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Do robots really destroy jobs? Evidence from Europe

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Do robots really destroy jobs? Evidence from Europe

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Abstract

While citizen opinion polls reveal that Europeans are concerned about the labour market consequences of technological progress, the understanding of the actual significance of this relationship is still imperfect. This paper assesses the impact of robot adoption on employment in Europe. Combining industry-level data on employment by skill-type with data on robot adoption and using different sets of fixed-effects techniques, we find that robot use is linked to an increase in aggregate employment. Contrary to some previous studies, we do not find evidence of robots reducing the share of low-skill workers across Europe. Since the overwhelming majority of industrial robots is used in manufacturing, our findings should not be interpreted outside of the manufacturing context. However, the results still hold when including non-manufacturing sectors and they are robust across a wide range of assumptions and econometric specifications.

Keywords: Robots, jobs, employment, low-skilled workers, inequality, European Union, economic activities

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Introduction

The impact of automation technologies on employment has been a highly debated topic since the beginning of the First Industrial Revolution. While previous technological advances have destroyed jobs in some sectors, job losses were usually offset by newly created jobs in other sectors in the medium to long term. This is exemplified by the well-documented shift from agriculture to manufacturing in the United States in the first half of the 20th century (Lebergott, 1966). Nonetheless, there is concern nowadays that the ongoing technological (digital) revolution may be different - that this time automation technologies may destroy more jobs than they create. News outlets often run stories about large-scale job destruction as a consequence of increased robot use, and in a recent Eurobarometer survey, 72% of respondents agreed to the statement that "*robots and artificial intelligence steal peoples' jobs*" (European Commission, 2017). Since not all jobs are equally exposed to automation, there are additional concerns about the impact of such trends on income inequality and social cohesion (Frey & Osborne, 2017; Graetz & Michaels, 2018).

In this paper we analyse the impact of one particular automation technology—advanced industrial robots—on total employment and on the share of low-skill employment in Europe over the last two and a half decades. Industrial robots can be defined as digitally controlled industrial machines whose purpose is the physical manipulation of objects.[1] They are often used in the literature as a proxy for advanced automation technologies, because data on their deployment are readily available since the early 1990s and they differ from traditional machinery in that they can handle tasks previously done by human workers, such as welding, bending and molding.

Combining data on the deployment of industrial robots across different economic sectors and European Union (EU) countries with data on employment by skill type, we construct a panel to explore the relationship between the increased use of robots and changes in total employment levels or in the share of low-skill employment between the years 1995 and 2015.[2] In contrast to a majority of the literature, we find that industrial robots are positively correlated with total employment. Also deviating from previous studies, we do not find evidence for a negative relationship between robot use and low-skill employment.[3] These results are very robust across a wide range of assumptions, estimator choices, sector selections and time periods and they hold whether we look at absolute numbers of robots, robots per 1000 workers or the percentile of robot density. We additionally control for country-sector and time fixed effects, changes in the capital-labor ratio, in capital formation and in the share of information and communications technology (ICT) capital and find that our results remain significant.

[1] For a precise definition of industrial robots according to ISO 8373:2012 see the first paragraph in Section 3.

[2] In particular, we look at the following countries: Austria, Belgium, Denmark, Finland, France, Greece, Germany, Ireland, Italy, the Netherlands, Portugal, Spain, Sweden and the United Kingdom. We use data on robot sales from the International Federation of Robotics (IFR, 2017) and employment data from the EU Labour Force Survey (EU LFS).

[3] We refrain from using an instrumental variables approach and hence are not in the position to interpret these relationships as causal. Graetz and Michaels (2018) have demonstrated that it is not straightforward to construct reliable instrumental variables for the analysis of this data and that the outcome does not change qualitatively compared to an OLS approach.

When interpreting the results in a policy context, the following points must be taken into account. First, our findings refer to recent and ongoing trends, but cannot be generalised into the future. Industrial robots have been around since the 1980s (although their broad deployment took place in the last two and a half decades, the period covered in this paper), and should not be confused with more advanced technologies such as AI-enhanced robots, that are not yet deployed at large scale. In the medium term, these more advanced robots may have much more disruptive potential. Second, since the overwhelming majority of industrial robots is used in manufacturing sectors, we cannot interpret these results outside of the manufacturing context. It would be particularly interesting to look at the effect of service robots on employment, but we are not aware of a dataset sufficiently rich for analysis (which may in fact reflect that service robots are still a relatively recent and rarely used technology). Third, judging from the explanatory power of the estimated models, the effect of robotisation is small compared to time and country-sector fixed effects, hence most of the variation we see in employment statistics are driven by other factors, such as a secular contraction of the manufacturing sector in Europe over the last decades (time fixed effects) and a shift in automotive manufacturing from Western to Eastern European countries (country-sector-specific effects). Fourth, we cannot fully discard the hypothesis that robots and employment are positively correlated because they both reflect higher investment and general economic success in specific sector-country pairs. We try to capture this effect to some extent by controlling for capital formation, but this does not suffice to completely discard this hypothesis. Fifth, if there are employment spillovers across sectors, the magnitude of the effect of robotisation on employment can be overstated (e.g., if robots displace workers who are then absorbed by other industries, one would be overestimating the negative effect of this technology on employment).

This paper is structured in the following way. After a review of the related literature in Section 2, we introduce the different datasets, indicators and methods we use in the analysis in the Section 3. In Section 4, we present some descriptive statistics and Section 5 contains the main results of the econometric analysis, as well as a robustness analysis and a critical discussion of our results in the light of previous research. Section 6 concludes and discusses policy implications.

Previous literature on robots and employment

The empirical literature on the effect of industrial robots on employment can be split into two groups: studies that use data from the International Federation of Robotics (IFR, 2017) as a source for information on robot deployment, and studies that use micro-economic data. In general, micro-economic studies tend to find a neutral or positive correlation between (low-skill) employment and the use of robots, suggesting a complementarity between robots and (low-skill) jobs. By contrast, the studies that rely on IFR data—which requires aggregation at the sectoral and national level—tend to find a negative correlation between robots and employment, at least for low-skilled workers. Overall, the studies are difficult to compare systematically, since they use different time periods, economic sectors and countries.

It is common in the literature using the IFR data to study the changes in employment and robot adoption over a specific time period by taking long differences between the first and the last year of the period. This reduces the importance of measurement error in the total variation but leads to a loss of data points. Graetz and Michaels (2018) use the EU Kapital Labour Energy Material Services (EU KLEMS) database to combine the IFR data with data on the share of low-, medium- and high-skill employment in different industries. Looking at changes in employment shares and robotisation between 1993–2007 in 14 sectors and 17 countries, they report a negative correlation between robotisation and the share of low-skill employment and no significant effect on total employment. Using a similar technique, Carbonero, Ernst and Weber (2018) analyse the period from 2000 to 2014 in 15 sectors and 41 countries. They find a negative correlation between robot adoption and total employment, which is more pronounced in developing countries but still exists in developed countries. De Backer, de Stefano, Menon and Suh (2018) analyse the period 2000 to 2014 and find a positive correlation between robots and employment in developed countries (depending on the the years analysed) and no correlation for developing countries. Borjas and Freeman use data from the American Community Survey (ACS) on employment and find that between 2004 and 2016 there has been a negative correlation between robots and employment, in particular low-skill employment, in the US.

Although the IFR data lacks regional detail, some authors choose to assign robots to different sub-national regions, based on the distribution of employment, in order to identify the effects of robot adoption based on spatial variation. Using this approach, Acemoglu and Restrepo (2019), Dauth, Findeisen, Südekum and Wößner (2017), Chiacchio, Petropopulos and Pichler (2018), and Antón, Fernández-Macías, Alaveras, Urzi Brancati and Klenert (2019) explore the impact of robots on employment on the US, Germany, different selections of EU countries, respectively. This approach has the advantage that local employment spillover effects between sectors are accounted for, since the smallest unit of analysis is a region, not a sector.

Acemoglu and Restrepo (2019) find a negative effect of robots on employment and wages.[4] Dauth et al. (2017) report a negative impact on industrial employment and wages in Germany (each robot destroys two manufacturing jobs), which is, however, counteracted by the effect of robots on the rest of the economy. The overall effect on total employment is thus neutral when employment spillovers between sectors are accounted for. The results of Chiacchio *et al*. (2018) suggest a negative impact of robotisation on employment and wages in six European countries. Antón et al.

[4] For an in-depth discussion of their results see Mishel and Bivens (2017). Acemoglu and Restrepo (2019) also make use of an industry-based strategy and find results similar to their regional analysis.

(2019) explore a wide range of specifications and find that the outcome strongly depends on the time period analysed: while results for the period 1995-2005 are ambiguous and strongly dependent on specific assumptions, positive effects of robots on employment prevail in the period 2005-2015. Throughout both periods the authors do not find evidence for an effect in terms of polarisation of labour markets in Europe. This approach is currently subject to several criticisms related to the validity of the so-called Bartik-type instruments (Adão, Kolesár & Morales, 2019; Apfel, 2019; Borusyak, Hull & Jaravel, 2018; Goldsmith-Pinkham, Sorkin & Swiftz, 2018; Jaeger, Ruist & Stuhler, 2018).

Another method for obtaining a richer dataset is combining the IFR data with micro-economic data on employment: this method assigns each household a measure of robot exposure, depending on the sector in which the household is employed. Dauth *et al.* (2017) find that, between 1994 and 2014 in Germany, every additional robot has destroyed two manufacturing jobs - however, this has been exactly offset by job creation in the service sector. Jansson and Karabulut (2019) directly analyse the effect of robot exposure on wealth ownership of households in Sweden between 1999 and 2007. They report a negative correlation between the two factors, which is especially pronounced for low-skill households.

Among the studies based solely on micro-economic data, Jäger, Moll and Lerch (2016) have the broadest geographical coverage. They use data from the European Manufacturing Survey for analysing the relationship between industrial robots, employment and productivity across 3000 firms in 6 EU countries and Switzerland for the year 2012. The authors find a neutral effect of robots on employment and a significant positive effect on productivity. Koch *et al.* (2019) use a panel of manufacturing firms in Spain, which covers the years 1990 to 2016 and around 1900 manufacturing firms. They find that robot adoption is correlated with increased employment and output, while non-robot-adopting firms had falling employment rates. Domini, Grazzi, Moschella, & Treibich (2019) confirm the existence of a positive correlation between automation and aggregate employment for the case of France. These studies suggest complementarity between employment and robots at the micro-level that seems harder to detect when looking at aggregate data.[5] This conclusion is also in line with Raj and Seamans (2018)'s call for more micro-based studies on AI and robotisation.

Some of the studies cited above go beyond our exclusive focus on employment (Carbonero *et al.*, 2018; de Backer *et al.* 2018; Graetz & Michaels, 2018). Additional studies using the IFR data focus more on the process of robot adoption (Fernández-Macías, Antón & Klenert, 2019; Jungmittag, 2019), on the effect of robots on productivity (Graetz & Michaels, 2018; Jungmittag & Pesole, 2019; Kromann, Malchow-Møller, Skaksen & Sørensen, 2019), and on the effects of robots on trade and offshoring (Carbonero *et al.*, 2018; de Backer *et al.* 2018; Krenz et al., 2018). It is also worth mentioning that there is an extensive body of literature examining the labour market consequences of technological change that goes beyond robots, mainly focused on the task-content of jobs and its effect on different segments of the labour force (see, among others, Autor, 2015, Barbieri, Piva, Mussida & Vivarelli, 2019, and Fernández-Macías & Hurley, 2016, for recent surveys on the topic).

