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Abstract
This paper investigates the contribution of industrial robots to employment change in manufacturing in a sample of 17 European countries and the USA over the period 2004 to 2019. We combine index decomposition analysis (IDA) and production-theoretical decomposition analysis (PDA). First, we use IDA to decompose employment change in the manufacturing industry into changes in (aggregate) manufacturing output, changes in the sectoral structure of the manufacturing industry, and changes in labour intensity which is a composite index of labour intensity change within each of the nine sub-sectors of total manufacturing. Second, we use PDA to further decompose labour intensity change to isolate the contribution of technical efficiency change, technological change, human capital change, change in non-robot capital intensity and change in robot capital intensity to employment change. In almost all of the countries considered, the labour intensity is falling in entire manufacturing, which has a dampening effect on employment. Robotisation contributes to this development by reducing labour intensities and employment in all countries and sub-sectors, though to varying degrees. Manufacturing output, in turn, grows in all countries (except Greece, Spain and Italy), which increases employment and counteracts or in some countries even more than offsets the dampening effect of declining labour intensities. The structural change within manufacturing has an almost neutral effect in many countries.

JEL-Classification: C43, J21, J24, O33
Keywords: automation, robotisation, decomposition, structural change, data envelopment analysis

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1. Introduction

Economic development in industrialized and emerging countries in recent decades has been characterized, inter alia, by a noticeable decline in employment in the manufacturing sector. The total number of hours worked in manufacturing fell on average by 12.13% in advanced European countries over the last fifteen years (2004-2019), with significant differences between individual countries, and by 5.37% in the USA. Between 2004 and 2019 the manufacturing sector's share in overall economic employment fell from 16.12% to 13.15% in advanced European countries and from 11.68% to 9.88% in the USA (OECD Detailed National Accounts statistics, Labour input by activity – ISIC Rev. 4). These changes document the shift of employment to other economic sectors and are often seen as a sign of deindustrialization in developed European countries and the USA.

Another key development across the entire manufacturing sector is the automation of production processes, particularly the increasing use of (industrial) robots. According to data from the International Federation of Robotics (Müller and Kutzbach, 2020) and again considering the time span 2004-2019, the number of robots in manufacturing has tripled in advanced Europe, while it has increased nearly fivefold in the same industries in the United States. The use of robots is only one part of automation, albeit a very important one and is often viewed as a proxy for the whole.

The decline in employment and robotisation are occurring simultaneously. This raises the question of whether the two happened at the same time by chance or whether they are connected in some way. The present study examines how the increasing use of robots contributes to the development of overall employment in manufacturing. This question has been discussed, both in theoretical works and in empirical studies. Theoretical studies show very different impact mechanisms, which are either labour-saving or labour-creating. The detailed works by Barbieri et al. (2020) and Acemoglu and Restrepo (2019a,b), among others, present a variety of theoretical considerations regarding market mechanisms and different impact channels, but do not provide a clear-cut conclusion regarding the net effect on employment. The impact depends on a number of factors, including model assumptions, parameters, elasticities and model calibrations. Ultimately, it remains up to empirical studies to answer the question. Empirical studies were carried out at different levels of aggregation, including the micro-level (i.e., workers and firms; e.g., Dauth et al. 2021; De Backer et al., 2018; etc.), the meso-level (i.e., industries, metropolitan areas/cities and regions; e.g., Graetz and Michaels, 2018; Dahlin, 2019; Kariel, 2021; etc.) and the macro-level (i.e., countries; e.g., Fu et al., 2021; Jung and Lim, 2020; etc.), and with different industry focuses. The findings of empirical studies depend on the selected sample (countries, industries and observation periods) as well as the data sources, the model specification and the unit of analysis (e.g., firm, sector, economy). The spectrum ranges from significantly positive to insignificant to significantly negative effects of robot use on employment.

We investigate the employment effects of robotisation at the manufacturing sub-sector level, using observations on nine manufacturing industries over the period 2004-2019 from 17 European economies and the USA. Sub-sectors are characterized by different production technologies, which is reflected by varying labour intensities across sectors, making them distinctly susceptible to changes in labour costs. Furthermore, due to technology heterogeneity, there are divergent potentials across sub-sectors for substituting labour with robots. In addition, the manufacturing sub-sector level offers an interesting political perspective, since wage bargaining between employer and employee representatives are usually undertaken at the level of manufacturing sub-sectors. The effects of the use of industrial robots on employment play an indirect role for this bargaining as it is influenced by possible labour cost savings as a result of replacement potentials of (human) labour through robots. Furthermore, sector level data sets cover also small enterprises which are underrepresented in most firm level data sets. In advanced economies, small firms present the majority of the total number of enterprises. Robot use plays a different role on the firm level according to non-random factors (e.g., size, business model) and random factors. Thus, when the interest is on the net effect on the economy, it is natural to work with aggregate level data, where the sub-sector level provides the most detail while still covering the whole economy.

Only few existing studies on the relationship between robot adoption and employment are based on country industrial data. The pioneering work with such data is Graetz and Michaels (2018). It includes data from 14 robot-using industries in 17 countries (USA, South Korea, Australia, and 14 European countries) from 1993 to 2007. The industries considered also include non-manufacturing sectors such as agriculture, mining, utilities, construction, and "education and R&D". The empirical results show that, on average, robots did not significantly reduce total employment. The data set used by Carbonero et al. (2018) comprised 15 manufacturing and non-manufacturing sectors in 41 developed and emerging countries from all over the world in the years 2005 to 2014. On average, they find a statistically significant negative impact (greater in emerging economies than in developed countries) of industrial robots on employment. An examination of manufacturing employment as a share of total employment shows a statistically weakly negative effect, again stronger in emerging than in developed countries. Kromann et al. (2020) consider 10 manufacturing industries in 9 countries (Japan, Germany, UK, France, Italy, Spain, Sweden, Finland, and Denmark) in the years 2004 to 2007. According to their results, robot use is associated with unchanged or higher employment in total manufacturing. De Vries et al. (2020) examined 19 industries in 37 high-income as well as emerging market and transition economies between 2005 and 2015. Their results indicate that there is no significant relationship between industrial robot adoption and aggregate employment growth. Klenert et al. (2023) use a data set covering 9 manufacturing and 5 non-manufacturing sectors in 14 countries of the European Union from 1995 to 2017. Their results indicate the use of robots is positively associated with aggregate employment in the manufacturing sector.

Those previous studies use regression techniques to investigate the employment effects of robotisation and report average effects across countries and industries. In contrast, to our knowledge, at the first time, we use a non-parametric approach, which combines index decomposition analysis (IDA) with production-theoretical decomposition analysis (PDA) and allows to provide country- and sector-specific estimates of robot induced employment changes. In this way, we gain deeper insights into individual manufacturing sub-sectors of the economy with high overall economic importance and a high degree of robotisation, such as the automotive industry, the machine and metal industry or the electronics and computer industry.

Few previous studies explicitly consider manufacturing and none address heterogeneous employment effects across manufacturing sub-sectors.

Our estimation procedure consists of two steps. First, we use IDA to decompose employment change in manufacturing into changes in (aggregate) manufacturing output (output effect), changes in the sectoral structure of manufacturing (output mix effect), and changes in labour intensity (intensity or productivity effect) which is a composite index of labour intensity change within each of the nine sub-sectors of total manufacturing. Second, we use PDA based on distance functions to further decompose labour intensity change to isolate the contribution of technical efficiency change, technological change, human capital change, change in non-robot capital intensity and change in robot capital intensity to employment change. Distance functions for the PDA are estimated by Data Envelopment Analysis and the procedure accounts for heterogeneity in production technologies across sub-sectors and time.

Our approach is anchored in production economic theory but does not require to assume a functional form of the production function (like Cobb-Douglas or CES), i.e., it is a non-parametric data driven approach. This allows to relax the often unrealistic assumptions made i) about the elasticities of substitution between inputs and ii) the nature of technological change (i.e. Hicks-neutral technological change). It also identifies the contribution of structural change to employment variation separately from technical efficiency change (i.e. movements towards the frontier) and technological change (i.e. shifts of the frontier). Finally, it enables to report country-specific and sub-sector-specific employment effects of robotisation instead of averages across countries and sectors. The decomposition methodology allows estimating the direct labour-saving effects, but not compensation effects which work (indirectly) via increases in output, and are thereof part of the output change component.

Results indicate, that labour intensity is falling (or in other words labour productivity is rising) in entire manufacturing and all sub-sectors in almost all countries examined, which has a dampening effect on employment. Robotisation contributes to this development by reducing labour intensities and thus employment in all countries and manufacturing sub-sectors, though to varying degrees. Manufacturing output, in turn, grows in all countries (except Greece, Spain and Italy), which increases employment and counteracts, or in some countries even more than offsets the dampening effect of declining labour intensities. The structural change within manufacturing contributes little in many countries.

The remainder of this paper is structured as follows. Section 2 describes the data, discusses the choice of the variables and provides selected descriptive statistics. It is followed by Section 3 which explains the applied methodology. Section 4 presents the empirical results. Section 5 summarizes our results and concludes.

2. Data

Our data set consists of four variables representing production factors, i) labour, ii) human capital, iii) non-robot physical capital, iv) robot capital, and one variable for the output, value added. We use three different data sources: First, input data for labour and non-robot physical capital as well as value added data are derived from OECD Detailed National Accounts statistics. Second, we take human capital information from the Penn World Table (PWT) version 10.0 (Feenstra et al., 2015). Third, we use data from the International Federation of Robotics (Müller and Kutzbach, 2020) to estimate industrial robot capital stocks.

2.1. Sample selection

Müller and Kutzbach (2020) provide data on annual robot installations and robot stocks for 1993–2019 for a comprehensive set of developed and emerging countries from around the world. While at the macroeconomic level this database is less limited in quality and coverage, at a more disaggregated level, such as individual industries or manufacturing sub-sectors, data availability is significantly lower and requires careful selection of countries and years, definition of industries, and in several cases data interpolation. Similar issues apply to labour market data and other national accounts data, which are available for many countries at the macroeconomic level, but only for relatively few at the industry-level. After checking the availability and quality of time series, we arrive at a sample of nine-manufacturing sub-sectors covering 18 countries and the years 2000 to 2019 resulting in a total number of 3,240 observations.[2] The industries considered ranges from "Manufacture of food products, beverages and tobacco" (C10-C12) to "Other manufacturing, repair and installation of machinery and equipment" (C31-C33) (see Table 2). Countries included are Austria, Belgium, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Italy, the Netherlands, Norway, Portugal, Slovak Republic, Spain, Sweden, United Kingdom, and the United States.

2.2. Robot capital stock variables

The International Federation of Robotics (IFR) provides data on annual robot installations by country, industry, and application (Müller and Kutzbach, 2020). The IFR uses the definition of a 'manipulating industrial robot' given by the ISO 8373:2012 standard from the International Organization for Standardization. Accordingly, an industrial robot is defined as 'an automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications' (Müller and Kutzbach, 2020, p. 23).

We construct the stock of industrial robots in physical units based on annual installations using the perpetual inventory method (PIM), assuming annual depreciation rates of 15%.[3] Section A

[2] Though, we have data for the period 2000 to 2019, the period of investigation in the Sections 2.4 and 4 is 2004–2019. The reasons for this are methodological considerations which are explained in Section 3.2.

[3] For the purpose of sensitivity analysis, we also created robot capital stock data assuming a depreciation rate of 10% as well as using a 'one-hoss shay' depreciation method assuming that the average operating service life of an industrial robot is 12 years. A comparison of these series reveals that they are highly correlated with each other (correlation coefficients higher than 99.8%). For this reason and based on the results of an empirical study on the macroeconomic level (Eder et al., 2023), we assume that the depreciation method has only a minor influence on the estimation results as well as on the conclusions.

of the supplementary material describes the data preparation steps and the construction of the robot installation series and the robot stock series in detail. Section B of the supplementary material provides figures on the evolution of our estimated robot stock series over the period 2000 to 2019 for each of the 18 countries and nine manufacturing sub-sectors in our sample. Thereafter, we derive monetary robot capital stocks in constant prices (of the base year and country) by multiplying the robot stock in physical units by the average unit price of robots in the United States in 2017 and use the monetary robot capital stocks only for the calculation of monetary non-robot capital stocks.

Kromann et al. (2020) and Graetz and Michaels (2018) report that the quality of robots increased markedly between 1990-2005. To account for quality changes in the robot stocks we follow Eder et al. (2023) and consider annual robot installations in efficiency units by multiplying the robot installations in physical units with an index of robot quality. The robot quality index is based on two price indices developed by the IFR (IFR, 2006; Chapter III and Annex C) for the period 1990-2005, one is quality adjusted and one is not. The robot quality index is derived by dividing the quality adjusted robot price index by the non-quality adjusted robot price index. For the years 2006-2019 we use forecasted values of the robot quality index based on a linear trend model.

At the industry level, robust-quality data on robot usage is only available for broad manufacturing sub-sectors. The grouping is only partially compatible with labour market and national accounts data. A compromise requires that the robot usage data is aggregated into nine broad manufacturing sub-sectors to be combinable with other data. The exact sector division is shown in subsection 2.4.

2.3. Labour, non-robot capital and output variables

The data for labour, non-robot physical capital and output is derived from OECD Detailed National Accounts statistics. In particular, labour input is measured as “Labour input by activity – ISIC Rev. 4” in annual million hours worked; The non-robot physical capital stocks are computed as “Net fixed assets by activity and by asset, ISIC Rev. 4” minus our estimated monetary robot capital stock described in section 2.2.; The output is measured by “Gross value added and its components by activity, ISIC Rev4”. The OECD statistics provide the time series of data measured in monetary units in national currencies valued at current year prices. To adjust this data for price differences over time, we brought it to the price level of 2015 using the respective price deflators from the OECD Detailed National Accounts statistics. Afterwards, the non-robot physical capital data as well as the output data were adjusted for spatial price differences and converted to million Euros using purchasing power parity (PPP) for 2015 from Eurostat for capital goods and for gross domestic product, respectively.[4]

[4] We are aware that adjusting for the spatial price differences of all different sectors of the economy with a single purchasing power parity per country brings with it a certain vagueness. However, the availability of PPP data leaves us with no other option. As far as we know, PPPs broken down by economic sector are only available for production GDP (cf. Olislager, Konijn, 2016).

Human capital is measured by the human capital index from the Penn World Table (PWT) version 10.0 (Feenstra et al., 2015). Its calculation follows a common approach in the literature and is based on data on years of schooling and returns to education. We follow Walheer (2016a, b) and assume the human capital endowment to be the same for all industries considered in the respective country. In this way, we account for interdependencies of the sectors which share the country's education system.

2.4. Descriptive Statistics

Figure 1 presents the employment development in hours worked across the entire manufacturing sector from 2004 to 2019 in four European regions as well as in the USA in the form of an index. The graph shows declining or stagnating employment for all regions. While in Central Europe and the USA employment has recovered after the downward trend during the crisis years of 2009/10 and has reached the level of 2004 (Central Europe) or not fully reached it (USA), this is not the case in the other regions. They have not recovered from the shock and employment in 2019 is well below pre-crisis levels.

