The contribution of industrial robots to labor productivity growth and economic convergence: A production frontier approach

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Abstract

This paper investigates the contribution of industrial robots to labor productivity growth and the process of economic convergence in 19 developed and 17 emerging countries in the period 1999 to 2019. To answer our research questions, we extend the non-parametric production frontier framework by considering industrial robots as a separate production factor. Production frontiers and distances to the frontiers are estimated by Data Envelopment Analysis, a method based on linear programming models. Considerable contributions of robotization to labor productivity growth are mainly found in emerging countries and are rather modest in most developed countries. In the period 2009 to 2019 robot capital deepening as a source of productivity growth has gained in importance in emerging countries but not in developed countries. Within the period 1999 to 2019 we find some evidence of i) unconditional β-convergence, ii) a reduction in the dispersion of productivity levels across economies (σ-convergence) and iii) a depolarization (shift from bimodal to unimodal distribution) of the labor productivity distribution. Non-robot physical capital deepening and robotization are the most important drivers of β-convergence. Robot capital deepening contributed to the depolarization of the labor productivity distribution and to σ-convergence. Though, the effect of robot capital deepening on the entire shift of the labor productivity distribution between 1999 and 2019 is modest and dominated by other growth factors such as technological change and non-robot physical capital deepening.

JEL-Classification: E24, O33, O47

Keywords: automation, robotization, decomposition, data envelopment analysis, emerging countries, developed countries

1. Introduction

Labor productivity growth drives economic growth and plays a central role for the wealth and development of nations and the improvement of living standards (Timmer et al., 2010; Mendez et al., 2020). Beside the general interest of policy makers, media and the public, the ongoing and accelerating diffusion of industrial robots (see, e.g., Dachs et al., 2022) attracted the attention of numerous scholars aiming to explore the impact of this current wave of automation on various economic outcomes, such as employment, wages, and labor productivity growth. The current empirical evidence, based on industry- and firm-level data, suggests a positive relationship between robot use and productivity growth (for studies based on industry-level data see, e.g., Dauth et al. (2017), Graetz and Michaels (2018), Jungmittag and Pesole (2019), Leitner and Stehrer (2019), Kromann et al. (2020), Bekthiar et al. (2021), for firm-level evidence see, e.g., EC (2015), Acemoglu et al. (2020), Ballestar et al. (2020), Bonfiglioli et al. (2020), Dixon et al. (2020), Koch et al. (2021)).

Despite the contemporary interest and the booming number of studies exploring the economic and social consequences of the ongoing diffusion of robots, relatively little is known about i) how the contribution of industrial robot usage to labor productivity growth differs across countries, and ii) if the worldwide diffusion of industrial robots contributes to a widening or closing of the productivity gap between rich and poorer countries. While previous studies on the impact of robotization on labor productivity mainly focused on OECD or developed countries, investigations including or focusing on emerging and developing countries are rare (exceptions are Jung and Lim, 2020; Zhu and Zhang, 2021; Fu et al., 2021).

First, we add to this literature by investigating whether and how the contribution of robot adoption to labor productivity growth differs between developed and emerging countries. Second, to the best of our knowledge we are the first to investigate if, and by how much, robots contribute to the convergence of labor productivity levels across countries. Consequently, we analyze how industrial robot adoption, and four other growth factors (i.e., technological change, efficiency change, non-robot physical capital accumulation and human capital accumulation) shape the entire distribution of labor productivity across a sample of 19 developed and 17 emerging countries over the period 1999 to 2019. We apply and extend the nonparametric production frontier approach developed by Kumar and Russell (2002), and refined by Henderson and Russell (2005). Hence, this study also contributes to the vast literature analyzing cross-country economic growth and convergence[1] and extends the non-parametric production frontier framework of Henderson and Russell (2005) by incorporating industrial robots. Contrary to many other studies (e.g., Graetz and Michaels, 2018; Cette et al., 2021a, 2021b) we apply quality-adjusted measures of industrial robot stocks.[2]

While previous studies are mostly based on regression techniques and focus on average effects, there are various reasons why we can expect that the impact of robotization on labor productivity growth differs across countries. First, Graetz and Michaels (2018) find diminishing marginal gains from increased use of robots. Hence, we can expect that the initial level of robot usage affects the potential labor productivity gains from increased robot diffusion. Since emerging countries are characterized by substantially lower robotization levels than developed countries (see, e.g., Soto, 2020) we might expect higher productivity gains from increasing robotization in emerging countries. Second, the productivity enhancing effect of robotization depends on the industrial structure of an economy and the related type of tasks that can be automated, as well as on the productivity of the workforce that is replaced by robots. However, a priori it is difficult to hypothesize if the economic structures favor the relative growth potential of emerging vis-à-vis developed countries or the other way around.

The rise of robots in emerging markets in the last 20 years is remarkable. While in developed countries (e.g., Germany, Japan, US) the use of industrial robots started to climb exponentially

[1] See Johnson and Papageorgiou (2020) for a review of the more recent (last ten to fifteen years) literature on cross-country economic convergence dynamics.

[2] Kromann et al. (2020) discuss the importance of adjusting robot stock measures for quality changes.

in the 1980s, at the start of the new millennium robots virtually played no role in the economies of, e.g., India, Turkey, or China. In 2016, China replaced Japan as the country with the highest robot stock, and nowadays more than 29 % of the global robot stock is in China (Müller and Kutzbach, 2020). Between 2014 and 2019 the stock of industrial robots grew by 33 %, 32 %, 19 %, and 17 % in China, Mexico, Turkey, and India, but only by 6 % in the United States, and 5 % in Western Europe (Müller and Kutzbach, 2020).[3] It will be interesting to investigate whether and by how much the apparent catching-up of emerging countries in terms of robotization translates into convergence of labor productivities.

Standard neoclassical growth theory predicts that countries with access to identical technologies should converge to common levels of labor productivity (Jungmittag, 2021). By incorporating robots in standard economic growth models Jungmittag (2021) shows that differences in the initial stock of robots and its growth rate might prevent countries to converge to common levels of labor productivity, and only conditional convergence towards country-specific steady states might be achieved.

The studies most closely related to ours are Cette et al. (2021a, 2021b) and Jungmittag (2021). Cette et al. (2021a, 2021b) apply the standard growth accounting methodology by Solow (1956, 1957) to isolate the contribution of industrial robots to labor productivity growth in 30 OECD countries over the period 1975-2019. This procedure provides country-specific estimates of the proximate sources of economic growth. Jungmittag (2021) investigates the convergence of robot densities in the manufacturing industries of 24 EU countries over the period 1995 to 2015. While Cette et al. (2021a, 2021b) do not analyze convergence processes, the empirical part in Jungmittag (2021) suffers from analyzing how the convergence in robot densities translates into convergence in labor productivity levels. Both studies focus on OECD countries.

[3] A discussion of the rise of robots in China is provided in Cheng et al. (2019), for Central and Eastern European countries see Eséfalvay (2020).

Contrary to the standard growth accounting procedure applied in Cette et al. (2021a, 2021b), we use the (deterministic) non-parametric production frontier approach developed by Kumar and Russell (2002), and refined by Henderson and Russell (2005), and extend it by considering industrial robots as separate production factor. The estimation of the production frontier is based on linear programming techniques known as Data Envelopment Analysis (DEA). The advantage of this approach over regression-based studies, which are heavily model-driven, is that it is a purely data-driven approach, which does not require assumptions about the functional form of the production function (e.g., Cobb-Douglas or CES), the existence of perfectly competitive markets and Hicks-neutral technological change (Badunenko and Romero-Ávila, 2013). Unlike standard growth accounting, this framework allows us to distinguish between efficiency change, i.e., movements toward the frontier, and technological change, i.e., shifts of the frontier (Badunenko and Romero-Ávila, 2013). The contribution of robots to technological change is assessed by comparing two different decompositions of labor productivity change: one with and one without considering industrial robots as separate production factor (Ceccobelli et al., 2012).

The remainder of this article is organized as follows: Section 2 describes the data and the construction of the quality-adjusted robot capital stock and provides some descriptive statistics on the development of robot intensities (i.e., the robot-labor ratio) of selected countries over the 1999-2019 period. Section 3 constructs the technology frontiers in 1999 and 2019 and provides the efficiency scores, i.e., the distance from the frontier, for each of the 36 countries analyzed. Section 4 presents the results of the decomposition of productivity growth into its five components. Section 5 assesses the relative importance of the five growth factors in shifting the entire productivity distribution. Section 6 provides some sensitivity analyses. Section 7 summarizes our results and concludes.

2. Data

We use two different data sources to construct the dataset for our analysis: First, input data for labor, human capital and non-robot physical capital, as well as output data is derived from the Penn World Table (PWT) version 10.0 (Feenstra et al., 2015). Second, we use data from the International Federation of Robotics (Müller and Kutzbach, 2020) to estimate industrial robot capital stocks.

2.1. Sample selection

The PWT 10.0 covers 183 countries between 1950 and 2019. Hence, the selection of our sample of a balanced panel of 36 developed and emerging countries for the period 1995-2019 with a total of 900 observations is mainly driven by the availability of data on industrial robot installations.[4] Müller and Kutzbach (2020) provide data on annual robot installations and robot stocks for 1993-2019 for Australia, Austria, Belgium, Czech Republic, Denmark, Finland, France, Germany, Hungary, Italy, Japan, Netherlands, Norway, Poland, Portugal, Republic of Korea, Russian Federation, Singapore, Slovakia, Slovenia, Spain, Sweden, Switzerland, Taiwan, United Kingdom and the United States. Japan, whose robot data are compromised by a severe break in 2001 due to a change in underlying robot definitions, could be included in the sample after a correction (see Section A of the supplementary material for more details). Up to 2011 the data for the United States also includes robot installations/stocks for Canada and Mexico. Based on information provided in the annual reports of the International Federation of Robotics (IFR, 2005-2020) and some simple assumptions we can separate the installations for North America before 2011, and include Canada, Mexico as well as the Unites States in our sample. In addition to these 28 countries, data on robot installations for Argentina, Brazil, China, Greece, India, Israel, Malaysia, South Africa, and Turkey becomes available from 1999

[4] Though, we have data for the period 1995 to 2019, the period of investigation throughout section 3 to 7 is 1999-2019. The reasons for this are methodological considerations which are explained in Section 3.1.

onwards. Section A of the supplementary material describes how we estimate robot installations prior to 1999 for those countries.

Finally, our data set excludes South Africa and is restricted to the period 1995-2019 because data on average annual hours worked by persons engaged in the PWT 10.0 is incomplete for South Africa (missing for 1993-2000 and 2015), as well as for Poland and Slovenia (missing for 1993 and 1994). Our sample of countries covers 86 % of global GDP and 93% of the world-wide robot stock in 2019.

2.2. Categorization of countries

Since one goal of this article is to investigate how the contribution of industrial robots to labor productivity growth differs between developed and emerging countries it seems natural to divide the countries in our sample into two groups. Our definition of country groups is based on real GDP per capita (in 2017 US$) in the starting year of our investigation period. Real GDP per capita is derived from the PWT 10.0 and calculated as CGDPE divided by POP. CGDPE is expenditure-side real GDP at current PPPs (in millions 2017 US$), and POP is a country's population (in millions). Countries having a real GDP per capita larger than 32,500 US$ in 1999 are classified as developed countries, and countries having a real GDP per capita lower than 27,500 US$ in 1999 are classified as emerging countries. Hence, 19 out of the 36 countries in our sample are developed countries, and 17 are emerging countries. The 19 developed countries include Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Israel, Italy, Japan, Netherlands, Norway, Singapore, Sweden, Switzerland, Taiwan, United Kingdom, United States. The 17 emerging countries are Argentina, Brazil, China, Czech Republic, Greece, Hungary, India, Malaysia, Mexico, Poland, Portugal, Republic of Korea, Russian Federation, Slovakia, Slovenia, Spain, and Turkey. The categorization of countries is comparable to that developed in Niebel (2018) and Walheer (2021). The latter uses the terms advanced and follower countries instead of developed and emerging countries.

2.3. Non-robot capital, labor input and output variables

The data for the non-robot physical capital, human capital, and output is derived from the Penn World Table (PWT) version 10.0 (Feenstra et al., 2015). The labor input, measured in annual million hours worked, is obtained as EMP×AVH, where EMP is the number of persons engaged (in millions) and AVH is the average annual hours worked by persons engaged. Human capital is measured by the human capital index HC. Its calculation follows a common approach in the literature and is based on data on years of schooling and returns to education.[5] The non-robot capital stocks are computed as $RN^{NA} \times RGDP^{O}/RGDP^{NA}$ minus our estimate of the monetary robot capital stock described in section 2.4. Whereas RN^{NA} is the total capital stock at constant 2017 national prices, $RGDP^{O}$ is output-side real GDP at chained PPPs and $RGDP^{NA}$ is real GDP at constant 2017 national prices, all three measured in million 2017 US$. Output is measured as $RGDP^{O}$.

2.4. Robot capital stock variables

The International Federation of Robotics (IFR) collects data on annual robot installations by country, industry, and application from nearly all major industrial robot suppliers worldwide and from national robot associations (Müller and Kutzbach, 2020; p.21). 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 i) using the perpetual inventory method (PIM), assuming annual depreciation rates of 5 %, 10 %

[5] Details on the calculation of the human capital index are provided in „Human capital in PWT 9.0": https://www.rug.nl/ggdc/docs/human_capital_in_pwt_90.pdf

and 15%, as well as ii) using a ‘one-hoss shay’ depreciation method assuming that the average operating service life of an industrial robot is 12 years. These procedures require that the time series of robot installation start sufficiently prior to the robot stock series. Section A 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.2. of the supplementary material provides figures on the evolution of our estimated robot stock series over the period 1995 to 2019 for each of the 36 countries in our sample. These figures also reveal how the initial robot stock varies according to the four different methods applied. Since country-specific price data on robots is not available, we derive monetary robot capital stocks by multiplying the robot stock in physical units by the average price of robots in the United States in 2017.

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 Hulten (1992) and consider annual robot installations in efficiency units by multiplying the robot installations in physical units by an index of technical efficiency (robot quality index). 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. The index and its forecast are shown in section B.1. in the supplementary material.

Throughout section 2.5. to 5 we present our results based on the quality-adjusted robot capital stock derived with the PIM assuming a depreciation rate of 15 %. The sensitivity of our results regarding different assumptions on robot capital depreciation and changes in robot quality is discussed in section 6.

2.5. Descriptive Statistics

Table 1 provides rankings of countries by robot intensities, as measured by the number of robots per one hundred million hours worked, for the years 1999 and 2019, as well as a country ranking by growth rates of robot intensities over the period 1999-2019. Developed countries are marked with an asterisk, emerging countries are not. To save space we only report the top ten and bottom ten countries for each ranking. The full ranking and detailed descriptive statistics of other variables used in our analysis are available in the supplementary material in section B.3. and B.4., respectively.

Table 1
Country ranking by (growth of) robot intensity

	Ranking by robot intensity in 1999		Ranking by robot intensity in 2019		Ranking by growth of robot intensity between 1999-2019	
Rank	Country	Robot Intensity	Country	Robot Intensity	Country	Growth rate of robot intensity
1	Japan*	136.99	Rep. of Korea	324.04	China	49,522%
2	Germany*	74.91	Japan*	199.36	India	7,527%
3	Singapore*	56.81	Germany*	187.09	Hungary	5,872%
4	Belgium*	45.13	Taiwan*	168.62	Poland	3,519%
5	Italy*	44.92	Singapore*	148.64	Turkey	2,442%
6	Sweden*	42.09	Slovenia	139.36	Czech Rep.	2,137%
7	Rep. of Korea	34.12	Czech Rep.	112.40	Slovenia	1,626%
8	Finland*	33.64	Slovakia	101.57	Slovakia	1,496%
9	Switzerland*	26.46	Italy*	98.32	Mexico	1,265%
10	France*	24.16	Sweden*	93.15	Argentina	1,171%
⋮	⋮	⋮	⋮	⋮	⋮	⋮
27	Israel*	1.67	Mexico	19.52	France*	141%
28	Mexico	1.43	Norway*	18.77	Norway*	129%
29	Brazil	1.19	Turkey	16.37	Sweden*	121%
30	Hungary	1.03	Israel*	14.64	Italy*	119%
31	Poland	0.78	Australia*	14.17	Finland*	86%
32	Turkey	0.64	Argentina	8.16	Australia*	63%
33	Argentina	0.64	Brazil	7.84	UK*	57%
34	Greece	0.42	Greece	4.13	Belgium*	49%
35	China	0.06	Russian Fed.	2.69	Japan*	46%
36	India	0.02	India	1.47	Russian Fed	4%

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 %. Developed countries and emerging countries are shown with and without asterisk, respectively.

Table 1 shows that in 1999 Japan was the country with by far the highest robot intensity, followed by other developed countries such as Germany, Singapore, Belgium and Italy. The countries with the lowest robot intensities in 1999 are almost exclusively emerging countries, with India having the lowest robot intensity, followed by China, Greece, Argentina and Turkey. We find that robot intensities increased in all countries, though the growth rates of robot intensities are highly heterogeneous.

The catching-up of the countries with the lowest robot intensities in terms of robot diffusion is remarkable: Seven out of the ten countries with the lowest robot intensities in 1999 rank among the top ten countries regarding robot intensity growth over the 1999 to 2019 period. The speed of robot diffusion was by far the fastest in China, followed by India, Turkey, and the Eastern European countries Hungary, Poland, Czech Republic, Slovenia, and Slovakia. This fast diffusion of robots in these countries enabled China, Poland, and Hungary to climb from rank 35, 31 and 30 to rank 23, 24, and 17, respectively. While in 1999 Slovakia, Slovenia, and the Czech Republic were ranked # 22, # 20, and # 24, respectively, in 2019 they are among the top ten countries with the highest robot intensities. Thus, it will be interesting to explore if, and by how much, the apparent catching-up of emerging countries in terms of robot intensities has contributed to the convergence of labor productivity across the 36 countries in our sample. Last but not least, it is worth mentioning that Taiwan and Republic of Korea have achieved about a ten-fold increase in robot intensities, whereas Republic of Korea displaced Japan as the country with the highest robot intensity, and Taiwan ascended from # 15 to # 4.

3. Technology Frontiers and Efficiency Measurement (Technological Catch-up)

3.1. Data Envelopment Analysis

Following Kumar and Russell (2002) and Henderson and Russell (2005) we construct the production frontier and associated efficiency levels of individual economies (distances from the 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. One of the major benefits of this approach is that it does not require a prior specification of the functional form of the technology.[6] It is a data-driven approach implemented with standard mathematical programming algorithms, which allows the data to tell the form of the production function.

Our technology contains five macroeconomic variables: aggregate output and four aggregate inputs, which are labor, human capital, (non-robot) physical capital, and robot capital. Let $\langle Y_{it}, L_{it}, H_{it}, K_{it}, R_{it} \rangle$, *t=1,2,…,T*, *i=1,2,…,N* represent *T* observations on these five variables for each of the *N* countries. The robot capital stock is subtracted from the total physical capital stock and considered as autonomous production factor, either in physical or monetary units.[7] This is motivated by the fact that industrial robots can perform a wide range of tasks with very little human intervention and almost independently of conventional machines[8] (cf. the definition of robots by the IFR in section 2), which allows them to replace human workers and normal machines almost completely. Furthermore, numerous authors incorporate robot capital as separate production factor into their analytical framework (for economic growth models see, e.g., Steigum, 2011; Prettner 2019; Lankisch et al., 2019; Krenz et al., 2021; Gasteiger and Prettner, 2022; for the analysis of elasticities of substitution with robots as a third production factor see DeCanio, 2016).

