Are machines stealing our jobs?

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Abstract

This work is aimed to contribute empirical evidence to the debate about the future of work in an increasingly robotised world. We implement a data-driven approach to study the technological transition in six leading countries of the Organisation for Economic Co-operation and Development (OECD). First, we perform a cross-country and cross-sector cluster analysis based on the OECD STtructural ANalysis (STAN) database. Second, using the International Federation of Robotics (IFR) database, we bridge these results with those regarding the sectoral density of robots. We show that the process of robotisation is industry- and country-sensitive. In the future, participants in the political and academic debate may be split into optimists and pessimists regarding the future of human labour; however, the two stances may not be contradictory.

JEL Classification

E24, E66, J24

Keywords

robotisation, labour dislocation, cluster analysis

Introduction

The purpose of this work is to offer an empirical contribution to the debate on the effects of robots on productivity, employment and wages by investigating the density of robots and labour dislocation in the economic sectors of six leading OECD countries. In the debate on the future of labour, which has raised significant interest in both the academic and political fields, there is general consensus that robots and artificial intelligence (AI) will substantially affect all aspects of our lives (Makridakis, 2017; Huang and Rust; 2018, Hägele et al., 2016; OECD, 2018c), especially employment and wages. However, the predictions of and reactions to their effects on societies and economies have been mixed, ranging from utopian to dystopian visions of the future. According to Dosi and Virgillito (2009, p.4): "New technologies may herald an economics of hope, with work for all and equitable social inclusion, or conversely, mass unemployment, mass inequality and social exclusion, leading to a 're-feudalisation' of Western societies"[ii]. The existence of radically opposite views of robotisation and its effects is not surprising because of the unprecedented complexity and pervasiveness of this process (Koninek and Stiglitz, 2017), which is leading the transition to the Fourth Industrial Revolution (Brynjolfsson et al., 2017).

The European Commission (2019), for instance, assumes that two scenarios are likely. The first scenario is pessimistic. Robotisation and AI-based machine learning will improve the prediction and decision-making capability of machines, leading to the prevalence of the substitution effect on the complementarity effect between workers and machines and, consequently, disruptive outcomes in terms of job losses and the disqualification of certain typologies of workers. This effect might prove to be so important that it causes medium and even long-term negative effects on employment and wages. In contrast, the second scenario is optimistic, suggesting that robots and AI will increase labour productivity, thanks to the complementarity between machines and humans, the latter of which will benefit from the ability of machines to do routine tasks because of the freedom to perform non-routinised social and intellectual jobs. Moreover, workers in jobs that complement technologies will experience substantial wage increases. However, workers that will be substituted by machines will experience diminished compensation and work opportunities. In addition, sectors where labour complements technology could absorb routine workers who are expelled mainly from the manufacturing sector[iii] because of a higher "job multiplier"[iv] (Moretti, 2012), which ultimately would lead to a higher level of long-run equilibrium in terms of employment, compensation and Gross Domestic Product (GDP).

While there is no consensus on the effects of robotisation, there is evidence that the use of robots and the pace of their technological growth have been industry-sensitive (Bessen, 2017; Mandfield, 1989; Camagni, 2017; Compagnucci et al., 2019). Until now, the introduction of robots has concerned the service sector only partially. The main effect is on the manufacturing sector (IFR, 2018), especially high- and medium-tech manufacturing (Piva and Vivarelli, 2018), which has the highest readiness in investment in innovation. In splitting the production process into different phases, automatable tasks are performed by machines, whereas non-automatable tasks (i.e., so-called residual activities) are carried out by humans (Decker, 2017). The sectoral risk of job automation was confirmed empirically by the OECD (2018a, 2018b), showing that, at least since 2011, regions that are specialised in tradable services, which are also highly urbanised and have highly educated human capital, are the least exposed to this threat.

However, the rapid increase in the number and types of tasks that a robot can perform, ranging from manual and routine cognitive tasks to non-routine manual and cognitive tasks, and the fact that not only agriculture and manufacturing (i.e., tangible production) but also the service sector (i.e., non-tangible production) are subject to robotisation and AI, has increased concerns about the future of work (Pew Research Centre, 2017). The ongoing wave of robotisation could affect routinised and low-skilled jobs (OECD, 2018b), and it might also displace well-paid and skilled jobs performed by highly educated workers in the advanced services sector. Big data and improvements in programming and algorithm applications have already become the standard in the financial, credit and insurance sectors. More importantly, the new frontier of robotics is focused on the development of robots that can expand the physical and mental abilities of human beings in numerous tasks, ranging from healthcare and medical intervention to defence and space exploration. This cutting-edge technology includes the development of social robots and their application to human–robot interactions (Breazeal et al., 2008), such as supporting the process of learning and training in work and education and helping patients in the execution and monitoring of physical rehabilitation and cognitive exercises (Gonzales et al., 2017).

If it is true that robotisation will produce different effects depending on the time and the sector (Bessen, 2017), it is also true that these effects will be country- and region-sensitive because the latter have different economic specialisations and are in different stages of development. A more or less knowledge intensive service-based economy or a more or less high-tech manufacturing production system as well as the institutional framework and education level (Acemoglu, 2002, 2015) could substantially affect the adoption of technology. Furthermore, this process could further exacerbate spatial inequalities (Giaoutzi and Stratigea, 1991; Sujarwoto and Tampubolon, 2016).

Without neglecting the importance of institutional factors, to identify the economic sectors and countries that have suffered severely from labour dislocation in the last two decades and to determine whether there are significant differences in the density of robots and their growth rate among country–sector pairs, in this study, we focus on a set of variables (i.e., productivity, value-added, relative price, hour worked, hourly wages and total wages) drawn from the OECD-Structural Analysis (STAN) database. We perform a cluster analysis using these variables and provide a taxonomy of the different clusters resulting from the analysis. We then relate these clusters to the ongoing robotisation process using data collected from the International Federation of Robotics (IFR). Our analysis supports the hypothesis that the technological transition is industry- and country-sensitive.

In using a data-driven approach, we aim to contribute to the debate on the effects of robots on our societies. Unlike other contributions based on IFR data (Acemoglu and Restrepo, 2018; Graetz and Michael, 2017), which investigated the causal relation between labour dislocation and robotisation over a longer period, in this work, no hypotheses are stated before we conduct the database analysis. However, although our approach has allowed us to achieve results that are not biased by *a priori* assumptions and restrictions, it obliges us to work with a limited database, which prevented the investigation of causal relationships[v].