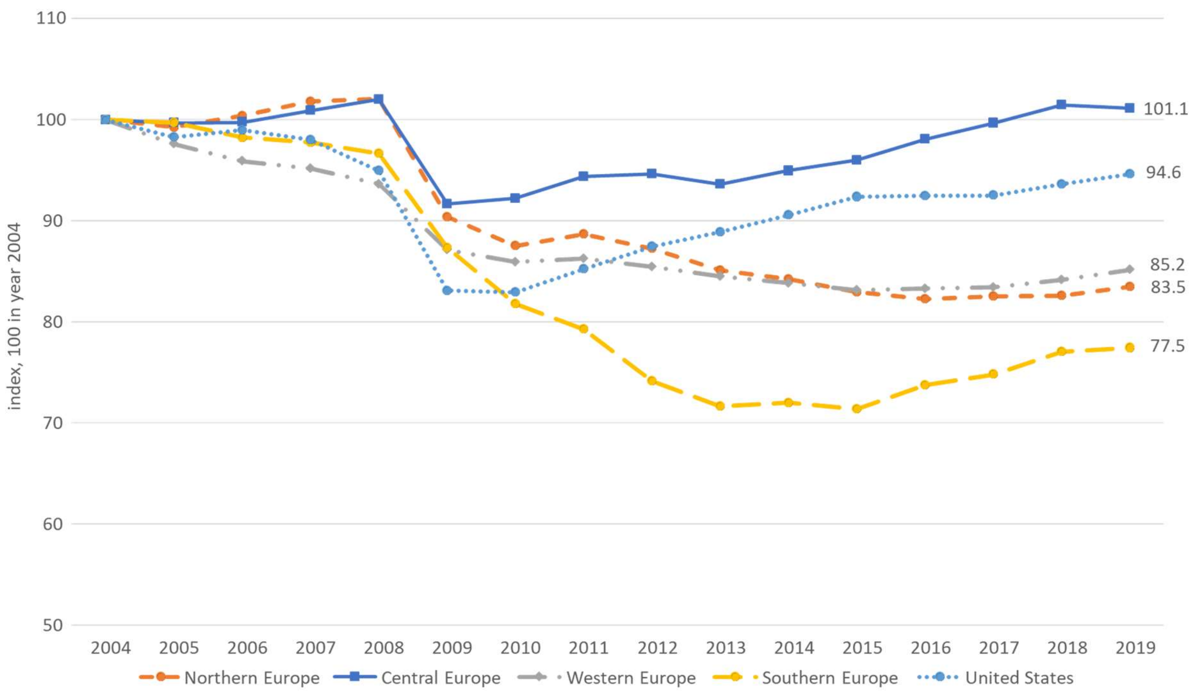

Figure 1 Index of employment (measured in hours worked) in total manufacturing in Northern, Central, Western, Southern Europe and the USA

Note: Northern Europe … Denmark, Finland, Norway and Sweden; Central Europe … Austria, Czech Republic, Germany, Hungary and Slovak Republic; Western Europe … Belgium, France, the Netherlands, and United Kingdom; Southern Europe … Greece, Italy, Spain and Portugal

Table 1 presents the robot intensities in total manufacturing in 2004 and 2019 as well as the growth rates, revealing above all the heterogeneity of the countries. What is striking is that Germany has by far the highest and Greece by far the lowest intensity in both years. Interestingly, the USA does not stand out regarding the robot intensity of its manufacturing sector. Robot intensity is increasing in all countries of this sample. Growth is highest in Hungary, the Slovak Republic and the Czech Republic and lowest in Finland, Germany and France. The high growth rates in the three Central and Eastern European countries clearly document the catching up of these three former transition countries.

Table 1
Robot intensity in total manufacturing by countries

Country	Robot intensity in 2004	Robot intensity in 2019	Growth rate of robot intensity 2004–2019
Denmark (DNK)	215.77	770.73	257.21%
Finland (FIN)	287.15	486.91	69.57%
Norway (NOR)	98.65	203.87	106.66%
Sweden (SWE)	298.31	763.28	155.87%
Austria (AUT)	196.17	611.00	211.46%
Czech Republic (CZE)c	38.23	446.86	1,068.91%
Germany (DEU)	559.33	1031.47	84.41%
Hungary (HUN)	12.40	323.80	2,511.98%
Slovak Republic (SVK)	25.85	466.76	1,705.45%
Belgium (BEL)	273.04	632.37	131.60%
France (FRA)	301.73	565.09	87.28%
Netherlands (NLD)	86.34	561.85	550.75%
United Kingdom (GBR)	113.51	231.99	104.38%
Greece (GRC)	4.85	43.37	794.19%
Italy (ITA)	328.01	615.61	87.68%
Portugal (PRT)	43.76	232.24	430.74%
Spain (ESP)	236.72	586.25	147.66%
United States (USA)	198.63	584.65	194.34%

Note: Robot intensity is measured as number of non-quality-adjusted robots per one hundred million hours worked. Number of robots are estimated with the perpetual inventory method assuming a depreciation rate of 15%.

Table 2 shows the average robot intensities of individual sub-sectors across the 18 countries in our sample. In 2004, robot intensity was highest in the “basic metals and fabricated metal products industry” (C24 + C25) and lowest in the “paper products industry + other manufacturing” (C16-C18 + C31-C33). This changed fundamentally by 2019. In 2019, the intensity is highest in the “automotive industry” (C29 + C30) followed by the “rubber and plastics industry” (C22 + C23). This change is due to the significant growth of the robot intensities in the automotive and plastic industry in the former transition countries in Central and Eastern Europe. Robot intensity is increasing in almost all sub-sectors. The highest growth by far is observed for the “paper products industry + other manufacturing” (C16-C18 + C31-C33), the “rubber and plastics industry” (C22 + C23) and the “automotive industry” (C29 + C30). The only sub-sector with a decline is the “textile industry” (C13-C15). This reflects the off-shoring activities in these industries to countries outside our sample. Detailed descriptive statistics of other variables used in our analysis are available in the supplementary material in section C.

Table 2
Robot intensities in manufacturing sub-sectors

Sub-sector	Robot intensity in 2004	Robot intensity in 2019	Growth rate of robot intensity 2004–2019
C10-C12	251.29	294.03	17.01%
C13-C15	68.51	25.96	-62.11%
C16-C18 + C31-C33	8.91	364.19	3,985.67%
C19-C21	64.86	192.46	196.74%
C22 + C23	27.92	1,015.39	3,536.65%
C24 + C25	528.28	964.55	82.58%
C26 + C27	474.12	796.74	68.05%
C28	218.16	312.59	43.28%
C29 + C30	48.60	1,286.50	2,546.90%

Note: Robot intensity is measured as number of robots per one hundred million hours worked. Number of robots are estimated with the perpetual inventory method assuming a depreciation rate of 15%.
C10-C12 … Manufacture of food products, beverages and tobacco, C13-C15 … Manufacture of textiles, wearing apparel, leather and related products, C16-C18 + C31-C33 … Manufacture of wood and paper products; printing + Other manufacturing, repair and installation of machinery and equipment, C19-C21 … Manufacture of basic pharmaceutical products and preparations + Manufacture of coke and refined petroleum products + Manufacture of chemicals and chemical products, C22 + C23 … Manufacture of rubber and plastics products, and manufacture of other non-metallic mineral products, C24 + C25 … Manufacture of basic metals and fabricated metal products, except machinery and equipment, C26 + C27 … Manufacture of computer, electronic, optical products; and manufacture of electrical equipment, C28 … Manufacture of machinery and equipment not elsewhere classified, C29 + C30 … Manufacture of transport equipment.

3. Methodology

Similar to Lin and Du (2014) we combine index decomposition analysis (IDA) with production-theoretical decomposition analysis (PDA). The procedure aims to overcome the weakness of PDA in potentially generating misleading conclusions regarding the effect of changes in industrial structure (output structure or output-mix) on changes in the outcome variable of interest (Lin and Du, 2014).

In addition to the weakness of PDA discussed in Lin and Du (2014),[5] we identify the following limitation of PDA regarding the estimation of output-mix effects: PDA relies on distance functions representing the distance of an input-output bundle from a production frontier. Most commonly, distance functions in PDA are estimated with Data Envelopment Analysis (DEA). DEA can handle multiple inputs and multiple outputs. However, the number of units under investigation (e.g., firms, sectors, regions, countries) relative to the number of input and output variables has to be sufficiently high to get reasonable estimates of a distance function (Dyson et al., 2001). Estimating output-mix effects in PDA requires to consider all relevant outputs as separate output variables in a DEA model (see, e.g., Wang, 2007, 2011, 2013). If the number of units under investigation is relatively small (e.g., few regions in a country exist; sectoral data is available only for a small number of countries) compared to the number of outputs (e.g.,

[5] Lin and Du (2014) prove (cf. Appendix A in Lin and Du, 2014) that due to the characteristics of distance functions PDA can, under certain conditions, reveal that a change in industrial structure from high-energy intensity to low-energy intensity industries contributes to an increase in energy intensity. As an example of such a counterintuitive result they mention the studies of Wang (2007, 2011).

outputs of many different sectors) the effect of changes in output structure on the change in the outcome variable of interest can hardly be estimated with PDA. Estimating the effect of changes in industry output structure with IDA is less restrictive and imposes fewer requirements on the data structure.

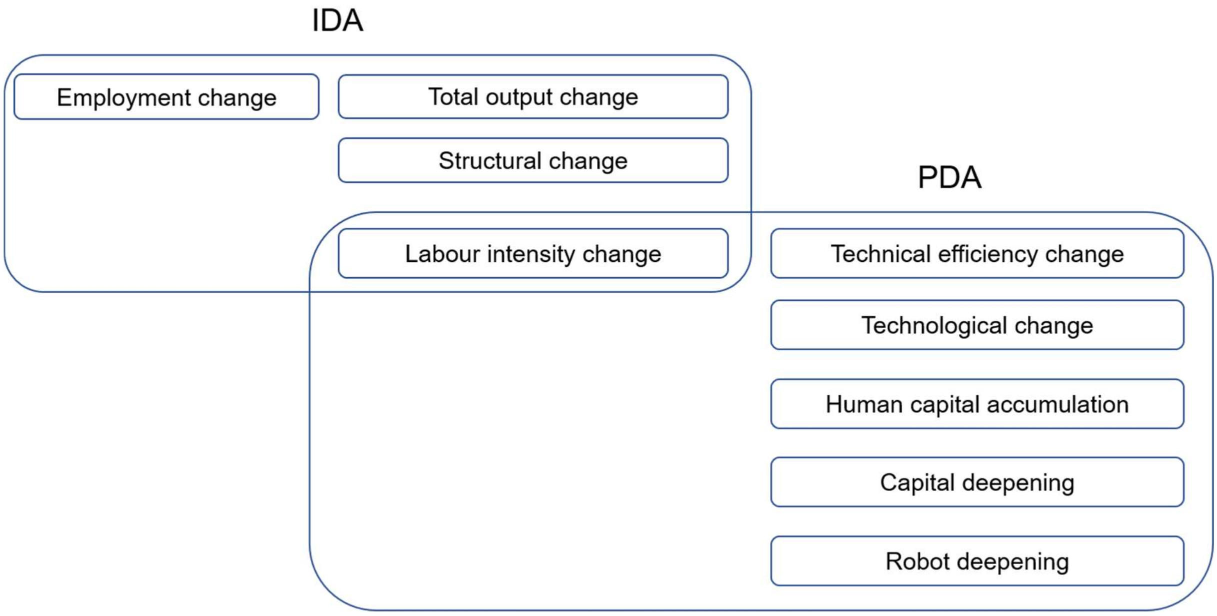

Figure 2 The framework of combined index decomposition analysis (IDA) and production-theoretical decomposition analysis (PDA) for separating out causes of employment change in manufacturing

Figure 2 visualizes our decomposition approach. In a first step we use IDA to decompose employment change into changes in aggregate output, change in structure and change in labour intensity. The IDA, in principle, can be carried out in two different perspectives. The first, which is the more natural and commonly applied one, decomposes employment change in the manufacturing industry into changes in manufacturing output, change in sectoral structure of the manufacturing industry, and change in labour intensity (see, e.g., Kopidou et al., 2016, for decomposing employment changes using this IDA approach). Accordingly, this kind of IDA can be performed separately for every country in the sample. Alternatively, the IDA can also decompose the change in employment of any sub-sector of manufacturing, aggregated over all countries considered, into change in the sub-sector's output, aggregated over countries, change in country-structure (i.e., changing distribution of the sub-sector's output over countries), and change in labour intensity. This kind of IDA is performed for every sub-sector in the sample. The labour intensity component of IDA is given a different meaning in the two alternative perspectives. While, in the first case, it is a composite index of labour intensity changes within each sub-sector of total manufacturing in a specific country, in the second case it is a composite index of labour intensity changes within each country regarding the respective manufacturing sub-sector. In a second step we use PDA to further decompose the sub-sectoral labour intensity changes to isolate the contribution of technical efficiency change, technological change, changes in the (non-robot) capital-labour ratio (capital deepening), and changes in the robot-labour ratio (robot deepening) to employment change (see, e.g., Färe et al., 2018, for a decomposition of employment changes using PDA).[6] The procedure accounts for heterogeneity in production technologies across (sub-)sectors and time. We will show in the following how integrating the IDA and PDA part involves a weighting scheme to aggregate the sub-sector and country-specific labour intensity changes and how this varies according to the different perspectives of IDA.

3.1. Index decomposition analysis

Several different index methods for IDA have been proposed. Following Ang (2004, 2005) we apply the multiplicative version of the logarithmic mean Divisia index (LMDI) approach due to its fulfilment of three desirable properties (factor-reversal, time-reversal, and zero-value robust). Consider N countries indexed with $n = 1, \dots, N$. The manufacturing sector of each country consists of M $(m = 1, \dots, M)$ different sub-sectors. Y_t^n, L_t^n and $I_t^n = L_t^n / Y_t^n$ is output (measured in value added), employment (measured in hours worked), and labour intensity of the entire manufacturing sector in country n at time t $(t = 1, \dots, T)$, respectively. Output, employment and labour intensity of sub-sector m in country n at time t is denoted as, $Y_{m,t}^n$, $L_{m,t}^n$, $I_{m,t}^n = L_{m,t}^n / Y_{m,t}^n$, respectively. $S_{m,t}^n = Y_{m,t}^n / Y_t^n$ is the share of output of sub-sector m in total manufacturing output of country n at time t. Manufacturing employment in country n can be expressed as follows:

$$L_t^n = \sum_{m=1}^{M} L_{m,t}^n = Y_t^n \sum_{m=1}^{M} \frac{Y_{m,t}^n}{Y_t^n} \frac{L_{m,t}^n}{Y_{m,t}^n} = Y_t^n \sum_{m=1}^{M} S_{m,t}^n \, I_{m,t}^n. \tag{1}$$

Following Ang (2005) the multiplicative form of the change in manufacturing employment from the base year b to current year c for country n is given by:

$$\Delta L^n = \frac{L_c^n}{L_b^n} = exp\left(\sum_{m=1}^{M} \frac{R(L_{m,c}^n, L_{m,b}^n)}{R(L_c^n, L_b^n)} ln\left(\frac{Y_c^n}{Y_b^n}\right)\right) \times exp\left(\sum_{m=1}^{M} \frac{R(L_{m,c}^n, L_{m,b}^n)}{R(L_c^n, L_b^n)} ln\left(\frac{S_{m,c}^n}{S_{m,b}^n}\right)\right) \times$$
$$exp\left(\sum_{m=1}^{M} \frac{R(L_{m,c}^n, L_{m,b}^n)}{R(L_c^n, L_b^n)} ln\left(\frac{I_{m,c}^n}{I_{m,b}^n}\right)\right) = \Delta Y^n \times \Delta S^n \times \Delta I^n, \tag{2}$$

where $\frac{R(L_{m,c}^n, L_{m,b}^n)}{R(L_c^n, L_b^n)} = \frac{(L_{m,c}^n - L_{m,b}^n)/(ln(L_{m,c}^n) - ln(L_{m,b}^n))}{(L_c^n - L_b^n)/(ln(L_c^n) - ln(L_b^n))}$ are the weights for each sub-sector m.

Equation (2) shows that the change in manufacturing employment in country n can be decomposed into three components: i) ΔY^n captures the effect of overall manufacturing output change (output effect), ii) ΔS^n represents the effect of industry structure change (output mix effect), and iii) ΔI^n describes the effect of labour intensity change which is a composite index of sub-sectoral labour intensity changes (intensity or productivity effect).

[6] While PDA has overwhelmingly used to study changes at the country-level with macroeconomic data (e.g., Kumar and Russell (2002), Henderson and Russell (2005), Badunenko and Romero-Avila (2013)), Walheer (2020) suggests a purely PDA-based approach to investigate contributions of sectors to country-level changes in the variable of interest. Contrary to IDA, the weights for aggregating the sector contributions are determined endogenously by DEA and are different for each component of the decomposition.