Following most of the macroeconomics literature, we assume that human capital enters the technology as a multiplicative augmentation of physical labor, so that our *NT* observations are $\langle Y_{it}, \hat{L}_{it}, K_{it}, R_{it} \rangle$, *t=1,2,…,T*, *i=1,2,…N*, where $\hat{L}_{it} == L_{it} H_{it}$ is the amount of labor input measured in efficiency units in country *i* at time *t*. Utilizing the "sequential production set"

[6] Though, the approach requires an assumption about returns to scale of the technology, as well as the assumption of free input and output disposability. For a detailed description of the approach and its assumption see, e.g., Ray (2004).

[7] Due to data unavailability, we derive the monetary robot capital stock for all countries by multiplying the robot stock in physical units by one price: the average price of robots in the United States in 2017. Since we apply radial DEA-models which are translation invariant, i.e., insensitive to a multiplication of a variable by a constant factor, the results are the same if the robot capital stock is measured in monetary or physical units.

[8] These capabilities set robots apart from earlier waves of automation (ordinary tools and normal machines) and more conventional ICT technologies, which left flexible movements in three dimensions firmly in human hands (Graetz and Michaels, 2018). Nevertheless, robot programming and maintenance still requires human labour.

formulation of Diewert (1980) to preclude implosion of the frontier over time, we construct the convex, free-disposal, constant-returns-to-scale technology in period *t*, using all the data up to that point in time, as

$$\Upsilon_t = \left\{ \begin{array}{l} \langle Y_{it}, \hat{L}_{it}, K_{it}, R_{it} \rangle \in \mathbb{R}_+^4 \mid Y \leq \sum_{\tau \leq t} \sum_i z_{i\tau} Y_{i\tau}, \ \hat{L} \geq \sum_{\tau \leq t} \sum_i z_{i\tau} \hat{L}_{i\tau}, \\ \qquad\qquad\qquad\qquad K \geq \sum_{\tau \leq t} \sum_i z_{i\tau} K_{i\tau}, \ R \geq \sum_{\tau \leq t} \sum_i z_{i\tau} R_{i\tau}, \\ \qquad\qquad\qquad\qquad z_{i\tau} \geq 0 \ \forall \ i, \ \tau \end{array} \right\}, \tag{1}$$

where $z_{i\tau}$ are the intensity variables. 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 1999, for which we estimate the frontier based on the observations for the period 1995-1999. 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 country *i* at time *t* is defined by

$$e_{it}(Y_{it}, \hat{L}_{it}, K_{it}, R_{it}) = \min \left\{ \lambda \mid \langle Y_{it} / \lambda, \ \hat{L}_{it}, \ K_{it}, \ R_{it} \rangle \in \Upsilon_t \right\} \tag{2}$$

This index is the inverse of the maximal proportional amount that output Y_{it} 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 *it* observation is on the period-*t* production frontier. 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.

3.2. Efficiency and Technological Catch-up

Table 2 shows the efficiency scores of each of the 36 countries for 1999 and 2019. The scores are presented for two cases: where the physical robot stock is treated as a separate production factor and where it is not. As expected[9], the introduction of robots as separate production factor slightly increases the mean efficiency score from 0.763 to 0.781 in 1999, and from 0.686 to 0.695 in 2019. Considering the country-specific efficiency scores we find that the efficiency index in 1999 and 2019 increases for 11 and 9 countries, respectively. For the rest of the countries the efficiency indexes remain unaltered. Table 2 shows that incorporating robots makes Greece move to the 1999 frontier[10], and irrespective of the inclusion of robots Norway, Poland and the United States are on the 1999 frontier. With or without robots, the United States and Poland remain on the frontier in 2019, whereas Norway is no longer on the 2019 frontier.

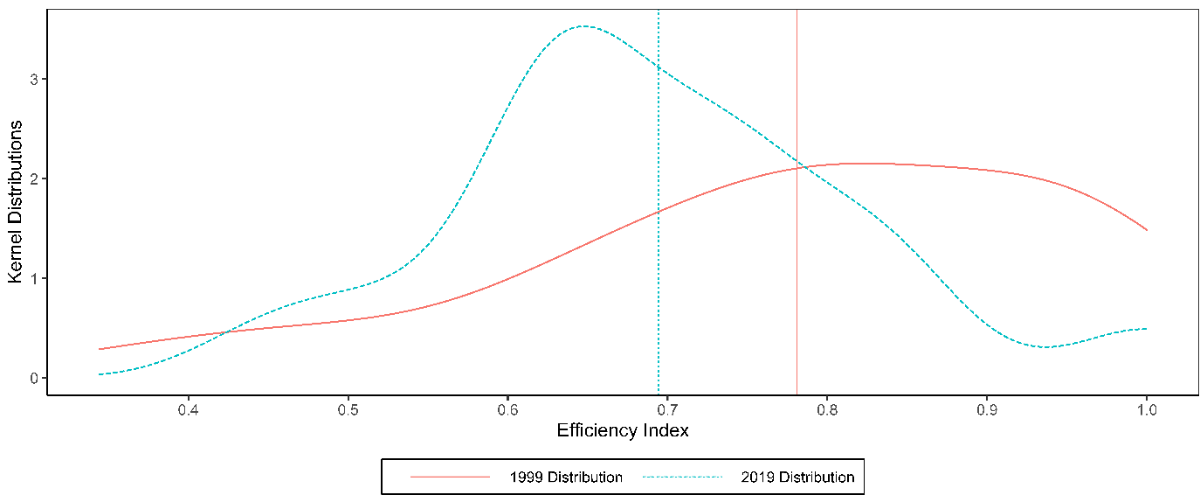

Fig. 1 Distributions of efficiency index (with robots). The solid curve is the estimated 1999 distribution, and the solid vertical line represents the 1999 mean value. The dashed curve is the estimated 2019 distribution, and the dashed vertical line represents the 2019 mean value.

[9] Incorporating additional input and output variables in a DEA-model leads to efficiency scores which are at least as high as in a DEA-model without these additional inputs and outputs.

[10] This is because Greece has the lowest endowments of robots in 1999 in our sample. Thereby, the DEA-model chooses the input weight for the robot stock input to be extraordinarily high relative to the other inputs. Hence, the change in the efficiency score (= the optimal ratio of weighted outputs to weighted inputs), when incorporating robots as additional production factor is relatively large. In other words, the low number of robots used in the production process relative to the output produced, i.e., the efficient use of the meagre robot endowment, makes Greece to be efficient.

Table 2
Efficiency Indexes

Country	Without Robots 1999	Without Robots 2019	With Robots 1999	With Robots 2019
Argentina	0.93	0.80	0.94	0.84
Australia	0.82	0.78	0.84	0.81
Austria	0.77	0.64	0.77	0.64
Belgium	0.95	0.61	0.95	0.61
Brazil	0.69	0.58	0.69	0.61
Canada	0.86	0.74	0.89	0.74
China	0.94	0.65	0.94	0.65
Czech Republic	0.41	0.57	0.42	0.57
Denmark	0.80	0.74	0.80	0.74
Finland	0.82	0.70	0.82	0.70
France	0.97	0.65	0.97	0.65
Germany	0.80	0.75	0.80	0.75
Greece	0.58	0.41	1.00	0.46
Hungary	0.61	0.63	0.62	0.63
India	0.71	0.67	0.76	0.67
Israel	0.85	0.81	0.90	0.84
Italy	0.95	0.52	0.95	0.52
Japan	0.68	0.64	0.68	0.64
Malaysia	0.59	0.65	0.59	0.65
Mexico	0.73	0.61	0.73	0.62
Netherlands	0.91	0.76	0.91	0.76
Norway	1.00	0.85	1.00	0.85
Poland	1.00	1.00	1.00	1.00
Portugal	0.63	0.44	0.63	0.44
Rep. of Korea	0.66	0.63	0.66	0.63
Russian Federation	0.34	0.62	0.34	0.70
Singapore	0.68	0.73	0.68	0.73
Slovakia	0.46	0.61	0.48	0.61
Slovenia	0.49	0.51	0.50	0.51
Spain	0.82	0.62	0.82	0.62
Sweden	0.82	0.72	0.82	0.72
Switzerland	0.78	0.77	0.78	0.77
Taiwan	0.80	0.84	0.80	0.84
Turkey	0.89	0.78	0.90	0.79
United Kingdom	0.72	0.68	0.72	0.70
United States	1.00	1.00	1.00	1.00
All countries (mean)	**0.76**	**0.69**	**0.78**	**0.69**

The DEA-models with robots are based on quality-adjusted physical robot stocks, which are estimated with the perpetual inventory method assuming a depreciation rate of 15 %.

Figure 1 plots the distributions of the efficiency index in 1999 and 2019. We find a substantial shift of probability mass away from efficiency scores above 0.8 toward lower parts of the distribution. The mean efficiency score declined from 0.78 to 0.69. We observe a decline in efficiency levels for 26 out of the 36 countries in our sample. This indicates that in the period 1999 to 2019 for most of the countries the distance to the frontier increased and that they were falling behind the best-performers against which they are benchmarked (in most cases inefficient countries are compared with Norway, Poland and the United States). The drop in efficiency levels is severe for the Southern European countries Greece, Italy, Spain, and Portugal, plus France. Only eight countries were able to catch-up to the technology leaders: five out of these eight are transition countries in Eastern Europe including Czech Republic, Hungary, Russian Federation, Slovakia, and Slovenia. The other three countries are the Southeast Asian countries Malaysia, Singapore, and Taiwan.

However, we also observe that efficiency levels are less dispersed in 2019 compared to 1999. It will thus be interesting to analyze whether convergence in efficiency levels drives the depolarization of the labor productivity distribution, i.e., a shift from a bimodal to a unimodal distribution.

4. Quinquepartite Decomposition of Labor Productivity Change

4.1. Conceptual Decomposition

We decompose labor productivity growth between base *(b)* and current *(c)* period into components attributable to (1) efficiency change (technological catch-up), (2) technological change (shifts in the frontier), (3) human capital accumulation, (4) physical (non-robot) capital deepening (increase in the capital-labor ratio), and (5) robot capital deepening (increase in the robot-labor ratio). Constant returns to scale and labor augmentation of human capital allow us to construct the production frontiers in the $\hat{y}-\hat{k}-\hat{r}$ space, where $\hat{y}=Y/\hat{L}$, $\hat{k}=K/\hat{L}$, and

$\hat{r} = R / \hat{L}$ are the ratios of output, capital and robots, respectively, to effective labor. Since by definition the efficiency index is the ratio of actual to potential output evaluated at the actual input quantities, the potential output per efficiency unit of labor in the two periods is given by $\bar{y}_b(\hat{k}_b, \hat{r}_b) = \hat{y}_b / e_b$, and $\bar{y}_c(\hat{k}_c, \hat{r}_c) = \hat{y}_c / e_c$, where e_b and e_c [11] are values of the efficiency indexes in the respective periods as calculated in Eq. (2). Accordingly,

$$\frac{\hat{y}_c}{\hat{y}_b} = \frac{e_c}{e_b} \times \frac{\bar{y}_c(\hat{k}_c, \hat{r}_c)}{\bar{y}_b(\hat{k}_b, \hat{r}_b)} \tag{3}$$

To isolate the effect of each component, we define two sets of new variables under the counterfactual assumption that human capital has not changed. The first set includes the ratio of (non-robot) physical capital to labor measured in efficiency units, and the ratio of robot capital to labor measured in efficiency units under the counterfactual assumption that human capital has not changed from its base period: $\tilde{k}_c = K_c / L_c H_b$ and $\tilde{r}_c = R_c / L_c H_b$. The second set is given by the ratio of (non-robot) physical capital to labor measured in efficiency units, and the ratio of robot capital to labor measured in efficiency units under the counterfactual assumption that human capital is equal to its current year period: $\tilde{k}_b = K_b / L_b H_c$ and $\tilde{r}_b = R_b / L_b H_c$. Then, $\bar{y}_b(\hat{k}_c, \hat{r}_c)$, $\bar{y}_b(\tilde{k}_c, \hat{r}_b)$, $\bar{y}_b(\tilde{k}_c, \tilde{r}_c)$ are the potential outputs per efficiency unit of labor at $(\hat{k}_c, \hat{r}_c)$, $(\tilde{k}_c, \hat{r}_b)$ and $(\tilde{k}_c, \tilde{r}_c)$ using the base-period technology, and $\bar{y}_c(\hat{k}_b, \hat{r}_b)$, $\bar{y}_c(\tilde{k}_b, \hat{r}_c)$, $\bar{y}_c(\tilde{k}_b, \tilde{r}_b)$ are the potential outputs per efficiency units of labor at $(\hat{k}_b, \hat{r}_b)$, $(\tilde{k}_b, \hat{r}_c)$, $(\tilde{k}_b, \tilde{r}_b)$ using the current-period technology. By multiplying the numerator and denominator of

[11] For ease of readability, we skip the subscript *i* (referring to the country under evaluation) in this section.

Eq. (3) alternatively by $\bar{y}_b(\hat{k}_c,\hat{r}_c)\bar{y}_b(\tilde{k}_c,\hat{r}_b)\bar{y}_b(\tilde{k}_c,\tilde{r}_c)$ and $\bar{y}_c(\hat{k}_b,\hat{r}_b)\bar{y}_c(\tilde{k}_b,\hat{r}_c)\bar{y}_c(\tilde{k}_b,\tilde{r}_b)$, we obtain two alternative decompositions of the growth of $\hat{y}$:

$$\frac{\hat{y}_c}{\hat{y}_b}=\frac{e_c}{e_b}\times\frac{\bar{y}_c(\hat{k}_c,\hat{r}_c)}{\bar{y}_b(\hat{k}_c,\hat{r}_c)}\times\frac{\bar{y}_b(\hat{k}_c,\hat{r}_c)}{\bar{y}_b(\tilde{k}_c,\tilde{r}_c)}\times\frac{\bar{y}_b(\tilde{k}_c,\hat{r}_b)}{\bar{y}_b(\hat{k}_b,\hat{r}_b)}\times\frac{\bar{y}_b(\tilde{k}_c,\tilde{r}_c)}{\bar{y}_b(\tilde{k}_c,\hat{r}_b)} \tag{4}$$

and

$$\frac{\hat{y}_c}{\hat{y}_b}=\frac{e_c}{e_b}\times\frac{\bar{y}_c(\hat{k}_b,\hat{r}_b)}{\bar{y}_b(\hat{k}_b,\hat{r}_b)}\times\frac{\bar{y}_c(\tilde{k}_b,\tilde{r}_b)}{\bar{y}_c(\hat{k}_b,\hat{r}_b)}\times\frac{\bar{y}_c(\hat{k}_c,\hat{r}_c)}{\bar{y}_c(\tilde{k}_b,\hat{r}_c)}\times\frac{\bar{y}_c(\tilde{k}_b,\hat{r}_c)}{\bar{y}_c(\tilde{k}_b,\tilde{r}_b)} \tag{5}$$

The growth of labor productivity, $y_t = Y_t / L_t$, can be decomposed into the growth of human capital and the growth of output per efficiency unit of labor, as follows:

$$\frac{y_c}{y_b}=\frac{H_c}{H_b}\times\frac{\hat{y}_c}{\hat{y}_b} \tag{6}$$

Combing Eq. (4) and Eq. (5) with Eq. (6), we obtain

$$\begin{aligned}\frac{y_c}{y_b}&=\frac{e_c}{e_b}\times\frac{\bar{y}_c(\hat{k}_c,\hat{r}_c)}{\bar{y}_b(\hat{k}_c,\hat{r}_c)}\times\left[\frac{\bar{y}_b(\hat{k}_c,\hat{r}_c)}{\bar{y}_b(\tilde{k}_c,\tilde{r}_c)}\cdot\frac{H_c}{H_b}\right]\times\frac{\bar{y}_b(\tilde{k}_c,\hat{r}_b)}{\bar{y}_b(\hat{k}_b,\hat{r}_b)}\times\frac{\bar{y}_b(\tilde{k}_c,\tilde{r}_c)}{\bar{y}_b(\tilde{k}_c,\hat{r}_b)}\\&\equiv EFF\times TECH^c\times HACC^b\times KACC^b\times RKACC^b\end{aligned} \tag{7}$$

and

$$\begin{aligned}\frac{y_c}{y_b}&=\frac{e_c}{e_b}\times\frac{\bar{y}_c(\hat{k}_b,\hat{r}_b)}{\bar{y}_b(\hat{k}_b,\hat{r}_b)}\times\left[\frac{\bar{y}_c(\tilde{k}_b,\tilde{r}_b)}{\bar{y}_c(\hat{k}_b,\hat{r}_b)}\cdot\frac{H_c}{H_b}\right]\times\frac{\bar{y}_c(\hat{k}_c,\hat{r}_c)}{\bar{y}_c(\tilde{k}_b,\hat{r}_c)}\times\frac{\bar{y}_c(\tilde{k}_b,\hat{r}_c)}{\bar{y}_c(\tilde{k}_b,\tilde{r}_b)}\\&\equiv EFF\times TECH^b\times HACC^c\times KACC^c\times RKACC^c\end{aligned} \tag{8}$$

Equation (7) and (8) decompose growth of labor productivity between period *b* and *c* into changes in efficiency (EFF), technology (TECH), human capital accumulation (HACC), the capital-labor ratio (KACC), and the robot-labor ratio (RKACC). For each component, only the variable of interest is different between the denominator and the numerator of each component. For instance, for $RKACC^b$ only the robot-labor ratio changed (from $\hat{r}_b = R_b/L_bH_b$ to $\tilde{r}_c = R_c / L_cH_b$) while all the other variables are held constant. Hence, *RKACC* indicates the contribution of the robot-labor ratio change to labor productivity growth. The same reasoning applies for the other components.