[5] However, estimates based on small units are not necessarily superior to estimates based on aggregated units (even if the aggregation is based on micro-data). This is particularly true if there are spillovers across units, for instance, a worker moving from a sector in which employment is reduced by a phenomenon—such as robots—to a sector where employment benefits from that phenomenon.

In sum, the reviewed literature is inconclusive on whether robots increase or decrease employment. Studies that use IFR data tend to find negative or null correlations between robotisation and employment, while studies that use micro-economic data find positive or neutral effects. How can this inconsistency be explained? On the one hand, the effects of robots on employment are likely to be small compared to other trends that occurred over the same time period (Mishel and Bivens, 2017). On the other hand, no two studies look at the same years, economic sectors and countries, which makes them hard to compare systematically.

As we show below, even though we use the IFR data we find a positive correlation between robotisation and total employment and no evidence for a negative correlation regarding the low-skill employment share. Our empirical analysis differs from previous studies in the following factors, which explain the difference in outcomes: (1) in our benchmark analysis, we focus on the manufacturing sectors, which contain the overwhelming majority of all industrial robots (including non-manufacturing sectors still leads to the same effects but with a reduced magnitude); (2) we use data from the EU Labour Force Survey (LFS) instead of EU KLEMS data (we also use EU KLEMS data as a robustness exercise which leads to significant differences in some estimations. The differences between the two datasets are discussed in Section 3); (3) we calculate robot density by dividing the number of robots in given country-sector pair by the stock of robots in the same country-sector in 1995, not by employment in each year, to avoid endogeneity issues. Graetz and Michaels (2018) is the study that is most similar to our study but comes to different conclusions and focus on more restricted period of analysis. We show that when we reintroduce these factors in our estimation we come to similar results as Graetz and Michaels (2018).[6] This is described in detail in Section 5.3.

Data and methods

Data description

In this paper, we use the World Robotics database, compiled by the International Federation of Robotics (IFR, 2017), as our source for data on annual shipments of industrial robots. The International Organisation for Standardisation defines an industrial robot as "*an automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications*" (ISO 8373:2012). For more details on the exact specification of these robots see Annex D.

The IFR data cover the period between 1993 and 2016 and more than 40 countries, including all EU 28 countries except for Cyprus and Luxembourg. Robots are classified according to the International Standard Industrial Classification of All Economic Activities Revision 4, which is equivalent to European Classification of Economic Activities Revision 2 (NACE Rev. 2). The data in manufacturing sectors are mostly provided at the two-digit level, whereas outside of manufacturing they are provided at the one-digit level only. It is evident from Figure 1 that almost all industrial robots in Europe are deployed in manufacturing, and that within manufacturing four

[6] When comparing our results to Graetz and Michaels (2018) we only refer to the results they obtain using an OLS estimator. They also use an instrumental variable approach, which aims at solving the endogeneity issue regarding robot density and at determining causality in the relationship between robotisation and employment.

subsectors—automotive (29-30), metal products (24-25), rubber and plastic (22-23) and machinery (28)—account for more than 80% of all industrial robots.

The IFR estimates the operational stock of industrial robots from annual robot shipments, by assuming that a robot depreciates at a rate of 100% after 12 years of use. Since we encountered several problems with the original stock data, we follow Graetz and Michaels (2018) in reconstructing the robot stock ourselves based on the annual shipment data and a yearly depreciation rate of 10%. Our results do not change qualitatively if we use depreciation rates of 5 or 15 % or assume full depreciation after 12 years.

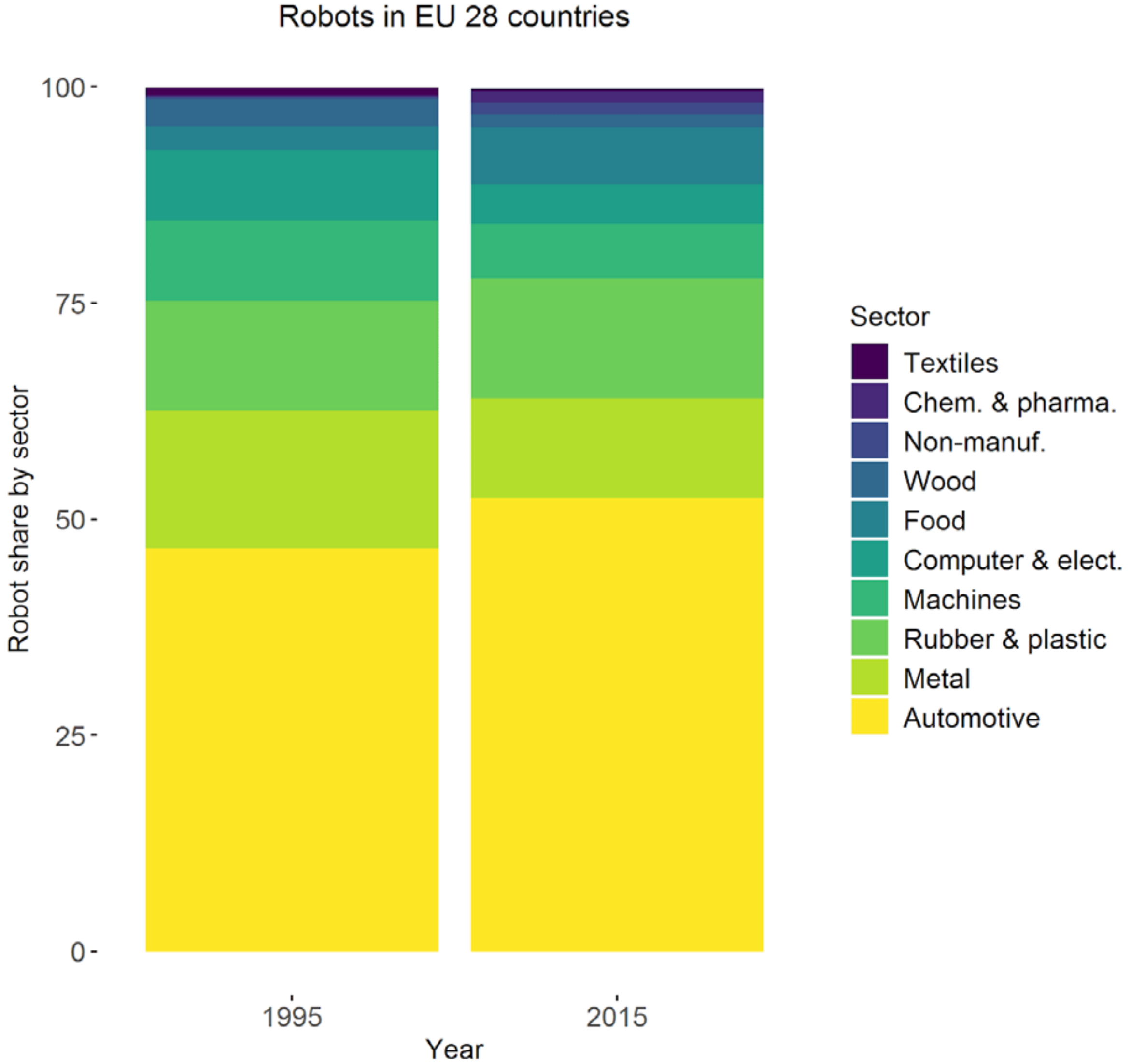
In order to get a relative measure of the degree of robot adoption independent of the size of an economic sector, we define an indicator of robot density as the number of robots per 1000 employees. For descriptive statistics, robot density is given as the number of robots divided by employment in each year. By contrast, when we use robot density as the independent variable in a regression analysis, we calculate it as the number of robots divided by employment in a base year (usually 1995). Still, in the robustness analysis we show that even when using absolute numbers our results remain qualitatively unchanged.

For data on total employment and employment by skill level, we rely on the European Labour Force Survey (EU-LFS). Employment is categorised by educational attainment according to the United Nations Educational, Scientific and Cultural Organization's 2011 International Standard Classification of Education (ISCED): low-skill employment corresponds ISCED 0–2, medium-skill employment to ISCED 3–4 and high-skill employment to ISCED 5–8. The EU-LFS covers more countries and years than EU KLEMS, which is the main reason for using the EU-LFS. This does not imply that EU-LFS data is superior to EU KLEMS - in fact, data on employment by skill level in EU KLEMS is mainly taken from the EU-LFS (Jäger, 2017). The EU-LFS data can vary significantly from year to year when looking at specific sectors or categories of employment. This is why, apart from yearly data, we also look at 3 and 5-year averages, which smooths out most of the short-term fluctuations, and long-difference estimators. However, there is no large difference in outcomes between the different methods.

Finally, we use a number of control variables, such as the capital-labour ratio, the ICT share of total capital stocks and gross fixed capital formation, from the 2017 release of the EU KLEMS database (van Ark & Jäger, 2017). However, since some country-sector pairs are missing, especially in capital accounting, using these control variables reduces the number of observations in some estimations. For countries that use a currency other than Euros we use exchange rates from EUROSTAT. Descriptive statistics for the variables used in this study are presented in Table C1.

Since the datasets cover different time periods, countries and sector aggregates, the more control variables we include the lower the number of observations becomes (see Table C1). Also, due to the change in NACE classification in 2007/8, some economic sectors are aggregated to ensure consistency over the entire time period. Since the aggregates differ between IFR and EU KLEMS data, we had to further aggregate sectors to a 'common denominator' to ensure proper matching between all datasets. See Table C2 in the appendix for the sector classification used in this study.

Figure 1. Sector shares in robot stock in the years 1995 and 2015 in Europe.



Note: Sectors: A: Agriculture, forestry and fishing, B: Mining and quarrying, D-E: Electricity, gas and water, F: Construction, P: Education, 10-12: Food, drink and tobacco, 13-15: Textiles, 16-18: Wood, paper and printing, 19-21: Fossil fuels, chemicals and pharmaceuticals, 22-23: Rubber, plastic and mineral products, 24-25: Metal products (excl. machines), 26-27: Computer, electronic and electrical equipment, 28: Machinery and equipment, 29-30: Automotive.

Source: Authors' analysis from World Robotics database

Methods

For most regression analyses in this paper we use estimations of the following form:

$$X_{cst} = \beta_1 + \beta_2\, robots_{cst} + \beta_3 controls_{cst} + \varepsilon_{cst}, \quad (1)$$

where *X* is the variable of interest (total employment, low-skill employment, low-skill employment share of total employment, change in total employment compared to the initial year), *robots* is a measure of robotisation (robot stock, robot density, percentile of robot density) and *controls* includes a vector of covariates (capital-labour-ratio, capital formation, ICT share of capital). The indexes *c*, *s* and *t* stand for the respective country, sector and year (or, in the case of averages over several years, *t* refers to each time period).

For the first-difference estimator, the estimation changes slightly to

$$\Delta X_{cst} = \beta_1 + \beta_2\, \Delta robots_{cst} + \beta_3 \Delta controls_{cst} + \varepsilon_{cst}. \quad (2)$$

In the case of the long-difference estimator, the estimation becomes

$$\Delta X_{cs} = \beta_1 + \beta_2\, \Delta robots_{cs} + \beta_3 \Delta controls_{cs} + \varepsilon_{cs}, \quad (3)$$

where *ΔX* refers to the change in the variable *X* between the first and the last year (in most cases between 1995 and 2015). In all the specifications above, we also control for time-, sector-, country- and sector-country-specific effects, as well as country- or sector-specific time trends in some of the models.