3.2. Production-theoretical decomposition analysis

To further investigate the drivers of labour intensity change in manufacturing we use PDA to divide labour intensity change between base year b and current year c in each sub-sector m of country n into i) technical efficiency change (EFF_m^n), ii) technological change ($TECH_m^n$), iii) human capital accumulation ($HACC_m^n$), iv) changes in the (non-robot) capital-labour ratio ($KACC_m^n$), and v) changes in the robot-labour ratio ($RKACC_m^n$):

$$\frac{I_{m,c}^n}{I_{m,b}^n} \equiv EFF_m^n \times TECH_m^n \times HACC_m^n \times KACC_m^n \times RKACC_m^n. \tag{3}$$

This decomposition requires an estimation of a separate cross-country production frontier for each individual sub-sector and efficiency levels of individual sub-sectors in individual countries (distances from the respective sub-sector frontier) using the nonparametric Data Envelopment Analysis (DEA) approach. The basic idea is to envelop the data in the smallest convex cone, and the upper boundary of this set then represents the "best practice" production frontier.

In addition to the two previously mentioned variables, employment $L_{m,t}^n$ (i.e., an input), and output $Y_{m,t}^n$, our technology considers human capital $H_{m,t}^n$, (non-robot) capital $K_{m,t}^n$, and robot capital $R_{m,t}^n$ as input variables. Following most of the macroeconomics literature, we assume that human capital, denoted as $H_{m,t}^n$, enters the technology as a multiplicative augmentation of physical labour, i.e., $\hat{L}_{m,t}^n = L_{m,t}^n H_{m,t}^n$, which is the amount of labour input measured in efficiency units. Thus, $\langle Y_{m,t}^n, \hat{L}_{m,t}^n, K_{m,t}^n, R_{m,t}^n \rangle$ represents our set of $N \times M \times T$ observations on these four variables.

Constant returns to scale and labour augmentation of human capital allow us to construct the production frontiers and efficiency indices. Utilizing the "sequential production set" formulation of Diewert (1980) to preclude implosion of the frontier over time, we construct the convex, free-disposal, constant-returns-to-scale technology for sub-sector m in year t, using all the data of sub-sector m up to that point in time, as

$$\Upsilon_{m,t} = \left\{ \begin{array}{l} \langle Y_{m,t}^n, \hat{L}_{m,t}^n, K_{m,t}^n, R_{m,t}^n \rangle \in \mathbb{R}_+^4 \,|\, Y_m \leq \sum_{\tau \leq t} \sum_n \lambda_{m,\tau}^n Y_{m,\tau}^n, \hat{L}_m \geq \sum_{\tau \leq t} \sum_n \lambda_{m,\tau}^n \hat{L}_{m,\tau}^n, \\ \qquad K_m \geq \sum_{\tau \leq t} \sum_n \lambda_{m,\tau}^n K_{m,\tau}^n, R_m \geq \sum_{\tau \leq t} \sum_n \lambda_{m,\tau}^n R_{m,\tau}^n \\ \lambda_{m,\tau}^n \geq 0 \forall n, m, \tau \end{array} \right\}, \tag{4}$$

where $\lambda_{m,\tau}^n$ are the intensity variables. τ represents all years from the beginning of the observation period up to time *t*. Like Los and Timmer (2005) we limit the decomposition analysis to the time span that starts four years after the first observations of robot stock data are available to us. Hence, the first year of the analysis is 2004, for which we estimate the frontier based on the observations for the period 2000-2004. This makes it less likely that frontier techniques observed for the first year of the analysis are dominated by unobserved combinations in the past, and avoids that part of what would be interpreted as frontier movements is confused with 'assimilation of knowledge', i.e., efficiency change (Los and Timmer, 2005).

The Farrell (1957) output-based efficiency index for sub-sector m in country n at time t is defined by

$$e^n_{m,t}\left(Y^n_{m,t}, \hat{L}^n_{m,t}, K^n_{m,t}, R^n_{m,t}\right) = min\{\theta^n_m | \langle Y^n_{m,t}/\theta^n_m, \hat{L}^n_{m,t}, K^n_{m,t}, R^n_{m,t}\rangle \in \Upsilon_{m,t}\}. \tag{5}$$

This index is the inverse of the maximal proportional amount that output $Y^n_{m,t}$ can be expanded while remaining technologically feasible, given the technology and input quantities. It is less than or equal to unity and takes the value of unity if and only if the mnt observation is on the period-t production frontier of sub-sector m. In our special case of a scalar output, the output-based efficiency index equals the ratio of actual to potential output, evaluated at the actual input quantities.

The decomposition is carried out according to the following two equations (6) and (7), which are obtained by forming the reciprocal of equations (7) and (8) in Eder et al. (2023), respectively:

$$\frac{I^n_{m,c}}{I^n_{m,b}} = \frac{e^n_{m,b}}{e^n_{m,c}} \times \frac{\bar{y}^n_{m,b}(\hat{k}^n_{m,c},\hat{r}^n_{m,c})}{\bar{y}^n_{m,c}(\hat{k}^n_{m,c},\hat{r}^n_{m,c})} \times \left[\frac{\bar{y}^n_{m,b}(\tilde{k}^n_{m,c},\tilde{r}^n_{m,c})}{\bar{y}^n_{m,b}(\hat{k}^n_{m,c},\hat{r}^n_{m,c})} \cdot \frac{H^n_{m,b}}{H^n_{m,c}}\right] \times \frac{\bar{y}^n_{m,b}(\hat{k}^n_{m,b},\hat{r}^n_{m,b})}{\bar{y}^n_{m,b}(\tilde{k}^n_{m,c},\hat{r}^n_{m,b})} \times \frac{\bar{y}^n_{m,b}(\tilde{k}^n_{m,c},\hat{r}^n_{m,b})}{\bar{y}^n_{m,b}(\tilde{k}^n_{m,c},\tilde{r}^n_{m,c})} \equiv EFF^n_m \times TECH^{n,c}_m \times HACC^{n,b}_m \times KACC^{n,b}_m \times RKACC^{n,b}_m \tag{6}$$

and

$$\frac{I^n_{m,c}}{I^n_{m,b}} = \frac{e^n_{m,b}}{e^n_{m,c}} \times \frac{\bar{y}^n_{m,b}(\hat{k}^n_{m,b},\hat{r}^n_{m,b})}{\bar{y}^n_{m,c}(\hat{k}^n_{m,b},\hat{r}^n_{m,b})} \times \left[\frac{\bar{y}^n_{m,c}(\hat{k}^n_{m,b},\hat{r}^n_{m,b})}{\bar{y}^n_{m,c}(\tilde{k}^n_{m,b},\tilde{r}^n_{m,b})} \cdot \frac{H^n_{m,b}}{H^n_{m,c}}\right] \times \frac{\bar{y}^n_{m,c}(\tilde{k}^n_{m,b},\hat{r}^n_{m,c})}{\bar{y}^n_{m,c}(\hat{k}^n_{m,c},\hat{r}^n_{m,c})} \times \frac{\bar{y}^n_{m,c}(\tilde{k}^n_{m,b},\tilde{r}^n_{m,b})}{\bar{y}^n_{m,c}(\tilde{k}^n_{m,b},\hat{r}^n_{m,c})} \equiv EFF^n_m \times TECH^{n,b}_m \times HACC^{n,c}_m \times KACC^{n,c}_m \times RKACC^{n,c}_m, \tag{7}$$

where $e^n_{m,b}$ and $e^n_{m,c}$ are values of the efficiency indexes of sub-sector m in country n in the years b and c, respectiveley, as calculated in equation. (5). $\bar{y}^n_{m,b}(\hat{k}^n_{m,b}, \hat{r}^n_{m,b}) = Y^n_{m,b}/e^n_{m,b}\hat{L}^n_{m,b}$ and $\bar{y}^n_{m,c}\left(\hat{k}^n_{m,c}, \hat{r}^n_{m,c}\right) = Y^n_{m,c}/e^n_{m,c}\hat{L}^n_{m,c}$ are potential output values per efficiency unit of labour in periods b and c, respectively. $\hat{k}^n_{m,b} = K^n_{m,b}/\hat{L}^n_{m,b}$, $\hat{k}^n_{m,c} = K^n_{m,c}/\hat{L}^n_{m,c}$ and $\hat{r}^n_{m,b} = R^n_{m,b}/\hat{L}^n_{m,b}$, $\hat{r}^n_{m,c} = R^n_{m,c}/\hat{L}^n_{m,c}$ denote the ratios of non-robot capital and robot capital to effective labour $\hat{L}^n_{m,b}$, $\hat{L}^n_{m,c}$, respectively, where $\hat{L}^n_{m,b} = L^n_{m,b}H^n_{m,b}$ and $\hat{L}^n_{m,c} = L^n_{m,c}H^n_{m,c}$ are the amount of labour input measured in efficiency units in year b and c, respectively. The ratio of (non-robot) physical capital to labour measured in efficiency units, and the ratio of robot capital to labour measured in efficiency units under the counterfactual assumption that human capital has not changed from its base period is given by $\tilde{k}^n_{m,c} = K^n_{m,c}/L^n_{m,c}H^n_{m,b}$ and $\tilde{r}^n_{m,c} = R^n_{m,c}/L^n_{m,c}H^n_{m,b}$, respectively. The ratio of (non-robot) physical capital to labour measured in efficiency units and the ratio of robot capital to labour measured in efficiency units under the counterfactual assumption that human capital is equal to its current year period is $\tilde{k}^n_{m,b} = K^n_{m,b}/L^n_{m,b}H^n_{m,c}$ and $\tilde{r}^n_{m,b} = R^n_{m,b}/L^n_{m,b}H^n_{m,c}$. Then, $\bar{y}^n_{m,b}(\hat{k}^n_{m,c}, \hat{r}^n_{m,c})$, $\bar{y}^n_{m,b}(\tilde{k}^n_{m,c}, \hat{r}^n_{m,b})$, $\bar{y}^n_{m,b}(\tilde{k}^n_{m,c}, \tilde{r}^n_{m,c})$ are the potential outputs per efficiency unit of labour at $(\hat{k}^n_{m,c}, \hat{r}^n_{m,c})$, $(\tilde{k}^n_{m,c}, \hat{r}^n_{m,b})$, and $(\tilde{k}^n_{m,c}, \tilde{r}^n_{m,c})$ evaluated against the base-period technology. $\bar{y}^n_{m,c}(\hat{k}^n_{m,b}, \hat{r}^n_{m,b})$, $\bar{y}^n_{m,c}(\tilde{k}^n_{m,b}, \hat{r}^n_{m,c})$,

$\bar{y}^n_{m,c}(\tilde{k}^n_{m,b},\tilde{r}^n_{m,b})$ are the potential outputs per efficiency units of labour at $(\hat{k}^n_{m,b},\hat{r}^n_{m,b})$, $(\tilde{k}^n_{m,b},\hat{r}^n_{m,c})$, and $(\tilde{k}^n_{m,b},\tilde{r}^n_{m,b})$ using the current-period technology as the reference-technology.

For each component of the decomposition, only the variable of interest is different between the denominator and the numerator of each component. For instance, for $RKACC^{n,b}_m$ only the robot-labour ratio changed (from $\hat{r}^n_{m,b} = R^n_{m,b}/L^n_{m,b}H^n_{m,b}$ to $\tilde{r}^n_{m,c} = R^n_{m,c}/L^n_{m,c}H^n_{m,b}$) while all the other variables are held constant. Hence, $RKACC$ indicates the contribution of the change in the robot-labour ratio to labour intensity change. The same reasoning applies for the other components.

While the decomposition in eq. (6) measures the contribution of technological change to labour intensity change by the shift in the frontier in the output direction at the current-period capital to efficiency-labour ratio, and the current-period robot to efficiency-labour ratio, the decomposition in equation. (7) measures the contribution of technological change to labour intensity change by the shift in the frontier in the output direction at the base-period capital to efficiency-labour ratio, and the base-period robot to efficiency-labour ratio. Similarly, equation. (6) measures the effect of (non-robot) physical and robot capital deepening, as well as human capital accumulation along the base-period frontier, whereas equation. (7) measures the effect of (non-robot) physical and robot deepening, as well as human capital accumulation along the current-period frontier.

These two decompositions do not yield the same results, i.e., the decomposition is path dependent. In fact, the two decompositions are only equal if technological change is Hicks-neutral. Though, one advantage of our approach is that it allows for non-neutral technological change. To overcome the path dependence of the decomposition we follow Kumar and Russel (2002), Henderson and Russell (2005) and others, and adopt the “Fisher Ideal” decomposition introduced by Caves et al. (1982) and Färe et al. (1994). This is based on the geometric averages of the two measures of the effects of technological change, human capital accumulation, (non-robot) physical capital deepening, and robot capital deepening:

$$\frac{I^n_{m,c}}{I^n_{m,b}} = EFF^n_m \times (TECH^{n,b}_m \cdot TECH^{n,c}_m)^{1/2} \times (HACC^{n,b}_m \cdot HACC^{n,c}_m)^{1/2} \times (KACC^{n,b}_m \cdot KACC^{n,c}_m)^{1/2} \times (RKACC^{n,b}_m \cdot RKACC^{n,c}_m)^{1/2} \equiv EFF^n_m \times TECH^n_m \times HACC^n_m \times KACC^n_m \times RKACC^n_m. \quad (8)$$

3.3. Combining index decomposition analysis and production-theoretical decomposition analysis

The following formula, which is obtained by substituting Equation (8) into Equation (2), connects the IDA to the PDA and gives the final decomposition:

$$\Delta L^n_{\square} = \frac{L^n_c}{L^n_b} = exp\left(\sum_{m=1}^{M} \frac{R(L^n_{m,c}, L^n_{m,b})}{R(L^n_c, L^n_b)} ln\left(\frac{Y^n_c}{Y^n_b}\right)\right)$$

$$
\times exp\left(\sum_{m=1}^{M}\frac{R(L_{m,c}^{n},L_{m,b}^{n})}{R(L_{c}^{n},L_{b}^{n})}ln\left(\frac{S_{m,c}^{n}}{S_{m,b}^{n}}\right)\right)
$$

$$
\times exp\left(\sum_{m=1}^{M}\frac{R(L_{m,c}^{n},L_{m,b}^{n})}{R(L_{c}^{n},L_{b}^{n})}ln(EFF_{m}^{n})\right)
$$

$$
\times exp\left(\sum_{m=1}^{M}\frac{R(L_{m,c}^{n},L_{m,b}^{n})}{R(L_{c}^{n},L_{b}^{n})}ln(TECH_{m}^{n})\right)
$$

$$
\times exp\left(\sum_{m=1}^{M}\frac{R(L_{m,c}^{n},L_{m,b}^{n})}{R(L_{c}^{n},L_{b}^{n})}ln(HACC_{m}^{n})\right)
$$

$$
\times exp\left(\sum_{m=1}^{M}\frac{R(L_{m,c}^{n},L_{m,b}^{n})}{R(L_{c}^{n},L_{b}^{n})}ln(KACC_{m}^{n})\right)
$$

$$
\times exp\left(\sum_{m=1}^{M}\frac{R(L_{m,c}^{n},L_{m,b}^{n})}{R(L_{c}^{n},L_{b}^{n})}ln(RKACC_{m}^{n})\right)
$$

$$
= \Delta Y_{\square}^{n} \times \Delta S_{\square}^{n} \times EFF_{\square}^{n} \times TECH_{\square}^{n} \times HACC_{\square}^{n} \times KACC_{\square}^{n} \times RKACC_{\square}^{n}, \tag{9}
$$

where $\Delta S_{\square}^{n}$ gives the contribution of changes in output/sectoral-mix to employment change of a specific country.

