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# Robotisation race in Europe: the robotisation chain approach

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**ABSTRACT**

Who leads the robotisation race in Europe? For the answer, this paper develops a novel analytical framework, primarily by applying the concept of the global value chain to robotisation. By doing this, we investigate in detail the entire robotisation chain, from robotics developers over robot manufacturers to companies that deploy the industrial robots. For the R&D-intensive part of the chain (robotics development), we analyse robotics patent data from PATSTAT combined with firm data from ORBIS while for the capital-intensive part (deployment of robots) the source of information is the International Federation of Robotics. Our results show that the European robotisation landscape is fragmented into three groups. The first includes economies (Sweden, Germany, Austria, Denmark and France) that have the highest densities both in robotics development and in robot deployment. Countries of the second group (Spain, Italy, Belgium, the Netherlands and Finland) possess good positions only in some specific parts of the chain, while the lagging behind region (the majority of Central and Eastern Europe) is integrated into the robotisation chain solely by robot deployment. Hence, one of the main related policy challenges is to find ways for upgrading along the robotisation chain.

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## Introduction: looking at the entire robotisation chain

While interest both in robotics and in the deployment of robots is growing, a comprehensive framework taking into account the entire robotisation chain by putting together every element of robotisation – from robotics developers over robot manufacturers to companies that use the robots – is still largely missing. This paper aims at closing this gap by outlining a novel analytical model of the robotisation chain, testing its relevance in Europe and addressing the central question: *How the particular European countries are engaged in robotisation?*

When it comes to robotisation there are currently two main streams of research in the literature. The first, coined as the future of work, places the possible job losses because of replacement of humans by robots in the centre (Frey and Osborne 2013; Arntz, Gregory, and Zierahn 2016; Acemoglu and Restrepo 2017; Manyika et al. 2017; Chiacchio, Petropoulos, and Pichler 2018; Lordan 2018; Nedelkoska and Quintini 2018; Frey 2019; Klenert, Fernández-Macías, and Antón 2020) while the second stream investigates the productivity gains and the economic benefits resulting from the deployment of industrial robots (CEBR 2017; Dauth et al. 2017; OECD 2017; UNCTAD 2017; Graetz and Michaels 2018; Jungmittag and Pesole 2019; Koch, Manuylov, and Smolka 2019; Kromann et al. 2020). Yet, these studies have one point in common: they focus almost exclusively on the

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deployment of industrial robots and pay much less attention, if any, to the route *prior* to instalment of industrial robots, namely the robotics development and the robot manufacturing. The mutual linkage is, however, evident. On the one hand, technological advances in robotics development and robot manufacturing push forward the deployment of robots, as cutting-edge robotics offer extra functionalities thus widening the range of potential industrial applications, while improvements in robot manufacturing could push down the prices of robots. On the other hand, the increasing demand of industrial manufacturers for application of robots in different production processes pulls the robotics innovation and robot manufacturing.

In this paper, hence, we outline first the analytical structure of the robotisation chain (Section 2) and shortly discuss the main data sources of the study (Section 3). Then we draw the contours of the global robotisation landscape (Section 4) and analyse in detail the territorial pattern of the robotisation chain in Europe (Section 5). The concluding remarks (Section 6) give further insights into the related policy and research questions.

## Analytical framework of the robotisation chain

The establishment of production networks – from planning and purchasing through parts production and assembly to sales and servicing – uniting many countries, companies and facilities in a complex value creation process was one of the greatest innovations of globalisation that triggered in the words of Baldwin (2016) a genuine 'global value chain revolution'. Equally, our model of the robotisation chain is drawn from the long-established literature on global value chains that started to proliferate in the 1990s (Porter 1985; Gereffi and Korzeniewicz 1994; Krugman 1995; Dicken 1998) insomuch that today the term has become commonplace (Rhodes, Warren, and Carter 2005; Gereffi 2018; Ponte, Gereffi, and Raj-Reichert 2019).

In the literature there are three main perspectives from which the global value chains should be analysed (Dicken 1998; Kaplinsky 2000; Kaplinsky and Morris 2001; Henderson et al. 2002; Gereffi and Fernandez-Stark 2016) and these perspectives are also relevant to the robotisation chain:

the *input-output structure*, i.e. the fragmentation of the chain, or, in other words, the number of suppliers in it, and what value is added at each stage and by whom;

the *governance and power structure*, i.e. who has influence or control over the value chain and what type of influence or control they exert, and

the *geographical structure*, i.e. the facilities and countries that are covered by the chain.

Taking the input-output structure, Leigh and Kraft (2018) make a clear distinction between the 'suppliers' that design, produce and sell the industrial robots and the 'robot-using manufacturers' which purchase, install and deploy the robots in different manufacturing industries. The robot-using manufacturers could purchase the robots directly from the suppliers or from intermediary 'integrators' that provide specific expertise to install the robots, although it is not unusual for large robot-using manufacturers to have their own in-house robotics capabilities.

By combining this initial taxonomy with the concept of the global value chains, the robotisation chain might be divided – in a simplified manner because almost each of them includes mixed forms – in five main parts which together form our model (see Figure 1):

The *Robotics Developers* (RDs) are companies, university departments and research institutions that carry out cutting-edge research in robotics as their main activity and in addition, they often have the ability to produce robots on a small scale or for experimentation purposes.

The *Robot Manufacturers* (RMs) are companies that have the production of robots as their main activity and supply the market with robots on a large scale, although they usually have their own robotics research facilities as well.

