Robots versus labor skills: a complementarity/substitutability analysis

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Abstract

The rise of artificial intelligence and automation is fueling anxiety about the replacement of workers with robots and digital technologies. Relying upon a (country-sector-year) constructed measure of robotic capital (RK), we study the extent of complementarity/substitutability between robots and workers at different skill levels (i.e., high-, medium- and low-skilled workers). The analysis points to a higher elasticity of substitution (EoS) - i.e., higher substitutability - between RK and unskilled labor, compared to skilled labor with a high degree of heterogeneity across time, sectors, countries. Interestingly, in most cases we found evidence of increasing RCSC over time with a steeper trend from the end of '90s and some hints of polarizing effects, according to which middle-skilled workers, typically employed in intermediate routine and/or codifiable tasks, are the most vulnerable to robotization.

Keywords: Automation, robotization, elasticity of substitution, technology, polarization

JEL Classification: C23, E24, J31, O33, O47.

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1 Introduction

The spread of robotization and, more generally, of automation is seen as one of the most challenging issues for the future of workers and their integration into society and economy of our communities (e.g., Ford, 2015; West, 2018; Susskind, 2020).

Among the major questions, the risk of disappearing of the middle-class and the increasing level of between-group inequality, as a result of a more intensive use of new technologies, has spurred an intense debate. As proof of this, Jaimovich *et al.* (2020) find that the likelihood of working in routine occupations between the pre-polarization era and the post-polarization one decreased roughly by 16%. Further causes of concern are linked to the ongoing COVID-19 pandemic, that might likely amplify this pattern, as argued by Okyere *et al.* (2020) for the cases of epidemic interactions, communications and meal delivery in China. Relatedly, Prettner and Bloom (2020) point out that the "hollowing out" effect of robots and automation is expected to be reinforced by the COVID-19 pandemic, while Leduc and Liu (2020) discusses how the pandemic-induced uncertainty about workers productivity may further trigger automation adoption. Muro *et al.* (2020) stress how "*Robots' infiltration of the workforce doesn't occur at a steady, gradual pace*" but is "*concentrated especially in bad times such as in the wake of economic shocks, when humans become relatively expensive as firms' revenues rapidly decline*". Ultimately, the rising concerns about the replacement of workers by this new wave of labor-saving technological change is even leading scholars to support robot taxation (e.g., Costinot and Werning, 2018; Thuemmel, 2018; Guerreiro *et al.*, 2020).[1]

A growing literature is currently dealing with the effects of robotization (and even more generally of automation) on various labor market outcomes: unemployment, participation, along with wage and inequality effects. At the same time, there has been a rising use of skills within the production process. For instance, the raw percentages of hours worked by skilled labor has increased by 6% on average across both sectors and countries, while the ones worked by unskilled labor dropped by 7% in the 1995-2005 period (see Battisti *et al.*, 2021). These two phenomena are jointly assessed in the race between technology and education, pioneered by Tinbergen (1974) and further explored by Goldin and Katz (2009), Autor *et al.* (2020) and many others. By making use of International Federation of Robotics (2019) data, we document that the share of robotic capital has dramatically increased from the '90s till to the end of the following decade of about 40%, reaching percentages of more than 2.5% in some industrial sectors in countries such as Japan, Germany, Italy and Spain, where a lot of job routines are robotized or automated.

As pointed out by Griliches (1969), the introduction of new technologies in production could give rise to adjustments in the relative demand for different labor skills which, in turn, are

[1] On the other hand, it should be acknowledged the positive role potentially and effectively played by robots during the COVID-19 outbreak, especially in terms of public health and services, addressing risks of infectious diseases, disinfection, surgical procedures, delivering foods and medication, as argued, among others, by Yang *et al.* (2020), Khan *et al.* (2020) and Tavakoli *et al.* (2020).

reflected in their relative wages. We focus on these issues by investigating whether robotic capital is complementary to some kinds of skills, to which we refer to as robotic capital-skill complementarity (RCSC) hypothesis. In so doing, we take into account other forms of capital and a wide array of skill types. Particularly, we build a specific stock of robotic capital and include it into different types of production functions at the country-sector level, distinguishing between robotic, ICT capital and the remainder. The robustness of our results are assessed using two different datasets and analysis frameworks. Our primarily dataset includes 8,217 observations, matched over 35 countries and 17 sectors (based on WIOD, 2015), while a secondary, and smaller dataset, includes 2,843 observations, matched over 15 countries and 17 sectors (based on EU KLEMS, 2009).

To the best of our knowledge, the present study represents the first attempt for investigating complementarity/substitutability between different kinds of automatized capital and skill types, from a country-industry perspective. In this respect, the main contributions of the study can be summarized as follows:

The main contributions of this work can be summarized as follows:

1. The robotic capital-skill complementarity hypothesis is examined using different samples, frameworks of analysis and methods. Our main outcomes point to an average lower elasticities of substitution (EoS) between robotic capital and skilled labor (i.e. more complementarity, then between robotic capital and unskilled labor.

2. The use of nonparametric methods allows us to relax functional forms assumptions on the production functions and to uncover high heterogeneity among time, sectors, countries.

3. In the majority of observations we find a growing spread among EoS patterns starting from the end of '90s

4. Finally, the different grouping of medium skill workers seem to give a hint of the more substitutable role of medium skills as inAcemoglu and Autor (2011).

The rest of the paper is organized as follows. Section 2 presents a survey about the recent theoretical and empirical works dealing with automation and robotization issues; Section 3 briefly illustrates the datasets construction, providing information on the main variables used throughout the analysis, as well as several insights with respect to the trends of robotization within the labor market; Section 4 sets up the basic analysis framework and reports the parametric and nonparametric test results; Section 5 contains concluding remarks.

2 Robotization and labor market related literature

This paper speaks to different strands of literature. First, it is inspired by works on automation and labor market outcomes, such as productivity, wages and unemployment, whereby efforts by researchers have been devoted in both the modelling and testing the impact of automation technologies, of which robotization represents a subset.

From a theoretical standpoint, the concerns recently posed by analysts and scholars on the consequences of the rapid outbreak of artificial intelligence, digital technologies and robots on labor market have prompted many studies on this field.[2] With specific reference to the employment effects, an optimistic view is offered by Nakamura and Zeira (2018), who develop a task-based model where all labor tasks are automatized if wages are adequately high: nonetheless, if the number of new jobs created grow sufficiently fast, the share of jobs mechanized each period shrinks and unemployment stemming from automation declines and converges to zero in the long-run. Relatedly, Irmen (Irmen) proposes a model in which a decline in population growth produces strong incentives for automation and fosters economic growth in the long-run. On the contrary, studies analyzing the wage and inequality impacts of automation have come to more worrisome conclusion. For instance, by developing a dynamic general equilibrium model incorporating investments in both robots and traditional capital, Berg *et al.* (2018) state that automation produce two contrasting effects: positive for growth and negative for equality. Analogously, Moll *et al.* (2019) argue that automation may exacerbate inequality via increasing returns to wealth, in a theoretical model linking technology to personal income and wealth distributions. On the same line, the growth model of directed technical change[3] proposed by Hemous and Olsen (2014), with machines complementing (replacing) high-skilled (low-skilled) labor and horizontal innovations (namely, the introduction of new products, which raises the demand for both skill types), leads to stagnating wages for low-skilled workers and intensification of wage disparities.

