Robotisation of the manufacturing industries in the EU: Convergence or divergence?

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Abstract

This paper investigates whether convergence or divergence of robot densities in the manufacturing industries of 24 EU countries occurred over the period from 1995 to 2015. An answer to this question permits immediate conclusions with regard to the success of convergence of labour productivities within the manufacturing industries of the EU, since it is expected that the use of robots will contribute to the growth of labour productivity. The empirical analysis is based on the robot data of the International Federation of Robotics and uses the convergence testing approach proposed by Rodrik (Q J Econ 128(1):165–204, 2013). Taking all results together, empirical evidence points to non-convergence of robot densities for a first period from 1995 to 2005, while there is relatively fast conditional as well as unconditional convergence for the second period from 2005 to 2015.

Keywords Convergence · Labour productivity · Robots · European Union

JEL Classification C21 · C23 · L6 · O33 · O47

1 Introduction

There is an increasing public and scientific economic debate on the impact of the growing deployment of robots on industrial production and employment. Although robots have been used in industrial production for a long time, the increasingly possible combination of robotisation, artificial intelligence and the second digital wave (e.g. machine-learning, internet of things, cloud computing, and big data) has fuelled this debate (Ballestar et al. 2020). Actually, robots and artificial intelligence have the potential of general-purpose

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technologies that can be applied in many ways and areas with far-reaching economic and social consequences (Bresnahan and Trajtenberg 1995; Cséfalvay 2019). The European Commission has introduced the term key enabling technologies for these technologies and has identified as such, among others, advanced manufacturing technologies such as robots and automation, which require the special attention of policy makers.

With regard to labour productivity, there is now some empirical evidence at both industry and firm level that there exists a positive relationship between robot density (measured as the number of robots per hour worked or per person employed) and productivity trends (e.g. Graetz and Michaels 2018; Jungmittag and Pesole 2019; Kromann et al. 2019; Dauth et al. 2017; Koch et al. 2019; Ballestar et al. 2020). These initially positive prospects are somewhat clouded by the fact that the increasing use of robots, in particular in connection with artificial intelligence and the second digital wave, could lead with the emergence of leading and lagging countries to divergence in robotisation or an ‘automation divide’ (Aghion et al. 2017; Bughin et al. 2018). A prime example of such a divide is the international digital divide created by the increasing use of ICT, which might be reinforced by the automation and robotisation gaps between countries (Bughin et al. 2018). Thus, the so far empirically confirmed positive relationship between robotisation and the development of labour productivity also could imply international divergence of labour productivity when international divergence in robot densities occurs. This problem is particularly serious for the European Union, since one of its fundamental objectives is to improve the lives of its citizens by promoting convergence towards better working and living conditions. This includes the upward convergence of the per capita incomes and labour productivity of the Member States (European Commission 2016).

However, convergence of per capita incomes and labour productivity is not only a political objective, but also an important prediction of the neoclassical growth theory. According to this theory, countries and also industries across countries with access to identical technologies should converge to a common level of per capita income or labour productivity (Mankiw et al. 1992) (from now on MRW). However, while for larger samples of countries only conditional convergence towards different long-run steady-state levels of income or labour productivity can be observed empirically, there is rather robust evidence for unconditional convergence of labour productivities within individual manufacturing industries for a large sample of countries (Rodrik 2013). The intensified deployment of industrial robots and their impact on labour productivity therefore also begs the question from this point of view as to whether there is, across countries, convergence or divergence of robot use in the manufacturing industries. Only with unconditional convergence of robotisation will unconditional convergence of labour productivities within individual manufacturing industries continue. Conditional convergence of robot use also implies only conditional convergence of labour productivities, while divergence of the former involves the risk of divergence of the latter.

This paper applies the approach of Rodrik (2013) in order to investigate empirically whether convergence or divergence of robot densities in the manufacturing industries of 24 EU countries occurred over the period from 1995 to 2015. The analysis is based on the robot data of the International Federation of Robotics (IFR) and shows, in a nutshell, that there is a non-convergence of robot densities for a first period from 1995 to 2005, but conditional as well as unconditional convergence for the second period from 2005 to 2015. Furthermore, an additional analysis shows that the convergence in the second period was mainly driven by the increased growth of robot densities in some Central and Eastern European countries. In particular, those country-industry pairs that already had a high proportion of foreign-controlled companies and/or a strong integration in international value chains at the beginning of the

period show an increased growth in robot densities. Thus, the main contribution of the paper is to add a new piece of evidence on the development of industrial robot use that is highly relevant from an EU policy perspective.

The paper proceeds as follows. Section 2 discusses the links between robotisation and labour productivity convergence from a theoretical point of view. It also summarises the recent empirical findings about the impact of robot densities on labour productivity at the industry and firm level. Section 3 presents the econometric approach to test for unconditional and conditional convergence and describes the data used. Section 4 contains the empirical results. Finally, a summary and some conclusions round off the paper in Sect. 5.

2 The links between robotisation and labour productivity convergence

Standard neoclassical growth theory leads to the conjecture that countries or industries in different countries with access to identical technologies should converge to a common level of per capita income or labour productivity. Consequently, many cross-country growth analyses assume identical exogenous rates of technical change. A typical example for this approach is the influential analysis in MRW, which has been reproduced—in spite of all criticism—many times. Behind this assumption lies the standard view of economists that technological progress enables producers to reduce the required amount of all inputs to produce one unit of output. Zeira (1998) points out that this view of technical progress does not fit in with many important innovations, which have contributed to economic growth since the industrial revolution. As one type of such innovations, he cites machines that replace workers in production, such as the steam engine, the train, the automotive, the computer and nowadays robots or general automation.