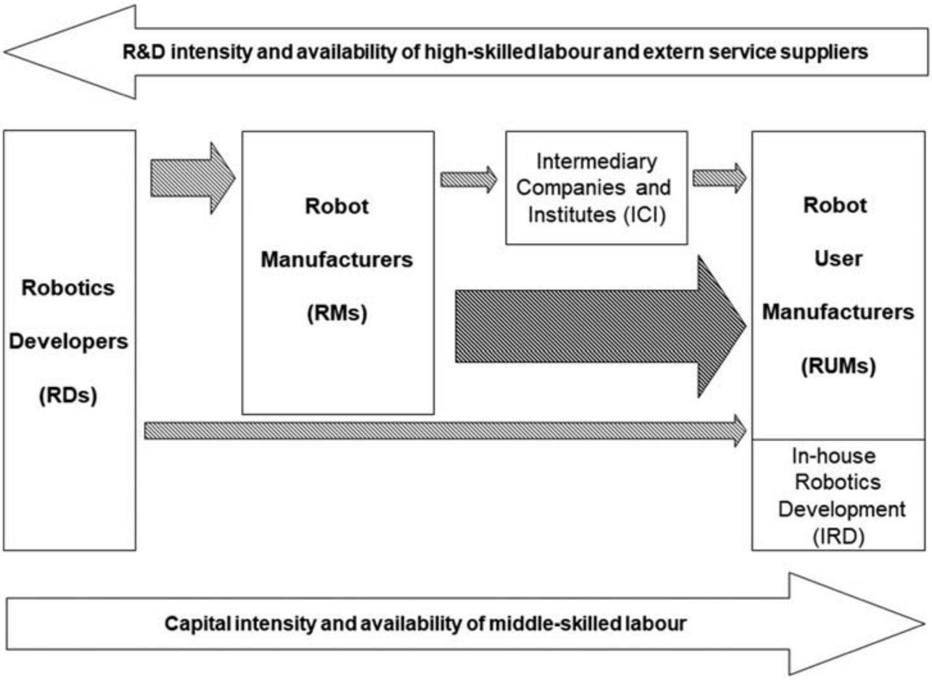


**Figure 1.** Model of the robotisation chain.

The *intermediary companies and institutions* (ICIs) are placed between the Robot Manufacturers and the companies which deploy the industrial robots and they provide unique knowledge that is required for installing and customising the robots in automated production.

The *Robot User Manufacturers* (RUMs) are the companies that purchase, and then install and deploy the industrial robots in different production processes in order to supply their consumers with products, which are based on automated production.

Finally, large Robot User Manufacturers mostly have their own *in-house robotics development* facilities (IRDs) partly for customising the robots supplied by Robots Manufacturers to their specific production processes and partly to develop robots customised to their particular requirements.

Nevertheless, in the literature (Kaplinsky and Morris 2001; Humphrey and Schmitz 2002; Rhodes, Warren, and Carter 2005; Gereffi and Fernandez-Stark 2016) it is also well understood that the relative importance of particular production and location factors vary significantly across the value chains. Based on this, we have developed a matrix that shows how the different players of the robotisation chain require distinct features with regard to R&D and capital, workforces' skills, external services and internal management (see Table 1). It is easy to conceive the idea that while R&D is a decisive feature across the entire chain, its relative importance increases from the Robot User

**Table 1.** Relative importance of production and location factors across the robotisation chain.

| | R&D intensity | Capital intensity | Scientific and high qualified employees | Middle-skilled workers | External suppliers and services | Internal management |
|---|---|---|---|---|---|---|
| Robotics Developers | +++ | + | +++ | + | +++ | + |
| Robots Manufacturers | ++ | ++ | ++ | ++ | ++ | ++ |
| Robot User Manufacturers | + | +++ | + | +++ | + | +++ |
| In-house Robotics Development | ++ | + | ++ | + | ++ | + |
| Intermediary Companies and Institutions | ++ | + | ++ | + | ++ | + |

Manufacturers over Robot Manufacturers to the Robotics Developers. Similarly, while Robot User Manufacturers need primarily access to middle-skilled workers capable to cooperate with robots, highly qualified, scientific workforces become increasingly important for robot manufacturing and they are vital for Robotics Developers. By contrast, the capital intensity shows a reverse direction as it is the lowest for Robotics Developers and the highest for Robot User Manufacturers which usually establish a complex production system with assembly lines, hardware and software support, and the purchase of robots is only part of the total capital-intensive investment (OECD 2019).

Regarding the second analytical perspective, that of the governance structure, there are two conflicting approaches in the literature. The first focuses on the gap that the deployment of robots might cause. López Peláez (2014) highlights the main feature of the '*robotics divide* which like the digital divide is the fault line between the haves and the have-nots, between states, companies and individuals that have access to advanced robotics technology and to the benefits that robotisation may offer and those which do not have access and miss these opportunities. Bughin et al. (2018) also argue that today an '*AI divide*' is emerging as Artificial Intelligence technologies (including robot-based automation) become more prevailing and estimate that the AI leaders (primarily developed countries) could benefit from additional 25% upside in GDP by 2030, while the followers (mostly emerging economies) may capture only half their upside. The reasons for the AI divide are very diverse. The overall trend of increasing capital share in the digital and highly automated industries since the 2000s (Aghion, Jones, and Jones 2017), the delicate interplay between innovation and regulation that favours the first-movers and deters the followers (Aghion, Antonin, and Bunel 2019), as well as unique factors, such as the 'rise of superstar firms' (Autor et al. 2020) could play an important role.

In contrast to this, scholars of the second approach look at governance issues in the context of interdependencies within the chain. As Ross (2016, 40) recognises: 'the countries that are best positioned are those that are developing and manufacturing robotics for export, that house the headquarters, the engineers, and the manufacturing facilities', while economies that only host Robot User Manufacturers without having robotics development and robot manufacturing are in a weaker position. Similarly, the UNIDO (2019) classifies the countries regarding their engagement both in development and in deployment of Advanced Digital Production (ADP) technologies (a category that includes the robots). The frontrunners are leading in all terrains, in developing, producing, exporting and deploying of ADP technologies (globally only 10 countries). The followers are to a lesser extent engaged and the subcategory of 'followers in production' includes economies that develop, produce and export ADP technologies (23 countries), while the 'followers in use' only import and deploy these technologies (17 countries).

The handicap for follower and lagging behind countries is the fact that the specific production and location requirements which emerge at the different parts of the robotisation chain are not ubiquitous and not easy to reproduce, not least because at present robotics is a relatively new industry. Thus, these two factors together lead us to the third analytical perspective, as currently the geographical pattern of the robotisation chain is characterised by an enormous concentration at each of its decisive parts.

Keisner, Raffo, and Wunsch-Vincent (2016) calculate that in 2015 80% of the Robotics Developers were home to only 10 countries, such as Japan, USA, China, Korea, Canada, Germany, Italy, France, United Kingdom and Switzerland. It comes then not as a surprise that between 1960 and 2011 applicants from these countries filed the overwhelming majority of robotics patents, although in Europe Denmark, Finland, the Netherlands, Sweden and Spain also had high presence of robotics firms measured by their patents relative to GDP. Because of the specific knowledge required, the Robotics Developers might concentrate in countries and regions that offer a vibrant ecosystem of universities and research institutes, specialised suppliers and manufacturers, high-skilled scientific workforces and risk-taking entrepreneurs. It belongs to the characteristic features of agglomeration economies that innovative regional clusters after reaching a critical mass become self-reinforcing systems (Glaeser 2010; Fujita and Thisse 2013), as it had happened in the information technologies (Saxenian 1996; Castells 2000), and we rightly expect this to happen again in the case of Robotics Developers.

