Who Is Afraid of Machines?

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Abstract

We study how various types of machines, namely, information and communication technologies, software, and especially industrial robots, affect the demand for workers of different education, age, and gender. We do so by exploiting differences in the composition of workers across countries, industries and time. Our dataset comprises 10 high-income countries and 30 industries, which span roughly their entire economies, with annual observations over the period 1982–2005. The results suggest that software and robots reduced the demand for low and medium-skill workers, the young, and women—especially in manufacturing industries; but raised the demand for high-skill workers, older workers and men—especially in service industries. These findings are consistent with the hypothesis that automation technologies, contrary to other types of capital, replace humans performing routine tasks. We also find evidence for some types of workers, especially women, having shifted away from such tasks.

JEL Classification: J21, J23, O33

Keywords: Automation, Robots, Employment, Labor Demand, Labor Income Share.

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1 Introduction

Machines have been transforming the workplace since their conception during the Industrial Revolution. Steam-powered factories replaced artisan shops, soon after which electrification enabled the mass production of a host of manufacturing products. Modern transportation technologies dramatically reduced the cost of distance, while information and communication technologies (ICT) facilitated access to information and communication, leading to new forms of production. More recently, the increasing usage of robots with enhanced capabilities and of artificial intelligence has generated new production modes, fueling widespread concerns that these new technologies will replace workers in an unprecedented number of occupations. Such shifts in the demand for labor can already be detected: In 2015 there were an estimated 1.63 million industrial robots performing activities previously done by humans, such as welding, painting, assembly, packaging and labeling. Yet, this number is expected to double by 2020 and its future scale and scope are difficult to predict.[1]

At least in the short run, this would inevitably result in some workers losing their jobs to machines. Other workers, however, may benefit. It is therefore crucial to ask which types of workers are vulnerable to replacement, and how the labor market effects of machines differ by workers' backgrounds. In addition, workers can respond to the onset of machines in various ways: Some may switch to low-paid jobs that are nonetheless hard to replace with machines, while others may acquire new skills allowing them to work in highly-paid jobs that are complementary to machines.[2]

To answer this question, this paper studies how the widespread use of machines affected different groups of workers in the recent past. Specifically, we conduct a comprehensive analysis of how various forms of capital such as ICT, software and especially industrial robots, affect the demand for workers of different education, age, and gender across several countries and industries over the last four decades. By systematically scrutinizing which groups of workers were either complemented or rendered redundant by different types of machines, we can also infer how such workers have responded so that we better prepare ourselves for the future.

[1] Frey and Osborne (2017) argue that almost half of U.S. employment is at risk of being automated over the next two decades. Brynjolfsson and McAfee (2014) suggest that, due to the potential of automation to efficiently perform a wide range of cognitive tasks, new technologies may increasingly serve as substitutes for these tasks rather than complements.

[2] For instance, women's education levels have been steadily rising in all advanced economies, resulting in women being employed in various jobs traditionally filled by men.

We start with a simple model that formalizes how the effect of new capital on the demand for labor generally depends on both workers' characteristics and the tasks that they perform. For instance, computers may complement highly-educated workers performing tasks that require intensive use of abstract skills, while robots may substitute less-educated workers performing routine tasks (Autor and Dorn, 2013). The model also suggests that it is important to distinguish between technologies that are used by humans as opposed to those that replace them. In both cases, better machines can potentially raise employment for all workers, like a tide that lifts all boats. But labor-replacing technologies are more likely to destroy jobs, especially when their diffusion becomes prevalent.

This framework motivates our empirical investigation, for which we use the EU KLEMS data on value-added, and factor inputs and payments for a sample of 30 industries spanning roughly the entire economy of 10 developed countries over the period 1982–2005. This dataset is unique in that it includes consistent industry-level information on employment levels (measured in hours) and wage bills by workers' education (high, medium, and low-skill), age (15–29, 30–49 and 50+ years old) and gender across countries and years.[3] Equally important for our purposes, it also includes a breakdown of capital into non-ICT, ICT net of software, and software capital.

As a preliminary step, we describe some of the basic trends in the data. We begin by documenting the remarkable expansion of ICT and software. While the stocks of these two types of capital accounted for less than 3% and 1% of industrial output in 1982, respectively, by 2005 they grew to slightly more than 20% and almost 5%. Over the same period, there have been profound changes in both the employment shares and income shares of different worker types.[4] High-skill, older and female workers experienced remarkable increases in both their employment levels and income shares between 1982 and 2005. In contrast, there were remarkable declines in the employment and income shares of low-skill and young workers. Employment shares also grew for medium-skill and male workers, but the changes were relatively small in magnitude, while the income share of the latter in fact declined.

Did the advent of new types of capital play a role in the aforementioned labor market trends? To get a sense of this, we explore how new technologies are related to specific tasks.

[3] In this paper, high-, medium- and low-skill are defined by educational attainment, as described in Section 3.1.

[4] Labor income shares are measured within an industry as the ratio of a particular group of workers' total wage bill to industrial output.

Using numerical measures of the task content of specific occupations from the Dictionary of Occupational Titles (DOT) and the Occupational Information Network (O*NET), we compute task-intensities for each worker type based on their occupational employment shares in the 1980 U.S. census. We then discuss how the advent of new technologies may have affected the supply and demand of each worker group depending on the task content of the occupations they work in. In particular, women display an interesting trend: they did and still do work more in occupations that are potentially more easily automated, but over time they have shifted toward occupations that are likely harder to automate.[5]

We start our main empirical analysis by estimating a labor demand equation in which the dependent variable is the (log-)employment level of each worker type, with non-ICT, ICT and software capital intensities as the main explanatory variables.[6] The results point to important differences in how labor demand is associated with the three capital inputs. Non-ICT capital is associated with employment growth for low-skill and female workers, while ICT is associated with employment growth for all worker types. In contrast, software capital is associated with employment losses for the medium skill, low skill and young.

