The contribution of robots to productivity and GDP growth

in advanced economies over 1960-2022

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Abstract

While the employment effects of robots are a matter of vivid debate among economists, only a few empirical studies have looked at their impact on productivity and growth at the country level. This paper provides new estimates of the robots' contribution to growth in a set of 29 advanced economies countries over the period 1960-2022. Based on a standard growth accounting framework, the user cost of robots is estimated according to two different methodologies. The estimated robots' contribution to growth largely differs between the two methodologies, suggesting that the value of the stock of robots, the decrease in their quality-adjusted price index or both may be undervalued. These findings call for further research on the robots' contribution to growth at the country level.

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The opinions and arguments expressed herein are those of the authors and do not necessarily reflect the official views of the OECD or its member countries.

1. Introduction

The employment effects of robots at the firm and the country level are a matter of vivid debate among economists (see for instance, among others, Brynjolfsson and McAfee, 2014; Autor, 2015; Acemoglu and Restrepo, 2020, Acemoglu *et al*., 2020; Aghion *et al.* 2020; Aghion *et al.*, 2022; Acemoglu *et al.*, 2023). Autor (2015) argues that robot diffusion and automation will have limited, negative effects on middle-wage, middle-education jobs. Using Canadian data, Dixon (2020) finds a similar employment impact of robotization. Based on a theoretical model and an empirical investigation on 13 advanced countries, Kapetaniou and Pissarides (2024) argue that the substitution between robots and jobs would depend on the country's innovation capabilities and openness. These results are consistent with those obtained by Shahin *et al.* (2024) on Spanish firm-level data. Acemoglu and Restrepo (2020) find a detrimental impact of robots on employment in the United States. Based on firm-level data in France over 2010-15, Acemoglu *et al.* (2020) find that adoption of robots is associated to an increase in value added, productivity and employment but to a decrease in labor shares and in production workers. Using a large dataset of French firm over 1994-2015, Aghion *et al.* (2020) find that firm-level employment increases after automation, including for low-skilled industrial workers. Acemoglu *et al.* (2023) estimate the effects of robot adoption on firm-level outcomes in the Netherlands using a firm dataset over the period 2009-2020. They find a positive effects on value added and hours worked for robot-adopting firms and negative outcomes on competitors in the same industry.

In their literature review on the topic, Aghion *et al.* (2022) explain the difference in the above findings by arguing that automation has two opposite effects on employment: on the one hand, it may displace certain workers, raising the possibility of technological unemployment; on the other, it may induce productivity gains, increase market demand and the scale of production, and in turn increase labor demand.

Some studies have focused on the impact of robot adoption on the labor share. For instance, Koch and Manuylov (2023) or Shahin *et al.* (2024), both based on analyses on Spanish data, and Shimizu and Momoda (2023), within a theoretical model, find that robots have a labour-saving bias, thus contributing to a decrease in the labor share.

Only a few empirical studies have looked at the effects of robot adoption on productivity and growth at the country level. Among the few exceptions, Graetz and Michaels (2015, 2018) find that increased robots per worker contributed approximately 0.36 percentage points to annual labor productivity growth in 17 countries from 1993 to 2007. Using the elasticities of productivity to robots by Graetz and Michaels (2015, 2018) in a growth accounting approach, Cette, Devillard and Spiezia (2021 and 2022) find similar effects for a set of 30 advanced economies over the period 1960-2019. In a recent paper, Bekhtiar *et al.* (2024) argue that some estimates of Graetz and Michaels (2015, 2018), i.e.: those where changes in robotization are measured as *percentiles*, are partly driven by industry-level heterogeneity as their sample includes both robotizing (i.e.: mainly manufacturing) and non-robotizing (i.e.: services) industries. Focusing estimation on robotizing industries only *"leads to a significant drop of the productivity effects during the period 1993–2007, cutting the estimated effect roughly in half*" (Bekhtiar *et al.*, 2024). Using the same data as Graetz and Michaels (2015, 2018) but on the extended 1993-2017 period, Almeida and Sequeira (2024) show that the estimated elasticity of productivity to robotization has largely decreased in the last decade of their estimation period compared to the previous sub-period. As a result, the productivity effects of robotization would have more than halved from the first to the second decade of their estimation period.

This study presents new estimates of the robots' contribution to productivity and GDP growth in 29 advanced economies as well as for the whole Euro Area over the period 1960-2022. In order to estimate the robots' contribution to growth, this paper uses a standard growth accounting framework, where the value-added elasticity of each production input is measured as its share in total inputs' remuneration. To compute the robots' remuneration, one has to estimate their user cost.

This paper uses two alternative methodologies to estimate robots' user cost. In the first methodology, the user cost of robots is computed using the relation proposed by Jorgenson (1963), where the unitary value of robots is drawn from the IFR database and the quality-adjusted price index of robots is proxied by the US price index of '*information processing equipment*' published by the BEA. In the second methodology, the user cost of robots is derived from the elasticity of labour productivity to robots estimated by Graetz and Michaels (2015).

Our results show that the estimated robots' contribution to growth appears much larger according to methodology 2 than methodology 1. Results from methodology 2 are consistent with the findings by Graetz and Michaels (2015, 2018) as well as Cette, Devillard and Spiezia (2021, 2022), who build on the former. The lower evaluation of robots' contribution to growth based on the methodology 1 may have two explanations. The first is that the quality-adjusted price index used in this methodology may underestimate the decrease in the user cost of robots, thus the improvement in their quality. The second explanation is that the value of the stock of robots could be underestimated in the IFR data, because of an undervaluation of their unitary value. The two explanations are probably at play. In addition, as argued by Bekhtiar *et al.* (2024), Graetz and Michaels (2015) may overestimate the productivity impact of robotization due to industry-level heterogeneity and the fact that they don't distinguish between robotizing and non-robotizing industries.

The paper is organized as follows. Section 2 presents the data for the analysis. Section 3 discusses the main trends in robots' diffusion in the largest economies of our dataset from 1960 to 2021. Section 4 details the two methodologies to estimate the robots' contribution to growth. Section 5 presents the estimates based on the two methodologies, while Section 6 concludes.