Meanwhile, although the growing empirical literature is attempting to address the many concerns regarding the impact of robotization on labor market outcomes, the evidence is far from clear-cut. For instance, pioneering works by Acemoglu and Restrepo (2020) and Graetz and Michaels (2018), employing new data from the International Federation of Robotics (IFR) on operational industrial robots, point to, respectively, a harmful effect of robotics on wages and employment in the US labor market from 1990 to 2007 and a favorable influence on productivity growth in 17 economies spanning the period 1993-2007.[4] Contrary to the non-significant association between robotization and total employment in Graetz and Michaels (2018), de Vries *et al.* (2020) provide evidence of a strong decline in the employment share of routine manual task-intensive jobs in a panel of 37 countries and 19 sectors over the years 2005-2015. On the same line, Chiacchio *et al.* (2018) report that the adverse impact of robot adoption comes at the expense of middle-educated workers. Similarly, by introducing an indicator for the ability of robots to execute different tasks, Carbonero *et al.* (2020) observe a strong, negative effect on

[2] Such concerns have been summarized in the expression "*Is this time different?*" by several contributions, such as Mokyr *et al.* (2015), Furman (2016) and Balsmeier and Woerter (2019), among others.

[3] On this point see, *inter alia*, Acemoglu (1998, 2002).

[4] By contrast, an ephemeral effect of robots on productivity has been recently documented by Cette *et al.* (2021).

worldwide employment, especially in emerging economies.[5] Positive impacts of robotization on employment are instead found by Klenert *et al.* (2020) and De Backer *et al.* (2018) in Europe and within MNEs, respectively. Opposite findings are highlighted by Compagnucci *et al.* (2019) in a panel of manufacturing industries of 16 OECD countries, with robots positively (negatively) correlated with the growth of hourly wages (hours worked). Likewise, Blanas *et al.* (2020) show that robots are associated with a decreasing (increasing) demand for the young, women, low- and medium-skilled workers (men, older and high-skilled workers).

Overall, it can be noticed that the empirical literature on this field usually produces mixed results, with evidences of drops in employment and participation, that may be temporary or focused in some sectors or for specific skills.

The second line of research examines the issues of inequality, whose contributions starting from Katz and Murphy (1992) and the literature on skill-biased technical change point to different substitutability degrees for skilled and unskilled workers, as in the recent work of Caselli (2016). Alongside these themes, this paper is related (to a limited extent) to the polarization of the labor force framework, namely the documented process, starting from the 1980s, for which employment has gradually becoming clustered at the tails of the occupational skill distribution (see, for instance, Acemoglu and Autor, 2011). Such a framework is based upon the so-called routine-biased technical change hypothesis (Autor *et al.*, 2003), whereby the "hollowing out" effect of automation leads to the disappearance of jobs requiring a well-defined set of repetitive tasks, typically assigned to middle-skilled workers.[6]

Furthermore, a relevant number of studies deals with problems of capital-skill complementarity at a general level of capital, such as Griliches (1969), Fallon and Layard (1975), Duffy *et al.* (2004) and Henderson (2009), whereas Krusell *et al.* (2000), Raveh and Reshef (2016), Eden and Gaggl (2018), Taniguchi and Yamada (2019) and Ohanian *et al.* (2021) investigate the effects of specific, non-neutral kinds of capital equipment. The complementarity/substitutability argument is important in the reversal discussion of technology adoption pioneered by Krugman (1979), because if a productive factor, such as unskilled labor, becomes less complementary to capital and the latter is increasingly more relevant in the production process, then this is equivalent to a higher opportunity cost for such factor, implying greater demand for unskilled labor saving technology, as in Koeniger and Leonardi (2007) or Alesina *et al.* (2018). The evidence

[5] As further evidence from a single country perspective, Faber (2020) observes a robust negative influence of robotization on employment within the Mexican labor market, in particular for men and low-skilled workers. Relatedly, Lankisch *et al.* (2019) and Dixon and Lim (2020) argue that automation can be considered as a crucial factor in explaining, respectively, the rising inequality and the decline of the US labor share. With specific reference to Portugal, Fonseca *et al.* (2018) point out job polarization as a result of rising automation and computerization. Conversely, Dauth *et al.* (2018) show sectoral adjustments in the composition of total employment in German labor markets over the years 2004-2014, with the creation of additional service sector jobs offsetting the losses in manufacturing industry.

[6] Additional empirical evidence in this direction is provided, among others, by David and Dorn (2013), Michaels *et al.* (2014), Jaimovich and Siu (2020) and vom Lehn (2020).

from this literature literature typically validates the hypothesis of more complementarity between capital and skilled workers. In particular, Krusell *et al.* (2000) analyze the phenomenon under investigation in the direction of this paper, by disaggregating capital in structures and equipment, finding the latter as less substitutable with skilled workers. On the same line, by paying attention to developing economies, Raveh and Reshef (2016) find that only R&D capital is complementary to skilled labor, while less innovative capital is complementary to unskilled. Analogously, Taniguchi and Yamada (2019) and Eden and Gaggl (2018) observe similar results for ICT capital in a panel of OECD countries and US, respectively. Lastly, Dao *et al.* (2020) argue that the downward trend of the labor share of income can substantially be explained by the high substitutability between routinized jobs and computer capital. This could be even more severe with robotic capital, insofar as the embodied content of technical progress may be higher, for instance, than ICT or other capital equipment. Moreover, Caselli and Manning (2019) show how under the assumption of a reduction of the relative price of investment goods driven by the new technology, the existing capital return will drop, implying a higher return for labor. The crucial empirical question, in such context, is whether and what workers benefit from this new wave of technological advances.

3 Data

In this section, we provide a brief overview of the relevant data used to carry out the present study (3.1), as well as a set of descriptive findings surrounding the relationship between the rise of automated capital and workers' replaceability (3.2).

3.1 The datasets

The empirical analysis builds upon the integration of data from different sources. In particular, we exploit information on robots from the Industrial Federation of Robotics (IFR, 2019), and merge these data with both WIOD (2015) and EU KLEMS (2009) releases, encompassing information on worker types, capital assets and value added, among others.[7] In so doing, we derive two distinct datasets on which the robotic capital-skill complementarity (RCSC) hypothesis can be tested. The WIOD dataset contains 8,217 observations, matched over 35 countries and 17 industries spanning the period 1995-2009, whereas the EU KLEMS dataset includes 2,843 observations, matched over 15 countries and 17 industries for the years 1994-2005.[8]

[7] Data on operational stock and deliveries of robots are provided by IFR (2019) according to ISIC Rev. 4 industry classification, contrary to ISIC Rev. 3.1 characterizing both the WIOD (2015) and EU KLEMS (2009) datasets. In order to merge the different coded sources, we make use of a correspondence table to convert IFR data from ISIC Rev. 4 to ISIC Rev. 3.1 industry classification.

[8] The set of countries, industries and time periods, driving the construction of the two datasets, are dictated by data availability. The list of countries and industries, as a result of the matching process, is reported in Section B of the Appendix.

The main variables employed throughout the empirical analysis are:

- Robotic capital stock, K_R. Data on stock, deliveries and average unit price of operational industrial robots are retrieved from the World Robotics: Industrial Robots and Service Robots (IFR, 2019). Following Graetz and Michaels (2018), we compute the robot stock (i.e., quantities) for each country-sector pairs using the perpetual inventory method based on robot deliveries (i.e., investments) and assuming a depreciation rate of 10 percent.[9] Specifically, we calculate $R_{S,cit} = R_{D,cit} + (1 - \delta)R_{S,cit-1}$, where c, i and t represent country, industry and time, respectively; R_S and R_D denote, respectively, the stock and deliveries of robots, whereas δ is the depreciation rate. Consequently, K_R, is obtained by

$$K_{R,cit} = \frac{R_{S,cit} * R_{P,ct}}{D_{cit}}$$

  where R^P represents the average unit price of industrial robots and D is the capital deflator;[10]

- Total capital stock, K, and value added, Y, from WIOD (2015) or EU KLEMS (2009);

- Non-robotic capital, K_{NR}, from WIOD (2015) or EU KLEMS (2009), computed as the difference between total (K) and robotic capital stock (K_R);

- ICT and other capital stock, K_I and K_O, respectively, from EU KLEMS (2009), as additional, disaggregated measures of capital;

- High-, medium- and low-skilled workers, from WIOD (2015) or EU KLEMS (2009), expressed in terms of hours worked, hourly wages, hours and income shares, depending on the specific estimated models.