Robots and employment in Europe: descriptive results

Manufacturing employment has been declining in Europe since the 1970s - a process often referred to as *deindustrialisation*. At the same time, in all advanced economies, service sectors are continuously increasing their share of employment at the expense of agriculture and manufacturing. The causes of this phenomenon are multiple and there is still a lively debate on the relative importance of each one of them (Wren, 2013). Among the most important factors discussed in the literature are income effects (as income grows, an increasing share of demand and economic activity is directed towards higher hierarchical needs, often corresponding to intangible services), sector-biased productivity growth (productivity growth is faster in manufacturing than in services, so that the latter tends to increase its share of total employment; Baumol, 1967), outsourcing (some activities of manufacturing are subcontracted to companies in the service sector, thus reducing the share of employment classified as manufacturing) and international trade (which generates specialisation in activities for which each country has better technology and factor endowments, and would tend to shift manufacturing employment from developed to developing economies).

This process of deindustrialisation is illustrated in Figure 2 for the main European economies and EU15 on average[7]. In 1970, all depicted countries had more than 20% of employment in manufacturing, in some cases even more than 30% (Germany and the UK). Nowadays, all countries shown have a percentage below 20%. In fact, except for Germany and Italy, the percentage is always below 15%, and it even goes below 10% in the UK and Sweden.

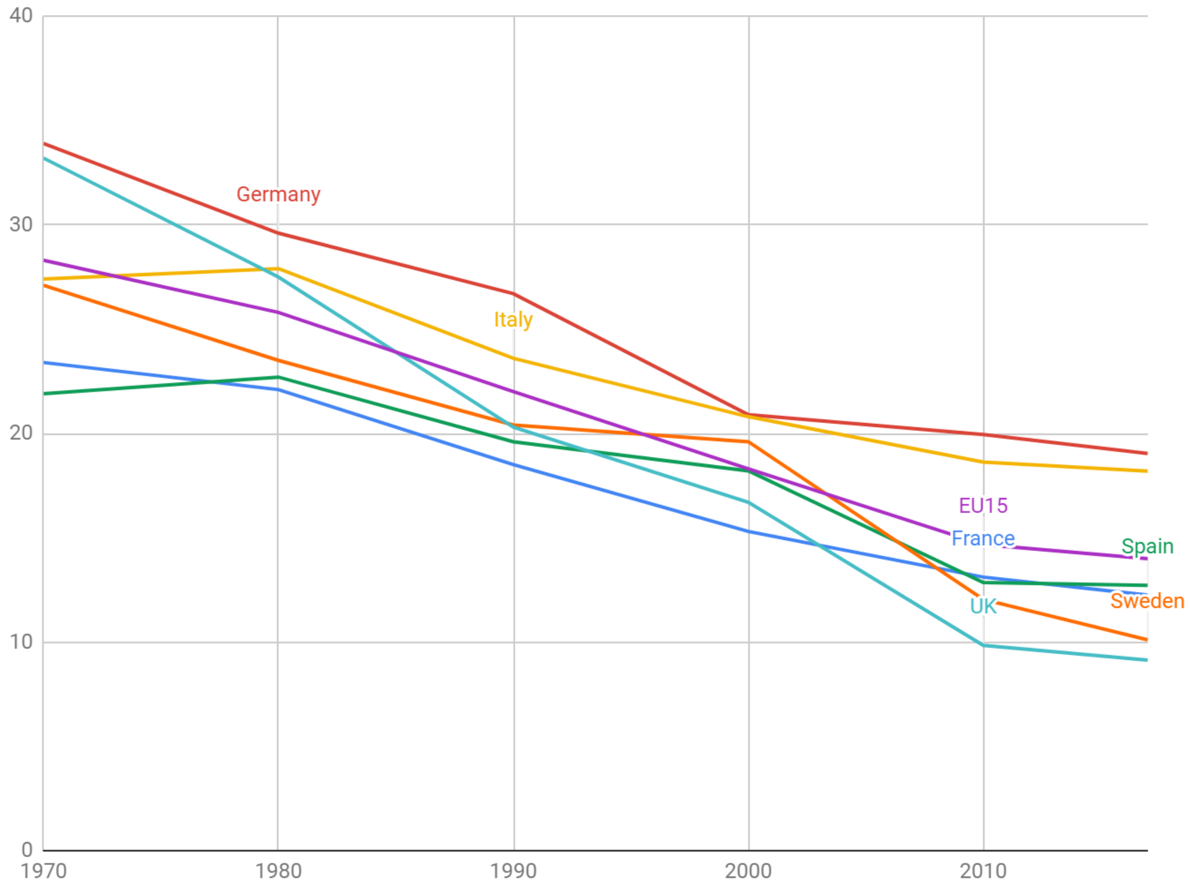
For most of the 20th Century, technological progress has been much faster in manufacturing than in services (see, e.g., Baumol [1967] and Baumol and Bowen [1965]). This generated a large differential in productivity growth between the two sectors which has been one of the main factors that reduced the share of employment in manufacturing relative to services. As discussed in Fernández-Macías et al. (2019), the advanced industrial robots that we are analysing in this paper should be understood as part of this long-run automation process, affecting mostly the last two decades shown in Figure 2.

The installation of advanced industrial robots took off in European manufacturing from the late 1990s (Fernández-Macías et al., 2019). If this would have provoked a major disruption in terms of employment, we would expect to see an acceleration in the pace of deindustrialisation over the last few decades in Figure 2. However, there seems to be a more or less continuous decline from the 1970s, with no generalised acceleration over the last two decades. There are some countries such as the UK and Sweden, that accelerated their rate of deindustrialisation after 2000, but in other countries, a *deceleration* took place instead over the same period (Germany, Italy, France). For the EU15 as a whole, the pace of decline is rather constant since the 1970s, in fact slowing down slightly in the most recent period.[8] In other words, the broad trends of employment in manufacturing do not suggest an acceleration of deindustrialisation as a result of a major technological disruption in the last 20 years, but rather a continuation of a secular decline in manufacturing employment that started decades earlier. Similar trends can be observed in other developed economies such as the US, Japan or Australia.

[7] EU15 refers to the number of EU member countries prior to 1 May 2004. These countries are: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, Sweden, the United Kingdom.

[8] Marschinski and Martínez Turegano (2019) show that this slowdown is even more pronounced when looking at deflated data instead of nominal indicators.

Figure 2: Share of employment in manufacturing in Europe (1970–2016).

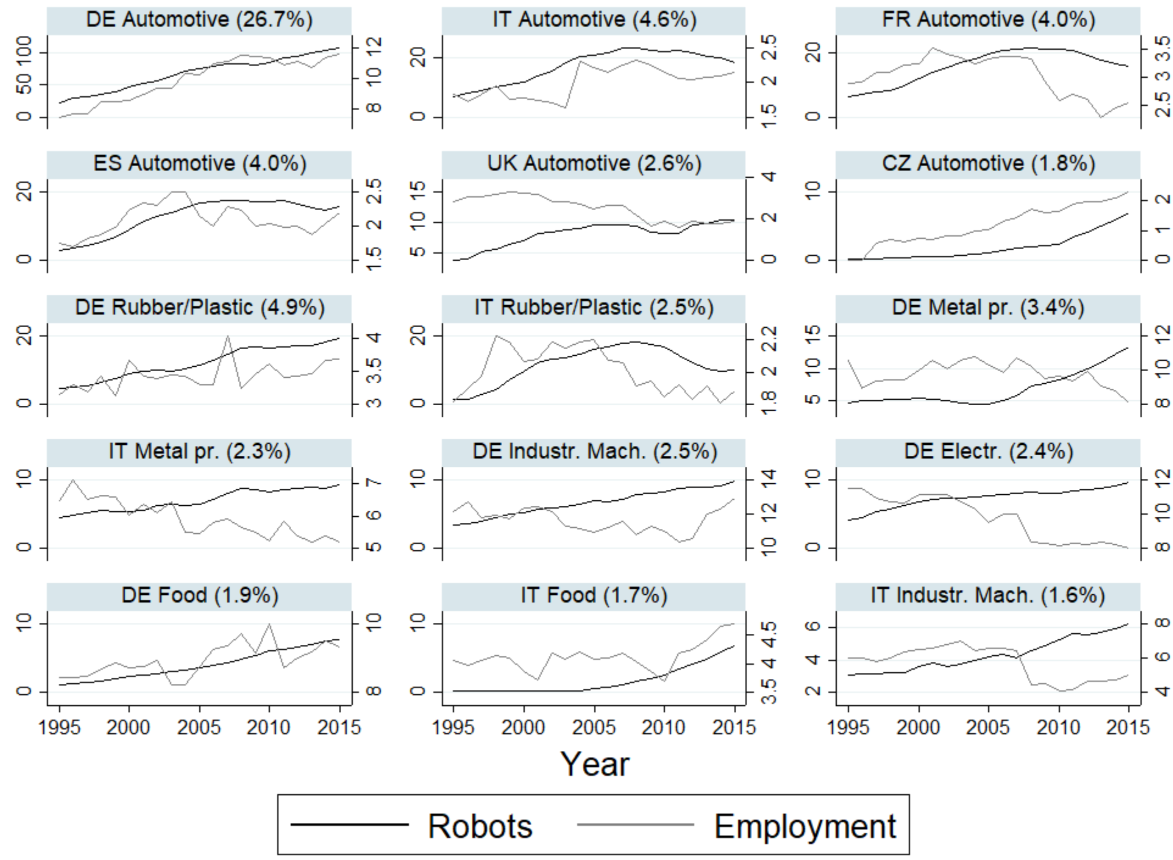


Source: Authors' analysis from EU KLEMS database and EUROSTAT.

But these very broad trends may conceal diverging developments across countries and sectors, perhaps reflecting a significant (though probably not major) labour replacement effect of advanced industrial robots in the last couple of decades. As a first simple approximation, Figure 3 shows the evolution over the last two decades of the stock of robots and employment for the 15 largest manufacturing sector-country pairs in Europe, which account for two thirds of all the industrial robots currently installed in the EU (the share of the total EU stock of robots of each sector-country is indicated in the chart subtitles: for instance, German car manufacturing accounts for 26.7% of all European industrial robots in 2015). The chart is purely illustrative, simply showing how the absolute number of robots and the absolute number of workers in those sectors have evolved over the last two decades.

Figure 3 does not suggest a large-scale replacement of employment by robots in most cases. For instance, in German car manufacturing (by far the heaviest user of robots in Europe), there has been a similar trend over the last two decades in terms of the stock of robots and the number of workers: both increased steadily and similarly (see the first chart in Figure 3). Italian, Spanish and Czech car manufacturing, as well as German rubber and plastics and food sectors follow a similar pattern. In other cases, the evolution of robot stocks and employment appear to go in opposite directions, more in line with the replacement hypothesis, for example in Italian metal sectors.

Figure 3: Absolute change in robot stocks and employment in the top 15 European sectors in terms of robots use (1995–2015).