While the decomposition in Eq. (7) measures technological change by the shift in the frontier in the output direction at the current-period capital/efficiency-labor ratio, and the current-period robot/efficiency-labor ratio, the decomposition in Eq. (8) measures technological change by the shift in the frontier in the output direction at the base-period capital/efficiency-labor ratio, and the base-period robot/efficiency-labor ratio. Similarly, Eq. (7) measures the effect of (non-robot) physical and robot capital deepening, as well as human capital accumulation along the base-period frontier, whereas Eq. (8) 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 Hick-neutral (as assumed by Solow (1957) and the conventional methods of growth accounting). Though, one advantage of the growth accounting approach used in this study 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, and obtained mechanically by multiplying the numerator and denominator of Eq. (3) by $(\overline{y}_b(\hat{k}_c,\hat{r}_c)\overline{y}_b(\tilde{k}_c,\hat{r}_b)\overline{y}_b(\tilde{k}_c,\tilde{r}_c))^{1/2}(\overline{y}_c(\hat{k}_b,\hat{r}_b)\overline{y}_c(\tilde{k}_b,\hat{r}_c)\overline{y}_c(\tilde{k}_b,\tilde{r}_b))^{1/2}$:

$$
\begin{aligned}
\frac{y_c}{y_b} &= EFF \times (TECH^b \cdot TECH^c)^{1/2} \times (HACC^b \cdot HACC^c)^{1/2} \\
&\times (KACC^b \cdot KACC^c)^{1/2} \times (RKACC^b \cdot RKACC^c)^{1/2} \\
&\equiv EFF \times TECH \times HACC \times KACC \times RKACC.
\end{aligned} \tag{9}
$$

4.2. Empirical Results

Table 3 shows the country-specific components of the decomposition of the growth rate of output per hour worked (labor productivity) for the period 1999 to 2019, both with and without considering robot capital as a separate production factor. The change in labor productivity is reported in the second column of Table 3, whereas the contributions in percentage terms of changes in each of the five components appear in column 3-7.[12] Likewise, the first row for each country reports the results from the quinquepartite decomposition considering robots as separate production factor, whereas the second row ignores the autonomous role of robots in the production process.

The mean contribution of efficiency change is negative (-7.1%). Physical capital deepening (27.7%) and technological change (22.7%) are by far the most important drivers of labor productivity growth, irrespective of the incorporation of robot capital or not. The mean contribution of robot capital deepening (10.9%)[13] is almost two times that of human capital accumulation (6.0%).

Comparing the mean contributions of the components of labor productivity change with and without separating robot capital from other physical capital reveals that a substantial part of physical capital accumulation, and to a lesser extend a part of technological progress, can be

[12] These contributions in percentage terms can be easily transformed into indexes using the formula *(PERCENTAGE/100 + 1)* so that Eq. (9) holds.

[13] The magnitude of the average percentage contribution rate of robot capital deepening to labour productivity growth (10.9/63.8=17%) is comparable to that found by Graetz and Michaels (2018) for a sample of 17 OECD countries for the period 1993 to 2007: They 'find that the contribution of the increased use of robots to productivity growth … accounts for 15% of the aggregate economy-wide productivity growth.'

attributed to robot capital accumulation. On average, the contribution of physical accumulation and technological progress to the 63.8 % labor productivity change falls from 37.8% to 27.7%, and from 27.6% to 22.7%, respectively. The reduced rate of technological progress might indicate that robot capital accumulation goes hand in hand with more general technological innovations that have the potential to push the production possibility frontier outward. The mean contributions of efficiency change and human capital accumulation are almost unchanged.

Table 4 presents mean changes in labor productivity and the five components of productivity change for eight groups of countries. We find that emerging countries experienced productivity gains more than two times that of developed countries primarily because of faster rates of (non-robot) physical capital accumulation and robot capital accumulation. Lower efficiency losses in emerging countries also contributed to this development. Somewhat counteracting this development, we find that technological progress in developed countries is substantially higher than in emerging countries. It is important to note, that while the mean growth rate of output per hour worked in emerging economies (90.5%) is twice that of developed countries (39.8%), the mean percentage change of the robot capital deepening index in emerging countries (20.3%) is ten times that of developed countries (2.6%). Therefore, emerging countries appear, on average to have benefited more from industrial robot expansion. A two-sample t test for differences in means indicates that the mean contribution of robot capital deepening in emerging countries is statistically and significantly higher than in developed countries at the one percent significance level. It is also interesting to note that for Greece and Israel, robot capital accumulation emerges as the main growth engine, whereas for China, Hungary, India, Slovakia, Slovenia, and Turkey robot capital deepening appears to be the second major contributor to productivity growth. In addition, robot capital accumulation is the third largest driver of labor productivity growth in Argentina, Czech Republic, Poland, Portugal, Russian Federation, and the United States.

Table 3
Percentage change of Quinquepartite Decomposition Indexes, 1999-2019

Country	Productivity Change	(EFF-1) × 100	(TECH-1) × 100	(HACC-1) × 100	(KACC-1) × 100	(RKACC-1) × 100
Argentina	40.5	-10.7	6.4	2.9	33.5	7.6
	40.5	-14.9	19.1	1.5	36.6	
Australia	35.8	-4.2	11.7	0.4	23.0	2.7
	35.8	-4.5	16.8	0.4	21.3	
Austria	50.2	-17.3	47.0	5.1	16.4	1.0
	50.2	-17.3	48.8	5.5	15.6	
Belgium	29.7	-35.7	77.1	3.8	9.7	0.0
	29.7	-35.7	77.1	3.8	9.7	
Brazil	40.7	-12.2	8.1	10.7	25.5	6.7
	40.7	-16.3	20.1	7.0	30.8	
Canada	24.1	-17.5	10.1	3.6	23.1	7.2
	24.1	-14.6	13.5	3.8	23.2	
China	252.2	-30.5	4.0	3.1	234.9	41.1
	252.2	-30.5	4.2	3.0	372.6	
Czech Republic	69.7	35.8	9.4	1.8	3.7	8.2
	69.7	39.1	14.6	1.2	5.2	
Denmark	60.5	-7.1	34.6	5.6	19.8	1.4
	60.5	-7.1	37.1	6.1	18.8	
Finland	27.0	-15.1	22.0	7.3	12.8	1.4
	27.0	-15.1	23.7	7.8	12.3	
France	34.8	-33.7	67.4	6.7	13.4	0.4
	34.8	-33.7	68.0	7.2	12.9	
Germany	33.8	-5.7	26.3	2.1	9.7	0.4
	33.8	-5.7	27.0	2.2	9.4	
Greece	15.3	-53.6	12.6	13.5	3.8	87.5
	15.3	-28.9	34.7	9.6	9.8	
Hungary	76.2	2.3	5.5	4.4	26.0	24.1
	76.2	4.1	13.5	5.2	41.7	
India	235.4	-12.5	2.6	6.6	99.8	75.4
	235.4	-6.4	4.0	3.5	233.0	
Israel	9.9	-6.0	5.4	4.8	-2.5	8.4
	9.9	-4.6	14.1	3.9	-2.8	
Italy	18.0	-45.3	76.9	8.5	12.3	0.1
	18.0	-45.3	76.9	8.7	12.2	
Japan	10.9	-5.6	13.9	2.4	0.6	0.0
	10.9	-5.6	13.9	2.4	0.6	
Malaysia	85.3	11.3	10.8	4.3	36.6	5.5
	85.3	9.9	19.1	1.8	39.1	
Mexico	21.9	-15.6	8.7	3.5	18.2	8.6
	21.9	-16.5	18.8	3.3	19.1	
Netherlands	34.4	-17.2	36.1	4.7	10.3	3.3
	34.4	-17.2	38.9	5.3	10.9	
Norway	66.0	-14.6	38.0	5.6	17.4	13.6
	66.0	-14.6	43.2	6.3	27.6	
Poland	104.1	0.0	10.3	2.3	69.6	6.7
	104.1	0.0	14.0	1.6	76.1	
Portugal	38.6	-30.3	44.1	9.9	8.6	15.6
	38.6	-30.3	56.4	8.3	17.4	
Rep. of Korea	91.3	-3.7	12.7	6.8	61.9	1.9
	91.3	-3.7	14.4	7.2	62.0	
Russian Fed.	193.5	102.2	2.0	2.7	34.1	3.3

Table 3 continued

Percentage change of Quinquepartite Decomposition Indexes, 1999-2019

Country	Productivity Change	(EFF-1) × 100	(TECH-1) × 100	(HACC-1) × 100	(KACC-1) × 100	(RKACC-1) × 100
	193.5	80.9	16.9	2.4	35.4	
Singapore	124.5	6.3	11.5	27.3	47.1	1.2
	124.5	6.3	11.9	28.1	47.4	
Slovakia	58.0	27.2	8.2	3.6	2.7	7.9
	58.0	32.7	11.4	4.3	2.5	
Slovenia	46.3	2.9	19.6	5.8	4.5	7.5
	46.3	3.8	23.9	6.3	7.1	
Spain	44.1	-24.3	46.3	8.0	19.5	0.9
	44.1	-24.3	47.8	8.6	18.7	
Sweden	38.6	-12.4	46.5	4.6	2.7	0.5
	38.6	-12.4	47.0	4.9	2.7	
Switzerland	66.1	-1.7	40.4	3.0	15.7	1.0
	66.1	-1.7	42.4	3.2	15.0	
Taiwan	27.3	4.9	9.9	6.9	0.7	2.6
	27.3	4.9	12.5	7.2	0.7	
Turkey	126.3	-12.7	10.4	16.6	47.6	36.5
	126.3	-12.8	19.7	18.1	83.5	
United Kingdom	28.3	-3.9	10.9	4.9	13.2	1.4
	28.3	-6.4	15.6	5.1	12.7	
United States	37.2	0.0	9.8	1.6	19.9	2.6
	37.2	0.0	12.6	1.6	19.9	
Mean	**63.8**	**-7.1**	**22.7**	**6.0**	**27.7**	**10.9**
	63.8	**-6.8**	**27.6**	**5.7**	**37.8**	

Table 4

Mean Percentage Changes of Quinquepartite Decomposition Indexes (Country Groupings)

Country Group	TE_b	TE_c	Product. Change	(EFF-1) × 100	(TECH-1) × 100	(HACC-1) × 100	(KACC-1) × 100	(RKACC-1) × 100
Emerging Countries+	0.71	0.65	90.5	-1.4	13.0	6.3	43.0	20.3
Developed Countries*	0.85	0.74	39.8	-12.2	31.3	5.7	14.0	2.6
Non-OECD†	0.72	0.71	124.9	7.3	6.9	8.1	64.0	17.9
OECD	0.80	0.69	46.32	-11.25	27.20	5.39	17.27	8.95
Transition§	0.61	0.67	114.3	20.0	8.4	3.4	53.6	14.1
Non-transition	0.82	0.70	51.6	-13.7	26.1	6.6	21.4	10.2
Asian Tigers$	0.68	0.70	67.9	2.6	11.8	9.6	29.4	2.2
Latin America&	0.79	0.69	34.4	-12.8	7.7	5.7	25.8	7.6
All countries	0.78	0.69	63.8	-7.1	22.7	6.0	27.7	10.9

+ Real GDP per capita < 27,500 (2017 US$) in 1999: Argentina, Brazil, China, Czech Republic, Greece, Hungary, India, Malaysia, Mexico, Poland, Portugal, Rep. of Korea, Russian Fed., Slovakia, Slovenia, Spain, Turkey.

* Real GDP per capita > 32,500 (2017 US$) in 1999: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Israel, Italy, Japan, Netherlands, Norway, Singapore, Sweden, Switzerland, Taiwan, United Kingdom, United States.

† Argentina, Brazil, China, India, Malaysia, Russian Fed., Singapore, Taiwan.

§ China, Czech Republic, Hungary, Poland, Russian Fed., Slovakia, Slovenia.

$ Japan, Malaysia, Rep. of Korea, Singapore, Taiwan.

& Argentina, Brazil, Mexico.

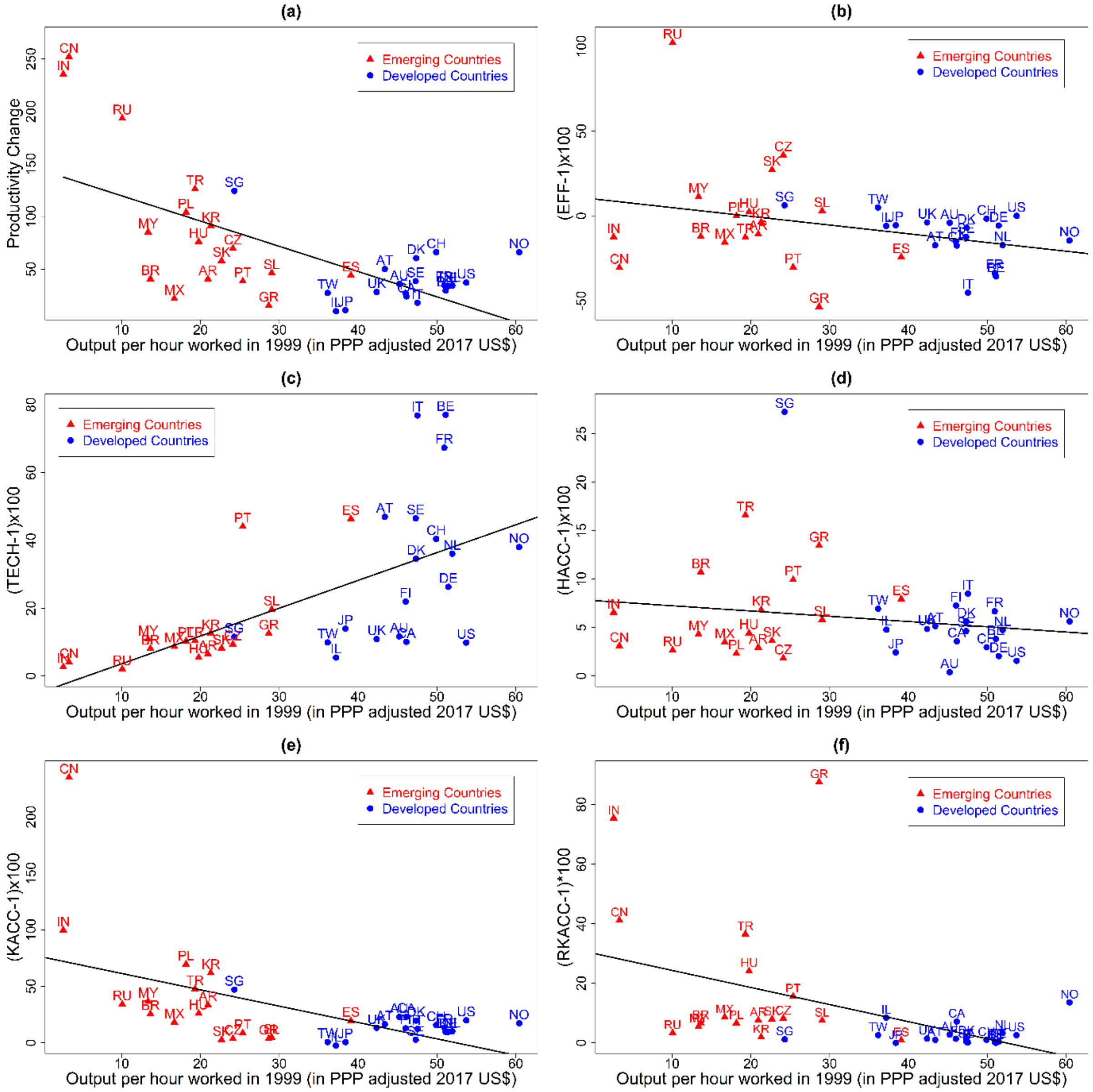

Fig. 2 Percentage change in output per hour worked and five decomposition indexes plotted against 1999 output per hour worked. Each panel contains a GLS regression line.

While studies analyzing earlier periods (e.g., Badunenko and Romero-Ávila (2013) for 1965-2005, or, Badunenko et al. (2013) for 1965-2007) find that OECD countries grew substantially faster than non-OECD countries, we find that this development reversed in the 1999-2019 period: Non-OECD countries experienced productivity gains almost three times that of OECD countries[14] primarily because of faster rates of (non-robot) physical capital accumulation and

[14] This result could be driven by the exclusion of non-OECD countries with poor growth performance: Contrary to previous studies our sample is rather small compared to other convergence studies, such as Kumar and Russell (2002), Henderson and Russell (2005), Badunenko et al. (2008), Badunenko and Romer-Ávila (2013), Badunenko et al. (2013) and others, and only includes developed and emerging countries. Particularly,

greater efficiency gains. Faster robot capital accumulation, though to a lesser extent, also contributed to this development. In fact, average efficiency change in OECD countries is negative, while non-OECD countries could technologically catch-up. In line with studies on earlier growth episodes, still, technological progress in OECD countries is substantially higher than in non-OECD countries. Similar patterns of development among OECD and non-OECD countries can be observed between transition and non-transition countries.

The poor growth performance of Latin America is caused primarily by efficiency losses and low technological progress. Technological catch-up (positive efficiency change) is only observed for a minority of countries/country groups including non-OECD, transition countries and the Asian Tigers. The trend of declining average efficiency levels found by Badunenko et al. (2008) for the period 1992 to 2000 seems to have continued over the last twenty years.

Fig. 2 gives a preliminary picture about which of the productivity growth components may have contributed to narrowing down the productivity gap between emerging and developed countries. Productivity growth and the five productivity-component growth rates are plotted against output per hour worked in 1999, along with GLS regression lines.[15] Panel (a) is a standard growth convergence equation: the statistical significance of the slope coefficient supports beta-convergence, i.e., countries with low initial levels of output per hour worked tend to grow faster than countries with high initial productivity levels. The statistically significant negative slopes in Panel (b), (e), (f) indicate that beta-convergence is primarily driven by (non-robot) physical capital accumulation, and, though to a lesser extent, by robot capital accumulation; efficiency change might also has contributed a bit to beta-convergence. The statistically significant positive regression slope coefficient in Panel (c) indicates that relatively wealthy countries have benefited much more from technological progress than have less-

developing countries from Africa and some Latin American countries (non-OECD) are excluded due to limited data availability on industrial robot usage. Robot installation data for some African countries (i.e., Egypt, Tunisia, and Morocco), except for South Africa, is only available from 2005 onwards (see, e.g., Klump et al., 2021).

[15] Detailed GLS-regression results are available in Table A1, Appendix A. The country codes used in Fig. 2 are explained in Table A2, Appendix A.

developed countries. Therefore, technological progress appears to have substantially widened international productivity disparities, and counteracts the tendency for physical capital, and robot capital accumulation to narrowing down cross-country productivity inequalities. Finally, the statistically insignificant regression coefficient in Panel (d) suggests that human capital accumulation has little effect on productivity disparities. Since these preliminary conclusions are based on first-moment characterizations of the productivity distribution and vulnerable to the Quah (1993, 1996, 1997) critique, we turn now to examine the evolution of the entire cross-section distribution of labor productivity.

5. Analysis of Productivity Distributions

Fig. 3 shows the distributions of output per hour worked across the 36 countries in our sample in 1999 and 2019. The solid (dotted) curve is the estimated 1999 (2019) distribution of output per hour worked, with their corresponding mean values shown as vertical lines. By visually inspecting both distributions, we observe i) a shift from a bimodal to a unimodal distribution[16], ii) a substantial rise in average levels of output per hour worked over the 20-year period, and iii) a reduction of the dispersion of productivity levels, as indicated by a decrease of the coefficient of variation (CV) from 0.476 in 1999 to 0.425 in 2019.[17]

Following Henderson and Russell (2005), we aim to explain these features of the change of the productivity distribution from 1999 to 2019 in terms of the five components of productivity change, paying particular attention to the robot capital deepening component.

[16] The results of the test developed by Silverman (1981) shown in Table 5, row 1 and 2, indicate that we can reject the null hypothesis of a single mode for the 1999 distribution at the 5 % significance-level (p-value=0.02), but we cannot reject the null of one mode (p-value=0.20) for the 2019 distribution.