The paper proceeds as follows. Section 2 provides a literature review. Section 3 describes the data and the methodology before presenting the results of the cluster analysis. Section 4 discusses the role of robotisation in enhancing productivity and causing labour dislocation. Finally, a brief conclusion is provided in Section 5.

Technological Change at the Time of Robots and AI: Is It Different This Time?

Technology has always been a key topic in economic research because of its effects on the performances of single firms, industries and countries as well as on workers, human capital and the income distribution between labour and capital. Since the late 18th century, the main concern regarding technological change has been its capacity to substitute human labour by machines, possibly leading to job losses or the so-called technological unemployment (Bennion, 1943). Although most scholars agree on the possibility that temporary unemployment would follow the introduction of new labour-saving technologies, there is no consensus about their long-term effects (Mokyr et al., 2015).

As Brynjolfsson et al. pointed out (2017, p. 33), "there are plenty of both optimists and pessimists about technology and growth". According to the pessimistic scenario, the main concerns have been the decreased importance of human labour compared with automated tasks and the impossibility of absorbing the surplus workforce in alternative employment opportunities. The labour-saving effects triggered by new technologies have been predicted to be higher than the creation of new jobs (Leontief, 1952; Arntz et al., 2016; Frey and Osborne, 2017). Based on the past two centuries, it may be agreed that the doomsayer's predictions have not been fulfilled. Mokyr (2002), for example, did not find evidence that technological unemployment occurred on a large scale during the first industrial revolution when mechanisation replaced only a few human activities. Similarly, Saint-Paul (2017), in discussing the introduction of the assembly line in the automotive sector in the early 19th century, found that it complemented low-skilled workers while it substituted highly skilled craftsmen, finally producing positive effects in the long run. According to Piketty and Zucman (2014), during Les Trente Glorieuses[vi] (the Glorious Thirty), productivity, employment and wages increased, triggering positive effects on well-being and the distribution of wealth, finally reducing the gap between the upper and lower classes.

Despite the evidence that improvements in technology do not necessarily result in technological unemployment (at least not in the long run) based on what has happened so far, why are robotisation and AI again splitting the academic and political debate between pessimists and optimists? Is it perhaps different this time?

Frank et al. (2019, p. 1) noted, "rising automation is happening in a period of growing economic inequality, raising fears of mass technological unemployment and a renewed call for policy efforts to address the consequences of technological change", which could lead to the rising of the so-called "useless class" (Harari, 2014) of humans who are not able to work because their professions have become obsolete. Dosi and Virgillito (2019) argued that robotisation and AI have intervened in the socioeconomic context, which has experienced radical, interlinked transformations during the last three decades: the ongoing process of globalisation and polarisation of manufacturing activities in China; the rising importance of the knowledge economy and the related dynamics in terms of wage polarisation and workforce casualisation; the increasing decoupling of productivity trends on the one hand and wage, employment and compensation trends on the other. After the 2007 crisis, notwithstanding the report that "labour markets are back to pre-crisis levels in terms of job quantity, with only a few notable exceptions" OECD (2018a), this trend was accompanied by a higher proportion of poor-quality jobs (i.e., casual and precarious jobs), which limit the wage growth (Chandrasekhar, 2018) of the so-called working poor, that is, people with low-paid jobs, whose incomes fall below the poverty line.

Considering this context, what impact do we expect from robots and AI, and which perspective appears to be closer to the empirical evidence? Answering this question is particularly challenging, not only because of the theoretical complexity of the issue but also because of the lack of affordable and reliable data, which prevents the increase in the quantity and quality of empirical studies.

Among the studies that assessed the effects of robots on productivity, Kromann et al. (2011) assumed that the stock of industrial robots affected the level of automation. In their study, the results of a cross-country and cross-industry analyses of the European Union level analysis of capital (K), labour (L), energy (E), materials (M) and service (S) inputs (EU-KLEMS) and IFR data between 2004 and 2007 showed that automation increased labour productivity, causing negative short-run and positive long-run effects on employment. Similarly, the European Commission Report on Robotics and Employment (EC, 2016) showed that the use of industrial robots allowed companies to significantly increase their level of productivity. Graetz and Michaels (2015) considered 14 industries in 17 countries from 1993 to 2007 and performed an ordinary linear regression (OLS) and two-stage least squares (2SLS) analyses on EU-KLEMS and IFR data. They found that the pairs of country–industry that experienced the highest level of robot densification also showed the highest gains in labour productivity. However, "larger increases in robot density translated into increasingly small gains in productivity, suggesting that there are some congestion effects (or diminishing marginal gains)" (Graetz and Michaels, 2015, p. 3). Finally, Dauth et al. (2018), using data on German labour markets between 1994 and 2014, found that regions that were more exposed to automation showed significant increases in labour productivity. The empirical evidence found in these previous studies was supported by predictions by the Centre for Economics and Business Research (2017), and the Boston Consulting Group (2015), according to which productivity was expected to substantially increase because of autonomation in the coming decades.

Nonetheless, although AI and robotisation have been expected to have a major impact on productivity, recent data indicated a marked and indisputable slowdown in global productivity, especially since the global financial crisis (United Nations, 2017). Surprisingly and paradoxically, this slowdown "appears orthogonal to recent technological advances" (Goldin et al., 2018, p. 1). The productivity slowdown was confirmed by the OECD (2019), which underlined the existence of substantial differences among countries, industries and firms in adopting technological improvement as well as the ways these gaps affect productivity. A review of the possible causes of this ongoing trend was provided by Goldin et al. (2018) and Brynjolfsson et al. (2017), who identified manifold causes: 1) the way in which technological change is taking place is characterised by an increasing share of obsolete investment in total investments; 2) a marked lag between the implementation of a technology and the occurrence of its effects; 3) measurement problems.

There are conflicting pieces of evidence regarding not only the relation between robotisation and AI on one hand and productivity on the other but also their possible effects on employment and wages. The review of the related literature revealed that the potential outcomes depend on the features of and interplay among the industries involved. According to Vivarelli (2014), Acemoglu (2002) and Acemoglu and Restrepo (2018), the labour-saving effects of technological improvement can be compensated by the following dynamics in different contexts: a) at the intra-industry level when the increasing productivity in a given sector spurs the growth of its output allowing increased labour demand for non-automated tasks (and jobs) within the same sector; b) at the cross-industry level when the increasing productivity in one sector positively affects the employment in other sectors through the price effect, wage effect, new industries effect and new investment effect. The price effect occurs whenever non-automated sectors expand their output and reduce their cost production in response to the fall in relative prices in the automated sectors, which then increases their labour demand. The wage effect can positively affect both the automated and the non-automated sectors. In the first case, the rise in workers' wages in innovative sectors positively affects the demand for goods and services, eventually causing an expansion. In the second case, decreasing wages in non-automated sectors leads to a reduction in their production costs and, potentially, their expansion. The new industries effect arises from the increase in the use of robots, which, to be produced, require new industrial plants and workforces. These new occupations have specific needs that are oriented toward new technologies and new products, thus reinforcing the growth of the whole sector. Finally, the new investment effect refers to evidence that because the accumulation of capital is the engine of economic growth, and technological improvements augment capital, increases in technologies are reflected in increases in labour.