2. The database

The database used in this study is an update of the database built by Cette, Devillard and Spiezia (2021 and 2022; see these papers for more details). In order to estimate the robots' contribution to growth, we have collected data on GDP at constant price 2015, hours worked and robots installed in 29 countries[1] - in addition to the Eurozone[2]- over 1951–2022. GDP data are drawn from several databases: the BEA, Eurostat, OECD, Penn World Table 1, and the UN. GDP deflators are those from the BEA for USA, INSEE for France, Eurostat, OECD and Penn World Table 1 for all other countries. Deflators have been extrapolated from 1950 to 1989 for the Czech Republic, Estonia, Lithuania, Latvia, Slovakia, Slovenia and from 1950 to 1969 for Hungary, assuming the same annual growth rate of the GDP deflator as the one observed in Germany. The number of hours worked is the average annual working time per worker multiplied by employment. The sources of these two indicators are the Long Term Productivity database (LTP) (Bergeaud, Cette and Lecat, 2016), the OECD Annual Labour Force Statistics, and the Conference Board Total Economy Database (TED). The LTP database contains data

1 These 29 countries are Australia, Austria, Belgium, Canada, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Israel, Italy, Japan, Latvia, Lithuania, Mexico, The Netherlands, Norway, New Zealand, Portugal, Slovakia, Slovenia, Spain, Sweden, the United Kingdom and the United States.

2 Euro Area has been reconstituted, aggregating Germany, France, Italy, Spain, The Netherlands, Belgium, Austria, Finland, Greece, Ireland, and Portugal, these 11 countries representing together, in 2018, 97% of the Euro Area GDP.

from 1950 for the following countries: Australia, Austria, Belgium, Canada, Germany, Denmark, Spain, Finland, France, United Kingdom, Greece, Israel, Italia, Japan, Mexico, The Netherlands, Norway, New-Zealand, Portugal, Sweden and USA. For the other countries, we use OECD and TED. The working time per worker is extrapolated for Czech Republic, Estonia, Hungary, Israel, Lithuania, Latvia, Slovakia and Slovenia from 1950 to 1994 at the latest, assuming the same annual growth rates of working time as the one observed in Germany.

Data on robots are drawn from the World Robotics - Industrial Robots statistics compiled by the International Federation of Robots (IFR), covering installations and the operational stocks of robots from 1983 to 2021[3], with partially available data. We consider industrial robots only, corresponding to the definition of the International Organization for Standardization (ISO 8373:2012): an ''*automatically controlled, reprogrammable multipurpose manipulator programmable in three or more axes*''. IFR collects data on robot installations by country, industry and application from nearly all industrial robot suppliers worldwide. It complements this information with data from several national robot associations, including Korean Association of Robot Industry (KAR), the Japanese Robot Association (JARA) and the Robotic Industries Association (RIA) providing data on North America. Prior 2004, country reports relied exclusively on data of national robot associations.

The operational stock of robots measures the number of robots currently deployed. JARA calculates and provides this figure for Japan. For all other countries, IFR calculates the operational stock assuming an average service life of 12 years with an immediate withdrawal from service afterwards (see IFR and UN ECE, 2001, for a discussion about the length of the service life). To complete the IFR database and extend the series back to 1960, Cette, Devillard and Spiezia (2021 and 2022) have estimated the stock of operational robots based on an OLS regression on the stock of each of the three ICT capital products (hardware, software and telecommunication), with fixed effects for countries and a common trend. This specification was privileged after robustness checks against alternative specifications.[4]

3. Robot diffusion

Robots can now perform a wide range of tasks, with very little or no human intervention. Unlike ICTs, they are able of flexible movements in three dimensions, which were previously exclusive to human beings.

Graetz and Michaels (2018) estimate that the price of industrial robots in six major developed economies (France, Germany, Italy, Sweden, the United Kingdom and the United States) in 1990-2005 fell by about 50% in nominal terms and 80% when adjusted for quality. Such a decrease has fueled rapid diffusion in robots in a number of economies.

The diffusion of robots started in the early 70s, first in Japan, followed by Germany (Chart 1). In other countries, robot diffusion started to pick about a decade later. Japan had the highest penetration of robots in the sample until 2011, when Germany took the lead. In Japan, the number of robots per million hours worked decreased in 1998-2003 due to the crisis of the IT sector, fluctuated in 2004-2008 decreased further in 2009-2017, following the delocalization of activities in the automobile, electrical and electronic industries, and increased sharply in 2017-2021.

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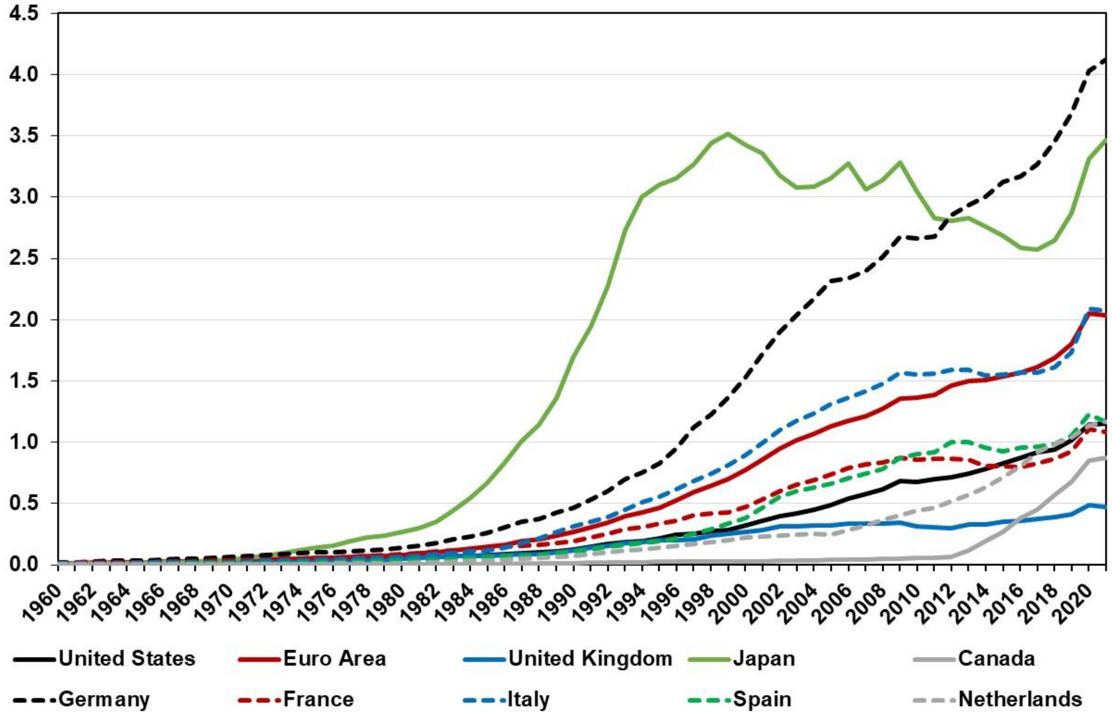
[3] Our two methodologies to evaluate the robot contribution to growth assume that the capital installed at the end of the year *t-1* contributes to the productivity in year *t*. For this reason, robot data available until 2021 allow us to evaluate robot contribution to growth until 2022.