As a further step, we study the association between changes in capital inputs and changes in employment across industries that differ in their exposure to automation, as measured by the routine-share index (RSH) of Autor et al. (2003). How different types of capital correlate with labor demand indeed varies by an industry's RSH. In particular, non-ICT capital is associated with higher employment growth in routine-intensive industries, suggesting that low-tech machines may complement routine tasks. In contrast, both ICT and software are associated with employment losses in more routine-intensive industries, and with employment gains in less routine-intensive industries.

These associations between capital and labor demand, while interesting, are just conditional correlations. To isolate a causal effect of automation, we augment our labor demand equation with a new variable that captures the effect of industrial robots comparing industries that differ in their (exogenous) potential for automation in countries that differ in their (predetermined) exposure to the worldwide surge in robots. In the spirit of a Bartik instrument, we first construct a measure of exposure to the worldwide surge in robots for each of the 10

[5]Importantly, our econometric analysis focuses only on labor demand effects, while any labor supply responses are accounted for by fixed effects.

[6]Observations are at the country-industry-year level. Since we control for country-year and country-industry fixed effects, as well as industry output, the coefficients of interest are identified by within-country changes in the capital inputs between industries, and are not driven by the contraction or expansion of industries.

countries examined using the UN COMTRADE data on bilateral trade in industrial robots. The idea is that a country is more exposed to robotization if it tends to import robots from countries that experienced relatively higher growth rates in their robot exports to the rest of the world. We then interact this country-level measure with the RSH index, which captures the within-country industry scope for automation.[7]

With this novel identification strategy, we find that industrial robots decrease the employment of low-skill workers while they increase the income shares of high and medium-skill workers, old workers and men. To shed more light on these results, we consider differential effects between manufacturing and services, both of which intensively utilize robotic technology but have experienced very different employment trends. The effect of robots on labor demand across (sub-)industries differ within each sector: In manufacturing, robots *lower* the employment of low-skill, young and female workers, while in services, they *increase* the employment of workers of all age groups, medium-skill and male workers. In both sectors, robots increase the income shares of the high-skill, old and male workers.

To gain more insight on the gender bias of new technologies, we also study the effects of robots on the employment levels and income shares of men and women stratified by skill levels. This is relevant because, as noted above, the employment share of high-skill women rose disproportionately higher than men. The exercise suggests that, indeed, the substitutability between robots and female workers is driven by the less-skilled ones. In contrast, the complementarity of robots to male workers is driven by the high-skilled.

Overall, our results suggest that robots displace workers performing routine tasks, especially in sectors where automation is more widespread such as in manufacturing. It may, however, create jobs in sectors where automation has started more recently, such as in services, and where new occupations are appearing. Robots are also likely to complement engineers, product designers and managers, all occupations that are dominated by high-skill, more senior and male workers. Qualitatively, we find that software has similar effects to those of robots. In contrast, ICT capital correlates with employment gains, mostly for medium and low-skill workers. These results are consistent with the view that ICT capital makes humans more productive, while software and robots can render them redundant, at least in some occupations (Acemoglu and Restrepo, 2017, 2018; Baldwin, 2019). Finally, to have a sense of how robust

[7]The sample used in this analysis begins only in 1996, the year in which information on trade in robots becomes available in UN COMTRADE, rather than 1982.

these findings will remain in the near future, we extend our analysis to the more recent period 2008–2015. Albeit more limited in industry and country coverage, this exercise confirms some of the main patterns discussed so far, suggesting that new technologies embodied in software may still displace routine, but not skilled, jobs.[8]

Before proceeding, we make two important remarks. First, our evidence suggests that machines likely had different effects across workers, but not necessarily that some workers were substituted. Even when we find negative employment effects, our estimation strategy can only detect losses relative to other industries, which do not necessarily imply a fall in the absolute level of employment. Second, despite a host of fixed effects, our results for non-ICT, ICT and software capital should be interpreted as conditional correlations, possibly affected by endogeneity. For instance, in industries that become more skill-intensive, firms may have a stronger incentive to invest in software. Nevertheless, our results unveil interesting correlations suggesting the existence of important complementarities between some factors. In the case of industrial robots, our empirical strategy likely identifies causal effects.

Related Literature The literature on technological change and labor outcomes is vast and still growing. The first influential stream of this literature studies the effects of new technologies on the relative demand for different types of workers, going at least as far back as Berman et al. (1994), which provided robust evidence that ICT increase the relative demand for more skilled workers. This led to numerous studies further focusing on the different evolution between high-skill versus low-skill workers (e.g. Krusell et al., 2003).

But as summarized in Acemoglu and Autor (2011), such a dichotomous division of the labor force is insufficient to capture long-run shifts in the structure of the labor market. Recent task-based approaches have found that the employment shares and wages of workers in routine occupations, who happen to fall in the middle of the wage distribution, have declined (Autor et al., 2003). Accordingly, they posit that ICT can be a main driver of "job polarization" (Autor and Dorn, 2013; Goos et al., 2014). Even more recent studies exploit newly-available data on industrial robots to study their potential impacts on the labor market, e.g., Acemoglu and Restrepo (2017); Graetz and Michaels (2018). The former finds that U.S. commuting zones that were more exposed to robots during the period 1990–2005 experienced large and robust negative effects on employment and wages. However, in a panel of 17 countries, the

[8]Unfortunately, the limited industry coverage does not allow us to build our proxy for robots using this sample.

latter finds that while robots reduced the employment share of low-skill workers, it only had a small effect on total employment.