Similarly, robot manufacturing is strongly concentrated, as the 28 robot suppliers that provide data for the International Federation of Robotics are headquartered in 12 countries, moreover, there are only four countries which are home to three or more Robot Manufacturers; Denmark and Switzerland each have three while Germany and Japan each have six companies (Leigh and Kraft 2018). Forge and Blackman (2010) also found that in Europe the major companies specialising in manufacturing of industrial robots were located only in eight countries (Germany, Switzerland, Sweden, Italy, France, United Kingdom, the Netherlands and Austria). For Robot Manufacturers it might be the domain knowledge in advanced manufacturing that could boost the territorial concentration, while the second driver is the market size, as currently the automotive and electronics companies deploy the majority of the robots, hence, the country's specialisation in these industries may provide the necessary market scale for establishing the robot manufacturers.

The Intermediary Companies and Institutions are concentrating strongly as well, and for instance, Leigh and Kraft (2018) show that in the USA they are located in close proximity to Robot User Manufacturers. The 'supplier-dense regions' with Robotics Developers specialising in research, design and development of robots are placed in the long-established high-tech clusters (e.g. Silicon Valley, Boston), while the 'integrator-dense regions' with Intermediary Companies and Institutions, which focus on the implementation and customisation of robotics systems, are clustering in the traditional industrial districts (e.g. the manufacturing belt around the Great Lakes).

Finally, robot deployment is also highly concentrated territorially and as Oséfalvay (2020) points out, in 2015 the majority of the approximately 1,600,000 industrial robots deployed worldwide, was at work only in five countries, namely Japan (18%), China (16%), USA (15%), Korea (13%) and Germany (11%). Adding the other EU member states to Germany's figures, Europe was leading with more than 400,000 robots (26%), and the combined share of the five leading economies, including Europe was 88% of the global robot stock. Evidently, the territorial pattern of robot deployment is influenced by a number of economic factors, such as the labour cost, the shrinking availability of labour forces, the countries' economic structure, industrial specialisation and developmental stage. Latest studies indicate, however, that in the context of falling robots' prices and increasing wages (Citigroup and Oxford Martin School 2016; CEBR 2017; Melrose and Tilley 2017; Chiacchio, Petropoulos, and Pichler 2018) high labour cost might work as a powerful incentive for companies deploying industrial robots, and the robots will be progressively put into work in countries and industries where high wages relative to robots' prices offer a quick return of capital-intensive investments (Atkinson 2018). Looking at Europe in more detail, Oséfalvay (2020) also underlines the close link between the high labour cost and the intensive robot deployment and argues that this link reflects and strengthens the already existing economic and geographic disparities across the continent.

At present the strong territorial concentration is the overall rule, however, old geographical wisdom teaches us that in case of new industries and technologies – though, with considerable time-lags – territorial diffusion and regional convergence will come, as these industries and technologies become mature and widespread. Therefore, we investigate three main hypotheses in detail:

First, while the expected geographical pattern is the extreme intense concentration across the whole robotisation chain, *at particular parts of the chain the European economies might differ from each other* significantly concerning scale and scope of their engagement.

Second, because the territorial concentration is highly influenced by the specific location requirements that emerge at distinct parts of the chain, the *specialisation* of certain European countries in specific part of the robotisation chain might mitigate the prevailing trend.

Third, and again despite the anticipated strong concentration, the very complex and dynamic nature of *the robotisation chain may offer the latecomers distinct ways for upgrading* along the robotisation chain.

In short, our central hypothesis is that while territorial concentration across the entire robotisation chain is unquestionable, it is neither necessarily relevant at every part of the chain, nor is permanent in the long run.

## Data and methodology

To capture the R&D-intensive parts of the robotisation chain (RDs, RMs, IRDs) this study retrieves and analyses patent data from *PATSTAT 2019 spring edition* maintained by the European Patent Office (EPO). The patents have long been widely used in accounting for technological innovation developed for commercial purposes and despite of their obvious limitations (Archibugi 1992; Fontana et al. 2013) the literature treats as a 'tolerable assumption' that they measure commercially useful innovation at national, regional and firm level (Griliches 1990). One advantage that patents offer in the analysis is due to the International Patent Classification scheme (IPC), which is a hierarchical classification system used primarily to classify and search patent documents according to technical fields. In this work we also use the Cooperative Patent Classification (CPC) which is an extension of the IPC and jointly managed by the EPO and the US Patent and Trademark Office.

In this study, we focus on patent families pertaining specifically to robotics following the methodology developed by UKIPO (2014) and replicated by WIPO (2015). More specifically, PATSTAT was queried for patent documents with IPC/CPC classes pertaining to robots and the term 'robots' or 'robotics' in the title and the abstract of the document. Given that, documents from all intellectual property offices were retrieved and in order to avoid double counting the unit of our analysis was the extended patent family (INPADOC). The patent families in this analysis are fractionally counted according to their year of worldwide first filing, and the patent assignee data from PATSTAT were matched with data from ORBIS at the level of individual companies (including subsidiaries where available) using a series of probabilistic string-matching algorithms.

For the capital-intensive part of the robotisation chain (RUMs) the primary source of information comes from the *International Federation of Robotics* (IFR) that provides consolidated measures of *robot stock* by country, year and industries breakdown, based on annual sales data of robot manufacturers (IFR 2019). Regarding robot densities, measured as number of industrial robots per 10,000 persons employed in respective industries, this paper applies the IFR data for the global analysis, but recalculates the densities for the European comparison by applying EU KLEMS employment data at industry and country level, while the IFR uses OECD STAN and ILOSTAT data for employment. Therefore, in this study for the European countries the robot density values *differ from the IFR measures due to the different denominators* (persons employed), though, the orders of magnitude of densities are similar to the densities computed by IFR.

By using these datasets, for analytical purposes we classify the main parts of the robotisation chain as follows:

The *Robot Manufacturers* are identified as companies that are working according to ORBIS in robot manufacturing (NACE 28.22, 28.99). Because the robotisation chain contains very high share of intangible assets and the robot manufacturing is a relatively new industry, we analyse the patent filing activity of this group of companies in order to gain a picture about their size and scale.

Based on PATSTAT and ORBIS data the *In-house Robotics Development* facilities are identified by robotics patents that have been filed by automotive or electronics companies, since these are the industries where currently the overwhelming majority of the industrial robots are at work.

Using the PATSTAT data the group of *Robotics Developers* were treated as entities that filed significant number of patent families in robotics, excluding those that according to ORBIS are also classified as Robot Manufacturers or as automotive or electronics manufacturers (IRDs).

For classification of the *Robot User Manufacturers* we use the data of the industrial robot stock and robot density provided by IFR.

Since the *intermediary companies and institutions* do not have significant patent filing activity in robotics, we omitted these from the analysis.