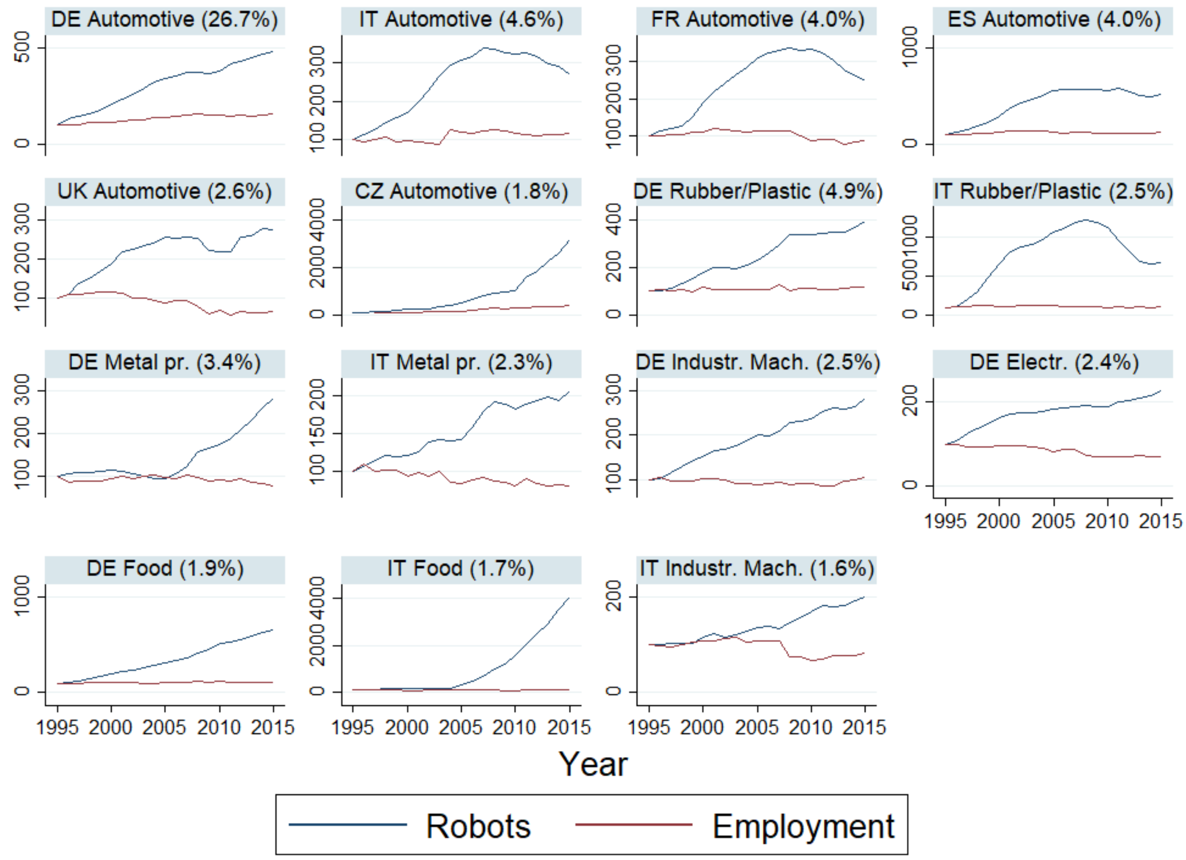


Note: % between parentheses refer to share of total EU robot stock in 2015. Y axes differ for robots and employment since values are displayed in absolute numbers. Left y axis: robot stock in thousands. Right y axis: employment in hundreds of thousands.

Source: Authors' analysis from World Robotics database and EU-LFS.

However, even for illustrative purposes, Figure 3 has the shortcoming that the scales used for representing robot stocks and employment are very different. This is fixed in Figure 4, which shows the same figures but values are given relative to the value in the first year (1995), so that both scales are comparable. We can immediately see that the magnitude of change of both variables is radically different: whereas robot stocks expanded significantly relative to the initial values, employment changed only marginally regardless of whether it moved up or down.

Figure 4: Relative change in robot stocks and employment in the top 15 European sectors in terms of robots use (1995–2015, 1995=100).



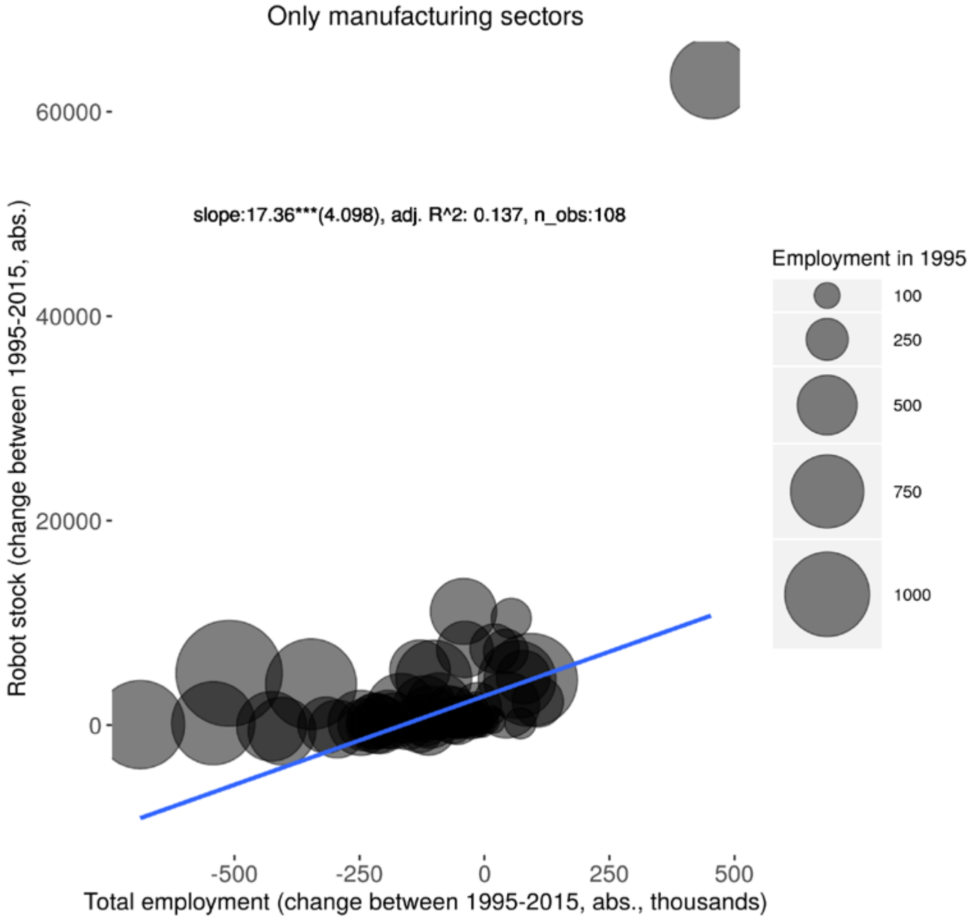
Note: % between parentheses refer to share of total EU robot stock in 2015. Robots and employment change os given in percent compared to the respective 1995 levels.

Source: Authors' analysis from World Robotics database and EU-LFS.

Figure 4 demonstrates that a simply descriptive approach is not sufficient to analyse such a complex problem: while in some country-sector pairs employment moves *with* the number of robots, in others it moves in the opposite direction. Country and sector specifics, time trends and other factors such as the capital-labour ratio have to be carefully accounted for using an econometric approach. Also, at least in relative terms, changes in employment appear to be smaller in magnitude than changes in robotisation.

Figure 5 presents a more complete exploration of the correlation between change in the absolute number of robots and employment between 1995 and 2015, covering this time all the available observations in the manufacturing sector. Each circle in the chart represents change in the absolute number of robots (vertical axis) and change in the absolute number of workers (horizontal axis) in a given sector-country combination, with the size of the circle representing initial employment. The figure shows that the empirical correlation between change in robots and change in employment is small but positive, as indicated by the regression line superimposed in the scatterplot, as well as the regression equation shown above. When non-manufacturing sectors are included in the analysis, the relation becomes weaker, but remains positive. The key point of Figure 5 is that the increase in robot stocks tends to go together rather than against overall employment, an empirical regularity that is difficult to square with the idea that advanced industrial robots are having a significant and disruptive labour displacement effect on European manufacturing.

Figure 5: Change in robot stocks and change in employment (1995–2015, absolute numbers, employment in thousands).

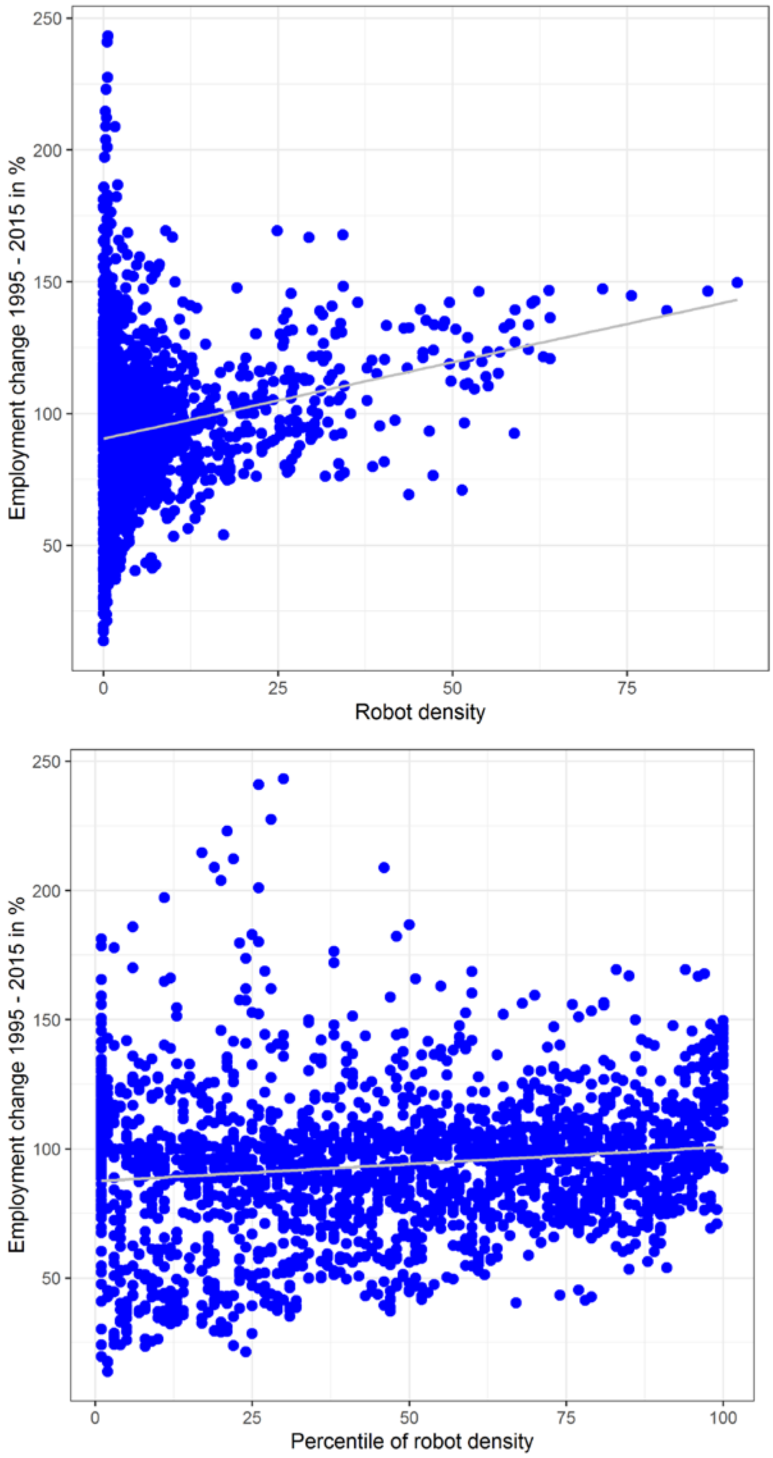


Note: The outlier in the top right corner is the German automotive sector.
Source: Authors' analysis from World Robotics database and EU-LFS.

