Journal of Productivity Analysis (2024) 61:157–181
https://doi.org/10.1007/s11123-023-00707-x

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

Andreas Eder[1,2] · Wolfgang Koller[1] · Bernhard Mahlberg[1,3]

Accepted: 29 September 2023 / Published online: 1 December 2023

Abstract

This paper investigates the contribution of industrial robots to labor productivity growth and cross-country economic convergence in a sample of 19 developed and 16 emerging countries over 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. We find a positive contribution of robotization to labor productivity growth for all countries in our sample. In the period after the financial crisis (2009 to 2019) the contribution of robot capital deepening to productivity growth gained in importance. Over the period 1999 to 2019 we find some evidence of i) unconditional β-convergence (countries with lower initial productivity levels grow faster), 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 in our sample. Accumulation of 'traditional' physical capital is the main driver of β-convergence. Robot capital deepening significantly contributed to economic convergence and the depolarization of the labor productivity distribution, but its effect on the entire shift of the labor productivity distribution is modest and dominated by other drivers of productivity growth such as 'traditional' physical capital deepening and technological change.

Keywords Automation · Robotization · Decomposition · Data envelopment analysis · Emerging countries · Developed countries

JEL Classification E24 · O33 · O47

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 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. 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

✉ Andreas Eder
andreas.eder@boku.ac.at

1 Institute for Industrial Research, Mittersteig 10/4, 1050 Vienna, Austria

2 Department of Economics and Social Sciences, Institute of Sustainable Economic Development, University of Natural Resources and Life Sciences, Vienna, Feistmantelstrasse 4, 1180 Vienna, Austria

3 Vienna University of Economics and Business, Welthandelsplatz 1, 1020 Vienna, Austria

is known about i) how the contribution of industrial robots to labor productivity growth differs across countries[1], and ii) if the worldwide diffusion of industrial robots contributes to a widening or closing of the productivity gap between rich and poorer economies. 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).

We aim to fill these gaps in the literature by investigating whether and how the contribution of robot adoption to labor productivity growth differs across a sample of 19 developed and 17 emerging countries over the period 1999–2019, and the subperiods before (1999–2009) and after (2009–2019) the financial crisis. To the best of our knowledge, this is the first study analyzing to what extent the worldwide diffusion of industrial robots contributed to the cross-country convergence of labor productivity levels.

The rise of robots in emerging markets in the last 20 years is remarkable. While in developed countries (e.g., Germany, Japan, USA) the use of industrial robots started to climb exponentially in the 1980s, at the beginning 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, respectively, but only by 6% in the United States, and 5% in Western Europe (Müller and Kutzbach 2020).[2] 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 productivity levels.

This article links three different strands of important literature: i) the non-parametric frontier production function literature based on the pioneering work of Farrell (1957), ii) the work on the sources of cross-country economic growth and international macroeconomic convergence (for a review of the literature see Johnson and Papageorgiou (2020), and iii) the literature on automation and economic growth. Regarding the latter there is no consensus in the theoretical literature on how automation should be modelled. The approaches can broadly be grouped into three categories: a) modelling automation as capital-augmenting technological change (Sachs and Kotlifkoff 2012; Nordhaus 2015), labor-augmenting technological change (Bessen 2017) or Hicks neutral technological change; b) differentiating between traditional capital and automation capital, both entering the production function as factor inputs, and regarding automation capital as a perfect substitute for (low-skilled) labor (Steigum 2011; Prettner 2019; Anthony and Klarl 2020; Gasteiger and Prettner 2022); c) the task-based approach to modelling automation advocated by Acemoglu and Restrepo (2018a, 2018b), which originates from the ideas of Zeira (1998).

Despite this theoretical effort and the empirical regression-based studies, not much has been done to model empirically the country-specific contributions of industrial robots—probably one of the most advanced areas of automation—to economic growth and their role in cross-country convergence dynamics. An exception is Cette et al. (2021a, 2021b) applying 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.

We advocate a refinement of the (deterministic) non-parametric production frontier approach introduced by Kumar and Russell (2002), and further developed by Henderson and Russell (2005), Badunenko and Romero-Ávila (2013), Walheer (2021) and others to investigate the contribution of automation capital to labor productivity growth and convergence. Our modelling approach extends the Henderson and Russell (2005) framework by differentiating between traditional physical capital (non-robot capital) and robot capital[3], both entering the production model as separate input factors. While the application of Ceccobelli et al. (2012) differentiates between ICT and non-ICT capital, to the best of our knowledge, we are the first that incorporate industrial robots into a production frontier framework. The estimation of the production frontier is based

[1] 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. Graetz and Michaels (2018) find diminishing marginal gains from increased robot usage. Hence, we can expect that the initial level of the robot stock 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. 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. Third, some macroeconomic growth models analyzing the consequences of automation predict that automation capital enables perpetual long-run growth and that the constant growth rate of GDP per worker in the balanced growth path increases with the share of savings devoted to the accumulation of automation capital (Prettner 2019; Jungmittag 2021).

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

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

on linear programming techniques known as Data Envelopment Analysis (DEA). A multiplicative decomposition of labor productivity growth into five components representing the contribution of technological change, efficiency change, human capital accumulation, non-robot physical capital deepening, and robot capital deepening to labor productivity growth is applied. The effect of these proximate sources of economic growth on the entire shift of the labor productivity distribution over the period under investigation and the convergence dynamics is analyzed by standard regression models, counterfactual analyses and statistical tests.

The advantage of this approach over theoretical macroeconomic models and 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 substitution and complementarity relationships among the inputs, the existence of perfectly competitive markets and Hicks-neutral technological change. 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).

It is well known that slacks, or zero multipliers, in radial DEA models can lead to an overestimation of efficiency scores. So far, the many authors applying and extending the decomposition analysis introduced by Kumar and Russell (2002) ignored the problem of non-zero slacks. Following Portela and Thanassoulis (2006) we provide a solution to this problem by extending existing facets of the production frontier and projecting inefficient observations on (observed or extended) facets with well-defined marginal rates of substitution/transformation only. We find that if slacks are pervasive, ignoring them in the decomposition analysis can produce misleading results.

The remainder of this article is organized as follows: Section 2 describes the data and the construction of the robot capital stocks, and provides some descriptive statistics on the development of robot intensities (i.e., the robot-labor ratio) of selected countries over 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 35 countries analyzed. Section 4 presents the results of the decomposition of productivity growth into its five components and the β-convergence analysis. Section 5 assesses the relative importance of the five growth factors in shifting the entire productivity distribution and their contribution to σ-convergence.[4] 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. The selection of our sample of a balanced panel of 35 developed and emerging countries for the period 1995–2019 with a total of 875 observations is mainly driven by the availability of data on industrial robot installations.[5] 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 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 due to incomplete data on average annual hours worked by persons engaged in PWT 10.0 (missing for 1993–2000 and 2015) and Greece, based on an overall evaluation of data quality and outlier analysis.

The final decision on the sample is guided also by outlier analyses and profited from suggestions by two anonymous reviewers. On the one hand, outlier analysis is based on

[4] Due to our endeavor to enhance comparability of methods and results we have accepted that Sections 3, 4 and 5, in particular, are structured similarly to corresponding parts in several other studies employing the productivity frontier approach, such as Badunenko et al. (2013) or Meng et al. (2023).

[5] Though, we have data for the period 1995 to 2019, the period of investigation throughout Sections 3 to 6 is 1999–2019. The reasons for this are methodological considerations which are explained in Section 3.1.

visual inspection of time series plots of variables and their ratios for every country considering available documentation and further information. In the case of Greece this reveals the exceptional pattern of the evolution of labor productivity, which shows a steep increase before 2008, followed by a long period of decline. We take this as a possible indication of unreliable data before 2008. We also apply a method of outlier detection tailored for DEA based on super-efficiency scores as suggested by Banker and Gifford (1988) and Banker et al. (1989); for a performance evaluation of this method see Banker and Chang (2006) and Banker et al. (2017). We calculate super-efficiency scores for all observations enveloped by the 1999 and 2019 production frontier, respectively. Super-efficiency scores above 1.1, classified as outliers, are only found for some observations on Greece and China. Since a sensitivity analysis of the results document considerable dependence on the inclusion of Greece, but not of China, we decided to exclude the first but include the latter. A sensitivity analysis of the results regarding the exclusion of China from the sample is provided in Section 6.3.

Our final sample spans the time period 1995–2019 and 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 35 countries in our sample are developed countries, and 16 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 16 emerging countries are Argentina, Brazil, China, Czech Republic, 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.[6] 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 $RGDP^{O}$.[7]

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% 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.

6 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.

7 The superscript NA indicates national-accounts based variables. The superscript O is used for output-side real GDP as opposed to expenditures-side real GDP denoted with superscript E in PWT 10.0. For details, please see https://www.rug.nl/ggdc/productivity/pwt/pwt-releases/pwt100.

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 35 countries in our sample. These figures also reveal how the initial robot stock varies according to the four different methods applied. We derive monetary robot capital stocks in constant prices (of the base year and country) by multiplying the robot stock in physical units by the average unit price of robots in the United States in 2017 and use the monetary robot capital stock only for the calculation of monetary non-robot capital stock as mentioned before in Section 2.3.

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

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	7527%
3	Singapore*	56.81	Germany*	187.09	Hungary	5872%
4	Belgium*	45.13	Taiwan*	168.62	Poland	3519%
5	Italy*	44.92	Singapore*	148.64	Turkey	2442%
6	Sweden*	42.09	Slovenia	139.36	Czech Rep.	2137%
7	Rep. of Korea	34.12	Czech Rep.	112.40	Slovenia	1626%
8	Finland*	33.64	Slovakia	101.57	Slovakia	1496%
9	Switzerland*	26.46	Italy*	98.32	Mexico	1265%
10	France*	24.16	Sweden*	93.15	Argentina	1171%
⋮	⋮	⋮	⋮	⋮	⋮	⋮
26	Russian Fed.	2.57	UK*	21.01	France*	141%
27	Israel*	1.67	Mexico	19.52	Norway*	129%
28	Mexico	1.43	Norway*	18.77	Sweden*	121%
29	Brazil	1.19	Turkey	16.37	Italy*	119%
30	Hungary	1.03	Israel*	14.64	Finland*	86%
31	Poland	0.78	Australia*	14.17	Australia*	63%
32	Turkey	0.64	Argentina	8.16	UK*	57%
33	Argentina	0.64	Brazil	7.84	Belgium*	49%
34	China	0.06	Russian Fed.	2.69	Japan*	46%
35	India	0.02	India	1.47	Russian Fed	4%

Robot intensity is measured as number of (non-quality-adjusted) robots per one hundred million hours worked. Number of robots are estimated with the perpetual inventory method assuming a depreciation rate of 15%. Developed countries and emerging countries are shown with and without asterisk, respectively 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 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, 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, 32 and 31 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 35 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

We refine the nonparametric Data Envelopment Analysis (DEA) approach used by Kumar and Russell (2002), Henderson and Russell (2005) and followers for constructing the production frontier and associated efficiency levels of individual economies (distances from the frontier). The basic idea is to envelop the data in a 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. 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 refinement of the radial DEA approach guarantees that the production frontier consists of full dimensional efficient facets (FDEF) (Olesen and Petersen 2015) only, which rules out projections of inefficient economies on weakly efficient parts of the frontier. Hence, no inputs are ignored in the efficiency evaluation, i.e., zero weights in the multiplier version and non-zero slacks in the envelopment version of the DEA model are avoided.

