large companies	0.0641	0.2486
Beauticians and make-up artists	0.1098	0.0781
Civil engineers and similar professions	0.1149	0.0858
Photographers and similar professions	0.1390	0.2331
Bartender and similar professions	0.1400	0.0466
Hairstylists	0.1635	0.0781
Plumbers and installers of hydraulic and gas pipes	0.1925	0.0444
Lawyers and attorneys	0.2105	0.0504
Computer programmers	0.2358	0.4050
Waiters and similar professions	0.2712	0.0466
Real Estate agents	0.3141	0.2163
Breeders and farmers	0.3498	0.2070
Operators in the catering sector	0.4010	0.1421
Athletes	0.4344	0.2582
Warehouse management and other similar professions	0.4486	0.4881
Bakers and Artisan pasta makers	0.4607	0.7657
Electricians	0.5199	0.6565
Statistical service employees	0.5367	0.5600
Journalists	0.5548	0.4467
Retail sales clerks	0.6043	0.4192
Payroll employees	0.6215	0.5600
Sales and distribution employees	0.6493	0.8070
Librarians and related professions	0.6879	0.7145
Stockbrokers, stockbrokers, securities brokers and related professions	0.7154	0.8070
Persons involved in the preparation, cooking and sale of fast food, snack bars, delicatessens and similar establishments	0.7493	0.7310
Travel agents	0.7616	0.1083
Accountant and related professions	0.8061	0.7403
Personnel management	0.8198	0.7145
Delivery personnel	0.8225	0.6393
Cashiers in commercial establishments	0.8321	0.8359
Unqualified personnel providing care services for buildings, equipment and property	0.8497	0.6393
Sale representatives	0.8515	0.8070
Customer information and support staff	0.8583	0.1083
Ushers and simlar professions	0.9050	0.6393

Taxi drivers, drivers of cars, vans and other vehicles	0.9165	0.6376
Operators	0.9365	0.1083
Factory line assemblers of machine parts	0.9788	0.8596

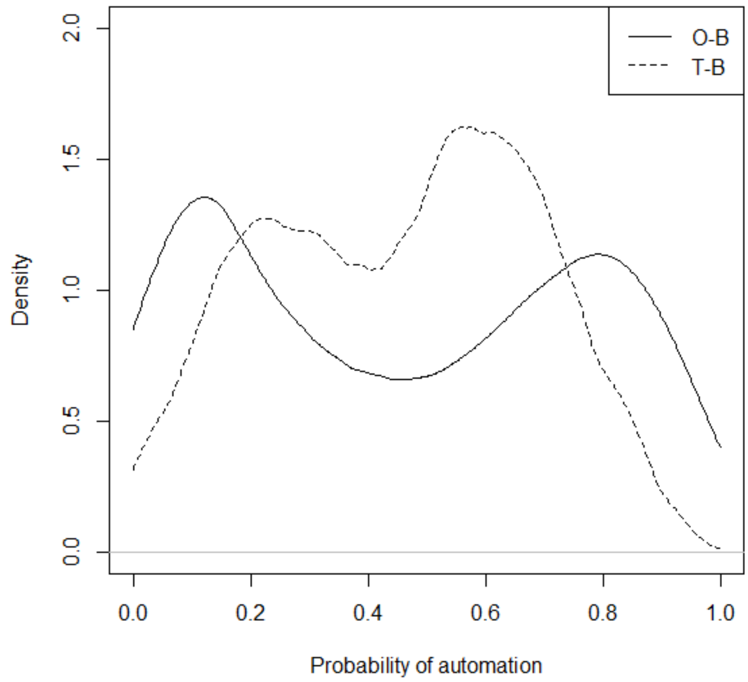
Source: Authors' calculations

As can be seen in Table 3, for most occupations the probability of automation according to the two methods differs by about 10-20%, although for some the difference is more relevant.