Using absolute numbers of industrial robots and persons employed makes the interpretation of the results more straightforward but complicates the comparison of country-sector pairs of different sizes. As mentioned in Section 3, for robot adoption, a solution is to construct a "robot density" indicator such as the number of robots per 1,000 workers in a sector. For total employment, we can look at the change in employment compared to the initial year. With regard to employment by educational attainment, we analyse shares of total employment. In the rest of this paper, to ensure that our results are robust to alternative parameterizations, we consider all these indicators and mention whenever the estimation results change qualitatively.

But even if we use a relative measure of robot adoption such as robot density, values are relatively small and the distribution has a long right tail (see Figure 6, top panel), which makes the fitting of a linear model more complicated since outliers in the tail might disproportionately impact the outcome. To check whether outliers drive our estimations outcomes and analoguous to Graetz and Michaels (2018), we additionally use the percentile of the robot density distribution as an independent variable to check for the robustness of our results (see Figure 6, bottom panel). We verify that this choice does not change the estimation qualitatively.

Figure 6: Robot density and change in total employment (1995–2015)

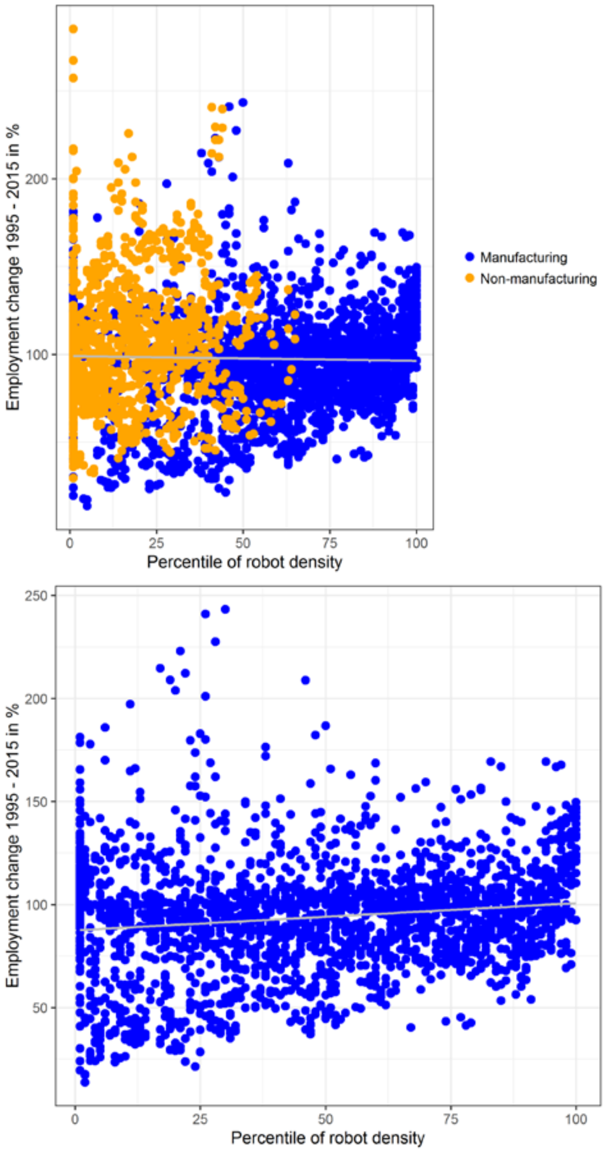


Notes: Top panel: Robot density and change in total employment compared to 1995. Bottom panel: Percentile of robot density and change in total employment compared to 1995. Only manufacturing sectors (10–12, 13–15, 16–18, 19–21, 22–23, 24–25, 26–27, 28, 29–30). 14 countries: AT, BE, DE, DK, ES, FI, FR, GR, IE, IT, NL, PT, SE, UK.

Source: Authors' analysis from World Robotics database and EU-LFS.

Another crucial point in the analysis is the selection of the analysed sectors. Since industrial robots are primarily used in the manufacturing sectors (see Figure 1), including non-manufacturing sectors (which tend to be large in terms of employment but lack significant robot deployment) such as Agriculture (A), Mining (B), Utilities (D–E), Construction (F) and Education (P) leads to the same conclusions but with a reduced magnitude, especially when the percentile of robot density is used as the independent variable. This is illustrated in Figure 7. Non-manufacturing sectors are plotted in orange and manufacturing sectors in blue. It can be seen right away that when the non-manufacturing sectors are included in the regression, the regression line is completely flat. When only manufacturing sectors are included, the regression line has a positive slope. Still, this effect is partially offset by controlling for sector/country fixed effects, as we discuss in the next section.

Figure 7: Percentile of robot density and change in total employment (1995–2016)



Notes: Left panel: Including non-manufacturing sectors (A, B, D-–E, F and P). Right panel: only manufacturing sectors (10–12, 13–15, 16–18, 19–21, 22–23, 24–25, 26–27, 28, 29–30). 14 countries: AT, BE, DE, DK, ES, FI, FR, GR, IE, IT, NL, PT, SE, UK.

Source: Authors' analysis from World Robotics database and EU-LFS.

Robots and employment in Europe: econometric analysis

This section provides a detailed econometric analysis of the relationship between robot adoption and total employment, as well as the composition of employment in terms of skill levels. We use a sectoral approach in the sense that each sector in each country at a given time counts as one observation.

Section 5.1 contains the main results, which are derived using a within-group Ordinary Least Squares (OLS) estimator, controlling for country-sector and time fixed effects. Standard errors are clustered at the country-sector level, robust to unknown forms of heteroskedasticity and serial correlation. We use yearly data for the main analysis, but we check if the results hold when averaging over three and five year periods in Section 5.2, where we also use a first-difference and a long-difference estimator (using only the initial and the final year in the case of the long-difference estimator). This also increases the comparability of the results to other studies such as Graetz and Michaels (2018). We do not weigh the observations, as some authors do, by within-country employment shares, except in Section 5.3, for comparison purposes to other literature. We additionally control for changes in the total stock of capital, in the ICT share of capital and in the capital-labour ratio. These variables are likely endogenous to some extent, but, as it is beyond the scope of this paper to solve this issue, we include them in some specifications in order to test the robustness of the econometric results.

We use different measures of robot adoption: the total robot stock in a country, robot density (calculated as the number of robots per 1,000 workers, see Section 3 for details), the percentile of the robot density distribution and, for the long-difference estimator, the percentile of change in robot density between the first and the last period (analogous to Graetz & Michaels, 2018). In terms of employment, we look at absolute numbers of total and low-skill employment, as well as at the share of low-skill employment and the change in total employment compared to the base year. We analyse two different time periods: 1995–2007 and 1995–2015. This makes our results comparable to previous studies which mostly stop in 2007 and it also has the advantage to check for possible distortions by the 2007 change in NACE classification and the financial crisis of 2007–2008.

Main results

Our main results are as follows. For the full period from 1995–2015, we find a significant positive correlation between the percentile of robot density and the change in total employment compared to 1995 (Table 1). The correlation remains positive when controlling for sector-country and time fixed effects and other explanatory variables, and when robot density or robot stock is used as the independent variable. The results in Table 1 can be interpreted as moving from one percentile in the robot density distribution to the next leading to an increase of 0.40 (+/− 0.12)% in total employment compared to 1995. Looking at the robot density directly instead of percentiles (see Table A1 in Annex A), the result can be interpreted as one additional robot per 1,000 workers being correlated with an increase of 1.31 (+/−0.22) % in total employment. Finally, in absolute numbers, this can be interpreted as one additional robot being correlated with 5 (+/− 2) additional workers (see Table A2 in Annex A). The exact magnitude of these correlations depends to some extent on the control variables, but this finding is very robust.

Table 1: The effects of robot density percentile on total employment (1995–2015)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Percentile of robot density	0.141* (0.065)	−0.416** (0.111)	0.457** (0.127)	0.479** (0.14)	0.395** (0.116)	0.373** (0.117)	0.518** (0.156)
Capital/labour ratio				−4.986 (16.261)	−28.466 (15.298)		−7.497 (17.127)
Gross fixed capital formation					0.001** (0.000)	0.001** (0.000)	
ICT capital share							−255.234 (187.917)
Sector/country fixed effects		✓	✓	✓	✓	✓	✓
Time fixed effects			✓	✓	✓	✓	✓
Adj. R^2	0.021	0.551	0.697	0.759	0.78	0.763	0.754
No. of observations	2,340	2,340	2,340	1,494	1,190	1,518	1,190

*Notes: Pooled OLS, yearly data, only manufacturing sectors. Results of regressing the change in total employment (in percent) on robot density percentile. This table corresponds to the right panel in Figure 6. Standard errors clustered at the country/sector level are displayed between parentheses. ** significant at the 1% level; * significant at the 5% level.*

Source: Authors' analysis from World Robotics database, EU-LFS and EU KLEMS.

We also find a very small, sometimes significant, correlation between robot adoption and the low-skill employment share that can be negative or positive, depending on the control variables and the choice of the estimator. When controlling for changes in the capital/labour ratio, the correlation becomes even smaller and is no longer significant (see Table 2). The correlation vanishes completely in all estimations when using a long-difference estimator (see Section 5.2). This behavior does not depend on the estimator we use, the choice of the independent variable (robot density, robot density percentile, robot stock) and the choice of the dependent variable (low-skill employment share, absolute low-skill employment numbers). We therefore conclude that with the available data we are not able to find conclusive evidence for a significant, robust correlation between robot adoption and low-skill employment, be it negative or positive, neither in absolute numbers, nor as a share of total employment.

Table 2: The effects of robot density percentile on low-skill employment share (1995–2015)

	(1)	(2)	(3)	(4)	(5)	(6)
Robot density	-0.001 (0.001)	-0.006** (0.001)	0.001 (0.001)	0.000 (0.001)	0.000 (0.001)	0.001 (0.001)
Capital/labour ratio				0.050* (0.025)	0.042 (0.026)	0.055* (0.027)
Gross fixed capital formation						0.000 (0.000)
ICT capital share					-1.052 (0.632)	
Sector/country fixed effects		✓	✓	✓	✓	✓
Time fixed effects			✓	✓	✓	✓
Adj. R^2	0.008	0.854	0.942	0.94	0.946	0.945
No. of observations	2,340	2,340	2,340	1,494	1,190	1,190

*Notes: Pooled OLS, yearly data, only manufacturing sectors. Results of regressing the low-skill employment share on robot density. Standard errors clustered at the country/sector level are displayed between parentheses. ** significant at the 1% level; * significant at the 5% level.*

Source: Authors' analysis from World Robotics database, EU-LFS and EU KLEMS.

For the first period (1995–2007), the effects regarding total employment are comparable to those of the full period when looking at relative numbers. One additional robot per 1000 workers is correlated with an increase of 1.17 (+/-0.19) % of total employment compared to 1995 (see Table 3). In absolute numbers, the effect in the first period is more pronounced (Table A3 in Annex A): one additional robot is correlated with 10 (+/-1) additional workers.