However, no condition ensures that one (or many) of the above conditions holds. As argued in Cirillo et al. (2015), at the industry level, labour demand can expand if and only if the output growth is larger than the productivity growth, the occurrence of which, however, is not obvious. First, there can be constraints on aggregate demand growth, which was pointed out by Vivarelli and Pianta (2000) with respect to stability rules in the European Union. Second, in the automation sectors, job creation depends on the sectoral elasticity of demand, which may vary over time and across sectors (Bessen, 2018). Furthermore, Bessen (2017) found that new technologies should have a positive effect on employment if they improve productivity in markets where there is a large amount of unmet demand. In the context of robotics and automation, he suggested that new computer technology is associated with employment declines in manufacturing, where demand has generally been met but is correlated with employment growth in less saturated non-manufacturing industries.

Third, in a fast-growing industry, the aggregate demand could be inelastic, eventually resulting in a reduction in labour demand, as Delli Gatti et al. (2012) explained based on the extended crisis theory (ECT). The authors showed that a persistent structural problem could arise when a large but distinctive sector (e.g., agriculture during the Great Depression but manufacturing nowadays) of an economy faces an uneven increase in productivity because of technological improvements. If this sector faces an inelastic demand curve, the relative price of the goods produced will fall, leading to the expulsion of the labour force. In the case of barriers to labour mobility, the workforce surplus remains trapped in the distinctive sector, causing a reduction in disposable income and, depending on the size of the sector, a fall in aggregate demand, which could spread throughout the entire economy. Delli Gatti et al. (2012 p. 375) noted, “Nowadays […] falling incomes in manufacturing yield a lack of demand for goods produced in the rest of the economy, namely the service sector”.

Finally, there may be labour displacement in advancing industries even in the presence of high elasticity. However, this result is “inconsistent with models of structural change that assume an underlying Cobb–Douglas production structure in each industry”, as pointed out in Autor and Salomons (2018, p. 7). Moreover, even when the condition of the expansion of aggregate demand is met, we may observe labour dislocation due to constraints on labour mobility. As noted by Vivarelli (2014), technological bias, which consists of a mismatch between workers’ skills and those required by new occupations in technologically advanced sectors (Acemoglu, 2002), could cause labour dislocation independently from labour demand. Acemoglu and Restrepo (2018) stressed that in the US, robotisation caused labour dislocation mainly in sectors affected by automation, both in terms of labour utilisation (the negative impact of which could be absorbed by other non-automating sectors) and of labour shares. In Graetz and Michaels (2017), although increasing productivity due to robotisation did not appear to affect post-crisis recoveries of world-leading economies (except the US), it had, a negative impact on labour share. As Felten et al. (2008) pointed out, if it is true that

AI may boost growth, the consequences for labour are less clear according to the preponderance of complementarity or the substitutability effect between humans and machines.

To conclude, Acemoglu (2002), the OECD (2012), Gries and Naudé (2018), and Brynjolfsson and McAfee (2014) focused on the role played by technological bias in shaping our societies. In particular, Acemoglu (2002) stressed the importance of technological bias in causing labour dislocation, while Gries and Naudé (2018, p. 23) highlighted the key role played by technology in shaping the labour market: "if labour income does not profit from the economic gains generated by progress in AI [and robotisation], consumption may stagnate and restrict growth". In their model, stagnation of labour income, *de facto* translates to stagnant aggregate demand. Finally, Brynjolfsson and McAfee (2014) noted that beginning in the 1980s, US productivity, median income, and employment, which had grown at the same pace after the Second World War, began to follow different trends; they termed this phenomenon the "Great Decoupling". While productivity continued to increase, the growth of median income slowed down and became negative during the last two decades. Employment followed the same trend, becoming almost flat between 2000 and 2007 when the economy was still expanding. They showed that the "Great Decoupling" mainly depended on the uneven distribution of salaries. College graduate incomes have constantly grown since the 1980s, while the rest of the US labour force has followed a flat income trend since the 1980s. Workers may have been replaced by machines in automatising sectors, and because of lack of the required skills, they are constrained to unemployment and/or to the reallocation to non-automatising, less knowledge intensive and less well-paid sectors (Compagnucci et al. 2018). In any case, this labour reallocation reduced the labour share, strengthening the fall in aggregate demand and potentially bringing on long-run stagnation or crisis. In the following sections, we determine whether this negative outlook is compatible with the empirical evidence and, eventually, the role of robots in this process.

Empirical Analysis

The empirical analysis is aimed at identifying the existence of common patterns among the economic sectors in different countries and their relationship with the robotisation process. We perform a cluster analysis, which is a multivariate statistical technique that splits a set of uncategorised data into a k number of groups (or clusters) based on their similarity. Observations belonging to the same cluster are more similar to each other than to those included in other clusters. Cluster analysis is based on an iterative algorithm that, starting in k initial cluster centres, minimises the Euclidean distance within each cluster between its mean or medians (k-clustering) and its observations while maximising the distance in terms of means or medians among the adjacent clusters.

The data-driven approach, which makes it possible to group a large number of observations based on several variables, has been used in a wide range of studies from cross-sectional to time-series and panel data analyses. Repkine (2012), for instance, identified groups of East Asian countries that were similar in economic terms, whereas Green and Henseke (2016) performed a conventional cluster kmedians analysis to split occupations into "graduate" and "non-graduate" jobs. In addition, Nasri and Zhang (2018) used a multi-dimensional cluster approach to measure the spatial structure of US metropolitan areas, and Kontsevaya (2017) applied a k-mean cluster approach to estimate the efficiency of the utilisation of subsidies to investments in agriculture in the Russian Federation. Theis and Weihs (2000) introduced a variant of cluster analysis, which is known as fuzzy-cluster analysis, to identify the number of distinct stages in Germany's business cycles. Finally, according to the Office for National Statistics (2017, p. 12)[vii], "k-means clustering analysis […] has been identified as an appropriate technique, as it allows the investigation of characteristics which may, in combination, differentiate between sharing and non-sharing economy businesses".