Regarding the territorial scope, we apply a threshold that in 2016 the robot stock in a given country must exceed 1000 robots, and globally 43 countries fulfilled the criterion. Based on this threshold, *17 EU member states* – Austria, Belgium, Czechia, Denmark, Finland, France, Germany, Hungary, Italy, Netherlands, Poland, Portugal, Romania, Sweden, Slovakia, Slovenia and Spain – have been analysed and in the following the notion of Europe refers to these countries. Central and Eastern Europe comprises Czechia, Hungary, Poland, Romania, Slovakia and Slovenia, while *Non-EU Europe* includes Norway, the United Kingdom and Switzerland. For global comparison the analysis has been expanded to the USA, China, Japan and Korea, to *South-East Asia* (Honk Kong, Indonesia, Malaysia, Philippines, Singapore, Thailand, Taiwan and Vietnam) and to the *Rest of the World* (Australia, Argentina, Brazil, Canada, India, Israel, Mexico, New-Zealand, Russia, South Africa and Turkey).

## Contours of the global robotisation landscape

Both robotics development and robot deployment belong to the most fast-growing global markets (see Figures 2 and 3). Between 1995 and 2016 the number of robot related patent families worldwide increased exponentially, it almost doubled every five years and while in 1995 there have been filed only 35 patents families, this figure jumped up to more than 1100 in 2016. In total 6210 robotics patens families have been filed over the whole period, the majority (61%) by the robotics developers and 32% by the in-house robotics developers, while the robot manufacturers own solely 7% of the patent families. Similarly, the number of industrial robots increased stunningly between 1995 and 2018, as in 1995 only 602,000 robots were deployed worldwide in the 43 countries analysed, though its number jumped almost to 1,600,000 in 2015 and to 2,350,000 in 2018.

The global distribution of the patent and the robot stock straightforwardly echoes the expected strong territorial concentration as the *Big Five* – Europe, USA, China, Japan and Korea – possess the overwhelming majority. Nevertheless, their positions vary significantly at the different parts of the robotisation chain both in respect to global share and to density (see Table 2).

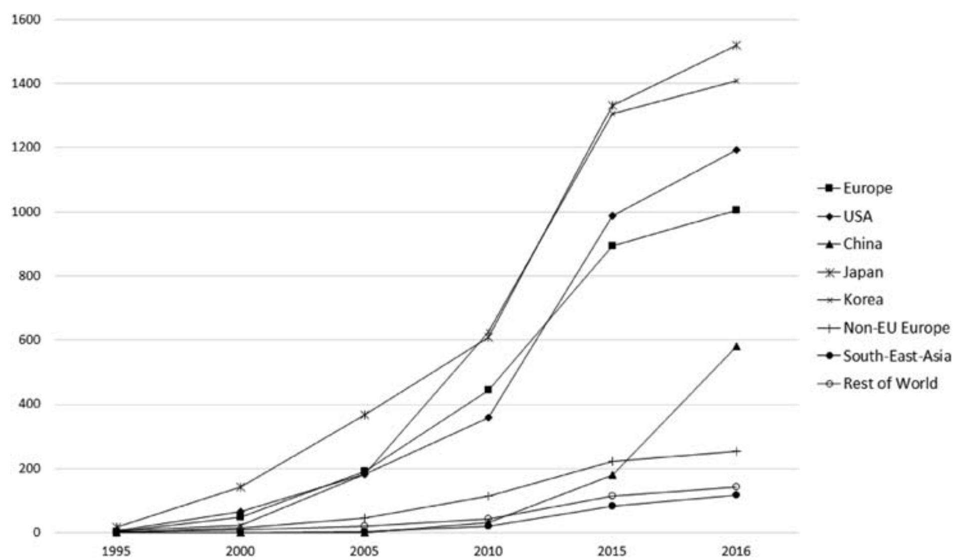


**Figure 2.** Development of the robot related patent stock by macro regions of the world, 1995–2016 (number of patent families).
Source: Authors' calculation based on PATSTAT and ORBIS data.

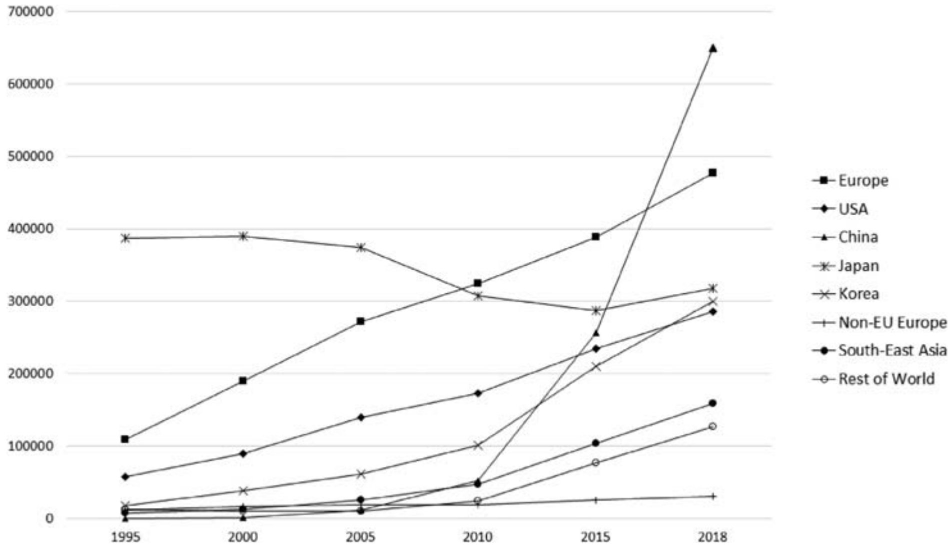


**Figure 3.** Development of the industrial robot stock by macro regions of the world, 1995–2018 (number of industrial robots installed).

Source: Authors' calculation based on data of IFR (2019).

As the global share, while currently China deploys more than one out of four robots of the global stock, its share concerning patents in robot manufacturing and in-house robotics development is meager. By contrast, Japan and Korea are the global leaders in in-house robotics (partly because of their industrial conglomerate structure, e.g. the *keiretsu* system in Japan and the *chaebols* in Korea), together they concentrate almost 40% of patents filed by robotics developers, and each country deploys a high number of robots in manufacturing. The biggest strength of the USA is in the robotics development, while Europe concentrates more than half of all patents filed by robot manufacturers, and also one out of five industrial robots of the global stock is at work in Europe.