Table 3: The effects of robot density on total employment (1995–2007)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Robot density	0.471** (0.137)	0.933** (0.134)	1.197** (0.173)	1.296** (0.169)	1.174** (0.189)	1.206** (0.209)	1.332** (0.187)
Capital/labour ratio				−38.752** (11.781)	−54.582** (13.448)		−41.263** (11.88)
Gross fixed capital formation					0.001* (0.000)	0.000 (0.000)	
ICT capital share							476.592 (295.068)
Sector/country fixed effects		✓	✓	✓	✓	✓	✓
Time fixed effects			✓	✓	✓	✓	✓
Adj. R^2	0.041	0.673	0.687	0.725	0.745	0.726	0.734
No. of observations	1,443	1,443	1,443	896	720	928	720

*Notes: Pooled OLS, yearly data, only manufacturing sectors. Results of regressing the change in total employment (in percent) on robot density. Standard errors clustered at the country/sector level are displayed between parentheses. ** significant at the 1% level; * significant at the 5% level.*

Source: Authors' analysis from World Robotics database, EU-LFS and EU KLEMS.

Regarding low-skill employment in the first period, we do not find a positive correlation between the low-skill employment share and any measure of robotisation, but we find a positive correlation in absolute numbers between low-skill employment and the robot stock. In the period 1995–2007 one additional robot is correlated with 2 (+/-1) additional low-skill workers (see Table 4). However, this does not imply a positive effect on the low-skill workers' share of total employment, since one additional robot is correlated with 10 (+/−1) additional workers (Table 3). Hence, only for sectors in which the low-skill workers' share of total employment is below 20%, an increase of two workers would lead to an increase in the low-skill employment share.

Table 4: The effects of robot stock on low-skill employment (1995–2007)

	1	2	3	4	5	6
Robot stock (abs.)	0.006* (0.003)	0 (0.001)	0.001** (0)	0.002** (0.001)	0.002** (0.001)	0.002** (0.001)
Capital/labour ratio				25.394 (21.665)	27.967 (23.952)	34.924 (27.728)
Gross fixed capital formation					16.473 (680.973)	
ICT capital share						0 (0)
Sector/country fixed effects		✓	✓	✓	✓	✓
Time fixed effects			✓	✓	✓	✓
Adj. R^2	0.065	0.95	0.959	0.963	0.963	0.963
No. of observations	1443	1443	1443	896	720	720

*Notes: Pooled OLS, yearly data, only manufacturing sectors. Results of regressing low-skill employment on robot stock. Standard errors clustered at the country/sector level are displayed between parentheses. ** significant at the 1% level; * significant at the 5% level.*

Source: Authors' analysis from World Robotics database, EU-LFS and EU KLEMS.

Robustness checks

This section analyses the robustness of our results with regard to variations in estimators, sector selection, averaging over years and the construction of the stock. Regarding estimators, we additionally use a first-difference and a long-difference estimator (which are different alternatives for controlling for time-invariant unobserved heterogeneity). The long-difference estimator only uses observations from the first and last year and thus has the additional advantage to filter out short-term fluctuations, that is, if there is a relevant measurement error in the robot variable, this estimator might reduce its weight on total variation compared to other estimators. On the other hand, it might yield distorted results since it omits a large number of observations. We find that both estimators confirm the results from the previous section (see Tables B1 and B2 in Annex B for results using long difference; results obtained using a first-difference estimator are available upon request).

In the benchmark analysis in the Section 5.1, we only include manufacturing sectors, since they comprise the large majority of all industrial robots (see also Figure 1). However, some other studies choose to also include sectors that have almost no industrial robots, whenever the data is available. Including all available economic sectors adds degrees of freedom but might increase unobserved heterogeneity and the likelihood of omitted relevant variables. We nevertheless redo the estimates for all economic sectors, to analyse whether our main findings are affected and for comparability with other studies. We find that, when non-manufacturing sectors are included, the correlation between total employment and robotisation is preserved in most cases but reduced in magnitude. We still do not find a correlation between the low-skill employment share and robotisation (see Tables B3 and B4 in Annex B).

To exclude the possibility that short-term fluctuations influence our main findings, we do the estimations also using 3 and 5 year averages. These fluctuations should be accounted for mostly by using time dummies, still we consider this a worthwhile robustness check. We find no qualitative differences in our results compared to the benchmark cases for either 3 or 5 year averages (for 5 year averages see Tables B5 and B6 in Annex B, results for 3 year averages are available on demand).

The data on the robot stock is in the original dataset delivered by the IFR has several flaws and thus most studies construct their own robot stocks from the IFR data on annual robot deliveries, assuming either a yearly depreciation rate or assuming the full depreciation of a robot after 12 years. The results in the benchmark analysis all use robot stock data compiled assuming a 10-year depreciation rate. We alternatively use a 5 and 15% year depreciation rate and also compile the stock under the assumption of full depreciation after 12 years. We find that these assumptions do not change our estimation results qualitatively (results for full depreciation after 12 years are given in Tables B7 and B8 in Annex B).

Comparison to previous research

The findings from Section 5.1 disagree with some of the results presented in Graetz and Michaels (2018) and other publications that analyse the relationship between robot adoption and employment. This is surprising to some extent, since we use the same data sources for the data on robots. Our results are, however, not directly comparable to Acemoglu and Restrepo (2019), Dauth, Findeisen, Südekum and Wößner (2017), Chiacchio et al. (2018) and Antón et al. (2019) since they derive their findings from spatial variation in robot exposure, while we look at variation between sectors.[9] In this section, we therefore focus on describing the roots of the differences between our analysis and the Graetz and Michaels (2018), another study that also analyses sectoral variation in robot exposure. Still, the main points also apply to other studies to some extent.

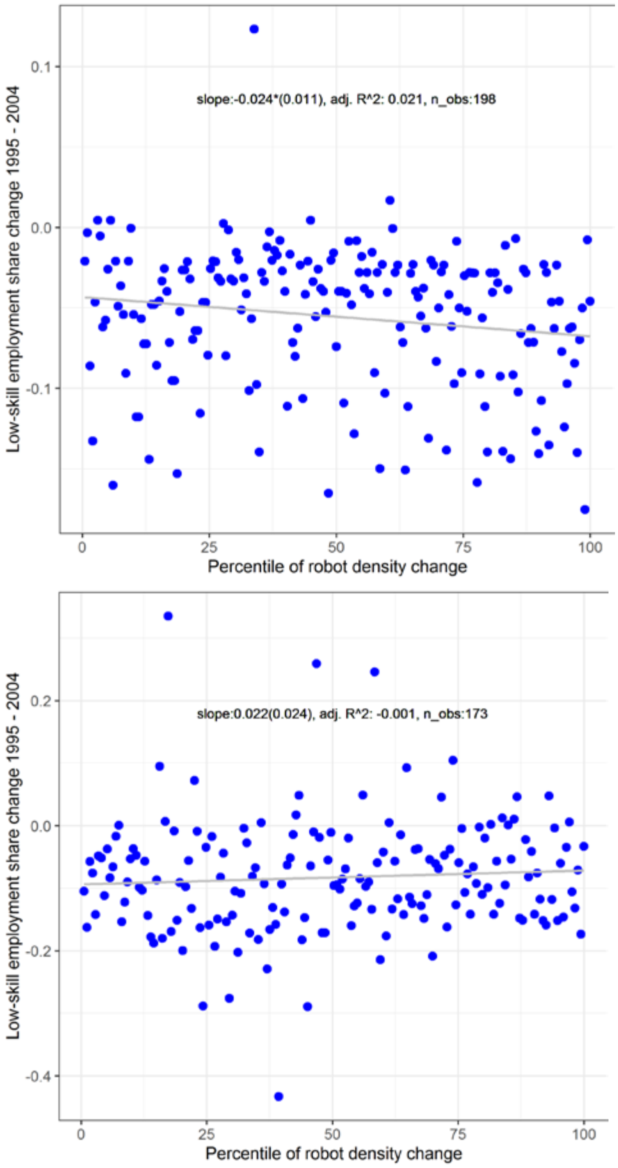
Regarding low-skill employment, we do not find robust evidence for correlations between robot adoption and the low-skill employment share, while Graetz and Michaels (2018) find a significant negative correlation that also appears to be robust over a large set of assumptions.[10] The majority of this difference is explained by the fact that we use data from the European Labour Force Survey

[9] The main difference between the spatial and the sectoral approach is that the former accounts for local employment spillovers, while the latter does not. Therefore, with a sectoral approach the magnitude of the relationship between robotisation and change in total employment might appear larger than it actually is.

[10] Although Graetz and Michaels (2018) additionally employ an instrumental variables-approach, their results are quite similar to those they obtained under OLS. Therefore, we refer here to the comparison between their OLS estimates and ours.

(LFS), while Graetz and Michaels (2018) rely on data from the 2008 release of EU KLEMS[11]. Applying Graetz and Michaels' methods to the LFS data yields an almost flat line, while the same method applied to the EU KLEMS 2008 data yields a significant negative correlation between robot adoption and low-skill employment shares (see Figure 8).

Figure 8: Correlation between change in robot density and change in low-skill employment share (1995–2004).



[11] EU KLEMS is based on the EU LFS but is supplemented with national data sources. For some country-sector pairs it appears that KLEMS data are a smoothed version of LFS data. However, the exact data smoothing procedure is not clear from the documentation of EU KLEMS. To check whether the smoothing affects the results, we made estimations averaging all variables over 3- and 5- year periods. It is not straightforward to tell which dataset provides better quality data. From the point of view of coverage however, both in terms of years and countries, the EU LFS is clearly superior.

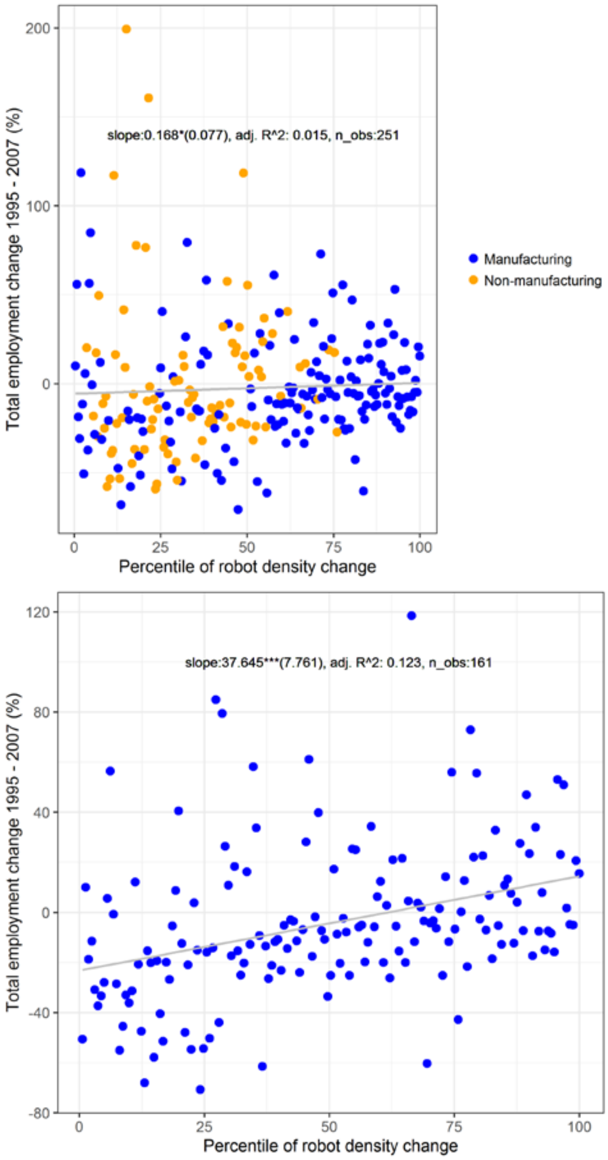
Figure 8: Left panel: using EU KLEMS data. Right panel: using LFS data. Both panels: standard errors clustered by sector, observations weighted by within-country employment share of sector (as Graetz & Michaels, 2018) and robot density calculated with yearly employment data. This allows for a direct comparison with Graetz and Michaels (2018), which demonstrates that differences in the findings regarding the low-skill employment share are mainly driven by differences between the EU KLEMS and the EU LFS datasets. 2004 is the last year for which employment data by skill level is reported in the 2008 edition of EU KLEMS.