Equation (9) separate out approximate causes of employment change in total manufacturing for each country under consideration. Note that each sub-sector m in a common international market consists of the sum of the respective sub-sectors over the n countries considered. For instance, the sub-sector of the automotive industry on a common international market consists of the automotive industries of the individual countries under consideration. The total employment of the international sub-sector is the sum of the employment in the sub-sectors of the individual countries, i.e., $L_{m,t}^{\square} = \sum_{n=1}^{N} L_{m,t}^{n}$ and its total output is the sum of the outputs of the sub-sectors in the individual countries, i.e., $Y_{m,t}^{\square} = \sum_{n=1}^{N} Y_{m,t}^{n}$. Employment in sub-sector m across all countries can be expressed as follows:

$$
L_{m,t}^{\square} = \sum_{n=1}^{N} L_{m,t}^{n} = Y_{m,t}^{\square} \sum_{n=1}^{N} \frac{Y_{m,t}^{n}}{Y_{m,t}^{\square}} \frac{L_{m,t}^{n}}{Y_{m,t}^{n}} = Y_{m,t}^{\square} \sum_{n=1}^{N} \sigma_{m,t}^{n}\, l_{m,t}^{n}, \tag{10}
$$

where $\sigma_{m,t}^{n} = Y_{m,t}^{n}/Y_{m,t}^{\square}$ is the share of output of country n in total sub-sector output of all N countries together at time t.

To estimate the approximate causes of employment change from base period b to current period c for each sub-sector m across all n countries considered we construct the following decomposition:

$$
\Delta L_{m}^{\square} = \frac{L_{m,c}^{\square}}{L_{m,b}^{\square}} = exp\left(\sum_{n=1}^{N}\frac{R(L_{m,c}^{n},L_{m,b}^{n})}{R(L_{m,c}^{\square},L_{m,b}^{\square})}ln\left(\frac{Y_{m,c}^{\square}}{Y_{m,b}^{\square}}\right)\right)
$$

$$
\begin{aligned}
&\times exp\left(\sum_{n=1}^{N}\frac{R(L_{m,c}^{n},L_{m,b}^{n})}{R(L_{m,c}^{\square},L_{m,b}^{\square})}ln\left(\frac{\sigma_{m,c}^{n}}{\sigma_{m,b}^{n}}\right)\right)\\
&\times exp\left(\sum_{n=1}^{N}\frac{R(L_{m,c}^{n},L_{m,b}^{n})}{R(L_{m,c}^{\square},L_{m,b}^{\square})}ln(EFF_{m}^{n})\right)\\
&\times exp\left(\sum_{n=1}^{N}\frac{R(L_{m,c}^{n},L_{m,b}^{n})}{R(L_{m,c}^{\square},L_{m,b}^{\square})}ln(TECH_{m}^{n})\right)\\
&\times exp\left(\sum_{n=1}^{N}\frac{R(L_{m,c}^{n},L_{m,b}^{n})}{R(L_{m,c}^{\square},L_{m,b}^{\square})}ln(HACC_{m}^{n})\right)\\
&\times exp\left(\sum_{n=1}^{N}\frac{R(L_{m,c}^{n},L_{m,b}^{n})}{R(L_{m,c}^{\square},L_{m,b}^{\square})}ln(KACC_{m}^{n})\right)\\
&\times exp\left(\sum_{n=1}^{N}\frac{R(L_{m,c}^{n},L_{m,b}^{n})}{R(L_{m,c}^{\square},L_{m,b}^{\square})}ln(RKACC_{m}^{n})\right)\\
&= \Delta Y_{m}^{\square}\times \Delta S_{m}^{\square}\times EFF_{m}^{\square}\times TECH_{m}^{\square}\times HACC_{m}^{\square}\times KACC_{m}^{\square}\times RKACC_{m}^{\square},
\end{aligned}
\tag{11}
$$

where $\frac{R(L_{m,c}^{n},L_{m,b}^{n})}{R(L_{m,c}^{\square},L_{m,b}^{\square})}=\frac{(L_{m,c}^{n}-L_{m,b}^{n})/(ln(L_{m,c}^{n})-ln(L_{m,b}^{n}))}{(L_{m,c}^{\square}-L_{m,b}^{\square})/(ln(L_{m,c}^{\square})-ln(L_{m,b}^{\square}))}$ are the weights for each country component n, and $S_{m}^{\square}$ describes the contribution of changes in country-mix to employment change in a specific sub-sector.

4. Results

Based on the novel combination of index decomposition analysis (IDA) and production theoretical decomposition analysis (PDA) presented in the previous section we found new insides into the relationship between robotization and employment in manufacturing sectors. Tables 3, 4 and 5 report the results on the approximate causes of employment change by country, country groups, and manufacturing sub-sectors, respectively. Note that we report percentage changes of the decomposition indices in equation. (9) and equation. (11). Hence, summing individual components does not give the overall employment change. Tables D1 to D3 in section D of the supplementary material provide the results for the multiplicative decomposition indexes before conversion to percentage changes. The second column of Table 3, 4 and 5 reports the country-specific, country-group specific and sub-sector-specific changes in employment for the period 2004 to 2019, respectively. Columns three, four and five of Table 3, 4 and 5 present the components of employment change resulting from IDA (i.e., output, structural, and labour intensity change). Columns six to ten of Table 3, 4 and 5 show the components of labour intensity change stemming from PDA (i.e., efficiency, technological, human capital, capital intensity, and robot intensity change). Or, to put it another way, columns three and four, together with columns six to ten, are the components of changes in employment shown in equation. (9) and equation. (11).

Table 3
Employment change (in percent) for total manufacturing by country and percentage change of decomposition indexes, 2004–2019

Country	Employment Change	$(\Delta Y^{n}-1)\times 100$	$(\Delta S^{n}-1)\times 100$	$(\Delta I^{n}-1)\times 100$	$(EFF^{n}-1)\times 100$	$(TECH^{n}-1)\times 100$	$(HACC^{n}-1)\times 100$	$(KACC^{n}-1)\times 100$	$(RKACC^{n}-1)\times 100$
Denmark (DNK)	–20.28	39.45	–19.92	–28.61	2.01	–13.60	–5.77	–4.79	–9.71
Finland (FIN)	–20.84	1.13	–3.06	–19.26	6.96	–16.20	–6.31	–0.69	–3.19
Norway (NOR)	–6.39	11.90	–0.24	–16.14	4.36	–10.92	–5.21	0.31	–5.14
Sweden (SWE)	–17.73	11.16	–0.54	–25.58	–0.31	–11.74	–4.28	–5.34	–6.65
Austria (AUT)	–0.46	44.78	–3.75	–28.57	–1.65	–11.31	–5.19	–4.08	–9.95
Czech Republic (CZE)	5.84	119.94	–0.98	–51.41	–13.00	–9.48	–0.87	–21.38	–20.83
Germany (DEU)	1.24	30.81	–2.95	–20.26	–6.52	–12.20	–0.94	–0.78	–1.15
Hungary (HUN)	–5.38	26.48	6.97	–30.06	54.30	–7.52	–5.29	–22.42	–33.30
Slovak Republic (SVK)	4.83	162.05	–5.65	–57.60	–14.31	–13.46	–7.06	–9.85	–31.76
Belgium (BEL)	–16.88	8.76	–7.80	–17.11	1.39	–11.10	–2.76	0.48	–5.88
France (FRA)	–17.71	8.82	–2.80	–22.21	2.63	–12.32	–6.49	–4.47	–3.22
Netherlands (NLD)	–8.09	24.45	–5.93	–21.49	10.21	–10.77	–4.90	0.55	–16.51
United Kingdom (GBR)	–16.32	18.55	1.14	–30.21	–14.77	–10.25	–2.40	–2.56	–4.07
Greece (GRC)	–24.09	–31.10	–12.33	25.66	56.79	–6.05	–3.56	–7.10	–4.78
Italy (ITA)	–18.48	–0.13	–0.16	–18.24	12.72	–14.19	–7.64	–3.80	–4.87
Portugal (PRT)	–17.15	10.88	–2.45	–23.40	42.93	–13.96	–8.05	–10.64	–24.19
Spain (ESP)	–29.80	–5.07	–2.62	–24.07	1.41	–12.81	–7.95	–2.87	–3.95
United States (USA)	–5.37	21.70	0.21	–22.41	5.94	–13.44	–2.63	–3.32	–10.11
Arithmetic Mean	**–11.84**	**28.03**	**–3.49**	**–23.94**	**8.39**	**–11.74**	**–4.85**	**–5.71**	**–11.07**

Note: ΔY^{n} … value added change, ΔS^{n} … structural change, ΔI^{n} … labour intensity change (= 1 / labour productivity change), EFF^{n} … efficiency change, $TECH^{n}$ … technical change, $HACC^{n}$ … human capital accumulation, $KACC^{n}$… capital intensity change, $RKACC^{n}$ … robot intensity change.

According to Table 3, total manufacturing employment fell in most countries over the 2004–2019 period. The Czech Republic, Slovak Republic, and Germany were the few exceptions. On average, employment decreased by 11.84%. Everywhere, except in Greece, we see a labour intensity decline (i.e., labour productivity increase), which dampened employment dynamics. In all countries except for Greece, Spain and Italy, we observe an increase in output (i.e., value added), which partially offset or, in a few countries, (Czech Republic, Slovak Republic and Germany) even overcompensate the decline in employment caused by the reduction in labour intensity. Structural change made an almost negligible contribution in all countries except for Denmark, Belgium and Greece. The mostly negative sign of the structural change component indicates a shift within the entire manufacturing sector towards less labour-intensive sub-sectors. On average, the contribution of output change, labour intensity change and structural change to employment change is 28%, –24% and –3.5%, respectively.

The contribution of the increased use of robots (robot capital deepening) to labour intensity and subsequently employment change is negative for every country indicating a clear labour replacing effect of industrial robots in total manufacturing. The results show that robot penetration dampened employment growth. However, robot penetration is the most important driver of labour intensity change in manufacturing in only a few countries (i.e., the Netherlands, and Slovak Republic). The component with the greatest contribution to reducing labour intensity in many countries is technological change. Its contribution is negative in all countries, as is that of robot deepening. Change in efficiency, human capital accumulation and non-robot capital deepening contribute comparatively little to changes in labour intensities. On average, efficiency change contributed 8.39%, technical change –11.74%, human capital accumulation –4.85%, non-robot capital deepening –5.71% and robot capital deepening –11.07% to the change in labour intensity.

Table 4 shows that Central Europe was the only region in Europe with growing employment in the manufacturing sector. The mean increase was 1.22%. Southern Europe, on the other hand, was the region with the weakest employment dynamics. Employment there fell by 22.38%, on average. Only in Central Europe output change induced employment growth could exceed the employment decline caused by a decreasing labour intensity. In all other regions, output growth could not compensate for the employment reduction due to a decline in labour intensity. In Southern Europe, manufacturing output even fell. The increasing penetration of robots dampened the employment development in all regions considered. In Central Europe it was the most important factor of labour intensity change. In the four other regions examined, technological progress reduced employment more than robot use. The change in the sectoral structure within the manufacturing sector as well as the change in human capital and non-robot capital deepening contributed comparably little to the employment development. The contribution of efficiency change was also relatively small in all regions except for Southern Europe.

Table 4

Mean employment change (in percent) for total manufacturing by country group and mean percentage change of decomposition indexes, 2004–2019

Country Group	Employment Change	(ΔY^n-1) ×100	(ΔS^n-1) ×100	(ΔI^n-1) ×100	(EFF^n-1) × 100	$(TECH^n-1)$ × 100	$(HACC^n-1)$ × 100	$(KACC^n-1)$ × 100	$(RKACC^n-1)$ × 100
Northern Europe*	–16.31	15.91	–5.94	–22.40	3.26	–13.11	–5.39	–2.63	–6.17
Central Europe+	1.22	76.81	–1.27	–37.58	3.76	–10.79	–3.87	–11.70	–19.40
Western Europe†	–14.75	15.15	–3.85	–22.76	–0.14	–11.11	–4.14	–1.50	–7.42
Southern Europe§	–22.38	–6.35	–4.39	–10.01	28.46	–11.75	–6.80	–6.10	–9.45
United States	–5.37	21.70	0.21	–22.41	5.94	–13.44	–2.63	–3.32	–10.11
All countries	**–11.84**	**28.03**	**–3.49**	**–23.94**	**8.39**	**–11.74**	**–4.85**	**–5.71**	**–11.07**

Note:

* Denmark, Finland, Norway, Sweden.

+ Austria, Czech Republic, Germany, Hungary, Slovak Republic.

† Belgium, France, Great Britain, Netherlands.

§ Greece, Italy, Spain, Portugal.

ΔY^n … output change, ΔS^n … structural change, ΔI^n … labour intensity change (= 1 / labour productivity change), EFF^n … efficiency change, $TECH^n$ … technical change, $HACC^n$ … human capital accumulation, $KACC^n$ … capital intensity change, $RKACC^n$ … robot intensity change.

Table 5
Employment change (in percent) for manufacturing sub-sectors and percentage change of decomposition indexes, 2004–2019

Sub-sector	Employment Change	$(\Delta Y_m - 1) \times 100$	$(\Delta S_m - 1) \times 100$	$(\Delta I_m - 1) \times 100$	$(EFF_m - 1) \times 100$	$(TECH_m - 1) \times 100$	$(HACC_m - 1) \times 100$	$(KACC_m - 1) \times 100$	$(RACC_m - 1) \times 100$
C10-C12	3.47	10.99	–0.14	–6.65	8.21	–1.68	–4.99	–0.87	–6.84
C13-C15	–39.72	–15.70	–1.54	–27.37	25.37	–23.03	–5.21	–6.18	–15.37
C16-C18 + C31-C33	–15.46	4.84	0.84	–20.04	14.04	–12.29	–3.74	–3.01	–14.38
C19-C21	5.04	7.86	1.98	–4.50	22.14	–7.14	–3.92	–3.08	–9.57
C22 + C23	–18.12	–0.47	3.84	–20.78	–9.19	–5.45	–4.22	–2.01	–1.70
C24 + C25	–8.10	11.76	0.04	–17.80	1.02	–12.19	–3.92	–3.13	–0.43
C26 + C27	–20.12	104.95	–0.16	–60.96	–38.19	–25.53	–3.02	–9.02	–3.88
C28	–0.47	16.91	2.40	–16.86	25.31	–13.93	–3.09	–5.06	–16.22
C29 + C30	5.25	48.11	2.04	–30.36	–0.28	–15.66	–2.35	–8.32	–7.51

Note:
C10-C12 … Food products, beverages and tobacco, C13-C15 … Manufacture of textiles, wearing apparel, leather and related products, C16-C18 + C31-C33 … Manufacture of wood and paper products: printing + Other manufacturing, repair and installation of machinery and equipment, C19-C21 … Manufacture of basic pharmaceutical products and preparations + Manufacture of coke and refined petroleum products + Manufacture of chemicals and chemical products, C22 + C23 … Rubber and plastics products, and other non-metallic mineral products, C24 + C25 … Manufacture of basic metals and fabricated metal products, machinery and equipment, C26 + C27 … Computer, electronic, optical products; electrical equipment, C28 … Manufacture of machinery and equipment not elsewhere classified, C29 + C30 … Manufacture of transport equipment.
ΔY_m … value added change, ΔS_m … structural change, ΔI_m … labour intensity change (= 1 / labour productivity change), EFF_m … efficiency change, $TECH_m$ … technical change, $HACC_m$ … human capital accumulation, $KACC_m$ … capital intensity change, $RACC_m$ … robot intensity change.

Table 5 presents employment trends and their drivers in nine manufacturing sub-sectors in advanced Europe and the USA. Employment fell in most manufacturing sub-sectors, most clearly in the textile industry (C13-C15) by almost –40% and at the least in the machinery and equipment industry (C28) by –0.5%. Only the automotive industry (C29 + C30), the chemical industry (C19-C21), and the food industry (C10-C12) experienced a rise in employment by +5.25%, +5.04% and +3.47% respectively.

In all manufacturing sub-sectors, we observe a reduction in labour intensity, thus reducing employment growth by the same proportion. In only a few sub-sectors the growth in output compensated the decline in employment caused by reduced labour intensity. In the textile industry (C13-C15) and, to a lesser extent, in the rubber and plastics industry (C22 + C23), the decline in output even contributed to a reduction in employment. According to our results, the use of robots reduced employment in all industries examined indicating a substitutive effect on employment. In the food industry (C10-C12), the paper products industry + other manufacturing (C16-C18 + C31-C33), the chemical industry (C19-C21) and the machinery and equipment industry (C28), the growing use of robots was actually the largest employment-reducing factor. Our analysis reveals substantial heterogeneity in employment and labour intensity changes across manufacturing sub-sectors. Not less diverse is the extent to which robots contributed to these developments.