[4] Detailed results of these econometric estimates are available upon request from the authors.

Chart 1. Robot diffusion, 1960-2021
Number of robots per million hours worked in selected countries

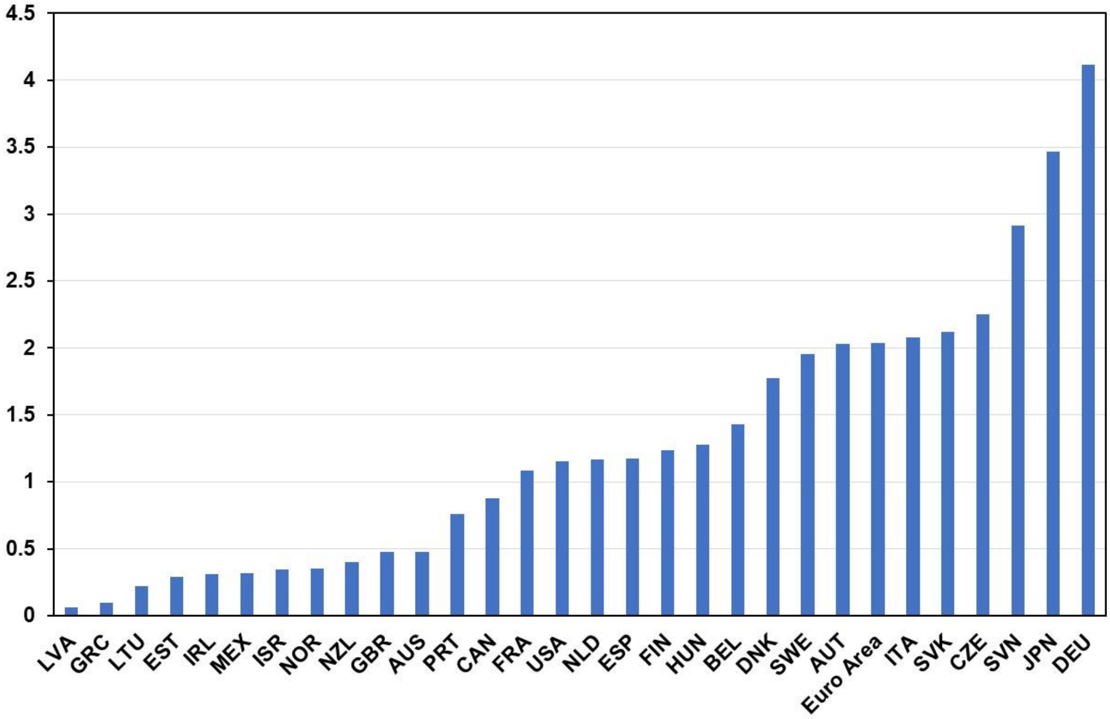


Source: IFR and authors' calculations.

In 2021, Germany (4.1), Japan (3.5) and Slovenia (2.9) were the three countries the highest number of robots per million hours worked (Chart 2). While penetration has been increasing steadily in other countries, the number of robots per millions of hours worked remains lower and exceed 2 only in Austria, the Czech Republic, Italy and the Slovak Republic. In 2021, the number of robots per million hours worked was below 1 in 13 countries out of 29 and ranged between 1 and 2 in 9 countries.

Robots tend to be concentrated in few manufacturing sectors. In 2021, transport equipment accounted for about 45% of the world stock of robots, Electronic, electrical and optical equipment for 30%, Rubber and plastic for 8% and Metal products for between 6%. Therefore, the observed patterns of diffusion also reflect country-specific specializations.

Chart 2. Robot diffusion, 2021
Number of robots per million hours worked



Source: IFR and authors' calculations.

4. Two methodologies to evaluate the robots' contribution to growth

In order to estimate the robots' contribution to growth, this paper uses a standard growth accounting framework, where the value-added elasticity of each production input is measured as its share in total inputs' remuneration.[5] A key piece of information necessary to compute the robots' remuneration is their user cost. As in general this is not observable, it has to be estimated.

This paper uses two alternative methodologies to estimate robots' user cost. In the first methodology, the user cost of robots is computed using the relation proposed by Jorgenson (1963), where the unitary value of robots is drawn from the IFR database and the quality-adjusted price index of robots is proxied by the US price index of '*information processing equipment*' published by the BEA. In the second methodology, the user cost of robots is derived from the elasticity of labour productivity to robots estimated by Graetz and Michaels (2015).

This section briefly explains the two methodologies while the next section compares their results. Interestingly, the estimated contribution of robots to growth varies significantly between these two methodologies.

[5] Assuming perfect competition, the remuneration of all inputs equals value added.

4.1. Methodology 1: Jorgenson's formula with the US 'information processing equipment' price index

We estimate the robot contribution to growth using a standard growth accounting framework. We consider here only the robots' contribution via capital deepening as industry-level information required to estimate the robots' contribution via Total Factor Productivity (*TFP*) is not available.

Let RCG_{tj} denote the robots' contribution to growth via capital deepening in year *t* and country *j*. For each country, RCG_t is obtained through the relation:

(1) $RCG_t = \alpha r_{T,t} \,.\, (\Delta kr_{t-1} - \Delta n_t - \Delta h_t)$

where KR_{t-1} stands for the stock of robots installed at the end of year *t-1* in constant, quality-adjusted price, N_t for total employment in year *t*, and H_t for the average annual hours worked per person the year t. Δ denotes one-year difference, e.g.: $\Delta X_t = X_t - X_{t-1}$ while variables in lowercase denote natural log $(x = ln(X))$. The growth rate of a variable is approximated by its difference in logarithm, e.g.: Δx_t.

The coefficient $\alpha r_{T,t}$ is the Törnquist index of the coefficient αr_t:

(2) $\alpha r_{T,t} = (\alpha r_t + \alpha r_{t-1})/2$.

