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The impacts of robots on labour productivity

A panel data approach covering 9 industries and 12 countries

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The impact of robots on labour productivity

A panel data approach covering 9 industries and 12 countries

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Abstract

Based on the expectation that the intensified use of robots contributes to the growth of labour productivity, this paper presents estimates of Cobb-Douglas production functions, using data for 12 EU countries and 9 manufacturing industries. The empirical results for the models pooling all available data confirm that stocks of robots per 1 million Euros non-ICT capital input contribute significantly to labour productivity growth in the period from 1995 to 2015. The results remain robust, when the whole observation period is split into two subsamples from 1995 to 2007 and from 2008 to 2015. Furthermore, the model is used to assess the impact of an increase of robots use on the labour productivity in each of the 9 manufacturing industries considered.

Keywords: Automation, labour productivity, panel data, production function, productivity measurement, robots

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Introduction

The public debate on the growing deployment of robots and productivity unfold mostly around the disruptive effects these new technologies will bring in our way of organising work, firms' activities and their improved performances. Robots and technological change in more general terms bear the expectation of boosting productivity by directly increasing total factor productivity. That is, every increase in value added that is not explained by growth in production inputs (namely capital and labour) is due to technological progress. The underlying assumptions are that the technology production function has constant return to scale and that technological progress equally impacts all production factors. However, if instead technological progress is labour (capital) augmenting, the input share of labour (capital) is miscalculated resulting in overestimation of the contribution of labour (capital) and an underestimation of total factor productivity. This bias is relevant when the rate of return of technological progress grows much faster than the rate of return of labour or other types of capital. Thus, robotisation can lead to a productivity paradox similar to that observed by economists during the 90's (the Solow paradox) when to a sharp increase in ICT investment did not correspond an increase in productivity growth. As of today, the increased use of industrial robots and the advances in Artificial Intelligence (AI) are posing similar challenges in estimating their impact on productivity.

The International Federation of Robotics (IFR), following the definition of the International Organization for Standardization, defines an industrial robot as "automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes" (ISO 8373) with the potential of automating the production processes by executing complete tasks. According to the 2017 IFR report, in 2015 sales of robots worldwide increased by 15% with respect to previous year and according to the Association for Advancing Automation (2019) a record number of robots were shipped to North America in 2018 with a 7% increase over 2017 and with more non-automotive companies installing robots.

However, before calling for the advent of a new industrial revolution, two points are worth making. First, the automation process date back to 1913 when Ford introduced the first car production assembly line. Since then the industrial manufacturing automation has been constantly evolving and spread from the automotive sector to other manufacturing sectors to reach also the service sector starting from the 70's (first ATM introduction). Hence the revolution started about 100 years ago. Second, the suggestive picture of fully automated factories with humanoid robots wandering around is very far from reality. Indeed, although the majority of the new industrial robots embed high-quality computing capabilities, improved operational degrees of freedom, and vision systems, they can only operate in highly structured environments and still require a certain level of human intervention. In other words, even if the advance in AI will eventually make robots smarter and gift them with cognitive abilities that may allow them to interacts with humans and among themselves, the current state of the art of industrial robots resolve mostly into handling, assembling and welding tasks.

Why this is important for productivity? If current industrial robots are 'only' a better and (perhaps) cheaper version than previous robots, then the expected boost in labour productivity should come from both an increase in capital investment (robot purchases) and labour quality. As such, industrial robots represent more a qualitative improvement in industrial mechanisation and automation than a radical innovation. Following this argument, the intensified use of robots leads to a kind of capital augmenting technical progress. This means that robots as part of the (non-ICT) capital input have an additional impact on labour productivity compared to traditional non-ICT or ICT capital. They not only substitute other types of non-ICT capital and labour, but they upgrade the non-ICT capital stock and allow to improve the quality of products and to expand the variety of products. At the same time, robots account for only 2% of total capital stock and are very concentrated in few manufacturing industries (e.g. car manufacturing, rubber and plastics products, metal and metal products).

On the other hand, if we are anticipating the advent of smart robots that in addition to higher performances will also provide new services and enable new form of work organisation (i.e. IoT technologies), then the real value we should try to quantify for productivity purposes is the one that comes from the embedded data sharing – or retention – and its rental value. Indeed, in a future where the economy will be increasingly data-driven, data capital should be encompassed in models of endogenous growth together with research and development (R&D) (Romer, 1990), human capital formation (Lucas, 1988) and Schumpeter's creative destruction (Aghion and Howitt 1992) as determinants and drivers of economic growth. This, as it has been done already for measuring the contribution of intangible capital (Corrado et al., 2009) using a growth accounting approach, could lead to a better measurement of factors of production and to a more accurate estimate of the impact of automation on productivity. Unfortunately the data on robots currently available do not permit to develop such a growth accounting approach as we miss information on robots prices and indirectly we cannot compute its capital services.

Another intertwined aspect of automation is how robots will affect employment. Industrial robots have the potential to realise the automation of production processes, i.e. to execute complete tasks by taking the place of human labour. Thus, unlike the standard labour saving (augmenting) technical progress, this kind of technical progress does not increase the productivity of a worker, but might completely superseded him (labour replacing technical progress).

Acemoglu and Restrepo (2017, 2018) develop different versions of a task-based general equilibrium model including robots and show that the equilibrium depends on two reverse effects. On the one hand, increased deployment of robots in the industry affects employment (and wages) negatively because of a *displacement effect* (by directly displacing workers from tasks they were previously performing). On the other hand, robots affect employment (and wages) also positively due to a *productivity effect*, since the resulting cost reductions increase product and labour demand in the industries concerned. Their estimates suggest that an extra robot per 1,000 workers reduces the employment to population ratio by 0.18-0.34 percentage points and wages by 0.25-0.5%.