In our analysis, we used the k-median- rather than the k-mean-method because the former is less sensitive to outliers, whose presence affected our database. The "cluster" approach allowed us to group the pairs sector i and country *j*[viii] (i.e., our observations) according to the trends in some selected variables (i.e., productivity, wages, prices and value-added over time). After identifying clusters with homogeneous behaviours, we created a taxonomy related to the specific behaviours of our subjects in the cluster according to the economic variables used.

The analysis was based on the OECDSTAN and IFR databases. STAN provides economic information over the period 2000–2015 for OECD countries, and IFR supplies data about the stock and growth rate of robots by sector and country. We chose to analyse six OECD leading countries: Denmark, France, Germany, Italy, the UK, and the US[ix] for the following reasons: a) they represent different models of development (this characteristic is particularly interesting because, as discussed in the literature review, both space and industry specialisation matter); b) comparable data for these countries are available from both databases (Meliciani, 2001). The analysis covered 21 economic sectors, which, in addition to the six considered countries, resulted in 126 statistical units. The total value added (VALK), relative prices proxied using sectoral and GDP deflators (VALP), hours worked (HRSE), hourly productivity (VALK/HRSE), total wages (WAGE) and hourly wages (WAGE/HRSE deflated using the sectoral deflator) were drawn from STAN. Robot density and the average growth rate of robots (discussed in the next section) were drawn from IFR.

A key role in determining the existence of labour dislocation due to technological improvements is played by productivity. Therefore, we classified our clusters according to their productivity dynamics. We labelled as A the clusters that showed an increase in productivity and a relative price reduction (which was expected, since automation reduces the costs of production). On the contrary, we labelled as B the clusters showing a flat productivity trend and growing relative prices. In addition, because we were interested in labour dislocation, we focused on wage dynamics using one or more positive or negative signs (+, ++, +++ and -, --, ---) to represent their intensity. Thus, if a sector behaved accordingly with the positive vision presented in the literature (e.g., if improvements in technology were mirrored both in sectoral employment and compensation growth), it was included in an A++ cluster, which thus experiences increasing productivity (A), increasing labour utilisation (+) and compensation (+). If a sector showed flat productivity, flat labour utilisation and decreasing compensations, it was included in a B- cluster, and so on.

The identification of clusters A and B helped us to corroborate Bessen's (2017) theoretical hypotheses of labour dislocation, as well as those underpinning the ECT (Delli Gatti et al., 2012). The relative dimension of cluster A, in which the labour demand may increase or decrease, and the capacity of labour to be relocated in sectors B+, B- or in unemployment, were crucial factors in determining whether the optimistic or the pessimistic vision was the most plausible.

The proposed approach to identifying the country–sector pairs falling in clusters A and B had two main advantages. First, as already mentioned, it allowed us to avoid bias, which could arise from applying predefined classifications to the data. Depending on the different institutional settings and economic specialisations, the composition of clusters A and B varied from country to country. Second, the cluster approach was more useful in linking these dynamics with the robotisation process. Because robots are a developing technology that requires large investments, arguably, they do not spread simultaneously throughout each country–sector. On the contrary, it is more likely that they spread faster in the sectors in which countries invest heavily, which may differ considerably among countries.

In analysing the data, we focused on variations instead of levels because the countries and sectors differed in terms of size. Specifically, we considered the index number of each variable with a base value of 100 in 2000. We performed the cluster analyses using the Stata *cluster kmedians* command. In Figure 1, which shows the within sum of square (WSS) matrix, its logarithm, the η^2 coefficient, and the proportional reduction of error (PRE), the plots indicate that the optimal number of clusters was eight (for technical details, see Makles, 2012).

Figure 1 about here

At *k = 8* (being k the number of clusters), there was a kink in the WSS corresponding to a η_8^2 reduction in the WSS of almost 80%. Although the log (WSS) and the PRE supported this value, they did not preclude that we could also consider the *k = 11* solution. In examining the cluster composition, however, we found that three additional clusters related to the *k = 11* solution were composed of one single sector; therefore, we chose the *k = 8* solution. However, even in the eight-cluster solution, we observed three single sector clusters:

information and communication in Denmark; electrical, electronic and optical equipment in France and the US.

Table 1 shows the descriptive statistics of the five clusters composed of more than one sector, and Table 2 reports the distribution in clusters of each sector in each country. Subsequently, we labelled each cluster according to the characteristics considered. As expected, although the analysis was more complex, the choice of avoiding predefined classifications appeared to lead to more realistic results.

Specifically, the dynamics of each cluster was as follows:

- A++: increasing productivity, increasing value-added, decreasing prices, increasing hourly wages, increasing hours worked and increasing total wages. This cluster included knowledge-intensive and high-tech activities, such as Information and Communications Technology (ICT) (in every country but Denmark), transport equipment (in Germany and the UK), and electrical, electronic and optical equipment (in Germany). Some comments could be raised about the presence of transport equipment, which is generally considered a mature market (i.e., increasing productivity, decreasing prices, and stagnating demand). Regarding Germany, the hours worked did not decrease because of the increasing competitiveness of German automotive production[x] in the global market. However, the increase in "hourly wage" showed that workers benefited from the increased productivity, which was confirmed by the increase in total wages. Other question could be raised regarding ICT services and transport and equipment in the UK. The prices of ICT services decreased because of the strong international competition during the period of analysis. Productivity as well as demand and added value increased because of continuous technological advances, whereas hours worked remained stable. Here again, as the increase in hourly wages signalled, workers benefited from the increased productivity. In these sectors, the demand for skilled workers is often higher than the supply, which leads to an adequate compensation level. All these considerations applied to transport equipment in the UK because of the relative importance of the manufacture of aircraft and spacecraft in that sector. The manufacture of aircraft and spacecraft is a high-tech sector in which the UK plays a leading role. Therefore, this cluster showed the most positive return to increased productivity. Increasing productivity was associated with an increase in employment as in the case of an elasticity of demand larger than one (Bessen, 2017). This cluster mainly supported the positive vision of the structural effects of robots and AI.