Zeira (1998) analyses the effects of this type of technological progress on economic growth in a growth model that is taken up in simplified form by Aghion et al. (2017). Following their presentation, the starting point is a production function

$$Y = AX_1^{\alpha_1} X_2^{\alpha_2} \cdot \dots \cdot X_n^{\alpha_n}, \text{ with } \sum_{i=1}^n \alpha_i = 1, \quad (1)$$

where Y is the total output and A is the level of technology. In Zeira's view, the X_i 's are intermediate products, but in line with Acemoglu and Autor (2011), they can also be considered as tasks. A unit of a hitherto non-automated task can be produced by a unit of labour, while a unit of an automated task can be produced by a unit of capital, that is

$$X_i = \begin{cases} L_i & \text{if not automated} \\ K_i & \text{if automated} \end{cases}. \quad (2)$$

If the aggregated capital and labour inputs (K and L) are optimally allocated to these tasks, the production function (apart from an unimportant constant) can be formulated as

$$Y_t = A_t K_t^\alpha L_t^{1-\alpha}, \quad (3)$$

where the exponent α indicates the total share and importance of automated tasks. Reformulating this production function into growth rates yields

$$g_Y = g + \alpha g_K + (1 - \alpha)g_L, \quad (4)$$

with g_Y , g , g_K and n as growth rates for Y , A , K and L . Using the standard assumptions of the neoclassical growth model, especially a constant investment rate, implies in the long-run a constant capital coefficient and therefore $g_Y = g_K$. Consequently, labour productivity (or income per capita in the neoclassical growth model) grows at a steady-state rate

$$g_{Y/L} = g_Y - n = \frac{g}{1 - \alpha}. \quad (5)$$

Thus, a higher degree of automation induces a larger capital share (and share of factor payments to capital) α and, because of the multiplier effect associated with capital accumulation, a higher long-run growth rate of labour productivity. With regard to the convergence of labour productivity, this result implies that *ceteris paribus* such convergence can only occur if there is convergence of degrees of automation to a common level.

Fully elaborated, the Zeira (1998) model shows that technology adoption depends on the prices of the production factors, and if they are endogenised, it depends on the productivity of the country and the discount rate. It also shows that technology adoption amplifies differences in the underlying parameters and helps explain internationally observed differences in per capita outputs. Similarly, 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.

The influence of robotisation on the convergence of labour productivity can also be shown by augmenting the MRW model to include the use of robots. This can be done by assuming that robots are necessary to implement automation as a form of technical progress. Becchetti and Adriani (2005), who examine the effects of the digital divide on levels and growth of income per workers across countries, put similar arguments forward. They assume that technological progress in the form of weightless, infinitely reproducible knowledge products (e.g. software and databases) can only diffuse if a certain stock of ICT hardware is available. In the following, the augmented MRW model by Becchetti and Adriani (2005) is used to show the influence of robotisation on the convergence of labour productivity. So to say, the digital divide of the first digital wave is replaced by the automation divide resulting from the connection of robotisation with artificial intelligence and the second digital wave (e.g. the internet of things, big data or 3D printing) within the framework of the Solow growth model.¹ Indeed, as in the first digital wave, when a clear link between human capital and workplace organisation was established, it can be expected that in the second digital wave the use of robots will be linked to different types of (partly freely available) knowledge flows (Ballestar et al. 2020).

The starting point of the model is a Cobb–Douglas production function with labour-augmenting technical progress:

$$Y_t = K_t^\alpha (A_t L_t)^{1-\alpha}, 0 < \alpha < 1, \quad (6)$$

with the same notation here and below as previously in the model of Zeira (1998). L and A grow at the exogenous rates n and g , i.e.

$$L_t = L_0 e^{nt}, \quad (7)$$

¹ In the following presentation, human capital is not included as an additional production factor in the production function because it is irrelevant for my theoretical argumentation.

$$A_t = A_0 e^{gt}, \quad (8)$$

so that the number of effective units of labour grows at the rate $n + g$. As before, it is assumed that a constant proportion of the output is invested. Furthermore, let $k = K/AL$ be the capital invested per effective unit of labour and $y = Y/AL$ be the output per effective unit of labour. Then $\dot{k}$ describes the development of k as

$$\begin{aligned} \dot{k}_t &= sy_t - (n + g + \delta)k_t \\ &= sk_t^\alpha - (n + g + \delta)k_t, \end{aligned} \quad (9)$$

where δ is the rate of depreciation. In the equilibrium we have $\dot{k} = 0$, so that the steady-state value k^* is

$$k^* = \left(\frac{s}{n + g + \delta} \right)^{1/(1-\alpha)}. \quad (10)$$

Inserting (10) into the production function and taking logs gives the steady-state labour productivity (or income per capita) as

$$\ln \left(\frac{Y_t}{L_t} \right) = \ln A_0 + gt + \frac{\alpha}{1-\alpha} \ln s - \frac{\alpha}{1-\alpha} \ln (n + g + \delta). \quad (11)$$

The standard MRW model assumes that $\ln A_0 + gt$ is a constant that is identical for all countries (cross-section units). Furthermore, it treats the rate of technical progress plus depreciation ($g + \delta$) as fixed and equal to 0.05 for all countries. Consequently, differences in the steady-state levels of labour productivity can only stem from differences in population growth and investment rates.

This changes, however, if it is assumed that robots are needed for automation and thus for the realisation of technical progress. Transferring the approach of Becchetti and Adriani (2005) to robotisation and automation, the relationship between robotisation, freely available technical knowledge and the overall level of technology can be specified in a simple way as

$$A_t = A_{TK(t)} A_{ROB(t)}, \quad (12)$$

with $A_{TK(t)} = A_{TK(0)} e^{g_{TK}t}$, $A_{ROB(t)} = A_{ROB(0)} e^{g_{ROB}t}$, and $g = g_{TK} + g_{ROB}$. A_{ROB} is a measure of the stock of robots and g_{ROB} the associated growth rate, while A_{TK} is the level of freely available technical knowledge and g_{TK} its growth rate.