Alternatively, Graetz and Michaels (2018) present a simple model for firms' decisions to use robots in their production and show – based on a production function with constant returns to scale – that a fall in the robot rental rate leads to a rise in labour productivity in robot-using industries by 0.36 percentage points between 1993 and 2007, but they find no evidence of a negative impact of robots on aggregate employment. More generally, Prettner (2019) introduce automation into a standard Solow growth model, where automation is a perfect substitute for labour.[1] He finds that this constellation opens up the potential for perpetual growth of per capita income driven solely by capital accumulation (the saving rate as well as the shares of savings devoted to traditional capital and automation capital). If the saving rate is sufficiently large, the long-run growth rate increases with the share of savings devoted to automation investments as long as the fraction of savings devoted to traditional capital is larger than the elasticity of output with respect to traditional capital. Lankisch et al. (2017) extend this model by introducing low-skilled and high-skilled labour, where automation capital is a perfect substitute for low-skilled labour, but an imperfect substitute for high-skilled labour. Their result is a rather similar log-run growth path for per capita income, whose growth rate additionally increases with the substitutability between low-skilled and high-skilled labour. Dauth et al. (2017) use a local labour market approach for Germany and find that the use of robots increases local labour productivity, but reduces the labour share in total income. While all these just mentioned studies are based on the robot data from the IFR, Koch et al. (2019)

[1] A similar approach is already presented in Steigum (2011).

use firm level data for Spanish manufacturing firms from 1990 to 2016 with the information whether firms are robot adopters or non-adopters. They identify two sources of aggregate productivity gains due to the adoption of robot technology by individual firms of a manufacturing sector. First, there is evidence for direct efficiency gains in those firms that adopt robots, and, secondly, for indirect gains through a productivity enhancing reallocation of labour across firms, away from non-adopters and toward adopters.

Our paper uses a production function approach to analyse the impact of robots on labour productivity in 9 manufacturing sectors of 12 EU countries. In order to include the robots per 1 million Euros non-ICT capital in a production function, we calculate robot stocks for the considered country-industry pairs for the period from 1993 to 2015 using the IFR robot data.

Our empirical analysis extends the recent empirical literature on the links between robots and productivity in various directions. While Graetz and Michaels (2018) only use in a more ad hoc approach a cross-section of growth rates of robot density and labour productivity over the period from 1993 to 2007, we estimate with panel data from 1995 to 2015 full Cobb-Douglas production functions.[2] These production functions are similar to those applied by Kromann et al. (2019), but these authors only have data for 10 manufacturing industries in 9 countries for the period from 2004 to 2007. Furthermore, our methods to calculate the robot stocks seem better suited to deal with the features and weaknesses of the IFR data. In addition, our study can be considered as a complement to the Koch et al. (2019) firm level study, adding a comprehensive panel data based country and sector perspective with regard to the impact of robots on labour productivity.

Our paper is structured as follow. The empirical model of our econometric analysis is developed in section 2. This section describes also the data used. The empirical results are presented in section 3. Finally, a summary and some conclusions round off the paper in section 4.

The empirical model and the data

Our empirical model follows the idea of Kromann et al. (2016) and is based on a Cobb-Douglas production function

$$Y_{ijt} = A_{ijt} C_{ijt}^{\alpha} Q_{ijt}^{\beta} L_{ijt}^{\gamma}, \tag{1}$$

where Y_{ij} represents value added in industry i in country j at time t. Furthermore, A denotes the technical efficiency or total factor productivity, C is the input of ICT capital, Q is the input of non-ICT capital and L is labour input. Since the robot stock of an industry is part of its non-ICT capital, it is assumed that the input of this capital has a quality and a quantity dimension, such that Q = qK, where K denotes the quantity of non-ICT capital and q is the (average) quality per unit of non-ICT capital input.

Taking into account the two dimensions of the capital input and taking logarithms, the production function can be re-written with labour productivity as the dependent variable as

$$y_{ijt} - l_{ijt} = a_{ijt} + \alpha(c_{ijt} - l_{ijt}) + \beta \ln(q_{ijt}) + \beta(k_{ijt} - l_{ijt}) + (\alpha + \beta + \gamma - 1) l_{ijt}, \tag{2}$$

[2] Although the approach of Graetz and Michaels (2018) is less structural, their empirical analysis involves the use of fixed effects techniques (taking long differences), deals with the problems created by the incompleteness of capital stock data and try to take into account the possible endogeneity of robot adaption through (quite subject to debate) instrumental variables. Thus, the main additional value of our paper compared to theirs comes from the more structural econometric modelling and the period of time considered.

where lowercase letters with the exception of q denote logs of the original variables. Furthermore, it is assumed that the quality of the non-ICT capital input depends on the intensity of industrial robots according to

$$q_{ijt} = e^{\lambda RI_{ijt}}, \tag{3}$$

where RI is the number of industrial robots used in industry i of country j in year t relative to the total non-ICT capital input of this industry-country pair in year t. Thus, the parameter λ reflects the efficiency of a unit of non-ICT capital input with a robot index of RI relative to a unit of non-ICT capital input in the absence of robots (RI = 0).

Including the robot index into the production function yields

$$y_{ijt} - l_{ijt} = a_{ijt} + \alpha(c_{ijt} - l_{ijt}) + \delta RI_{ijt} + \beta(k_{ijt} - l_{ijt}) + \varepsilon l_{ijt}, \tag{4}$$

where $\delta = \beta\lambda$ is the margin return to RI. If this parameter is positive, industrial robots have an extra effect compared to other types of non-ICT capital and industries with higher (or faster growing) RI realise higher (or faster growing) labour productivity. Furthermore, $\varepsilon = \alpha + \beta + \gamma - 1$ capture economies of scale, and if $\varepsilon = 0$, there are constant returns to scale in production.