Table 1 about here

- A+: Increasing productivity, increasing value added, decreasing prices, increasing hourly wages, decreasing hours worked and increasing total wages. Despite the reduction in the number of hours worked, this cluster fully recovered the loss in aggregate demand by increasing wages. This cluster was compatible with skill-biased technological change theory (Autor et al., 2003; Autor and Dorn, 2013). On one hand, technological improvement and capital raised the demand for highly skilled workers, and consequently, their wage premium; on the other hand, they may have caused increasing wage inequality and unemployment.
- A-: Increasing productivity, decreasing value added, decreasing prices, increasing hourly wages, substantially decreasing hours worked and decreasing total wages. All sectors included in this cluster belonged to manufacturing. It is worth noting that the textile sector in all countries was included in this cluster and that the UK had the highest number of manufacturing sectors in this cluster, followed by Denmark and Italy. A- was compatible with sectors where the elasticity of demand was lower than 1 (Bessen, 2017), which meant that increasing productivity generated negative structural effects. It behaved as a fast-growing sector facing the inelastic demand of ECT; hence, its labour utilisation at the end of the period was almost halved.
- B+: flat productivity, increasing value added, increasing prices, increasing hourly wages, increasing hours worked and increasing total wages. It included only two industrial sectors (construction in the UK and food and beverages in France) and about half of the economic activities

in the service sector. B+ behaved similar to the tertiary sector in Baumol (1967) and the stagnant (slowly growing) sector in ECT.

Table 2 about here

- B-: flat productivity, flat value added, increasing prices, decreasing hourly wages, decreasing stable hours worked and decreasing total wages. This cluster included sectors om both industry and services: construction, education, transportation and storage were included in this cluster in almost every country. It is worth noting that all the manufacturing sectors in this cluster were low-tech. The inclusion of education, financial and insurance activities was not surprising. In most cases, because education systems are part of the wider public sphere, they were negatively affected by the austerity policies following the 2007 crisis.: Financial and insurance activities, on the contrary, were affected negatively mainly by ICT diffusion, which triggered a shift towards Internet based services (as in the case of mobile banking), thus reducing the workforce in those sectors.

Figure 2 shows the dynamics of each cluster between 2000 and 2015 in terms of hours worked and wages. Specifically, the relative dimension of each cluster in terms of the variable under investigation is reported on the left axis, and the right axis shows the total hours (left graph), total wages and labour share (right graph). The significant evidence shown in Figure 2 is that the clusters in which productivity was rising showed a decrease in their relative share and that only the A++ cluster increased its relative weight although not in all countries.

Figure 2 about here

Notwithstanding the positive intra-industry effect of increased productivity on employment, the increase in occupation in cluster A++ (less than 2% in relative terms) was smaller than that in cluster B+ (more than 10%

in relative terms), where productivity was stagnant (which may explain the above-mentioned stagnation of productivity). Moreover, the A- and A+ clusters, which ranged respectively from 5% to 15% of the total hours worked in 2000, showed a clearly declining path, thus supporting the labour dislocation literature. Moreover, cluster A++ showed the largest wage increase as well as a stagnant relative weight (right graph), which corroborates the hypotheses of the skill bias (Acemoglu, 2002) and Great Decoupling (Brynjolfsson and McAfee, 2014) literature. Only a few workers in each country (between 5% to 20%) benefited by the positive return from technology, and most employees experienced flat or decreasing wage dynamics.

In addressing the question about the future prevailing scenario, because the empirical evidence in our study showed that total wages followed an increasing trend in all countries (except Italy), we argue that the most pessimistic vision (i.e., ECT) is not likely to occur in the next few years. Although wages, except during the crisis period, followed a growth path, this was only one factor. In line with the labour dislocation and technological bias theories, labour shares decreased in all countries (only Denmark followed a different path). Although aggregate output increased, workers' purchasing power increased at a much lower rate than in the entire economy (Brynjolfsson and McAfee, 2014; Compagnucci et al., 2018).

The ongoing structural change in the increased productivity in clusters A (and to a lesser extent in B +) has stimulated economic growth but also reduced employment (in terms of hours worked) and has consequently decreased the wages of workers who are expelled from clusters A, causing increased inequality and reducing labor shares.

Fantastic Robots and Where to Find Them

In the previous section, we sought to identify whether there were common dynamics among sectors and countries based on STAN data. In this section, we use data from IFR to focus on the specific role of industrial robots in enhancing productivity and eventually causing labour dislocation. To the best of our knowledge, IFR is the most comprehensive database on installed industrial robots per sector and country since the 1990s. Nevertheless, data on some countries and sectors are missing: for example, data on the US are available only since 2011, while prior to that year, they are provided jointly with data on Canada.

To find evidence of the correlation between robotisation and cluster dynamics at the country–sector level, we focused on data on the period from 2011–2015, which were the closest to the time-series data used in the cluster analysis. The analysis was based on two key indicators: robot intensity (the number of robots installed in a given sector divided by the number of employees in that sector in thousands) and the average growth rate of robots. Because important differences in the process of robotisation affect the manufacturing and service sectors, we present the descriptive statistics in two tables: Table 3 is focused on manufacturing, and Table 4 is focused on services. The descriptive statistics at the country–sector level are provided in Appendix A.

Table 3 about here

Regarding the manufacturing sector, cluster A++ and A+, not surprisingly, showed the highest level of robotisation. Both clusters were characterised by the highest growth in productivity although there were important differences. As discussed in the previous section, A++ showed increasing productivity coupled with increasing employment and labour remuneration. These peculiarities, however, were shown in a very limited number of sectors: electrical, electronic and optical equipment in Germany; transport equipment in Germany and the UK (Table 2). The A+ cluster, faced with raising productivity, experienced increased wages in line with increased productivity, but the workforce decreased. Finally, A- and, to a lesser extent, B- had the lowest intensity of robots although the latter showed the highest increase in the number of robots.

Although causal inferences are not appropriate when the panel of data is limited, these results suggest that in manufacturing clusters with the highest robotisation growth rates the number of hours worked was decreased: A+, A- and B- showed this common trend. Nonetheless, the cluster that expanded in terms of both employment and wages was also the cluster most significantly affected by the robotisation process. Cluster B- experienced the highest robot growth rate and the worst productivity performance and decrease in employment. This result suggests that the economic activities included in this cluster may have been negatively affected by a fall in aggregate demand (e.g., the construction sector after the 2007 crisis), or they could have had a measurement problem (e.g., the outcome in the education sector was difficult to measure). Moreover, because productivity was given by the ratio between output value-added and employees when robotisation affected traditional industries, increased productivity was limited (e.g., food, beverages and tobacco). This cluster, which included very different industries, requires further investigation.