Technological progress also reduced employment in all sectors. It dampened employment more than any other component in the textile industry (C13-C15), the basic metals and fabricated metal products industry (C24 + C25) and in the automotive industry (C29 + C30). In the rubber and plastics industry (C22 + C23) and computer, electronic and electrical equipment industry (C26 + C27), efficiency change reduced employment the most. The contributions of structural change (i.e., international relocation of production), growth in human capital and increased use of non-robotic capital were comparatively small across all manufacturing sub-sectors.

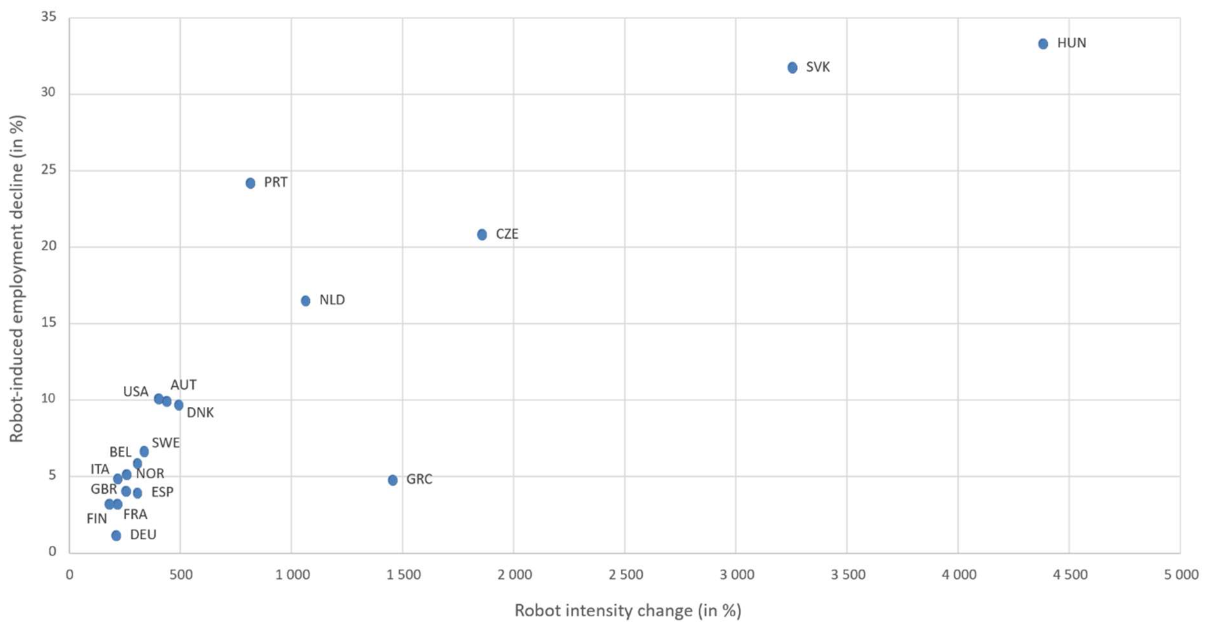

Figure 3 Robot Intensity change and robot induced employment decline in total manufacturing, 2004 to 2019

Figure 3 shows the positive relationship between the robot intensity change and robot induced employment decline in total manufacturing in the countries examined over the period 2004 to 2019. The more the number of robots per employee increases (i.e., the more robot deepening occurs), the greater the labour savings. The figure shows saturation and a decreasing marginal product. The higher the growth in robot intensity, the smaller the additional robot-induced employment decline. Greece is an exception that seems to break this rule. However, the situation in Greece was dominated by austerity policy during the observation period, which might explain the deviant behaviour.

The conclusions of this analysis are hardly comparable with the results of other empirical studies. The overall result of a negative relationship between the development in total employment in the manufacturing sector and the increasing penetration of industrial robots was also found in other studies (such as in Carbonero et al., 2018) examining different country samples and study periods. But none of the previous studies reported any country specific and sub-sector specific results. The only previous study that is quite similar to ours in terms of country sample, study period and disaggregation into sub-sectors is Jestl (2024). However, it was carried out on the basis of regional data. Robot deployment data from the IFR is only available at the country- and sector-level and has to be broken down to regional level. This procedure results in robot exposure as a proxy variable of regionally used robot stock and might deviate from actual robot use of individual industries in individual regions. Such a proxy variable could bias the empirical results.

5. Conclusions

The relationship between the use of robots and employment development is intensively discussed in the general public as well as in science. Theoretical considerations present positive and negative arguments and are therefore ambiguous in their answers. It remains an open question for empirical investigations.

We analyse the contribution of robotisation and seven other growth factors to total employment change over the period 2004 to 2019 in manufacturing and its sub-sectors in 17 advanced European countries and the USA. Thereby, we combine index decomposition analysis (IDA) with production-theoretical decomposition analysis (PDA). IDA decomposes the change in employment into changes in output, structural change and changes in labour intensity (the reciprocal of labour productivity). The PDA separates out changes in labour intensities into components associated with changes in technical efficiency (technological catch-up), changes in technology (frontier shift), human capital accumulation, non-robot capital deepening (i.e., change of non-robot capital to labour ratio) and robot capital deepening (i.e., change of robot capital to labour ratio). The PDA is based on the non-parametric production frontier approach of Färe et al. (2018). In the spirit of Eder et al. (2023) we extend it by considering industrial robots as separate production factor. The required production frontiers and distances to the frontiers are estimated by Data Envelopment Analysis (DEA), a method based on linear programming models.

Previous literature on the employment effects of robotisation apply regression analysis techniques and report average effects of robot penetration on employment change across firms, industries or countries. In contrast to this, our decomposition approach allows to provide estimates of individual employment effects differentiated by industries and countries. Few previous studies explicitly considered manufacturing and none addressed heterogeneous employment effects across manufacturing sub-sectors. The distinction between individual sub-sectors or industries makes sense because they are characterized, among others, by differences in production technologies, automation potentials and actual levels and changes in robot deployment. Sub-sector level analyses also provide an interesting political perspective, since collective bargaining on wages, working hours and labour conditions between employer and employee representatives are usually undertaken for individual sub-sectors and not for manufacturing as a whole. The effects of the use of industrial robots on employment play an indirect role for this bargaining as they are influenced by possible labour cost savings as a result of replacement (potentials) of (human) labour through robots. The substitutability of labour varies considerably across individual sub-sectors due to technology differences.

Our analysis reveals substantial heterogeneity in employment and labour intensity (i.e., the inverse of labour productivity) changes across manufacturing sub-sectors. Not less diverse is the extent to which robots contributed to these developments. Our findings show that labour intensity decreased (or, in other words, labour productivity increased) in total manufacturing of all countries (with the exception of Greece) studied and in all sub-sectors during the sample period, contributing to a decrease in employment. Robotisation contributed by lowering labour intensities and thus employment in all countries and manufacturing sub-sectors, albeit to different extents. Our results therefore confirm the negative relationship between robot adoption and employment growth found in previous studies (e.g., Carbonero et al., 2018; Jestl, 2024). Substantial contributions of robotisation to employment decline are found particularly in manufacturing of Czech Republic, Hungary, the Netherlands, Portugal and Slovak Republic as well as in textile industry, in wood and paper industry and in machinery and equipment industry.

Output, in turn, rose, leading to increased employment and, in many countries and manufacturing sub-sectors, counteracting the negative impact of declining labour intensities. The structural changes within manufacturing had little effect in many countries and in most sub-sectors. Apart from robot deepening, only technical progress contributed considerably to the change in labour intensity. The contributions of efficiency change, human capital accumulation and non-robot capital deepening are comparatively small in total manufacturing of almost all countries and in almost all sub-sectors examined.

Our results show the robot penetration as part of labour-saving technical progress in the manufacturing industry. In times of demographic change, increasing application of industrial robots may help alleviating any shortage of skilled workers in production facilities in some sectors. Abeliansky and Prettner (2024) explore how automation could potentially mitigate the adverse economic impacts of population ageing. Basic theoretical analysis indicates that a slower (or negative) growth rate of the labour force tends to accelerate automation. Empirical data shows that a larger proportion of the population aged 55 and above, along with lower population growth, encourages the uptake of industrial robots, as evidenced by studies such as Acemoglu and Restrepo (2022) and Abeliansky and Prettner (2023). Recognizing that automation is, to some degree, a natural reaction to the decrease in labour supply caused by population ageing could provide insight into why we have not seen labour shortages despite population aging.

Like any other sub-sector level studies our decomposition methodology estimates the direct labour-saving effects, but not compensation effects which work (indirectly) via increases in output, and are thereof part of the output change component (Montobbio et al., 2023, p. 21). Future research should develop an approach for sub-sector level studies capturing possible indirect employment effects of robotization based on a multi-sectoral model. The indirect effects could compensate for the negative direct effects and possibly result in positive net effects. A suitable model would reflect the interdependencies of the individual sectors of an economy.

Another interesting research question would be to investigate what type of labour in terms of skill levels, occupations, tasks, age, income, etc. is substitutable and to what extent. This question has already been addressed, but only at the country (e.g., Albinowski and Lewandowski, 2024; de Vries et al., 2020) or regional level (e.g., Borjas and Freeman, 2019; Stemmler, 2019) and not at total manufacturing or manufacturing sub-sector level. The substitutability of older workers might be a solution of skill shortage in the context of demographic change. Last but not least, we are aware that robotisation is only a part of new current technologies (including digitalisation and artificial intelligence). Consequently, it would be useful to expand our analysis to include the indicators of digitalisation, which are covered, for example, by the Digital Economy and Society Index (DESI) of the European Commission.

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The contribution of industrial robots to employment change in manufacturing: A combination of index decomposition analysis and production-theoretical decomposition analysis

Supplementary Material

A. Overview on the preparation of the robot installations and stocks data

Data on robot installations and stocks have been obtained from the International Federation of Robotics (IFR). Based on this data base and on additional information gained from the annual reports (IFR, 2005-2020) we prepared our data base consisting of time series for installations and several measures of stocks for total manufacturing and nine manufacturing sub-sections in 18 countries. These data preparation steps aim at correcting, enhancing, and expanding the original data as seen appropriate for our research project. The issues described and the data preparation applied by us have considerable overlap with the ones described by Klump at al. (2021) and by other scientific work based on the IFR data. The manipulation steps can be grouped into six broad groups: i) simple resolution of inconsistencies in the IFR data set, e.g., when data on installations and stocks of robots are not consistent with each other; ii) disaggregation over countries of aggregated data when the annual reports of IFR give sufficient information on approximate shares for disaggregation; iii) extrapolation back in time of installations and stocks when time series start with stocks higher than installations; iv) extrapolation back in time of installation and stocks when official time series start with identical values for installation and stocks but plausibility considerations and, occasionally, verbal explanations in the annual reports suggest that the “true” numbers of installations and stocks start earlier than that; v) taking account of country specific information from annual reports to make adjustment of the time series, vi) distribution of sectoral aggregated or unspecified values to the most detailed industry scheme used by IFR, by using the proportions found in the following year and applying an iterative procedure starting from the most recent year and iterating back to the beginning of the time series. For further details on steps i) to v), which are needed for the preparation of sectoral aggregated data, the reader is referred to the Supplementary Material of Eder et al. (2024). As a final step of the data preparation the data on installations are aggregated from the level of 17 IFR-reported industries to the 9 industries used in the present analysis.

For reasons of space the data preparation has not been described in full detail here. Detailed information on robot stock data in total manufacturing and the manufacturing sub-sectors of each country in the sample are available upon request from the authors.

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B. Evolution of robot stocks

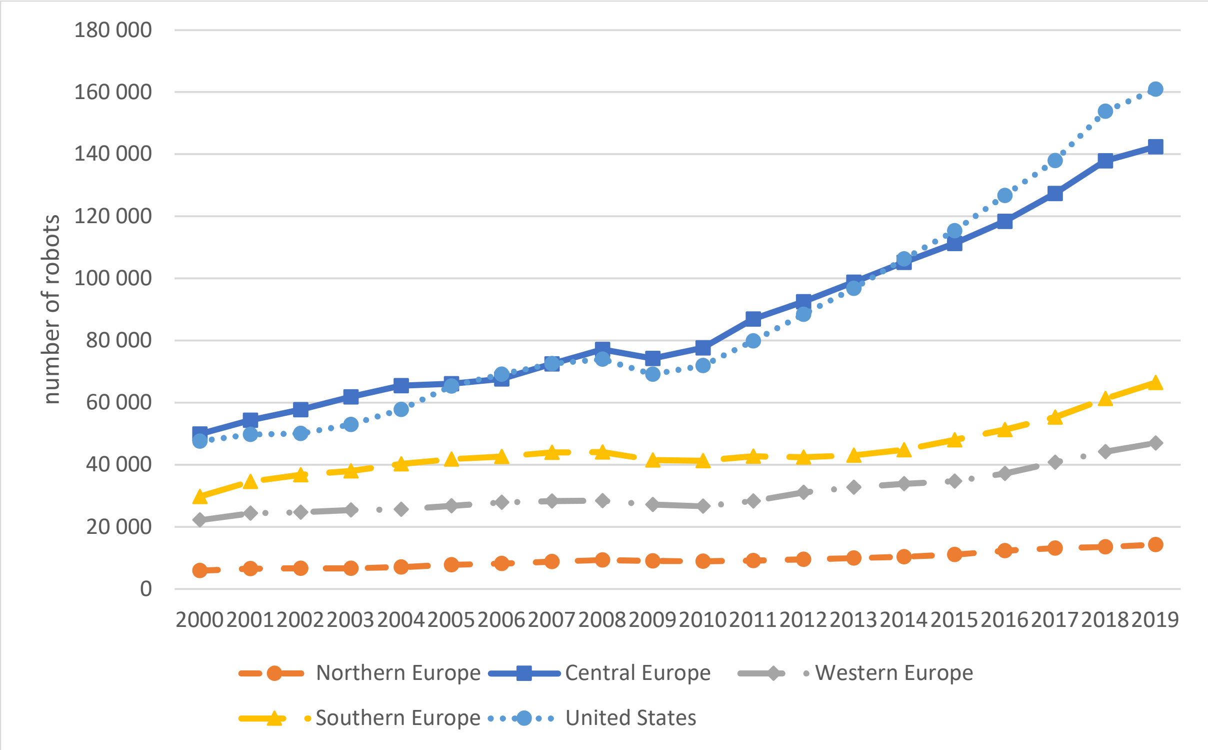

Figure B1 Evolution of (non-quality-adjusted) robot stocks in total manufacturing in four European country groups and the USA over 2000–2019

Note: Northern Europe … Denmark, Finland, Norway and Sweden; Central Europe … Austria, Czech Republic, Germany, Hungary and Slovak Republic; Western Europe … Belgium, France, Great Britain and the Netherlands; Southern Europe … Greece, Italy, Spain and Portugal