All variables are expressed in real prices and PPP adjusted 2005 international dollars, using the PPP conversion factor from Inklaar and Timmer (2014). Descriptive statistics, based on both the WIOD (2015) and EU KLEMS (2009) datasets, are reported in section C of the Appendix.

3.2 Robotic capital penetration in advanced economies

The stock of robotic capital has risen substantially in advanced economies over the past decades. To have an apples-to-apples comparison, the total real capital evolution in the period 1995-2009 from Penn World Table 10 (Feenstra *et al.*, 2015) shows an increase on the order of 40% in Spain,

[9] As in Graetz and Michaels (2018), to check the robustness of our findings, the robotic capital variable is also constructed using depreciation rates of 5 and 15 percent.

[10] The complete strategy used to measure robotic capital stock is detailed in section A of the Appendix. As a robustness check, in the case of the EU KLEMS sample, the robotic capital stock has also been computed using non-ICT and other machinery and equipment capital deflators, without affecting the core outcomes of the analysis.

20% for countries as Italy, Japan and Germany. The same economies on average doubled the robotic capital (in the case of Spain, it increased more than three times). Additionally, United States witnessed a more substantial growth around 230%. Such an expansion was driven, in particular, by strong robotic investments in the rubber and plastic, wood products, electronics and transport equipment industrial sectors.[11]

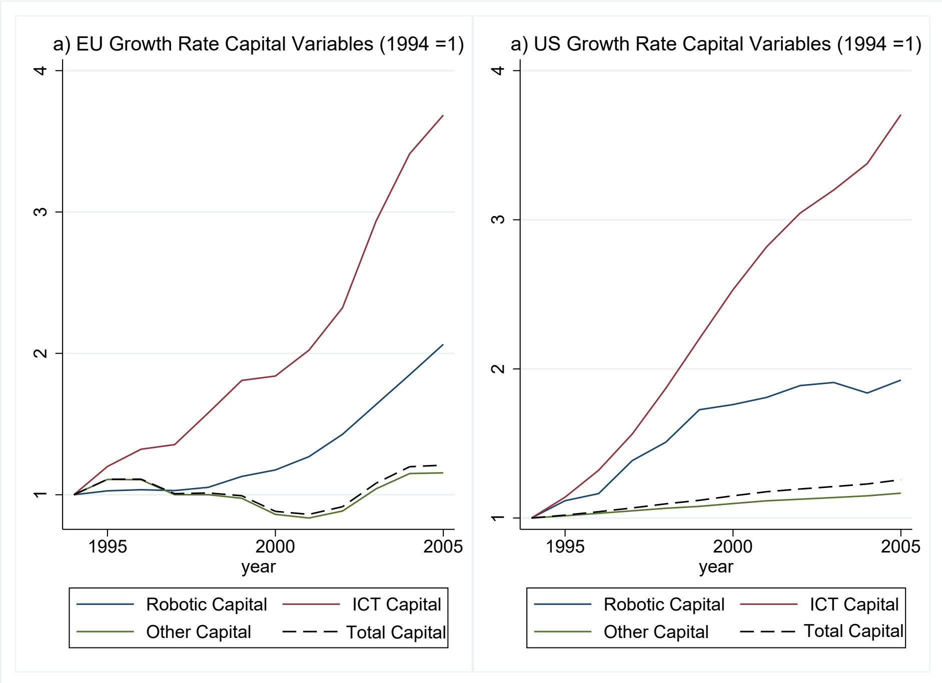

Figure 1: Capital stock evolution, 1994-2005

Figure 1 indicates that the evolution of automated capital equipment has been much pronounced than the rest either in USA or EU, thus providing a clear picture about the strong penetration of automation and digital technologies within the productive processes.[12]

On this point, as shown in panel a) of Figure 2 below, in the period under investigation the share of robotic capital has touched peaks of about 2.5%-3% in Japan, Spain, Italy and Germany, particularly in wood products, electronics and transport equipment industries (ISIC Rev. 3.1 codes 20, 30t33 and 34t35, respectively), in panel b) of Figure 2.[13]

[11]The robotic capital evolution for a subset of countries and industries is provided in section C of the Appendix.

[12]A similar trend is highlighted by Schivardi and Schmitz (2018) for ICT capital in a sample of OECD economies. In our EU KLEMS sample, the share of ICT capital in total capital recorded an average of about 8.2%, with maxima exceeding 25% in industries of Austria, Australia, Denmark, Finland, United Kingdom, Slovenia and United States.

[13]Code descriptions of the ISIC Rev. 3.1 industries are reported in Table B2 of the Appendix.

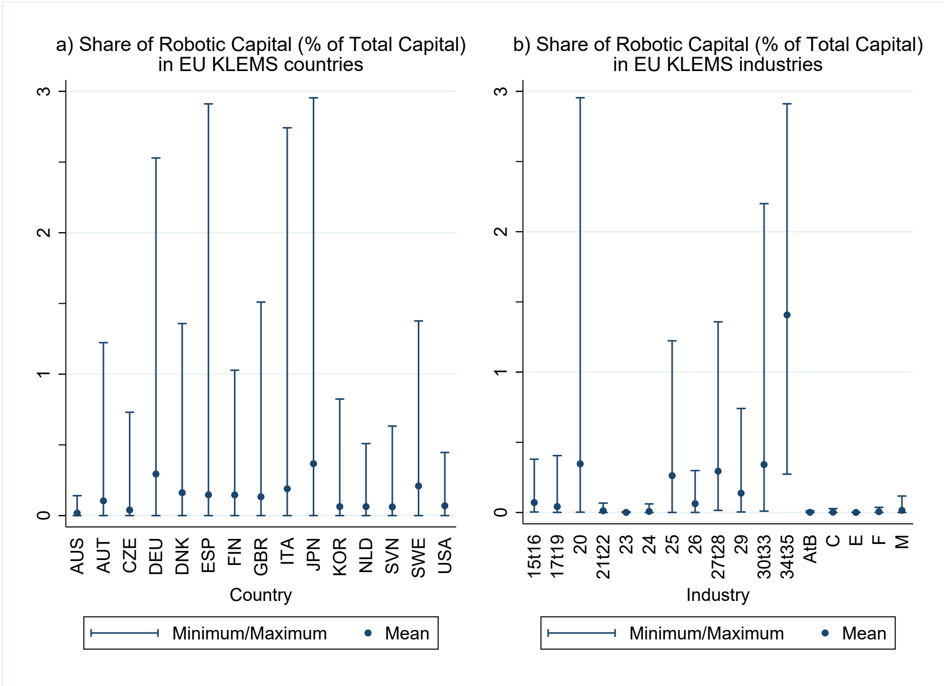

Figure 2: Share of robotic capital
in EU KLEMS countries and industries, 1994-2005

What this tells us is that the capital composition of production factors shifted toward a more intensive use of robots, as further highlighted in Figure 3 below. Looking to the stock of robots over workers deepening - the so-called *robot density*, as in Graetz and Michaels (2018) - in the period 1995-2017 the growth continues steadily the tendency, either looking to hours worked, or to number of employees.[14] Such descriptive evidence suggests that the share of robotic capital, as pointed out in Figure 1, may have grown up following a similar trend.

The increased robotization of the production process raises the question about relative prices and directed technical change. Figure 4 shows that the relative current price ratio of robots versus workers strongly and steadily decreased in two countries for which we have original price data. The difference is interesting because while in Germany the decrease continued after 2005, in the USA the series became rather flat. One possible interpretation is that in a country with more flexible wages, the usually rigid nominal floor is less binding than in another with more stringent labor market institutions.

To sum up, we see how: i) robotic capital grew more than the rest of capital (almost in line

[14] Being not constrained by robot prices data, the robot density variables are computed using the EU KLEMS (2019) release (Adarov *et al.*, 2019; Stehrer *et al.*, 2019) to exploit the full length of the IFR series on stock of industrial robots.