In order to estimate the production function (4), we have to restrict the technical efficiency parameter a_{ijt}. In the simplest case, a_{ijt} can be expressed as the sum of a constant a_0 and a random error that is uncorrelated with the regressors, so that ordinary least squares (OLS) estimation of equation (4) would yield consistent estimates of the other regression coefficients. However, if there are differences in labour productivity between countries or between sectors or overall changes over time that are correlated with (but not caused by the robot index or the other regressors), OLS will provide inconsistent estimates. Thus, we include different specifications of fixed country and industry effects in the empirical model in order to allow a_{ijt} to vary systematically across countries and industries, e.g. due to different production technologies. Furthermore, we include different specifications of fixed time effects to capture trends in labour productivity that might be correlated with the development of the number of robots used. The production function (4) with the simplest specification for the fixed effects is:

$$y_{ijt} - l_{ijt} = a_0 + \alpha(c_{ijt} - l_{ijt}) + \delta RI_{ijt} + \beta(k_{ijt} - l_{ijt}) + \varepsilon l_{ijt}, + b_i + d_j + e_t + u_{ijt}, \tag{5}$$

where bi, dj and et are fixed industry, country and time effects. The remaining random error term is represented by u_{ijt}. The more complex specifications of the fixed effects are combinations of

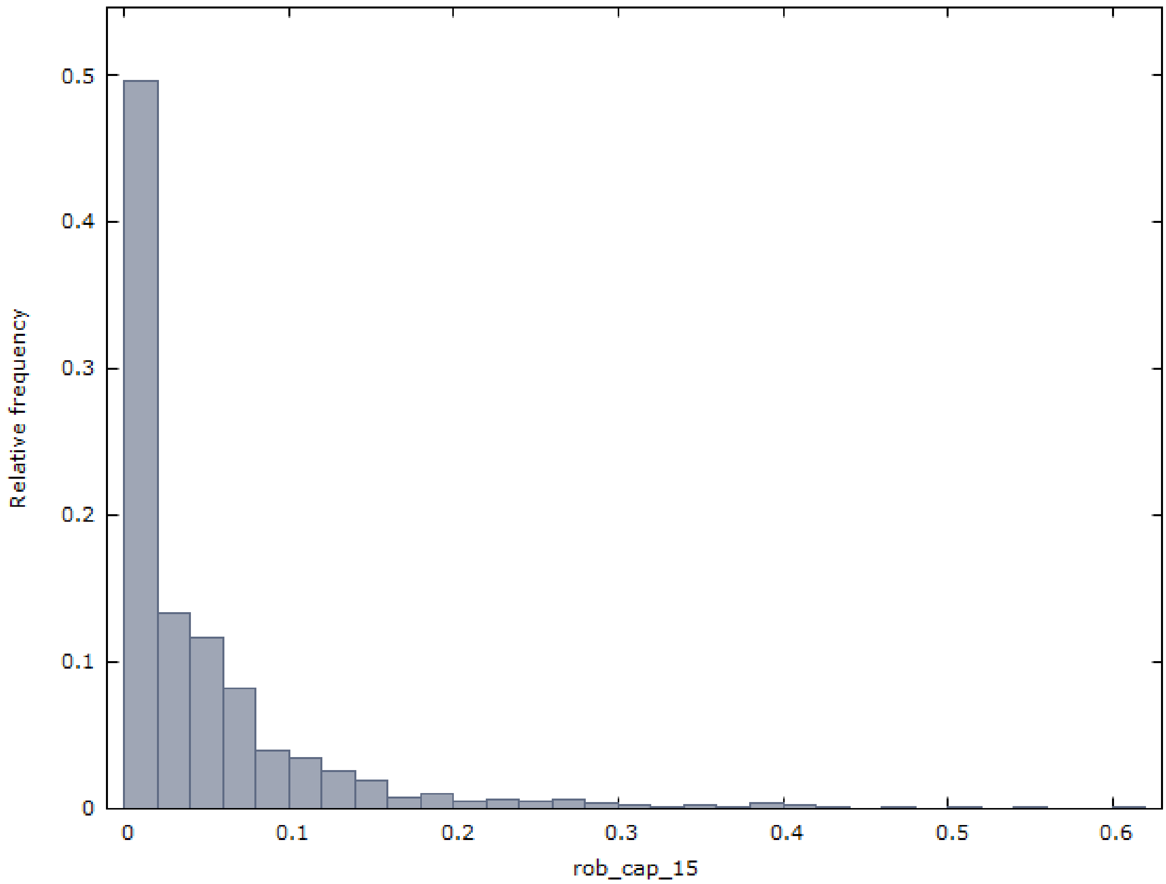
1. Fixed industry effects and fixed country-time effects,
2. Fixed country effects and fixed industry-time effects, and
3. Fixed country-time effects, fixed sector-time effects and fixed country-industry effects. [3]

Next, we discuss our data. Our main source of information on robots is the International Federation of Robotics (IFR, 2017), which collects consolidated data provided by nearly all industrial robot suppliers worldwide. As already mentioned, the definition of industrial robots is based on the

[3] The latter specification is more flexible than the often used specification with country-sector and time fixed effects, since it allows for country-specific trends (e.g. national business cycles) and sector-specific trends common to all countries. The more restrictive specification with country-sector and time fixed effects only allows for time trends common to all countries and sectors, which might introduce a omitted-variable bias.

International Organization for Standardization (ISO) 8373:2012: an "automatically controlled, reprogrammable multipurpose manipulator programmable in three or more axes" (ISO 8373). That is an industrial robot is "a machine that embodies the following characteristics: can be reprogrammed, is multipurpose in function, allows for physical alteration, and is mounted on an axis" (IFR, 2017).