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 $\langle Y_{it}, L_{it}, H_{it}, K_{it}, R_{it} \rangle$, $t = 1,2,\ldots,T$, $i = 1,2,\ldots,N$ 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.[8] 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[9] (cf. the definition of robots by the IFR in Section 2), which allows them to replace human workers and normal machines almost completely. Thereby, we follow numerous authors incorporating robot capital as separate production factor into their analytical macroeconomic frameworks (for economic growth models see, e.g., Steigum 2011; Prettner 2019; Lankisch et al. 2019; Krenz et al. 2021; Anthony and Klarl 2020; 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 $\langle Y_{it}, \widehat{L}_{it}, K_{it}, R_{it} \rangle$, $t = 1,2,\ldots,T$, $i = 1,2,\ldots N$, where $\widehat{L}_{it} = L_{it}H_{it}$ is the amount of labor input measured in efficiency units in country i at time t.

[8] 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.

[9] 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.

Following Portela and Thanassoulis (2006) we construct a convex, constant-returns-to-scale (CRS) technology that only allows for trade-offs among inputs, as well as between inputs and outputs, that are observed on full dimensional efficient facets (FDEF) (Olesen and Petersen 2015) of the frontier.[10] Thus, only trade-offs observed in the data are allowed and judgments by experts or the researchers are prevented. The approach modifies the production frontier by extending existing facets and thereby guarantees that countries are projected on FDEF (observed or extended) only, and that no factor of production is ignored in the performance evaluation (i.e., zero weights in the multiplier version, or non-zero slacks in the envelopment version of the DEA model are avoided).

In a first step, we use the R package *Qhull* to identify all $k_t = 1, \ldots, K_t$ FDEF that constitute the efficient frontier in period t and identify the corresponding unique, non-zero DEA inputs and output weights $\langle v_{\hat{L}}^{*F_{k_t}}, v_K^{*F_{k_t}}, v_R^{*F_{k_t}}, u_Y^{*F_{k_t}} \rangle$, where F_{k_t} denotes the k[th] efficient facet of the period t production possibility set. We allow the frontier in period t to include all trade-offs observed in the data up to that point in time. 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 observed trade-offs based on the data for the period 1995–1999 are allowed. 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).

To extend existing facets we simultaneously collect information on input and output optimal weights of the period t frontier in the transformation matrix D_t:

$$D_t = \begin{bmatrix} -v_{\hat{L}}^{*F_{1_t}} & -v_K^{*F_{1_t}} & -v_R^{*F_{1_t}} & u_Y^{*F_{1_t}} \\ \vdots & \vdots & \vdots & \vdots \\ -v_{\hat{L}}^{*F_{K_t}} & -v_K^{*F_{K_t}} & -v_R^{*F_{K_t}} & u_Y^{*F_{K_t}} \end{bmatrix} = \begin{bmatrix} -A_t & B_t \end{bmatrix} \quad (1)$$

When the matrix is applied to the observed data the three inputs and the single output are transformed into K_t 'netputs'. Using these netputs the efficiency score for observation it can be obtained by solving the following envelopment model with K_t constraints, where z_{it} is the vector of inputs and output of observation it, i.e., $z_{it} = \left[X_{it}, Y_{it}\right] = \left[\widehat{L}_{it}, K_{it}, R_{it}, Y_{it}\right]^T$:

$$e_{it} = \min\{e_{it} | \lambda_{it} D_t z_{it} + e_{it} A_t X_{it} \geq B_t Y_{it},\ \ \lambda_{it} \geq 0\} \quad (2)$$

The elements of $D_i Z_{it}$ in (2) are zero for observations lying on a FDEF when CRS is assumed. As referent units necessarily lie on a FDEF, the above reduces to choosing the efficiency scores, e_{it}, for each observation it as the maximum value of the weighted outputs to the weighted inputs ($B_t Y_{it}/A_t X_{it}$). No linear program needs to be solved for this purpose. If we have information regarding the trade-offs applying at the efficient frontier we simply have to find, $e_{it} = \max_{k_t}\left\{\frac{u_Y^{*F_{k_t}} Y_{it}}{v_{\hat{L}}^{*F_{k_t}} \hat{L}_{it} + v_K^{*F_{k_t}} K_{it} + v_R^{*F_{k_t}} R_{it}}\right\}$, by using the optimal weights corresponding to each facet. The efficiency scores provided by the model are radial in relation to the modified frontier (with extended facets), and therefore can be interpreted in the same way as traditional DEA scores (for details see Portela and Thanassoulis 2006). Hence, the efficiency index can be interpreted as the maximal proportional amount that inputs X_{it} can be contracted while remaining technologically feasible. Due to the assumption of CRS $1/e_{it}$ can be interpreted as the maximal proportional amount that output Y_{it} can be expanded while remaining technologically feasible, given the technology and input quantities. e_{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 efficiency index e_{it} 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 35 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. The introduction of robots as separate production factor leaves mean efficiency for 1999 unaltered at 0.73, and slightly reduces mean efficiency from 0.69 to 0.68 in 2019. Considering the country-specific efficiency scores up to two decimal places, we find that the efficiency index in 1999 and 2019 changes for 23 and 28 countries, respectively.[11] Table 2 shows that 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.

[10] Marginal rates of transformation and substitution are well defined only on FDEF, and therefore it is important to assess units relative to projections on facets of this type.

[11] In fact, the introduction of robots changes efficiency scores for all countries (except for those being efficient with and without robots) if more than two decimal places are considered. These differences correspond to our expectations and document the importance of the use of robots for production efficiency of a country.

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	0.68	0.64	0.68	0.61
Belgium	0.70	0.61	0.68	0.58
Brazil	0.69	0.58	0.69	0.61
Canada	0.86	0.74	0.89	0.74
China	0.94	0.65	0.91	0.65
Czech Republic	0.41	0.57	0.42	0.54
Denmark	0.78	0.74	0.77	0.71
Finland	0.82	0.70	0.81	0.69
France	0.75	0.65	0.74	0.63
Germany	0.79	0.75	0.77	0.69
Hungary	0.61	0.63	0.62	0.62
India	0.71	0.67	0.76	0.67
Israel	0.85	0.81	0.89	0.84
Italy	0.69	0.52	0.68	0.49
Japan	0.68	0.64	0.65	0.57
Malaysia	0.59	0.65	0.59	0.65
Mexico	0.73	0.61	0.73	0.62
Netherlands	0.83	0.76	0.83	0.74
Norway	1.00	0.85	1.00	0.85
Poland	1.00	1.00	1.00	1.00
Portugal	0.54	0.44	0.54	0.43
Rep. of Korea	0.66	0.63	0.65	0.50
Russian Federation	0.34	0.62	0.34	0.70
Singapore	0.68	0.73	0.67	0.68
Slovakia	0.46	0.61	0.48	0.58
Slovenia	0.48	0.51	0.48	0.48
Spain	0.74	0.62	0.73	0.60
Sweden	0.66	0.72	0.65	0.69
Switzerland	0.73	0.77	0.72	0.75
Taiwan	0.80	0.84	0.79	0.73
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)	**0.73**	**0.69**	**0.73**	**0.68**

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 0.73 toward lower parts of the distribution. The mean efficiency score declined from 0.73 to 0.68. We observe a decline in efficiency levels for 24 out of the 35 countries. 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, Italy, Spain, and Portugal, plus France. Only seven countries were able to catch-up to the technology leaders: three out of these seven are transition countries in Eastern Europe including Czech Republic, Russian Federation, and Slovakia. The others are the two Southeast Asian countries Malaysia, Singapore, and the European countries Sweden and Switzerland.

However, we also observe that efficiency levels are less dispersed in 2019 compared to 1999 as indicated by a decrease of the coefficient of variation of the productivity distribution in Fig. 1 from 0.22 in 2019 to 0.19 in 1999. It will thus be interesting to analyze whether convergence in efficiency levels drives the convergence and 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 $\overline{y}_b(\hat{k}_b,\hat{r}_b)=\hat{y}_b/e_b$, and $\overline{y}_c(\hat{k}_c,\hat{r}_c)=\hat{y}_c/e_c$, where e_b and e_c[12] are values of the efficiency indexes in the respective periods as calculated in Eq. (2). Accordingly,

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

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

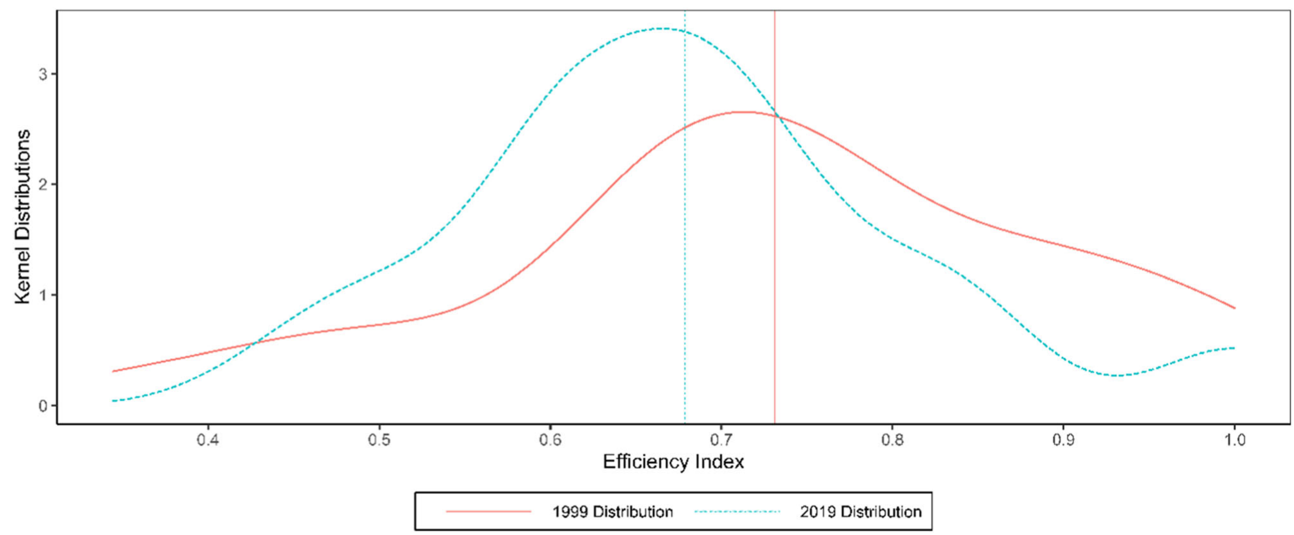

Fig. 1 Distributions of efficiency index (with robots). The solid curve is the estimated 1999 distribution, and the solid vertical line represents the 1999 mean value. The dashed curve is the estimated 2019 distribution, and the dashed vertical line represents the 2019 mean value