The coefficient αr_t is the share of the robot capital remuneration in GDP:

(3) $\alpha r_t = (CR_t \,.\, KR_{t-1})/(PQ_t \,.\, Q_t)$

where CR_t stands for the user cost of robot capital, KR for the stock of robots' quality adjusted, PQ for the GDP deflator, and Q for GDP in volume.

The user cost of robot capital CR is calculated following the relation proposed by Jorgenson (1963):

(4) $CR_t = PR_t.(i_t + \delta R - \Delta pr_t)$

where PR stands for the quality adjusted robot price, i for the long-term nominal interest rate (here the 10-year sovereign debt interest rate), and δR for the depreciation rate of the robots.

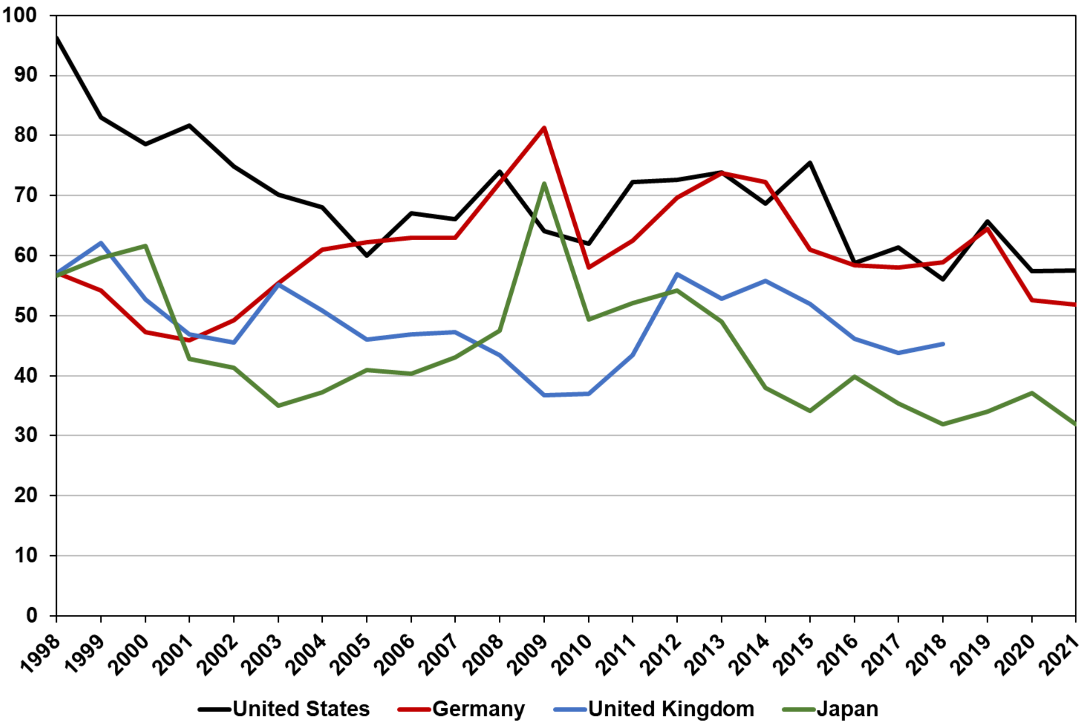
δR is assumed to be constant. We set δR at 10% a year, i.e.: the depreciation rate of standard equipment. This rate is higher than 4% to 7% proposed by Klump *et al.* (2021), which seems to us very low. As a robustness test, we have used lower (δR = 5%) and higher (δR = 15% and 20%) depreciation rates but these changes had very small effects on the results.[6]

The calculation of *KR* is made in two steps. First, we calculate the stock of robots in current value (*KRCV*) and then we divide it by a quality-adjusted robots price index (*QARP*).

The stock of robots in current value (*KRCV*) is computed as equals the number of robots (*NR*) times the unitary value of robots (*UVR*): *KRCV =NR*UVR*. The number of robots (*NR*) is obtained from IFR, see above. The International Federation of Robotics (IFR) evaluates the unitary value of robots (*UVR*), in national currency, for different countries. Chart 3 shows the *UVR* in the US, Germany, the UK and Japan from 1998 to 2021. The *UVR* ranges between USD 30 000 to USD 100 000. As UVR data are not available for all countries, we use the German UVR for all European countries and the US UVR for all other countries, using smoothed annual exchange rates to convert EUR and national currencies into USD.

6 These results are available upon request from the authors.

Chart 3. Unitary value of robots (UVR) (USD thousand)



Note: National currency converted to USD based on smoothed annual exchange rate.
Source: IFR and authors' calculation.

Concerning the quality-adjusted robot price index (*QARP*), direct evaluations are not available over the whole period. The IFR published estimates over the period 1990-2005, based on the price of robots' components from the US National Accounts computed by the BEA. Based on these estimates, the annual growth rate of *QARP* in the US was -11.1 % (see Klump *et al*., 2021, Table 3.b). Using the same methodology, the Bank of Japan (2022) estimates that the annual growth rate of *QARP* in Japan over the same period was -28.6%. The gap between these two figures highlights the complexity of estimating quality-adjusted price for robots.

In this study, we use the US '*information processing equipment*' price index computed by the BEA as a proxy for the *QARP*. From 1990 to 2005, this index fell by 70%, a value that is not distant from the 80% decrease in the quality-adjusted price of industrial robots (-80%) estimated by Graetz and Michaels (2018) over the same period in a sample of six economies (France, Germany, Italy, Sweden, the UK and the US). It corresponds to an average annual decrease of almost 8% from 1990 to 2005. Over the whole period 1960-2022, the annual growth rate of the US '*information processing equipment*' price index was -3.3%, compared to 2.7% for private fixed equipment.

In all countries other the US, we adjusted the US '*information processing equipment*' price index following the method suggested by Schreyer (2000), which assumes that the robots' price in a country relative to the robots' price the US is equal to that country's GDP deflator relative to the US GDP deflator.

4.2. Methodology 2: Based on the econometric estimates by Graetz and Michaels (2015)

An alternative methodology to estimating the robots' user cost is based on the estimates by Graetz and Michaels (2015) on a panel of 14 countries (Table 1). Their estimates seem consistent - as far as a comparison is possible - to the ones by Acemoglu *et al.* (2020) on a panel of French firms.