Figure 1. *Frequency distribution of robots per 1 million Euro non-ICT capital input (robot stocks with perpetual inventory method and 15% depreciation rate)*



Source: International Federation of Robotics (IFR) (2017), EUKLEMS (2017 release), own calculations

The IFR collects data on annual shipment (sales) from 1993 to 2016 and compiles a measure of robot stock based on the assumption that the average service life of a robot is approximately 12 years. That is to say the stock of robots do not show any input or output decay over the service life and it is withdrawn altogether at the end of the twelfth year (one-hoss shay depreciation). Given that the service life of robots might be affected by the introduction of new technology with subsequent effects on its capital service, in line with the mainstream literature on productivity (e.g. Graetz and Michaels, 2018), we recomputed the stock of robots using the perpetual inventory method assuming depreciation rates of 5%, 10% and 15%. In order to do so, we need to implement two adjustments on the original IFR data. First, for some of the countries in the initial years there is only aggregate country data with no information at industry level. In order to disaggregate the data for the total economy at industry level, we take the average industry share for all the years with available information to consequently reallocate the total. Secondly, starting from 2008 the number of robots in the "unspecified" category grows discernibly. For these countries we use the same average industry share as above to redistribute the unspecified category.

The second source of information comes from EUKLEMS data (2017 release) that reports information on inputs, outputs and prices at industry-country level up to 2015. IFR and EUKLEMS use different industry classifications and report data for different level of industry aggregation. We used the most detailed breakdown available in the EUKLEMS and we consistently match these data with the IFR data. Our analysis covers nine different manufacturing industries over the period 1995-2015 in 12 EU countries. Labour productivity is calculated as real value added divided by total hours worked by persons engaged. Labour input is measured as total hours worked by persons engaged. Following O'Mahony and Timmer (2009), real ICT capital and real non-ICT capital inputs are calculated by multiplying the volume indices of ICT and non-ICT capital services (2010 = 100) by the respective capital stock in 2010.

Figure 1 shows for the whole observation period from 1995 to 2015 the frequency distribution of robots per 1 million Euro non-ICT capital input, based on robot stocks calculated with the perpetual inventory method and a 15% depreciation rate. It is obvious that these robot densities are rather small (between zero and 0.03 robots per 1 million Euro non-ICT capital input) for approximately 50 % of the observations. More detailed descriptive statistics for the individual manufacturing industries can be found in Table 1. The largest mean and median values for the robot densities can be found in the transport equipment industry, followed by the rubber and plastic products, metal and metal products as well as machinery and equipment industries. It is also obvious that the dispersions of robot densities (measured by the standard deviation and the interquartile range) are also rather large in these industries.

Table 1. *Descriptive statistics for the stock of robots per 1 million Euro non-ICT capital input (robot stocks with perpetual inventory method and 15% depreciation rate)*

Industry	*Mean*	*Median*	*Standard deviation*	*Inter-quartile range*	*Mini-mum*	*Maxi-mum*	*Nobs*
All nine industries	*0.046*	*0.021*	*0.067*	*0.056*	*0.000*	*0.619*	*2010*
10-12: food products, beverages, tobacco	*0.021*	*0.012*	*0.021*	*0.028*	*0.000**	*0.085*	*225*
13-15: textiles, wearing apparel, etc.	*0.012*	*0.004*	*0.017*	*0.013*	*0.000**	*0.100*	*225*
16-18: wood and paper product, etc.	*0.014*	*0.006*	*0.019*	*0.010*	*0.000**	*0.096*	*225*
20-21: chemical products, etc.	*0.003*	*0.001*	*0.003*	*0.004*	*0.000*	*0.014*	*210*
22-23: rubber and plastics products, etc.	*0.088*	*0.068*	*0.062*	*0.081*	*0.010*	*0.277*	*225*
24-25: metals and metal products	*0.053*	*0.048*	*0.039*	*0.057*	*0.003*	*0.164*	*225*
26-27: electrical and optical equipment	*0.022*	*0.017*	*0.016*	*0.020*	*0.000**	*0.090*	*225*
28: machinery and equipment	*0.045*	*0.044*	*0.032*	*0.048*	*0.001*	*0.154*	*225*
29-30: transport equipment	*0.157*	*0.125*	*0.113*	*0.136*	*0.010*	*0.619*	*225*

** Greater than zero, but smaller than 0.000.*

Source: International Federation of Robotics (IFR) (2017), EUKLEMS (2017 release), own calculations

Empirical results

In this section, we present the results of the estimations of various versions of our empirical model in equation (5).

Table 2 shows the estimation results including a robot index that is based on a robot stock calculated by the perpetual inventory method with a 15% depreciation rate. The models (1) and (2) in this table are least square dummy variable (LSDV) regressions including fixed country, industry and time effects. The model (1) reveals a highly significant partial production elasticity for the capital input per hour as well as statistically highly significant impacts of labour (hours worked) and the robot index. The production elasticity of capital input shows the expected size around one third and the statistical significance of labour confirms that there are increasing economies of scale in the production of the manufacturing industries. The coefficient for the robot index implies that one additional robot per 1 million Euro non-ICT capital input would increase labour productivity by 44%.

However, such an interpretation is not very informative, since the observed robot stock per 1 million Euro non-ICT capital input is much lower than one. The industry with the highest deployment of robots, transport equipment, uses on average 0.157 robots per 1 million Euro non-ICT capital input with a standard deviation of 0.113. Thus, an increase of its robot index by one standard deviation would increase its labour productivity by 5%. Similarly, if the transport equipment industry of an average EU country would increase its robot index from the 25% quartile to the 75% quartile, its labour productivity would be 6% higher. In model (2), total capital input is divided into ICT capital and non-ICT capital, however the estimate of the ICT capital coefficient is not statistically significant, while the other coefficients remain very similar to model (1).

The models (3) and (4) include fixed industry effects and fixed country-time effects. Thus, these models allow that the sectors of each country can follow a different flexible country-specific trend. Similarly, the models (5) and (6) include fixed country effects and fixed sector-time effects, so that the industries over all 12 EU countries can follow flexible sector specific trends. However, the inclusion of these more flexible trends does not change significantly the estimation results for the input factors and the robot index. Finitely, the models (7) and (8) capture fixed effects in a very flexible form with country-time, industry-time and country-industry effects. Surely, these models might be over-parametrised, because they lead to higher production elasticities for the capital input and to unrealistic high economies of scale. However, the impact of robot index, whose point estimate also increase, remains statistically significant at a little bit lower level.