Table 4 about here

The role of robotisation in the service sector was difficult to assess. In the IFR database, all industries in the service sector are in only two categories: all other non-manufacturing and education/research. Information about the former is provided in Table. It was not surprising that the evidence of robotisation was not comparable with the values observed in manufacturing because services are generally provided by human activity. However, other results were significant. First, there were important differences in the relative weight of each cluster among countries. Second, the growth rate of robotisation in this macro-group was particularly high. While it is quite normal to have high growth rates starting from values close to 0, the potential expansion of robotisation in these sectors is huge. Because of the development of AI, it is likely that these sectors would also be substantially affected by automation and would have the same consequences experienced in the manufacturing workforce. Because services involved more than 60% of the total workforce in each country, the potential consequences for the labour market are dramatic. Therefore, policymakers should place this issue high on their agenda.

Table 5 about here

Finally, education (Table 5) was included in the B- cluster in all six countries. This evidence appears to counter the fact that modern societies are increasingly driven by the knowledge economy. Three main factors could explain this result. On one hand, the measurement of productivity in education is one of the most complex and probably less reliable operations in a cross-country analysis (Bradley et al., 2010; National Research Council and Sullivan, 2012). On the other hand, education, as previously explained, is mainly publicly funded (at least in EU countries), and it was negatively affected by the austerity policies following the 2007 crisis. Third, education is strictly related to population growth and the demand for education. These two variables, depending on the period analysed, could be negatively affected by the decreasing demand for education due to low birth rates. Nonetheless, further investigations of the implications of robotisation in this sector may be needed.

Conclusion

The results of previous theoretical and empirical investigations differ regarding the effects of robotisation and AI on productivity, employment and wages. Both optimists and pessimists, however, agree on the pervasiveness of the structural changes that economies now face because of robotisation and AI. In this work, we provided empirical evidence that both positive and negative scenarios could result from different economic structures with different economic specialisations. This finding implies differences in the ability and capacity to adopt new technologies. Moreover, different outcomes result from the peculiar and complex (Myrdal, 1957) circle of causation among productivity, employment, wages and aggregate demand. This further implies that this process is time-sensitive and depends on the current stage of development in a country as well as its socio-institutional features. The latter are not considered in this work.

In performing the cross-country and cross-sector cluster analysis, we showed that the resulting country–sector pairs were synthesised in five main clusters. The first cluster (A++) was the most robotised, showing that increasing productivity may be coupled with increasing labour utilisation and compensation, which is in line with the optimistic vision of the future. Nonetheless, this cluster, which was mainly composed of high technology industries, was by far the smallest in terms of the share of employment. The second and third clusters (A+ and A-) showed that while productivity increased with robotisation, labour utilisation decreased. The sectors in these clusters may experience labour dislocation; however, in A+, the wage increase was large enough to compensate for the decreasing trend in employment. In A-, the halving of labour utilisation negatively affected total wages. Finally, clusters B+ and B- included the stagnant sectors in terms of productivity. Nonetheless, B-, which experienced faster robotisation, showed labour dislocation.

The “doomsayers’ perspective” seems far from being realised because total wages increased in all countries except Italy. Overall, the results were in line with the optimistic vision. Clusters A- and A+ experienced the fastest growth in both robotisation and labour dislocation, which affected about 15% of the total labour force. This percentage may increase in the short to medium term because of the rapid expansion in the robotisation of sectors in cluster B, which at present employ more than 25% of the total labour force.

Although robots will not completely replace the human workforce in the short run, the issue of labour dislocation must be addressed by targeted policies because of its negative effects on employment and wealth polarisation in our countries. Specifically, because robotisation seems to be growing faster than the capacity of workers to acquire new skills, policies based on sustained income in conjunction with adult learning will be increasingly necessary in the near future.

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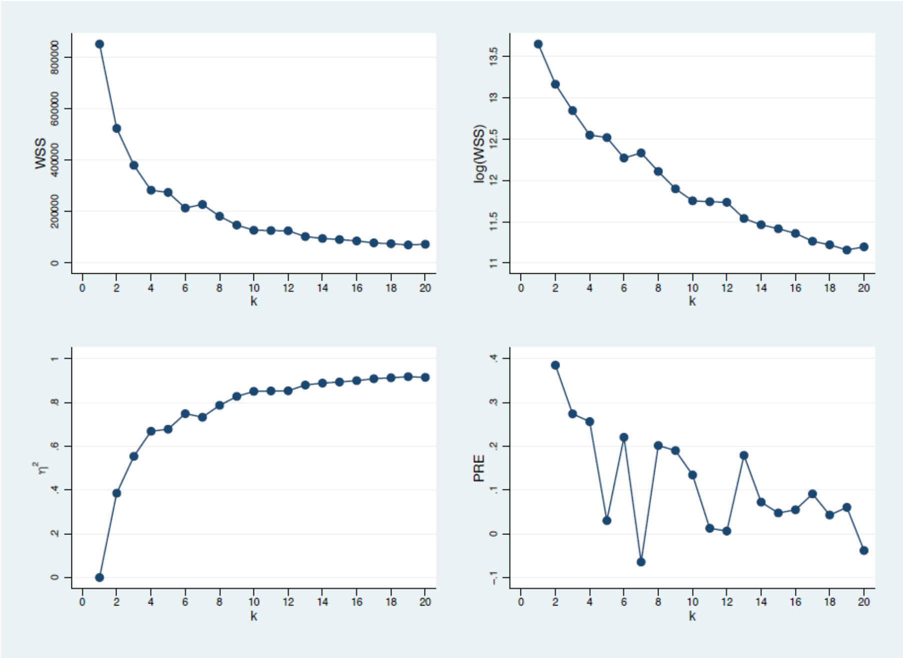
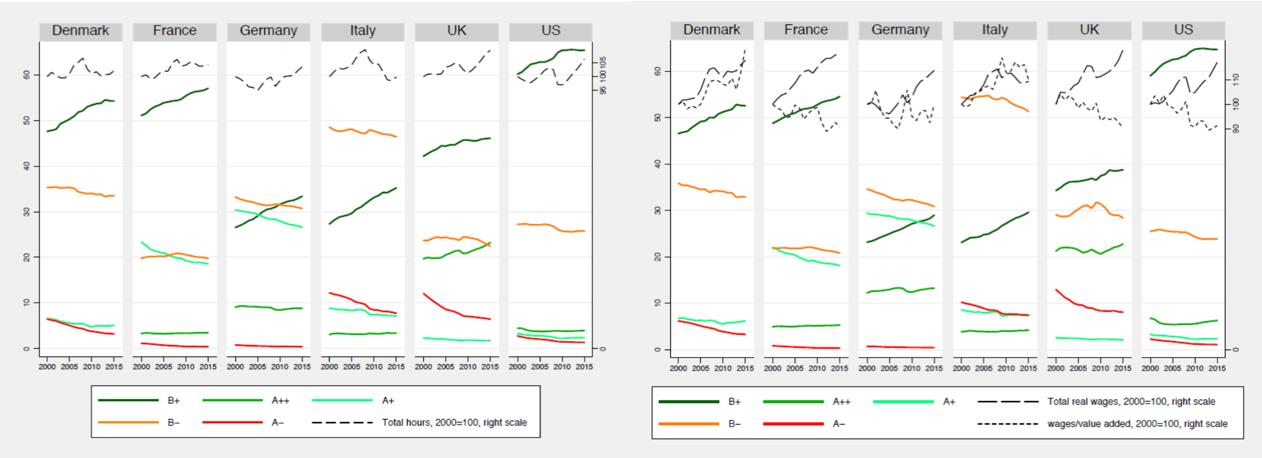
Figure 1: WSS, log (WSS), η^2, and PRE for all K cluster solutions