Similarly, a recent study by the European Commission (2016) finds no direct effects of industrial robots on employment across 3000 manufacturing firms in 7 European countries.[9] Using data on French firms, Bonfiglioli et al. (2019) show that while robot adoption and employment growth are positively correlated, an increase in robot intensity is followed by job losses, especially for production workers. Other recent papers show that even when robots may seem to have no effect, this may be masking employment losses in some sectors that are offset by employment gains in others. Using patents related to automation, Mann and Püttman (2017) find that although automation led to employment losses in U.S. manufacturing, this was more than compensated for by gains in the service sector. Related, Dauth et al. (2018) find similar effects across local labor markets in Germany, but also find that it may have reduced manufacturing plants' incentives to hire young labor market entrants. Autor and Salomons (2017) show that employment falls as productivity rises *within* an industry, but that these negative effects are more than offset by positive spillovers to other industries.

The latter set of papers is related to our postulation that the effects of new technologies on different types of workers are heterogeneous, and that worker responses may also differ. For instance, young workers or women may start to work in different jobs or industries if employment is negatively affected by robots. In this vein, there is also a literature that focuses on how older workers are affected by new technologies. Most confirm that older workers make less use of ICT or computers (Friedberg, 2003; Schleife, 2006; de Koning and Gelderblom, 2006), but evidence on how their labor market outcomes are affected is mixed (Borghans and ter Weel, 2002; Aubert et al., 2006; Schleife, 2006; Beckmann and Schauenberg, 2007; Rønningen, 2007; Behaghel et al., 2014).[10] Most recently, Acemoglu and Restrepo (2018) find that robots substitute for middle-aged workers, and also provide evidence for the reverse causal direction: aging is associated with more automation across countries and also U.S. commuting zones. However, they do not focus on how the adoption of robots affects the relative demands for all age groups.

[9] They do find that robots are more likely used in larger firms, in export-oriented firms and in those utilizing batch production.

[10] On the other hand, there does seem to be a clear effect on older workers' retirement decisions: Bartel and Sicherman (1993) find that workers in U.S. industries with a faster rate of technological change tend to retire later, but that unexpected variations in this rate induce them to retire earlier. Hægeland et al. (2007) confirm a similar effect in Norway. Friedberg (2003) finds that impending retirees acquire fewer computer skills, but that those who do, retire later.

To the best of our knowledge, little attention has been given to how technological change affects the demand for workers by gender, which we assess in conjunction with the demand for workers by education and by age. Juhn et al. (2014) and Rendall (2017) argue that new technologies have created jobs for women by lowering the demand for manual skill, but systematic evidence is lacking. Furthermore, few have asked how the effects of new technologies may differ by type of capital, such as ICT, software and robots.

Our approach to answer these questions is closely related to Michaels et al. (2014); Graetz and Michaels (2018), who also use the EU KLEMS data to examine how wage bill shares and labor productivity are affected by ICT and robots, respectively. But there are several important differences. The first paper studies relative, as opposed to absolute, demand for workers of different education levels. They find that ICT has a polarizing effect. Compared to our work, they do not consider age or gender, do not distinguish between ICT and software, and do not try to measure automation. The second paper studies the effect of robots, mostly on labor productivity, using data from the International Federation of Robots (IFR). Besides focusing on a different main outcome variable, we follow a novel identification strategy relying on a different source with information on bilateral trade of robots. Given the challenge of measuring the use of industrial robots, we view our alternative approach as a valuable complement. Finally, both papers focus on long-run effects through the use of long differences. Instead, we exploit the annual frequency of the data, as we believe that the shorter-run displacement and adjustment of workers are just as interesting.

2 A Simple Model of Workers, Machines and Tasks

To set ideas for the empirical analysis, we present a simple task-based model similar to Acemoglu and Autor (2011). Let Y denote the output of a single industry.[11] Output Y is produced by combining capital (machines) with different types of workers. The type of a worker (e.g., high-skill worker) and the set of all types of workers are denoted by j and G, respectively. Let Y_j denote the contribution of worker type j, which is combined across G, to

[11] Focusing on a single industry allows us to save on notation and to be consistent with the empirical analysis where the unit of observation is an industry. It is, however, straightforward to extend the analysis to a multi-industry economy.

produce industrial output Y according to

$$Y = \left(\sum_{j \in G} A_j Y_j^{\epsilon} \right)^{1/\epsilon} \quad \text{with } \epsilon < 1.$$

The elasticity of substitution across groups is $1/(1-\epsilon)$, which is increasing in ϵ, while A_j is an exogenous productivity parameter.

To produce Y_j, workers and capital must perform a unit measure of different tasks:

$$Y_j = \left(\int_0^1 [x_j(z)]^{\alpha_j} \, dz \right)^{1/\alpha_j} \text{with } \alpha_j < 1. \tag{1}$$

The elasticity of substitution across tasks is $1/(1-\alpha_j)$, which is increasing in α_j. Tasks can be performed either by workers or machines. A share $(1-\kappa_j)$ of tasks cannot be automated and hence are performed by one unit of worker type j. The complementary share κ_j of tasks can be automated and are performed by one unit of capital.[12]

Now let (K_j, L_j) denote the quantity of capital and labor, respectively, used for the production of Y_j. Since (K_j, L_j) are not differentiated by task z, $x_j(z) \equiv x_j$ for all z. Then, symmetry in how capital and workers of type j are used for the production of x_j implies

$$K_j = \kappa_j x_j, \quad \text{and} \quad L_j = (1-\kappa_j) x_j,$$

where $\kappa_j \in (0,1)$ is the share of automated tasks. Substituting these in (1) yields:

$$Y_j = \left[\kappa_j^{1-\alpha_j} K_j^{\alpha_j} + (1-\kappa_j)^{1-\alpha_j} L_j^{\alpha_j} \right]^{1/\alpha_j}.$$

Ceteris paribus, an increase in the quantity of machines used in production, K_j, raises the output produced by workers of type j and the effect is stronger, the higher is κ_j:

$$\frac{\partial Y_j}{\partial K_j} = (\kappa_j Y_j / K_j)^{1-\alpha_j}. \tag{2}$$