The Tables 3 and 4 shows the estimation results for the same models, but with robot indexes based on robot stocks with depreciation rates of 10% and 5%. These lower depreciation rates do not affect the estimates of the capital and labour coefficients, but the coefficients of the robot index become a little bit lower with a depreciation rate of 10% for the robot stock and distinctively lower with a depreciation rate of 5%. However, in all cases the robot index still has a highly significant impact on labour productivity. The results with a depreciation rate of 5% are very similar to the results in Table 5, where the robot stock is depreciated according the approach of the International Federation of Robotics (IFR), which assumes that all robots have a lifetime of 12 years and are then taken out of the stock.

The impact of the robot index decreasing with the depreciation rates confirms the guideline of the German Ministry of Finance (Bundesministerium der Finanzen, 1989-2001) that the economic lifetime of industrial robots is between five and six years, implying depreciation rates between 15% and 20%. Insofar, our highest depreciation rate of 15% is at the lower bound of this official guideline.

In order to check whether the impact of robots on labour productivity has changed over time, we split our whole observation period in two sub-periods from 1995 to 2007 and from 2008 to 2015. The estimation results in Table 6 show that the impact of the robot index increased in all models from the first to the second sub-period. Since robot densities grew rather continuously in most industries during the observation period, these results suggest that robots have to reach a certain critical mass in order to achieve their full beneficial impact on labour productivity.

Table 2. *Fixed effects estimation results for 12 EU countries and 9 manufacturing industries (robot stocks with perpetual inventory method and 15% depreciation rate)*

	Dependent variable: ln(value added/hours)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln(cap/hours)	0.325***		0.302***		0.302***		0.454***	
	(0.039)		(0.039)		(0.037)		(0.113)	
ln(cap_ict/hours)		-0.014		-0.005		-0.000		0.008
		(0.033)		(0.033)		(0.032)		(0.109)
ln(cap_oth/hours)		0.339***		0.311***		0.306***		0.432***
		(0.048)		(0.046)		(0.044)		(0.111)
ln(hours)	0.088***	0.089***	0.087***	0.088***	0.098***	0.098***	0.322**	0.308**
	(0.031)	(0.032)	(0.031)	(0.032)	(0.031)	(0.032)	(0.149)	(0.145)
Robot index	0.442***	0.459***	0.478***	0.492***	0.532***	0.541***	0.603*	0.594**
	(0.148)	(0.149)	(0.149)	(0.149)	(0.144)	(0.144)	(0.311)	(0.304)
Country effects	Yes	Yes			Yes	Yes		
Industry effects	Yes	Yes	Yes	Yes				
Time effects	Yes	Yes						
Country-time effects			Yes	Yes			Yes	Yes
Industry-time effects					Yes	Yes	Yes	Yes
Country-industry effects							Yes	Yes
Adjusted R^2	0.915	0.917	0.920	0.921	0.920	0.920	0.969	0.969
Log-likelihood	641.0	659.0	804.7	821.9	780.6	792.6	1906.1	1907.9
NOBS	2010	2010	2010	2010	2010	2010	2010	2010

Notes: Heteroskedasticity and autocorrelation robust standard errors (Arellano, 1987 and 2003) in parentheses.[4] ***, ** and * indicate statistical significance at the 1 %, 5 % and 10 % level, respectively.

Source: International Federation of Robotics (IFR) (2017), EUKLEMS (2017 release), own calculations.

[4] Comprehensive discussions about the adequate use of cluster-robust standard errors, including the Arellano estimator, can be found in Cameron and Miller (2015) and Abadie et al. (2017).

Table 3. *Fixed effects estimation results for 12 EU countries and 9 manufacturing industries (robot stocks with perpetual inventory method and 10% depreciation rate)*

	Dependent variable: ln(value added/hours)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln(cap/hours)	0.325***		0.302***		0.302***		0.459***	
	(0.039)		(0.039)		(0.037)		(0.114)	
ln(cap_ict/hours)		-0.014		-0.005		-0.001		0.007
		(0.033)		(0.033)		(0.032)		(0.110)
ln(cap_oth/hours)		0.340***		0.311***		0.306***		0.436***
		(0.048)		(0.046)		(0.044)		(0.112)
ln(hours)	0.088***	0.090***	0.087***	0.088***	0.098***	0.099***	0.328**	0.313**
	(0.031)	(0.032)	(0.031)	(0.032)	(0.031)	(0.032)	(0.149)	(0.145)
Robot index	0.308***	0.324***	0.365***	0.377***	0.382***	0.391***	0.542**	0.534**
	(0.110)	(0.110)	(0.111)	(0.111)	(0.104)	(0.104)	(0.234)	(0.231)
Country effects	Yes	Yes			Yes	Yes		
Industry effects	Yes	Yes	Yes	Yes				
Time effects	Yes	Yes						
Country-time effects			Yes	Yes			Yes	Yes
Industry-time effects					Yes	Yes	Yes	Yes
Country-industry effects							Yes	Yes
Adjusted R^2	0.915	0.916	0.920	0.921	0.919	0.920	0.969	0.969
Log-likelihood	639.0	657.0	804.5	821.8	778.0	790.1	1908.5	1910.2
NOBS	2010	2010	2010	2010	2010	2010	2010	2010

Notes: Heteroskedasticity and autocorrelation robust standard errors (Arellano, 1987 and 2003) in parentheses. ***, ** and * indicate statistical significance at the 1 %, 5 % and 10 % level, respectively.

Source: International Federation of Robotics (IFR) (2017), EUKLEMS (2017 release), own calculations.