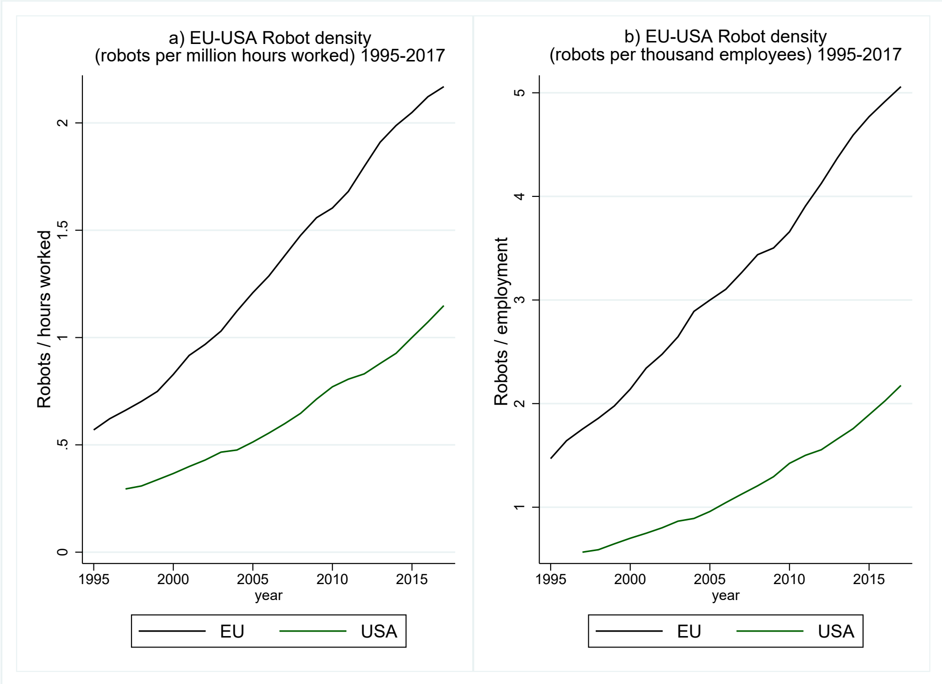

Figure 3: Robot density, 1995-2017

with ICT), ii) the robotic capital deepening was strong, iii) the relative prices of robots went down. These descriptive findings suggest a strong pressure on workers that in some countries may be satisfied through price reduction (typically in real terms) and in other through quantity reduction, which happens to be the usual outcome analyzed in the extant literature.

This way we wonder which kind of workers may be more substitutable by robots, with respect their marginal products (proxied by wages) and their complementarity with respect to robots. The latter issue follows, for example, the intuition of Acemoglu and Autor (2011) about the mechanized and/or routinized tasks that may be replaceable by machines. If medium-skilled workers were, for instance, more replaceable by robotic capital, this process should drive towards wage polarization and increasing inequality, as pointed out in France by Davis *et al.* (2020).

4 Estimation strategy and benchmark results

In the light of what has emerged in the descriptive evidence, this section deals with the empirical assessment of the RCSC hypothesis. Specifically, subsection 4.1 provides a parametric framework aimed at estimating the EoS between different robotic capital stock and skill groups. Subsequently, in the subsection 4.2, by employing non-parametric techniques, we will inquire into the potential heterogeneity of the EoS across (groups of) countries, industries and time.

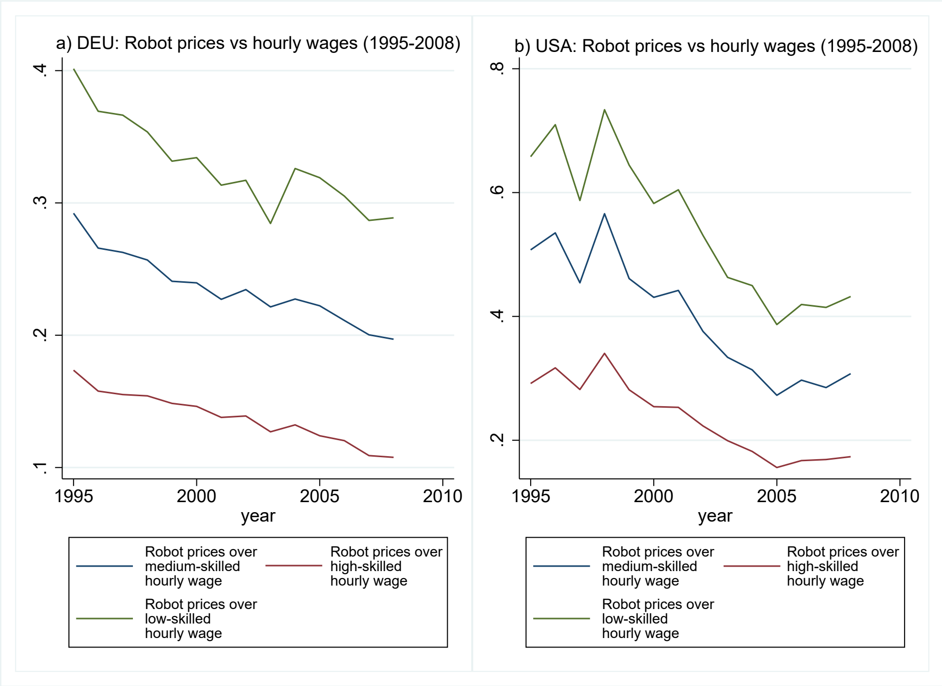

Figure 4: Relative cost of robots, 1998-2008

4.1 Parametrics

By borrowing from the contributions of Krusell *et al.* (2000) and Eden and Gaggl (2018), a standard formulation which enables incorporating distinct kinds of capital and derive different substitutability degrees among factor inputs is offered by Cobb-Douglas production function (removing subscripts for countries, industry and time to ease notation) over non-robotic capital, K_{NR}, assumed as neutral with respect to skill types, and a constant elasticity of substitution (CES) over non-neutral robotic capital equipment[15], K_R, skilled and unskilled labor, S and U, respectively:

$$Y = K_{NR}^{\alpha}\left[\beta[\gamma(K_R)^{\rho} + (1-\gamma)(S)^{\rho}]^{\frac{\sigma}{\rho}} + (1-\beta)(U)^{\sigma}\right]^{\frac{1-\alpha}{\sigma}} \tag{1}$$

where Y represents aggregate output; β and γ are distribution parameters; ρ and σ govern the elasticity of substitution between K_R and S, and between the K_R-S composite and U,

[15]In accordance with the International Standard Industrial Classification of all Economic Activities (ISIC Rev. 4), robots are group under 'general-purpose machinery', specifically under 'lifting and handling equipment' and 'other special-purpose machinery'. As these are reported within the broader heading of machinery (i.e., non-ICT capital), robots are not part of ICT capital, which covers computers and telecommunication equipment. We are grateful to Robert Inklaar for his comment on this point.

respectively.[16]

By assuming that the markets for inputs are competitive, the first-order conditions of profit-maximizing behavior and price-taking firms imply (simultaneously) estimating the following system of two equations:

$$\ln\left(\frac{K^S_{R,cit}}{S^S_{cit}}\right) = \ln\left(\frac{\gamma}{1-\gamma}\right) + \rho\ln\left(\frac{K_{R,cit}}{S_{cit}}\right) + \epsilon_{1,cit} \tag{2}$$

$$\ln\left(\frac{U^S_{cit}}{Q^S}\right) = \ln\left(\frac{\beta}{1-\beta}\right) + \sigma\ln\left(\frac{U_{cit}}{Q}\right) + \epsilon_{2,cit} \tag{3}$$

where c, i and t represent country, industry and time, respectively; $Q = \left\{\gamma K^{\rho}_{R,cit} + [1-\gamma]\,(S_{cit})^{\rho}\right\}^{\frac{1}{\rho}}$ is the composite term comprising robotic capital and skilled labor; K^S_R, S^S, U^S, Q^S denote the income shares of K_R, S, U and Q, respectively, while ϵ_1 and ϵ_2 are the error terms, allowed to be correlated across equations. The EoS between robotic capital and skilled labor, $1/(1-\rho)$, is derived by equation (2), while the EoS between the K_R-S composite (i.e., Q) and U, $1/(1-\sigma)$, is identified from equation (3).