Under perfect competition, workers are paid their marginal product. Hence, the wage bill of

[12] The implicit assumption is that machines are cheaper than workers, so that labor is not used to perform tasks that can be automated. The exact condition for this to be the case is derived below.

workers of type j is:

$$w_j L_j = \frac{\partial Y}{\partial L_j} \cdot L_j = Y^{1-\epsilon} \cdot A_j Y_j^{\epsilon-\alpha_j} \cdot (1-\kappa_j)^{1-\alpha_j} L_j^{\alpha_j}. \tag{3}$$

Equations (2)–(3) illustrate how a change in K_j affects the demand for workers of type j. According to (2), an increase in K_j raises group j output Y_j, and the effect is stronger the larger the share of automated tasks, κ_j. Then, holding Y constant, (3) shows that this decreases the demand for workers of type j only if $\epsilon < \alpha_j$.[13] Intuitively, when $\epsilon < \alpha_j$, machines can more easily substitute for workers of type j (high α_j) compared to other worker types (low ϵ), implying that less workers of type j are needed. Conversely if $\epsilon > \alpha_j$, it is relatively harder for machines to substitute for workers of type j, thereby leading to a rise in the demand for these workers.

What is the effect of an increase in industrial capital $K \equiv \sum_j K_j$ on labor demand? For simplicity, suppose that $K_j = \omega_j K$ with $\omega_j > 0$ constant for each $j \in G$. From (3), it is straightforward that an increase in K will affect all workers in the same direction only if all the α_j's lie on the same side of ϵ. And even if this were the case, the magnitudes would differ depending on κ_j: Tasks performed by certain worker types are more vulnerable to automation than tasks performed by other types. Hence, changes in K are likely to be biased toward certain worker types, and the effects are likely to be heterogeneous across industries as well. All else equal, an increase in K will reduce the demand for workers of type j relative to j' if type j workers are more substitutable by machines relative to type j' workers, i.e., $\alpha_j > \alpha_{j'}$. Similarly, an increase in K will have a stronger effect on workers of type j relative to j' if the first group performs a larger number of tasks that are subject to automation.

So far, we have examined the effect of capital accumulation on the demand for labor. However, the model can also deliver insights about another form of technological change often associated with automation: The increase in the share of tasks that can be performed by machines (κ_j). Consider the effect of κ_j on the output that is produced by workers of type j:

$$\frac{\partial Y_j}{\partial \kappa_j} = \frac{1-\alpha_j}{\alpha_j} \cdot Y_j^{(1-\alpha_j)} \cdot \left[\left(\frac{K_j}{\kappa_j} \right)^{\alpha_j} - \left(\frac{L_j}{1-\kappa_j} \right)^{\alpha_j} \right].$$

All else equal, automation increases output when $\frac{K_j}{L_j} > \frac{\kappa_j}{1-\kappa_j}$, that is, when the level of automation is sufficiently low. When this condition is satisfied, tasks performed by capital

[13] Following equation (3), we will control for output in the empirical analysis.

are cheaper than those performed by workers, so shifting tasks from humans to machines lowers the production cost of Y_j. As κ_j grows, however, the value of further automation declines, because the existing capital stock is distributed across more tasks.

Equation (3) can then be used to study how κ_j affects the demand for labor. There are two effects. First, automation displaces workers in some tasks, thereby lowering the demand for workers of type j. Second, automation raises productivity, which in turn increases the demand for workers of type j when $\epsilon > \alpha_j$.[14] However, the second effect becomes weaker as κ_j increases. This implies that when $\epsilon > \alpha_j$, the effect of automation may be non-monotonic. Initially, for sufficiently low κ_j, the productivity effect may dominate. In this range, automation raises productivity to such an extent that it increases the demand for workers employed in the remaining non-automated tasks. Instead, when κ_j is already high, the displacement effect must dominate and hence, machines will replace workers.[15]

How does the model guide our subsequent empirical investigation? First, different types of technological change associated with the introduction of new capital inputs can have different effects on employment. Computing and communication equipment (e.g. PCs, telephones, digital networks) allow humans to perform their tasks more efficiently. Hence, they are more likely to increase labor productivity and can potentially, but not necessarily, create new jobs for all workers. Automation and robots, instead, by automating a certain range of tasks, are likely to exert displacement effects that can potentially, albeit not necessarily, shed jobs for all workers, especially in the short run. Since robot capabilities are propped up by computer codes, software is also more likely to have such a negative impact.

Second, all these effects are heterogeneous. Different capital inputs may substitute some workers, but complement others. For instance, while robots controlled by computer software may replace workers in routine tasks (e.g. assembly), they may increase the demand for engineers and software developers. Third, the effects may also differ across broadly-defined sectors (that subsume industries). For example, it seems more likely that the displacement effect would be more dominant in manufacturing, where the share of jobs requiring intensive use of routine-manual skills is disproportionately high. Furthermore, we can expect the

[14] Acemoglu and Restrepo (2017) emphasize another possible effect, namely, that new tasks are created when others are automated. Here we interpret an increase in κ_j as automation net of task creation.

[15] These simple comparative statics still hold when both automation and capital accumulation are endogenous. For instance, Acemoglu et al. (2015), Acemoglu and Restrepo (2017), Hémous and Olsen (2018) and Dechezleprêtre et al. (2019) show how to make κ_j a choice variable. Bonfiglioli et al. (2019) endogenize both κ_j and K_j, and derive conditions under which employment is a hump-shaped function of automation.

displacement effect to be even stronger in manufacturing where machines already perform a wide range of tasks. In service industries, instead, automation is still in its infancy, suggesting that the displacement effect may be dominated by an increase in productivity. Hence, the net effect of the introduction of new machines may be new jobs for all workers, and especially, for those whose tasks require interpersonal skills that are particularly valuable in services and (at least for now) less automatable.