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. There is also a high probability of automation in occupations that seem to be immune, such as occupations in the service sector (e.g. persons involved in the preparation of food) and in sales (e.g. retail sales clerks, cashiers). On the other hand, occupations with a low probability of automation have high levels of perception, manipulation, creative intelligence and social intelligence. These occupations concern the following sectors: management and finance (e.g. business managers), legal (e.g. lawyers), education (e.g. pre-primary school teachers), health care (e.g. dentists, medical doctors), art (e.g. photographers). Occupations with an average probability of automation include warehouse managers, bakers and journalists.

Figure 1 illustrates the resulting distribution of the probability of automation of occupations. As stated the theory and seen above, the results obtained with the occupation-based approach follow a bipolar structure, with many occupations having a high or low probability of automation and few falling into the intermediate category. On the other hand, the results obtained with the task-based approach show less extreme values at the two poles: a lower number of occupations has a low or high probability of automation, while most of them are associated with an average level of automation.

Figure 1 Distribution of the probability of automation using the "occupation-based approach" and the "task-based approach"



Source: Authors' calculations

The probabilities of automation have been applied to employment data concerning the total workforce and the percentage of male and female workers. The results obtained are shown in Table 4.

Table 4 Distribution of Italian workers by category of risk of replacement

Risk of Replacement (Probability of Automation)	Percentage of workers (men and women) at risk (Number of workers) M or F		Percentage of workers at risk (Number of workers) M		Percentage of workers at risk (Number of workers) F	
	O-B approach	T-B approach	O-B approach	T-B approach	O-B approach	T-B approach
Low Risk (0 – 0.30)	30.2% (6.48 mln)	26.4% (5.67 mln)	20.8% (2.48 mln)	20.0% (2.38 mln)	39.5% (3.38 mln)	30.5% (2.61 mln)
Moderate Risk (0.31 – 0.70)	36.6% (7.86 mln)	55.5% (11.90 mln)	37.9% (4.52 mln)	59.8% (7.12 mln)	35.7% (3.05 mln)	52.8% (4.52 mln)
High Risk (0.71 - 1)	33.2% (7.12 mln)	18.1% (3.87 mln)	41.2% (4.92 mln)	20.2% (2.40 mln)	24.8% (2.13 mln)	16.7% (1.43 mln)

Source: Authors' calculations

Table 4 shows how the two methods used lead to different results regarding the distribution of the workforce according to the risk of replacement by the machines. While the occupation-based approach (O-B) yields 33.2% of Italian workers presenting a high risk, this percentage drops to 18.1% according to the task-based approach (T-B).

It is appropriate to compare our results with those obtained by the authors mentioned in Paragraph 2 and covering the main countries, including Italy. In the case of the estimates made using the O-B approach, the share of workers at high risk of replacement by machines we calculate is lower than that estimated for other countries yet remains significant. On the other hand, if we consider the results obtained on the basis of the T-B approach, we have obtained the same share of workers with a high risk of replacement, while our estimates differ as regards the shares of workers with a low and medium risk of replacement. In the latter case, Italy is one of the countries where the share of workers at high risk of replacement is among the highest.

If we consider gender differences, it results that men face a greater risk than women. This difference is due to the different distribution of workers in occupations with a higher or lower probability of automation.

Looking at the automation probabilities obtained, we can also see the presence of an inverse relationship between skills and wages and the probability of automation, which has also been identified by Frey and Osborne (2015, 2017), Haldane (2015) and Nedelkoska and Quintini (2018). It appears that jobs with a low probability of automation (less than 30%) generally employ higher-skilled workers who receive high wages. Examples include doctors, lawyers, engineers and professors. On the other hand, jobs with a high probability of automation (above 70%) generally employ lower-skilled workers who receive lower wages. Consider for example warehouse managers, sales assistants, switchboard operators, cashiers, assistant chefs, vehicle drivers. From the observation of these results it emerges that unlike in the earlier waves of technological progress, artificial intelligence mainly puts low-skill occupations at risk, while past technologies mainly affected middle-skilled workers, thus provoking job polarization (Nedelkoska and Quintini, 2018).