Table 4. *Fixed effects estimation results for 12 EU countries and 9 manufacturing industries (robot stocks with perpetual inventory method and 5% depreciation rate)*

	Dependent variable: ln(value added/hours)							
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
ln(cap/hours)	*0.325****		*0.302****		*0.302****		*0.459****	
	(0.039)		*(0.039)*		*(0.037)*		*(0.116)*	
ln(cap_ict/hours)		*-0.014*		*-0.006*		*-0.001*		*0.003*
		(0.033)		*(0.033)*		*(0.032)*		*(0.112)*
ln(cap_oth/hours)		*0.340****		*0.311****		*0.307****		*0.438****
		(0.048)		*(0.046)*		*(0.044)*		*(0.113)*
ln(hours)	*0.089****	*0.090****	*0.088****	*0.088****	*0.099****	*0.099****	*0.333***	*0.315***
	(0.031)	*(0.032)*	*(0.031)*	*(0.032)*	*(0.031)*	*(0.032)*	*(0.149)*	*(0.145)*
Robot index	*0.189***	*0.203***	*0.256****	*0.265****	*0.245****	*0.253****	*0.389***	*0.383***
	(0.080)	*(0.080)*	*(0.078)*	*(0.077)*	*(0.075)*	*(0.075)*	*(0.175)*	*(0.174)*
Country effects	*Yes*	*Yes*			*Yes*	*Yes*		
Industry effects	*Yes*	*Yes*	*Yes*	*Yes*				
Time effects	*Yes*	*Yes*						
Country-time effects			*Yes*	*Yes*			*Yes*	*Yes*
Industry-time effects					*Yes*	*Yes*	*Yes*	*Yes*
Country-industry effects							*Yes*	*Yes*
Adjusted R2	*0.915*	*0.916*	*0.920*	*0.921*	*0.919*	*0.920*	*0.969*	*0.969*
Log-likelihood	*636.6*	*654.6*	*803.8*	*821.8*	*774.6*	*786.7*	*1908.3*	*1910.1*
NOBS	*2010*	*2010*	*2010*	*2010*	*2010*	*2010*	*2010*	*2010*

Notes: Heteroskedasticity and autocorrelation robust standard errors (Arellano, 1987 and 2003) *in parentheses. ***, ** and * indicate statistical significance at the 1 %, 5 % and 10 % level, respectively.*

Source: International Federation of Robotics (IFR) (2017), EUKLEMS (2017 release), own calculations.

Table 5. *Fixed effects estimation results for 12 EU countries and 9 manufacturing industries (robot stock with stepwise 12 years depreciation)*

	Dependent variable: ln(value added/hours)							
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
ln(cap/hours)	*0.324****		*0.301****		*0.301****		*0.448****	
	(0.039)		*(0.039)*		*(0.037)*		*(0.113)*	
ln(cap_ict/hours)		*-0.013*		*-0.005*		*-0.000*		*0.005*
		(0.033)		*(0.033)*		*(0.032)*		*(0.111)*
ln(cap_oth/hours)		*0.338****		*0.310****		*0.305****		*0.427****
		(0.048)		*(0.046)*		*(0.044)*		*(0.111)*
ln(hours)	*0.088****	*0.089****	*0.087****	*0.088****	*0.098****	*0.099****	*0.328***	*0.312***
	(0.031)	*(0.032)*	*(0.031)*	*(0.031)*	*(0.031)*	*(0.032)*	*(0.149)*	*(0.145)*
Robot index	*0.187***	*0.197***	*0.239****	*0.247****	*0.242****	*0.247****	*0.303**	*0.297***
	(0.080)	*(0.080)*	*(0.081)*	*(0.080)*	*(0.077)*	*(0.077)*	*(0.169)*	*(0.304)*
Country effects	*Yes*	*Yes*			*Yes*	*Yes*		
Industry effects	*Yes*	*Yes*	*Yes*	*Yes*				
Time effects	*Yes*	*Yes*						
Country-time effects			*Yes*	*Yes*			*Yes*	*Yes*
Industry-time effects					*Yes*	*Yes*	*Yes*	*Yes*
Country-industry effects							*Yes*	*Yes*
Adjusted R^2	*0.915*	*0.917*	*0.920*	*0.921*	*0.919*	*0.920*	*0.969*	*0.969*
Log-likelihood	*636.5*	*654.1*	*802.1*	*819.2*	*774.6*	*786.5*	*1904.0*	*1905.8*
NOBS	*2010*	*2010*	*2010*	*2010*	*2010*	*2010*	*2010*	*2010*

Notes: Heteroskedasticity and autocorrelation robust standard errors (Arellano, 1987 and 2003) *in parentheses. ***, ** and * indicate statistical significance at the 1 %, 5 % and 10 % level, respectively.*

Source: International Federation of Robotics (IFR) (2017), EUKLEMS (2017 release), own calculations.

Table 6. *Fixed effects estimation results for 12 EU countries and 9 manufacturing industries (two subsamples) (robot stocks with perpetual inventory method and 15% depreciation rate)*

	Dependent variable: ln(value added/hours)							
	Period 1995 – 2007							
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
ln(cap/hours)	*0.300****		*0.281****		*0.290****		*0.526****	
	(0.044)		*(0.048)*		*(0.046)*		*(0.180)*	
ln(cap_ict/hours)		*-0.009*		*-0.007*		*-0.000*		*-0.016*
		(0.037)		*(0.038)*		*(0.037)*		*(0.125)*
ln(cap_oth/hours)		*0.312****		*0.292****		*0.296****		*0.524****
		(0.052)		*(0.054)*		*(0.053)*		*(0.178)*
ln(hours)	*0.064**	*0.066**	*0.070**	*0.071**	*0.065**	*0.065*	*0.346**	*0.320**
	(0.037)	*(0.039)*	*(0.038)*	*(0.040)*	*(0.039)*	*(0.040)*	*(0.192)*	*(0.176)*
Robot index	*0.408***	*0.422***	*0.502***	*0.513****	*0.436***	*0.442***	*0.011*	*0.000*
	(0.192)	*(0.191)*	*(0.198)*	*(0.196)*	*(0.205)*	*(0.203)*	*(0.384)*	*(0.380)*
Country effects	*Yes*	*Yes*			*Yes*	*Yes*		
Industry effects	*Yes*	*Yes*	*Yes*	*Yes*				
Time effects	*Yes*	*Yes*						
Country-time effects			*Yes*	*Yes*			*Yes*	*Yes*
Industry-time effects					*Yes*	*Yes*	*Yes*	*Yes*
Country-industry effects							*Yes*	*Yes*
R^2	*0.920*	*0.921*	*0.921*	*0.922*	*0.917*	*0.918*	*0.984*	*0.984*
Log-likelihood	*410.3*	*420.9*	*473.8*	*484.5*	*438.8*	*447.1*	*1561.7*	*1569.0*
NOBS	*1207*	*1207*	*1207*	*1207*	*1207*	*1207*	*1207*	*1207*