The RCSC hypothesis for the specifications in (2)-(3) is verified if:

$$1/(1-\rho) < 1/(1-\sigma) \implies \sigma > \rho$$

Estimates are carried out using the generalized method of moments (GMM) technique, treating all the input factors as endogenous and exploiting their lagged values as instruments. Table 1 reports the results of our benchmark estimates.[17] In this respect, our findings provide a broad confirmation of the RCSC assumption. Specifically, the EG procedure points to this direction when applied to both the WIOD and EU KLEMS samples, where the EoS between the robotic-capital and skilled labor, $1/(1-\rho)$, is lower than between the K_R-S composite and unskilled labor, $1/(1-\sigma)$, which implies $\sigma > \rho$.

The robustness of results presented in Table 1 are assessed in several ways. Firstly, in line with suggestions by Graetz and Michaels (2018), we check whether the RCSC hypothesis is sensitive to

[16] The specification in (1) implies the crucial assumption of treating K_{NR} as completely neutral with respect to different skill groups. Nonetheless, due to data availability - especially from a macro perspective - and constraints imposed by the functional forms, there are not many ways to overcome this issue, and such a formulation turns out to be suitable in our case to test our RCSC hypothesis.

[17] As an extended analysis, we also test the total capital-skill complementarity hypothesis, from a country-industry perspective, in the spirit of Duffy *et al.* (2004). Estimations performed on both the WIOD and EU KLEMS samples generally confirm the hypothesis of a lower EoS between capital stock and skilled labor. Additionaly, we also find evidence of the robotic (and ICT) capital-skill complementarity hypothesis according to the four- and six-factor production functions proposed by Taniguchi and Yamada (2019). Results of these specifications are not presented here for reasons of space, but are available upon request.

Table 1: Estimated elasticities of substitution

Production functions	$1/(1-\rho)$	$1/(1-\sigma)$	Obs.
	K_R & S	$\{K_R, S\}$ & U	
Eqs. (2)-(3) WIOD (1995-2009)	2.711	3.464	4501
Eqs. (2)-(3) EU KLEMS (1994-2005)	9.943	30.657	1449

Notes: The estimated coefficients and standard errors are reported in Table D1 of the Appendix.

a different computation of the robotic capital stock, using a 5 and 15 percent depreciation rate.[18] In both cases, our main findings turn out to be unchanged, thus providing broad confirmation of the robotic capital-skill complementarity hypothesis.

4.2 Nonparametrics

In order to relax the assumption of CES functional forms and of homogeneity parameters among observations we employ in this section kernel density estimations in the spirit of Henderson (2009).

Specifically, consider a general nonparametric function as $m_{c,i,t}(\cdot)$ (see, for instance, Battisti *et al.*, 2021, for a production function based application):

$$Y_{cit} = m(\boldsymbol{K}_{NR,cit}, \boldsymbol{K}_{R,cit}, \boldsymbol{S}_{cit}, \boldsymbol{U}_{cit}, \boldsymbol{d}_{ct}, \boldsymbol{d}_t) \tag{4}$$

where, discrete variables: $d_{c,t}$, d_t represent respectively a country-sector effect and a time effect. While the latter is ordered by nature, the former has no natural ordering. In a parametric setting this would quickly eliminate degrees of freedom, while in a nonparametric setting we may smooth across both time and sector in order to leverage neighbors cells for local information (see Li and Racine, 2007).

Then we took the gradients of derivates, as in Henderson (2009), to extract the Morishima individual pairwise elasticities (with H representing the Hessian matrix), σ, between inputs q and l for the multiple-input production technology $y = m(x_1, x_2, \ldots, x_p)$:

$$\sigma_{ql} = \frac{m_l}{x_q}\frac{H_{ql}}{|H|} - \frac{m_l}{x_l}\frac{H_{ql}}{|H|} = \frac{m_l x_l}{m_q x_q}\left(\sigma^A_{ql} - \sigma^A_{ll}\right) \tag{5}$$

where σ^A denote the Allen-Uzawa EoS.

Table 2 below reports the median results of EoS among robotic capital and skilled/unskilled

[18] To save space, the outcomes of these alternative estimated models are relegated in Section D of the Appendix.

workers for groups of countries/sectors.

Table 2: Estimated median Morishima elasticities of substitution

	Benchmark		**RK $\delta = 5\%$**		**RK $\delta = 15\%$**	
	EoS KR-S	EoS KR-U	EoS KR-S	EoS KR-U	EoS KR-S	EoS KR-U
Quartile values						
1st quartile	-4.297	-1.231	-4.089	-1.324	-4.193	-1.327
	(0.318)	(0.367)	(0.340)	(0.383)	(0.339)	(0.420)
2nd quartile	0.000	0.104	0.000	0.097	-0.002	0.128
	(2.447)	(2.794)	(2.586)	(2.821)	(2.381)	(3.050)
3rd quartile	0.633	5.311	0.737	5.131	0.604	6.135
	(26.432)	(29.950)	(26.520)	(29.592)	(24.848)	(32.036)
Groups of Countries						
Europe	0.006	0.146	0.009	0.146	0.002	0.205
	(2.347)	(2.692)	(2.411)	(2.678)	(2.318)	(3.058)
Non-Europe	-0.031	0.003	-0.037	0.001	-0.025	0.000
	(3.030)	(3.485)	(3.069)	(3.579)	(2.768)	(2.957)
Major Countries						
DEU	0.008	0.007	0.004	-0.001	0.003	0.000
	(0.067)	(0.093)	(0.077)	(0.086)	(0.049)	(0.063)
ESP	0.029	0.138	0.028	0.208	0.058	0.116
	(0.305)	(0.306)	(0.208)	(0.363)	(0.289)	(0.324)
FRA	0.052	0.038	0.060	0.044	0.065	0.033
	(0.115)	(0.207)	(0.115)	(0.192)	(0.127)	(0.229)
GBR	0.026	0.084	0.030	0.113	0.036	0.091
	(0.424)	(0.355)	(0.421)	(0.382)	0.415	(0.433)
ITA	0.010	0.001	-0.014	0.004	0.005	0.002
	(0.204)	(0.072)	(0.211)	(0.083)	(0.254)	(0.092)
JPN	-0.013	0.000	-0.014	-0.003	-0.011	0.001
	(0.089)	(0.055)	(0.049)	(0.036)	(0.081)	(0.035)
KOR	-0.452	-0.001	-0.321	0.001	-0.081	-0.012
	(7.536)	(6.999)	(5.686)	(6.443)	(7.020)	(7.539)
USA	-0.001	0.002	-0.004	0.008	-0.001	-0.002
	(0.155)	(0.077)	(0.179)	(0.141)	(0.110)	(0.081)
Major Industries						
20	0.030	0.417	0.059	0.460	0.001	0.617
	(2.185)	(3.836)	(2.341)	(4.090)	(2.164)	(4.670)
25	0.172	-0.025	0.174	-0.023	0.247	-0.022
	(0.684)	(0.997)	(0.900)	(1.183)	(0.858)	(1.339)
27t28	0.069	0.079	0.064	0.057	0.043	0.085
	(0.246)	(0.312)	(0.288)	(0.349)	(0.308)	(0.376)
30t33	0.109	0.246	0.130	0.221	0.102	0.258
	(1.028)	(1.267)	(0.955)	(1.356)	(1.069)	(1.418)
34t35	0.039	-0.019	0.045	-0.059	0.052	-0.019
	(0.653)	(0.575)	(0.788)	(0.684)	(0.689)	(0.659)
Other groupings						
Share of RK $\leq$ median	-22.453	12.508	-16.162	10.139	-21.541	11.009
	(129.128)	(151.097)	(131.585)	(144.813)	(133.228)	(154.724)
Share of RK $\geq$ median	0.026	0.063	0.029	0.059	0.020	0.083
	(1.093)	(1.280)	(1.118)	(1.316)	(1.145)	(1.446)

Notes: Time and country-by-sector fixed effects included. Standard errors in parentheses beneath each coefficient.