However, there are also exceptions. There are jobs that have a low probability of automation but employ low-skilled workers receiving low wages. For example, photographers, tailors, plumbers, hairdressers and waiters. Moreover, there is no shortage of jobs with a high probability of automation that employ middle-skilled or high-skilled workers receiving medium or high wages. Consider for example the cases of accountants, tax advisors and payroll workers.

The presence of these exceptions is linked to the ability or inability of the technology to automate the various work activities. It is above all the presence of engineering bottlenecks that determine these exceptions. In fact, occupations with a low probability of automation, but employing lower-skilled workers receiving low wages, involve to a significant extent non-automatable activities such as the identification and movement of objects, creative thinking, and the administration of care and assistance to other people. Employment involving these tasks protects workers from the risk of machines replacing them.

5. Conclusions

5.1 Factors affecting actual automation

If we observe the results obtained by cited economists and us, we note that there is great variability about the percentage of workers at risk of replacement based on different methods and the numbers of jobs that could be destroyed. As noted by Winick (2018), who tried to sum up these estimations shown in Table 5, "predictions range from optimistic to devastating, differing by tens of millions of jobs even when comparing similar time frames" and "although these predictions are made by dozens of global experts in economics and technology, no one seems to be on the same page. There is really only one meaningful conclusion: we have no idea how many jobs will actually be lost to the march of technological progress".

Table 5 Predicted Jobs destroyed and created by automation

When	Where	Jobs Destroyed	Jobs Created	Predictor
2016	Worldwide		900,000 to 1,500,000	Metra Martech
2018	US jobs	13,852,530*	3,078,340*	Forrester
2020	Worldwide		1,000,000 - 2,000,000	Metra Martech
2020	Worldwide	1,800,000	2,300,000	Gartner
2020	Sampling of 15 Countries	7,100,000	2,000,000	World Economic Forum (WEF)
2021	Worldwide		1,900,000 - 3,500,000	The International Federation of Robotics
2021	US jobs	9,108,900*		Forrester
2022	Worldwide	1,000,000,000		Thomas Frey
2025	US jobs	24,186,240*	13,604,760*	Forrester
2025	US jobs	3,400,000		ScienceAlert
2027	US jobs	24,700,000	14,900,000	Forrester
2030	Worldwide	2,000,000,000		Thomas Frey
2030	Worldwide	400,000,000 - 800,000,000	555,000,000 - 890,000,000	McKinsey
2030	US jobs	58,164,320*		PWC
2035	US jobs	80,000,000		Bank of England
2035	UK jobs	15,000,000		Bank of England
No Date	US jobs	13,594,320*		OECD
No Date	UK jobs	13,700,000		IPPR

* This value is Technology Review's extrapolation on a percentage of jobs lost or gained in the report. The percentage is converted to number based on the number of jobs in the US when the prediction was made according to the BLS.

Source: Winick (2018)

In addition to this, we should bear in mind that actual automation depends on many factors.

The technical feasibility requirement is the most important aspect to consider in order to understand whether a job will be automated or not in the future. It implies the need to design and adapt technology that is able to complete a job at the required performance level. In this respect, the need to program instructions for the performance of tasks seems to be a constraint on automation. Moreover, as noted by Nedelkoska and Quintini (2018), "the path between commercial introduction of a product and its wide-spread use is long and uncertain" and "the fact that a technology has commercial value does not guarantee its diffusion and it certainly does not guarantee that it will diffuse to a degree which disrupts the way people work".

The decision of a company related to the automation of a work activity requires the consideration of the following aspects: the cost to be incurred to develop and employ the technology; the economic benefits that can (or cannot) be obtained, the amount of which can be significant and even exceed the savings resulting from the reduction of labor costs; the characteristics of the labor market in terms of workers' skills, work supply and demand, which can make it more convenient to hire workers than to automate the tasks to be performed. While large companies may be better prepared for the adoption of new technologies, with reference to the Italian context which is characterized by small companies, Bruno and Polli (2017) observe that the adoption of automated production processes is limited by the reduced investment capacity of companies, and in cases where it occurs, "could lead to the redefinition of professional figures within individual companies, rather than the loss of jobs" (our translation from Italian).