Finally, the model above assumes one type of capital for illustration.[16] In the empirical analysis, we proxy for K (for each industry) using different types of capital, which are expected to have different elasticities and also to differ in their ease of being used to automate tasks. In addition to analyzing the effect of technology on workers of different background, we aim at identifying such potential differences in the substitutability or complementarity between types of workers and types of capital.

3 Data and descriptive statistics

3.1 Data and variables

The main data source for our empirical analysis is the EU KLEMS, from which we construct our benchmark sample comprising 10 countries and 30 industries over the period 1982–2005. The countries included are mostly advanced European economies: Austria, Denmark, Finland, Italy, Netherlands, Spain, and the United Kingdom; plus Australia, Japan and the United States. Industries are identified by their two-digit NACE Rev. 1.1. codes, and span roughly the entire economy of each country (Table 3.1).

The EU KLEMS is particularly suitable for our analysis for three reasons. First, its data are comparable across country-industry-year cells. Second, for each cell, it includes information on the wage bill and employment of workers by education level, age and gender, where employment is measured as the number of hours worked by persons engaged in production. There are three education categories: high skill (HS), corresponding to workers with at least a bachelor's degree, medium skill (MS), corresponding to workers with upper-secondary education or vocational training, and low skill (LS), corresponding to workers with lower-secondary

[16] There are various ways we could include multiple types of capital, which would only clutter the equations without adding much insight.

education or no formal qualification.[17] There are also three age categories: young (Y), prime (P) and old (O), comprising workers aged 15–29, 30–49 and 50+ years old, respectively.

Table 3.1: Industries

NACE code	Industry Name	NACE code	Industry Name
AtB	Agriculture, Hunting, Forestry, and Fishing	E	Electricity, Gas and Water Supply
C	Mining and Quarrying	F	Construction
15–16	Food products, Beverages and Tobacco	50	Wholesale and Retail; Motor Vehicles
17–19	Textiles, Textile Products, Leather and Footwear	51	Wholesale, expect Motor Vehicles
20	Wood and Products of Wood and Cork	52	Retail, except Motor Vehicles
21–22	Pulp, Paper, Paper Products, Printing and Publishing	H	Hotels and Restaurants
23	Coke, Refined Petroleum Products and Nuclear Fuel	60–63	Transportation and Storage
24	Chemicals and Chemical Products	64	Post and Telecommunications
25	Rubber and Plastics Products	J	Financial Intermediation
26	Other Non-Metallic Mineral Products	70	Real Estate
27–28	Basic Metals and Fabricated Metal Products	71–74	Other Business Activities
29	Machinery and Equipment, n.e.c.	L	Public Administration and Defense
30–33	Electrical and Optical Equipment	M	Education
34–35	Transport Equipment	N	Health and Social Work
36–37	Manufacturing n.e.c.; Recycling	O	Other Community, Social and Personal Services

Source: EU KLEMS. Industry codes are NACE Rev. 1.1.

Third, for each country-industry-year cell, the EU KLEMS includes information on real fixed stocks of capital by type, namely, non-ICT, ICT net of software, and software capital.[18] Information on real gross value added is drawn from the same data source. All real variables are computed in 1995 US dollars (USD) using real exchange rate data from the OECD.

We calculate the income share by education level, by age, and by gender as the ratio of the respective real wage bill to real gross value added within an industry. Similarly, capital input intensities are calculated as the ratios of real non-ICT, ICT net of software and software capital stocks to real gross value added.

3.2 The Rise of Machines

In Figure 1, we show the evolution of the industrial capital to output ratio (K_i/Y_i) for each type of capital from 1982 to 2005. Since the unit of observation in our empirical analysis is a country-industry-year cell, we first compute the within-country averages of K_i/Y_i across all industries, weighted by the employment share of each industry in 1982.[19] We then calculate the unweighted average across countries. While the ratio of non-ICT capital stock to output is close to 2.4 in 1982, the stocks of ICT and software capital accounted for only less than 3% and 1% of real gross value added, respectively. These patterns are also observed for each

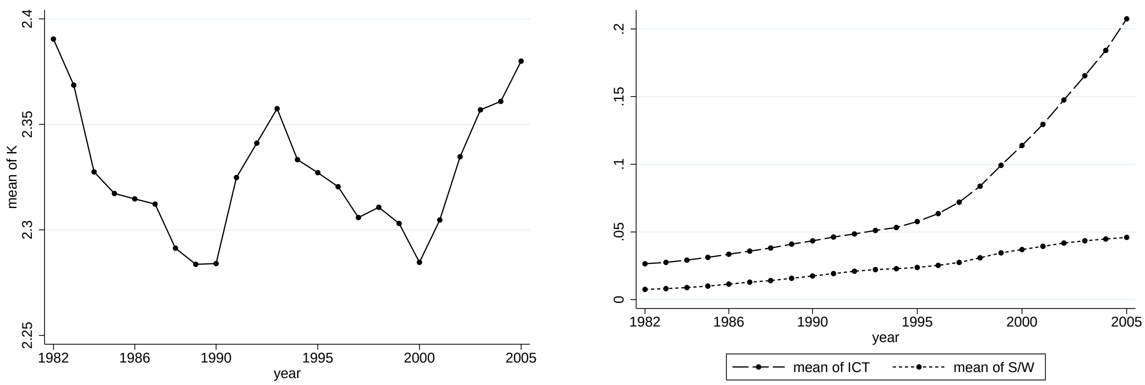
[17] Throughout the paper, levels of "skill" refer to these categories of education.

[18] Non-ICT capital includes transport equipment, other machinery and equipment, total non-residential investment, residential structures, and other assets. ICT includes computing equipment and communication equipment.