High global share in some part of the robotisation chain is not always coupled with high density, although the latter indicates in a more precise manner how deeply the robotisation transforms the economy in question. First, while in recent years in China the number of industrial robots skyrocketed up to 650,000 robots, the Chinese robot density remained relatively low compared to its

**Table 2.** Global distribution of the main activities across the robotisation chain and their densities (robotics patents per 100,000 employees in manufacturing (2016), industrial robot stock per 10,000 employees in manufacturing (2018)).

| | Robotics developers (patents) | | Robots manufacturers (patents) | | In-house robotics development (patents) | | Robot user manufacturers (industrial robots) | |
|---|---|---|---|---|---|---|---|---|
| | Global share % | Density | Global share % | Density | Global share % | Density | Global share % | Density |
| Europe | 14.1 | 0.6 | 57.8 | 1.3 | 10.7 | 0.5 | 20.3 | – |
| *Germany* | *6.2* | *1.5* | *45.7* | *1.3* | *7.0* | *0.8* | *9.2* | *338* |
| USA | 22.0 | 2.4 | 11.9 | 0.2 | 15.3 | 0.9 | 12.1 | 217 |
| China | 12.8 | 0.2 | 1.7 | 0.1 | 4.2 | 0.1 | 27.7 | 140 |
| Japan | 22.3 | 3.7 | 7.8 | 0.2 | 32.4 | 2.7 | 13.6 | 327 |
| Korea | 17.2 | 7.6 | 17.8 | 0.9 | 34.4 | 7.8 | 12.8 | 774 |
| *Big Five* | *88.4* | – | *97.0* | – | *97.0* | – | *86.5* | – |
| Non-EU Europe | 1.5 | – | 2.2 | – | 0.8 | – | 1.3 | – |
| South-East Asia | 3.4 | – | 0.6 | – | 1.4 | – | 6.8 | – |
| RoW | 9.4 | – | 2.4 | – | 1.5 | – | 4.8 | – |
| Total | 100.0 | | 100.0 | – | 100.0 | – | 100.0 | |

Source: Authors' calculation based on PATSTAT, ORBIS and EUROSTAT data for robotics patent stock and density and of IFR (2019) for robot stock and density.

competitors and the densities of patent filing activities are the lowest in China. Second, the USA concentrates more than one-fifth of all patents of the robotics developers globally, though the density is lagging. Furthermore, most contrastingly, Korea and Japan have not only high global shares but also the highest densities in respect to Robotics Developers and In-house Robotics Development, and these countries also have very intense robot deployment. Finally, Europe and particularly Germany have very high share and high density in the deployment of industrial robots and in patent filings by robot manufacturers, which in this case are partly subsidiaries of overseas companies.

In summary, while the Big Five dominate the global robotisation landscape, not every of them possesses equally strong position across the whole chain. Japan and Korea are robustly engaged in every part of the robotisation chain, Europe is very strong in robot manufacturing and robot deployment, the USA has its firm competitive advantages in robotics development, and at present China is a rival in the industrial deployment of robots.

## European race for robotisation

The number of robotics patents in Europe followed the global trend and increased very rapidly over the period between 1995 and 2016. Consequently, the stock of patents more than doubled during that period from 444 in 1995 to 1000 patents in 2016. The Robotics Developers have filed the majority (53%) of the patents, while the Robot Manufacturers contributed with 26% and the In-house Robotics Developers with 21% to the total patent stock. Similarly, the stock of robots in manufacturing increased four times, from 109,000 in 1995 up to 477,000 robots in 2018, and the robot densities have been continuously above the global average in most of Europe throughout the period.

Robotics development in Europe is concentrated in just a few countries with almost 60% of the patents filed coming from Germany (576 patens). Germany, together with France (133) and Sweden (121) are responsible for over 80% of the patents from robotics developers. These three countries,

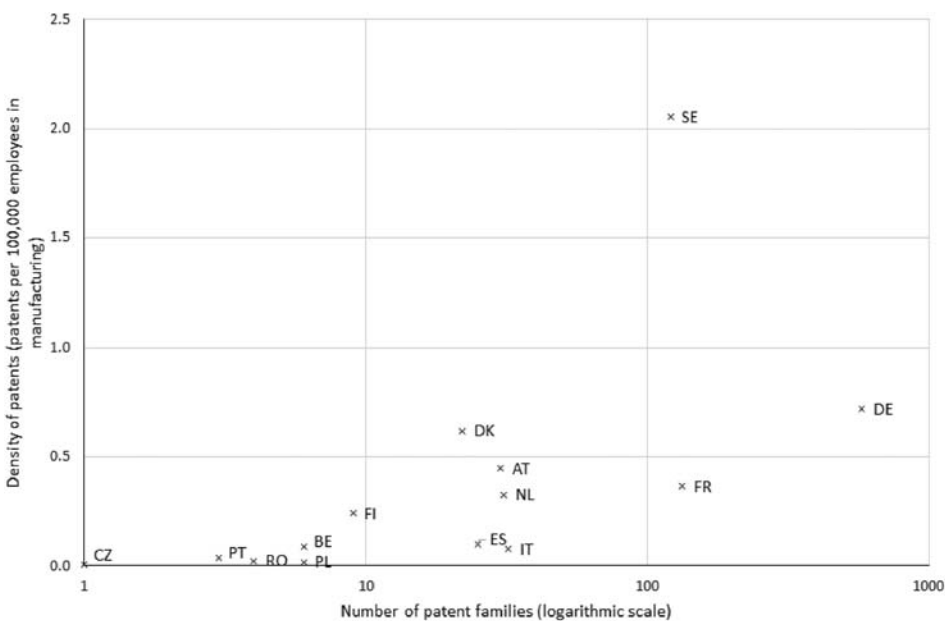


**Figure 4.** Robotics patent stock and patent density in Europe (average = 0.35 patents per 100,000 employees in manufacturing, Pearson's $r = 0.3690$, $p$-value = 0.19).

Source: Authors' calculation based on data of PATSTAT, ORBIS and EUROSTAT for robotics patent stock and density.

along with Italy, the Netherlands and Austria, account for over 90% of the European robotics patent stock (see Figure 4). Nevertheless, from the 17 EU economies analysed, three countries – Hungary, Slovakia and Slovenia – do not have robotics patents.

The deployment of industrial robots reveals somewhat balanced across different territories, notwithstanding that only four large economies possess almost three quarter of the European manufacturing robot stock (Germany 45%, Italy 13%, France and Spain each 8%). Nevertheless, while Germany and Spain have densities well above the European average, in Italy and France the densities remain relatively modest despite the high number of robots installed (see Figure 5). Robot density figures also indicate the convergence of smaller economies. Sweden, Belgium, Denmark, Slovenia, Austria and the Netherlands have densities above or slightly below the European average, despite their rather low robot stocks., However, Central and Eastern European countries are behind the curve both in respect to the number of manufacturing robots (exception is Czechia) and in terms of robot densities (exception is Slovenia).