Source: Authors' analysis from World Robotics database, EU-LFS and EU KLEMS.

While our results indicate a robust positive correlation between total employment and robot adoption, Graetz and Michaels (2018) do not find evidence for such a relationship. This case is a bit more complicated, since the differences arise from more than one factor. In fact, there are a total of four factors to consider, with the first two having the largest impact. First, Graetz and Michaels (2018) use the 2011 edition of EU KLEMS for data on total employment while we rely on the EU LFS. Second, when calculating the robot density, we use employment in the year 1995 in the denominator to avoid making employment endogenous, while Graetz and Michaels (2018), by contrast, use employment in each year in the denominator. The third and fourth factor are their choice to weigh robot densities by their within-country share of total employment and to include non-manufacturing sectors and countries with almost no robots. Still, when using data from KLEMS 2011, we demonstrate how relaxing each of these differing assumptions leads us from finding no significant correlation to finding a significant positive correlation, even when using the exact same data as Graetz and Michaels (2018). The main process is summarized in Figure 9.

In sum, this subsection demonstrates that Graetz and Michaels (2018)'s results using OLS estimations regarding the effect of robots on employment shares and total employment do not hold when some crucial factors are changed in the estimations. Taken together with the robustness checks in Subsection 5.2, it becomes evident that the effect of robots on employment (and employment shares by skill level) tend to be small and to some extent sensitive to the assumptions made. Still, we argue that the results reported in Subsection 5.1 are more robust than Graetz and Michaels' (2018) findings, since we analyse a longer time scale (21 years) than they do (11 years for the analysis on skill shares and 14 years for the analysis on total employment) and due to the large number of robustness checks we perform.

Figure 9: Correlation between change in robot density and change in total employment (1995–2004).



*Notes: Both panels use the same data from the 2011 edition of EU KLEMS. Left panel: specifications similar to Graetz and Michaels (2018): observations weighted by employment share in the country, robot density not normalized to 1995, non-manufacturing sectors included, dependent variable: change in the log of hours worked. Right panel: our specifications: observations unweighted, robot density normalized to 1995, only manufacturing sectors included, dependent variable: change in total employment since 1995 in percent. Standard error values in figures are clustered by sector. In sum, for total employment, the difference between Graetz and Michaels (2018) and our analysis is less in the data we use and more in the different assumptions in the estimation***.**

Source: Authors' analysis from World Robotics database, EU-LFS and EU KLEMS.

Conclusions

It has been much debated in the recent literature, whether increased use of robots has a detrimental effect on employment and, in particular, on low-skill employment. This debate has even reached public opinion and policy circles and the general tone has been rather pessimistic, stressing the potential of robots to replace workers. The current paper critically assesses this hypothesis using panel data on the deployment of robots in European manufacturing and employment by skill level over the last two and a half decades.

Our results suggest some skepticism regarding the allegedly disruptive effect of robots in employment in the recent past. In fact, we find a positive correlation between recent robot adoption in Europe and total employment for a wide range of specifications. For the period 1995 to 2015, our results demonstrate that one additional robot is correlated with five (+/−2) additional workers. In relative terms, the result can be interpreted as one additional robot per 1000 workers being correlated with an increase of 1.31 (+/−0.22) % in total employment. Regarding low-skill employment, we do not find evidence for the hypothesis that industrial robots reduce the share of low-skill employment after controlling for other factors such as sector-country and time-fixed effects, capital/labour ratios and (ICT and total) capital formation.

These results do not concur with the popular narrative of robots destroying jobs at a large scale. By contrast, our results demonstrate that country-sector pairs that have high levels of automation are more resilient to the ongoing decline in manufacturing, especially in terms of employment. Moreover, this suggests that powerful demand effects might be at play that ensure employment growth, despite labour-saving technical progress (Bessen, 2018). The current debate about robots increasing inequality might hence be misleading (Mishel and Bivens, 2017).

Previous studies on this topic generally fall into two camps. The first camp uses robot and employment data on the country/sector level and generally finds negative or no effects of robots on total employment and negative effects on low-skill employment. The second camp uses micro-economic data and generally finds a positive or neutral effect of robot adoption on total employment, as well low-skill employment at the firm level. Our analysis belongs to the first camp in terms of data and methods, but deviates from most other studies of that camp in terms of estimation outcomes. This difference is mainly a consequence of using a different data source on employment by skill level, a longer time series, the way we determine the robot density indicator and the fact that in our benchmark case we only analyse manufacturing sectors, since these are the sectors that employ the overwhelming majority of robots.

Of course, there are some important caveats to our results. First, we use a dataset on industrial robots. An industrial robot is a relatively established technology, which mostly relies on reprogrammable mechanical arms being able to move in three dimensions and which is generally used for tasks such as handling, welding and molding. However, it must also be acknowledged that industrial robots are essentially the only type of robots that have a measurable economic impact as of today. Second, data availability is a general problem when it comes to analysing the effect of new technologies such as AI, robots or similar technologies on society, and industrial robots are just a rough approximation of such a technology (Frank et al., 2019; Raj & Seamans, 2018). However, data availability reflects economic relevance to some extent, and while some of these new technologies may have an enormous disruptive potential, there is not much evidence yet supporting any large-scale effects. Third, the positive correlation we find between robot adoption and total employment has to be interpreted against the backdrop of a contracting manufacturing sector in

Europe. Our results imply that national industries with a higher robot adoption tend to be more resilient in terms of employment than the rest. This contradicts the idea that robots are replacing workers on any significant scale, but it cannot be understood either as proof that robot adoption is causally linked to employment growth. Most likely, both robot adoption and employment tend to go together because they reflect some underlying variable such as the resilience, competitiveness or innovative capacity of some national industries.

There is no doubt that robots have an effect on how we work and live that will likely increase over the coming decades. Still, our results demonstrate that, in the case of industrial robots, their impact on employment has mostly been positive (or neutral, in the case of low-skill employment). Taken together with findings from the literature showing that industrial robots have increased productivity (Graetz and Michaels, 2018; Jungmittag and Pesole, 2019), the benefits of this specific technology seem to outweigh their potential costs. However, in order to assess the final impact of these robots or any other technology on inequality, we would need to discuss issues such as ownership structures and tax systems, which goes beyond the scope of this paper. As a starting point, our work demonstrates that, so far, industrial robots do not represent a major disruption regarding employment in Europe.

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Annex A: Additional estimates

Table A1: The effects of robot density on total employment (1995–2015)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Robot density	0.580** (0.124)	-0.008 (0.293)	1.47** (0.181)	1.547** (0.162)	1.313** (0.222)	1.398** (0.204)	1.586** (0.172)
Capital/labour ratio				−11.897 (13.065)	−24.85 (14.309)		−12.811 (13.871)
Gross fixed capital formation					0.001* (0.000)	0.000 (0.000)	
ICT capital share							−108.504 (175.343)
Sector/country fixed effects		✓	✓	✓	✓	✓	✓
Time fixed effects			✓	✓	✓	✓	✓
Adj. R^2	0.047	0.529	0.711	0.795	0.803	0.786	0.794
No. of observations	2,340	2,340	2,340	1,494	1,190	1,518	1,190

*Notes: Pooled OLS, yearly data, only manufacturing sectors. Results of regressing the change in total employment (in percent) on robot density. Standard errors clustered at the country/sector level are displayed between parentheses. ** significant at the 1% level; * significant at the 5% level.*

Source: Authors' analysis from World Robotics database, EU-LFS and EU KLEMS.

Table A2: The effects of robot stock on total employment (1995–2015)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Robot stock (abs.)	0.025** (0.006)	0.006** (0.002)	0.009** (0.001)	0.010** (0.001)	0.006** (0.002)	0.005** (0.002)	0.011** (0.001)
Capital/labour ratio				136.664** (51.122)	95.764 (53.066)		175.71** (65.54)
Gross fixed capital formation					0.003 (0.002)	0.004* (0.002)	
ICT capital share							−911.321 (1112.831)
Sector/country fixed effects		✓	✓	✓	✓	✓	✓
Time fixed effects			✓	✓	✓	✓	✓
Adj. R^2	0.261	0.956	0.968	0.968	0.971	0.972	0.969
No. of observations	2,340	2,340	2,340	1,494	1,190	1,518	1,190

*Notes: Pooled OLS, yearly data, only manufacturing sectors. Results of regressing total employment in absolute numbers on robot stock. Standard errors clustered at the country/sector level are displayed between parentheses. ** significant at the 1% level; * significant at the 5% level.*

Source: Authors' analysis from World Robotics database, EU-LFS and EU KLEMS.

Table A3: The effects of the robot stock on total employment (1995–2007)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Robot stock (abs.)	0.029** (0.007)	0.009** (0.001)	0.011** (0.001)	0.011** (0.001)	0.01** (0.001)	0.01** (0.001)	0.012** (0.001)
Capital/labour ratio				−16.376 (43.17)	−44.631 (54.435)		−11.131 (45.853)
Gross fixed capital formation					0.002 (0.001)	0.001 (0.001)	
ICT capital share							1232.948 (1040.975)
Sector/country fixed effects		✓	✓	✓	✓	✓	✓
Time fixed effects			✓	✓	✓	✓	✓
Adj. R^2	0.223	0.987	0.988	0.986	0.987	0.988	0.986
No. of observations	1,443	1,443	1,443	896	720	928	720

*Notes: Pooled OLS, yearly data, only manufacturing sectors: Results of regressing total employment in absolute numbers on robot stock. Standard errors clustered at the country/sector level are displayed between parentheses. ** significant at the 1% level; * significant at the 5% level.*

Source: Authors' analysis from World Robotics database, EU-LFS and EU KLEMS.

Annex B: Robustness checks

Table B1: The effects of robot density percentile change on total employment change (long difference, 1995–2015)

	(1)	(2)	(3)
Percentile robot density change	56.064** (10.599)	64.919** (8.715)	38.192* (15.866)
Country/sector effects	No/No	Yes/No	No/Yes
Adj. R^2	0.194	0.288	0.338
No. of observations	123	123	123

*Notes: Long difference, only manufacturing sectors: Results of regressing change in total employment (in percent) on the robot density change percentile. Standard errors clustered at the country/sector level are displayed between parentheses (clustering at the sector level yields similar results). No additional control variables used, since this would reduce the number of observations too much to make meaningful estimates. ** significant at the 1% level; * significant at the 5% level.*

Source: Authors' analysis from World Robotics database, EU-LFS and EU KLEMS.

Table B2: The effects of robot density percentile change on the change in low-skill employment share (long difference, 1995–2015)

	(1)	(2)	(3)
Percentile robot density change	0.030 (0.039)	−0.025 (0.029)	0.042 (0.075)
Country/sector effects		✓	
Sector effects			✓
Adj. R^2	−0.002	0.396	0.028
No. of observations	107	107	107

*Notes: Long difference, only manufacturing sectors: Results of regressing the change in low-skill employment share on robot density change percentile. Standard errors clustered at the country/sector level are displayed between parentheses (clustering at the sector level yields similar results). No additional control variables used, since this would reduce the number of observations too much to make meaningful estimates. ** significant at the 1% level; * significant at the 5% level.*

Source: Authors' analysis from World Robotics database, EU-LFS and EU KLEMS.