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: $\tilde{k}_c = K_c/L_cH_b$ and $\tilde{r}_c = R_c/L_cH_b$. 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: $\tilde{k}_b = K_b/L_bH_c$ and $\tilde{r}_b = R_b/L_bH_c$. Then, $\overline{y}_b(\hat{k}_c, \hat{r}_c)$, $\overline{y}_b(\tilde{k}_c, \hat{r}_b)$, $\overline{y}_b(\tilde{k}_c, \tilde{r}_c)$ 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 $\overline{y}_c(\hat{k}_b, \hat{r}_b)$, $\overline{y}_c(\tilde{k}_b, \hat{r}_c)$, $\overline{y}_c(\tilde{k}_b, \tilde{r}_b)$ 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 Eq. (3) alternatively by $\overline{y}_b(\hat{k}_c, \hat{r}_c)\overline{y}_b(\tilde{k}_c, \hat{r}_b)\overline{y}_b(\tilde{k}_c, \tilde{r}_c)$ and $\overline{y}_c(\hat{k}_b, \hat{r}_b)\overline{y}_c(\tilde{k}_b, \hat{r}_c)\overline{y}_c(\tilde{k}_b, \tilde{r}_b)$, we obtain two alternative decompositions of the growth of $\hat{y}$:

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

and

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

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

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

and

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

Equations (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 $\left(\overline{y}_b(\hat{k}_c,\hat{r}_c)\overline{y}_b(\tilde{k}_c,\hat{r}_b)\overline{y}_b(\tilde{k}_c,\tilde{r}_c)\right)^{1/2}$ $\left(\overline{y}_c(\hat{k}_b,\hat{r}_b)\overline{y}_c(\tilde{k}_b,\hat{r}_c)\overline{y}_c(\tilde{k}_b,\tilde{r}_b)\right)^{1/2}$:

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

In the following, the results of the productivity analysis are presented both through summary statistic for individual countries and country groups (Section 4.2) and in a distributional analysis (Section 5). The distributional analysis is based on and complements the results presented in Section 4.2. It reveals certain patterns of the productivity distribution (such as dispersion, double peaks and polarization) and of its changes and provides some statistical tests.

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.[13] 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 (−4.5%). Physical capital deepening (37.3%) is by far the most important driver of labor productivity growth, irrespective of the incorporation of robot capital or not. The magnitude of the mean contribution of robot capital deepening (11.8%)[14] is comparable to that of technological change (10.5%) but more than three times that of human capital accumulation (3.3%).

Comparing the mean contributions of the components of labor productivity change with and without separating robot capital from other physical capital reveals that part of physical capital accumulation, technological progress, and efficiency change can be attributed to robot capital accumulation. On average, the contribution of physical capital accumulation, technological progress and efficiency change to the 65.2% labor productivity change falls from 45.4% to 37.3%, 16.1% to 10.5%, and from −2.3% to −4.5%, respectively. The reduced rate of technological progress and efficiency change 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 and facilitate movements towards the frontier. The mean contribution of human capital accumulation stays 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

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

[14] The magnitude of the average percentage contribution rate of robot capital deepening to labour productivity growth (11.8/65.2 = 18%) 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.'

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 (AR)	40.5	−10.7	6.1	3.0	33.3	8.0
	40.5	−14.9	19.1	1.5	36.6	
Australia (AU)	35.8	−4.2	8.9	0.2	26.0	3.1
	35.8	−4.5	14.3	0.2	24.2	
Austria (AT)	50.2	−10.3	16.6	1.7	32.7	6.4
	50.2	−7.0	19.6	2.2	32.0	
Belgium (BE)	29.7	−14.3	20.2	1.1	21.1	2.9
	29.7	−12.0	21.1	1.4	20.1	
Brazil (BR)	40.7	−12.2	7.7	10.8	25.4	7.1
	40.7	−16.3	20.1	7.0	30.8	
Canada (CA)	24.1	−17.5	8.1	1.7	25.6	9.0
	24.1	−14.6	13.5	2.1	25.3	
China (CN)	252.2	−29.0	−0.3	3.3	233.3	44.4
	252.2	−30.5	4.2	3.2	371.4	
Czech Republic (CZ)	69.7	29.5	7.0	1.7	3.5	16.4
	69.7	39.1	14.6	1.2	5.2	
Denmark (DK)	60.5	−7.8	14.8	2.0	39.9	6.2
	60.5	−4.8	18.4	2.6	38.8	
Finland (FI)	27.0	−15.3	12.9	2.9	24.2	3.9
	27.0	−15.1	17.0	3.5	23.5	
France (FR)	34.8	−15.6	19.2	2.1	27.1	3.2
	34.8	−14.2	21.1	2.6	26.4	
Germany (DE)	33.8	−10.8	13.4	0.8	18.1	11.1
	33.8	−4.8	17.4	1.0	18.5	
Hungary (HU)	76.2	0.1	4.5	3.1	31.8	23.9
	76.2	4.1	13.5	5.2	41.7	
India (IN)	235.4	−12.5	1.8	7.3	156.7	36.7
	235.4	−6.4	4.0	3.5	233.0	
Israel (IL)	9.9	−5.5	4.8	4.8	−2.5	8.7
	9.9	−4.6	14.1	3.9	−2.8	
Italy (IT)	18.0	−27.6	20.0	2.4	26.1	5.1
	18.0	−24.7	21.2	3.0	25.4	
Japan (JP)	10.9	−12.0	10.2	1.2	0.6	12.3
	10.9	−5.6	13.9	2.4	0.6	
Malaysia (MY)	85.3	11.3	9.7	4.3	36.2	6.9
	85.3	9.9	19.1	1.8	39.1	
Mexico (MX)	21.9	−15.6	7.5	3.5	18.1	9.9
	21.9	−16.5	18.8	3.3	19.1	
Netherlands (NL)	34.4	−10.6	14.7	1.6	21.3	6.3
	34.4	−9.2	18.7	2.3	21.9	
Norway (NO)	66.0	−14.8	13.9	1.8	46.3	14.9
	66.0	−14.6	18.9	2.6	59.4	
Poland (PL)	104.1	0.0	8.6	2.3	68.3	9.1
	104.1	0.0	14.0	1.6	76.1	
Portugal (PT)	38.6	−19.4	9.8	4.6	25.9	18.8

Table 3 (continued)

Country	Productivity Change	(EFF-1) × 100	(TECH-1) × 100	(HACC-1) × 100	(KACC-1) × 100	(RKACC-1) × 100
	38.6	−18.0	20.2	3.2	36.2	
Rep. of Korea (KR)	91.3	−22.4	14.1	3.9	66.8	24.8
	91.3	−3.7	14.4	7.2	62.0	
Russia (RU)	193.5	102.2	2.0	2.7	34.4	3.1
	193.5	80.9	16.9	2.4	35.4	
Singapore (SG)	124.5	1.0	9.5	15.2	60.6	9.8
	124.5	6.3	11.9	19.0	58.6	
Slovakia (SK)	58.0	20.2	7.8	2.7	2.8	15.5
	58.0	32.7	11.4	4.3	2.5	
Slovenia (SL)	46.3	−0.7	10.7	2.3	10.7	17.6
	46.3	6.5	17.1	2.9	14.0	
Spain (ES)	44.1	−17.6	16.6	2.7	40.0	4.4
	44.1	−16.1	19.5	3.4	38.9	
Sweden (SE)	38.6	5.6	16.7	1.7	5.2	5.2
	38.6	8.1	19.5	2.0	5.1	
Switzerland (CH)	66.1	3.7	15.8	1.1	31.4	4.2
	66.1	5.6	19.0	1.3	30.5	
Taiwan (TW)	27.3	−7.7	10.8	3.6	0.7	19.4
	27.3	4.9	12.5	7.2	0.7	
Turkey (TR)	126.3	−12.7	6.6	7.1	78.0	27.7
	126.3	−12.8	16.6	8.7	104.7	
United Kingdom (UK)	28.3	−3.8	9.8	2.1	16.6	2.1
	28.3	−6.4	15.3	2.4	16.0	
United States (US)	37.2	0.0	7.4	1.5	20.1	4.8
	37.2	0.0	12.6	1.6	19.9	
Mean	**65.2**	**−4.5**	**10.5**	**3.3**	**37.3**	**11.8**
	65.2	**−2.3**	**16.1**	**3.5**	**45.4**	

of (non-robot) physical capital accumulation and, to a lesser extent, robot capital accumulation. Efficiency gains and higher contributions of human capital accumulation in emerging countries also supported 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 the mean percentage change of the robot deepening index for emerging countries is 17.2%, and the corresponding value for developed countries 7.3%. 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 Taiwan and Slovenia, robot capital accumulation emerges as the main growth engine, whereas for China, Czech Republic, Hungary, India, Japan, Poland, Slovakia, and Turkey robot capital deepening appears to be the second major contributor to productivity change. Note that, only two of the countries listed above, i.e., Taiwan and Japan, are classified as developed countries.

The poor growth performance of Latin America is caused primarily by efficiency losses and low contributions of (non-robot) physical capital accumulation to productivity growth. Technological catch-up (positive efficiency change) is only observed for a minority of countries/country groups including emerging countries, non-OECD, and transition countries. 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.

Figure 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

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[a]	0.67	0.64	95.2	0.7	7.5	4.1	54.1	17.2
Developed Countries[b]	0.78	0.71	39.8	−8.8	13.0	2.6	23.2	7.3
Non-OECD	0.71	0.69	124.9	5.3	5.9	6.3	72.6	16.9
OECD[c]	0.74	0.68	47.5	−7.4	11.9	2.4	26.9	10.3
Transition[d]	0.61	0.65	114.3	17.5	5.8	2.6	55.0	18.6
Non-transition	0.76	0.69	52.9	−10.0	11.7	3.4	32.9	10.1
Asian Tigers[e]	0.67	0.63	67.9	−6.0	10.8	5.6	33.0	14.6
Latin America[f]	0.79	0.69	34.4	−12.8	7.1	5.7	25.6	8.4
All countries	0.73	0.68	65.2	−4.5	10.5	3.3	37.3	11.8

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

[b]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

[c]OECD countries as of 2019

[d]China, Czech Republic, Hungary, Poland, Russia, Slovakia, Slovenia

[e]Japan, Malaysia, South Korea, Singapore, Taiwan

[f]Argentina, Brazil, Mexico

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 (d), (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; human capital accumulation also contributed to beta-convergence. The statistically significant positive regression slope coefficient in Panel (c) indicates that relatively wealthy countries have benefited more from technological progress than have less-developed countries. Therefore, technological progress appears to have 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 (b) suggests that efficiency change 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. Quah's critique to previous approaches to examine convergence (basically those based on analysing β- and σ-convergence) points out that conclusions are based just on (two) summary statistics. However, relying on two specific moments of the distribution (i.e., mean and the standard deviation) may give an incomplete illustration and hide important results. Instead, empirical works should consider the entire distribution. This could reveal some significant features such as the existence of multiple modes.

5 Analysis of productivity distributions

Figure 3 shows the distributions of output per hour worked across the 35 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

[15] Detailed GLS-regression results are available in the Appendix, Table 8. The country codes used in Fig. 2 are explained in Table 9 of the Appendix.

[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 = 0.01), but we cannot reject the null of one mode (p-value = 0.15) for the 2019 distribution.