Table 1. Estimated elasticities of labour productivity and worked hours to robots

		Δln(VA/NH)	*Δln(NH)*	*Δln(TFP)*
a	*Δ (NR/NH)*	0.144		
b	*Δ (NR/NH)*		0.044	
c	*Δ percentile of (NR/NH)/100*	0.873		
d	*Δ percentile of (NR/NH)/100*			0.663

Note: NR stands for number of robots, NH stands for million hours worked, VA per value added and *TFP* for Total Factor Productivity. All estimates are instrumental variables (IV).
Source: Graetz and Michaels (2015), Tables A7(2), A6(2) and 6(2).

a and *b* stand for, respectively, the estimated elasticity of labour productivity (0.144) and worked hours (0.044) to the number of robots per hours worked (*NR/NH*) in robots-using industries. These estimates compound the effects of robots on labour productivity via capital deepening and *TFP*.

The two effects can be separated based on the estimates *c* and *d* reported in Table 1 as well. *c* is the estimated elasticity of labour productivity to *percentile changes* in the number of robots per hour worked. *d* is the estimated elasticity of *TFP* to *percentile changes* in the number of robots per hours worked. Taken together, *c* and *d* imply that 76% (i.e.: d/c = 0.663/0.873) of the estimated contribution of robots to labour productivity occurs via *TFP* while the remaining 24% is accounted for by capital deepening. As *c* and *d* are estimated on the same sample as *a*, the above ratios can be used to decompose the elasticity *a* into two components: the estimated contribution of the *number of robots per hours worked* to labour productivity via *TFP*, *e* = 0.76*0.144 = 0.1044; and the elasticity of labour productivity to the number of robots per hour worked via capital deepening, *f* = 0.24*0.144 = 0.0396.

Under the standard hypothesis of profit maximisation, (e) and (b) provide an implicit estimate of the user cost of robots. From:

(5) $\partial lnQ = e*\partial(NR/NH)$ and

(6) $\partial lnNH = b*\partial(NR/NH)$

one obtains

(7) $\partial lQ/\partial NR = e*(NR/NH)*(Q/NR)/[1-b*(NR/NH)]$

which, under profit maximization, must equal the real user cost of robots (CR_t).

From the above equality, it follows that the share of robots' remuneration in the value added of robot-using industries equals:

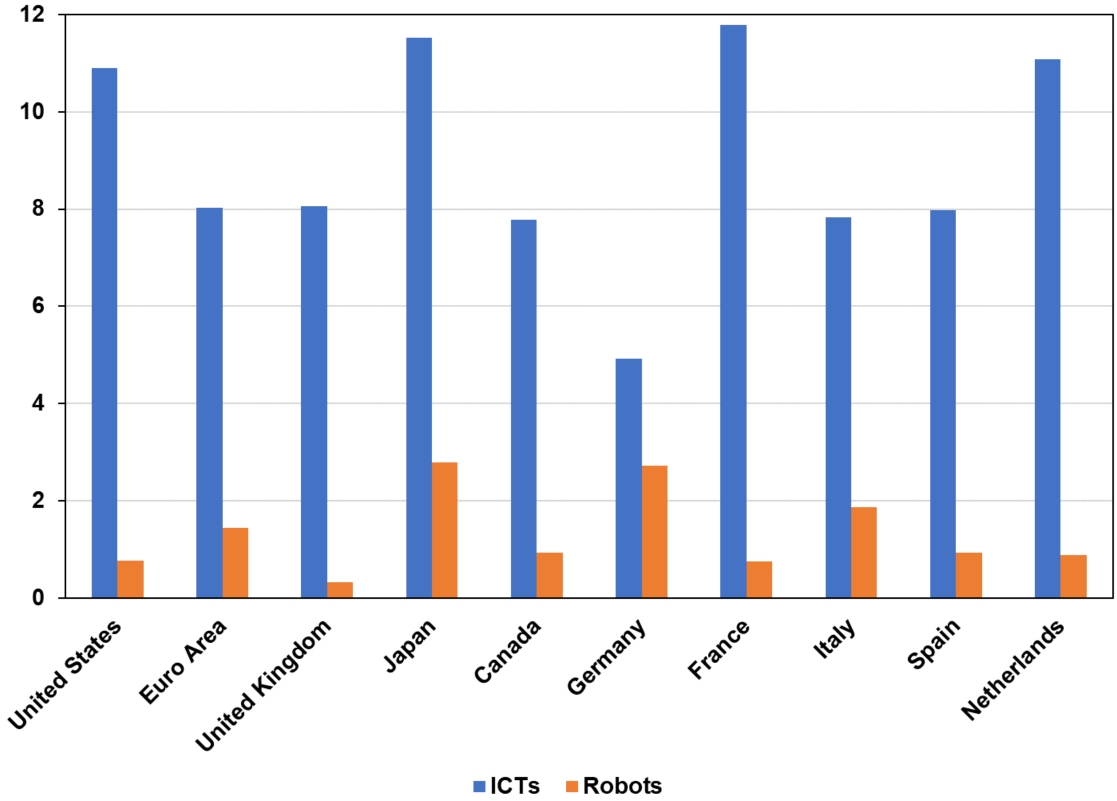
(8) $\alpha r_t = e*(NR/NH)/[1-b*(NR/NH)]$

In turn, by multiplying (8) by the value-added weights of robots-using industries,[7] one obtains the share of robots' remuneration in GDP, as shown in Chart 4 for selected countries.

[7] Robot-using industries include ISIC Rev.4 01-03, 05-09, 10-32, 35-39, 41-43 and 72.

Finally, as robots are included in the stock of non-ICT capital, their remuneration is subtracted from the remuneration of non-ICT capital. The robots' contribution to growth is then calculated as in equations (1) and (2) above.

Chart 4. ICT and robot capital remuneration, as a share of GDP (%) – 2021



Note: Robots' remuneration is estimated based on methodology 2.
Source: IFR and authors' calculation.

5. Results

Our findings extend the estimates from Graetz and Michaels (2015, 2018) to a wider set of countries (29) over a longer time period (from 1960 to 2022), based on the two methodologies presented above. The second methodology accounts for the robots' contribution to growth via both capital deepening and *TFP* whereas the first accounts for capital deepening only. Tables 2 and 3 below present the results for 9 countries (the G7, Spain and the Netherlands) as well as the Euro Area.[8] As robots' diffusion started to pick up in the mid-1970s, we comment their contribution to growth over four sub-periods: 1960-1975, before the first oil shock and the emergence of robotization; 1975–1995, from the first oil shock to the onset of the ICT diffusion; 1995–2005, at the peak of the ICT diffusion; and 2005–2022, the most recent period, which includes the Great Recession, the COVID and the inflationary crises.