[17] The coefficient of variation is frequently applied to measure sigma-convergence. While Panel (a) in Fig. 2 provides some evidence for beta-convergence, the decreased coefficient of variation points towards sigma-convergence across the countries in our sample.

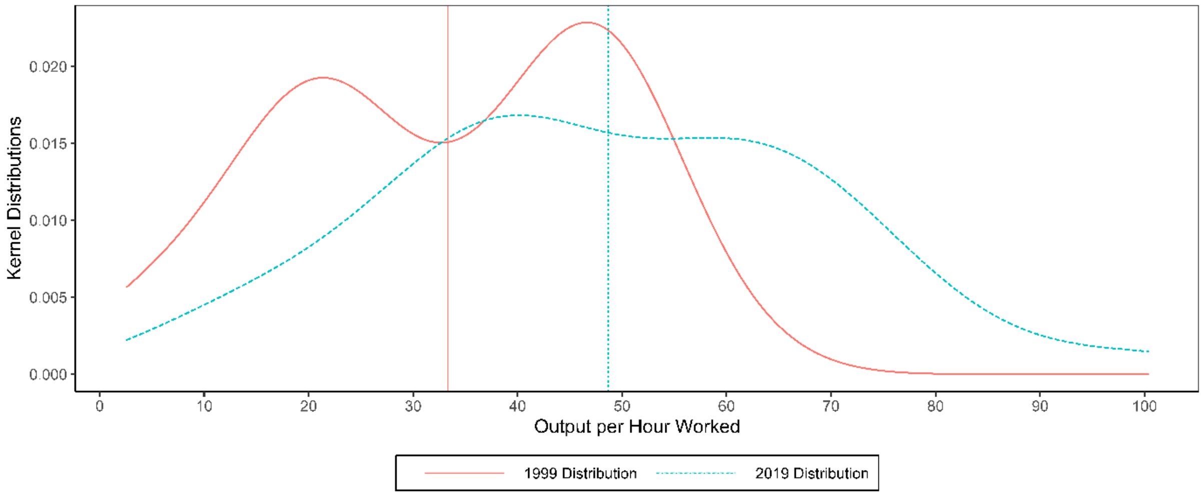

Fig. 3 Distributions of labor productivity. The solid curve is the estimated 1999 distribution, and the solid vertical line represents the 1999 mean value. The dotted curve is the estimated 2019 distribution, and the dashed vertical line represents the 2019 mean value.

Using the quinquepartite decomposition of productivity growth, we rewrite Eq. (9) as follows:

$$y_c = (EFF \times TECH \times HACC \times KACC \times RKACC) \times y_b \tag{10}$$

Where b = 1999 and c= 2019. Accordingly, the labor productivity distribution in the current year can be constructed by consecutively multiplying the labor productivity distribution in the base year by each of the five components. To isolate the impact of each component, we create counterfactual distributions by introducing each of the components in sequence. For instance, we assess the shift of the labor productivity distribution attributable solely to efficiency changes by examining the counterfactual distribution of the variable,

$$y^E = EFF \times y_b \tag{11}$$

assuming no technological change, no human capital accumulation, no (non-robot) capital deepening, and no robot capital deepening. This counterfactual distribution is shown, along with the actual distribution in the base (solid curve) and current period (dashed curve), as a dotted curve in Panel (a) of Fig. 4. We then include sequentially more components in the counterfactual distribution to isolate their effects. For instance, we can add technological change to y^{E}:

$$y^{ET} = (EFF \times TECH) \times y_b = TECH \times y^{E} \tag{12}$$

This isolates the joint effect of efficiency change and technological progress on the productivity distribution and is drawn in Panel (b) of Fig. 4. The additional effect of human capital accumulation on the distribution y^{ET} can be assessed by multiplying by HACC such that:

$$y^{ETH} = (EFF \times TECH \times HACC) \times y_b = HACC \times y^{ET} \tag{13}$$

drawn in Panel (c) of Fig. 4. Panel (d) in Fig. 4 incorporates the effect of capital deepening in y^{ETH} such that:

$$y^{ETHK} = (EFF \times TECH \times HACC \times KACC) \times y_b = KACC \times y^{ETH} \tag{14}$$

The effect of the last component, robot capital deepening, can be deduced from comparing the counterfactual distribution of y^{ETHK} and the actual distribution in 2019.

We employ the bootstrapped, calibrated version of the Silverman (1981) test[18] for multimodality to statistically assess which component (or set of components) causes the shift from bimodality to unimodality in the productivity distributions. In addition, we use the

[18] For further details, see Hall and York (2001) and Henderson et al. (2008).

bootstrapped version of the Li (1996) test to identify the component (set of components) that contribute(s) to the overall change in the distribution of labor productivity. The Silverman (1981) and the Li (1996) test results are reported in Table 5 and 6, respectively.

Table 5 shows that each of the following three components alone can explain the emergence of unimodality in the distribution: efficiency change, technological change, and robot capital deepening. The corresponding p-values in rows 3, 4 and 7 (0.11, 0.44, and 0.14) in Table 5 indicate that we cannot reject the null-hypothesis of unimodality when each of the single effect of *EFF*, *TECH*, and *RKACC* on the 1999 distribution is isolated. When we consider the combined effect of two or more components, we find that only the combined effects of *KACC* and *HACC* (row 15) as well as the combined effects of *EFF*, *TECH*, *KACC* and *HACC* (row 28), allow us to reject the null hypothesis of unimodality at the 5 % significance level. This i) indicates that capital deepening and human capital accumulation counteract and dominate the depolarizing (combined) effect of efficiency change and technological change, and ii) provides additional support for the hypothesis that robot capital deepening contributes to the depolarization of the labor productivity distribution. Panel (a) of Fig. 4, 6 and 5 show the emergence of unimodalism in the counterfactual distributions due only to the effect of *EFF*, *TECH* and *RKACC*, respectively. The almost re-emergence of bimodality when the effect of *KACC* is added to *RKACC* is shown by the dotted curve in Panel (b) of Fig. 5.

The Li-test results shown in Table 6 indicate that technological change, and (non-robot) physical capital deepening are the main contributors to the overall change in the shape of the productivity distribution from 1999 to 2019. Row 3 and 4 reveal that each, the effect of *TECH* and *KACC* alone, can explain the shift from the 1999 to the 2019 distribution.[19] Unsurprisingly, so does any combination of two or more productivity component effects which include *TECH*,

[19] The isolated effect of technological change on the 1999 productivity distribution is shown in Panel (a) of Fig. 6. Its relevance can also be inferred by comparing the counterfactual distribution in Panel (d) of Fig. 5 with the actual 2019 distribution. The same reasoning applies for the capital deepening effect regarding Panel (d) in Fig. 6.

KACC, or both, except for *EFF* and *KACC*, as well as *EFF*, *KACC*, and *RKACC*. Distributional equality between the 2019 productivity distribution and counterfactual distributions evaluating the effect of efficiency change, human capital accumulation, and robot capital deepening alone, or any combination of two or three of these components on the 1999 distribution, can be rejected at the 5 % significance level (see p-values in row 2, 5, 6, 9, 10, 16, and 22 in Table 6).

Figures 3-6 illustrate that (non-robot) physical capital deepening and efficiency change are the main drivers behind the decreased dispersion of the labor productivity distribution. Robot capital deepening contributes to the decreased dispersion and human capital accumulation has little or no effect. The only component which counteracts the tendency for these components to narrowing the cross-country productivity inequalities is technological change. For instance, as shown in Panel (a) of Fig. 5 introducing the robot capital deepening component reduces the CV of the 1999 labor productivity distribution from 0.476 to 0.454. Further, sequentially adding the effect of (non-robot) physical capital deepening, human capital accumulation, and efficiency change results in a further decrease of the CV from 0.454 to 0.405, 0.402, and 0.371, respectively.

Next, we inspect the shift of the 1999 mean value of output per hour worked (solid vertical line in Fig. 4-6) to its 2019 mean value (dashed vertical line Fig. 4-6). We observe a shift from 33.3 to 48.68 (both in 2017 PPP adjusted US$). For instance, in Fig. 5 the largest change, in absolute values, in output per hour worked is induced by technological progress, followed by capital deepening, efficiency change, human capital accumulation and robot capital deepening.[20] Whereas efficiency change is the only component that tends to decrease output per hour worked. The magnitude of the average percentage contribution rate of robot capital deepening to labor productivity growth (2.25/15.38=14.6%) in Fig. 5 is comparable, though somewhat

[20] Fig. 5 shows that the effect or robot capital deepening increases the 1999 mean value of output per hour worked from 33.3 to 35.55 US$. Adding sequentially the effect of capital deepening, human capital accumulation, and efficiency change, results in a mean value of 41.74, 44.16, and 39.08, respectively. Adding the last component, technological change, induces an increase from 39.08 to 48.68.

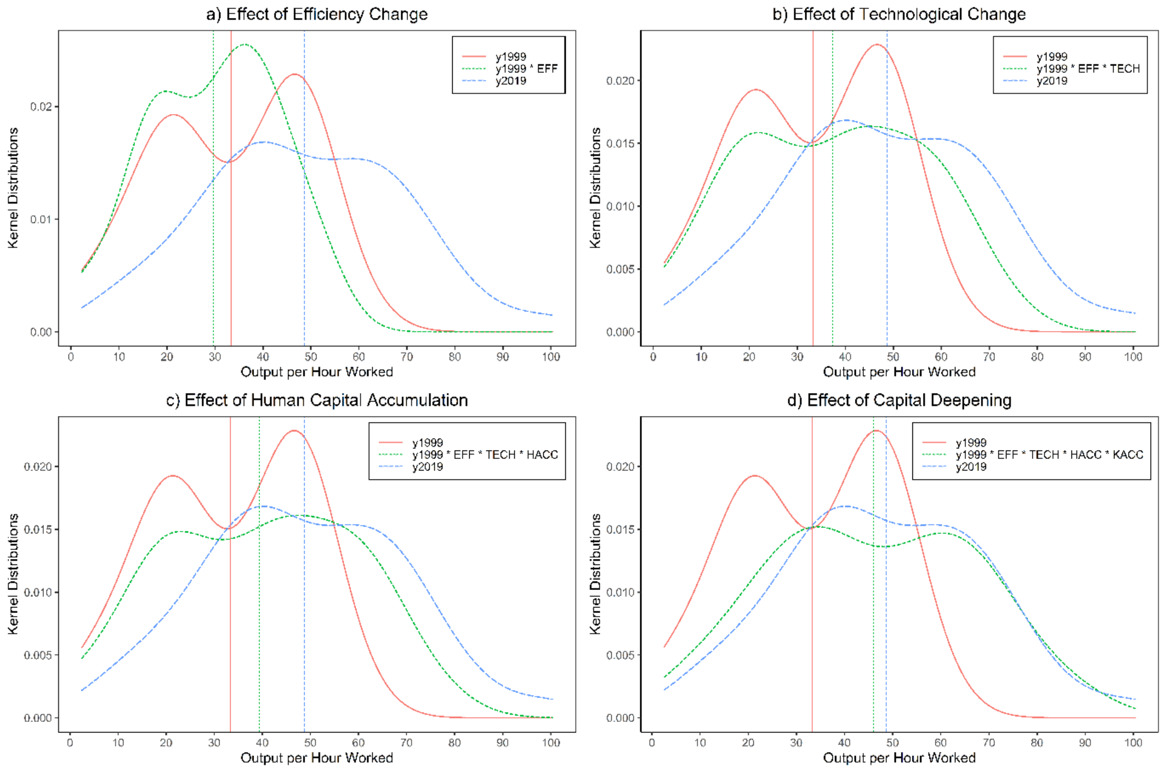

Fig. 4 Counterfactual distributions of output per hour worked. In each panel, the solid curve is the actual 1999 distribution, the dashed curve is the actual 2019 distribution. The dotted curves in each panel are the counterfactual distributions isolating, sequentially, the effects of efficiency ch., technological ch., human capital accumulation, and capital deepening. The vertical lines represent the mean values of the corresponding distributions.

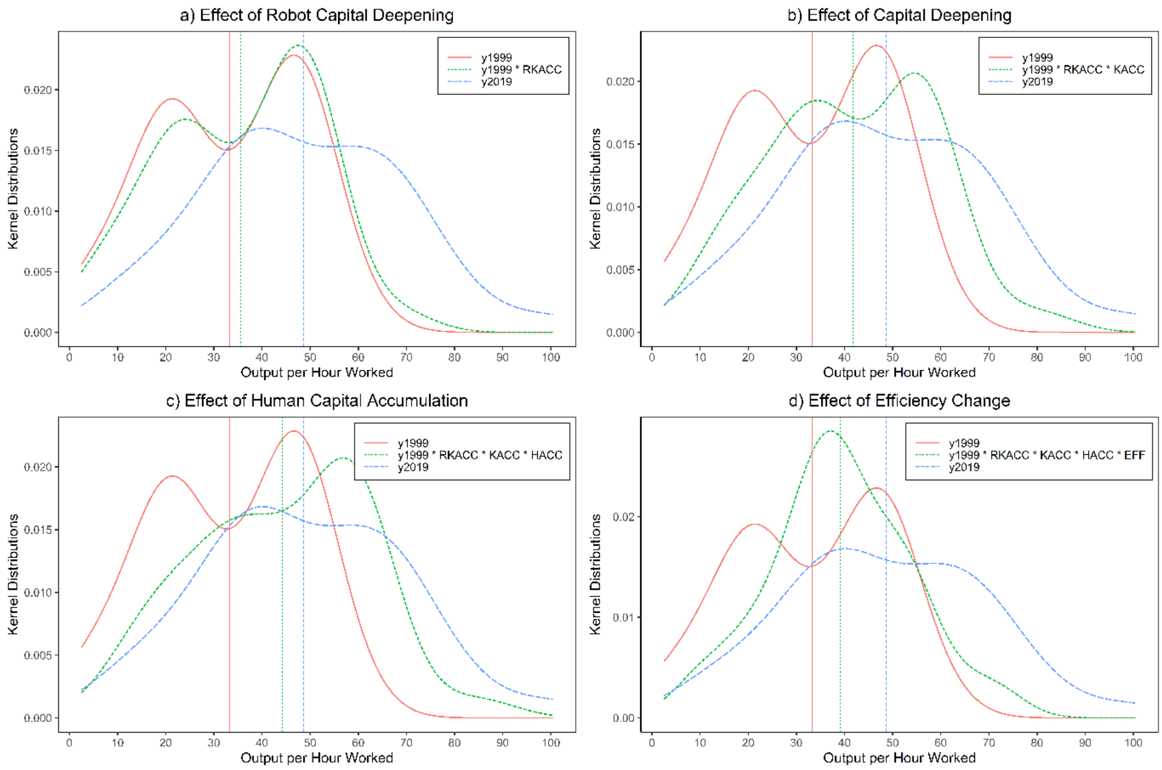

Fig. 5 Counterfactual distributions of output per hour worked. In each panel, the solid curve is the actual 1999 distribution, the dashed curve is the actual 2019 distribution. The dotted curves in each panel are the counterfactual distributions isolating, sequentially, the effects of robot capital deepening, capital deepening, human capital accumulation, and efficiency ch.. The vertical lines represent the mean values of the corresponding distributions.

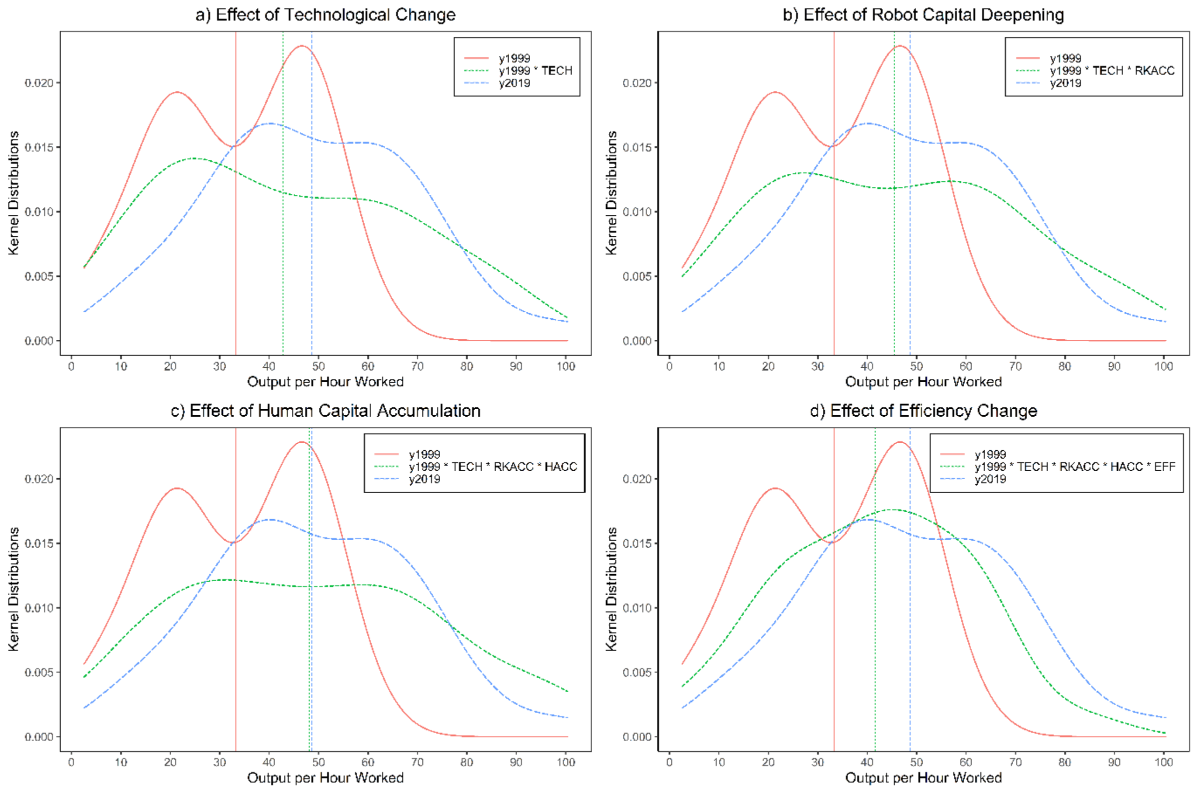

Fig. 6 Counterfactual distributions of output per hour worked. In each panel, the solid curve is the actual 1999 distribution, and the dashed curve is the actual 2019 distribution. The dotted curves in each panel are the counterfactual distributions isolating, sequentially, the effects of technological change, capital deepening, human capital accumulation, and efficiency change. The vertical lines represent the mean values of the corresponding distributions.

smaller[21] to the 17% (=10.9/63.8) percentage contribution rate found in the second last row of Table 4 (cf. footnote 15).