Some general results we may draw are: i) an overall evidence of RCSC, ii) this effect is stronger for European and countries with higher endowment of automation, iii) these findings are robust to different capital stock computations (according changing shares for perpetual inventory method).

Then, given the nature of nonparametric estimation we may look for the dynamics of this EoS patterns, as in Figures 5 and 6. Quite interestingly a large common trend shows a cross patterns of EoS, with a reverse around end of '90s - early '00s and a growing spread over time. This may be interpreted as a hint of higher and higher relative complementarity of the high skilled workers during the pattern of development (and of robotization).

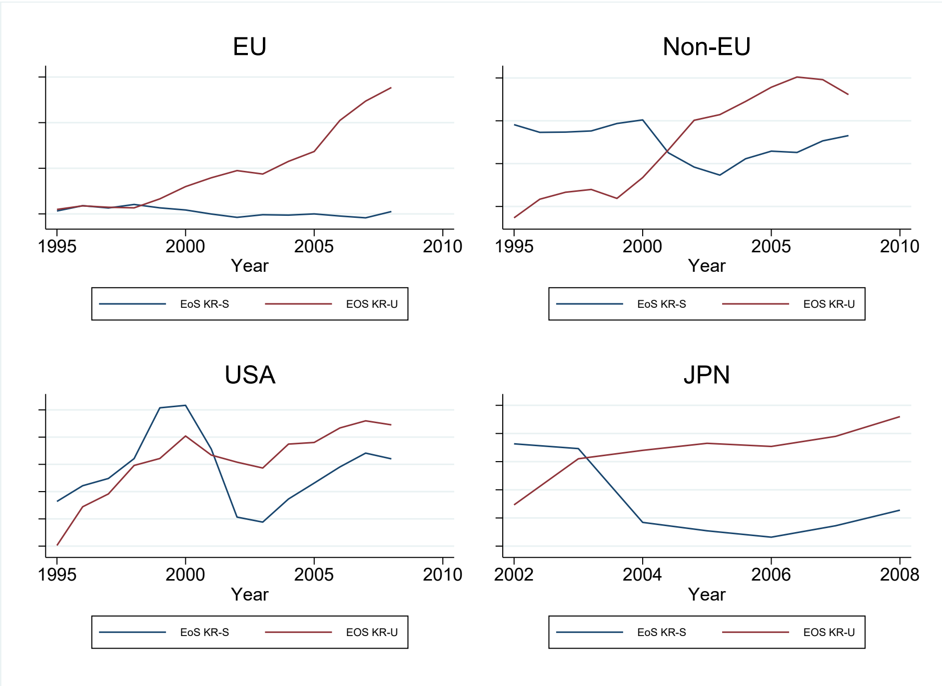

Figure 5: Median Morishima EoS evolution in selected (groups of) countries, 1995-2008

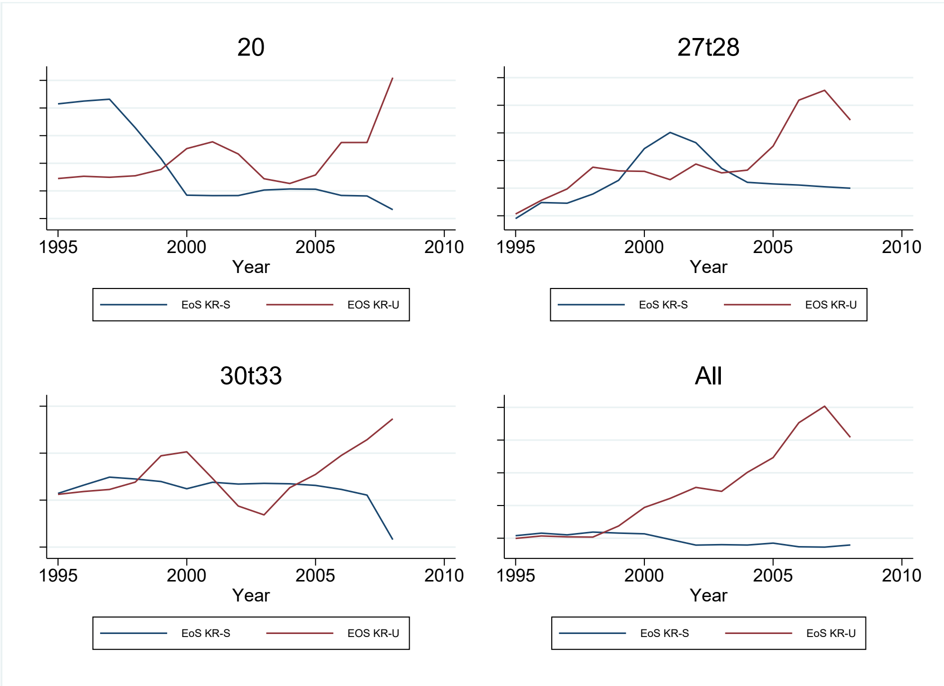

Figure 6: Median Morishima EoS evolution in selected industries and overall, 1995-2008

5 Concluding remarks

The rising concerns stemming from the intensive use of automation in production are driving many scholars towards a better understanding of its labor market implications. Furthermore, the pressure exerted by the COVID-19 pandemic for a complete rethinking of the productive process is fueling a heated debate on whether robots, computerization and digital technologies will lead either to a job destruction or creation.

In this paper, we participate to the current discussion by investigating the extent of complementarity between robotic capital and different skill types. Specifically, relying upon a constructed measure of robotic capital stock , we study whether robotic capital is complementary to skilled workers and substitute to unskilled labor - as envisaged by Tinbergen (1974) in the so-called "race between technology and education". The empirical analysis is carried out using two distinct samples of countries and industries, mainly based upon the IFR, WIOD and EU KLEMS datasets, over the years 1994-2009 and 1994-2005, respectively. Our main findings consistently point to a lower elasticity of substitution between robotic capital and skilled labor, compared to unskilled employees.

This looks quite robust across countries and sectors, over time, but with a high degree of heterogeneity. A common turning point in the relationship among skills and robots seem to lie in the end of '90s when a growing automation is coupling with a bigger relative demand for high-skilled workers, when the robots will become increasingly important in the production process and able to reproduce even more complex tasks.

By and large, policymakers face numerous challenges. In the short run, the focus should be placed in new organizational needs of production, exceedingly influenced by the ongoing COVID-19 pandemic. Moreover, the advent of improved robots as well as new technological developments, typically incorporated in intangible assets, such as those related to the artificial intelligence, may dramatically impact workers in the medium- and long-run. Thus, in terms of policy implications, the robotic (plus ICT) capital-skill complementarity suggests measures aimed at improving productivity, wage and education differentials for lower-skilled labor.

Overall, our study casts additional light on understanding the mechanisms underlying the current forces operating in the labor markets, especially in manufacturing industries of advanced and transition economies. If on the one hand industrial robots, as a subset of the broader category of automation technologies, turn out to be a powerful engine of economic growth, on the other hand they appear to be associated with intensifying inequalities.

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Appendix

A The measurement of the robotic capital stock

The robotic capital measure employed throughout the analysis is built upon two variables: the stock of industrial robots and their price.