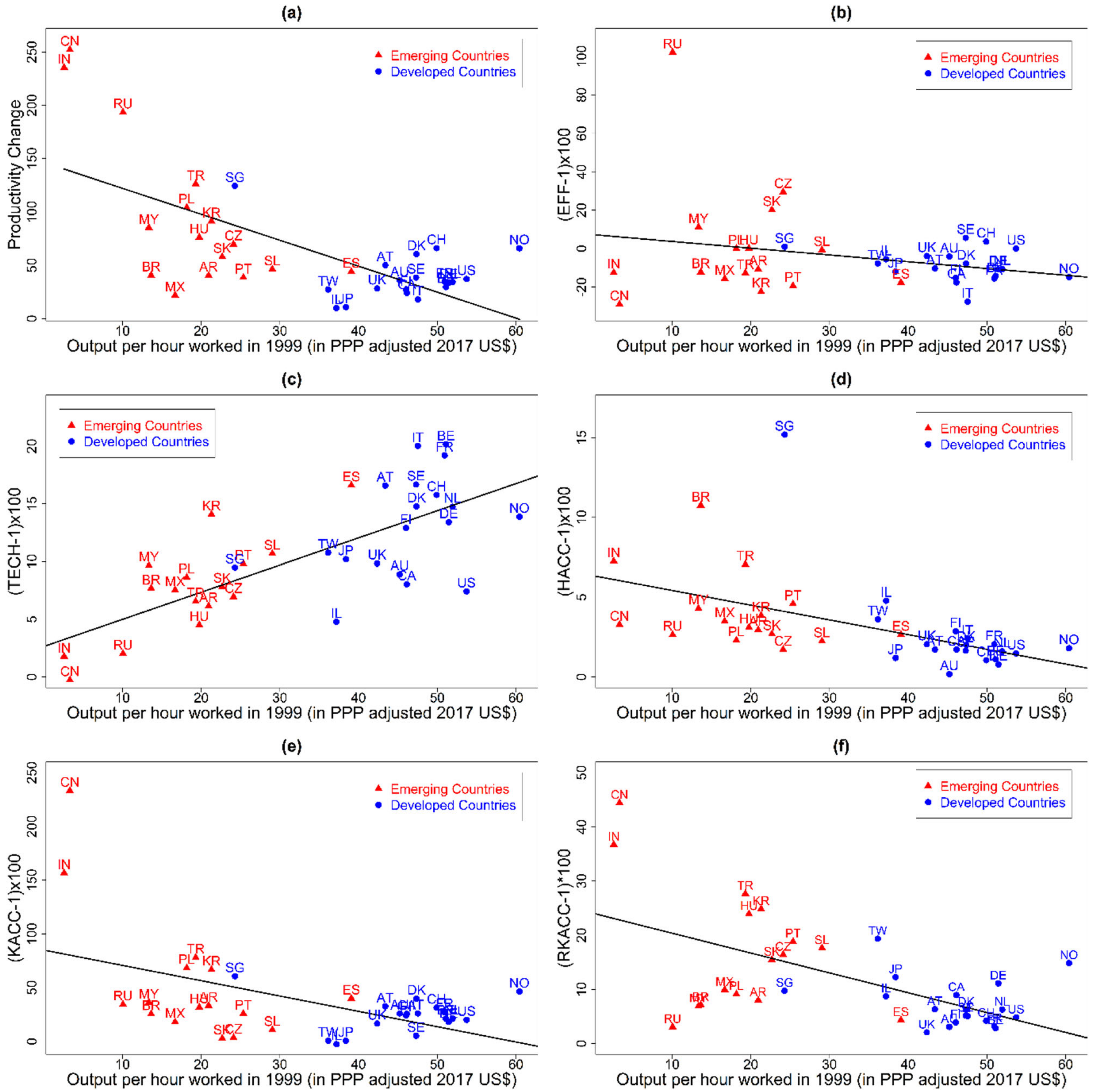

Fig. 2 Percentage change in output per hour worked (**a**) and percentage change in five decomposition indexes (**b–f**) plotted against 1999 output per hour worked. Each panel contains a GLS regression line

the dispersion of productivity levels, as indicated by a decrease of the coefficient of variation (CV) from 0.480 in 1999 to 0.424 in 2019.[17]

Following Henderson and Russell (2005) and others, 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. Using the quinquepartite decomposition of productivity growth, we rewrite Eq. (9) as follows:

$$y_c = (EFF \times TECH \times HACC \times KACC \times RKACC) \times y_b. \quad (10)$$

[17] The coefficient of variation is the most widely used indicator for σ-convergence in the empirical macroeconomic literature (Benedek and Koczisky 2015; Ram 2021) and is calculated as the ratio between the standard deviation and the mean of a variable. While Panel (a) in Fig. 2 provides some evidence for β-convergence, the decreased coefficient of variation points towards σ-convergence across the countries in our sample.

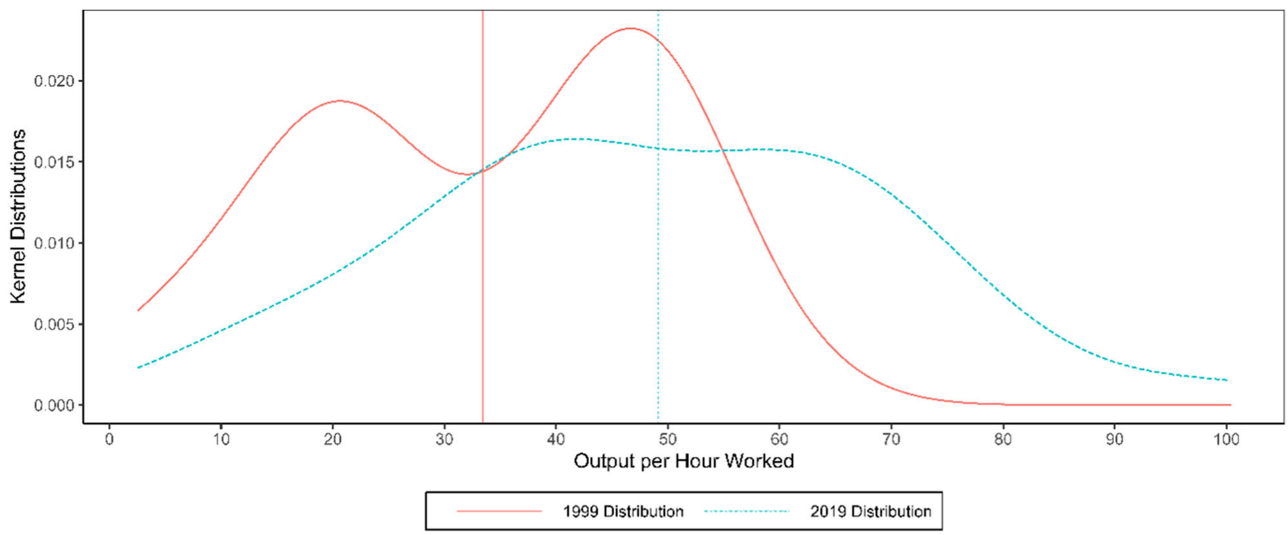

Fig. 3 Distributions of labor productivity. The solid curve is the estimated 1999 distribution, and the solid vertical line represents the 1999 mean value. The dotted curve is the estimated 2019 distribution, and the dashed vertical line represents the 2019 mean value

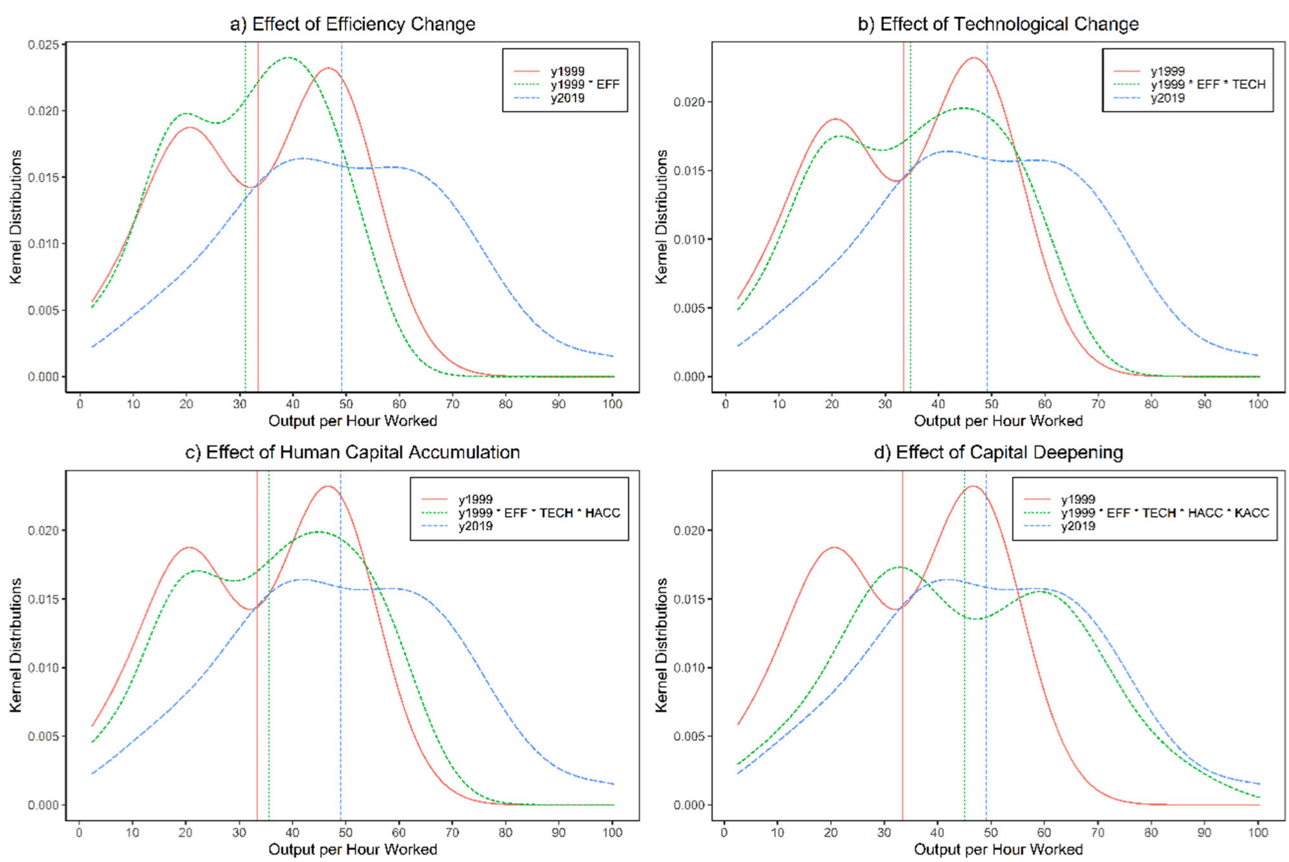

Fig. 4 Counterfactual distributions of output per hour worked. In each panel, the solid curve is the actual 1999 distribution, the dashed curve is the actual 2019 distribution. The dotted curves in each panel are the counterfactual distributions isolating, sequentially, the effects of efficiency ch.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