To sum up, the evidence from the counterfactual distributional analysis and statistical tests in Table 5 and 6 indicates that (i) the depolarization (shift from bimodal to unimodal distribution) of the labor productivity distribution and (ii) the increase in average output per hour worked are primarily driven by technological change, and, in the case of (ii) by (non-robot) capital deepening. Efficiency change and robot capital deepening significantly contribute to depolarization. (iii) The decreased dispersion of levels of productivity across countries is

[21] The reason for this lower percentage contribution rate is that the second last line of Table 3, the unweighted means of productivity change and its components, provides the average importance of robot capital deepening across countries. But the robot capital deepening component incorporated into the distributional analysis in Fig.5 is essentially weighted by the initial level of output per hour worked. Recall that the mean robot capital deepening effect was relatively small among developed (countries with relatively high initial output per hour worked) and relatively large among emerging economies (countries with relatively low initial output per hour worked).

primarily driven by (non-robot) capital deepening and efficiency change, whereas robot capital deepening somewhat contributes to this development. (iv) The overall effect of robot capital deepening on the change of the labor productivity distribution for the 1999-2019 period is modest and dominated by other components. Nevertheless, the contribution of robot capital deepening to the increase in average output per hour worked should not be neglected.

Table 5
Modality Tests (p-values)

	H_0: Distribution Has One Mode H_1: Distribution Has More than One Mode	Bootstrap p-Value
1	$f(y_{1999})$	0.02
2	$f(y_{2019})$	0.20
3	$f(y_{1999} \times \mathit{EFF})$	0.11
4	$f(y_{1999} \times \mathit{TECH})$	0.44
5	$f(y_{1999} \times \mathit{KACC})$	0.00
6	$f(y_{1999} \times \mathit{HACC})$	0.04
7	$f(y_{1999} \times \mathit{RKACC})$	0.14
8	$f(y_{1999} \times \mathit{EFF} \times \mathit{TECH})$	0.11
9	$f(y_{1999} \times \mathit{EFF} \times \mathit{KACC})$	1.00
10	$f(y_{1999} \times \mathit{EFF} \times \mathit{HACC})$	0.15
11	$f(y_{1999} \times \mathit{EFF} \times \mathit{RKACC})$	0.38
12	$f(y_{1999} \times \mathit{TECH} \times \mathit{KACC})$	0.10
13	$f(y_{1999} \times \mathit{TECH} \times \mathit{HACC})$	0.66
14	$f(y_{1999} \times \mathit{TECH} \times \mathit{RKACC})$	0.06
15	$f(y_{1999} \times \mathit{KACC} \times \mathit{HACC})$	0.02
16	$f(y_{1999} \times \mathit{KACC} \times \mathit{RKACC})$	0.05
17	$f(y_{1999} \times \mathit{HACC} \times \mathit{RKACC})$	0.38
18	$f(y_{1999} \times \mathit{EFF} \times \mathit{TECH} \times \mathit{KACC})$	0.28
19	$f(y_{1999} \times \mathit{EFF} \times \mathit{TECH} \times \mathit{HACC})$	0.15
20	$f(y_{1999} \times \mathit{EFF} \times \mathit{TECH} \times \mathit{RKACC})$	0.35
21	$f(y_{1999} \times \mathit{EFF} \times \mathit{KACC} \times \mathit{HACC})$	0.97
22	$f(y_{1999} \times \mathit{EFF} \times \mathit{KACC} \times \mathit{RKACC})$	0.74
23	$f(y_{1999} \times \mathit{EFF} \times \mathit{HACC} \times \mathit{RKACC})$	0.77
24	$f(y_{1999} \times \mathit{TECH} \times \mathit{KACC} \times \mathit{HACC})$	0.14
25	$f(y_{1999} \times \mathit{TECH} \times \mathit{KACC} \times \mathit{RKACC})$	0.19
26	$f(y_{1999} \times \mathit{TECH} \times \mathit{HACC} \times \mathit{RKACC})$	0.14
27	$f(y_{1999} \times \mathit{KACC} \times \mathit{HACC} \times \mathit{RKACC})$	0.46
28	$f(y_{1999} \times \mathit{EFF} \times \mathit{TECH} \times \mathit{KACC} \times \mathit{HACC})$	0.01
29	$f(y_{1999} \times \mathit{EFF} \times \mathit{TECH} \times \mathit{KACC} \times \mathit{RKACC})$	0.38
30	$f(y_{1999} \times \mathit{EFF} \times \mathit{TECH} \times \mathit{HACC} \times \mathit{RKACC})$	0.83
31	$f(y_{1999} \times \mathit{EFF} \times \mathit{KACC} \times \mathit{HACC} \times \mathit{RKACC})$	0.85
32	$f(y_{1999} \times \mathit{TECH} \times \mathit{KACC} \times \mathit{HACC} \times \mathit{RKACC})$	0.28

We employ the bootstrapped calibrated Silverman test of multimodality due to Hall and York (2001) with 1,000 bootstrap replications.

Table 6

Distribution Hypothesis Tests (p-values)

	H_0: Distributions Are Equal H_1: Distributions Are Not Equal	Bootstrap p-Value
1	$g(y_{2019})$ vs. $f(y_{1999})$	0.01
2	$g(y_{2019})$ vs. $f(y_{1999} \times EFF)$	0.00
3	$g(y_{2019})$ vs. $f(y_{1999} \times TECH)$	0.12
4	$g(y_{2019})$ vs. $f(y_{1999} \times KACC)$	0.08
5	$g(y_{2019})$ vs. $f(y_{1999} \times HACC)$	0.02
6	$g(y_{2019})$ vs. $f(y_{1999} \times RKACC)$	0.02
7	$g(y_{2019})$ vs. $f(y_{1999} \times EFF \times TECH)$	0.23
8	$g(y_{2019})$ vs. $f(y_{1999} \times EFF \times KACC)$	0.03
9	$g(y_{2019})$ vs. $f(y_{1999} \times EFF \times HACC)$	0.00
10	$g(y_{2019})$ vs. $f(y_{1999} \times EFF \times RKACC)$	0.00
11	$g(y_{2019})$ vs. $f(y_{1999} \times TECH \times KACC)$	0.08
12	$g(y_{2019})$ vs. $f(y_{1999} \times TECH \times HACC)$	0.28
13	$g(y_{2019})$ vs. $f(y_{1999} \times TECH \times RKACC)$	0.50
14	$g(y_{2019})$ vs. $f(y_{1999} \times KACC \times HACC)$	0.35
15	$g(y_{2019})$ vs. $f(y_{1999} \times KACC \times RKACC)$	0.33
16	$g(y_{2019})$ vs. $f(y_{1999} \times HACC \times RKACC)$	0.04
17	$g(y_{2019})$ vs. $f(y_{1999} \times EFF \times TECH \times KACC)$	0.88
18	$g(y_{2019})$ vs. $f(y_{1999} \times EFF \times TECH \times HACC)$	0.53
19	$g(y_{2019})$ vs. $f(y_{1999} \times EFF \times TECH \times RKACC)$	0.48
20	$g(y_{2019})$ vs. $f(y_{1999} \times EFF \times KACC \times HACC)$	0.06
21	$g(y_{2019})$ vs. $f(y_{1999} \times EFF \times KACC \times RKACC)$	0.04
22	$g(y_{2019})$ vs. $f(y_{1999} \times EFF \times HACC \times RKACC)$	0.01
23	$g(y_{2019})$ vs. $f(y_{1999} \times TECH \times KACC \times HACC)$	0.10
24	$g(y_{2019})$ vs. $f(y_{1999} \times TECH \times KACC \times RKACC)$	0.42
25	$g(y_{2019})$ vs. $f(y_{1999} \times TECH \times HACC \times RKACC)$	0.60
26	$g(y_{2019})$ vs. $f(y_{1999} \times KACC \times HACC \times RKACC)$	0.64
27	$g(y_{2019})$ vs. $f(y_{1999} \times EFF \times TECH \times KACC \times HACC)$	0.89
28	$g(y_{2019})$ vs. $f(y_{1999} \times EFF \times TECH \times KACC \times RKACC)$	0.95
29	$g(y_{2019})$ vs. $f(y_{1999} \times EFF \times TECH \times HACC \times RKACC)$	0.80
30	$g(y_{2019})$ vs. $f(y_{1999} \times EFF \times KACC \times HACC \times RKACC)$	0.05
31	$g(y_{2019})$ vs. $f(y_{1999} \times TECH \times KACC \times HACC \times RKACC)$	0.21

The functions g(.) and f(.) are (kernel) distribution functions. We employ bootstrapped Li (1996) tests with 5,000 bootstrap replications and the Silverman's (1986) adaptive rule-of-thumb bandwidth.

6. Sensitivity Analyses for Quinquepartite Decomposition

Having presented the results for a sample of 36 countries over the period 1999-2019 based on a specific robot stock estimate obtained from the perpetual inventory model (PIM) and assuming a depreciation rate of 15 %, we now turn the focus to present the summary results form a wide array of sensitivity analyses.

We examine the robustness of our results with respect to the following changes, paying particular attention to differences between emerging and developed countries: i) the use of alternative robot stock estimates based on different assumptions about robot capital depreciation and the change in the average robot quality, and ii) the investigation of the subperiods 1999-2009, and 2009-2019. While Table 7 reports means of country groups, country-specific results of the sensitivity analyses are available in section B.5. in the supplementary material.

6.1. Alternative Robot Stock Estimates

Panel A in Table 7 shows that the average efficiency scores (both in the 1999 and the 2019) are identical to two decimal places, regardless of whether we estimate the robot stock with the perpetual inventory method assuming a 5 %, 10 % or 15 % depreciation rate, or if we assume an average service life of robots of 12 years with an immediate withdrawal from service afterwards (one-hoss shay depreciation). Accordingly, the mean contribution of the five productivity components to average productivity growth show little variation with respect to the robot stock estimates. For instance, the mean contribution of robot capital deepening across emerging, developed and all countries, ranges from 19.5 to 20.6 %, 2.6 to 3.0 %, and 10.7 to 11.3 %, respectively.

However, for some individual countries the results can vary substantially between different types of robot stock estimates. For instance, regarding the contribution of robot capital deepening we find the largest uncertainties for the Czech Republic (8.2-16.3 %), Slovenia (4.6-8.1 %), the Netherlands (3.3-5.5 %), Portugal (15.6-21.1 %), and Canada (7.2-9.0 %). For all other countries the differences in the robot capital deepening component between different robot stock estimates are negligible.

Table 7

Mean Efficiency Scores and Percentage Change of Quinqupartite Decomposition Indexes

	TE_b	TE_c	Productivity Change	(EFF-1) × 100	(TECH-1) × 100	(HACC-1) × 100	(KACC-1) × 100	(RKACC-1) × 100
Period 1999-2019								
Panel A: Alternative robot stock estimates								
One-hoss shay depreciation, 12 years, quality change adjusted								
Emerging	0.71	0.65	90.5	-1.7	13.0	6.3	44.0	19.5
Developed	0.85	0.74	39.8	-12.3	31.3	5.7	13.8	2.8
All	0.78	0.69	63.8	-7.3	22.7	6.0	28.0	10.7
PIM, δ =5 %, quality change adjusted								
Emerging	0.71	0.65	90.5	-1.9	12.7	6.3	43.0	20.6
Developed	0.85	0.74	39.8	-12.4	31.3	5.8	13.7	3.0
All	0.78	0.69	63.8	-7.4	22.5	6.0	27.5	11.3
PIM, δ=10 %, quality change adjusted								
Emerging	0.71	0.65	90.5	-1.5	12.9	6.3	43.0	20.3
Developed	0.85	0.74	39.8	-12.3	31.4	5.8	13.9	2.7
All	0.78	0.69	63.8	-7.2	22.6	6.0	27.6	11.0
PIM, δ=15 %, quality change adjusted								
Emerging	0.71	0.65	90.5	-1.4	13.0	6.3	43.0	20.3
Developed	0.85	0.74	39.8	-12.2	31.3	5.7	14.0	2.6
All	0.78	0.69	63.8	-7.1	22.7	6.0	27.7	10.9
PIM, δ=15 %, no quality change								
Emerging	0.71	0.65	90.5	-1.4	14.5	6.0	41.5	19.3
Developed	0.85	0.74	39.8	-12.3	32.1	5.8	14.3	1.7
All	0.78	0.70	63.8	-7.2	23.8	5.9	27.2	10.0
Panel B: Without robots								
Emerging	0.68	0.63	90.5	-0.84	20.7	5.5	64.2	
Developed	0.84	0.73	39.8	-12.12	33.7	6.0	14.2	
All	0.76	0.69	63.8	-6.8	27.6	5.7	37.8	
Subperiod 1999-2009								
Panel C: With robots (PIM, δ=15 %, quality adjustment)								
Emerging	0.71	0.69	49.3	1.1	9.0	2.6	23.9	10.0
Developed	0.85	0.72	24.2	-13.8	27.8	2.4	11.0	1.3
All	0.78	0.71	36.1	-6.8	18.9	2.5	17.1	5.5
Panel D: Without robots								
Emerging	0.68	0.66	49.3	0.7	13.5	2.4	32.0	
Developed	0.84	0.72	24.2	-13.3	28.3	2.4	11.6	
All	0.76	0.69	36.1	-6.7	21.3	2.4	21.3	
Subperiod 2009-2019								
Panel E: With robots (PIM, δ=15 %, quality adjustment)								
Emerging	0.69	0.65	24.8	-3.7	2.9	1.8	19.5	6.8
Developed	0.72	0.74	12.4	2.0	2.2	1.3	6.0	0.6
All	0.71	0.69	18.3	-0.7	2.5	1.5	12.3	3.5
Panel F: Without robots								
Emerging	0.66	0.63	24.8	-2.2	5.6	1.6	21.2	
Developed	0.72	0.73	12.4	1.6	3.2	1.4	5.9	
All	0.69	0.69	18.3	-0.2	4.4	1.5	13.1	

PIM is perpetual inventory method, and δ is the assumed depreciation rate.

Comparing the average contribution rates of the growth components with and without adjusting the robot stock estimates for robot quality changes, reveals that overall, there are only modest changes and the qualitive results discussed above remain unaltered. Though, the average contribution of robot capital deepening to labor productivity growth is somewhat reduced for both emerging and developed countries if quality-changes of robots are ignored. Larger deviations are mainly found for some individual countries. For most of the countries we find that ignoring quality-changes leads to an underestimation of the contribution of robot capital deepening to labor productivity growth.

6.2. Subperiods

Panel C and E in Table 7 present the mean productivity growth rates and the five components for the subperiods 1999-2009, and 2009-2019, respectively. Panel D and F show the corresponding results for the decomposition ignoring robot capital as a separate production factor. First, we can observe that, for both developed and emerging countries, average productivity growth substantially slows down in the period after the financial crisis (2009-2019); in both groups of countries the average productivity growth rate over the period 2009-2019 is about half of the average growth rate of the subperiod before. The average growth rate of output per hour worked across all 36 countries is 36.1 % and 18.3 % for the 1999-2009, and the 2009-2019 period, respectively.

However, not only the magnitude of productivity growth changes, but we also observe a shift in the relative importance of the five productivity growth components: considering the averages across all countries we observe that in the 1999-2009 period technological progress (18.9 %) and (non-robot) capital deepening (17.1 %) are more or less equally contributing to productivity growth (line 3 in Panel C). Whereas, in the 2009-2019 period the (non-robot) physical capital deepening becomes the major driver of productivity growth (line 3 in Panel E). Its magnitude (12.3 %) is more than three times as high as the second largest contributor, robot capital deepening (3.5 %), and almost five times as large as the contribution of technological progress (2.5 %). Hence, the finding that technological progress is the main force behind the transformation of the productivity distribution between 1999 and 2019 is mainly driven by the period before the financial crisis.

Furthermore, we observe that the contribution of robot capital deepening to productivity growth gains in importance in the period after the financial crisis. While robot capital deepening was the fourth largest driver of productivity growth across all 36 countries in the 1999-2009 (line 3 in Panel C) period it becomes the second most important driver in the 2009-2019 period (line 3 in Panel E). This development is mainly driven by emerging countries: we observe an increasing importance of the contribution of robot capital deepening to productivity growth for emerging countries but not for developed countries. The main finding in section 4.2. that the contribution of robot capital deepening to productivity growth is considerably higher in emerging than in developed countries over the 1999-2019 period, holds for both, the 1999-2009 and the 2009-2019 period. The gap in the contribution of robot capital deepening to productivity growth between emerging and developed countries seems to amplify in the period after the financial crisis.

Finally, for both subperiods we compare the results of the decomposition considering robots as separate production factor with the results of the decomposition that does not. Regarding the 1999-2009 period, line 3 in Panel C and Panel D of Table 7 reveal the tendency that incorporating robot capital as separate production factor into the analysis substantially reduces the average contribution to productivity growth attributable to (non-robot) physical capital deepening and technological progress as found in our baseline results for the 1999-2019 period. This trend seems to be broken as indicated by line 3 in Panel E and F over the 2009-2019 period: the robot capital deepening component absorbs relatively little form the (non-robot) physical capital component, which shows a fall from 13.1 % to 12.3 %, but mainly reduces the average contribution to productivity growth attributable to technological progress (reduction from 4.4

% to 2.5 %) and efficiency change (-0.2 % to -0.7 %). This indicates that ignoring robots as separate production factor would efficiency change and technological progress capture the favorable effect of industrial robots on the catching up to the frontier and the outward shift of the frontier, respectively, over the 2009-2019 period.

6.3. Summing up

To sum up the sensitivity analysis shows that i) the baseline results presented in section 4 and 5 are robust to other assumptions about the depreciation of the robot capital stock and ii) that the development after the period of the financial crisis is characterized by a slowdown of average productivity growth and a change in the relative importance of the productivity growth components. In particular, the average contributions of (non-robot) physical capital and robot capital deepening to productivity growth have gained in importance, and that of technological progress declined over the last decade relative to the 1999-2009 period. Due to the low productivity growth performance over the 2009-2019 period relative to the decade before, the development over the 1999-2019 period tends to overproportionally reflect the pre-crisis growth patterns.

7. Conclusion

First, we analyze the contribution of robotization and five other growth factors (i.e., efficiency change, technological change, non-robot physical capital deepening, and human capital accumulation) to labor productivity growth over the period 1999 to 2019 in 19 developed and 17 emerging countries. Second, we study if and by how much industrial robots contributed to convergence of cross-country productivity levels observed in our sample. We apply the non-parametric production frontier approach developed by Kumar and Russell (2002), and refined by Henderson and Russell (2005) and extend it by considering industrial robots as separate production factor. Production frontiers and distances to the frontiers are estimated by Data Envelopment Analysis, a method based on linear programming models.

Our results confirm the positive relationship between robot adoption and labor productivity growth found in previous studies. However, substantial contributions of robotization to labor productivity growth over the period 1999 to 2019 are mainly found in emerging countries, such as India, China, Turkey, Greece, Portugal, Mexico, Argentina, Brazil and the Eastern European countries Hungary, Slovenia, Slovakia, and the Czech Republic. For developed countries the contribution of robot capital deepening to labor-productivity growth is much less important, except for Israel, Canada and Norway. We observe that the contribution of robot capital deepening to productivity growth gains in importance in the 2009-2019 period after the financial crisis for emerging countries, but not for developed countries.