Looking for the drivers behind the territorial patterns, and while obviously there are many influencing factors, our results support the assumption that countries with good availability of highly qualified scientific workforces become leaders in robotics development (see Figure 6). Sweden, Denmark, Austria, and France have both patent density and share of Science, Engineering and ICT professionals to manufacturing employment above the European average (5.5%), while in countries where the share of scientific and ICT workforces in manufacturing employment is below 5% (Romania, Poland, Czechia, Portugal, Italy and Spain) the robotics patent densities are below the European average as well.

Taking the labour cost as the most important driver of different robot densities, the relationship is also clear-cut: the higher the labour cost, the higher the robot density (see Figure 7). Once again, the most striking issue is the West-East divide. In the top four countries with the highest robot densities (Germany, Sweden, Belgium and Denmark) also the labour costs in manufacturing are the highest, above 40 euros per hour, while in the bottom four countries with the lowest densities (Romania, Poland, Portugal and Hungary) the labour costs are below 12 euros per hour.

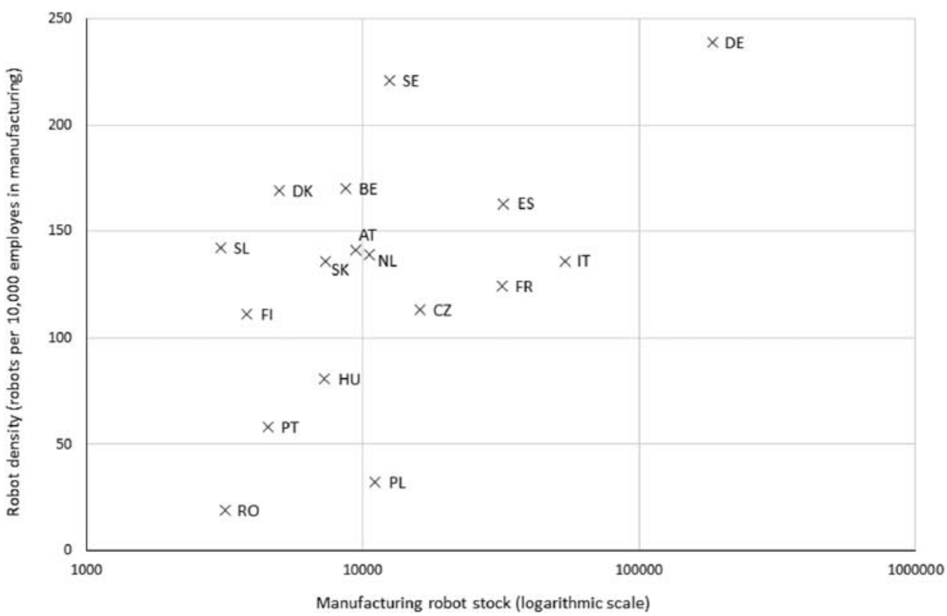


**Figure 5.** Manufacturing robot stock and robot density in manufacturing, selected European countries, 2018 (average = 141 robots per 10,000 employees in manufacturing, Pearson's $r = 0.5184$, $p$-value = 0.033).

Source: Authors' calculation based on data of IFR (2019) for robot stock and EU KLEMS for employment.

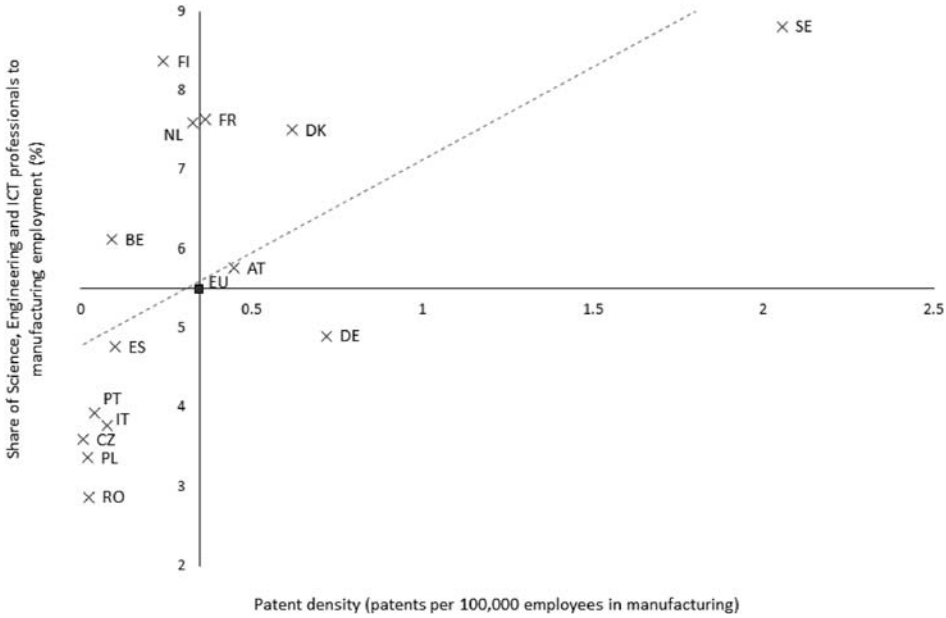


**Figure 6.** Patent density in Europe and the share of Science, Engineering and ICT professionals to manufacturing employment (average = 0.35 patents per 100,000 employees in manufacturing, average = 5.5% of Science, Engineering and ICT professionals to manufacturing employment, Pearson's $r = 0.6207$, $p$-value = 0.014).

Source: Authors' calculation based on data of PATSTAT, ORBIS and EUROSTAT for robotics patent stock and density, and employment.