[8] Results concerning other countries are available upon request from the authors.

5.1. Results from methodology 1

The robot contribution to growth computed through a standard growth accounting methodology (eq. 1 above) is presented in Table 2 for different countries and sub-periods. As indicated above, we consider here only the capital deepening channel of this contribution.

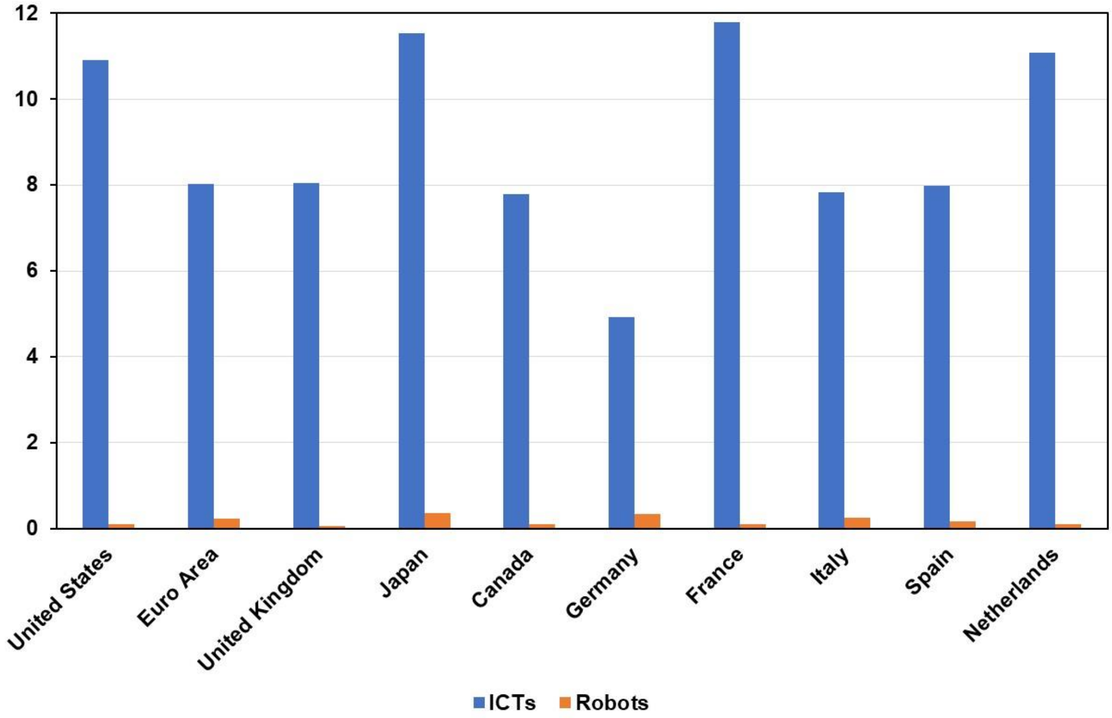
Table 2. Methodology 1: Annual robots' contribution to growth via capital deepening (in pp)

	1960-1975	1975-1995	1995-2005	2005-2022	1960-2022
United States	0.0010	0.0010	0.0020	0.0011	0.0011
Euro Area	0.0001	0.0012	0.0046	0.0021	0.0020
United Kingdom	-0.0001	0.0008	0.0015	0.0004	0.0008
Japan	0.0000	0.0001	0.0001	0.0000	0.0000
Canada	0.0000	0.0002	0.0002	0.0010	0.0004
Germany	0.0003	0.0020	0.0088	0.0036	0.0033
France	0.0001	0.0008	0.0025	0.0009	0.0011
Italy	-0.0003	0.0015	0.0052	0.0024	0.0025
Spain	0.0003	0.0006	0.0034	0.0019	0.0017
The Netherlands	0.0001	0.0004	0.0008	0.0011	0.0006

Source: Authors' calculation.

It appears that the robots' contribution to growth is very small according to methodology 1, and much smaller than the contribution based on methodology 2 (see below). Even in Germany, the country where robot diffusion is the largest, annual robots' contribution to growth is very small. These findings reflect the fact that the value of the capital stock of robots is very low. Chart 5 compares the capital coefficients (i.e.: the capital stock relative to GDP in current value) for robots and ICTs in 2021: the ICT capital coefficient is at least 50 times bigger than the capital coefficient for robots. Another quality-adjusted robot price index (*QARP*) data with a faster decline than the one here used (the US '*information processing equipment*' price index computed by the BEA) would not be enough to explain alone the very small robots' contribution to growth. The low value of the stock of robots in the IFR data largely contribute to this result. Indeed, this value is smaller than the value of the ICTs capital stock (Chart 5). The two explanations are probably both at play.

Chart 5. Capital coefficient of ICTs and robots (%) 2021
Ratios of the ICT capital stock and the robot capital stock to GDP, current value



Source: Author calculation.

5.2. Results from methodology 2

The robots' contribution to growth computed through methodology 2 is shown in Table 3. This methodology accounts for the robots' contribution both via capital deepening and the *TFP*.

As methodology 2 is equivalent to the one used by Cette, Devillard and Spiezia (2021, 2022), the estimates differ only slightly from theirs. The small differences observed come from the update of the database and the inclusion of the effects of robots on working hours (as shown in Table 1). The estimated robots' contribution to growth appears smaller than in Graetz and Michaels (2015, 2018). This difference is likely to reflect the fact that we implicitly exclude for the scope of the analysis industries with small robots' penetration. Therefore, the above estimates should be considered as a lower bound for this methodology.

Average yearly robots' contribution to productivity growth appears the largest in Germany, particularly in the period 1995–2005 (0.63 percentage points). In Japan, robots' contribution reached a peak in 1975–1995 (0.78 pp.), dropped in the next two periods (-0.12 pp. in 1995-2005 and none in 2005-2022) following the slowdown in robots' diffusion commented above. In the period 2005–2022, the contributions of robots increased significantly in Eastern European countries, further to insourcing of manufacturing activities, particularly in the automobile sector. In the same period, robots' contribution was also sizeable in Germany (0.57 pp.), Canada (0.22), the Netherlands (0.24), Italy (0.17), the United States (0.16) and Spain (0.14). While robotization appears like a significant source of growth in some countries and sub-periods, due to productivity gains via both capital deepening and *TFP*, its contribution is much smaller than the ICT contribution (Cette, Devillard and Spiezia, 2021 and 2022).