We find some evidence of unconditional beta-convergence, and sigma-convergence in our sample of 36 robot-adopting countries over the period 1999 to 2019. First, countries with lower initial productivity levels experienced, on average, faster productivity growth. After (non-robot) physical capital deepening, robotization is the second most important driver behind this development. Second, the dispersion of levels of productivities across countries decreased, as indicated by the reduced coefficient of variation of the productivity distribution in 2019 relative to 1999. This is primarily driven by (non-robot) capital deepening and efficiency change, but robotization also contributed to this development. However, the effect of robot capital deepening on the shift of the entire labor productivity distribution is rather modest and dominated by other growth factors such as technological change. Nevertheless, statistical tests confirm that robotization significantly contributed to the depolarization (a shift from a bimodal to unimodal distribution) of the labor productivity distribution.

Note that our sample of countries is not representative for the entire world and only includes robot adopting countries. In particular, developing countries from Africa and some Latin American countries are excluded due to limited data availability on industrial robot usage.

Including non-robot adopting countries in our sample could lead to very different results regarding the convergence of worldwide labor productivity levels. It is conceivable that an analysis based on such a larger sample of countries could reveal that industrial robot diffusion contributes to a widening of worldwide income and productivity disparities.

Furthermore, we find that disembodying robot capital from total physical capital and considering robots as separate production factor changes the relative importance of the growth factors: On average, the importance of physical capital deepening and technological change decrease by about the same magnitude as the robot capital deepening component gains in importance. This indicates that robotization is not only affecting productivity growth via capital accumulation but might be linked to broader technological innovations that have the potential to push the world production frontier outward.

The application of industrial robots is highly concentrated in a few manufacturing sectors, such as the automobile, electrical/electronics, metal, and machinery industry (Müller and Kutzbach, 2020). For less developed countries that have a sufficiently large manufacturing sector and a favorable industry structure, robotization provides a chance to boost productivity levels and to contribute to the catching-up with developed countries. Future research could analyze how the effects of robotization on labor productivity growth, employment change and convergence differ across robot using industries.

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Appendix A

Table A1
Growth regressions of the percentage change in output per hour worked and the five decomposition indices on output per hour worked in base (1999) period

Variable	Dependent Variable					
	(a) Productivity Change	(b) (EFF-1) × 100	(c) (TECH-1) × 100	(d) (HACC-1) × 100	(e) (KACC-1) × 100	(f) (RKACC-1) × 100
Constant	143.77***	10.02	-4.61	7.80***	75.86***	30.06***
	(17.50)	(9.71)	(6.55)	(1.94)	(13.75)	(6.99)
Output per hour worked in 1999	-2.40***	-0.51*	0.82***	-0.05	-1.45***	-0.57***
	(0.48)	(0.26)	(0.18)	(0.05)	(0.37)	(0.19)
Number of obs.	36	36	36	36	36	36
R-squared	0.429	0.101	0.384	0.030	0.306	0.212

Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively. Coefficient estimates of GLS-regressions are reported. Standard errors are shown in parenthesis.

Table A2
Country-Codes and Classification

Emerging Countries		Developed Countries	
Code	Country	Code	Country
AR	Argentina	AU	Australia
BR	Brazil	AT	Austria
CN	China	BE	Belgium
CZ	Czech Republic	CA	Canada
GR	Greece	DK	Denmark
HU	Hungary	FI	Finland
IN	India	FR	France
MY	Malaysia	DE	Germany
MX	Mexico	IL	Israel
PL	Poland	IT	Italy
PT	Portugal	JP	Japan
KR	Republic of Korea	NL	Netherlands
RU	Russian Federation	NO	Norway
SK	Slovakia	SG	Singapore
SL	Slovenia	SE	Sweden
ES	Spain	CH	Switzerland
TR	Turkey	TW	Taiwan
		UK	United Kingdom
		US	United States

Emerging countries: GDP per capita < 27,500 (2017 US$) in 1999. Developed countries: Real GDP per capita > 32,500 (2017 US$) in 1999.

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 36 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, Jurkat and Schneider (2021) and by other scientific work based on the IFR data. The manipulation steps can be grouped into five 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 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. In the following we describe these data preparation procedures in more detail. It should be noted that several countries are undergoing more than one of the procedures sketched above.).

Simple resolution of inconsistencies. For six countries in our sample (Argentina, Australia, Greece, Israel, and Slovenia) we found that data for the installations of robots were stated as zero from 2014 on, even though considering the continuation of the robot stock series they could be inferred to be positive.[22] In fact, given that the stock series is calculated by IFR using the one-hoss-shay method (OHS) with an asset live of 12 years, i.e., making the assumption that robots have to be replaced by new robots after 12 years of usage, we can deduce the exact values for the installation series.

Disaggregation of aggregated data. This group of data manipulation steps concerns two groups of countries: first, Australia and New Zealand, and second, United States, Mexico and Canada. The IFR reports separate data series for Australia and New Zealand only from 2005. For 2002-2004 the IFR database provides data for Australia and New Zealand only in aggregated form. Data on installations in New Zealand in 2002-2004 are nevertheless reported in the annual reports and thus can be used to construct the series for Australia. Prior to 2002 the Australian data series cover only Australia and need no correction. Similarly, the installations time series for North America in 1999-2010, though only given in disaggregated form in the database, are provided separately for Canada, Mexico and United States in the annual reports. Prior to 1999 we disaggregated the installations series by using the average shares of the three countries for the years 1999-2001. The stock data (OHS) for 1993-2001 were disaggregated by also using these shares and for 2002 and 2003 by partially considering the newly available installations data; from 2004 on, the regular OHS procedure could be used to recalculate the disaggregated values of robot stocks for all three countries.

Extrapolation back in time based on reverse-OHS. For 26 countries the time series started in 1993. For these countries the stocks in 1993 are higher than the installations, thus revealing prior data collections or assumptions taken by IFR about robot installations prior to 1993. Given the OHS-method consistently applied by IFR, this allowed us to calculate earlier stocks and installations by reversing OHS, furnishing us plausible time series in most cases. Even the

[22] The same issue is present for many other countries in the IFR database as well, among them Ireland, Philippines, New Zealand. A possible reason for this might be the application of compliance rules for privacy protection, which, however, is seemingly only applied to the installation series.

numbers for the Russian Federation, which has an interesting history of early adoption of industrial robots in the days of the Soviet Union (see Cooper, 1984) and therefore is reported by IFR to have a robot stock of 30000 and installations of 0 in 1993 cannot be discarded a-priori. If we want to be able to calculate robot stock measures alternative to the OHS robot stock presented by IFR we cannot escape the necessity to extrapolate the installations series back in time. However, since these data are not published by IFR in the strict sense of the word, we used it only to calculate the robot stocks series, including the initial robot stocks in 1995, by the permanent inventory method (PIM)

Extrapolation back in time based on plausibility considerations. For eight countries in our sample (Brazil, China, Greece, Israel, India, Malaysia, Argentina, and Turkey) the data series start in 1999 with the same value for installations and stocks, which must be considered as implausible, even in cases of small installations. As occasionally is admitted by IFR the true installations series must start earlier and stocks corrected accordingly (e.g., in the case of Malaysia the annual report 2005 on page 150 says this about the reported robot stock in 2004: "This value has to be considered as a minimal value."). Therefore, using the observed pattern of growth, we extrapolated the installations series back for earlier years 1987-1998. For most countries a linear growth trend was assumed and the value for 1998 was chosen so that it fitted well with the observed average for 1999-2001. For China, based on its growth experience in robot installations 2000-2006, we assumed exponential growth with an approximate annual growth of 58% prior to the start of the official IFR data in 1999. All the extrapolations for earlier years, of course, were not allowed to furnish negative values.

Taking account of country specific information. For several countries the annual reports contain information that suggests correction of the data published in the database. For Turkey IFR reports a large increase in installation in 2005 and concedes that "this was the result of more complete data and increasing investments by the automobile industry" (IFR, 2006, p. 126). Not knowing the exact relevance of the underreporting prior to 2005, we assumed its share to be

50% of the increase in that year and correspondingly estimated proportionally higher values than reported for all years up to 2004. For Brazil and Argentina, the annual reports of IFR (2005 and later) also describe a severe problem of underreporting. IFR (2005) is most explicit about this problem, stating among others, that in 2004 about 500-600 units should be added to the sum of these countries and that the "true operational stock can be assumed to be much higher." We thus multiplied the original series for these countries by a factor between 1,56 and 2,64 where we tried to find a middle way between preserving the variation in the original series and integrating all available information about underreporting. For Japan, there is a break in the time series between 2000 and 2001 due to a change in the underlying definition of industrial robots. Before, Japanese data also include dedicated machinery and thus are overstated. After scrutinizing the data by application type, we find that the break is occurring exclusively in the class of assembling and disassembling robots, which otherwise displays a stable development in the years around the break. We decided that the number of robot installations to be subtracted in years prior to 2001 can be estimated by applying the same proportion as in the years just before and after the break in that class. After this correction to the installation series was used to calculate the OHS-based stock series.

For reasons of space the data preparation has not been described in full detail here. More details can be requested directly from the authors.

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B. Figures and Tables

B.1. Robot quality index

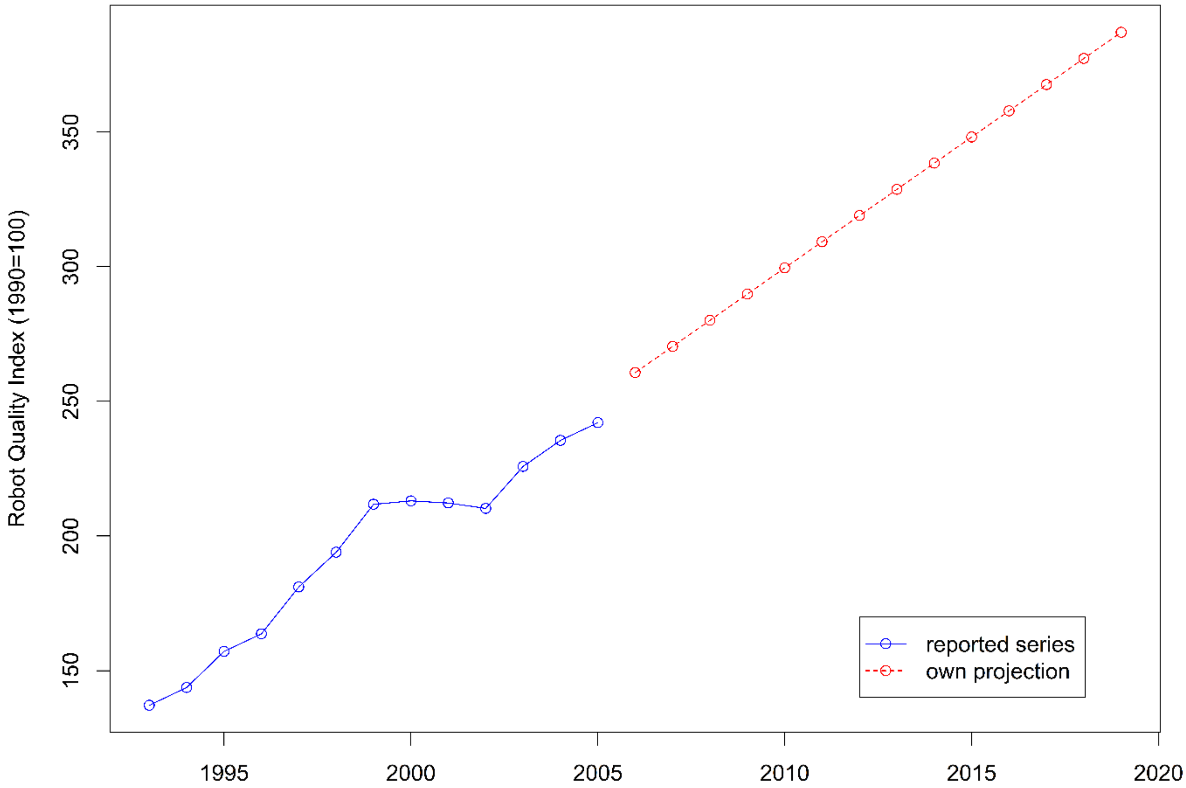

Fig. B1 Evolution of the quality index of robots 1993-2005 as reported by IFR and own projection based on an estimated linear trend.

B.2. Evolution of robot stocks

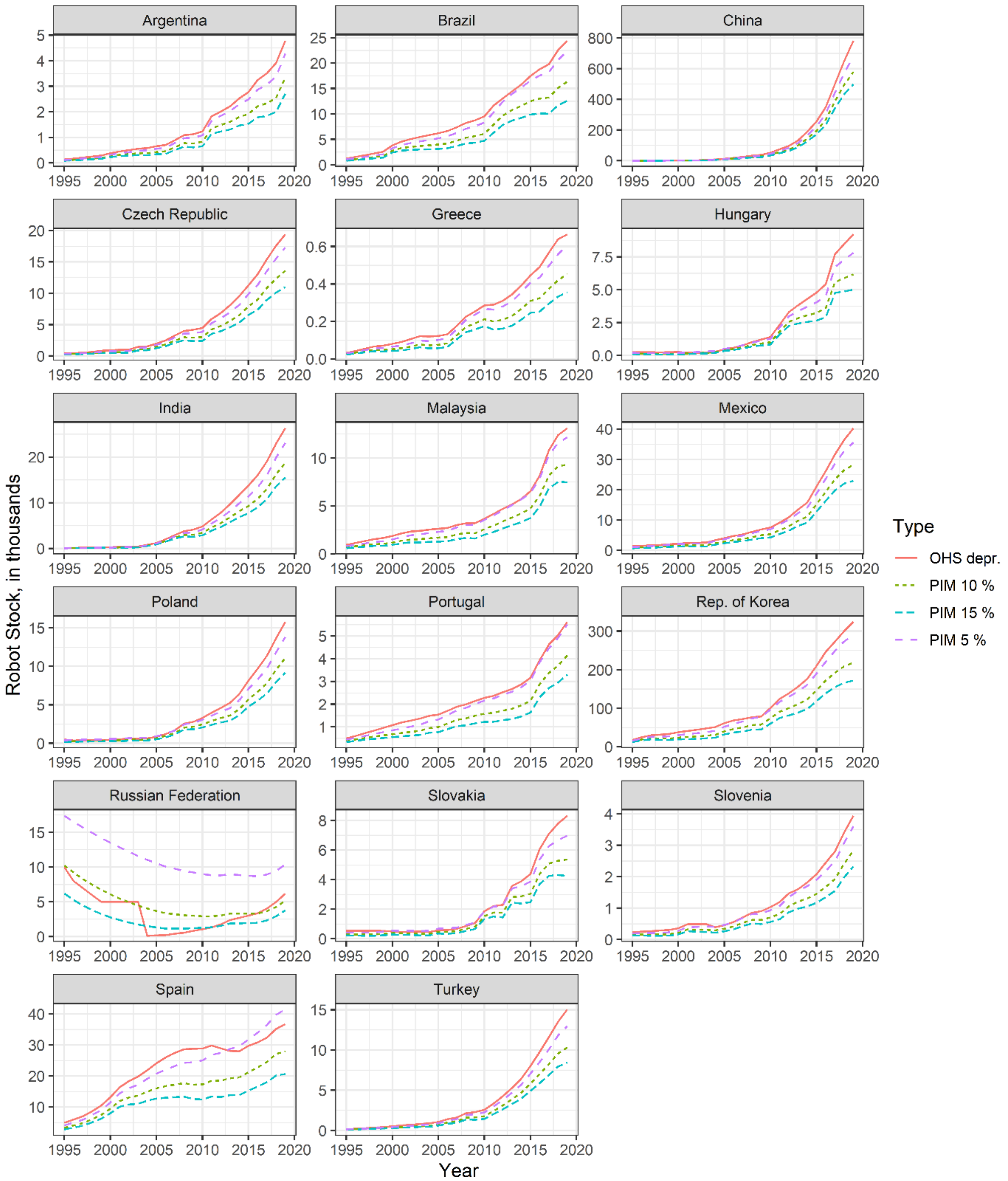

Fig. B2a Evolution of robot stocks (non-quality-adjusted) in emerging countries over 1995-2019 based on PIM 15 %, PIM 10 %, PIM 5 %, and one-hoss-shay depreciation assuming a 12-year service life of robots.

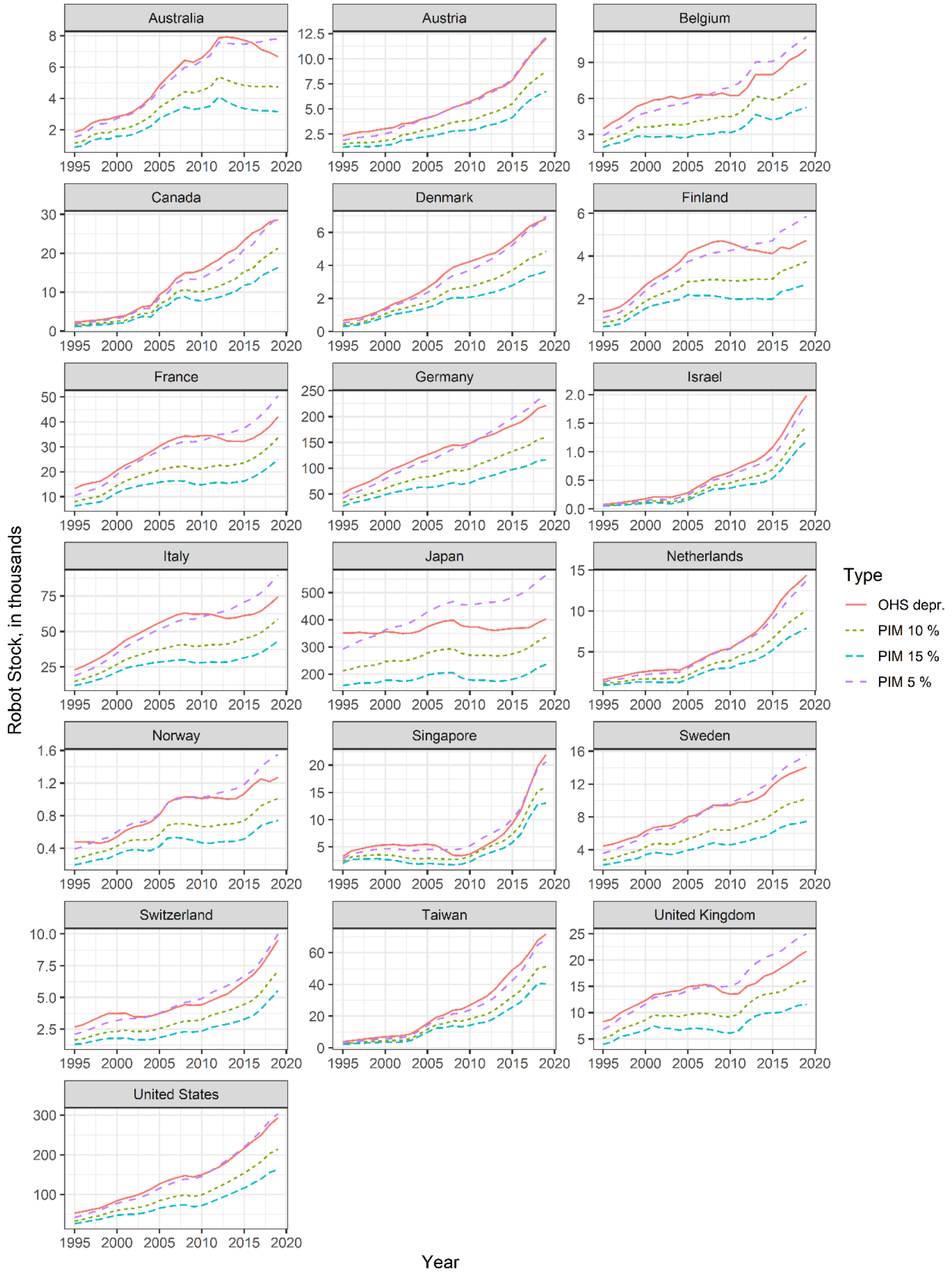

Fig. B2b Evolution of robot stocks (non-quality-adjusted) in developed countries over 1995-2019 based on PIM 15 %, PIM 10 %, PIM 5 %, and one-hoss-shay depreciation assuming a 12-year service life of robots.