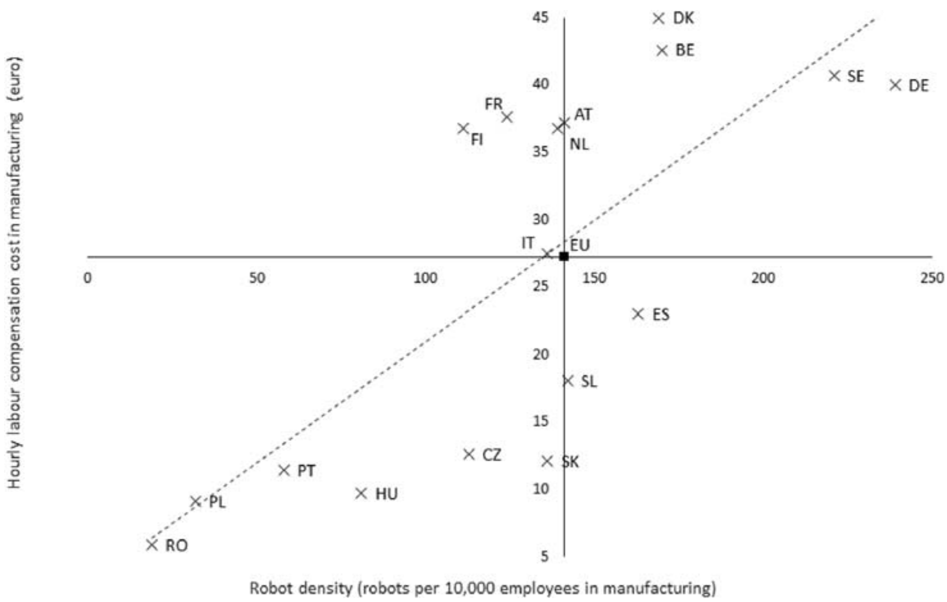


**Figure 7.** Robot density and hourly labour compensation costs in manufacturing, selected European countries, 2018 (average robot density = 141 robots per 10,000 employees in manufacturing, average labour cost in manufacturing: 27.3 euros, Pearson's $r = 0.7528$, $p$-value = 0.00032).

Source: Authors' calculation based on data of IFR (2019) for robot stock, EU KLEMS for employment, and EUROSTAT for labour cost.

There is only one particular industry in which Central and Eastern Europe shows some evidences of convergence, as due to three decades of continuous offshoring of European and oversees car manufacturers, the region has become an automotive production hub of European significance (Pavlínek 2017) and today manufactures around 25% of the European motor vehicles (OICA 2020). This has also led to a strong sectoral specialisation in robotisation, since in Central and Eastern Europe just about two out of three manufacturing robots (63%) is at work in the automotive industry, well above the European average of 50%.

The Location Quotient (LQ) figures, which are the share of automotive robots in manufacturing robot stock in a given country relative to the European average, indicate that the whole region is disproportionately specialising in the automotive sector. Central and Eastern European countries have LQ values higher than the threshold of one and Slovenia and Slovakia have already been caught up concerning automotive robot densities (see Figure 8). Whereas in Denmark, Finland, the Netherlands and Italy industrial robots are deployed in more diversified industries as in these countries at present more than three out of four manufacturing robots are at work in industries other than automotive.

These contrasting trends raise in the words of Cséfalvay (2020) the concern of a *dependent robotisation* in Central and Eastern Europe, both in terms of a sectoral dependence from a single industry (car manufacturing) and in terms of structural dependence, meaning that robotisation in the region is largely relying on the localisation decisions of global firms.

The more detailed analysis of the whole robotisation chain indicates that in Europe there are three main groups of countries with significantly different positions (see Table 3):

The countries of the first group – Sweden, Germany, Austria, Denmark and France – have densities in every part of the robotisation chain which are mostly well above the European average values. Their leadership is based on the fact that they are equally strong in robotics development – though with differences regarding Robotics Developers, Robot Manufacturers and In-house Robotics Developers – as well as in robot deployment.

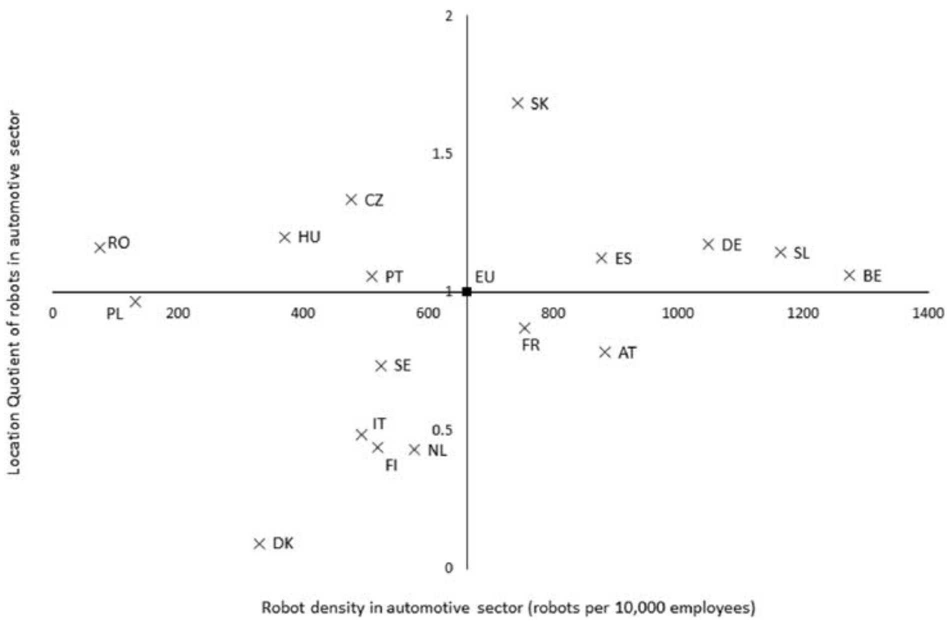


**Figure 8.** Robot density and location quotient in the automotive sector, selected European countries, 2018 (Europe average = 663 robots per 10,000 employees in automotive sector).

Source: Authors' calculation based on data of IFR (2019) for automotive robot stock, EU KLEMS for employment in automotive sector in year 2017.

**Table 3.** Relative position of the European countries across the Robotisation chain, based on densities in the main activities (robotics patents per 100,000 employees in manufacturing, robot stock per 10,000 employees in manufacturing, 0 = non-existent).

| | Robotics developers | | | Robots manufacturers | | | In-house robotics developers | | | Robot user manufacturers | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | High | Avg. | Low | High | Avg. | Low | High | Avg. | Low | High | Avg. | Low |
| *Strong participation across the whole robotisation chain* | | | | | | | | | | | | |
| SE | 1.076 | | | | 0.085 | | 0.873 | | | 221 | | |
| DE | 0.296 | | | 0.255 | | | 0.198 | | | 239 | | |
| AT | 0.294 | | | | | 0.051 | 0.109 | | | | 141 | |
| DK | 0.541 | | | | 0.085 | | | | 0 | 169 | | |
| FR | 0.129 | | | | | 0.041 | | | 0.014 | | 124 | |
| *Strong participation in specific parts of the robotisation chain* | | | | | | | | | | | | |
| ES | | 0.084 | | | | 0.004 | | | 0.012 | 163 | | |
| IT | | | 0.044 | | | 0.028 | | | 0.005 | | 136 | |
| BE | | 0.090 | | | | 0 | | | 0 | 170 | | |
| NL | 0.318 | | | | | 0 | | | 0.011 | | 139 | |
| FI | 0.241 | | | | | 0 | | | 0 | | | 111 |
| *Integration to the robotisation chain by robot deployment* | | | | | | | | | | | | |
| SL | | | 0 | | | 0 | | | 0 | | 142 | |
| SK | | | 0 | | | 0 | | | 0 | | 136 | |
| PT | | | 0.046 | | | 0 | | | 0 | | | 58 |
| CZ | | | 0.008 | | | 0 | | | 0 | | | 113 |
| HU | | | 0 | | | 0 | | | 0 | | | 81 |
| PL | | | 0.018 | | | 0 | | | 0 | | | 32 |
| RO | | | 0.035 | | | 0 | | | 0 | | | 19 |
| *EU* | | *0.087* | | | *0.182* | | | *0.071* | | | *141* | |