Table 5 Modality Tests (p-values)

	H_0: Distribution Has One Mode H_1: Distribution Has More than One Mode	Bootstrap p-Value
1	$f(y_{1999})$	0.01
2	$f(y_{2019})$	0.15
3	$f(y_{1999} \times EFF)$	0.10
4	$f(y_{1999} \times TECH)$	0.01
5	$f(y_{1999} \times KACC)$	0.00
6	$f(y_{1999} \times HACC)$	0.04
7	$f(y_{1999} \times RKACC)$	0.15
8	$f(y_{1999} \times EFF \times TECH)$	0.17
9	$f(y_{1999} \times EFF \times KACC)$	0.04
10	$f(y_{1999} \times EFF \times HACC)$	0.25
11	$f(y_{1999} \times EFF \times RKACC)$	0.26
12	$f(y_{1999} \times TECH \times KACC)$	0.01
13	$f(y_{1999} \times TECH \times HACC)$	0.04
14	$f(y_{1999} \times TECH \times RKACC)$	0.08
15	$f(y_{1999} \times KACC \times HACC)$	0.01
16	$f(y_{1999} \times KACC \times RKACC)$	0.03
17	$f(y_{1999} \times HACC \times RKACC)$	0.30
18	$f(y_{1999} \times EFF \times TECH \times KACC)$	0.01
19	$f(y_{1999} \times EFF \times TECH \times HACC)$	0.20
20	$f(y_{1999} \times EFF \times TECH \times RKACC)$	0.23
21	$f(y_{1999} \times EFF \times KACC \times HACC)$	0.08
22	$f(y_{1999} \times EFF \times KACC \times RKACC)$	0.52
23	$f(y_{1999} \times EFF \times HACC \times RKACC)$	0.31
24	$f(y_{1999} \times TECH \times KACC \times HACC)$	0.00
25	$f(y_{1999} \times TECH \times KACC \times RKACC)$	0.01
26	$f(y_{1999} \times TECH \times HACC \times RKACC)$	0.12
27	$f(y_{1999} \times KACC \times HACC \times RKACC)$	0.08
28	$f(y_{1999} \times EFF \times TECH \times KACC \times HACC)$	0.09
29	$f(y_{1999} \times EFF \times TECH \times KACC \times RKACC)$	0.23
30	$f(y_{1999} \times EFF \times TECH \times HACC \times RKACC)$	0.29
31	$f(y_{1999} \times EFF \times KACC \times HACC \times RKACC)$	0.15
32	$f(y_{1999} \times TECH \times KACC \times HACC \times RKACC)$	0.20

We employ the bootstrapped calibrated Silverman test of multimodality due to Hall and York (2001) with 1000 bootstrap replications

Where $b = 1999$ and $c = 2019$. Accordingly, the labor productivity distribution in the current year can be constructed by consecutively multiplying the labor productivity variable 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^{EIH} such that:

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

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. $f(y_{1999})$	0.011
2	$g(y_{2019})$ vs. $f(y_{1999} \times EFF)$	0.005
3	$g(y_{2019})$ vs. $f(y_{1999} \times TECH)$	0.076
4	$g(y_{2019})$ vs. $f(y_{1999} \times KACC)$	0.494
5	$g(y_{2019})$ vs. $f(y_{1999} \times HACC)$	0.015
6	$g(y_{2019})$ vs. $f(y_{1999} \times RKACC)$	0.032
7	$g(y_{2019})$ vs. $f(y_{1999} \times EFF \times TECH)$	0.051
8	$g(y_{2019})$ vs. $f(y_{1999} \times EFF \times KACC)$	0.114
9	$g(y_{2019})$ vs. $f(y_{1999} \times EFF \times HACC)$	0.009
10	$g(y_{2019})$ vs. $f(y_{1999} \times EFF \times RKACC)$	0.021
11	$g(y_{2019})$ vs. $f(y_{1999} \times TECH \times KACC)$	0.409
12	$g(y_{2019})$ vs. $f(y_{1999} \times TECH \times HACC)$	0.089
13	$g(y_{2019})$ vs. $f(y_{1999} \times TECH \times RKACC)$	0.402
14	$g(y_{2019})$ vs. $f(y_{1999} \times KACC \times HACC)$	0.661
15	$g(y_{2019})$ vs. $f(y_{1999} \times KACC \times RKACC)$	0.984
16	$g(y_{2019})$ vs. $f(y_{1999} \times HACC \times RKACC)$	0.040
17	$g(y_{2019})$ vs. $f(y_{1999} \times EFF \times HACC \times RKACC)$	0.640
18	$g(y_{2019})$ vs. $f(y_{1999} \times EFF \times TECH \times HACC)$	0.059
19	$g(y_{2019})$ vs. $f(y_{1999} \times EFF \times TECH \times RKACC)$	0.163
20	$g(y_{2019})$ vs. $f(y_{1999} \times EFF \times KACC \times HACC)$	0.154
21	$g(y_{2019})$ vs. $f(y_{1999} \times EFF \times KACC \times RKACC)$	0.514
22	$g(y_{2019})$ vs. $f(y_{1999} \times EFF \times HACC \times RKACC)$	0.024
23	$g(y_{2019})$ vs. $f(y_{1999} \times TECH \times KACC \times HACC)$	0.456
24	$g(y_{2019})$ vs. $f(y_{1999} \times TECH \times KACC \times RKACC)$	0.478
25	$g(y_{2019})$ vs. $f(y_{1999} \times TECH \times HACC \times RKACC)$	0.605
26	$g(y_{2019})$ vs. $f(y_{1999} \times KACC \times HACC \times RKACC)$	0.975
27	$g(y_{2019})$ vs. $f(y_{1999} \times EFF \times TECH \times KACC \times HACC)$	0.735
28	$g(y_{2019})$ vs. $f(y_{1999} \times EFF \times TECH \times KACC \times RKACC)$	0.990
29	$g(y_{2019})$ vs. $f(y_{1999} \times EFF \times TECH \times HACC \times RKACC)$	0.256
30	$g(y_{2019})$ vs. $f(y_{1999} \times EFF \times KACC \times HACC \times RKACC)$	0.553
31	$g(y_{2019})$ vs. $f(y_{1999} \times TECH \times KACC \times HACC \times RKACC)$	0.403

The functions g(.) and f(.) are (kernel) distribution functions. We employ bootstrapped Li (1996) tests with 5000 bootstrap replications and the Silverman's (1986) adaptive rule-of-thumb bandwith

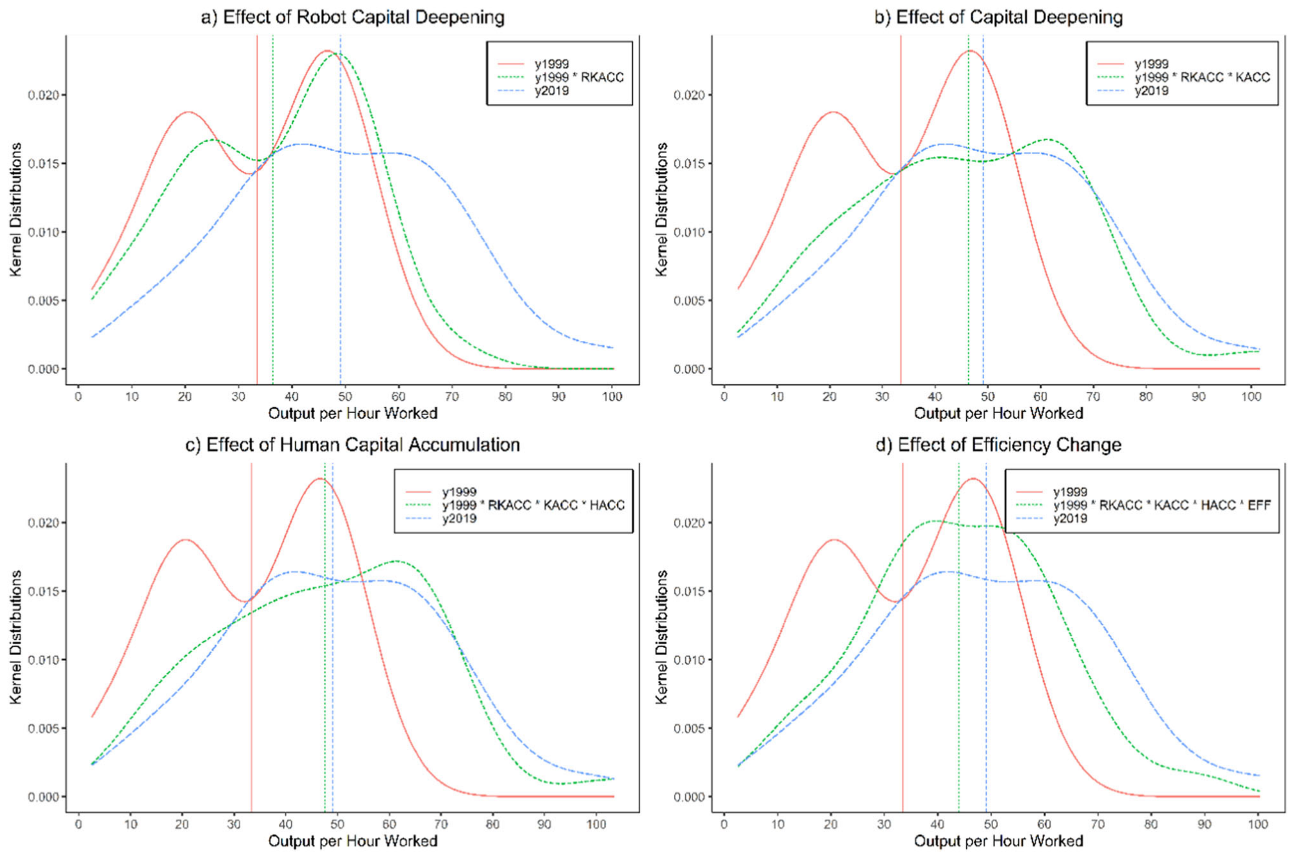

Fig. 5 Counterfactual distributions of output per hour worked. In each panel, the solid curve is the actual 1999 distribution, the dashed curve is the actual 2019 distribution. The dotted curves in each panel are the counterfactual distributions isolating, sequentially, the effects of robot capital deepening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

The effect of the last component, robot capital deepening, can be deduced from comparing the counterfactual distribution of y^{EIHK} 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 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 Tables 5 and 6, respectively.

Table 5 shows that when introduced alone, efficiency change (*EFF*) and robot capital deepening (*RKACC*) could bring about the unimodality in the distribution. The corresponding p-values in rows 3 and 7 (0.10 and 0.15) in Table 5 indicate that we cannot reject the null-hypothesis of unimodality when the single effects of *EFF* and *RKACC* on the 1999 distribution are isolated. Panel (a) of Figs. 4 and 5 also show the emergence of unimodalism in the counterfactual distributions due only to the effect of *EFF* and *RKACC*, respectively. When we consider the combined effect of two components, we find that the presence of either of these effects helps induce unimodality of the distribution (rows 8, 10, 11, 13, 14, and 17). However, capital deepening (*KACC*) exerts a counteracting effect towards a bipolar distribution and leads to a rejection of the null hypothesis of unimodality at the 5% significance level even when combined with *EFF* or *RKACC* (rows 9 and 16). A similar pattern is revealed by inspecting rows 18 to 27 of Table 5, where three components are combined together: whenever one of the effect of *EFF* or *RKACC* is imposed on the 1999 distribution, unimodality cannot be rejected, except for those cases where *KACC* is also present and at the same time coincides only with one of the *EFF* or *RKACC* components. When combining four components the null hypothesis of unimodality cannot be rejected at the 5% significance level. Thus, capital deepening counteracts the depolarizing (combined) effect of efficiency change and robot capital deepening.