Note: Authors' elaboration from the STAN database.

Figure 2: Labour dislocation hours worked (left) and wages (right)



Note: authors' elaboration from the STAN database.

Table 1: Cluster (k-median) Results

CLUSTER		PRODUCTIVITY	VALUE ADDED	RELATIVE PRICE	HOURLY WAGE	HOURS WORKED	TOTAL WAGES
A++	**Mean**	170.45	177.50	71.57	167.89	106.24	175.81
	Median	166.87	182.92	67.27	174.58	109.62	174.33
	N	9	9	9	9	9	9
A+	**Mean**	141.85	111.29	86.93	140.57	79.66	110.87
	median	133.92	108.34	88.90	140.24	77.04	111.10
	n	19	19	19	19	19	19
A-	**mean**	143.50	73.54	89.92	140.70	52.40	72.55
	median	135.50	74.73	89.48	139.70	57.93	73.27
	n	17	17	17	17	17	17
B+	**mean**	104.41	125.16	104.25	109.5718	122.4583	132.5686
	median	110.70	125.13	103.18	110.4702	118.2017	132.127
	n	38	38	38	38	38	38
B-	**mean**	103.21	100.03	115.36	97.42	98.12	94.67
	median	100.93	98.06	112.78	93.75	97.17	97.05
	N	40	40	40	40	40	40

Note: Authors' elaboration from the STAN database. Mean and median values are computed on the "n" country-sectors in the cluster.

Table 2: Country–Sector Distribution of Clusters

	DENMARK	FRANCE	GERMANY	ITALY	UK	US
MANUFACTURING AND CONSTRUCTION						
CONSTRUCTION	B-	B-	B-	B-	B+	B-
ELECTRICAL, ELECTRONIC AND OPTICAL EQUIPMENT	A+	Out	A++	A+	A-	out
FOOD PRODUCTS, BEVERAGES AND TOBACCO	A-	B+	B-	B-	A+	B-
FURNITURE; OTHER MANUFACTURING; REPAIR AND INSTALLATION OF MACHINERY AND EQUIPMENT	A+	A+	B-	B-	A-	A+
TEXTILES, WEARING APPAREL, LEATHER AND RELATED PRODUCTS	A-	A-	A-	A-	A-	A-
TRANSPORT EQUIPMENT	A-	B-	A++	A+	A++	A+
WOOD AND PAPER PRODUCTS, AND PRINTING	A-	A+	A+	A-	A-	A-
BASIC METALS AND FABRICATED METAL PRODUCTS; MACHINERY AND EQUIPMENT	B-	A+	B-	A+	A-	B-
PLASTIC AND CHEMICAL PRODUCTS, GLASS, CERAMICS, STONE, MINERAL PRODUCTS	A+	A+	A+	A-	A-	B-
SERVICES						
ACCOMMODATION AND FOOD SERVICE ACTIVITIES	B+	B+	B-	B+	B+	B+
ARTS, ENTERTAINMENT AND RECREATION	B-	B+	B-	B+	B+	B+
EDUCATION	B-	B-	B-	B-	B-	B-
FINANCIAL AND INSURANCE ACTIVITIES	B+	B+	B-	B-	B-	B+
HUMAN HEALTH AND SOCIAL WORK ACTIVITIES	B+	B+	B+	B-	B+	B+
INFORMATION AND COMMUNICATION	Out	A++	A++	A++	A++	A++
OTHER SERVICE ACTIVITIES	B-	A+	B-	B+	B+	B-
PROFESSIONAL, SCIENTIFIC AND TECHNICAL	B+	B+	B+	B+	A++	B+
PUBLIC ADMINISTRATION AND DEFENCE; COMPULSORY SOCIAL SECURITY	B-	A+	A+	B-	B-	B+
REAL ESTATE ACTIVITIES	B+	B+	B+	B-	B+	B+
TRANSPORTATION AND STORAGE	B-	B-	B+	B-	B-	B-
WHOLESALE AND RETAIL TRADE, REPAIR OF MOTOR VEHICLES AND MOTORCYCLES	B+	B+	A+	B+	B+	B+

Note: authors' elaboration from STAN database.

Table 3: Manufacturing, Clusters and Robots

		ROBOT INTENSITY IN 2015= ROBOT/EMPLOYEES (THOUSANDS)	ROBOT AVERAGE GROWTH RATES BETWEEN 2011 AND 2015
A++	Mean	47	3.54
	Median	37	3.29
A+	Mean	17	7.09
	Median	10	2.43
A-	Mean	8	13.41
	Median	2	6.38
B+	Mean	3	-2.16
	Median	3	-2.16
B-	Mean	13	10.38
	Median	6	13.13

Note: authors' elaboration from the IFR database.

Table 4: Services, Clusters and Robots

	ROBOT INTENSITY IN 2015= ROBOT/EMPLOYEE(THOUSANDS)	ROBOT AVERAGE GROWTH RATES BETWEEN 2011 AND 2015	PERCENTAGE OF SERVICE SECTORS IN CLUSTER:			
			B+	A++	A+	B-
DENMARK	0.002	n/a	54%	0	0	36%
FRANCE	0.002	44.58	63%	9%	18%	9%
GERMANY	0.015	47.14	36%	9%	18%	36%
ITALY	0.003	51.87	45%	9%	0	45%
UK	0.001	32.46	54%	18%	0	27%
US	0.002	33.34	72%	9%	0	18%

Note: authors' elaboration from the IFR database.