Table B3: The effects of robot density on total employment (using 5-year averages, 1995–2015)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Robot density	0.625** (0.126)	−0.143 (0.342)	1.613** (0.204)	1.700** (0.175)	1.416** (0.247)	1.498** (0.234)	1.771** (0.191)
Capital/labour ratio				−5.305 (14.054)	−17.354 (15.742)		−5.416 (14.756)
Gross fixed capital formation					0.001 (0.000)	0.001 (0.000)	
ICT/non-ICT cap. ratio							3.971 (194.777)
Sector/country fixed effects		✓	✓	✓	✓	✓	✓
Time fixed effects			✓	✓	✓	✓	✓
Adj. R^2	0.056	0.496	0.72	0.802	0.815	0.799	0.803
No. of observations	470	470	470	311	247	311	247

*Notes: Pooled OLS, data averaged over 5 years, only manufacturing sectors. Results of regressing the change in total employment (in percent) on robot density. Standard errors clustered at the country/sector level are displayed between parentheses. ** significant at the 1% level; * significant at the 5% level.*

Source: Authors' analysis from World Robotics database, EU-LFS and EU KLEMS.

Table B4: The effects of robot density on low-skill employment share (using 5-year averages, 1995–2015)

	1	2	3	4	5	6
Robot density	-0.002 (0.001)	-0.007** (0.002)	0.001 (0.001)	0.000 (0.001)	0 (0.001)	0.001 (0.001)
Capital/labour ratio				0.067* (0.028)	0.054 (0.03)	0.069* (0.032)
Gross fixed capital formation					-0.898 (0.739)	
ICT capital share						0.000 (0.000)
Sector/country fixed effects		✓	✓	✓	✓	✓
Time fixed effects			✓	✓	✓	✓
Adj. R^2	0.007	0.875	0.953	0.943	0.945	0.945
No. of observations	470	470	470	311	247	247

*Notes: Pooled OLS, data averaged over 5 years, only manufacturing sectors. Results of regressing low–skill employment share on robot density. Standard errors clustered at the country/sector level are displayed between parentheses. ** significant at the 1% level; * significant at the 5% level.*

Source: Authors' analysis from World Robotics database, EU-LFS and EU KLEMS.

Table B5: The effects of robot density on total employment (all sectors, 1995–2015)

	1	2	3	4	5	6	7
Robot density	0.333* (0.131)	0.002 (0.29)	0.632** (0.239)	0.618* (0.253)	0.614* (0.243)	0.634** (0.233)	0.675** (0.254)
Capital/labour ratio				2.224 (3.817)	−0.066 (3.234)		2.02 (3.744)
Gross fixed capital formation					0.001** (0.000)	0.001** (0.000)	
ICT capital share							−130.837 (237.005)
Sector/country fixed effects		✓	✓	✓	✓	✓	✓
Time fixed effects			✓	✓	✓	✓	✓
Adj. R^2	0.009	0.53	0.564	0.588	0.646	0.634	0.592
No. of observations	3,682	3,682	3,682	2,430	1,936	2,468	1,936

*Notes: Pooled OLS, yearly data, all economic sectors. Results of regressing the change in total employment (in percent) on robot density. Standard errors clustered at the country/sector level are displayed between parentheses. The effects when only analysing manufacturing sectors remain significant (but less so) and become smaller—Table A1 displays the results when only using manufacturing sectors. ** significant at the 1% level; * significant at the 5% level.*

Source: Authors' analysis from World Robotics database, EU-LFS and EU KLEMS.

Table B6: The effects of robot density on low-skill employment share (all sectors, 1995–2015)

	1	2	3	4	5	6
Robot density	-0.001 (0.001)	-0.007** (0.001)	0.000 (0.001)	0.000 (0.001)	-0.001 (0.001)	-0.001 (0.001)
Capital/labour ratio				0.004 (0.005)	0.002 (0.005)	0.002 (0.005)
Gross fixed capital formation					0.138 (0.641)	
ICT capital share						0.000 (0.000)
Sector/country fixed effects		✓	✓	✓	✓	✓
Time fixed effects			✓	✓	✓	✓
Adj. R^2	0.003	0.893	0.949	0.943	0.952	0.953
No. of observations	3,682	3,682	3,682	2,430	1,936	1,936

*Table B6: Pooled OLS, yearly data, all sectors. Results of regressing low-skill employment share on robot density. Standard errors clustered at the country/sector level are displayed between parentheses. The result remains non-significant when compared to the case in which only manufacturing sectors are analysed (Table A2). ** significant at the 1% level; * significant at the 5% level.*

Source: Authors' analysis from World Robotics database, EU-LFS and EU KLEMS.

Table B7: The effects of robot density on total employment (12-year full depreciation, 1995–2015)

	1	2	3	4	5	6	7
Robot density	0.446** (0.085)	0.025 (0.189)	0.982** (0.118)	1.054** (0.115)	0.894** (0.14)	0.928** (0.128)	1.071** (0.121)
Capital/labour ratio				-13.813 (13.115)	-26.504 (14.37)		-14.115 (14.085)
Gross fixed capital formation					0.001* (0.000)	0.000* (0.000)	
ICT capital share							-130.98 (173.843)
Sector/country fixed effects		✓	✓	✓	✓	✓	✓
Time fixed effects			✓	✓	✓	✓	✓
Adj. R^2	0.049	0.528	0.711	0.796	0.805	0.786	0.795
No. of observations	2,338	2,338	2,338	1,492	1,188	1,516	1,188

*Notes: Pooled OLS, yearly data, only manufacturing sectors. Results of regressing the change in total employment (in percent) on robot density. The robot stock is calculated assuming full depreciation after 12 years. In the benchmark estimate (see Table A1), we assume a 10% depreciation rate. The results are similar but a little bit smaller in magnitude. Standard errors clustered at the country/sector level are displayed between parentheses. ** significant at the 1% level; * significant at the 5% level.*

Source: Authors' analysis from World Robotics database, EU-LFS and EU KLEMS.

Table B8: The effects of robot density on low-skill employment shares (12 year full depreciation, 1995–2015)

	1	2	3	4	5	6
Robot density	-0.001 (0.001)	-0.004** (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)
Capital/labour ratio				0.051* (0.025)	0.043 (0.026)	0.054* (0.027)
Gross fixed capital formation					-1.057 (0.629)	
ICT capital share						0.000 (0.000)
Sector/country fixed effects		✓	✓	✓	✓	✓
Time fixed effects			✓	✓	✓	✓
Adj. R^2	0.008	0.853	0.942	0.94	0.946	0.945
No. of observations	2,338	2,338	2,338	1,492	1,188	1,188

*Notes: Pooled OLS, yearly data, all economic sectors: Results from regressing low-skill employment share on robot density. The robot stock is calculated assuming full depreciation after 12 years. In the benchmark estimate (see Table A1), we assume a 10% depreciation rate. The results are similar and remain non-significant. Standard errors clustered at the country/sector level are displayed between parentheses. ** significant at the 1% level; * significant at the 5% level.*

Source: Authors' analysis from World Robotics database, EU-LFS and EU KLEMS.

Annex C: Descriptive Statistics and sector classification

Table C1: Descriptive statistics of the main variables

	1995-2015			1995			2015		
	Mean	SD	N	Mean	SD	N	Mean	SD	N
Robot stock	1,069	4,515	3,682	564	1,923	168	1,560	6,681	180
Robot density	3.6	8.7	3,682	1.8	4.2	168	5.4	11.7	180
Total employment (in thousands)	323.7	480.0	3,682	346.9	477.5	168	301.5	497.4	180
Low-skill employment (in thousands)	102.5	177.8	3,682	139.2	204.6	168	67.2	113.8	180
Low-skill share	0.32	0.19	3,682	0.43	0.22	168	0.24	0.16	180
ICT capital share	0.01	0.01	2,208	0.01	0.01	84	0.02	0.02	87
Capital labour ratio	0.74	1.58	2,430	0.47	0.52	84	0.83	1.79	100
GFCF (in million EUR, 2010)	42,194	73,542	2,468	33,362	59,343	97	54,172	94,810	87

Source: Authors' analysis from World Robotics Database, EU-LFS and EU KLEMS.

Table C2: Sector classification

Sector code	Sector description	Components
A	Agriculture, forestry and fishing	A
B	Mining and quarrying	B
D-E	Electricity, gas and water	D, E
F	Construction	F
P	Education	P
10-12	Food, drink and tobacco	10, 11, 12
13-15	Textiles	13, 14, 15
16-18	Wood, paper and printing	16, 17 , 18
19-21	Fossil fuels, chemicals and pharmaceuticals	19, 20, 21
22-23	Rubber, plastic and mineral products	22, 23
24-25	Metal products (excl. machines)	24, 25
26-27	Computer, electronic and electrical equipment	26, 27
28	Machinery and equipment	28
29-30	Automotive	29, 30

Notes: Sector classification based on NACE Rev 2. We had to aggregate some sectors to either ensure consistency over the change in NACE classifications in 2007/8 or for consistency between different data sources. All sectors with more than one component in the right column are aggregated. For instance, sector D-E is an aggregate of sectors D and E. Prior to 2008, in the NACE Rev 1.1 classification, D and E were denoted only by the letter E. For ensuring consistency over the entire time period we hence have to aggregate the two sectors.

Annex D: What kind of robots are we talking about?

The term robot is widely used in Science Fiction literature to refer to humanoid machines that serve humankind and often end up rebelling against it, embodying fears of uncontrolled technology and working class revolt. But the robots we analyse in this paper, which are the actually existing robots widely used in manufacturing (but rarely in other sectors) are very different from those of Science Fiction literature. These robots are digitally controlled industrial machinery (often mechanical arms) whose main purpose is the physical manipulation of objects. The IFR data we use in this paper also includes information on what these robots actually do (their “applications”). In Europe, 55% of all European robots perform “handling operations and machine tending”, which essentially involve moving things from one place to another with a certain degree of precision. The second category is welding and soldering (22%), which involves joining materials or items together by using high heat to melt the joining parts or by putting some filler metal into the joint. The third category is assembling and disassembling (5%), which refers to the sequential addition of standardised interchangeable parts to a complex product (such as a car, an electric appliance or electronic goods). Other significant (but much less prevalent) applications of robots in Europe involve painting, cutting, etc.

In other words, what industrial robots actually do is physical tasks that involve the moving and precise manipulation of objects within industrial processes. This is crucial for assessing the potential effect of robots on employment, since the amount of human labour still deployed on this kind of tasks is small, precisely because of the accumulated effect of many decades or even centuries of automation. Recent assessments of the task content of jobs across different sectors in Europe (Fernández-Macías et al., 2019; Fernández-Macías, Hurley & Bisello 2016) show that even within manufacturing, the intensity of physical tasks involving strength and dexterity (the ones replaceable by robots) is marginal compared to intellectual and problem-solving tasks. In fact, employment in manufacturing itself is rather small in Europe nowadays, between 10 and 20% in most European countries (it is only above 20% in the Visegrad region), again largely as a result of previous waves of automation. Thus, the potential for labour replacement of the types of robots we are talking about seems perforce rather limited.

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