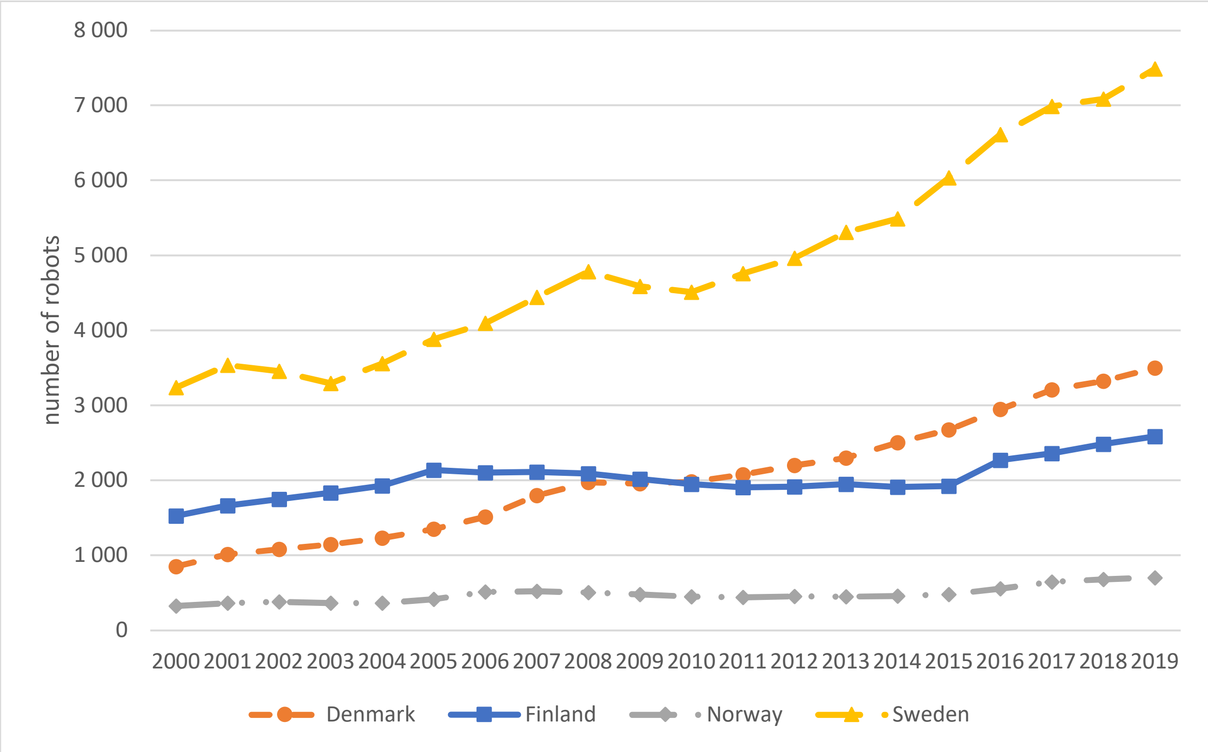

Figure B2 Evolution of (non-quality-adjusted) robot stocks in total manufacturing in Northern European countries over the period 2000–2019

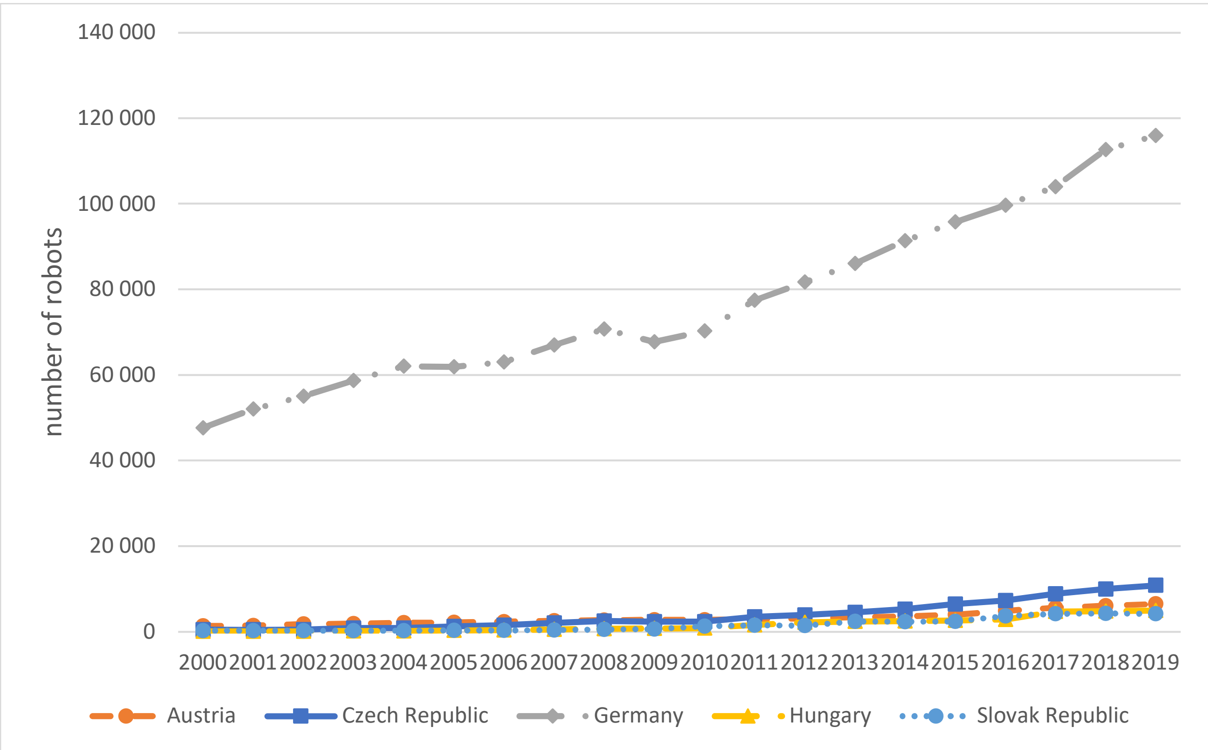

Figure B3 Evolution of (non-quality-adjusted) robot stocks in total manufacturing in Central European countries over the period 2000–2019

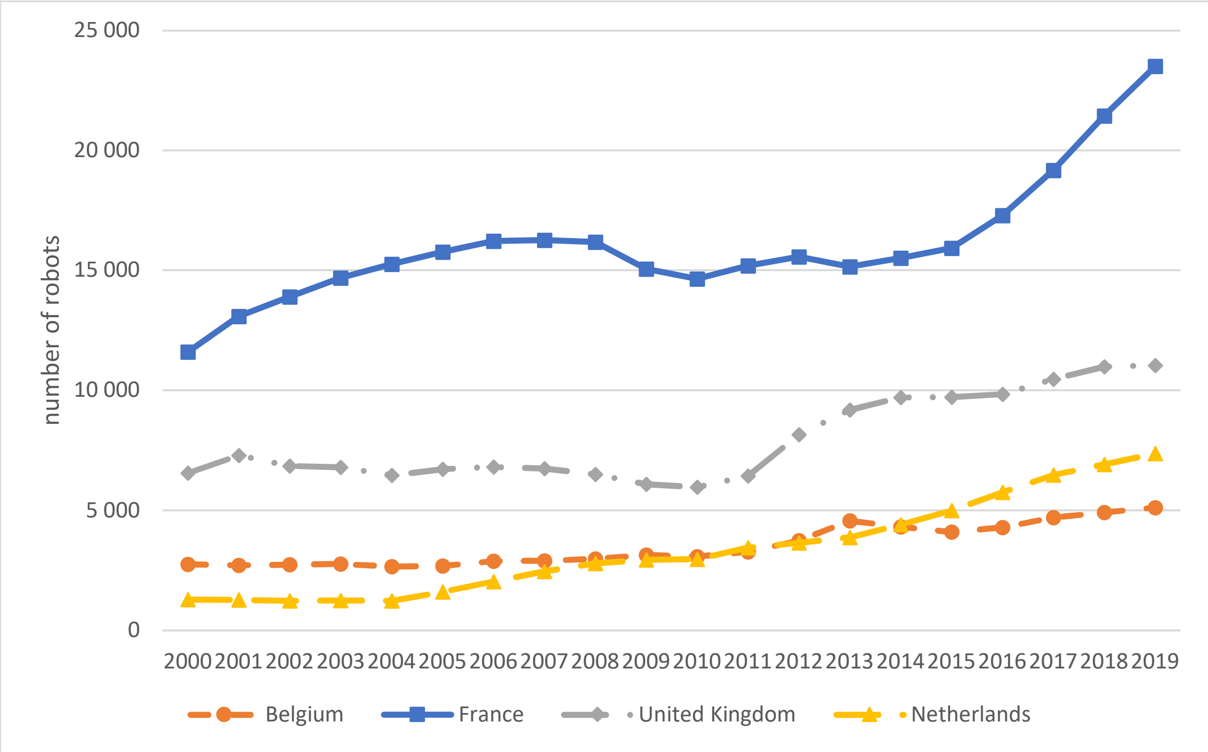

Figure B4 Evolution of (non-quality-adjusted) robot stocks in total manufacturing in Western European countries over the period 2000–2019

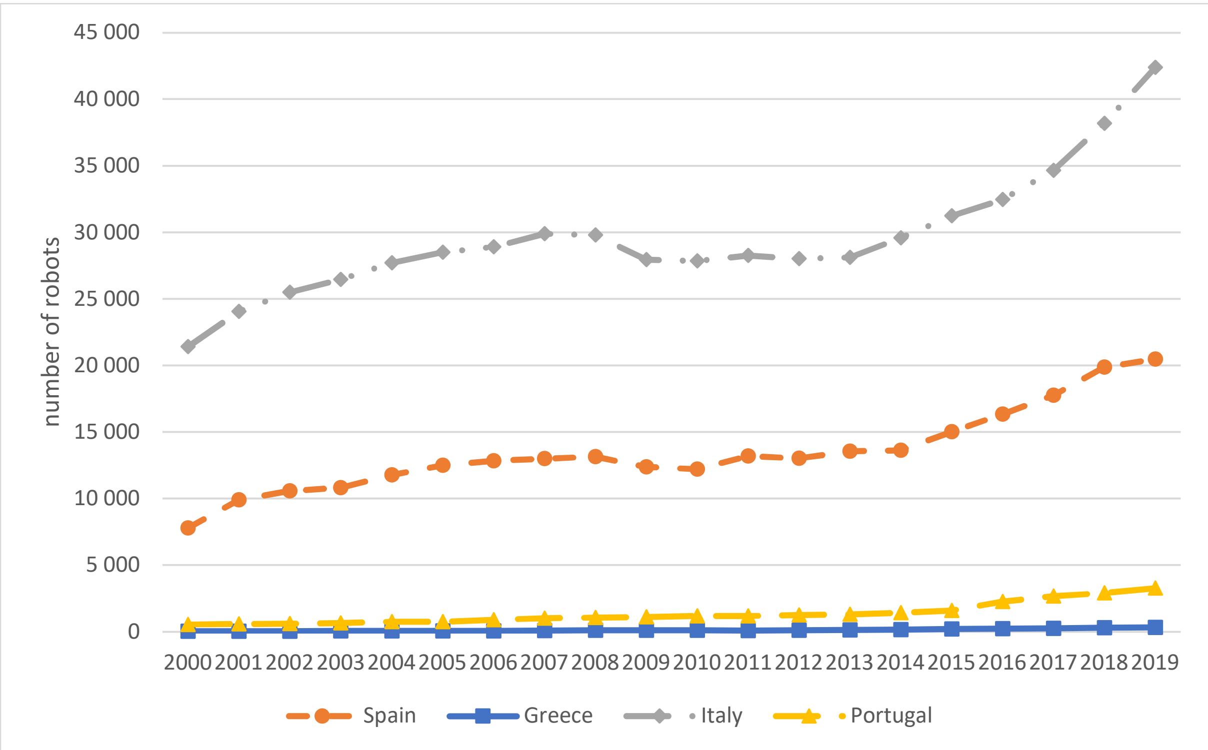

Figure B5 Evolution of (non-quality-adjusted) robot stocks in total manufacturing in Southern European countries over the period 2000–2019

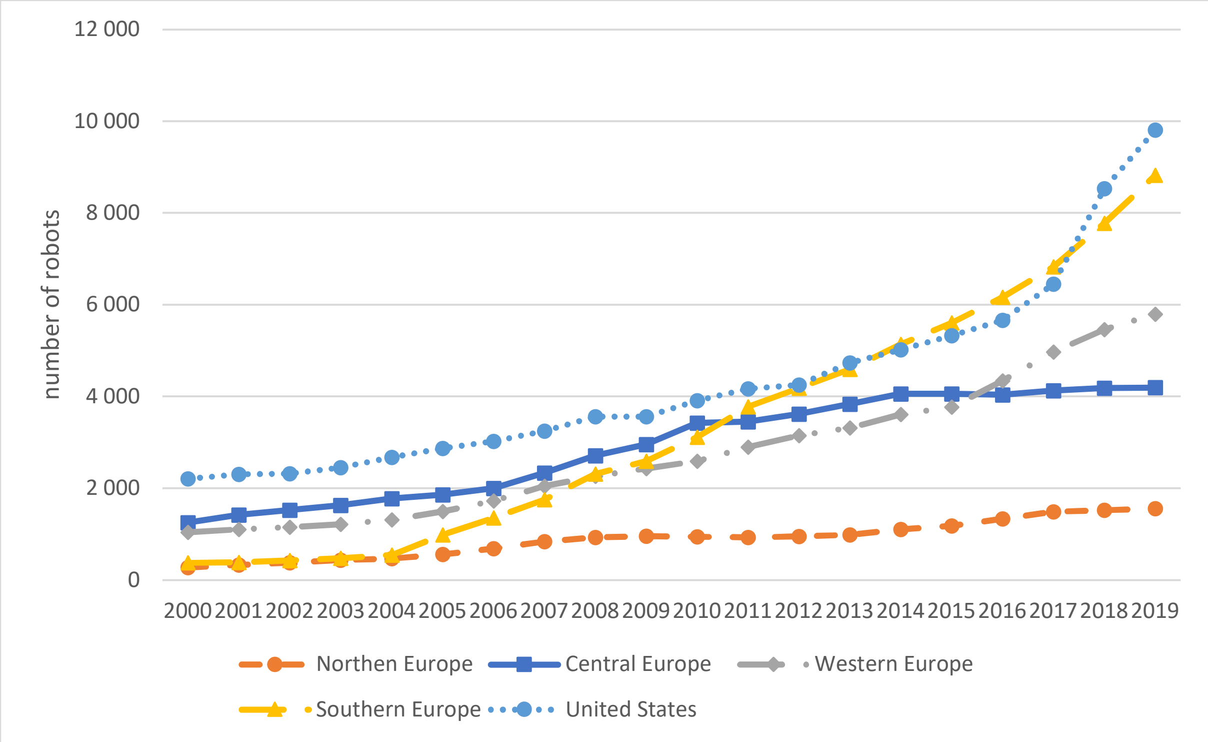

Figure B6 Evolution of (non-quality-adjusted) robot stocks in C10-C12 (Food products, beverages and tobacco) in four European country groups and the USA over 2000–2019

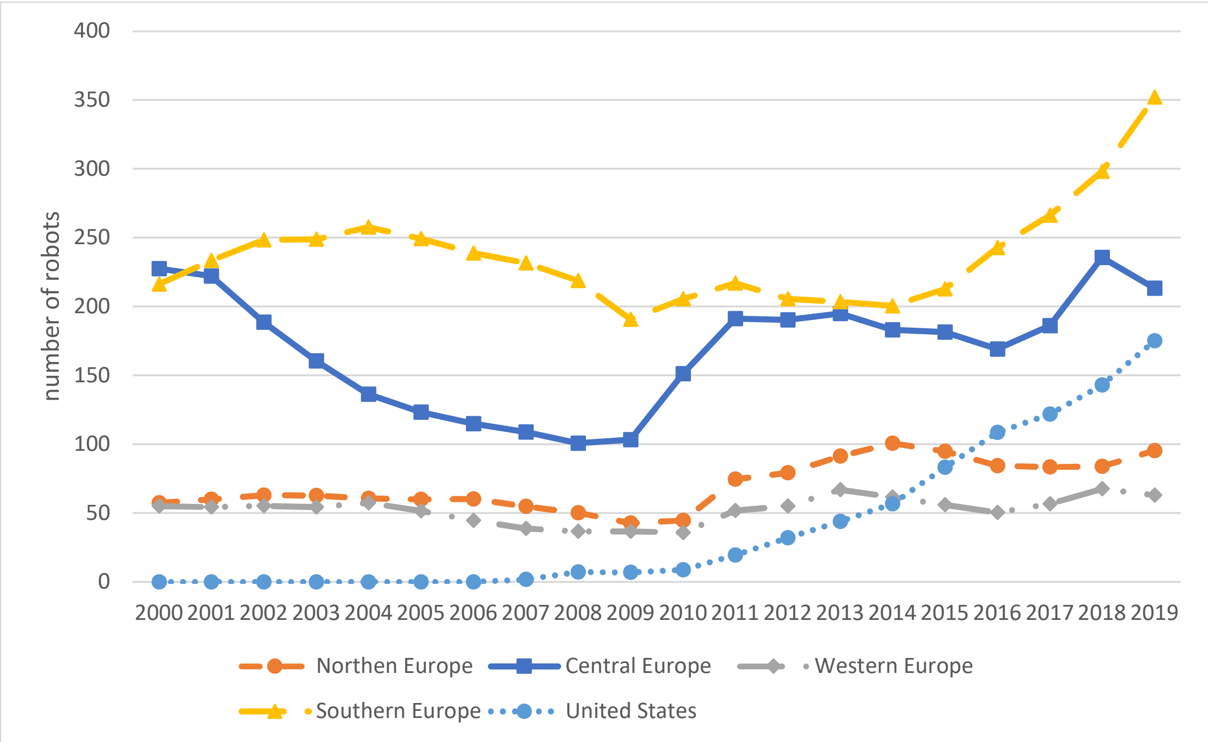

Figure B7 Evolution of (non-quality-adjusted) robot stocks in C13-C15 (Manufacture of textiles, wearing apparel, leather and related products) in four European country groups and the USA over 2000–2019