Inserting this augmented specification of the level of technology into the log-linear relationship for the steady-state labour productivity (11) yields

$$\ln \left(\frac{Y_t}{L_t} \right) = \ln A_{TK(0)} + g_{TK}t + \ln A_{ROB(0)} + g_{ROB}t + \frac{\alpha}{1-\alpha} \ln s - \frac{\alpha}{1-\alpha} \ln (n + g_{TK} + g_{ROB} + \delta). \quad (13)$$

In contrast to the standard MRW model, labour productivity is now also influenced by the robot stock in the initial period and by its growth rate. On the one hand, both quantities appear at the beginning of the equation in the term for labour-augmenting technical progress, which MRW consider to be a constant across countries. On the other hand, the term for the country-specific rate of technical progress plus the rate of depreciation ($g + \delta$) can no longer be treated as fixed and the same for all countries, because it now includes the

growth rate of the robot stock in addition to the rate of freely available technical progress. Consequently, country-specific differences in robotisation generally will lead to only conditional convergence of labour productivity towards country-specific steady states.²

The impact of robotisation on the convergence of labour productivity becomes even clearer when the relationship between labour productivity growth, its determinants in the steady state and the initial level of labour productivity is derived. Let y^* be the steady state level of income per effective unit of labour and y_t the value at time t . Approximating around the steady state, the speed of convergence is given as

$$\frac{d \ln Y_t}{dt} = \lambda (\ln y^* - \ln y_0), \quad (14)$$

where $\lambda = (n + g + \delta)(1 - \alpha)$. This differential equation has the solution (Chiang and Wainwright 2005, 476):

$$\ln y_t = (1 - e^{-\lambda t}) \ln y^* + e^{-\lambda t} \ln y_0. \quad (15)$$

Subtracting the log of initial income per effective unit of labour y_0 from both sides yields

$$\ln y_t - \ln y_0 = (1 - e^{-\lambda t}) \ln y^* - (1 - e^{-\lambda t}) \ln y_0. \quad (16)$$

Finally, substituting (13) for y^* and expressing the left side of (16) in terms of labour productivity gives

$$\begin{aligned} \ln \left(\frac{Y_t}{L_t} \right) - \ln \left(\frac{Y_0}{L_0} \right) &= (1 - e^{-\lambda t}) \ln A_{TK(0)} + g_{TK}t + (1 - e^{-\lambda t}) \ln A_{ROB(0)} + g_{ROB}t \\ &+ (1 - e^{-\lambda t}) \frac{\alpha}{1 - \alpha} \ln s - (1 - e^{-\lambda t}) \frac{\alpha}{1 - \alpha} \ln (n + g_{TK} + g_{ROB} + \delta) - (1 - e^{-\lambda t}) \ln y_0. \end{aligned} \quad (17)$$

The emergence of the initial stock of robots and its growth rate in this growth or convergence equation again implies that an absolute convergence of labour productivity across countries may be prevented with country-specific differences for these two variables.

From an empirical point of view, there have been some empirical studies analysing the impact of the growing deployment of industrial robots on the labour productivity in manufacturing industries. Most of these studies use the robot data from the IFR. Graetz and Michaels (2018) use a cross-section approach for 14 industries in 17 countries and find that the growth in robot intensity (robots per million hours worked) from 1993 to 2007 contributes to the growth of labour productivity in the same period.

Methodologically different to this study, Jungmittag and Pesole (2019) estimate with panel data covering 9 industries and 12 EU countries from 1995 to 2015 full Cobb–Douglas production functions and present robust evidence that stocks of robots per EUR 1 million of non-ICT capital input contribute significantly to labour productivity growth. Their results remain robust when the whole observation period is split into two subsamples from

² Of course, robotisation, just like ICT hardware in Becchetti and Adriani (2005), could have been considered in the production function in other ways. It would be conceivable, for example, to include robots as a further production factor alongside physical and human capital. Then different investment rates for robots would lead to conditional convergence of labour productivity to country-specific steady states. The advantage of the approach used here, however, is that it takes into account the interplay between freely available technical progress and the robots necessary for its implementation.

1995 to 2007 and from 2008 to 2015. The production function approach of Jungmittag and Pesole (2019) is similar to the one applied by Kromann et al. (2019), but the latter authors only have data for 10 manufacturing industries in 9 countries for the period from 2004 to 2007. Furthermore, the method of the former authors to calculate the robot stocks seems better suited to deal with the features and weaknesses of the IFR data.³

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. In contrast to the formerly mentioned studies, Koch et al. (2019) use firm-level data for Spanish manufacturing firms from 1990 to 2016 including the information as to 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 of direct efficiency gains in those firms that adopt robots, and, secondly, of indirect gains through a productivity-enhancing reallocation of labour across firms, away from non-adopters, and towards adopters.

Ballestar et al. (2020) use the same Spanish data source but focus on the impacts of robots and knowledge flows on the labour productivity of manufacturing small and medium enterprises (SME) with 10 to 200 workers. Their sample includes 1515 SME from 2008 and 1380 SME from 2015. They find that the adoption of robots by SME induced via direct and indirect effects an increase of labour productivity by 2% in 2008 and by 5% in 2015. At the same time they also found that their knowledge flow variable also generate positive effects on SME's labour productivity and robotisation in 2015. Additionally, by splitting their sample into robotised and non-robotised firms, they show that there is a complementary relationship between robot usages and knowledge flows. In 2015, the direct effect of knowledge flows on labour productivity in robotised SME was substantially larger than in non-robotised firms, which did not occur in 2008. The authors conclude from their findings that the explanation of labour productivity in manufacturing SME would have moved towards a model in which the multifactor productivity components (knowledge flows and robotisation) and human capital would have gained in importance. In sum, the literature on the impact of robotisation has focused on productivity and employment, but so far not addressed convergence of robotisation and its link to convergence of labour productivity.

3 Methodology and data issues

The econometric approach to test for convergence of robot densities follows the approach applied by Rodrik (2013) to test for convergence of labour productivity in various manufacturing industries. Robot density r_{ijt} for each industry i , country j and period t is defined as robot stock per 1 000 persons engaged. It is assumed that growth of the robot density in each industry $\dot{r}_{ijt}$ depends on country-specific conditions and a convergence effect. The latter is proportional to the gap between each industry's initial robot density and the leading robot adopter r_{it}^* . Thus, growth of robot density is given by:

$$\dot{r}_{ijt} = \beta (\ln r_{it}^* - \ln r_{ijt}) + D_j, \quad (18)$$

³ This method is also used in this study to calculate robot densities as robot stock per 1000 persons employed. The method is described in the next section.

where D_j is a dummy variable capturing all time- and industry-invariant country fixed effects. The coefficient β is the convergence coefficient that has to be estimated (β -convergence).