Table 3. Methodology 2: Annual robots' contribution to growth via capital deepening and TFP (pp)

		1960-1975	1975-1995	1995-2005	2005-2022	1960-2022
United States	***Cap. Deep.***	0.00	0.01	0.03	0.04	0.02
	TFP	0.01	0.03	0.08	0.12	0.06
Euro Area	***Cap. Deep.***	0.00	0.02	0.07	0.06	0.04
	TFP	0.01	0.07	0.25	0.19	0.12
United Kingdom	***Cap. Deep.***	0.00	0.01	0.02	0.01	0.01
	TFP	0.01	0.03	0.05	0.03	0.03
Japan	***Cap. Deep.***	0.01	0.19	-0.03	0.00	0.07
	TFP	0.03	0.59	-0.09	0.00	0.19
Canada	***Cap. Deep.***	0.00	0.00	0.00	0.05	0.00
	TFP	0.00	0.00	0.01	0.17	0.06
Germany	***Cap. Deep.***	0.01	0.04	0.15	0.14	0.08
	TFP	0.02	0.13	0.48	0.43	0.25
France	***Cap. Deep.***	0.00	0.02	0.04	0.02	0.02
	TFP	0.01	0.05	0.13	0.07	0.06
Italy	***Cap. Deep.***	0.00	0.03	0.09	0.04	0.05
	TFP	0.01	0.09	0.29	0.13	0.13
Spain	***Cap. Deep.***	0.00	0.01	0.07	0.03	0.03
	TFP	0.01	0.03	0.23	0.11	0.08
Netherlands	***Cap. Deep.***	0.00	0.01	0.01	0.06	0.02
	TFP	0.00	0.02	0.04	0.18	0.07

Source: Authors' calculation

5.3. Analysis of the results

A comparison of Tables 2 and 3 above shows that the estimated robots' contribution to growth appears much larger according to methodology 2 than methodology 1. For instance, the yearly capital deepening effect in Japan in 1975-1995 was equal to 0.19 pp. according to methodology 2 and 0.0001 pp. based on methodology 1. Similarly, in Germany in 1995-2005, the yearly capital deepening effect was equal to 0.15 pp. and 0.0088 pp. depending on the methodology used.

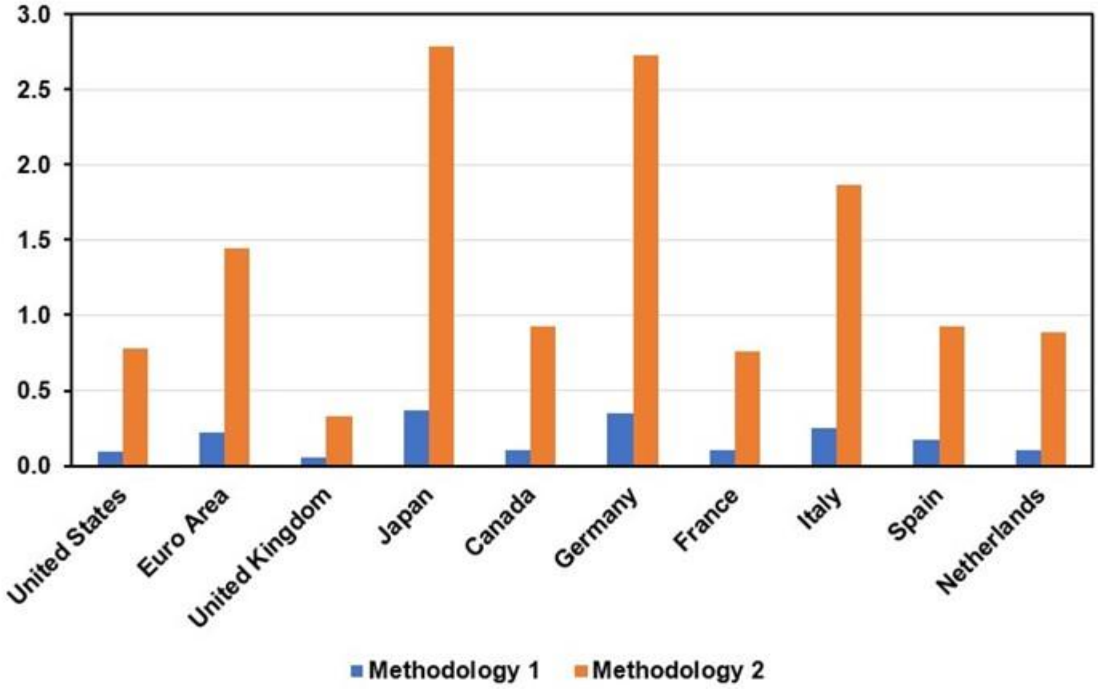
As discussed above, the two methodologies differ in the way the user cost of robots is estimated. Methodology 1 uses the unitary value of robots from IFR and the US '*information processing equipment*' quality-adjusted price index whereas methodology 2 derives the user cost from econometric estimates of the elasticities of productivity and worked hours to the number of robots.

These findings suggest that the low contribution estimated through methodology 1 could have three explanations. The first is that the quality-adjusted price index of robots may imply a lower decrease in the user cost of robots than the one obtained by the econometric estimate. The second explanation is that the IFR data may underestimate the value of the stock of robots because of an undervaluation of the unitary value of robots (*UVR*).

The first explanation is tempered by the observation that the difference between the results of the two methodologies is so wide that it would imply an unlikely large "underestimation" in the price index. The second explanation seems to account for the bulk of the difference in the estimates. Chart 6 compares the robots' remuneration as a share of GDP in 2021, i.e.: the Tornquist coefficient $\alpha r_{T,t}$ in equation (1), between the two methodologies. The coefficient is bigger in methodology 2 than in methodology 1 by a factor of 6 (in Spain and the United Kingdom) to 9 (in Canada, the Netherlands and the United States). A larger value of the Tornquist coefficient is likely to account for a large share of the difference in the results of the two methodologies.

The third explanation may be that Graetz and Michaels (2015) overestimate the productivity impact of robotization, as argued by Bekhtiar *et al.* (2024).