Source: Authors' calculation based on data of PATSTAT, ORBIS and EUROSTAT for robotics patent stock and density, and employment, and of IFR for robot stock, and EU KLEMS for employment.

The countries of the second group – Spain, Italy, Belgium, the Netherlands and Finland – do not participate in every part of the robotisation chain, many of them lack the robot manufacturing and are weak concerning the in-house robotics development, but they have relatively well performing Robotics Developers and also deploy industrial robots intensively.

Finally, the countries of the third group, all Central and Eastern European countries and Portugal, have only recently started to converge with their European counterparts, in particular by the deployment of industrial robots. However, this is often almost exclusively limited to the automotive industry. Where they are still very far behind is the robotics development, moreover, according to patent data at present, the robot manufacturing and the in-house robotics development are non-existent in this group.

## Policy implications and further research challenges

While this study offers only the first and current snapshot, though, the present global and European robotisation landscape raises three long-term policy questions:

the first relates to the upgrading along the robotisation chain,
the second issue is the opportunity of reshoring the previously offshored production processes,
while the third policy challenge is to assess the impact that the participation in the different parts of the robotisation chain may have on employment.

Evidence of the global value chain research indicates that while the increased engagement of the less developed and emerging economies in the global value chains fostered the globalisation, this integration also contributed enormously to their catching-up process, – though to very different extent (Kaplinsky 2000; Kaplinsky and Morris 2001; Henderson et al. 2002; Baldwin and Lopez-

Gonzalez 2013; Taglioni and Winkler 2016; World Bank 2017; Gereffi 2018; UNIDO 2018; Ponte, Gereffi, and Raj-Reichert 2019; Raei, Ignatenko, and Mircheva 2019). Similarly, in robotisation, the catching-up process advances at various rates, and the quickest and perhaps the easiest way to converge is the deployment of industrial robots. Countries such as Central and Eastern European ones which offer relatively well-skilled labour at low wages and have already been integrated into different global value chains might opt for this option. These countries, however, lack the extremely R&D intensive robotics development and robot manufacturing that requires domain knowledge in advanced manufacturing. In other words, while market liberalisation, integration into the European single market and the comparatively well-skilled but cheap labour were sufficient to attract robot-based manufacturing, upgrading along the robotisation chain requires new policies that focus on increasing the R&D capacities of the lagging countries.

However, the upgrading along the robotisation chain is to some extent hampered by the fact that robot-based automation and application of digital technologies in manufacturing (Industry 4.0) increase the opportunities to produce geographically closer to the consumer markets of the developed countries (Propis De and Bailey (Eds.) 2020). Consequently, companies may reconsider their value chains, and this could result in reshoring the previously offshored production processes (which depending on reshoring choices and geographical distance could have different forms, such as back-shoring, home-shoring, or near-shoring) (Pegoraro, Propris De, and Chidlow 2020). Studies indicate that in Europe the reshoring has already started (Dachs and Kinkel 2013; Gray et al. 2013; Fratocchi et al. 2014; De Backer and Flaig 2017; Mauro et al. 2018; Dachs et al. 2019; Kinkel, Pegoraro, and Coates 2020) as the gap between offshoring and back-shoring activities has become smaller over the past two decades. Nevertheless, in Europe the average share of companies active in reshoring at all manufacturing companies is currently very low and varying from 3% in Germany over around 6% in Belgium and France up to 9% in Sweden (Kinkel, Pegoraro, and Coates 2020).

Today it is uncertain how in Europe the reshoring process will be developing in the future, but it is safe to say that the jobs which were offshored from developed countries to developing ones during the great wave of globalisation will never return. Due to reshoring driven by robotisation it is not the jobs that will return, but the production with automated plants and robotised factories requiring much fewer and much higher-skilled employees. Therefore, the large advanced European economies face a trade-off between the expected job losses in low-skilled activities that the deployment of robots in manufacturing may cause and the relatively small increase of higher skilled jobs and the significant productivity gains that reshoring with robotised factories make possible.

This leads us to the third policy challenge, that of the employment impact of robotisation, since the particular parts of the robotisation chain have very different effects on jobs. In essence, the fast growing literature on the future of work applies a comparison between the skills demands of the current jobs held by humans and the (future) skills of robots, based on what today or in the future technologically is (or will be) possible, and by doing this predicts and assesses the workers' risks of being displaced by automation. These assessments are, however, characterised by a high degree of uncertainty and a number of theoretical and analytical drawbacks as they take at face value what technologically is possible, focus exclusively on the quantitative side of the employment effects, exclude the impact of increased productivity on job creation and fully neglect the country-specific and industry related factors (Iséfalvay 2019). Nevertheless, our model of the robotisation chain clearly highlights an additional weakness: these studies treat the robotisation extreme narrowly and analyse only one fraction of the chain, the effects that Robot User Manufacturers might have on employment. It is more than obvious, however, that other parts of the robotisation chain, primarily the robotics development and the robot manufacturing could contribute to the creation of new jobs and these must be included into the whole picture when it is about assessing the robotisation's impacts on jobs. Indeed, this is the point, where the various engagements of the European countries in the particular parts of the robotisation chain come again into play. The net employment effect across the whole robotisation chain might be significantly different in countries that have strong positions *in all the three* important elements of the robotisation chain than in countries that only deploy industrial robots and lack the job-creating parts of the robotics chain.

Whether it is about the upgrading along the robotisation chain, the reshoring of the previously offshored production or the employment effects of robotisation, further analyses, in particular at firm-level could contribute significantly to the design of appropriate country-specific policies. Similarly, while this study is based on aggregate data, researches that use microdata could reveal a more detailed picture about the robotisation chain. Finally, while we have focused on industrial robots, the widespread deployment of services robots may provoke significant changes in the European race for robotisation in the years to come.

## Disclosure statement

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