Introducing an error term ε_{ijt} that is uncorrelated with other explanatory variables and substituting $\beta \ln r_{it}^*$ equivalently by a set of industry $\times$ time fixed effects, D_{it} , yields the feasible estimation equation:

$$\dot{r}_{ijt} = -\beta \ln r_{ijt} + D_{it} + D_j + \varepsilon_{ijt}. \quad (19)$$

Rodrik (2013) suggests including additional separate industry and period dummies in order to capture any additional confounding residual systematic variation.

If this equation should be estimated as a cross-section over a single period, the industry $\times$ time fixed effects D_{it} are reduced to industry fixed effects D_i . Thus, the estimation equation is now given as:

$$\dot{r}_{ijt} = -\beta \ln r_{ijt} + D_i + D_j + \varepsilon_{ijt}. \quad (20)$$

According to this specification, the estimate of β measures conditional convergence (country-industry pairs converge to their individual long-run robot densities), since the country-specific conditions are captured explicitly by the country fixed effects. A simple test of unconditional convergence (for a given sector all countries converge to a common long-run robot density) is to drop the country dummies and to inspect whether the estimated β -coefficient remains negative and statistically significant.

Next, the data used is discussed. The 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. The definition of industrial robots is based on the International Organization for Standardization (ISO) standard 8373:2012 and determines that 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).

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 that the stock of robots does 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), the stock of robots is recomputed using the perpetual inventory method assuming depreciation rates of 5%, 10% and 15%.⁴ In order to do so, it is necessary to implement two adjustments of 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, the average industry shares for all the years with available information are taken to consequently reallocate the total. Secondly, starting from 2008 the number of robots in the “unspecified” category grows discernibly. For these

⁴ I thank Annarosa Pesole (JRC Seville) for providing the calculations of the robot stocks. The guideline of the German Ministry of Finance for depreciation of assets assumes an economic lifetime of industrial robots between 5 and 6 years, implying depreciation rates between 15 and 20%. The highest depreciation of 15% used to calculate the robot stocks is at the lower bound of this official guideline.

countries, the same average industry share as above is used to redistribute the unspecified category.

In order to calculate industries' robot densities as robot stocks per 1 000 persons engaged, the latter data is taken from the EU KLEMS database (2017 release). The IFR and EU KLEMS use different industry classifications and report data for different levels of industry aggregation as well as different periods. This paper uses the most detailed breakdown available in the EU KLEMS database and consistently matched this data with the IFR data. Altogether, the analysis covers nine different manufacturing industries over the period 1995–2015 in 24 EU countries.⁵

4 Empirical results

4.1 Descriptive statistics and σ -convergence

The presentation of the empirical results starts with some descriptive statistics for the robot densities shown in Table 1. These statistics are based on robot stocks with a 15% depreciation rate. The mean robot density increased in all 9 industries considerably from 1995 to 2015, but there is a large variation between the industries. The industries with the lowest mean densities in 2015 are wood and paper products etc. (1.10 robots per 1000 persons engaged), textiles etc. (1.31) and chemicals etc. (1.42), while the industries with the highest mean robot densities in 2015 are transport equipment (23.86), rubber and plastics products (7.93) as well as basic metals and fabricated metal products (4.52). However, there is also a large variation in robot densities within the sectors. This is, on the one hand, obvious from the minimum and maximum values, and, on the other hand, from the coefficients of variation (C.V.). The coefficient of variation is a measure for so-called σ -convergence, i.e. the diminution of variation of robot densities over time. In almost all industries, this coefficient increases for the period from 1995 to 2005, but decreases from 2005 to 2015. Thus, the first period seems to be an episode of σ -divergence, while the second period is characterised by a reduction of variation of robot densities (σ -convergence). The only exception is the textile industry with a very low mean robot density.⁶

Whether this result is driven by the entry of new countries into the industry clubs of robot adopters or whether it also holds for the 16 countries with data available for 1995 is an interesting question. Table 2 displays the coefficients of variation for this group of countries for five different years. In the first period from 1995 to 2005, the coefficients of variation for several sectors remain more or less at the same level, while the second period from 2005 to 2015 is characterised by a stronger tendency toward σ -convergence in almost all industries. However, some industries show for this group of countries the same patterns of divergence and convergence as the coefficients of variation for all available countries in each period.

⁵ The necessary data is not available for Cyprus, Croatia, Luxemburg and Malta. Furthermore, available data for the included countries increases over the period considered from 136 observations in 1995 to 200 observations in 2015. Details can be found in Table 1.

⁶ This result is driven by Denmark, which has a very high and unusual robot density in this industry (18.89 in 2015). The maximum value for the other 17 countries is 1.29 (Germany).

Table 1 Descriptive statistics for the robot densities in EU two-digit manufacturing industries (with 15% depreciation rate)

NACE	Industry	Year	No of obs.	Mean	Minimum	Maximum	C. V.
10–12	All 9 industries	1995	136	2.64	0.00*	25.02	1.74
		2005	196	3.25	0.00*	48.37	2.26
		2015	200	5.81	0.00*	64.15	1.79
13–15	Food products, beverages and tobacco	1995	16	0.64	0.01	3.57	1.40
		2005	22	1.16	0.00*	7.03	1.45
		2015	23	2.95	0.03	12.18	1.19
16–18	Textiles, wearing apparel, leather and related products	1995	15	0.25	0.00*	1.76	1.89
		2005	18	0.51	0.00*	6.04	2.77
		2015	18	1.31	0.01	18.89	3.35
20–21	Wood and paper products, printing and publishing	1995	16	0.51	0.00*	2.39	1.35
		2005	21	0.79	0.00*	6.46	1.94
		2015	21	1.10	0.00*	6.03	1.29
22–23	Chemicals and chemical products	1995	9	0.25	0.01	0.75	1.17
		2005	21	0.29	0.00*	0.85	0.96
		2015	22	1.42	0.06	4.95	1.00
24–25	Rubber and plastics products, non-metallic mineral products	1995	16	3.16	0.39	7.94	0.71
		2005	23	4.90	0.01	18.60	1.06
		2015	24	7.93	0.05	25.70	0.84
26–27	Basic metals and fabricated metal products	1995	16	2.69	0.11	7.65	0.92
		2005	23	2.32	0.00*	12.46	1.40
		2015	23	4.52	0.21	14.54	0.93
	Electrical and optical equipment	1995	16	1.72	0.07	5.76	0.96
		2005	23	1.93	0.00*	8.79	1.25
		2015	23	2.84	0.02	12.89	1.06