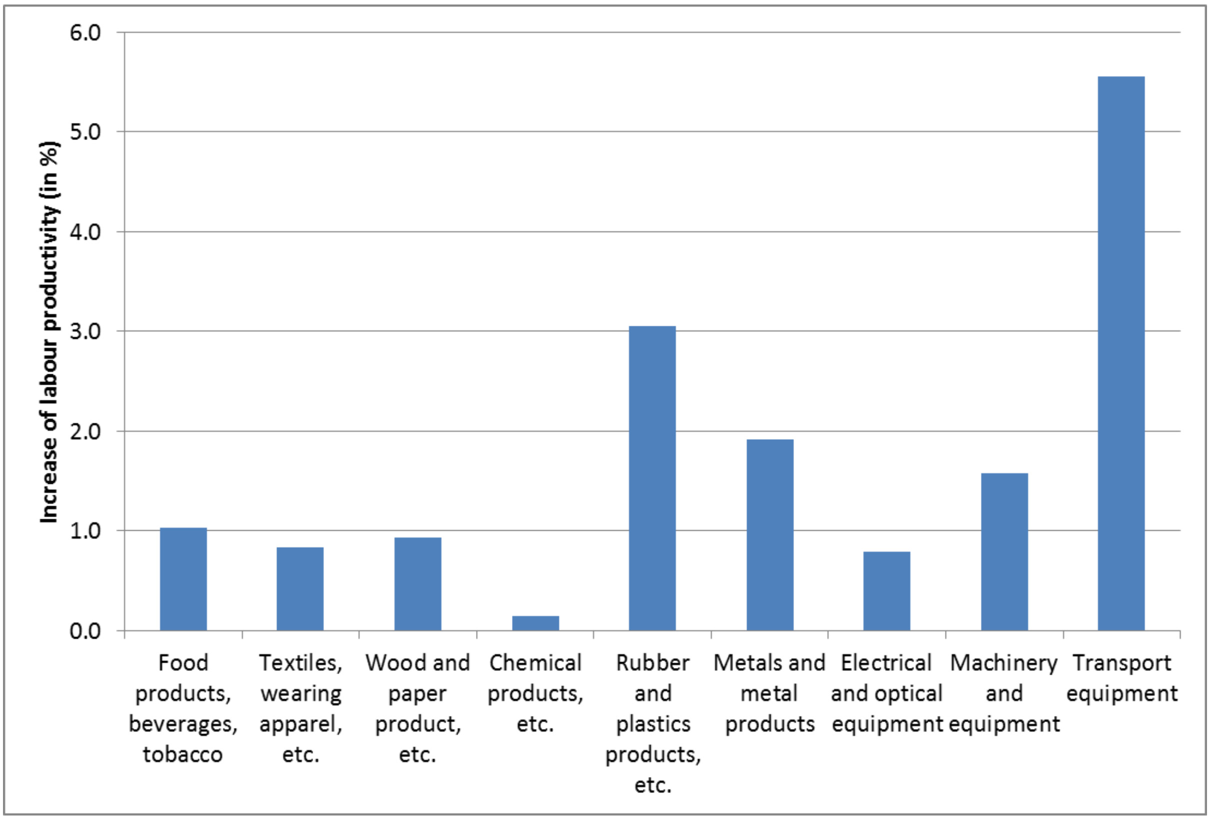
Period 2008 – 2015								
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
ln(cap/hours)	*0.296**** *(0.034)*		*0.291**** *(0.036)*		*0.294**** *(0.035)*		*0.268** *(0.138)*	
ln(cap_ict/hours)		*0.024* *(0.035)*		*0.026* *(0.038)*		*0.022* *(0.036)*		*0.270* *(0.216)*
ln(cap_oth/hours)		*0.279**** *(0.044)*		*0.273**** *(0.046)*		*0.278**** *(0.045)*		*0.261*** *(0.121)*
ln(hours)	*0.129**** *(0.029)*	*0.126**** *(0.029)*	*0.130**** *(0.030)*	*0.127**** *(0.030)*	*0.130**** *(0.030)*	*0.127**** *(0.030)*	*0.061* *(0.191)*	*0.313* *(0.270)*
Robot index	*0.660**** *(0.159)*	*0.668**** *(0.158)*	*0.642**** *(0.170)*	*0.650**** *(0.169)*	*0.666**** *(0.166)*	*0.674**** *(0.164)*	*0.735*** *(0.328)*	*0.736*** *(0.327)*
Country effects	*Yes*	*Yes*			*Yes*	*Yes*		
Industry effects	*Yes*	*Yes*	*Yes*	*Yes*				
Time effects	*Yes*	*Yes*						
Country-time effects			*Yes*	*Yes*			*Yes*	*Yes*
Industry-time effects					*Yes*	*Yes*	*Yes*	*Yes*
Country-industry effects							*Yes*	*yes*
R^2	*0.939*	*0.939*	*0.936*	*0.937*	*0.937*	*0.938*	*0.978*	*0.978*
Log-likelihood	*450.6*	*454.1*	*472.0*	*476.0*	*471.1*	*474.5*	*993.1*	*996.6*
NOBS	*803*	*803*	*803*	*803*	*803*	*803*	*803*	*803*

Notes: Heteroskedasticity and autocorrelation robust standard errors (Arellano, 1987 and 2003) *in parentheses. ***, ** and * indicate statistical significance at the 1 %, 5 % and 10 % level, respectively*

Source: International Federation of Robotics (IFR) (2017), EUKLEMS (2017 release), own calculations..