Chart 6. Robot capital remuneration, as a share of GDP (%) – 2021



Source: Author calculation.

6. <u>Conclusion</u>

While the employment effects of robots are a matter of vivid debate among economists, only a few empirical studies have looked at their impact on productivity and growth at the country level. This paper has provided new estimates of the robots' contribution to growth in a set of 29 countries over the period 1960-2022. Based on a standard growth accounting framework, the user cost of robots has been estimated according to two different methodologies: in the first methodology, the user cost is derived based on the value of the stock of robots and the US '*information processing equipment*' quality-adjusted price index; in the second, the user cost is derived from the previous econometric estimates of the elasticities of productivity and worked hours to the number of robots.

The estimated robots' contribution to growth appears to be much larger according to methodology 2 than methodology 1. Results from methodology 2 are consistent with the results by Graetz and Michaels (2015, 2018) as well as Cette, Devillard and Spiezia (2021, 2022), who build on the former.

These findings suggest three possible explanations of the low evaluation of robot contribution to growth in the methodology 1. On one hand, the quality-adjusted price index used in methodology 1 may underestimate the decrease of user cost of robots, thus the increase of their quality. On the other, the value of the stock of robots installed could be underestimated in the IFR data, because of an undervaluation of the unitary value of the robots. Both explanations are probably at play. The third explanation of the large gap between our two estimates may be due to Graetz and Michaels (2015) overestimating the productivity impact of robotization because of industry-level heterogeneity, as argued by Bekhtiar *et al.* (2024). In addition, as shown by Almeida and Sequeira (2024), the productivity impact of robotization has strongly decreased over time, as the productivity-enhancing effects for later adopters – firms and industries- were smaller than for earlier ones.

Yet, while the above-mentioned factors may contribute to an explanation, the wide difference between the results of the two methodologies used in this paper calls for further research on the robots' contribution to growth at the country level.

References

Acemoglu, Daron, and Pascual Restrepo (2020). "Robots and jobs: Evidence from US Labor Markets", *Journal of Political Economy*, 128(6), 2188-2244.

Acemoglu, Daron, Claire Lelarge and Pascual Restrepo (2020). "Competing with Robots: Firm-level Evidence from France ", *AEA papers and proceedings* (Vol. 110, pp. 383-388).

Acemoglu, Daron, Hans R. A. Koster and Ceren Ozgen (2023): "Robots and Workers: Evidence from The Netherlands ", *NBER Working Papers* n° 31009.

Aghion, Philippe, Céline Antonin, Simon Bunel and Xavier Jaravel (2020): "What Are the Labor and Product Market Effects of Automation? New Evidence from France ", *mimeo*.

Aghion, Philippe, Céline Antonin, Simon Bunel and Xavier Jaravel (2022): "The Effects of Automation on Labor Demand: A Survey of the Recent Literature ", *CEPR Discussion Papers*, n° DP16868, February.

Almeida, Derick and Tiago Neves Sequeira (2024): "Robots at work: New evidence with recent data", The Manchester School, Forthcoming.

Autor, David H. (2015). "Why Are There Still So Many Jobs? The History and Future of Workplace Automation ", *Journal of economic perspectives*, 29(3), 3-30.

Bank of Japan (2022), "Corporate Goods Price Index ", " Producer Price Index " https://www.stat-search.boj.or.jp/ssi/cgi-bin/famecgi2?cgi=$nme_a000_en&lstSelection=PR01.

Bekhtiar, Karim, Benjamin Bittschi and Richard Sellner (2024): "Robots at work? Pitfalls of industry-level data", Journal of Applied Econometrics, Vol. 39, pp. 1180–1189.

Bergeaud, Antonin, Gilbert Cette and Remi Lecat (2016). "Productivity Trends in Advanced Countries between 1890 and 2012 ", *The Review of Income and Wealth* 62(3): 420–444.

Brynjolfsson, Erik and Andrew McAfee (2014). *The Second Machine Age – Work, Progress and Prosperity in a Time of Brilliant Technologies*. New York: W. W. Norton & Company.

Cette, Gilbert, Aurélien Devillard and Vincenzo Spiezia (2021). "The Contribution of Robots to Productivity Growth in 30 OECD Countries over 1975–2019 ", *Economics Letters*, 200, 109762.

Cette, Gilbert, Aurelian Devillard and Vincenzo Spiezia (2022). "Growth Factors in Developed Countries: a 1960–2019 Growth Accounting Decomposition ", *Comparative Economic Studies*, 1-27.

Dixon, Jay (2020): "The Employment Consequences of Robots: Firm-level Evidence", Statistics Canada, Analytical Studies Branch Research Paper Series, 2 November.

Graetz, Georg and Guy Michaels (2015): "Robots at Work ", *CEPR Discussion Papers*, No. 10477, March.

Graetz, Georg and Guy Michaels (2018): "Robots at Work ", *The Review of Economics and Statistics*, Vol. 100, Issue 5, December, pp. 753-768.

International Federation of Robots (IFR) and United Nation Economic Commission for Europe (UN ECE) (2001). “Annex B: Measuring Service Lives of Industrial Robots – Pilot Study” in *World robotics 2001*, United Nations, New York-Geneva.

Jorgenson, Dale (1963): “Capital Theory and Investment Behavior “, *The American Economic Review* 53 (2), pp. 247-259.

Kapetaniou, Chrystalla and Christopher A. Pissarides (2024): “Productive robots and industrial employment: The role of national innovation systems”, International Economic Review, October, Forthcoming.

Klump, Rainer, Anne Jurkat Anne and Florian Schneider (2021). “Tracking the Rise of Robots: A Survey of the IFR Database and its Applications “, *MPRA Papers*, No. 109814, September.

Koch, Michael and Ilya Manuylov (2023): “Measuring the Technological Bias of Robot Adoption and its Implications for the Aggregate Labor Share “, *Research Policy*, 52.

Schreyer, Paul (2000): “The Contribution of Information and Communication Technology to Output Growth: A Study on the G7 Countries “, *OECD Science, Technology and Industry Working Papers 2000/2*, OECD.

Shahin, Taraneh, María Teresa Ballestar de las Heras and Ismael Sanz (2024): “Robots in action”, The World Economy, Vol. 47, pp. 2828–2854.

Shimizu, Ryosuke and Shohei Momoda (2023): “Does Automation Technology Increase Wage?”, *Journal of Macroeconomics* (forthcoming).