Sometimes the adoption of a technology is not successful as the process requires significant changes in the structure and management that not all companies are able to implement such as: the implementation of parallel innovations in the business model and organizational structure of the company, the redefinition of roles and processes, the market selection of experienced staff or the training of workers already employed.

There are also external factors that can hinder companies' decision to automate. Social issues can make the figure of the worker essential, especially in cases where an aesthetic aspect is involved in the provision of the service or its client or recipient is in a particular psychological state (in the latter case, think of medical services). Workers can also update their skills in order to protect themselves against the risk of replacement by machines, something which, as illustrated below, will become increasingly difficult in the future. Finally, work activities could be modified to make them complementary to technology.

On the other hand, technology itself can lead to the creation of new jobs through four main mechanisms. First, machines need to be developed, produced and installed òand the production of technologies can create a demand for jobs in new sectors and occupations. Secondly, new technologies can lead to lower production costs and lower prices for goods and services, which leads to higher consumer demand and increased demand for the labor necessary for production (the so-called "compensation effect"). Thirdly, technologies that are complementary to workers increase their productivity, resulting in increased wages or employment or both, which in turn leads to an increase in labor income and in the demand for goods and services, that in turn the company meets with increased production and greater labor demand. Finally, technologies can help to create new products, sectors and jobs. Some estimations about the number of jobs created by automation are shown in Table 5.

However, it should be noted that in the future technologies may create a decreasing number of jobs and at the same time increase the number of jobs that can be automated. Future jobs will be created in sectors that do not currently exist, as has been the case in the past. For example, in the United States, one third of the jobs created in the last 25 years did not exist previously and concerned areas such as IT development, hardware manufacturing, app creation and IT systems management (McKinsey Global Institute, 2017b). In addition, more than 1,500 types of work have been created since the invention of the computer, including database administrators and web designers, and new industries, such as the audio and video streaming industry. However, as Frey and Osborne (2015) observe, the amount of new jobs created is extremely small: overall the workers employed in these industries represent 0.23% of the total workers, although this percentage will increase in the future. The workers employed in these industries are better educated than the average of the workers and the average wage paid to these workers is more than twice the median wage in the United States (Frey and Osborne, 2015).

Existing business technology also makes it possible to run a large company and create significant wealth with very few workers. For example the "big-four" digital giants (Apple, Facebook, Google and Microsoft) achieved large revenue levels with relatively few employees. High-tech companies that provide intangible services through the internet (Facebook, Google, Twitter and LinkedIn) manage to achieve an annual income of billions of dollars with less than 60,000 employees. The possibility of using advanced technologies in production, warehouse management and distribution also allows companies that produce physical goods, sometimes in addition to immaterial services, to achieve an annual income of billions of dollars with a small workforce (think of companies such as Sony, Intel and Amazon).

5.2 Some economic policy implications

Even if, as a result of the factors mentioned above, the actual automation of jobs may be lower than expected, it is still necessary to intervene immediately. Governments must adopt policies in order to obtain the benefits offered by new technologies and limit the negative impact on workers. There are many solutions that can be adopted, but three of particular importance concern job creation, training of workers, wage and income support.

At present, it is very important to create jobs, both because job growth since 2000 has been very low and because technology enables more and more jobs to be automated. The number of jobs created must be sufficient and they must be of good quality (i.e. offering high wages and protection against job loss, wage decrease and unemployment). In addition, the creation of jobs involving many non-automatable work activities should be encouraged in order to offer jobs to workers displaced by technology and protect them against the risk of future replacement. Consequently, the sectors in which jobs should be created are, for example, personal services, tourism, health and education.