[19] This is to keep the relative importance of industries constant across all years within each country.

country examined (Appendix Table A1). However, in the 23 years that followed, the ratios of ICT and software capital stocks to output grew by an order of magnitude, to slightly more than 20% and almost 5%, respectively. In contrast, the ratio of non-ICT capital to output does not seem to have evolved in any particular manner.[20]

Figure 1: Non-ICT capital, ICT capital net of software, and software capital



(a) Traditional Capital (b) ICT and software

Notes: K: ratio of non-ICT capital stock to real gross value-added; ICT: ratio of real ICT capital stock net of software capital stock to real gross value-added; S/W: ratio of real software capital stock to real gross value-added. We first average the ratios across industries within each country using as weights each industry's employment share in country-wide employment in 1982. We then calculate the unweighted average across countries by year.
Source: Authors' calculations based on EU KLEMS.

Despite the erratic movements of the non-ICT capital to output ratio and its decline in many countries, heterogeneous changes across country-industry pairs may at least partly reflect differences in new types of structures and equipment, and contain further information about intangible investments that are not fully captured in the data. As noted in McGrattan and Prescott (2014); McGrattan (2017), most national accounts data have only recently begun to account for investments in intangible capital. A large part of intangible investments are speculated to be part of ICT capital, especially software, but much was unaccounted for previously and even today.[21] In particular, the second study finds that intangible investments are highly correlated with investments in traditional capital such as equipment. Thus, intangible investments not captured in ICT may still be reflected in non-ICT capital.

[20] We also calculate the unweighted average of the capital-output ratios across countries within each industry by year. The within-industry patterns and trends are very similar to those within each country and are shown in the Appendix Table A2.

[21] For example, it is difficult to account for software developed in-house; cloud-computing is another challenge (Byrne et al., 2017). In the U.S., even as they attempt to account for intangible capital, how they categorize such investments have been changing with almost every new revision (e.g. Chute et al., 2018).

Related, even if the relative size of ICT and software may seem small even in 2005, much of the intangible investments into these types of capital may not be captured in the data. Investment data in the U.S. revised to include intangibles reveal that they can comprise as much as a third or more of total investments (McGrattan and Prescott, 2014). Furthermore, these types of capital may have higher depreciation rates than traditional types of capital, so that stocks (which are present-discounted value sums) may be small even if they can have a large impact on the labor market (Aum et al., 2018).

3.3 Employment and Income Shares by Worker Type

In Table 3.2, we show the employment and income shares by skill, by age and by gender, averaged across all countries in the sample for 1982 and 2005. Similarly as we did for capital, we first average employment and income shares across industries within each country using each industry's employment share in 1982 as weights, and then calculate the unweighted average across countries by year.[22] According to the top panel of the table, the employment share of high-skill (HS) workers almost doubled from 1982 to 2005, while the employment share of low-skill (LS) workers in 2005 became almost half of what it was in 1982. The employment share of medium-skill (MS) workers, which is the highest in both years, increased over the same period but by much less than the increase in the employment share of high-skill workers. Income shares by skill display very similar patterns as the employment shares. In particular, the income share of high- and medium-skill workers increased between 1982 and 2005, but that of the high-skilled increased by more. In contrast, low-skill workers' income share dropped by more than half.

The second panel of Table 3.2 reveals that while the employment and income shares of the middle-aged (P) and oldest (O) workers increased between 1982 and 2005, those of the youngest (Y) fell.[23] Since younger workers tend to be of higher skill (i.e., more educated) than their older counterparts, this cannot be solely due to changes in labor supply—there must be an accompanying drop in the demand for young workers.[24] Indeed, we will later see

[22]The within-country and within-industry average employment and income shares by skill, by age, and by gender are shown in the Appendix Tables A3–A8. For the production of the statistics by industry, we calculate the unweighted averages of employment and income shares across countries within each industry by year.

[23]In Appendix Table A9, we also produce country-wide employment shares by age-skill cells, averaged across countries without country weights. According to this table, the middle-aged and oldest workers of all skill levels, except for the middle-age low-skilled, experienced increases in their employment shares between 1982 and 2005. In contrast, the youngest workers of all skill levels experienced declines in their employment shares over the same period.

[24]In fact, such a change in the demand structure may be contributing to younger individuals' labor supply

Table 3.2: Employment and income shares

	1982 mean			2005 mean		
by Educ	HS	MS	LS	HS	MS	LS
Employment share	0.094	0.521	0.385	0.177	0.618	0.205
Income share	0.107	0.416	0.257	0.179	0.439	0.113
by Age	Y	P	O	Y	P	O
Employment share	0.336	0.472	0.191	0.246	0.521	0.233
Income share	0.221	0.408	0.151	0.136	0.413	0.183
by Gender	M		F	M		F
Employment share	0.651		0.351	0.618		0.382
Income share	0.558		0.223	0.478		0.254

Notes: HS: tertiary degree or above; MS: upper-secondary degree or equivalent; LS: the rest. Y: 15–29 years old, P: 30–49 years old, O: 50+ years old. M: Male, F: Female. We first average the employment and income shares across industries within each country using as weights each industry's employment share in country-wide employment in 1982. We then calculate the unweighted average across countries by year.
Source: Authors' calculations based on EU KLEMS.

that at least in the U.S., younger workers tend to work in more routine jobs, and in our main cross-country sample, they seem to be negatively affected by the rise of machines—although the exact results somewhat vary by the type of capital and empirical specification.

Last, the well-known improvement in women's status in the labor market is evident in the third panel of Table 3.2: Their employment and income shares increased between 1982 and 2005, while those of men decreased.[25] It is important to keep this in mind as we proceed. In the following sub-section, we will see that—at least in the U.S.—women tended to work in more routine jobs in the 1980s (such as desk secretaries and bank tellers), which potentially exposed them more to the threat of replacement by machines. But it seems that that women in later years increased their education levels in a way that prepared themselves for jobs and/or tasks that were less negatively affected by the newer types of capital.[26]

decisions, by driving them to continue education rather than join the workforce. In addition, this may also lead to younger workers being negatively selected.