As for the robot stock variable construction, the procedure largely follows that proposed by Graetz and Michaels (2018), which we refer to for more detailed information.

Data on average unit price of robots are retrieved from the IFR reports. This is computed as the ratio of the turnover of total robot systems to the number of robots delivered in a specific country. The IFR provides a series of average unit price of robots (in current, thousand dollars) for a small group of countries.[19] Specifically, robot prices are available for Japan, United States, Germany, Rep. of Korea, United Kingdom and France, from 1995 to 2008; whereas, for Italy, robot prices are available from 1995 to 2006. Therefore, the 2007 and 2008 Italy's robot price observations are computed using the average robot price growth rate for countries for which we have original prices data.

At this point, the main necessary assumption we need to impute the average unit price of robots for the remaining countries (in both the WIOD and EU KLEMS samples) relies upon the geographical, economic proximity. In particular:

- European countries take on average robot prices of Germany, United Kingdom, France and Italy;
- American countries take on robot prices for the United States;
- Asian countries (plus Australia) take on average prices of Japan and Rep. of Korea.

In order to obtain robot prices data for the years 1994 and 2009, the series are smoothed by employing uniformly weighted moving averages, with 1 lagged term, 1 forward term and the current observation in the filter.[20]

The robotic capital stock, K_R, is calculated by multiplying the number of industrial robots, R^S, by their price, R^P, and converted in real terms applying the country-sector specific capital deflator, D:

$$K_{R,cit} = \frac{R^S_{cit} * R^P_{ct}}{D_{cit}} \tag{A1}$$

Finally, the constructed robotic capital measure in (A1) is expressed in real PPP 2005 adjusted international dollars using the PPP conversion factor from Inklaar and Timmer (2014).

[19] See, for instance, IFR (2005).

[20] The specified procedure is only applied to the WIOD sample. As for the EU KLEMS sample, whose series ends in 2005, only the observation referring to 1994 is computed.

B Countries and industries

Table B1: List of WIOD and EU KLEMS countries

Code	Country	WIOD	EU KLEMS
AUS	Australia	$\surd$	$\surd$
AUT	Austria	$\surd$	$\surd$
BEL	Belgium	$\surd$	
BGR	Bulgaria	$\surd$	
BRA	Brazil	$\surd$	
CHN	China	$\surd$	
CZE	Czech Republic	$\surd$	$\surd$
DEU	Germany	$\surd$	$\surd$
DNK	Denmark	$\surd$	$\surd$
ESP	Spain	$\surd$	$\surd$
EST	Estonia	$\surd$	
FIN	Finland	$\surd$	$\surd$
FRA	France	$\surd$	
GBR	United Kingdom	$\surd$	$\surd$
GRC	Greece	$\surd$	
HUN	Hungary	$\surd$	
IDN	Indonesia	$\surd$	
IND	India	$\surd$	
IRL	Ireland	$\surd$	
ITA	Italy	$\surd$	$\surd$
JPN	Japan	$\surd$	$\surd$
KOR	Korea, Republic of	$\surd$	$\surd$
LTU	Lithuania	$\surd$	
LVA	Latvia	$\surd$	
MLT	Malta	$\surd$	
NLD	Nederlands	$\surd$	$\surd$
POL	Poland	$\surd$	
PRT	Portugal	$\surd$	
ROU	Romania	$\surd$	
RUS	Russian Federation	$\surd$	
SVK	Slovakia	$\surd$	
SVN	Slovenia	$\surd$	$\surd$
SWE	Sweden	$\surd$	$\surd$
TUR	Turkey	$\surd$	
USA	United States	$\surd$	$\surd$

Table B2: List of WIOD and EU KLEMS industries

Code	Label	Description
AtB	Agriculture	Agriculture, hunting, forestry, and fishing
C	Mining	Mining and quarrying
15t16	Food products	Food, beverages and tobacco
17t19	Textiles	Textiles, textile products, leather and footwear
20	Wood products	Wood and products of wood and cork
21t22	Paper	Pulp, paper, paper products, printing and publishing
23	Fuel	Coke, refined petroleum and nuclear fuel
24	Chemical	Chemicals and chemical products
25	Rubber and plastics	Rubber and plastics
26	Other Mineral	Other non-metallic mineral
27t28	Metal	Basic metals and fabricated metal
29	Machinery	Machinery, nec
30t33	Electronics	Electrical and optical equipment
34t35	Transport equipment	Transport equipment
E	Utilities	Electricity, gas and water supply
F	Construction	Construction
M	Education, R&D	Education

Notes: Industries codes are ISIC Rev. 3.1.

C Descriptive statistics and figures

Table C1a: Main variables' average by Country

Country	Stock of Robots	Robotic capital on Employment	Non-Robotic capital on Employment	Relative wages	Value added	No. of Observations
AUS	46.293	.03	302.022	1.491	10509.93	255
AUT	130.188	.206	225.864	.975	4987.27	221
BEL	211.233	.268	284.293	1.243	5785.329	255
BGR	.652	0	2.472	9.646	100.169	255
BRA	70.557	.009	79.819	5.593	16133.6	255
CHN	413.073	.003	32.716	2.154	202000	176
CZE	49.487	.04	83.914	1.084	2269.901	221
DEU	3588.96	.349	159.498	1.086	48120.88	221
DNK	67.447	.238	508.95	.91	2956.056	221
ESP	595.599	.148	196.129	3.142	16602.87	221
EST	.061	.001	42.473	.901	181.45	255
FIN	92.983	.159	206.993	1.01	3847.649	221
FRA	866.935	.187	186.31	1.359	28331.04	221
GBR	474.093	.112	258.041	1.352	27731.79	221
GRC	2.538	.006	131.87	2.11	2927.796	255
HUN	13.179	.016	56.833	1.562	1397.541	221
IDN	4.567	0	23.395	155.909	9550.066	253
IND	25.997	.002	46.724	2.504	47121.29	255
IRL	1.759	.008	166.377	1.127	2814.42	208
ITA	1364.387	.363	220.465	2.442	25709.43	221
JPN	15316.05	.757	614.343	.85	113000	136
KOR	1603.355	.111	228.519	.925	22805.63	255
LTU	.076	.001	187.915	.951	1868.649	255
LVA	.05	0	26.134	1.08	184.874	251
MLT	.065	.003	98.179	9.725	117.693	240
NLD	83.204	.112	358.798	1.305	7809.654	221
POL	32.308	.011	46.532	1.114	5621.846	221
PRT	45.144	.095	151.37	9.917	2960.333	238
ROU	1.737	0	4.364	9.646	431.732	255
RUS	502.529	.027	13.309	1.228	7647.916	255
SVK	27.51	.053	89.841	.98	1136.932	255
SVN	18.35	.074	99.434	1.396	557.447	255
SWE	256.437	.224	234.57	1.035	7393.451	221
TUR	16.337	0	17.82	5.408	1812.973	255
USA	3599.99	.22	459.937	1.044	173000	255

Source: Authors' calculations based on IFR (2019) and WIOD (2015).

Table C1b: Main variables' average by Industry

Industry	Stock of Robots	Robotic capital on Employment	Non-Robotic capital on Employment	Relative wages	Value added	No. of Observations
15t16	310.424	.053	85.367	2.571	20659.5	485
17t19	28.779	.032	77.63	2.572	10048.35	474
20	167.245	.096	59.604	2.523	4150.209	485
21t22	39.865	.007	75.895	2.427	12819.83	485
23	1.505	.006	501.609	2.272	8336.451	453
24	65.474	.013	151.32	2.478	19740.53	485
25	479.463	.187	71.364	2.426	7804.844	485
26	104.729	.052	123.465	2.582	9660.287	485
27t28	963.747	.141	75.124	2.442	24972.12	485
29	393.695	.065	60.914	2.421	18970.35	485
30t33	2773.199	.205	86.08	2.403	47502.88	485
34t35	5733.377	.79	80.099	2.4	19849.87	485
AtB	8.719	.002	107.896	7.994	45295.3	485
C	2.515	.02	455.86	2.774	13749.1	485
E	3.757	.001	664.415	1.492	20505.67	485
F	16.889	.001	22.798	3.748	43029.93	485
M	69.259	.003	36.228	80.151	23083.03	483

Source: Authors' calculations based on IFR (2019) and WIOD (2015).