The Li-test results shown in Table 6 indicate that (non-robot) physical capital deepening, and to a lesser extent

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

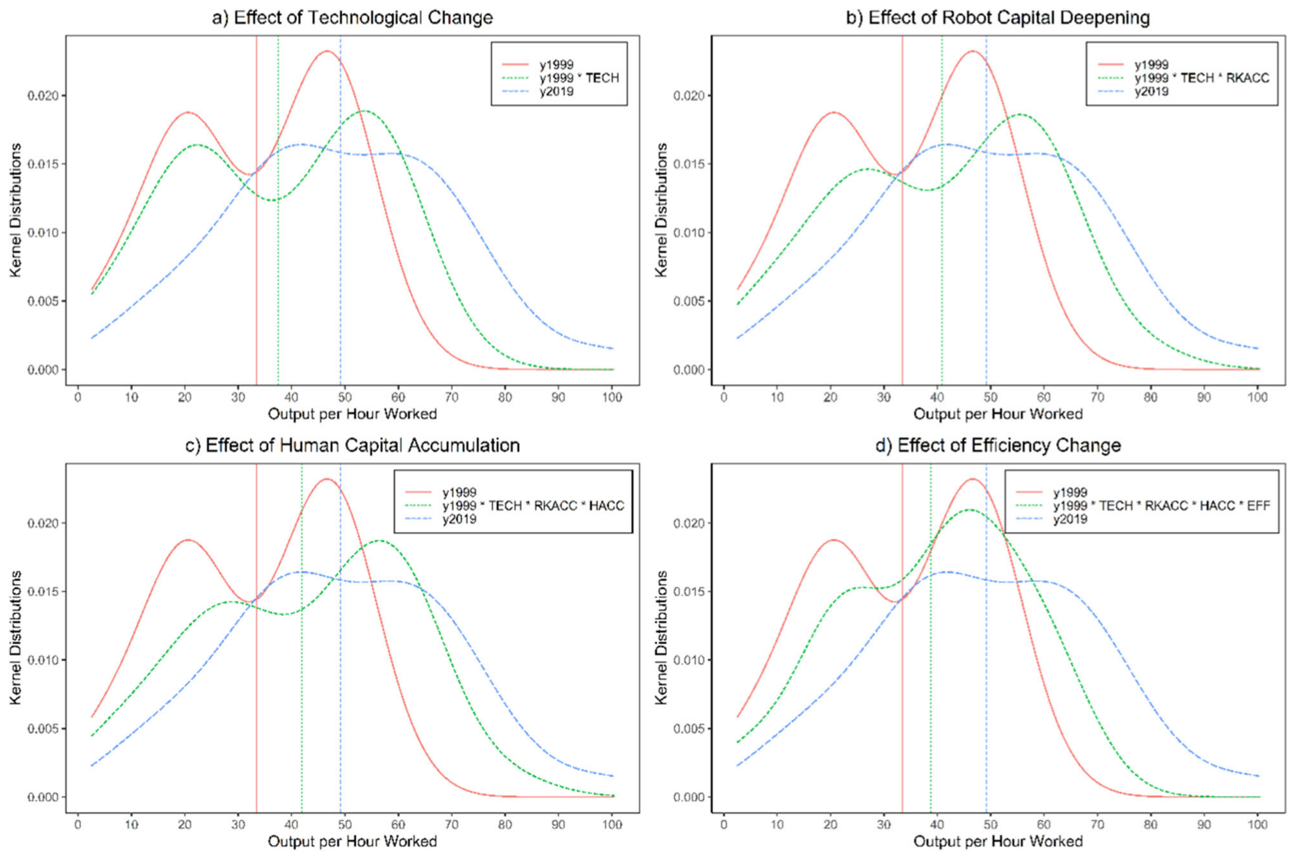

Fig. 6 Counterfactual distributions of output per hour worked. In each panel, the solid curve is the actual 1999 distribution, and the dashed curve is the actual 2019 distribution. The dotted curves in each panel are the counterfactual distributions isolating, sequentially, the effects of technological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

technical change, 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 the introduction of either the effect of *TECH* or *KACC* alone to the 1999 distribution renders it statistically indistinguishable from the 2019 distribution at the 10% and 5% significance level, respectively.[19] Unsurprisingly, so does any combination of two or more productivity change component effects which include *TECH*, *KACC*, or both. 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 all components of labor productivity change except technical change have a moderate effect of reducing the dispersion of the labor productivity distribution. 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 0.480 to 0.458. 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 0.458 to 0.445, 0.436, and 0.4016, respectively.

Next, we inspect the shift of the 1999 mean value of output per hour worked (solid vertical line in Figs. 4–6) to its 2019 mean value (dashed vertical line Figs. 4–6). We observe a shift from 33.4 to 49.13 (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 capital deepening, followed by technical change, efficiency change, robot capital deepening and human capital accumulation.[20] Efficiency change is the only component that tends to decrease output per

[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.

[20] Fig. 5 shows that the effect or robot capital deepening increases the 1999 mean value of output per hour worked from 33.44 US$ to 36.46 US$. Adding sequentially the effect of capital deepening, human capital accumulation, and efficiency change, results in a mean value of 46.33 US$, 47.60 US$, and 43.94 US$, respectively. Adding the last component, technological change, induces an increase from 43.94 US$ to 49.13 US$.

hour worked. Robot capital deepening induces a shift mainly of the lower part of the distribution. The magnitude of the average percentage contribution rate of robot capital deepening to labor productivity growth (3.03/15.69 = 19.3%) in Fig. 5 is comparable to the 18.1 (=11.8/65.2) percentage contribution rate found in the second last row of Table 3 (cf. footnote 14).

To sum up, the evidence from the counterfactual distributional analysis and statistical tests in Tables 5 and 6 indicates that i) the increase in average output per hour worked is primarily driven by (non-robot) capital deepening, and to a lesser extent, also by technological change and robot capital deepening. However, only focusing on changes of the first moment of the productivity distribution would mask (ii) that the depolarization (shift from bimodal to unimodal distribution) of the labor productivity distribution and the decreased dispersion of productivity levels across countries (σ-convergence) is primarily driven by efficiency change and robot capital deepening[21], and (iii) that the overall effect of robot capital deepening on the change of the entire labor productivity distribution for the 1999–2019 period is modest and dominated by other growth drivers such as (non-robot) physical capital deepening and technological change.

6 Sensitivity analyses for quinquepartite decomposition

Having presented the results for a sample of 35 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 from a wide array of sensitivity analyses. We examine the robustness of the results presented in Section 4 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, ii) the investigation of the subperiods 1999–2009, and 2009–2019, and iii) the exclusion of potential outlying observations. 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 almost identical up to two decimal places, regardless of whether we estimate the quality adjusted 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 14.7% to 17.3%, 6.8% to 7.6%, and 10.4% to 12.0%, respectively.

However, for some individual countries the results can vary substantially between different types of quality-adjusted robot stock estimates. For instance, regarding the contribution of robot capital deepening we find the largest uncertainties for Norway (6.1%–14.9%), Portugal (7.2%–18.8%), Turkey (13.5%–27.7%), India (33.3%–49.1%), China (41.2%–53.7%) and Hungary (18.2%–23.9%). For all other countries the differences in the robot capital deepening component between different quality-adjusted robot stock estimates are of less importance.

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, especially for developed countries, if quality-changes of robots are ignored. Hence, for the majority 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 D and F in Table 7 present the mean productivity growth rates and its five components for the subperiods 1999–2009, and 2009–2019, respectively. Panel E and G 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 35 countries is 36.5% and 19.0% 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 (8.2%) was the second largest

[21] Whereas, non-robot physical and human capital accumulation also contribute to the decreased dispersion of productivity levels, technical change counteracts this development.

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	0.67	0.64	95.2	0.8	7.2	3.9	53.6	17.3
Developed	0.78	0.71	39.8	−8.3	11.9	2.5	23.6	7.6
All	0.73	0.68	65.2	−4.2	9.7	3.1	37.3	12.0
PIM, δ = 5%, quality change adjusted								
Emerging	0.68	0.64	95.2	0.5	8.1	3.8	57.2	14.8
Developed	0.78	0.71	39.8	−8.7	12.5	2.5	23.8	7.3
All	0.73	0.68	65.2	−4.5	10.5	3.1	39.1	10.7
PIM, δ = 10%, quality change adjusted								
Emerging	0.67	0.64	95.2	0.7	8.0	3.8	57.2	14.7
Developed	0.78	0.71	39.8	−8.8	12.9	2.5	24.0	6.8
All	0.73	0.68	65.2	−4.4	10.6	3.1	39.2	10.4
PIM, δ = 15%, quality change adjusted								
Emerging	0.67	0.64	95.2	0.7	7.5	4.1	54.1	17.2
Developed	0.78	0.71	39.8	−8.8	13.0	2.6	23.2	7.3
All	0.73	0.68	65.2	−4.5	10.5	3.3	37.3	11.8
PIM, δ = 15%, not quality change adjusted								
Emerging	0.68	0.64	95.2	0.2	10.0	3.9	54.3	15.0
Developed	0.78	0.71	39.8	−8.4	14.8	2.5	23.5	5.0
All	0.73	0.68	65.2	−4.5	12.6	3.1	37.6	9.6
Panel B: Removing potential outliers (without China)								
PIM, δ = 15%, quality change adjusted								
Emerging	0.67	0.64	84.8	1.3	8.1	3.9	42.4	18.2
Developed	0.78	0.71	39.8	−8.8	13.0	2.6	23.1	7.4
All	0.73	0.68	58.4	−4.4	10.8	3.2	31.6	12.1
Panel C: Without robots								
Emerging	0.67	0.65	95.2	2.4	15.2	3.8	71.7	
Developed	0.78	0.73	39.8	−6.2	16.9	3.3	23.4	
All	0.73	0.69	65.2	−2.3	16.1	3.5	45.4	
Subperiod 1999–2009								
Panel D: With robots (PIM, δ = 15%, quality adjustment)								
Emerging	0.67	0.67	51.0	3.3	4.3	2.1	27.7	9.3
Developed	0.78	0.71	24.2	−8.5	11.4	1.3	17.1	2.7
All	0.73	0.69	36.5	−3.1	8.2	1.7	21.9	5.7
Panel E: Without robots								
Emerging	0.67	0.67	51.0	3.1	8.2	1.9	35.7	
Developed	0.78	0.72	24.2	−7.6	12.7	1.3	17.9	
All	0.73	0.70	36.5	−2.7	10.6	1.6	26.1	
Subperiod 2009–2019								
Panel F: With robots (PIM, δ = 15%, quality adjustment)								
Emerging	0.67	0.64	26.7	−3.5	1.7	1.7	19.4	7.9
Developed	0.71	0.71	12.4	−0.3	1.1	1.0	6.1	4.1
All	0.69	0.68	19.0	−1.7	1.4	1.3	12.2	5.9
Panel G: Without robots								
Emerging	0.67	0.65	26.7	−1.4	5.8	1.6	22.1	
Developed	0.72	0.73	12.4	1.6	3.2	1.3	5.9	
All	0.70	0.69	19.0	0.2	4.4	1.4	13.3	