Table 1 (continued)

NACE	Industry	Year	No of obs.	Mean	Minimum	Maximum	C. V.
28	Machinery and equipment n.e.c.	1995	16	2.18	0.07	6.52	1.05
		2005	22	1.95	0.00*	7.78	1.16
		2015	22	3.79	0.06	13.16	0.90
29–30	Transport equipment	1995	16	11.20	0.69	25.02	0.76
		2005	23	14.18	0.02	48.37	1.15
		2015	24	23.86	0.33	64.15	0.84

*Greater than zero, but smaller than 0.00

Table 2 Coefficients of variation for the robot densities of 16 countries with observations for 1995

NACE	Industry	1995	2000	2005	2010	2015
	All 9 industries*,**	1.74	1.77	1.90	1.54	1.50
10–12	Food products, beverages and tobacco	1.40	1.18	1.14	0.87	0.86
13–15	Textiles, wearing apparel, leather and rel. products**	1.89	2.23	2.51	2.47	3.06
16–18	Wood and paper products, printing and publishing	1.35	1.57	1.64	1.39	1.05
20–21	Chemicals and chemical products*	1.17	1.14	0.78	0.92	0.85
22–23	Rubber and plastics products, non-metallic mineral products	0.71	0.97	0.76	0.56	0.57
24–25	Basic metals and fabricated metal products	0.92	0.99	1.06	0.77	0.62
26–27	Electrical and optical equipment	0.96	0.93	0.93	0.76	0.81
28	Machinery and equipment n.e.c.	1.05	0.88	0.86	0.87	0.65
29–30	Transport equipment	0.76	0.80	0.81	0.60	0.44

*In 1995 and 2000 there are only 9 observations available for the chemical industry

**In all years there are only 15 observations available for the textiles etc. industry

Table 3 Cross-section tests for β -convergence (dependent variable: growth of robot density in EU two-digit manufacturing industries over a decade)

	1995–2005		2005–2015		2005–2015	
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Robot depreciation rate: 15%</i>						
Log initial robot density	−0.020*** (0.007)	−0.005 (0.005)	−0.046*** (0.005)	−0.045*** (0.002)	−0.050*** (0.007)	−0.048*** (0.004)
Country fixed effects	Yes	No	Yes	No	Yes	No
Sector fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R ²	0.444	0.066	0.857	0.755	0.768	0.673
Number of countries	16	16	23	23	16	16
Number of observations	136	136	196	196	143	143
<i>Robot depreciation rate: 10%</i>						
Log initial robot density	−0.018*** (0.007)	−0.005 (0.004)	−0.044*** (0.005)	−0.044*** (0.002)	−0.047*** (0.006)	−0.044*** (0.004)
Country fixed effects	Yes	No	Yes	No	Yes	No
Sector fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R ²	0.443	0.074	0.878	0.786	0.773	0.674
Number of countries	16	16	23	23	16	16
Number of observations	136	136	196	196	143	143
<i>Robot depreciation rate: 5%</i>						
Log initial robot density	−0.017*** (0.006)	−0.004 (0.004)	−0.041*** (0.004)	−0.042*** (0.002)	−0.042*** (0.005)	−0.038*** (0.003)
Country fixed effects	Yes	No	Yes	No	Yes	No
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R ²	0.439	0.086	0.895	0.806	0.773	0.668
Number of countries	16	16	23	23	16	16
Number of observations	136	136	196	196	143	143

NB: Heteroskedasticity-consistent standard errors (HC 1) in brackets

***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively

4.2 β -convergence

Table 3 shows the results of cross-section tests for β -convergence according to Eq. (20) for the robot densities calculated with all three depreciation rates. The models (1) and (2) in the first panel with a robot stock depreciation rate of 15% are estimated for the period from 1995 to 2005 and 16 EU countries. Model (1) shows for all three depreciation rates that there is a slow conditional convergence toward country-industry pair-specific levels of robot densities with estimates of β between -0.017 (5% depreciation rate) and -0.20 (15% depreciation rate), implying a yearly convergence speed between 1.7% and 2.0%. Dropping the country fixed effects in model (2) reveals that there is no unconditional β -convergence during the first period from 1995 to 2005.

The models (3) and (4) are estimated for the second period from 2005 to 2015 with the available observations for 23 countries. Looking at the models with a 15% depreciation rate, the estimated convergence coefficient of 4.6% in model (3) is statistically highly significant below an error of 1%. The country fixed effects are dropped in model (4) and the convergence coefficient remains nearly unchanged with a rather fast unconditional convergence of 4.5% per year. The models (5) and (6) are cross-section regressions for the more recent period from 2005 to 2015 and the 16 countries with data available for 1995. The estimated convergence coefficients are very similar to those from models (3) and (4). Thus, independent of the chosen group of countries, there is statistically highly significant evidence for a relatively fast convergence of robot densities within the EU during the period from 2005 to 2015.

The second and third panel in Table 3 show the cross-section regression results based on robot densities calculated with 10% and 5% depreciation rates. The results are very similar to those in the first panel, but the convergence speed decreases slightly with the chosen depreciation rate. Thus, on the one hand, the cross-section results with an only conditional convergence of robot densities in the first period from 1995 to 2005 and a rather fast unconditional convergence in the second period from 2005 to 2015 seem to be robust with regard to the depreciation rate used to calculate the robot densities. On the other hand, the convergence speeds decreasing slightly with the depreciation rates might confirm the guideline of the German Ministry of Finance that the economic lifetime of industrial robots is between 5 and 6 years.

In order to investigate further the changes of the convergence speeds over time, the cross-section tests for β -convergence in the EU two-digit manufacturing industries over 5-year periods were repeated. Table 4 shows the results for the robot densities calculated with a depreciation rate of 15%. The models (1) and (2) were estimated for the period from 1995 to 2000 with the available observations for 16 countries. The estimated convergence coefficient in model (1) indicates at a significance level of at least 5% a conditional convergence speed of 2.8%, but model (2) shows that there is no unconditional convergence during this period. The models (3) to (6) document that there is neither conditional nor unconditional convergence during the period from 2000 to 2005. The models (3) and (4) are estimated with all available data for 18 countries, while the models (5) and (6) are estimated including only the 16 countries with data available for 1995. Thus, these more detailed estimations confirm the finding that there is no unconditional convergence between 1995 and 2005.