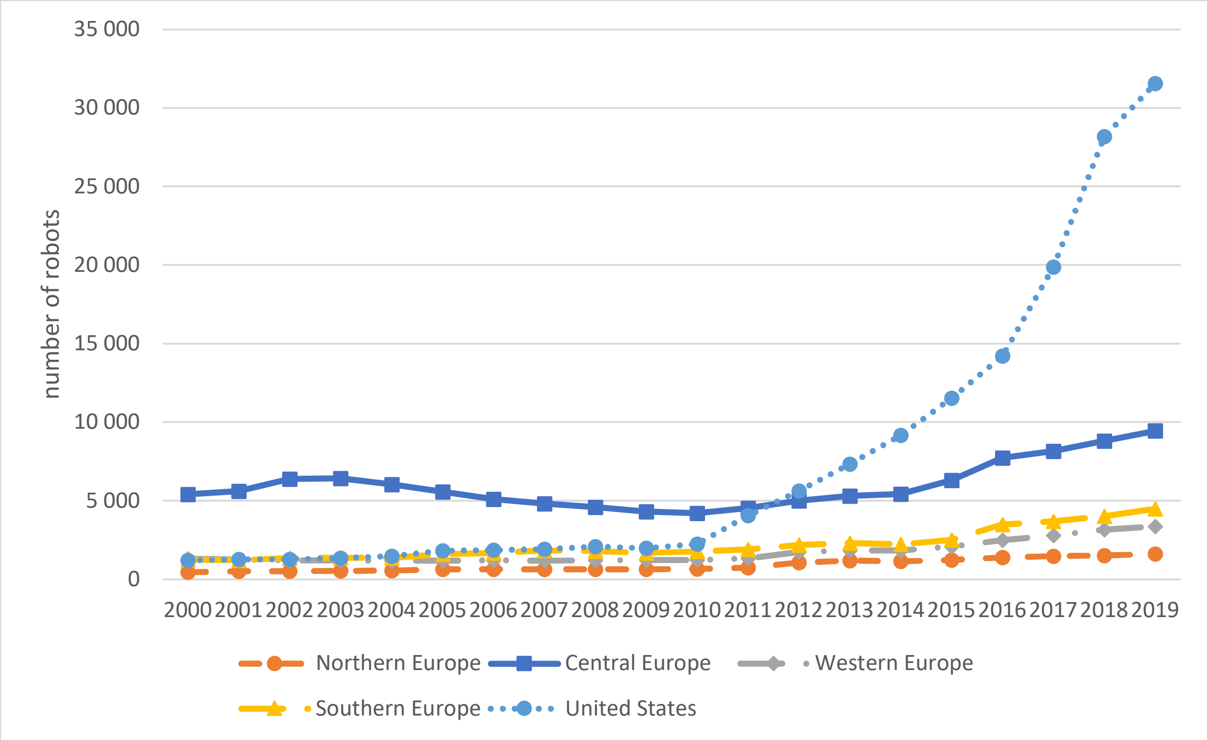

Figure B8 Evolution of (non-quality-adjusted) robot stocks in C16-C18 + C31-C33 (Manufacture of wood and paper products: printing + Other manufacturing, repair and installation of machinery and equipment) in four European country groups and the USA over 2000–2019

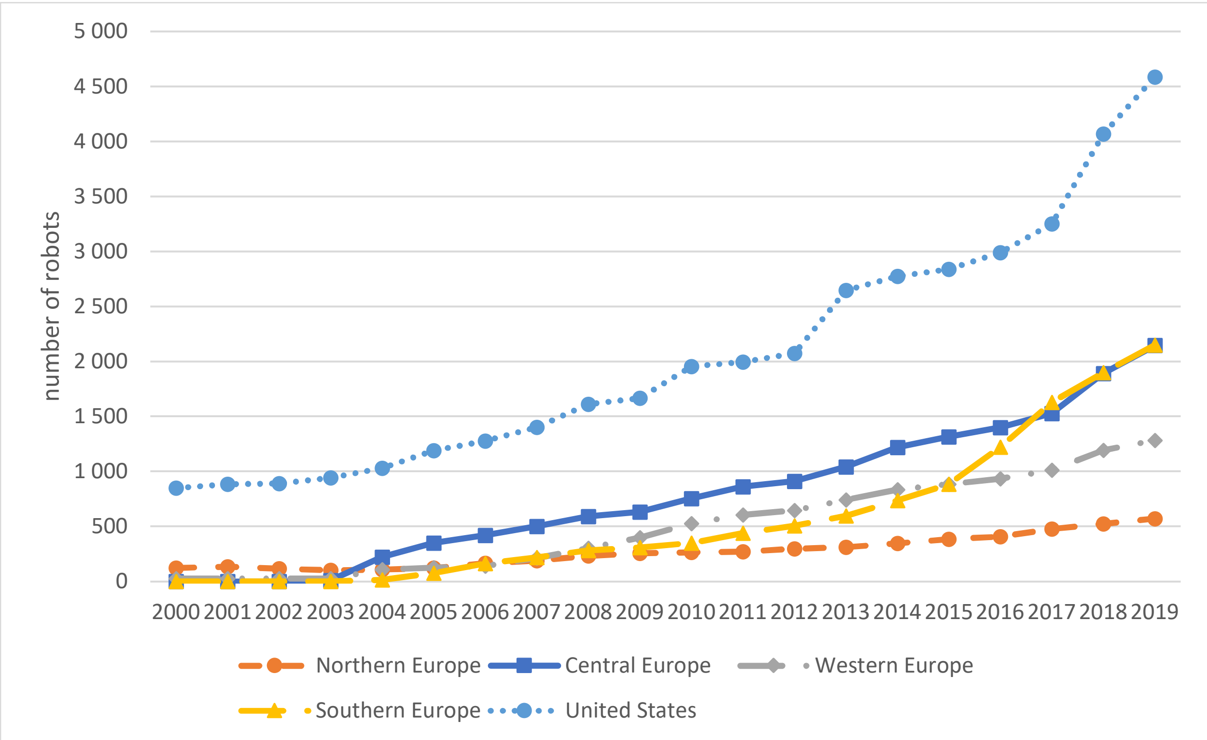

Figure B9 Evolution of (non-quality-adjusted) robot stocks in C19-C21 (Manufacture of basic pharmaceutical products and preparations + Manufacture of coke and refined petroleum products + Manufacture of chemicals and chemical products) in four European country groups and the USA over 2000–2019

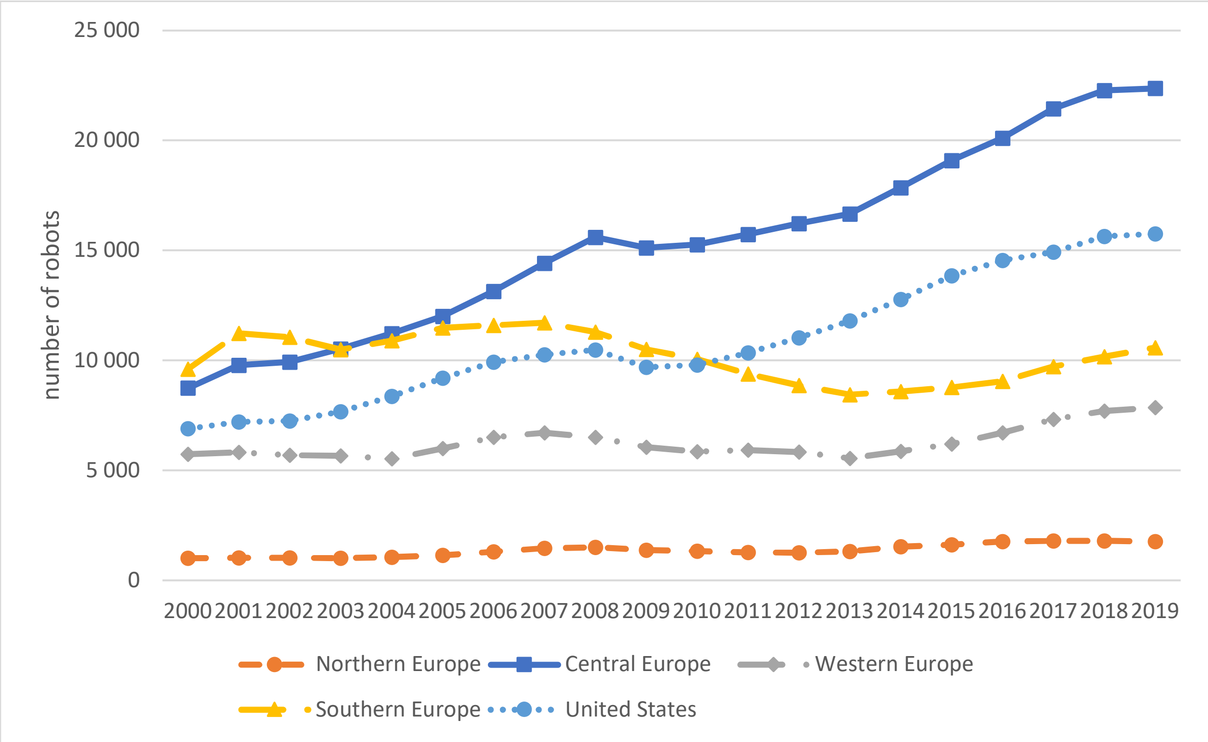

Figure B10 Evolution of (non-quality-adjusted) robot stocks in C22 + C23 (Rubber and plastics products, and other non-metallic mineral products) in four European country groups and the USA over 2000–2019

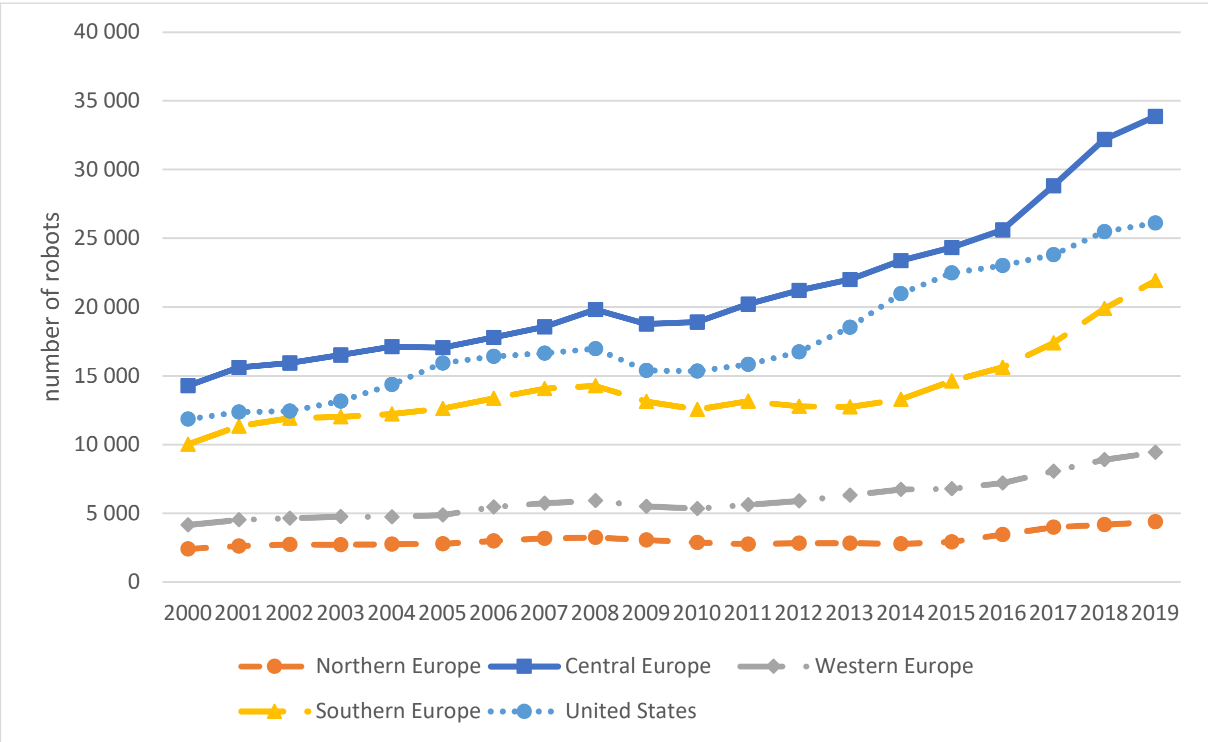

Figure B11 Evolution of (non-quality-adjusted) robot stocks in C24 + C25 (Manuf. of basic metals and fabricated metal products, except mach. & equip.) in four European country groups and the USA over 2000–2019

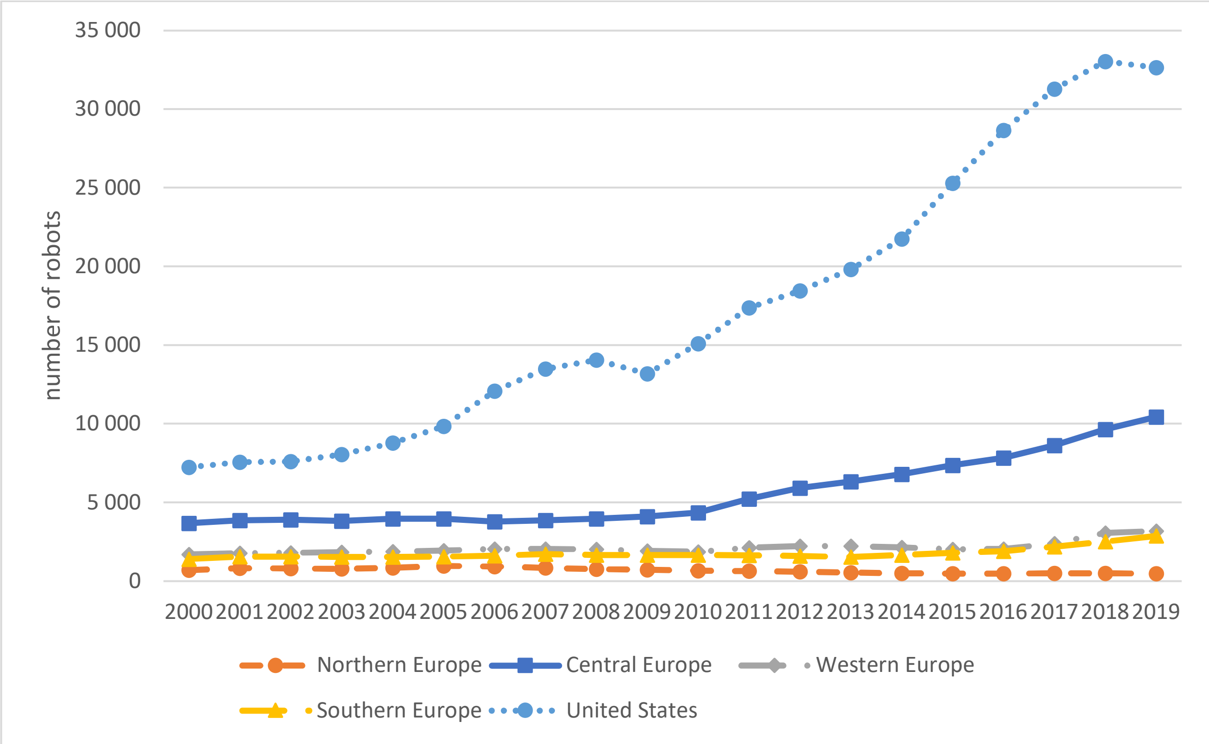

Figure B12 Evolution of (non-quality-adjusted) robot stocks in C26 + C27 (Computer, electronic, optical products; electrical equipment) in four European country groups and the USA over 2000–2019