Table C2a: Main variables' average by Country

Country	Stock of Robots	Robotic capital on Employment	Non-Robotic capital on Employment	Relative wages	Value added	No. of Observations
AUS	33.525	.019	260.077	1.501	9456.825	192
AUT	75.392	.115	210.899	1.207	4929.727	192
CZE	14.65	.015	75.474	1.238	1998.928	176
DEU	3258.643	.31	150.146	1.294	45400.91	204
DNK	66.922	.209	435.599	1.158	3242.643	156
ESP	501.656	.13	184.237	2.789	15767.8	204
FIN	80.883	.137	190.975	1.171	3359.581	204
GBR	453.913	.104	267.929	1.067	25726.79	204
ITA	1258.485	.316	206.255	.563	24663.34	204
JPN	14931.87	.788	435.317	.909	102000	187
KOR	778.618	.05	219.753	.963	19126.85	192
NLD	62.753	.076	346.264	.998	7605.651	192
SWE	290.93	.24	215.718	1.125	6730.833	168
USA	1391.272	.082	430.585	1.039	175000	192

Source: Authors' calculations based on IFR (2019) and EU KLEMS (2009).

Table C2b: Main variables' average by Industry

Industry	Stock of Robots	Robotic capital on Employment	Non-Robotic capital on Employment	Relative wages	Value added	No. of Observations
15t16	643.016	.08	103.547	1.403	29174.68	166
17t19	80.12	.067	103.166	1.519	17470.11	166
20	750.922	.294	80.596	1.219	6312.17	166
21t22	114.551	.014	90.668	1.105	25216.76	166
23	2.569	.006	605.189	1.144	9461.048	142
24	124.42	.015	218.475	1.146	31984.63	142
25	500.475	.217	90.864	1.173	13027.24	142
26	303.234	.096	148.213	1.209	14964.87	166
27t28	2429.709	.298	108.637	1.176	40231.81	166
29	1539.644	.159	87.917	1.079	35004.82	166
30t33	9556.847	.541	113.203	1.071	90054.86	166
34t35	21106.19	2.313	154.337	1.073	38009.5	83
AtB	18.332	.003	182.642	1.926	38032.15	166
C	5.155	.044	916.473	1.252	15236.69	166
E	10.398	.002	1245.522	.961	32416.68	166
F	27.586	.001	24.575	1.247	66625.78	166
M	157.536	.006	59.239	.959	41514.68	166

Source: Authors' calculations based on IFR (2019) and EU KLEMS (2009).

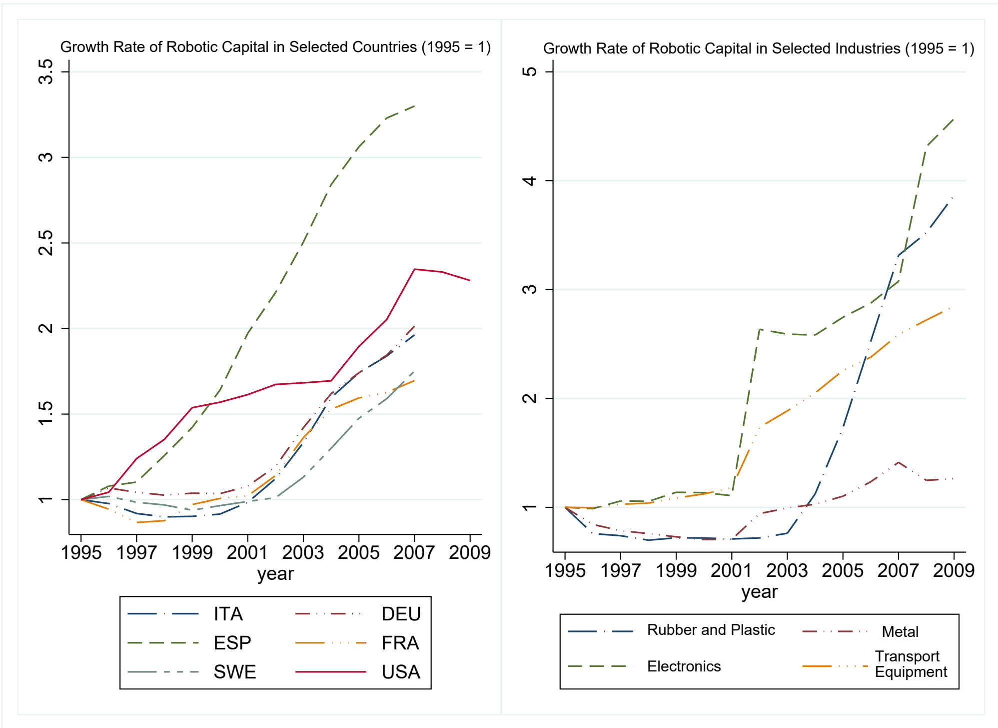

Figure C1: Robotic capital evolution
in selected WIOD countries and industries
1995-2009

D Estimation results

Table D1: Benchmark GMM parameter estimates

	ρ	σ	β	γ	Obs.
Eqs. (2)-(3)	0.631***	0.711***	0.415***	0.231***	4501
WIOD (1995-2009)	(0.012)	(0.013)	(0.013)	(0.006)	
Eqs. (2)-(3)	0.899***	0.967***	0.306***	0.305***	1449
EU KLEMS (1994-2005)	(0.014)	(0.019)	(0.009)	(0.011)	

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. All the models are simultaneously estimated using GMM estimation techniques, with lagged values of input factors as instrumental variables and HAC robust standard errors.

Table D2: Robustness checks: Estimated elasticities of substitution

	$1/(1-\rho)$	$1/(1-\sigma)$	Obs.
Robotic capital $\delta = 5\%$			
	K_R & S	$\{K_R, S\}$ & U	
Eqs. (2)-(3)	2.764	3.310	4501
WIOD (1995-2009)			
Eqs. (2)-(3)	9.776	15.557	1449
EU KLEMS (1994-2005)			
Robotic capital $\delta = 15\%$			
	$1/(1-\rho)$	$1/(1-\sigma)$	Obs.
	K_R & S	$\{K_R, S\}$ & U	
Eqs. (2)-(3)	2.657	3.696	4501
WIOD (1995-2009)			
Eqs. (2)-(3)	8.455	67.369	1255
EU KLEMS (1994-2005)			

Notes: The estimated coefficients and standard errors are reported in Table D3.

Table D3: Robustness checks: GMM parameter estimates

Robotic capital $\delta = 5\%$					
	ρ	σ	β	γ	Obs.
Eqs. (2)-(3)	0.638***	0.697***	0.416***	0.248***	4501
WIOD (1995-2009)	(0.011)	(0.012)	(0.006)	(0.006)	
Eqs. (2)-(3)	0.897***	0.935***	0.319***	0.308***	1344
EU KLEMS (1994-2005)	(0.014)	(0.020)	(0.009)	(0.011)	
Robotic capital $\delta = 15\%$					
	ρ	σ	β	γ	Obs.
Eqs. (2)-(3)	0.623***	0.729***	0.411***	0.215***	4501
WIOD (1995-2009)	(0.012)	(0.013)	(0.006)	(0.006)	
Eqs. (2)-(3)	0.881***	0.985***	0.2999***	0.295***	1255
EU KLEMS (1994-2005)	(0.015)	(0.018)	(0.008)	(0.012)	

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. All the models are simultaneously estimated using GMM estimation techniques, with lagged values of input factors as instrumental variables and HAC robust standard errors.