The models (7) to (10) reveal conditional as well as unconditional convergence of robot densities during the period from 2005 to 2010. The estimates of the models (7) and (8), which are based on all available observations for 23 EU countries, yield

Table 4 Cross-section tests for β -convergence (dependent variable: growth of robot density (with 15% depreciation rate) in EU two-digit manufacturing industries over 5-year periods)

	1995–2000			2000–2005			2010–2015							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Log initial robot density	–0.028** (0.012)	–0.004 (0.006)	–0.009 (0.007)	–0.011 (0.005)	–0.009 (0.007)	–0.004 (0.005)	–0.055*** (0.015)	–0.061*** (0.007)	–0.030** (0.014)	–0.027*** (0.009)	–0.112*** (0.013)	–0.057*** (0.008)	–0.100*** (0.015)	–0.088*** (0.011)
Country fixed effects	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R ²	0.342	0.048	0.494	0.054	0.494	0.021	0.657	0.499	0.325	0.265	0.588	0.387	0.714	0.586
Number of countries	16	16	18	18	18	16	23	23	16	16	24	24	16	16
Number of observations	136	136	153	153	153	136	196	196	143	143	200	200	143	143

NB: Heteroskedasticity-consistent standard errors (HC 1) in parentheses

***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively

Table 5 Panel data tests for β -convergence (dependent variable: growth of robot density (with 15% depreciation rate) in EU two-digit manufacturing industries over 5-year periods)

	1995–2015		1995–2005		2005–2015	
	(1)	(2)	(3)	(4)	(5)	(6)
Log initial robot density	−0.074*** (0.008)	−0.044*** (0.004)	−0.021*** (0.007)	−0.008** (0.004)	−0.100*** (0.009)	−0.060*** (0.005)
Country fixed effects	Yes	No	Yes	No	Yes	No
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time x industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R ²	0.458	0.371	0.331	0.051	0.550	0.462
Number of countries	24	24	18	18	24	24
Number of observations	685	685	289	289	396	396

NB: Heteroskedasticity-consistent standard errors (HC 1) in brackets

***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively

rather similar high conditional and unconditional convergence speeds of 5.5% and 6.1% respectively. The estimated convergence coefficients are clearly lower, but still statistically highly significant, in the models (9) and (10), which include only those 16 EU countries with data available for 1995. Compared to 2005 from 2010, the convergence seems to have accelerated in the period from 2010 to 2015. For the sample of all 24 available EU countries (the models 11 and 12), the estimated coefficient of conditional convergence is 11.2%, while its counterpart for unconditional convergence is 5.7%.⁷ The models (13) and (14) based on the 16 EU countries with data available for 1995 yield more similar, statistically highly significant estimates for the coefficients of conditional and unconditional convergence. For this last period, the rate of unconditional convergence increases to 8.8%.

In order to further check the robustness of the cross-section results, panel data models were estimated to test for β -convergence. All these models are based on 5-year periods and include industry fixed effects, time fixed effects and time $\times$ industry fixed effects. The models testing for conditional convergence additionally comprise country fixed effects. Table 5 summarises the results. The models (1) and (2) were estimated with data from all four 5-year periods from 1995 to 2015 and a maximum of 24 EU countries in the last 5-year period. The estimated coefficient for conditional convergence is 7.4% and statistically highly significant far below the 1% significance level. Model (2) shows that the estimate for the convergence coefficient remains statistically highly significant but decreases to 4.4% when unconditional convergence is tested by dropping the country fixed effects. However, the other estimates in Table 5 reveal that this result is largely driven by the strong convergence in the second half of the whole observation period. Model (3) and (4) are

⁷ This result is in line with the conditional convergence results in the literature for income per capita and labour productivity (Rodrik 2013). Rodrik (2013) also discusses the argument of Barro (2015) that growth regressions with country fixed effects might yield upwardly biased estimates of the convergence speed when the time horizon is short. The conditional convergence estimates should be considered as upper bounds.

panel data models for the two 5-year periods from 1995 to 2005. Model (3) indicates with 2.1% a rather slow conditional convergence, and model (4) that the speed of unconditional convergence, while still statistically significant at the 5% level, is very slow at only 0.8% per year. In the second subsample with two 5-year periods from 2005 to 2015, the speed of both types of convergence increases considerably to 10% for conditional convergence and 6% for unconditional convergence. Thus, the panel data models provide some evidence that there are some country-specific differences with regard to robotisation readiness in the manufacturing industries of the EU, which lead to a higher speed of conditional convergence compared to the speed of unconditional convergence. Nevertheless, the speed of unconditional convergence is relatively fast and statistically highly significant.

Finally, the robustness of the convergence evidence is checked by β -convergence tests on an industry-by-industry basis for the two periods from 1995 to 2005 and 2005 to 2015. The underlying regression models only contain the growth rates of robot densities as a dependent variable and the initial robot density at the beginning of each period as an explanatory variable. The estimates of the β -convergence coefficients are shown in Table 6. Since these regression models are based on only 16 to 23 observations, one should not be too demanding with regard to the statistical significance of these industry-specific estimates. However, the results are very clear-cut. No industry shows any evidence of unconditional convergence during the first period from 1995 to 2005. The picture changes completely for the second period from 2005 to 2015. Statistically highly significant unconditional convergence can now be confirmed for all industries with relatively similar convergence speeds between 3.7% and 5.5%.