B.3. Robot intensity (growth) ranking

Table B1

Country ranking by (growth of) robot intensity

	Ranking by robot intensity in 1999		Ranking by robot intensity in 2019		Ranking by growth of robot intensity between 1999-2019	
Rank	Country	Robot Intensity	Country	Robot Intensity	Country	Growth rate of robot intensity
1	Japan*	136.99	Rep. of Korea	324.04	China	49,522%
2	Germany*	74.91	Japan*	199.36	India	7,527%
3	Singapore*	56.81	Germany*	187.09	Hungary	5,872%
4	Belgium*	45.13	Taiwan*	168.62	Poland	3,519%
5	Italy*	44.92	Singapore*	148.64	Turkey	2,442%
6	Sweden*	42.09	Slovenia	139.36	Czech Rep.	2,137%
7	Rep. of Korea	34.12	Czech Rep.	112.40	Slovenia	1,626%
8	Finland*	33.64	Slovakia	101.57	Slovakia	1,496%
9	Switzerland*	26.46	Italy*	98.32	Mexico	1,265%
10	France*	24.16	Sweden*	93.15	Argentina	1,171%
11	Spain	22.58	Austria*	92.07	Taiwan*	944%
12	Austria*	19.46	Denmark*	89.05	Greece	875%
13	Denmark*	17.77	Switzerland*	70.80	Rep. of Korea	850%
14	United States*	17.04	Belgium*	67.18	Israel*	776%
15	Taiwan*	16.16	Finland*	62.63	Canada*	639%
16	UK*	13.42	Spain	61.64	Portugal	559%
17	Netherlands*	11.18	Hungary	61.54	Brazil	558%
18	Australia*	8.67	United States*	58.32	Malaysia	438%
19	Norway*	8.19	France*	58.18	Netherlands*	418%
20	Slovenia	8.07	Netherlands*	57.93	Denmark*	401%
21	Canada*	6.78	Canada*	50.13	Austria*	373%
22	Slovakia	6.36	Portugal	35.71	United States*	242%
23	Portugal	5.42	China	28.73	Spain	173%
24	Czech Rep.	5.02	Poland	28.11	Switzerland*	168%
25	Malaysia	4.19	Malaysia	22.55	Singapore*	162%
26	Russian Fed.	2.57	UK*	21.01	Germany*	150%
27	Israel*	1.67	Mexico	19.52	France*	141%
28	Mexico	1.43	Norway*	18.77	Norway*	129%
29	Brazil	1.19	Turkey	16.37	Sweden*	121%
30	Hungary	1.03	Israel*	14.64	Italy*	119%
31	Poland	0.78	Australia*	14.17	Finland*	86%
32	Turkey	0.64	Argentina	8.16	Australia*	63%
33	Argentina	0.64	Brazil	7.84	UK*	57%
34	Greece	0.42	Greece	4.13	Belgium*	49%
35	China	0.06	Russian Fed.	2.69	Japan*	46%
36	India	0.02	India	1.47	Russian Fed.	4%

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 %. Developed countries and emerging countries are shown with and without asterisk, respectively.

B.4. Descriptive statistics

Table B2

Descriptive Statistics of Input and Output Variables used for DEA-models by country groups

	Emerging Countries (n=425)	Developed Countries (n=475)	All (n=900)
Output (output-side real-GDP at 2017 PPP adjusted mill. US$)	1,792,303 (42,179-20,257,660)	2,028,410 (79,247-20,595,844)	1,916,915 (42,179-20,595,844)
Efficiency units of labor (mill. hours worked × human capital index)	443,561 (4,922-4,676,128)	127,914 (10,171-1,047,767)	276,970 (4,922-4,676,128)
Non-robot physical capital stock (in PPP adjusted mill. 2017 US$)	7,456,401 (380,878-80,446,479)	9,372,176 (349,194-69,157,981)	8,467,504 (349,194-80,446,479)
Quality-adjusted industrial robot stock (in physical units based on PIM with δ=15 %)	25,895 (24-1,333,562)	40,810 (49-589,222)	33,767 (24-1,333,562)

Mean of variables are reported. Minimum and maximum observed values are shown in parenthesis. Means are based on a balanced panel of 17 emerging and 19 developed countries for the years 1995-2019 covering 900 observations.

Table B3
Descriptive statistics of levels of labor productivity, capital intensities and human capital index by country groups in 1999 and 2019

	Emerging Countries (n=17)	Developed Countries (n=19)	All (n=36)
	Year 1999		
Labor productivity (Output per hour worked, PPP-adjusted 2017 US$)	19.30 (2.59-39.08)	45.83 (24.30-60.44)	33.30 (2.59 -60.44)
Robot intensity (quality-adjusted number of robots per mill. hours worked)	6.77 (0.03-41.38)	38.62 (2.13-155.03)	23.58 (0.03-155.03)
Non-robot capital intensity (non-robot physical capital stock per hour worked, PPP-adjusted 2017 US$)	119.64 (8.68-246.49)	239.52 (122.79- 341.21)	182.91 (8.68-341.21)
Human capital index	2.67 (1.75-3.53)	3.20 (2.66-3.57)	2.95 (1.75-3.57)
			Year 2019
Labor productivity (Output per hour worked, PPP-adjusted 2017 US$)	31.99 (8.68-56.30)	63.62 (40.87-100.33)	48.68 (8.68-100.33)
Robot intensity (quality-adjusted number of robots per mill. hours worked)	149.32 (3.88-836.85)	210.59 (34.20-497.92)	181.66 (3.88-836.85)
Non-robot capital intensity (non-robot physical capital stock per hour worked, PPP-adjusted 2017 US$)	174.19 (33.56-348.39)	321.26 (145.88-457.68)	251.81 (33.56-457.68)
Human capital index	3.13 (2.17-3.85)	3.57 (3.15-4.35)	3.36 (2.17-4.35)

Mean of variables are reported. Minimum and maximum observed values are shown in parenthesis. The quality-adjusted number of robots is estimated with the perpetual inventory method assuming a depreciation rate of 15 %. The quality index of robots shown in Fig. B1 is used to adjust robot installations for quality changes.

Table B4
Descriptive statistics of growth rates of labor productivity, capital intensities and human capital index over the period 1999 to 2019

	Emerging Countries (n=17)	Developed Countries (n=19)	All (n=36)
Labor productivity growth (%)	90.5 (15.26-252.15)	39.8 (9.89-124.50)	63.8 (9.89-252.15)
Robot intensity growth (%)	9,451.3 (268.8-92,066.3)	662.5 (202.3-2087.7)	4,812.7 (202.3 92,066.3)
Non-robot capital intensity growth (%)	88.0 (3.9-435.2)	34.8 (-3.7-97.6)	59.9 (-3.7-435.2)
Human capital index growth (%)	18.5 (4.0-54.0)	12.4 (0.7-63.4)	15.3 (0.7-63.4)

Mean of variables are reported. Minimum and maximum observed values are shown in parenthesis. Quality-adjusted number of robots are estimated with the perpetual inventory method assuming a depreciation rate of 15 %. The quality index of robots shown in Fig. B1 is used to adjust robot installations for quality changes.

B.5. Detailed results of sensitivity analysis

Table B5a

Country-specific results of sensitivity analysis for subperiods 1999-2009 and 2009-2019, with and without robot capital as separate production factor

Country/ Subperiod	Productivity Change	(EFF-1) × 100	(TECH-1) × 100	(HACC-1) × 100	(KACC-1) × 100	(RKACC-1) × 100
Argentina						
1999-2009	6.2	-1.3	3.1	1.4	0.5	2.5
	6.2	-4.8	9.2	1.8	0.5	
2009-2019	32.3	-9.5	2.6	2.7	29.9	6.9
	32.3	-10.6	9.5	1.3	33.5	
Australia						
1999-2009	17.5	-3.0	7.1	-0.7	11.8	1.8
	17.5	-1.0	7.4	-0.7	11.2	
2009-2019	15.6	-1.2	1.4	0.5	14.6	0.1
	15.6	-3.6	4.7	0.7	13.8	
Austria						
1999-2009	26.7	-21.0	39.9	3.0	11.1	0.2
	26.7	-21.0	40.2	3.0	11.0	
2009-2019	18.5	4.7	1.1	0.6	11.4	0.0
	18.5	4.7	1.1	0.6	11.4	
Belgium						
1999-2009	26.0	-36.2	76.2	2.5	9.3	0.0
	26.0	-36.2	76.2	2.5	9.3	
2009-2019	2.9	0.7	0.0	0.7	1.5	0.0
	2.9	0.7	0.0	0.7	1.5	
Brazil						
1999-2009	26.5	4.5	3.6	4.7	8.5	2.8
	26.5	3.2	7.5	4.7	8.8	
2009-2019	11.3	-16.0	3.4	7.1	13.8	5.1
	11.3	-18.9	11.8	4.7	17.1	
Canada						
1999-2009	8.8	-13.3	6.1	1.3	13.2	3.2
	8.8	-10.0	6.0	1.3	12.6	
2009-2019	14.1	-4.8	3.4	0.4	13.8	1.4
	14.1	-5.1	5.3	0.4	13.6	
China						
1999-2009	120.3	-7.2	2.2	0.6	113.0	8.4
	120.3	-7.2	2.3	0.5	130.9	
2009-2019	59.8	-25.2	0.2	0.3	109.2	1.6
	59.8	-25.2	0.3	0.3	112.3	
Czech Republic						
1999-2009	42.4	17.9	6.8	1.3	4.9	6.4
	42.4	20.7	8.9	0.8	7.5	
2009-2019	19.2	15.2	3.8	0.2	-2.2	1.7
	19.2	15.2	5.4	0.3	-2.2	

Table B5a (continued)
Country-specific results of sensitivity analysis for subperiods 1999-2009 and 2009-2019, with and without robot capital as separate production factor

Country/ Subperiod	Productivity Change	(EFF-1) × 100	(TECH-1) × 100	(HACC-1) × 100	(KACC-1) × 100	(RKACC-1) × 100
Denmark						
1999-2009	32.6	-14.8	30.2	2.5	16.4	0.3
	32.6	-14.8	30.7	2.6	16.2	
2009-2019	21.0	9.1	1.4	0.8	8.4	0.0
	21.0	9.1	1.4	0.8	8.4	
Finland						
1999-2009	19.4	-9.7	16.8	3.8	9.1	0.0
	19.4	-9.7	16.8	3.8	9.1	
2009-2019	6.3	-5.9	3.0	0.9	8.4	0.3
	6.3	-5.9	3.3	1.1	8.3	
France						
1999-2009	18.9	-35.3	63.6	3.1	9.0	0.0
	18.9	-35.3	63.6	3.1	9.0	
2009-2019	13.4	2.5	0.2	1.6	8.6	0.0
	13.4	2.5	0.2	1.6	8.6	
Germany						
1999-2009	19.7	-11.6	21.8	1.5	9.5	0.0
	19.7	-11.6	21.8	1.5	9.5	
2009-2019	11.8	6.6	2.7	0.2	2.0	0.0
	11.8	6.6	2.7	0.2	2.0	
Greece						
1999-2009	22.7	-16.8	2.1	5.6	0.3	36.4
	22.7	-15.8	30.2	4.4	7.2	
2009-2019	-6.0	-44.3	0.0	4.1	0.3	61.4
	-6.0	-15.6	2.4	1.3	7.2	
Hungary						
1999-2009	63.0	0.0	1.9	3.2	27.8	21.2
	63.0	0.7	5.4	3.3	48.7	
2009-2019	8.1	2.3	4.7	1.1	-3.1	3.1
	8.1	3.4	6.7	1.2	-3.1	
India						
1999-2009	92.6	-8.9	0.4	2.1	50.0	37.5
	92.6	-5.5	3.3	0.6	96.2	
2009-2019	74.2	-3.9	0.0	0.5	71.6	5.1
	74.2	-0.9	0.3	0.3	74.7	
Israel						
1999-2009	-4.6	-4.1	2.1	2.7	-9.1	4.3
	-4.6	-0.1	5.0	1.2	-10.1	
2009-2019	15.2	-1.9	3.0	2.5	7.1	4.0
	15.2	-4.5	9.4	3.0	7.0	

Table B5a (continued)
Country-specific results of sensitivity analysis for subperiods 1999-2009 and 2009-2019, with and without robot capital as separate production factor

Country/ Subperiod	Productivity Change	(EFF-1) × 100	(TECH-1) × 100	(HACC-1) × 100	(KACC-1) × 100	(RKACC-1) × 100
Italy						
1999-2009	7.7	-45.6	74.0	4.5	8.8	0.0
	7.7	-45.6	74.0	4.5	8.8	
2009-2019	9.6	0.6	0.0	2.4	6.4	0.0
	9.6	0.6	0.0	2.4	6.4	
Japan						
1999-2009	9.7	-8.5	9.2	1.3	8.3	0.0
	9.7	-8.5	9.2	1.3	8.3	
2009-2019	1.1	3.2	5.5	0.8	-7.8	0.0
	1.1	3.2	5.5	0.8	-7.8	
Malaysia						
1999-2009	56.0	13.6	5.8	2.5	24.9	1.4
	56.0	12.7	7.5	2.6	25.5	
2009-2019	18.8	-2.0	5.9	1.9	8.1	3.9
	18.8	-2.5	10.1	2.3	8.1	
Mexico						
1999-2009	18.1	-10.0	3.1	1.8	21.3	3.2
	18.1	-10.9	6.7	1.8	22.0	
2009-2019	3.2	-6.2	5.2	1.8	-2.0	4.8
	3.2	-6.3	10.0	2.2	-2.0	
Netherlands						
1999-2009	27.9	-18.9	36.8	2.3	10.5	1.9
	27.9	-18.9	37.6	2.4	11.9	
2009-2019	5.0	2.0	1.3	0.6	0.6	0.4
	5.0	2.0	1.6	0.7	0.6	
Norway						
1999-2009	75.6	-7.2	38.3	3.7	17.2	12.4
	75.6	-7.2	40.3	3.9	29.8	
2009-2019	-5.4	-8.0	0.1	0.4	2.0	0.2
	-5.4	-7.9	0.2	0.5	2.0	
Poland						
1999-2009	39.4	0.0	5.6	1.6	24.9	4.0
	39.4	0.0	8.9	1.0	26.7	
2009-2019	46.5	0.0	6.7	1.3	31.8	2.8
	46.5	0.0	7.1	1.2	35.2	
Portugal						
1999-2009	22.6	-33.9	44.4	4.1	7.9	14.3
	22.6	-33.9	54.8	3.2	16.1	
2009-2019	13.0	5.4	0.3	1.2	5.5	0.1
	13.0	5.4	0.3	1.4	5.4	

Table B5a (continued)
Country-specific results of sensitivity analysis for subperiods 1999-2009 and 2009-2019, with and without robot capital as separate production factor

Country/ Subperiod	Productivity Change	(EFF-1) × 100	(TECH-1) × 100	(HACC-1) × 100	(KACC-1) × 100	(RKACC-1) × 100
Rep. of Korea						
1999-2009	51.6	0.0	5.4	1.8	41.4	0.0
	51.6	0.0	5.4	1.8	41.4	
2009-2019	26.2	-3.7	6.9	2.1	20.0	0.0
	26.2	-3.7	6.9	2.1	20.0	
Russian Fed.						
1999-2009	120.0	80.0	0.7	1.4	20.3	-0.5
	120.0	68.0	6.8	1.3	21.2	
2009-2019	33.4	12.3	0.1	1.0	10.0	6.8
	33.4	7.7	9.1	1.3	12.1	
Singapore						
1999-2009	64.4	11.5	5.8	3.5	34.6	0.0
	64.4	11.5	5.8	3.5	34.6	
2009-2019	36.6	-4.7	4.4	8.3	24.2	2.1
	36.6	-4.7	6.1	8.8	24.2	
Slovakia						
1999-2009	48.5	23.1	4.1	3.1	8.5	3.6
	48.5	27.8	4.1	3.2	8.2	
2090-2019	6.4	3.3	4.9	1.5	-5.7	2.5
	6.4	3.8	7.0	1.6	-5.7	
Slovenia						
1999-2009	24.3	-8.5	20.4	2.3	4.4	5.6
	24.3	-7.7	22.1	2.2	8.0	
2009-2019	17.7	12.5	2.5	1.0	0.3	0.8
	17.7	12.5	3.2	1.2	0.3	
Spain						
1999-2009	23.2	-25.1	40.0	3.7	13.3	0.0
	23.2	-25.1	40.0	3.7	13.3	
2009-2019	16.9	1.0	1.0	1.1	13.4	0.0
	16.9	1.0	1.0	1.1	13.4	
Sweden						
1999-2009	21.1	-21.9	46.4	2.7	3.1	0.0
	21.1	-21.9	46.4	2.7	3.1	
2009-2019	14.4	12.1	1.8	0.6	-0.3	0.0
	14.4	12.1	1.8	0.6	-0.3	
Switzerland						
1999-2009	35.4	-9.7	33.0	1.6	10.8	0.1
	35.4	-9.7	33.2	1.7	10.7	
2009-2019	22.7	8.9	1.1	0.3	10.9	0.2
	22.7	8.9	1.4	0.4	10.7	

Table B5a (continued)
Country-specific results of sensitivity analysis for subperiods 1999-2009 and 2009-2019, with and without robot capital as separate production factor

Country/ Subperiod	Productivity Change	(EFF-1) × 100	(TECH-1) × 100	(HACC-1) × 100	(KACC-1) × 100	(RKACC-1) × 100
Taiwan						
1999-2009	15.8	-2.0	7.2	3.6	5.8	0.6
	15.8	-2.0	7.7	3.7	5.8	
2009-2019	9.9	7.0	6.3	2.0	-5.3	0.0
	9.9	7.0	6.3	2.0	-5.3	
Turkey						
1999-2009	61.3	-8.9	3.1	2.9	34.7	23.9
	61.3	-10.0	6.8	3.6	62.0	
2009-2019	40.3	-4.2	1.1	2.2	29.9	9.2
	40.3	-3.1	4.8	2.7	34.5	
United Kingdom						
1999-2009	14.2	-6.4	7.8	2.3	10.5	0.2
	14.2	-7.4	9.2	2.4	10.3	
2009-2019	12.3	2.6	1.7	0.4	5.8	1.2
	12.3	1.1	4.8	0.6	5.5	
United States						
1999-2009	23.5	-3.8	5.6	1.0	19.8	0.6
	23.5	-3.8	6.2	1.0	19.8	
2009-2019	11.1	4.0	3.9	0.3	0.8	1.7
	11.1	4.0	5.6	0.4	0.8	