[25] Appendix Table A9, which stratifies genders by skill, reveals that women of all skill levels experienced increases in their average country-wide employment shares between 1982 and 2005, with the highest increase among more skilled women.

[26] However, such labor supply responses are accounted for by fixed effects in our econometric analysis.

Table 3.3: Task scores by education, age and gender

1980	HS	MS	LS	Y	P	O	M	F
R-Cognitive	-0.037	0.122	-0.319	-0.142	0.242	0.138	-0.046	-0.106
R-Manual	0.572	0.054	-0.774	0.110	-0.187	0.116	-0.077	-0.013
NR-Cognitive Analytical	-0.557	-0.099	0.890	0.075	-0.128	-0.175	0.130	-0.009
NR-Cognitive Interpersonal	-0.395	-0.097	0.711	0.039	-0.067	-0.177	0.110	0.032
NR-Manual	0.510	0.051	-0.700	0.245	-0.418	0.084	-0.051	-0.019
RTI	-0.072	0.085	-0.172	-0.176	0.299	0.093	-0.049	-0.036
2010	HS	MS	LS	Y	P	O	M	F
R-Cognitive	-0.230	0.051	-0.233	-0.144	0.027	0.007	-0.082	-0.093
R-Manual	0.586	-0.003	-0.788	-0.064	-0.433	-0.096	-0.250	-0.282
NR-Cognitive Analytical	-0.785	-0.151	0.886	0.156	0.160	-0.126	0.232	0.223
NR-Cognitive Interpersonal	-0.480	-0.027	0.711	0.133	0.267	-0.005	0.237	0.250
NR-Manual	0.540	0.063	-0.710	0.112	-0.511	-0.079	-0.171	-0.217
RTI	-0.080	-0.036	-0.169	-0.209	0.068	-0.003	-0.112	-0.094

Notes: HS: tertiary degree or above; MS: upper-secondary degree or equivalent; LS: the rest. Y: age 16–29, P: age 30–49, O: age 50-65. M: Male, F: Female. The RTI index is constructed following Autor and Dorn (2013), which itself is a composite of five extracted DOT measures following Autor et al. (2003). All other measures are constructed from O*NET following Acemoglu and Autor (2011). All six measures are standardized to have a mean 0 and standard deviation of 1. Group-specific means are computed using hours-weighted employment weights from the 1980 and 2010 U.S. IPUMS Census, respectively.

3.4 Task Content of Occupations by Worker Characteristics

As implied by the model of Section 2, we believe that new types of capital substitute for or complement specific tasks performed by workers, rather than directly affect workers based on age or gender (Michaels et al., 2014). Following Acemoglu and Autor (2011), Table 3.3 summarizes the means of task scores for the different groups of workers that we consider.[27,28]

The scores in the first five rows of the table are constructed from O*NET, which contains scales on 400 different types of tasks for each occupation. From this information, Acemoglu and Autor (2011) construct broader-based measures of routine-cognitive, routine-manual, non-routine(-cognitive) analytical, non-routine(-cognitive) interpersonal and non-routine manual tasks. Each measure is standardized to have a mean of zero and standard deviation of one. Using these standardized measures, we compute the hours-weighted mean for each worker group from the 1980 U.S. census. The routine-task intensity index (RTI) in the last row of the table was used in Autor and Dorn (2013). This index collapses five task measures

[27] Appendix Table A10 summarizes the same statistics by education×age and education×gender.

[28] However, they do not distinguish workers by age, nor do they make an extensive analysis by gender.

extracted from the 1977 Dictionary of Occupational Titles (DOT), similar to the ones in the first five rows of Table 3.3.[29]

In the table, it is clear that in 1980, medium-skill, young and female U.S. workers worked in more routine-intensive jobs than their respective counterparts. Not surprisingly, the reason for which American women have a relatively high RTI in 1980 is not because they worked in routine-manual occupations (e.g. factory-line workers), but because they worked in routine-cognitive occupations (e.g. secretaries).[30]

Taken together, we can posit from Tables 3.2-3.3 that the demand for medium-skill and young workers may have dropped because those workers tended to work in routine jobs, the required tasks of which were replaced by new types of capital.[31] But such a line of reasoning is less obvious for women—even though they tend to work in routine jobs, recall from the previous subsection that women's employment and wages rose significantly relative to men's. This is what leads to our conjecture that, more than any other group of workers, women altered their labor supply toward cognitive jobs in response to the decline in the demand for routine jobs. Indeed, in Appendix Figures A1-A2, it is clear that between 1980 and 2010 in the U.S., women's employment shifted toward higher-wage jobs, which tend to be of higher skill, at a faster rate than men.[32]

This is also consistent with how the mean task scores change from 1980 to 2010. Note that the means change only because the composition of occupations performed by each group changes, not because the scores themselves change: For any occupation, the scores are a constant, fixed characteristic. Between the two years, there is a secular decline and rise in routine and non-routine cognitive measures, respectively, across the board. For medium-skill and young workers, there is a noticeable drop in mean routine scores, indicating that as their employment fell, the content of their work also became less routine: the medium-skill now work in more manual jobs, and young workers in more cognitive jobs. But the changes are the most stark for women, and furthermore, this is despite their larger employment share.

[29]Specifically, RTI = log[R-cognitive + R-manual)/2] − log[NR-analytical + NR-interpersonal)/2] − log[NR-manual]. For details about how the five measures are extracted from the DOT, refer to Autor et al. (2003). Based on these five measures, the same authors also construct industry-level routine-intensity measures, which we use in the econometric analysis.