4.3 Additional results

The very clear finding that unconditional convergence of robot densities within the EU did not take place between 1995 and 2005, whereas it was very pronounced between 2005 and 2015, raises the question which factors have driven the shifts in growth rates of robot densities between these two periods. In order to explain the changes of these growth rates for the 16 countries with data available already for the first period from 1995 to 2005, I ran regressions of the following type:

$$\dot{r}_{ij0515} - \dot{r}_{ij9505} = \alpha + \sum_{k=1}^K \beta_k X_{ijk05} + \varepsilon_{ij0515}, \quad (1)$$

where X_{ijk05} are either time-invariant effects or explanatory variables from the initial year 2005 (or the nearest possible year) of the second period. The average shift of the growth rates of robot densities for the 9 industries and 16 countries of the sample is 4.99 percentage points (p.p.). Model (1) in Table 7 includes only country fixed effects and it is obvious that the shifts of the growth rates for Hungary (28.1 p.p.), Slovakia (26.7 p.p.), Czech Republic (10.2 p.p.) and the Netherlands (11.2 p.p.) are much larger than the average shift. On the other hand, there are negative shifts of the growth rates for Finland and Spain. Thus, the convergence of robot densities in the second period from 2005 to 2015 seems to be strongly driven by the increases of the robot densities in at least some Central and Eastern European countries. Altogether, the country-fixed effects explain 54.1% of the variance of the shifts of the growth rates. Model (2) confirms this conclusion. Besides the constant, it contains only a dummy variable for the Central and Eastern European countries (East), which is statistically highly significant and explains 26.9% of the variance of the

Table 6 Cross-section tests for β -convergence by industry (dependent variable: growth of robot density over a decade)

NACE	Industry	1995–2005		2005–2015	
		No of countries	β -coefficient	No of countries	β -coefficient
10–12	Food products, beverages and tobacco	16	–0.011 (0.015)	22	–0.042*** (0.007)
13–15	Textiles, wearing apparel, leather and rel. products	15	–0.007 (0.012)	18	–0.037*** (0.008)
16–18	Wood and paper products, printing and publishing	16	0.005 (0.011)	21	–0.045*** (0.005)
20–21	Chemicals and chemical products	9	–0.007 (0.010)	21	–0.055*** (0.005)
22–23	Rubber and plastics products, non-metallic mineral products	16	–0.023* (0.012)	23	–0.048*** (0.006)
24–25	Basic metals and fabricated metal products	16	–0.012 (0.010)	23	–0.046*** (0.006)
26–27	Electrical and optical equipment	16	0.007 (0.015)	23	–0.046*** (0.005)
28	Machinery and equipment n.e.c.	16	–0.010 (0.009)	22	–0.050*** (0.007)
29–30	Transport equipment	16	–0.011 (0.017)	23	–0.041*** (0.008)

NB: Heteroskedasticity-consistent standard errors (HC 1) in brackets

***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively

Table 7 Growth shifts regressions: The impact of country effects

Independent variables	(1)		(2)	
	Coefficient	Standard error	Coefficient	Standard error
Constant	–	–	0.009	0.878
East	–	–	0.160***	0.027
Austria	0.030**	0.012	–	–
Belgium	0.057***	0.016	–	–
Czech Republic	0.102***	0.025	–	–
Germany	0.004	0.022	–	–
Denmark	–0.019	0.047	–	–
Spain	–0.078	–1.606	–	–
Finland	–0.080***	0.025	–	–
France	–0.006	0.013	–	–
Hungary	0.281***	0.055	–	–
Italy	–0.001	0.035	–	–
Netherlands	0.112***	0.023	–	–
Portugal	0.065	0.024	–	–
Sweden	–0.013	0.046	–	–
Slovenia	0.037	0.028	–	–
Slovakia	0.267***	0.041	–	–
Great Britain	0.011	0.034	–	–
R^2	0.541		0.269	
Adjusted R^2	0.484		0.263	
Number of observations	136		136	

NB: Heteroskedasticity-consistent standard errors (HC 1) in the corresponding columns

***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively

shifts. The coefficient estimates of this model show that the average shift for the Western and Southern European countries was only 0.9 p.p., while it was 16 p.p. higher for the Central and Eastern European countries. In this respect, these estimates confirm the findings of the narrative and descriptive analysis of Cséfalvay (2019) that the expansion of the robot stocks in the Central and Eastern European countries has significantly advanced the EU-wide convergence of robot densities in the period from 2005 to 2015.

Another possibility would be that the different shifts in the growth rates of robot densities are significantly determined by industry-specific factors. The model in Table 8 contains only industry-fixed effects. Although the shifts for some industries across all countries are larger than the average shift of 4.99 percentage points, the dispersion is not as pronounced as for the country-fixed effects. Overall, industry fixed effects explain only 6.5% of the total variance of shifts in growth rates between the two periods.

The fact that the Central and Eastern European countries played an important role in the convergence of robot densities in the second period from 2005 to 2015 is certainly also related to their accession to the EU in 2004, with which they became a fully integrated part of the European Single Market after the economic transformation from centrally planned to market economies in the 1990s (Cséfalvay 2019). Linked to this whole process was a strong inflow of foreign direct investment and the integration into international value chains. The

Table 8 Growth shifts regressions: The impact of sector effects

Independent variables		Coefficient	Standard error
NACE	Industry		
10–12	Food products, beverages and tobacco	0.036	0.036
13–15	Textiles, wearing apparel, leather and rel. products	0.041	0.046
16–18	Wood and paper products, printing and publishing	0.071*	0.042
20–21	Chemicals and chemical products	0.114**	0.047
22–23	Rubber and plastics products, non-metallic mineral products	−0.020	0.015
24–25	Basic metals and fabricated metal products	0.084***	0.023
26–27	Electrical and optical equipment	0.046	0.042
28	Machinery and equipment n.e.c.	0.073***	0.026
29–30	Transport equipment	0.032	0.029
R^2		0.065	
Adjusted R^2		0.006	
Number of observations		136	

NB: Heteroskedasticity-consistent standard errors (HC 1) in the corresponding column

***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively

Table 9 Growth shifts regressions: The impact of foreign controlled firms (FDI) and imported intermediates (IIM)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	−0.016 (0.021)	−0.018 (0.020)	0.015 (0.010)	−0.013 (0.021)	−0.013 (0.018)	0.004 (0.014)	−0.008 (0.013)
East		0.143*** (0.027)			0.149*** (0.027)		0.136*** (0.027)
FDI	0.239*** (0.070)	0.111* (0.064)					
East x FDI			0.357*** (0.063)				
IIM				0.250*** (0.082)	0.099 (0.066)		
FDI x IIM						0.577*** (0.140)	0.288** (0.122)
Adjusted R^2	0.092	0.276	0.276	0.065	0.268	0.127	0.286
Number of observations	136	136	136	136	136	136	136

NB: Heteroskedasticity-consistent standard errors (HC 1) in brackets

***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively

models in Table 9 include two variables to capture this process. Firstly, they contain the share of persons employed in foreign-controlled enterprises out of total persons employed in an industry i in a country j in 2008 (the first available year for this data). Secondly, they include the share of intermediate products in the total imports of an industry i in a country j in 2005. The first variable was calculated based on data of Eurostat's Foreign Affiliate

Statistics (FATS), while the second variable was calculated based on data of the OECD's Trade in Value Added (TiVA) database. In addition, some models include the already mentioned dummy variable for Central and Eastern European countries (East).