Job creation can be achieved or facilitated by various measures that may also be taken in conjunction with one another. Labor regulation can be reduced to achieve ideal flexibility. Excessive labor regulation increases labor costs and reduces the number of quality jobs. A different view states that less regulation could lead to the disappearance of quality jobs (Bourguignon 2005). Job creation can be facilitated by supporting economic growth through birth of start-ups, which is essential for the creation of new jobs, although, as pointed out above, existing business technologies now allow these to be run as capital-intensive enterprises rather than labor-intensive ones. In any case, it is useful to stimulate investment and simplify the process of setting up new businesses, to promote new forms of entrepreneurship based on recent technologies and to encourage self-employment. The promotion of innovation and support for research must continue, as in the past they have led to the invention of technologies that have created significant positive effects. Intervention through taxation would also be advisable. At present, using the capability of technology to perform many jobs effectively and efficiently is extremely attractive and may lead to the economy becoming less labor-intensive in the future. To avoid companies making the choice to adopt technology rather than hire workers, or deciding to employ workers only if they can be paid a very low wage, taxation on labor should be reduced and taxation on capital increased.

As far as the education and training of workers is concerned, in the past, when technology was able to perform a large number of routine jobs, sizeable investments in education increased the average educational level of American workers, prevented an increase in economic inequality, and allowed workers to protect themselves against the risk of replacement by machines (Brynjolfsson and McAfee, 2011). While the education and training of workers remain important (Brynjolfsson and McAfee, 2014; Frey and Osborne, 2015), education does not necessarily protect against the risk of replacement because technological advances such as machine learning and artificial intelligence allow even non-routine jobs to be automated (Ford, 2015). In any case, the importance of workers' education and training for the future should not be overlooked. Moreover, as Nedelkoska and Quintini (2018) observe, it is necessary to keep in mind that “the effects of technological change on the employment and wage outcomes of citizens are deeply dependent on how well educational and training institutions can anticipate demand shifts and how quickly and substantively they can respond to them. While it may be difficult to control the diffusion of technologies, it is certainly possible to mitigate their “dark side” by designing timely and adequate institutional responses”.

The changes to be implemented in the training systems are as follows. Workers must be given the skills they need to work in a highly automated and smart work environment: the worker will have greater autonomy, will have access to all company information, and will share the risks and results incurred by the company. Consequently, education and training systems must no longer focus solely on the development of basic skills (reading, writing and computer skills), which will remain fundamental but will no longer be sufficient; instead, they must place greater emphasis on aspects such as creativity, flexibility, leadership, entrepreneurship, problem solving capabilities and social skills. Higher education systems should intensify their relationship with the world of work by providing for greater exposure to work environments. In addition, all education systems must be able to adapt quickly to technological change and promote lifelong learning: it will be essential for workers to have the right skills and constantly update them in order to obtain or keep a job, or transfer to a less automatable job. Unfortunately, it seems that both the possibility of participating in on-the-job or off-site training courses and the duration of such courses are significantly shorter for workers who are at high risk of being replaced by machines.

As far as wage and income support is concerned, the aim is to reduce economic inequality caused by technology because it has several negative effects. Among these, the reduction in consumption leads in turn to a fall in demand, which affects all economic sectors and hampers overall economic growth. Thus, it also causes a slowdown in the development and adoption of new technologies. In order to support wages and incomes, it is possible to introduce a social security system adapted to the new conditions of the labor market, put into place income redistribution, or provide a universal basic income or a guaranteed minimum income. However, it should be noted that wage and income support policies must be accompanied by other measures as they alone do not address the root of the problem.

Adopting these policies, especially those aimed at creating new jobs, is particularly important for European countries compared to the United States. The United States is in fact a technologically advanced country, where many technologies are designed and developed and then spread to the rest of the world. In the future, the technologies developed in the United

States will be particularly attractive to European companies and yet their diffusion in Europe may have many negative effects. European countries will not be able to fully benefit from the positive effects on jobs linked to the invention of new technologies and which compensate for part of the destruction of jobs resulting from their spread. To limit the negative effects, new jobs must be created and workers must be trained at the same time as these technologies spread.

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