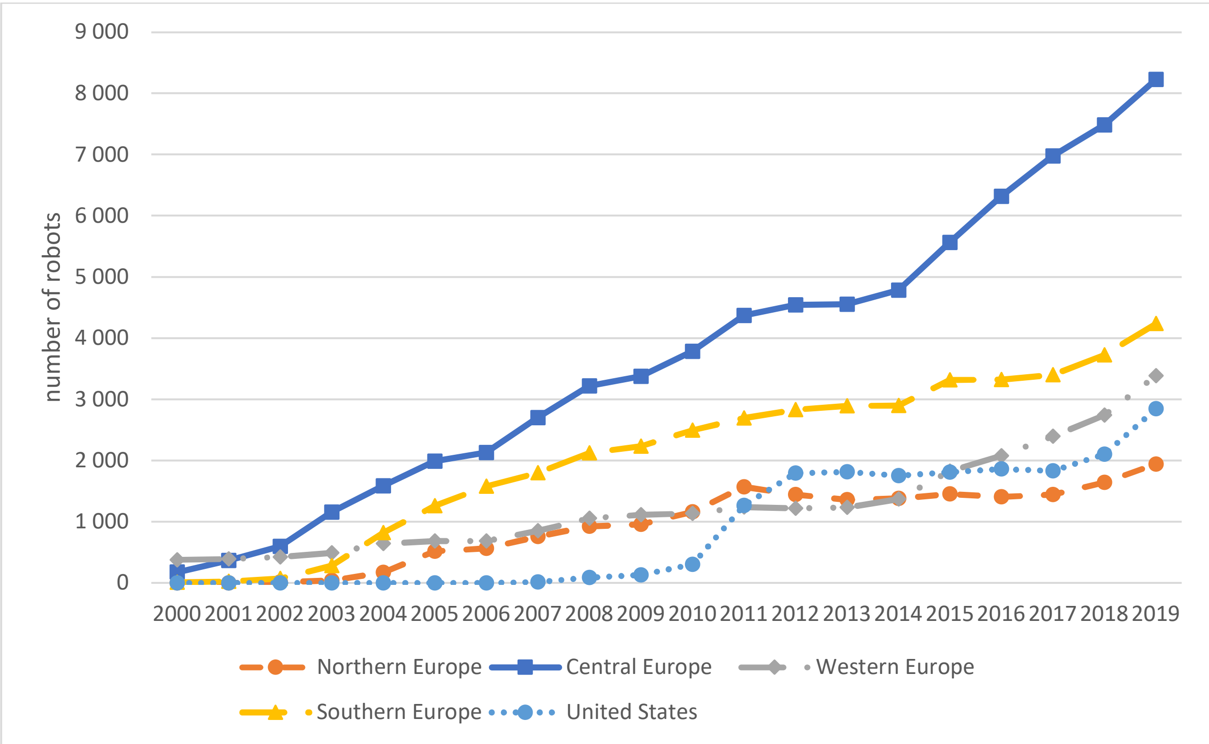

Figure B13 Evolution of (non-quality-adjusted) robot stocks in C28 (Manufacture of machinery and equipment n.e.c.) in four European country groups and the USA over 2000–2019

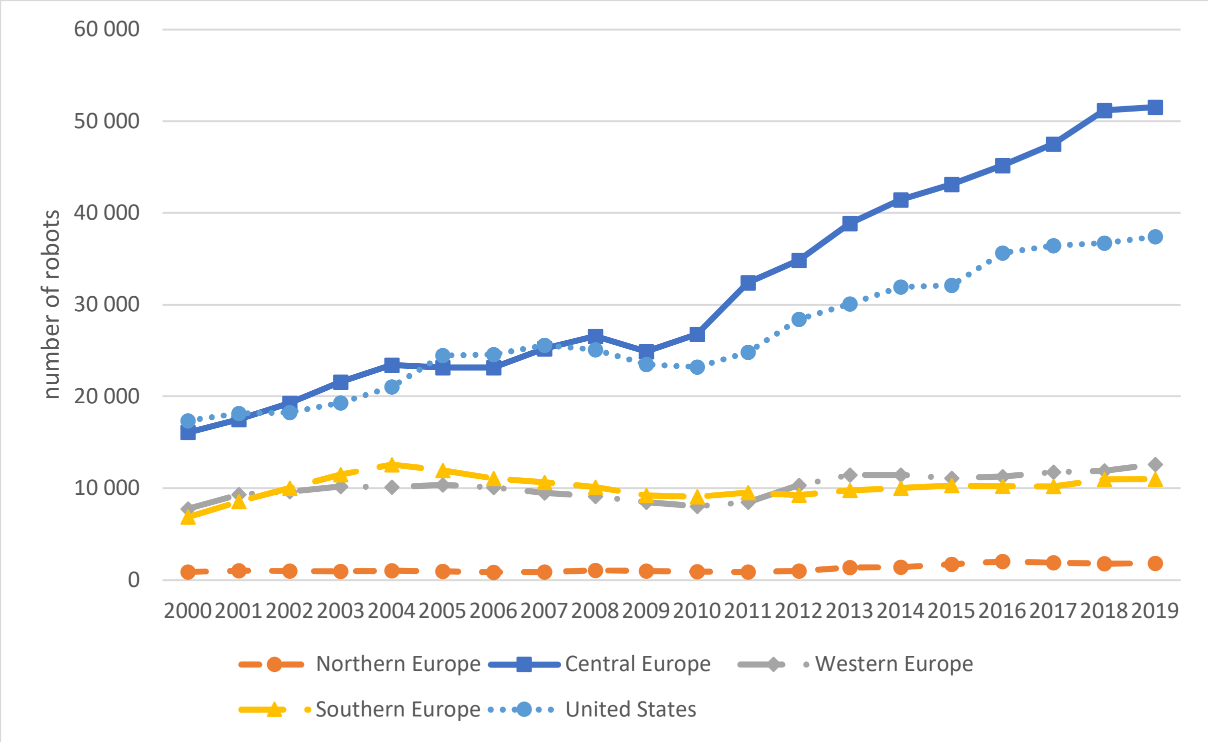

Figure B13 Evolution of (non-quality-adjusted) robot stocks in C29 + C30 (Manufacture of transport equipment) in four European country groups and the USA over 2000–2019

C. Descriptive statistics

Table C1
Descriptive statistics of input and output variables in total manufacturing

	mean	minimum	maximum
Output (real gross value added at 2015 PPP-adjusted mill. EUR)	182,667	6,376	1,741,841
Efficiency units of labour (mill. hours worked × human capital index)	13,974	1,217	127,478
Non-robot physical capital stock (in PPP-adjusted mill. 2015 EUR)	308,568	22,176	2,878,274
Quality-adjusted industrial robot stock (in physical units based on PIM with δ=15%)	28,663	46	411,869

Note: Means are based on a balanced panel of 18 countries' manufacturing sectors for the years 2000–2019 covering 360 observations.

Table C2
Descriptive statistics of levels of employment, labour intensity, capital intensities and human capital index in 2004 and 2019 in total manufacturing

	mean	minimum	maximum
Year 2004			
Labour intensity (mill. hour worked per output, PPP-adjusted 2015 EUR)	0.034	0.020	0.079
Robot intensity (quality-adjusted number of robots per mill. hours worked)	2.76	0.07	8.40
Non-robot capital intensity (non-robot physical capital stock per hour worked, PPP-adjusted 2015 EUR)	67.15	23.99	133.35
Human capital index	3.18	2.23	3.62
Year 2019			
Labour intensity (mill. hour worked per output, PPP-adjusted 2015 EUR)	0.024	0.014	0.045
Robot intensity (quality-adjusted number of robots per mill. hours worked)	12.96	1.13	25.99
Non-robot capital intensity (non-robot physical capital stock per hour worked, PPP-adjusted 2015 EUR)	83.90	30.56	138.39
Human capital index	3.41	2.51	3.85

Note: The quality-adjusted number of robots is estimated with the perpetual inventory method assuming a depreciation rate of 15%. The quality index of robots is used to adjust robot installations for quality changes.

Table C3
Descriptive statistics of growth rates of labour productivity, capital intensities and human capital index in total manufacturing over the period 2004 to 2019

	mean	minimum	maximum
Employment growth (in %)	–11.84	–29.80	5.84
Output growth (in %)	28.27	–31.39	164.81
Labour intensity growth (in %)	–26.88	–60.41	10.63
Robot intensity growth (in %)	912.56	179.40	4,381.05
Non-robot capital intensity growth (in %)	29.91	–4.01	78.69
Human capital index growth (in %)	7.47	1.86	12.52

Note: Quality-adjusted number of robots are estimated with the perpetual inventory method assuming a depreciation rate of 15%. The quality index of robots is used to adjust robot installations for quality changes. Mean, minimum and maximum over 18 countries.

D. Multiplicative Decomposition Indexes

Table D1

Multiplicative Decomposition Indexes of Employment Change for Total Manufacturing, 2004-2019

Country	Employment Change	ΔY^n	ΔS^n	ΔI^n	EFF^n	$TECH^n$	$HACC^n$	$KACC^n$	$RKACC^n$
Austria	0.995	1.448	0.962	0.714	0.983	0.887	0.948	0.959	0.901
Belgium	0.831	1.088	0.922	0.829	1.014	0.889	0.972	1.005	0.941
Czech Republic	1.058	2.199	0.990	0.486	0.870	0.905	0.991	0.786	0.792
Germany	1.012	1.308	0.971	0.797	0.935	0.878	0.991	0.992	0.989
Denmark	0.797	1.394	0.801	0.714	1.020	0.864	0.942	0.952	0.903
Spain	0.702	0.949	0.974	0.759	1.014	0.872	0.920	0.971	0.961
Finland	0.792	1.011	0.969	0.807	1.070	0.838	0.937	0.993	0.968
France	0.823	1.088	0.972	0.778	1.026	0.877	0.935	0.955	0.968
Greece	0.759	0.689	0.877	1.257	1.568	0.939	0.964	0.929	0.952
Hungary	0.946	1.265	1.070	0.699	1.543	0.925	0.947	0.776	0.667
Italy	0.815	0.999	0.998	0.818	1.127	0.858	0.924	0.962	0.951
Netherlands	0.919	1.245	0.941	0.785	1.102	0.892	0.951	1.006	0.835
Norway	0.936	1.119	0.998	0.839	1.044	0.891	0.948	1.003	0.949
Portugal	0.828	1.109	0.975	0.766	1.429	0.860	0.919	0.894	0.758
Slovak Republic	1.048	2.620	0.943	0.424	0.857	0.865	0.929	0.901	0.682
Sweden	0.823	1.112	0.995	0.744	0.997	0.883	0.957	0.947	0.934
United Kingdom	0.837	1.186	1.011	0.698	0.852	0.898	0.976	0.974	0.959
United States	0.946	1.217	1.002	0.776	1.059	0.866	0.974	0.967	0.899
Geometric mean	**0.876**	**1.223**	**0.963**	**0.744**	**1.066**	**0.882**	**0.951**	**0.940**	**0.883**

Note:

ΔY^n … value added change, ΔS^n … structural change, ΔI^n … labour intensity change, EFF^n … efficiency change, $TECH^n$ … technical change, $HACC^n$ … human capital accumulation, $KACC^n$… capital intensity change, $RACC^n$ … robot intensity change. Employment Change = $\Delta Y^n * \Delta S^n * \Delta I^n$, $\Delta I^n = EFF^n * TECH^n * HACC^n * KACC^n * RACC^n$

Table D2

Multiplicative Decomposition Indexes of Employment Change for Total Manufacturing (Country Groupings)

Country Group	Employment Change	ΔY^n	ΔS^n	ΔI^n	EFF^n	$TECH^n$	$HACC^n$	$KACC^n$	$RKACC^n$
Northern Europe*	0.835	1.151	0.937	0.774	1.032	0.869	0.946	0.973	0.938
Central Europe+	1.011	1.690	0.986	0.607	1.011	0.892	0.961	0.879	0.797
Western Europe†	0.852	1.150	0.961	0.771	0.994	0.889	0.958	0.985	0.924
Southern Europe§	0.775	0.923	0.955	0.879	1.265	0.882	0.932	0.938	0.901
United States	0.946	1.217	1.002	0.776	1.059	0.866	0.974	0.967	0.899
All countries	**0.876**	**1.223**	**0.963**	**0.744**	**1.066**	**0.882**	**0.951**	**0.940**	**0.883**

Note:

*Denmark, Finland, Norway, Sweden.

+ Austria, Czech Republic, Germany, Hungary, Slovak Republic.

† Belgium, France, Great Britain, Netherlands.

§ Greece, Italy, Spain, Portugal.

ΔY^n … value added change, ΔS^n … structural change, ΔI^n … labour intensity change, EFF^n … efficiency change, $TECH^n$ … technical change, $HACC^n$ … human capital accumulation, $KACC^n$… capital intensity change, $RACC^n$ … robot intensity change. Employment Change = $\Delta Y^n * \Delta S^n * \Delta I^n$, $\Delta I^n = EFF^n * TECH^n * HACC^n * KACC^n * RACC^n$

Table D3

Multiplicative Decomposition Indexes of Employment Change for Total Manufacturing (Sector Groupings)

Sectors Group	Employment Change	ΔY_{m}	ΔS_{m}	ΔI_{m}	EFF_{m}	$TECH_{m}$	$HACC_{m}$	$KACC_{m}$	$RKACC_{m}$
C10-C12 [α]	1.035	1.110	0.999	0.934	1.082	0.983	0.950	0.991	0.932
C13-C15 [β]	0.603	0.843	0.985	0.726	1.254	0.770	0.948	0.938	0.846
C16-C18 + C31-C33 [γ]	0.845	1.048	1.008	0.800	1.140	0.877	0.963	0.970	0.856
C19-C21 [δ]	1.050	1.079	1.020	0.955	1.221	0.929	0.961	0.969	0.904
C22 + C23 [ε]	0.819	0.995	1.038	0.792	0.908	0.946	0.958	0.980	0.983
C24 + C25 [ζ]	0.919	1.118	1.000	0.822	1.010	0.878	0.961	0.969	0.996
C26 + C27 [η]	0.799	2.050	0.998	0.390	0.618	0.745	0.970	0.910	0.961
C28 [θ]	0.995	1.169	1.024	0.831	1.253	0.861	0.969	0.949	0.838
C29 + C30 [ι]	1.052	1.481	1.020	0.696	0.997	0.843	0.977	0.917	0.925

Note:

[α] Food products, beverages and tobacco.

[β] Manufacture of textiles, wearing apparel, leather and related products.

[γ] Manufacture of wood and paper products: printing + Other manufacturing, repair and installation of machinery and equipment

[δ] Manufacture of basic pharmaceutical products and preparations + Manufacture of coke and refined petroleum products + Manufacture of chemicals and chemical products.

[ε] Rubber and plastics products, and other non-metallic mineral products.

[ζ] Manuf. of basic metals and fabricated metal products, except mach. & equip.

[η] Computer, electronic, optical products; electrical equipment

[θ] Manufacture of machinery and equipment n.e.c.

[ι] Manufacture of transport equipment

ΔY_{m} … value added change, ΔS_{m} … structural change, ΔI_{m} … labour intensity change, EFF_{m} … efficiency change, $TECH_{m}$ … technical change, $HACC_{m}$ … human capital accumulation, $KACC_{m}$… capital intensity change, $RACC_{m}$ … robot intensity change. Employment Change = $\Delta Y_{m} * \Delta S_{m} * \Delta I_{m}$, $\Delta I_{m} = EFF_{m} * TECH_{m} * HACC_{m} * KACC_{m} * RACC_{m}$