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

driver of productivity growth (line 3 in Panel D) but is of rather minor importance in the period 2009–2019 (1.4%) (line 3 in Panel F). Non-robot capital deepening remains by far the most important driver of productivity growth in both, the 1999–2009 (21.9%) and 2009–2019 (12.2%) period. In the period after the financial crisis robot capital deepening as a driver of productivity growth gains in relative importance and becomes the second largest contributor to productivity growth across the 35 countries in our sample.[22] The increasing importance of robot

[22] While in the 1999-2009 period the growth of the robot capital deepening index was about four times lower than the growth rate of the (non-robot) physical capital deepening index (5.7% relative to 21.9%), in the period 2009–2019 it is about only half times lower (5.9% relative to 12.2%).

capital deepening in the period 2009–2019 is particularly pronounced in developed countries, where the growth rate of the robot capital deepening index increases from 2.7% to 4.1%, whereas overall labor productivity growth halved from 24.2% to 12.4%. Nevertheless, the main finding in Section 4.2. that the mean percentage change of the robot deepening index for emerging countries is higher than in developed countries over the 1999–2019 period, holds for both, the 1999–2009 (9.3% in emerging vs. 2.7% in developed countries) and the 2009–2019 period (7.9% in emerging vs. 4.1% in developed countries). However, the gap in the average growth rate of the robot capital deepening index between emerging and developed countries narrows 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, comparing line 3 in Panel D and Panel E of Table 7 reveals 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 F and G 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 13.3% to 12.2%, but mainly reduces the average contribution to productivity growth attributable to technological progress (reduction from 4.4% to 1.4%) and efficiency change (0.2% to −1.7%). 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 Potential outliers

Following the super-efficiency procedure for outlier identification introduced by Banker and Gifford (1988) we find high super-efficiency scores (above 1.2) for some observations for China. This identifies China as potential outlier. Therefore, we exclude China from our sample to check the sensitivity of the results of the decomposition analysis in Section 4. Panel B of Table 7 provides arithmetic means of productivity change and its components for the groups of emerging, developed and all countries after removing China from the sample based on robot stock estimates with the perpetual inventory method assuming a depreciation rate of 15%. Country-specific results are available in Table B5c of the supplementary material.

We find that for the vast majority of countries the exclusion of China does not affect the decomposition results, except for India, Rep. of Korea, Poland and Singapore. While the results for India change substantially[23], changes for Rep. of Korea are moderate and negligible for Poland and Singapore. Therefore, the mean values in Panel B of Table 7 only change slightly and the largest changes are observed for the group of emerging countries. Having in mind that the exclusion of China reduces average productivity growth for emerging countries from 95.2% to 84.8%, we find that for emerging countries the average robot capital deepening and the average non-robot physical capital deepening component increases from 17.2% to 18.2%, and decreases from 54.1% to 42.4% respectively. The latter can be explained by the fact that the contribution of traditional physical capital deepening to productivity growth is relatively large and the most important driver of productivity growth in China.

6.4 Summing up

To sum up, the sensitivity analysis shows that overall i) the baseline results presented in Sections 4 and 5 are robust to other assumptions about the depreciation of the robot capital stock and ii) the exclusion of potential outliers. iii) 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, after the financial crisis the average contribution of robot capital deepening to productivity growth has gained in importance, especially in developed countries but to a lesser extend also in emerging countries. The importance of technological progress as a driver of growth declined over the 2009–2019 period relative to 1999–2009.

7 Conclusion

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 16 emerging countries, and 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), refined by Henderson and Russell (2005) and others, and extend it by considering industrial robots as separate production factor.

[23] For India we find that both, the non-robot capital and the robot capital deepening component increase from 156.7% to 169.4% and from 36.7% to 73%, respectively. The efficiency change component declines from −12.5% to −32.8%.

Production frontiers and distances to the frontiers are estimated by Data Envelopment Analysis (DEA), a method based on linear programming models. One weakness of radial DEA models is that slacks, i.e., leftover portions of inefficiencies after proportional (radial) reductions in all inputs (expansions of all outputs), may arise. This can distort the DEA estimates and Pareto-Koopmans inefficient countries can be located on the production frontier. So far, the many previous authors applying the decomposition analysis in the spirit of Kumar and Russell (2002) ignored this problem. Following Portela and Thanassoulis (2006), we provide a solution to this problem and find that if slacks are pervasive, ignoring them in the decomposition analysis can produce misleading results.

Our results confirm the positive relationship between robot adoption and labor productivity growth found in previous studies (e.g., Graetz and Michaels 2018; Cette et al. 2021a, 2021b). Substantial contributions of robotization to labor productivity growth over the period 1999 to 2019 are found in both, developed and emerging countries. Examples for the latter are the Eastern European countries Hungary, Slovenia, Slovakia and Czech Republic but also Argentina, Brazil, Mexico, China, India, and Portugal. Considerable contributions of robotization to labor productivity growth are also found for certain developed countries (Canada, Germany, Israel) and the Asian countries Japan, Republic of Korea and Taiwan. We observe that after the financial crisis (2009–2019) the contribution of robot capital deepening to productivity growth gains in importance, especially for developed countries, but to a lesser extent also for emerging countries.

We find some evidence of unconditional beta-convergence, and sigma-convergence in our sample of 35 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 seems to be 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 result is primarily driven by the dynamics of efficiency change and robot capital deepening across countries. To a lesser extent, human capital accumulation and (non-robot) capital deepening also contributed to this development. However, the effect of robot capital deepening on the shift of the entire labor productivity distribution is modest and dominated by other growth factors such as (non-robot) physical capital deepening. Finally, 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, technological change and efficiency 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 and facilitate movements towards the frontier.

Our results indicate, that the fast diffusion of industrial robots in emerging market economies in the two decades prior to the covid–19 pandemic substantially contributed to improving their living standards and competitiveness vis-à-vis developed countries. For developed countries, the diffusion of industrial robots mitigated the losses in competitiveness. Analyzing the proximate causes of economic growth does not allow us to derive direct policy recommendations. For designing policies that create a favorable environment for robot adoption, a deeper understanding on the fundamental causes of robot adoption is needed.

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 sectoral convergence differ across industries.

Supplementary information The online version contains supplementary material available at https://doi.org/10.1007/s11123-023-00707-x.

Acknowledgements The authors gratefully acknowledge the valuable comments received on previous versions of this paper from two anonymous reviewers and from Mikulas Luptacik and Oleg Badunenko as well as from the participants of the First (Virtual) African Productivity Workshop in December 2021, the 17th European Workshop on Efficiency and Productivity Analysis in June 2022, Porto, Portugal, and the Annual Meeting of the Austrian Economic Association in September 2022, Vienna, Austria. Moreover, the authors wish to thank the Anniversary Fund of the Oesterreichische Nationalbank for its financial support (project number: 18288). The usual disclaimers apply.

Funding This work was supported by the Anniversary Fund of the Oesterreichische Nationalbank (grant number 18288). Open access funding provided by University of Natural Resources and Life Sciences Vienna (BOKU).

Compliance with ethical standards

Conflict of interest The authors declare no competing interests.

8 Appendix

Table 8 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	146.56*** (17.39)	7.27 (8.58)	2.65* (1.40)	6.35*** (1.01)	85.01*** (15.43)	24.04*** (3.20)
Output per hour worked in 1999	−2.43*** (0.47)	−0.35 (0.23)	0.24*** (0.04)	−0.09*** (0.03)	−1.43*** (0.42)	−0.37*** (0.09)
Number of obs.	35	35	35	35	35	35
R-squared	0.448	0.065	0.538	0.258	0.262	0.353

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 9 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
HU	Hungary	DK	Denmark
IN	India	FI	Finland
MY	Malaysia	FR	France
MX	Mexico	DE	Germany
PL	Poland	IL	Israel
PT	Portugal	IT	Italy
KR	Republic of Korea	JP	Japan
RU	Russian Federation	NL	Netherlands
SK	Slovakia	NO	Norway
SL	Slovenia	SG	Singapore
ES	Spain	SE	Sweden
TR	Turkey	CH	Switzerland
		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

References

Acemoglu D, Lelarge C, Restrepo P (2020) Competing with robots: Firm-level evidence from France. AEA Pap Proc 110:383–388

Acemoglu D, Restrepo P (2018a) Modeling Automation. AEA Pap Proc 2018(108):48–53. https://doi.org/10.1257/pandp.20181020

Acemoglu D, Restrepo P (2018b) The race between man and machine: Implications of technology for growth, factor shares and employment. Am Econ Rev 108:1488–1542. https://doi.org/10.1257/aer.20160696

Anthony J, Klarl T (2020) The implications of automation for economic growth when investment decisions are irreversible. Econ Lett 186:108757. https://doi.org/10.1016/j.econlet.2019.108757

Badunenko O, Henderson DJ, Russell RR (2013) Polarization of the worldwide distribution of productivity. J Product Anal 40:153–171. https://doi.org/10.1007/s11123-012-0328-5

Badunenko O, Henderson DJ, Zelenyuk V (2008) Technological change and transition: Relative contributions to worldwide growth during the 1990s. Oxf Bull Econ Stat 70:461–492. https://doi.org/10.1111/j.1468-0084.2008.00508.x

Badunenko O, Romero-Ávila D (2013) Financial development and the sources of growth and convergence. Int Econ Rev 54:629–663. https://doi.org/10.1111/iere.12009

Banker RD, Gifford JL (1988) A relative efficiency model for the evaluation of public health nurse productivity. Mellon University Mimeo, Carnegie

Banker RD, Das S, Datar SM (1989) Analysis of cost variances for management control in hospitals. Res Gov Nonprofit Account 5:269–291

Banker RD, Chang H (2006) The super-efficiency procedures for outlier identification, not for ranking efficient units. Eur J Op Res 175:1311–1320

Banker RD, Chang H, Zheng Z (2017) On the use of super-efficiency procedures for ranking efficient units and identifying outliers. Ann Op Res 250:21–35

Ballestar MT, Díaz-Chao Á, Sainz J, Torrent-Sellens J (2020) Knowledge, robots and productivity in SMEs: Explaining the second digital wave. J Bus Res 108:119–131. https://doi.org/10.1016/j.jbusres.2019.11.017

Bekthiar K, Bittschi B, Sellner R (2021) Robots at work? Pitfalls of industry level data. EconPol Work Pap 58. https://www.ifo.de/en/publications/2021/working-paper/robots-work-pitfalls-industry-level-data