Table B5b
Country-specific results of sensitivity analysis for various measures of robot stocks, period 1999-2019

Country (Prod. Ch. in %)/ Robot Capital Measure	(EFF-1) × 100	(TECH-1) × 100	(HACC-1) × 100	(KACC-1) × 100	(RKACC-1) × 100
Argentina (Prod. Ch. = 40.5)					
OHS depr., qual. ch. adj.	-10.8	6.5	3.0	33.5	7.6
PIM 5 %, qual. ch. adj.	-10.8	6.4	2.8	33.7	7.7
PIM 10 %, qual. ch. adj.	-10.8	6.4	2.9	33.6	7.6
PIM 15 %, **not** qual. ch. adj.	-10.3	6.2	2.4	32.9	8.5
Australia (Prod. Ch. = 35.8)					
OHS depr., qual. ch. adj.	-4.3	11.9	0.4	22.6	3.1
PIM 5 %, qual. ch. adj.	-4.8	12.1	0.4	22.1	3.8
PIM 10 %, qual. ch. adj.	-4.4	11.9	0.4	22.9	3.0
PIM 15 %, **not** qual. ch. adj.	-4.0	12.9	0.4	22.9	1.6
Austria (Prod. Ch. = 50.2)					
OHS depr., qual. ch. adj.	-17.3	47.1	5.1	16.4	0.9
PIM 5 %, qual. ch. adj.	-17.3	47.0	5.1	16.3	1.0
PIM 10 %, qual. ch. adj.	-17.3	47.0	5.1	16.4	1.0
PIM 15 %, not qual. ch. adj.	-17.3	47.7	5.2	16.2	0.6
Belgium (Prod. Ch. = 29.7)					
OHS depr., qual. ch. adj.	-35.7	77.1	3.8	9.7	0.0
PIM 5 %, qual. ch. adj.	-35.7	77.1	3.7	9.8	0.0
PIM 10 %, qual. ch. adj.	-35.7	77.1	3.8	9.7	0.0
PIM 15 %, **not** qual. ch. adj.	-35.7	77.1	3.8	9.7	0.0
Brazil (Prod. Ch. = 40.7)					
OHS depr., qual. ch. adj.	-12.5	8.3	10.5	25.7	6.8
PIM 5 %, qual. ch. adj.	-12.5	8.3	10.0	25.9	7.2
PIM 10 %, qual. ch. adj.	-12.3	8.2	10.4	25.7	6.9
PIM 15 %, **not** qual. ch. adj.	-11.8	8.4	10.7	25.2	6.3
Canada (Prod. Ch. = 24.1)					
OHS depr., qual. ch. adj.	-17.4	9.9	3.6	22.4	7.8
PIM 5 %, qual. ch. adj.	-17.6	10.0	3.6	21.2	9.0
PIM 10 %, qual. ch. adj.	-17.5	10.1	3.6	22.4	7.8
PIM 15 %, **not** qual. ch. adj.	-17.6	11.3	3.6	22.5	6.7
China (Prod. Ch. = 252.2)					
OHS depr., qual. ch. adj.	-30.5	4.0	3.1	237.9	39.9
PIM 5 %, qual. ch. adj.	-30.5	4.0	3.1	232.0	42.4
PIM 10 %, qual. ch. adj.	-30.5	4.0	3.1	233.4	41.8
PIM 15 %, **not** qual. ch. adj.	-30.5	4.1	3.1	214.2	50.4

Abbreviations: Prod. Ch.: Productivity change; OHS depr.: one-hoss-shay depreciation; qual. ch. adj.: quality change adjusted; PIM 5 % (resp., 10 %, 15 %): permanent inventory method with δ=5 % (resp., 10 %, 15 %).

Table B5b (continued)

Country-specific results of sensitivity analysis for various measures of robot stocks, period 1999-2019

Country (Prod. Ch. in %)/ Robot Capital Measure	(EFF-1) × 100	(TECH-1) × 100	(HACC-1) × 100	(KACC-1) × 100	(RKACC-1) × 100
Czech Rep. (Prod. Ch. = 69.7)					
OHS depr., qual. ch. adj.	30.5	9.5	2.0	2.6	13.5
PIM 5 %, qual. ch. adj.	28.2	8.3	2.1	2.6	16.6
PIM 10 %, qual. ch. adj.	34.0	8.2	2.0	2.9	11.5
PIM 15 %, **not** qual. ch. adj.	26.7	14.4	1.1	4.0	11.4
Denmark (Prod. Ch. = 60.5)					
OHS depr., qual. ch. adj.	-7.1	34.5	5.6	19.7	1.6
PIM 5 %, qual. ch. adj.	-7.1	34.5	5.6	19.6	1.6
PIM 10 %, qual. ch. adj.	-7.1	34.6	5.6	19.7	1.4
PIM 15 %, **not** qual. ch. adj.	-7.1	35.2	5.6	19.6	1.1
Finland (Prod. Ch. = 27.0)					
OHS depr., qual. ch. adj.	-15.1	21.9	7.3	12.8	1.4
PIM 5 %, qual. ch. adj.	-15.1	21.9	7.3	12.8	1.4
PIM 10 %, qual. ch. adj.	-15.1	21.9	7.3	12.8	1.4
PIM 15 %, not qual. ch. adj.	-15.1	22.9	7.4	12.6	0.6
France (Prod. Ch. = 34.8)					
OHS depr., qual. ch. adj.	-33.7	67.3	6.7	13.4	0.4
PIM 5 %, qual. ch. adj.	-33.7	67.3	6.7	13.4	0.4
PIM 10 %, qual. ch. adj.	-33.7	67.3	6.7	13.4	0.4
PIM 15 %, **not** qual. ch. adj.	-33.7	68.0	6.8	13.1	0.2
Germany (Prod. Ch. = 33.8)					
OHS depr., qual. ch. adj.	-5.7	26.2	2.1	9.7	0.4
PIM 5 %, qual. ch. adj.	-5.7	26.1	2.1	9.7	0.5
PIM 10 %, qual. ch. adj.	-5.7	26.2	2.1	9.7	0.4
PIM 15 %, **not** qual. ch. adj.	-5.7	27.0	2.2	9.4	0.0
Greece (Prod. Ch. = 15.3)					
OHS depr., qual. ch. adj.	-53.2	12.5	14.5	3.9	84.3
PIM 5 %, qual. ch. adj.	-51.7	10.6	14.3	2.9	83.6
PIM 10 %, qual. ch. adj.	-52.9	11.8	13.9	3.4	85.7
PIM 15 %, **not** qual. ch. adj.	-45.8	15.2	8.9	1.5	66.9
Hungary (Prod. Ch. = 76.2)					
OHS depr., qual. ch. adj.	2.5	5.7	4.5	28.9	20.7
PIM 5 %, qual. ch. adj.	2.4	5.6	4.4	28.0	21.8
PIM 10 %, qual. ch. adj.	2.4	5.5	4.4	27.0	22.9
PIM 15 %, **not** qual. ch. adj.	2.4	5.7	4.4	27.1	22.8

Abbreviations: Prod. Ch.: Productivity change; OHS depr.: one-hoss-shay depreciation; qual. ch. adj.: quality change adjusted; PIM 5 % (resp., 10 %, 15 %): permanent inventory method with δ=5 % (resp., 10 %, 15 %).

Table B5b (continued)
Country-specific results of sensitivity analysis for various measures of robot stocks, period 1999-2019

Country (Prod. Ch. in %)/ Robot Capital Measure	(EFF-1) × 100	(TECH-1) × 100	(HACC-1) × 100	(KACC-1) × 100	(RKACC-1) × 100
India (Prod. Ch. = 235.4)					
OHS depr., qual. ch. adj.	-12.1	2.6	6.3	111.5	65.3
PIM 5 %, qual. ch. adj.	-12.2	2.6	6.3	103.9	71.7
PIM 10 %, qual. ch. adj.	-12.3	2.6	6.4	101.7	73.7
PIM 15 %, **not** qual. ch. adj.	-16.7	1.8	9.5	91.4	88.8
Israel (Prod. Ch. = 9.9)					
OHS depr., qual. ch. adj.	-7.3	6.1	4.9	-2.1	8.8
PIM 5 %, qual. ch. adj.	-8.2	5.8	5.6	-2.1	9.3
PIM 10 %, qual. ch. adj.	-7.0	5.6	5.1	-2.2	8.8
PIM 15 %, **not** qual. ch. adj.	-9.0	8.5	3.6	-2.1	9.7
Italy (Prod. Ch. = 18.0)					
OHS depr., qual. ch. adj.	-45.3	76.9	8.5	12.3	0.1
PIM 5 %, qual. ch. adj.	-45.3	76.9	8.4	12.3	0.1
PIM 10 %, qual. ch. adj.	-45.3	76.9	8.5	12.3	0.1
PIM 15 %, not qual. ch. adj.	-45.3	76.9	8.7	12.2	0.0
Japan (Prod. Ch. = 10.9)					
OHS depr., qual. ch. adj.	-5.6	13.9	2.4	0.6	0.0
PIM 5 %, qual. ch. adj.	-5.5	13.9	2.4	0.6	0.0
PIM 10 %, qual. ch. adj.	-5.6	13.9	2.4	0.6	0.0
PIM 15 %, **not** qual. ch. adj.	-5.6	13.9	2.4	0.6	0.0
Malaysia (Prod. Ch. = 85.3)					
OHS depr., qual. ch. adj.	11.1	11.5	4.2	36.6	5.0
PIM 5 %, qual. ch. adj.	10.9	11.2	4.2	36.7	5.4
PIM 10 %, qual. ch. adj.	11.1	11.0	4.3	36.7	5.4
PIM 15 %, **not** qual. ch. adj.	11.3	12.9	3.9	36.5	3.9
Mexico (Prod. Ch. = 21.9)					
OHS depr., qual. ch. adj.	-15.8	8.8	3.5	18.3	8.6
PIM 5 %, qual. ch. adj.	-15.7	8.8	3.4	18.3	8.6
PIM 10 %, qual. ch. adj.	-15.7	8.8	3.5	18.3	8.6
PIM 15 %, **not** qual. ch. adj.	-15.6	9.2	3.4	18.2	8.2
Netherlands (Prd. Ch. = 34.4)					
OHS depr., qual. ch. adj.	-17.2	35.8	4.8	9.3	4.3
PIM 5 %, qual. ch. adj.	-17.2	35.6	4.8	8.2	5.5
PIM 10 %, qual. ch. adj.	-17.2	35.9	4.8	9.4	4.2
PIM 15 %, **not** qual. ch. adj.	-17.2	36.9	4.9	11.4	1.4

Abbreviations: Prod. Ch.: Productivity change; OHS depr.: one-hoss-shay depreciation; qual. ch. adj.: quality change adjusted; PIM 5 % (resp., 10 %, 15 %): permanent inventory method with δ=5 % (resp., 10 %, 15 %).

Table B5b (continued)

Country-specific results of sensitivity analysis for various measures of robot stocks, period 1999-2019

Country (Prod. Ch. in %)/ Robot Capital Measure	(EFF-1) × 100	(TECH-1) × 100	(HACC-1) × 100	(KACC-1) × 100	(RKACC-1) × 100
Norway (Prod. Ch. = 66.0)					
OHS depr., qual. ch. adj.	-14.6	37.6	5.7	16.1	15.1
PIM 5 %, qual. ch. adj.	-14.6	38.1	5.7	16.9	14.0
PIM 10 %, qual. ch. adj.	-14.6	38.0	5.6	17.1	13.8
PIM 15 %, **not** qual. ch. adj.	-14.6	39.2	5.7	24.6	6.0
Poland (Prod. Ch. = 104.1)					
OHS depr., qual. ch. adj.	0.0	10.2	2.4	69.6	6.7
PIM 5 %, qual. ch. adj.	0.0	10.4	2.3	69.7	6.5
PIM 10 %, qual. ch. adj.	0.0	10.3	2.3	69.6	6.6
PIM 15 %, **not** qual. ch. adj.	0.0	10.2	2.2	69.7	6.7
Portugal (Prod. Ch. = 38.6)					
OHS depr., qual. ch. adj.	-30.3	42.6	10.2	8.4	16.7
PIM 5 %, qual. ch. adj.	-31.2	38.9	10.4	8.5	21.1
PIM 10 %, qual. ch. adj.	-30.5	41.8	10.1	8.6	17.6
PIM 15 %, not qual. ch. adj.	-30.4	52.7	7.8	12.9	7.1
Rep. Korea (Prd. Ch. = 91.3)					
OHS depr., qual. ch. adj.	-3.6	12.9	6.8	61.8	1.8
PIM 5 %, qual. ch. adj.	-3.6	12.7	6.8	61.8	1.9
PIM 10 %, qual. ch. adj.	-3.6	12.7	6.8	61.9	1.9
PIM 15 %, **not** qual. ch. adj.	-3.6	14.4	7.2	61.3	0.4
Russia (Prod. Ch. = 193.5)					
OHS depr., qual. ch. adj.	102.2	2.0	2.6	33.3	4.0
PIM 5 %, qual. ch. adj.	100.6	4.4	2.4	34.7	1.6
PIM 10 %, qual. ch. adj.	102.2	2.8	2.6	34.7	2.2
PIM 15 %, **not** qual. ch. adj.	105.9	3.3	2.9	33.9	0.1
Singapore (Prod. Ch. = 124.5)					
OHS depr., qual. ch. adj.	6.3	11.6	27.4	47.1	1.1
PIM 5 %, qual. ch. adj.	6.2	11.5	27.5	47.1	1.1
PIM 10 %, qual. ch. adj.	6.3	11.5	27.4	47.1	1.1
PIM 15 %, **not** qual. ch. adj.	6.3	11.9	28.1	47.3	0.0
Slovakia (Prd. Ch. = 58.0)					
OHS depr., qual. ch. adj.	27.7	8.2	3.7	2.6	7.4
PIM 5 %, qual. ch. adj.	27.6	8.3	3.7	2.6	7.4
PIM 10 %, qual. ch. adj.	27.4	8.2	3.7	2.6	7.7
PIM 15 %, **not** qual. ch. adj.	27.2	9.5	3.7	2.6	6.6

Abbreviations: Prod. Ch.: Productivity change; OHS depr.: one-hoss-shay depreciation; qual. ch. adj.: quality change adjusted; PIM 5 % (resp., 10 %, 15 %): permanent inventory method with δ=5 % (resp., 10 %, 15 %).

Table B5b (continued)

Country-specific results of sensitivity analysis for various measures of robot stocks, period 1999-2019

Country (Prod. Ch. in %)/ Robot Capital Measure	(EFF-1) × 100	(TECH-1) × 100	(HACC-1) × 100	(KACC-1) × 100	(RKACC-1) × 100
Slovenia (Prod. Ch. = 46.3)					
OHS depr., qual. ch. adj.	3.8	19.7	5.6	6.6	4.6
PIM 5 %, qual. ch. adj.	2.6	18.9	6.5	4.1	8.1
PIM 10 %, qual. ch. adj.	2.9	19.6	5.8	4.5	7.5
PIM 15 %, **not** qual. ch. adj.	3.8	20.6	5.6	7.4	3.0
Spain (Prod. Ch. = 44.1)					
OHS depr., qual. ch. adj.	-24.3	46.2	8.0	19.5	0.9
PIM 5 %, qual. ch. adj.	-24.3	46.2	8.0	19.5	1.0
PIM 10 %, qual. ch. adj.	-24.3	46.3	7.9	19.5	0.9
PIM 15 %, **not** qual. ch. adj.	-24.3	47.1	8.0	19.2	0.5
Sweden (Prod. Ch. = 38.6)					
OHS depr., qual. ch. adj.	-12.4	46.5	4.6	2.7	0.5
PIM 5 %, qual. ch. adj.	-12.4	46.5	4.6	2.7	0.5
PIM 10 %, qual. ch. adj.	-12.4	46.5	4.6	2.7	0.5
PIM 15 %, not qual. ch. adj.	-12.4	47.0	4.9	2.6	0.0
Switzerland (Prd. Ch. = 66.1)					
OHS depr., qual. ch. adj.	-1.7	40.5	3.0	15.7	0.9
PIM 5 %, qual. ch. adj.	-1.7	40.5	3.0	15.7	1.0
PIM 10 %, qual. ch. adj.	-1.7	40.5	3.0	15.7	1.0
PIM 15 %, **not** qual. ch. adj.	-1.7	41.3	3.0	15.5	0.5
Taiwan (Prod. Ch. = 27.3)					
OHS depr., qual. ch. adj.	4.9	9.9	6.9	0.7	2.5
PIM 5 %, qual. ch. adj.	4.9	9.9	6.9	0.7	2.6
PIM 10 %, qual. ch. adj.	4.9	9.9	6.9	0.7	2.6
PIM 15 %, **not** qual. ch. adj.	4.9	10.6	6.9	0.7	1.9
Turkey (Prod. Ch. = 126.3)					
OHS depr., qual. ch. adj.	-12.7	10.4	16.5	46.3	37.7
PIM 5 %, qual. ch. adj.	-12.7	10.3	16.5	46.4	37.7
PIM 10 %, qual. ch. adj.	-12.7	10.4	16.6	47.0	37.1
PIM 15 %, **not** qual. ch. adj.	-12.5	10.3	16.5	47.7	36.3
U. Kingdom (Prd. Ch. = 28.3)					
OHS depr., qual. ch. adj.	-4.1	10.9	4.9	13.1	1.7
PIM 5 %, qual. ch. adj.	-4.3	11.1	4.9	13.1	1.8
PIM 10 %, qual. ch. adj.	-4.1	11.0	4.9	13.2	1.6
PIM 15 %, **not** qual. ch. adj.	-3.6	11.4	5.1	13.1	0.6

Abbreviations: Prod. Ch.: Productivity change; OHS depr.: one-hoss-shay depreciation; qual. ch. adj.: quality change adjusted; PIM 5 % (resp., 10 %, 15 %): permanent inventory method with δ=5 % (resp., 10 %, 15 %).

Table B5b (continued)

Country-specific results of sensitivity analysis for various measures of robot stocks, period 1999-2019

Country (Prod. Ch. in %)/ Robot Capital Measure	(EFF-1) × 100	(TECH-1) × 100	(HACC-1) × 100	(KACC-1) × 100	(RKACC-1) × 100
Un. States (Prd. Ch. = 37.2)					
OHS depr., qual. ch. adj.	0.0	9.8	1.6	19.9	2.6
PIM 5 %, qual. ch. adj.	0.0	9.8	1.6	19.9	2.6
PIM 10 %, qual. ch. adj.	0.0	9.8	1.6	19.9	2.6
PIM 15 %, **not** qual. ch. adj.	0.0	10.5	1.6	19.8	2.1

Abbreviations: Prod. Ch.: Productivity change; OHS depr.: one-hoss-shay depreciation; qual. ch. adj.: quality change adjusted; PIM 5 % (resp., 10 %, 15 %): permanent inventory method with δ=5 % (resp., 10 %, 15 %).