Model (1) in Table 9 confirms that the share of persons employed in foreign-controlled enterprises has a highly significant impact on the robot density. This influence is slightly lower if a dummy variable for the Central and Eastern European countries is included in the regression (model (2)). It seems, therefore, that the presence of foreign controlled enterprises has contributed especially in the Central and Eastern European countries to an increase in the growth rate of robot density. For this reason, model (3) includes the FDI variable as an interaction term with the EAST variable, i.e. the FDI variable is set to zero for the Western and Southern European countries. This interaction term exerts a highly significant positive effect and the explanatory power of model (3) is the same as that of model (2) with an adjusted $R^2=0.276$. Model (4) shows that the initial share of intermediate products in the total imports of an industry also has a highly significant positive impact on the growth of robot density. However, this influence disappears when the dummy variable for the Central and Eastern European countries is included in the model (5). If the product of the FDI variable and the intermediates variable is used as an interaction term in the model (6), this variable also exerts a highly significant positive influence. Even though the coefficient estimate has halved, this influence remains highly significant if the dummy variable for the Central and Eastern European countries is also included in the model (7). Moreover, this model has the highest explanatory power with an adjusted $R^2=0.286$.⁸ In summary, it appears that the combination of foreign-controlled companies and integration into international value chains has had a positive effect on the growth of robot densities, especially in the Central and Eastern European countries, and has thus promoted the convergence of robot densities within the EU.

5 Conclusions

Using the convergence testing approach of Rodrik (2013), this paper investigates empirically whether convergence or divergence of robot densities in nine manufacturing industries of 24 EU countries occurred over the period from 1995 to 2015. The results show very clearly that there is only—if at all—conditional but no unconditional convergence of robot densities during the first period from 1995 to 2005. Only one panel data model out of the numerous model variants applied points to very slow unconditional convergence for the first period. For the second period from 2005 to 2015, there is overwhelming evidence of fast unconditional convergence within the EU to industry-specific robot density levels.

Furthermore, the additional regression results show that the unconditional convergence in the second period from 2005 to 2015 is strongly driven by increased growth rates of the robot densities of some Central and Eastern European countries that joined the EU in 2004. Here, particularly those country-industry pairs show high increases in the growth rates of robot densities, which at the beginning of the second period had high shares of persons

⁸ Models (2), (3) and (7) were also estimated with industry fixed effects. Essentially, these additional estimates support the just presented findings. In model (2), the influence of the FDI variable remains with a coefficient estimate of 0.249 at $\alpha=0.012$ highly significantly different from zero. In model (7), the estimate for the impact of the interaction term (0.486 instead of 0.288) was also considerably higher than in the model without industry fixed effects.

employed in foreign-controlled enterprises and/or high shares of intermediate products in their imports. Cséfalvay (2019) argues that the large inflow of foreign direct investment into this region and its integration into international value chains has been triggered, at least in part, by global companies' search for cheap and at the same time relatively highly skilled labour. Given the current technological possibilities of automation, he diagnoses a "winning formula" for those European global companies operating in medium or highly skilled industries: the use of robots for routine and highly automatable activities and, in parallel, the employment of low-cost skilled labour for the complementary activities, ideally in geographical proximity to the main consumer markets. With this development comes also the challenge for the industrial policy in Central and Eastern Europe to avoid the trap of dependent robotisation.

The finding of unconditional convergence of the robot densities has some further policy implications. Generally, it can be expected that country-specific conditions that are correlated with initial robot densities—e.g. innovation environment, education policies, labour market policies or more generally automation or robotisation readiness—play a role in determining the speed of catch-up and convergence.⁹ If so, estimates of β -convergence coefficients should become larger when fixed effects are included in the regression model. Thus, these robotisation readiness factors might have played a role in the first period from 1995 to 2005, where mostly only conditional convergence of robot densities within the EU (if at all) can be observed. For the second period from 2005 to 2015, the rates of conditional and unconditional convergence are in most cases very similar, pointing to the fact that country-specific factors do not play an important role in the speed of catch-up and convergence of densities of industrial robots in the individual manufacturing industries of the EU. Only the panel data models provide some evidence that there are some country-specific differences with regard to robotisation readiness in the manufacturing industries of the EU. However, these remaining differences do not prevent the industry-by-industry cross-section tests for β -convergence from conforming for each industry unconditional convergence during the second period from 2005 to 2015.

With regard to labour productivity in the manufacturing industries of the EU, the evidence for unconditional convergence suggests that the intensified deployment of robots does not impede or slow down the convergence of labour productivities within the individual manufacturing industries of the EU. However, there might be a convergence-retarding effect on aggregate labour productivity (for the whole manufacturing sectors as well as for the whole economies), because EU countries are differently specialised in the production of robot-intensive industries. For example, Germany, strongly specialised in the very robot-intensive production of automobiles, might experience a higher level of aggregate labour productivity than a country that is less specialised in this area.

Finally, convergence of robot densities also implies that the industry-specific labour displacement effects are similar in all EU countries. Thus, the total labour market effects in the individual EU countries depend, on the one hand, on their industrial specialisation in robot-intensive activities, and, on the other hand, on their national capabilities to allow workers to switch to other industries and/or to upgrade their qualifications and human capital to perform new tasks which are complementary to robots or cannot be done by robots.

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⁹ The Economist Intelligence Unit (2018) uses these three policy areas to construct an automation readiness index.

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