The results from the econometric analysis can be used in different ways to assess the impact of an increase of robot densities and robot stocks on labour productivity in the analysed manufacturing sectors. One possibility is to calculate for each industry the impact of a one standard deviation increase of robot densities. The results of this exercise are displayed in Figure 2. Since the industries with the highest mean and median values of robot densities also realised the highest standard deviations, the four industries with the highest average robot density also show the largest increase of labour productivity. A one standard deviation increase of the robot density (based on a robot stock calculated with a 15% depreciation rate) implies an increase of labour productivity by 5.6% in the transport equipment industry, followed by 3.1% for the rubber and plastic products industry, 1.9% for metals and metal products industry and still 1.6% for the machinery and equipment industry.

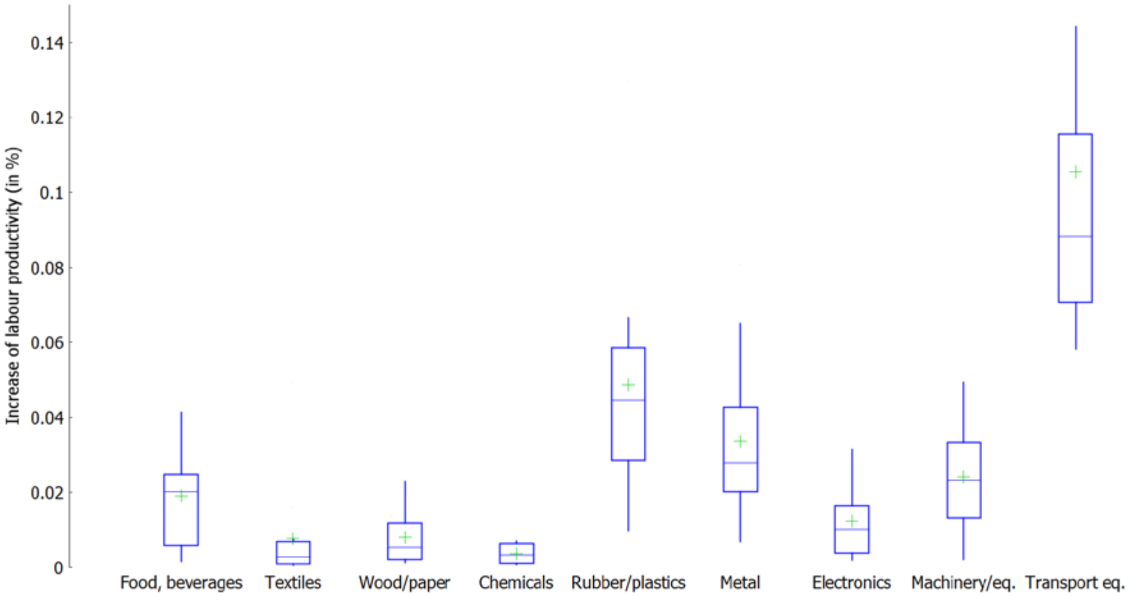
Figure 2. The impact of a one standard deviation increase of robots per 1 million Euro non-ICT capital input (robot stocks with perpetual inventory method and 15% depreciation rate) on labour productivity



Source: International Federation of Robotics (IFR) (2017), EUKLEMS (2017 release), own calculations

Another possibility is to calculate the impact of a one percent increase of sector robot stocks on labour productivity for a certain year with a given non-ICT capital stock. We chose for this exercise the year 2014 and Figure 3 shows the boxplots for each industry in the 12 EU countries considered. Such an increase in the deployment of robots also has the largest effect on the labour productivity in the transport equipment industry, followed by the industries manufacturing rubber and plastics products, metals and metal products as well as machinery and equipment. In the transport equipment industry, a 1% increase of the 2014 robot stocks would increase labour productivity on average by 0.105% (the green cross). The median increase for the 12 EU countries within the same increase would be 0.088% (the line within the box, whereby the box represents the interquartile range). The results for the other industries can be interpreted analogously.

Figure 3. Impact of a one percent increase of robot stocks (perpetual inventory method and 15% depreciation rate) in 2014 on labour productivity



Source: International Federation of Robotics (IFR) (2017), EUKLEMS (2017 release), own calculations

Conclusions

Our paper analyses the impact of industrial robots on labour productivity within a production function framework with panel data for 9 manufacturing industries and 12 EU countries over a longer time period of 21 years. Compared to Kromann et al. (2019), on the one hand, we apply their approach to a much broader dataset with regard to the country and time coverage. On the other hand, unlike their study, which uses the given IFR robot stock which "one-hoss shay" depreciation and several problematic allocations and non-allocations of the data to the industries, we reallocated some data to industries according to the approach of Graetz and Michaels (2018) and recalculated alternative robot stocks using the perpetual inventory method.

Our estimation results show that robots deployed in industrial production have – compared to other non-ICT capital – an additional impact on labour productivity. This capital augmenting effect of robots contributes to total factor productivity and via this channel also increases labour productivity. Insofar, our results confirm those of Kromann et al. (2019), but, based on a broader and more elaborated dataset, our estimates of the coefficients for the robot intensity are smaller than theirs.

Furthermore, the country-sector distribution of robots presented suggests that they represent the latest iteration of a very long-term process of industrial automation more than a break-through innovation. That is, it is plausible that the expected gains in productivity and employment will restrain to those countries and industries with an already consistent stock of industrial robots and that the positive spillovers will depend on how difficult will be the automation process in different industries and countries. Indeed, the analysis shows that with the current level of robot technology, the substantial effects are limited to a few industries with an already large deployment of robots (transport equipment industry, rubber and plastic products industry, metals and metal products industry and machinery and equipment industry). Particularly in these sectors robots seem to upgrade the non-ICT capital stock and allow to improve the quality of products and to expand the variety of products.

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