Table 5: Education and Robot

	ROBOT INTENSITY IN 2015 = ROBOT/EMPLOYEE(THOUSANDS)	ROBOT AVERAGE GROWTH RATES BETWEEN 2011 AND 2015	CLUSTER
DENMARK	0.3	0.02	B-
FRANCE	0.1	22.21	B-
GERMANY	0.8	-1.52	B-
ITALY	0.1	8.79	B-
UK	0.1	3.69	B-
US	0.1	35.93	B

Note: authors' elaboration from IFR database.

Appendix A (source: own calculation based on IFR Database)

Table 1A: Robot Intensity and Robot Average Growth Rate: Denmark, France, Germany

		robot intensity 2015	robot average growth rates (2011-–2015)
DENMARK	Construction	0.21	+24.71%
	Basic metals and fabricated metal products; machinery and equipment	41.01	-1.22%
	Electrical, electronic and optical equipment	15.52	-1.13%
	Food products, beverages and tobacco	17.33	+10.25%
	Furniture; other manufacturing; repair and installation of machinery and equipment	2.04	-1.21%
	Plastic and chemical products, Glass, ceramics, stone, mineral products	19.63	+10.11%
	Textiles, wearing apparel, leather and related products	27.33	+6.13%
	Transport equipment	35.40	+9.79%
	Wood and paper products, and printing	14.34	-6.37%
	Education	0.31	+0.02%
	All other services	0.002	.
FRANCE	Construction	0.14	+23.10%
	Basic metals and fabricated metal products; machinery and equipment	10,27	+0.73%
	Electrical, electronic and optical equipment	5,52	-0,40%
	Food products, beverages and tobacco	5,15	+7,25%
	Furniture; other manufacturing; repair and installation of machinery and equipment	1,84	+9,37%
	Plastic and chemical products, Glass, ceramics, stone, mineral products	10,75	-0,06%
	Textiles, wearing apparel, leather and related products	0,47	-1,68%
	Transport equipment	76,55	-6,70%
	Wood and paper products, and printing	3,34	+9,42%
	Education	0,13	+22,21%
	All other services	0,002	+44,58%
GERMANY	Construction	0,09	+10,32%
	Basic metals and fabricated metal products; machinery and equipment	20,26	+5,03%
	Electrical, electronic and optical equipment	10,17	+2,27%
	Food products, beverages and tobacco	7,69	+3,50%
	Furniture; other manufacturing; repair and installation of machinery and equipment	3,65	-10,90%
	Plastic and chemical products, Glass, ceramics, stone, mineral products	18,91	+2,43%
	Textiles, wearing apparel, leather and related products	1,81	+7,13%
	Transport equipment	93,52	+3,29%
	Wood and paper products, and printing	3,19	-10,82%
	Education	0,775	1,52%
	All other services	0,015	+47,19%

Table 2A: Robot Intensity and Robot Average Growth Rate: Italy, UK and US

		robot intensity 2015	robot average growth rates (2011--2015)
ITALY	Construction	0.22	+13.12%
	Basic metals and fabricated metal products; machinery and equipment	25.83	+2.56%
	Electrical, electronic and optical equipment	6.43	+1.57%
	Food products, beverages and tobacco	14.80	+20.86%
	Furniture; other manufacturing; repair and installation of machinery and equipment	3.11	+2.84%
	Plastic and chemical products, Glass, ceramics, stone, mineral products	21.23	-8.74%
	Textiles, wearing apparel, leather and related products	0.65	-2.07%
	Transport equipment	61.89	-5.26%
	Wood and paper products, and printing	4.41	+8.09%
	Education	0.10	+8.78%
	All other services	0.003	+51.87%
UK	Construction	0.07	-11.57&
	Basic metals and fabricated metal products; machinery and equipment	4.10	+11.08%
	Electrical, electronic and optical equipment	2.34	+0.71%
	Food products, beverages and tobacco	2.95	+8.42%
	Furniture; other manufacturing; repair and installation of machinery and equipment	1.14	+6.84%
	Plastic and chemical products, Glass, ceramics, stone, mineral products	6.95	+6.38%
	Textiles, wearing apparel, leather and related products	0.16	+1.79%
	Transport equipment	36.71	+5.06%
	Wood and paper products, and printing	0.41	-7.68%
	Education	0.08	+3.69%
	All other services	0.001	+32.46%
US	Construction	0.19	+26.70%
	Basic metals and fabricated metal products; machinery and equipment	10.88	+15.94%
	Electrical, electronic and optical equipment	25.73	+17.37%
	Food products, beverages and tobacco	5.63	+14.15%
	Furniture; other manufacturing; repair and installation of machinery and equipment	7.09	+64.87%
	Plastic and chemical products, Glass, ceramics, stone, mineral products	9.61	+14.20%
	Textiles, wearing apparel, leather and related products	0.28	+60.10%
	Transport equipment	69.23	+15.32%
	Wood and paper products, and printing	0.35	+126.21%
	Education	0.05	+35.93%
	All other services	0.002	+33.34%

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[i] Corresponding author.

[ii] Dosi and Virgillito (2019) discussing Freeman (1992) and Freeman and Soarte (1994).

[iii] According to Bárány and Siegel (2018) and the OECD (2018b), manufacturing, among the economic sectors, was the most affected by automation in the recent past and is likely to be the most affected in the near future (McKynsey and Company, 2017).

[iv] The multiplier effect is the effect according to which each new high-tech job in the US creates five additional jobs in the service economy.

[v] Therefore, reverse causality in the relation cannot be excluded because robotization can be considered the reaction of firms to increasing salaries and labour utilization. This hypothesis, however, seems less plausible given the ongoing reduction of labour shares.

[vi] The French economist Jean Fourastié called the years between the late 1940s and the early 1970s 'les trente glorieuses', which stand out as the period of the fastest economic growth in Europe's history (Crafts and Toniolo, 2012).

[vii] UK National Statistical Office.

[viii] For instance, Italy-"Food Products, Beverages and Tobacco", Germany-"Food Products, Beverages and Tobacco", Italy - "Transport Equipment", etc.

[ix] Data on Japan are not complete in the STAN database.

[x] According to Eurostat (2009), in 2006, Germany was ranked first in the manufacture of motor vehicles, trailers and semi-trailers (NACE Division 34) in terms of value-added (68,225 million Euro—four times the value added of France, which ranked second at 47.4% of EU27 value-added in this sector) and persons employed (840,400 employees—three times the French workforce, which ranked second at 37.6% of EU27 employment in this sector).