Benedek J, Kocziszky G (2015) Paths of Convergence and Polarization in the Visegrád Countries. In: Lang T, Henn S, Sgibnev W, Ehrlich K (eds) Understanding Geographies of Polarization and Peripheralization. New Geographies of Europe. Palgrave Macmillan, London, https://doi.org/10.1057/9781137415080_12

Bessen JE (2017) Automation and Jobs: When Technology Boost Employment. Boston University Law and Economics Research Paper 17–09. https://scholarship.law.bu.edu/cgi/viewcontent.cgi?article=1809&context=faculty_scholarship

Bonfiglioli A, Rosario C, Fadinger H, Gina G (2020) Robot imports and firm-level outcomes. CESifo Working Paper No. 8741. https://www.econstor.eu/bitstream/10419/229559/1/cesifo1_wp8741.pdf

Caves DW, Christensen LR, Diewert WE (1982) The economic theory of index numbers and the measurement of inputs, output, and productivity. Econometrica 50:1393–1414

Ceccobelli M, Gitto S, Mancuso P (2012) ICT capital and labour productivity growth: A non-parametric analysis of 14 OECD-countries. Telecommun Policy 36:282–292. https://doi.org/10.1016/j.telpol.2011.12.012

Cette G, Devillard A, Spiezia V (2021a) The contribution of robots to productivity growth in 30 OECD countries over 1975-2019. Econ Lett 200:109762. https://doi.org/10.1016/j.econlet.2021.109762

Cette G, Devillard A, Spiezia V (2021b) Growth factors in developed countries: A 1960-2019 growth accounting decomposition. Comp Econ Stud. https://doi.org/10.1057/s41294-021-00170-3

Cheng H, Jia R, Li D, Li H (2019) The rise of robots in China. J Econ Perspect 33:71–88. https://doi.org/10.1257/jep.33.2.71

Cséfalvay Z (2020) Robotization in Central and Eastern Europe: Catching up or dependence. Eur Plan Stud 28:1534–1553. https://doi.org/10.1080/09654313.2019.1694647

Dachs B, Fu X, Jäger A (2022) The diffusion of industrial robots. In: Kurz HD, Schütz M, Strohmaier R, Zilian SS (Eds.) The Routledge Handbook of Smart Technologies (Chapter 15). Taylor & Francis Group, Routledge

Dauth W, Findeisen S, Südekum J, Wößner N (2017) German robots—The impact of industrial robots on workers. CEPR discussion paper 12306. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3039031

DeCanio SJ (2016) Robots and humans—complements or substitutes? J Macroecon 49:280–291. https://doi.org/10.1016/j.jmacro.2016.08.003

Dixon J, Hong B, Wu L (2020) The robot revolution: Managerial and employment consequences for firms. NYU Stern School of Busines. https://doi.org/10.2139/ssrn.3422581

EC (European Commission), Directorate-General for the Information Society and Media, Zanker C, Moll C, Jäger A, et al. (2015). Analysis of the impact of robotic systems on employment in the European Union. Publications Office. https://data.europa.eu/doi/10.2759/516348

Färe R, Grosskopf B, Norris M, Zhang Z (1994) Productivity growth, technical progress, and efficiency change in industrialized countries. Am Econ Rev 84:66–83

Farrell MJ (1957) The measurement of productive efficiency. J R Stat Soc 120:253–290. https://doi.org/10.2307/2343100

Feenstra RC, Inklaar R, Timmer MP (2015) The next generation of the Penn World Table. Am Econ Rev 105:3150–3182. https://doi.org/10.1257/aer.20130954

Fu XM, Bao Q, Xie H, Fu X (2021) Diffusion of industrial robots and inclusive growth: Labour market evidence form cross country data. J Bus Res 122:670–684. https://doi.org/10.1016/j.jbusres.2020.05.051

Gasteiger E, Prettner K (2022) Automation, stagnation, and the implications of a robot tax. Macroecon Dynam 26:218–249. https://doi.org/10.1017/S1365100520000139

Graetz G, Michaels G (2018) Robots at work. Rev Econ Stat 100:753–768. https://doi.org/10.1162/rest_a_00754

Hall P, York M (2001) On the calibration of Silverman's test for multimodality. Stat Sinica 11:515–536

Henderson DJ, Russell RR (2005) Human capital and convergence: A production-frontier approach. Int Econ Rev 46:1167–1205. https://doi.org/10.1111/j.1468-2354.2005.00364.x

Henderson DJ, Parameter CF, Russell RR (2008) Modes, weighted modes and calibrated modes: evidence of clustering using modality tests. J Appl Econ 23:607–638. https://doi.org/10.1002/jae.1023

Hulten CR (1992) Growth accounting when technical change is embodied in capital. Am Econ Rev 85:964–980

International Federation of Robotics (2006) World Robotics 2006. IFR Statistical Department, VDMA Services GmbH, Frankfurt am Main, Germany

International Federation of Robotics (2005-2020). World Robotics: Industrial Robots. Annual Reports, IFR Statistical Department. http://www.worldrobotics.org

Johnson P, Papageorgiou C (2020) What remains of cross-country convergence. J Econ Lit 58:129–175. https://doi.org/10.1257/jel.20181207

Jung WJ, Lim DG (2020) Industrial robots, employment growth, and labor cost: A simultaneous equation analysis. Technol Forecast Soc Change 159:120202. https://doi.org/10.1016/j.techfore.2020.120202

Jungmittag A (2021) Robotisation of the manufacturing industries in the EU: Convergence or divergence. J Technol Transf 46:1269–1290. https://doi.org/10.1007/s10961-020-09819-0

Jungmittag A, Pesole A (2019) The impacts of robots on labour productivity. A panel data approach covering 9 industries and 12 countries. Seville: European Commission. JRC118044. https://ec.europa.eu/jrc/sites/default/files/jrc118044.pdf

Koch M, Manuylov I, Smolka M (2021) Robots and firms. Econ J 131:2533–2584. https://doi.org/10.1093/ej/ueab009

Krenz A, Prettner K, Strulik H (2021) Robots, reshoring, and the lot of low-skilled workers. Eur Econ Rev 136:103744. https://doi.org/10.1016/j.euroecorev.2021.103744

Kromann L, Malchow-Møller N, Skaksen JR, Sørensen A (2020) Automation and productivity – a cross-country. cross-industry comparison. Ind Corp Change 29:265–287. https://doi.org/10.1093/icc/dtz039

Kumar S, Russell RR (2002) Technological change, technological catch-up, and capital deepening: Relative contributions to growth and convergence. Am Econ Rev 92:527–548. https://doi.org/10.1257/00028280260136381

Lankisch C, Prettner K, Prskawetz A (2019) How can robots affect wage inequality. Econ Modelling 81:161–169. https://doi.org/10.1016/j.econmod.2018.12.015

Leitner S, Stehrer R (2019) In need of higher productivity growth. WIIW Working Paper 171. https://wiiw.ac.at/the-automatisation-challenge-meets-the-demographic-challenge-inneed-of-higher-productivity-growth-dlp-5158.pdf

Li Q (1996) Nonparametric testing of closeness between two unknown distribution functions. Econom Rev 15:261–274. https://doi.org/10.1080/07474939608800355

Los B, Timmer MP (2005) The 'appropriate technology' explanation of productivity growth differentials: An empirical approach. J Dev Econ 77:517–531. https://doi.org/10.1016/j.jdeveco.2004.04.001

Mendez C (2020) Convergence clubs in labor productivity and its proximate sources: Evidence from developed and developing countries. Springer, Singapore

Meng Y, Parmeter CF, Zelenyuk V (2023) Is newer always better? A reinvestigation of productivity dynamics using updated PWT data. J Product Anal 59:1–13. https://doi.org/10.1007/s11123-022-00649-w

Müller C, Kutzbach N (2020) World Robotics 2020 – Industrial Robots. IFR Statistical Department, VDMA Services GmbH, Frankfurt am Main, Germany

Niebel T (2018) ICT and economic growth – Comparing developing, emerging and developed countries. World Dev 104:197–211. https://doi.org/10.1016/j.worlddev.2017.11.024

Nordhaus WD (2015) Are we approaching an economic singularity? Information technology and the future of economic growth. National Bureau of Economic Research Working Paper 21547. https://www.nber.org/papers/w21547

Olesen OB, Petersen NC (2015) Facet Analysis in Data Envelopment Analysis. In: Zhu J (Ed.) Data Envelopment Analysis. International Series in Operations Research & Management Science, vol 221. Springer, Boston, MA., p 145–190. https://doi.org/10.1007/978-1-4899-7553-9_6

Portela MCAS, Thanassoulis E (2006) Zero weights and non-zero slacks: Different solutions to the same problem. Ann Op Res 145:129–147. https://doi.org/10.1007/s10479-006-0029-4

Prettner K (2019) A Note on the Implications of Automation for Economic Growth and the Labor Share. Macroecon Dynam 23:1294–1301. https://doi.org/10.1017/S1365100517000098

Quah D (1993) Galton's fallacy and tests of the convergence hypothesis. Scand J Econ 95:427–443. https://doi.org/10.2307/3440905

Quah D (1996) Convergence empirics across economies with (some) capital mobility. J Econ Growth 1:95–124. https://doi.org/10.1007/BF00163344

Quah D (1997) Empirics for growth and distribution: Stratification. polarization. and convergence clubs. J Econ Growth 2:27–59. https://doi.org/10.1023/A:1009781613339

Ram R (2021) International convergence in population happiness: evidence from recent data. Appl Econ 53:3984–3991. https://doi.org/10.1080/13504851.2017.1391992

Sachs JD, Kotlifkoff LJ (2012) Smart machines and long-term misery. National Bureau of Economic Research Working Paper 18629. https://www.nber.org/papers/w18629

Silverman BW (1981) Using kernel density estimates to investigate multimodality. J R Stat Soc 43:97–99. https://doi.org/10.1111/j.2517-6161.1981.tb01155.x

Silverman BW (1986) Density estimation for statistics and data analysis. Chapman and Hall, London (UK)

Solow RW (1956) A contribution to the theory of economic growth. Q J Econ 70:65–94. https://doi.org/10.2307/1884513

Solow RW (1957) Technical change and aggregate production function. Rev Econ Stat 39:312–320. https://doi.org/10.2307/1926047

Soto DA (2020) Technology and the future of work in emerging economies: What is different. OECD Social, Employment and Migration Working Papers No. 236. https://doi.org/10.1787/55354f8f-en

Steigum E (2011) Chapter 21 Robotics and Growth. In: de La Grandville O (Ed.) Economic Growth and Development (Frontiers of Economics and Globalization. Vol. 11). Emerald Group Publishing Limited, Bingley, p 543–555. https://doi.org/10.1108/S1574-8715(2011)0000011026

Timmer PM, Inklaar R, O'Mahony M, van Ark B (2010) Economic growth in Europe: A comparative industry perspective. Cambridge University Press, New York (US)

Walheer B (2021) Labor productivity and technology heterogeneity. J Macroecon 68:103290. https://doi.org/10.1016/j.jmacro.2021.103290

Zeira J (1998) Workers, Machines, and Economic Growth. Q J Econ 113:1091–1117

Zhu H, Zhang X (2021) The impact of robots on labor productivity and employment: Evidence from the three largest economies. https://doi.org/10.2139/ssrn.3969627