[30]Although gender is not accounted for, Lee and Shin (2017) document that the profession of secretaries was among those that declined the most in terms of employment shares.

[31]The direction of change in employment shares by worker group are qualitatively the same in the U.S. census as the EU KLEMS average, and quantitatively more pronounced; See Appendix Table A10.

[32]However, men always did and still do comprise a larger share of higher-wage jobs. This may explain the finding in Section 5.3 that new machines were more beneficial for men.

American women not only participate in the labor market much more than before, but also in much more cognitive jobs than their predecessors.

The fact that workers' labor supply and skill acquisition decisions may have responded toward tasks and/or occupations that are less negatively (or positively) affected by the advent of new types of capital makes assessment more difficult, since labor supply and demand effects may differ. For example, by pushing women toward higher skill jobs, we may conclude that the new technologies benefited them. However, such labor supply decisions would point more toward women's higher adaptability than a positive effect of technological change. Indeed, since men were already working in those high-skill jobs that were more complemented by the new types of capital, and more men still are, the labor demand effects were still skewed against women and favorable for men, and would have been even stronger absent any labor supply response from either group.

4 Econometric model and estimation strategy

We estimate the effects of capital inputs and automation on employment using a standard empirical specification for labor demand:

$$\ln E_{ict}^{j} = \alpha_{ct} + \alpha_{ic} + \beta_{y}^{j} \cdot \ln Y_{ict} + \boldsymbol{\beta}_{k}^{j} \cdot \mathbf{k}'_{ict-1} + \epsilon_{ict}^{j}, \tag{4}$$

where the dependent variable, $\ln E_{ict}^{j}$, is the log of employment, measured in hours, of worker group $j \in G$, where $G = \{\mathrm{HS}, \mathrm{MS}, \mathrm{LS}\}$, $\{\mathrm{Y}, \mathrm{P}, \mathrm{O}\}$ or $\{\mathrm{M}, \mathrm{F}\}$, in industry i in country c in year t. The vector $\mathbf{k}_{ict-1}$ comprises the main explanatory variables: namely, the ratios of real non-ICT, ICT net of software, and software capital stocks to real gross value-added. We do not use logs for these variables for two reasons. First, they represent shares. Second, the values of ICT and software for some country-industry pairs in early years of the sample are close to zero, resulting in negative values that are extremely large when in logs (Michaels et al., 2014). Given the specification, the coefficient vector $\boldsymbol{\beta}_{k}^{j}$ captures the percentage change in employment of worker group j associated with a one percentage point change in the capital input stock to value-added ratio. In order to mitigate the potential simultaneity bias, the key explanatory variables are lagged by one year.[33]

[33] As the forward-looking perspective of the representative firm cannot be precluded, the use of first lags can only mitigate, rather than eliminate, the simultaneity bias. Missing values generated by the lag operator are

The log of real gross value-added, $\ln Y_{ict}$, capturing industry scale, is included in the set of controls. This way, we ensure that the coefficient estimates in $\boldsymbol{\beta}_k^j$ are not spuriously driven by the expansion or contraction of industries, which, in turn, is likely to change their capital input intensities. Including output is also consistent with equation (3) in the model. Yet, we will also preform robustness checks without this variable. To control for time-varying country characteristics, we include country-year fixed effects, α_{ct}. Among other factors, these fixed effects account for changes in the aggregate supply of production factors, trade openness, and relative wages, assuming that wages are determined in labor markets at the national level (Michaels et al., 2014). Finally, we include country-industry fixed effects, α_{ic}, capturing time-invariant unobserved characteristics of country-industry pairs, such as the initial level of technology and the pattern of specialization. This implies that the coefficient estimates are identified through changes in the variables from their respective country-industry means. Equation (4) is estimated by Ordinary Least Squares (OLS) with standard errors clustered by country-industry pair. In all estimations, the specification is weighted by the share of each industry's employment in country-wide employment in 1982, the first year of the benchmark sample, as in Michaels et al. (2014).

Equation (4) is also estimated with the income share of worker group j as the dependent variable, instead of log employment. This is calculated as the ratio of the real wage bill of worker group j to gross value added within an industry. In Section 5.2, we also propose a new empirical strategy aimed at identifying the effects of industrial robots on the employment levels and income shares of different worker groups over the time period 1996–2005.

5 Econometric Results

5.1 Capital inputs and labor demand: 1982–2005

We start off the econometric analysis by studying the correlation of capital inputs with the demand for different worker types over the sample period 1982–2005. The results are shown in Table 5.1. The dependent variable is the employment level of workers by skill (columns 1–3), age (columns 4–6), and gender (columns 7–8). The positive and statistically significant coefficient estimates of log output in all columns imply that growing industries employ more workers across the board. More importantly for our purposes, as already stressed in Section 4,

replaced with zeros (Arellano and Bond, 1991).

Table 5.1: Capital inputs and labor demand, 1982–2005

Dep. var: $\ln E$	(1) HS	(2) MS	(3) LS	(4) Y	(5) P	(6) O	(7) M	(8) F
$\ln Y_t$	0.42***	0.32***	0.38***	0.50***	0.39***	0.39***	0.41***	0.39***
	[0.07]	[0.07]	[0.09]	[0.10]	[0.07]	[0.07]	[0.07]	[0.09]
K_{t-1}	0.0052	0.0053	0.013*	0.013	0.014	0.017	0.0097	0.027**
	[0.008]	[0.007]	[0.008]	[0.009]	[0.009]	[0.01]	[0.01]	[0.01]
ICT_{t-1}	0.40**	0.36**	0.59***	0.61***	0.43**	0.45*	0.43**	0.59***
	[0.2]	[0.2]	[0.2]	[0.2]	[0.2]	[0.2]	[0.2]	[0.2]
$\mathrm{S/W}_{t-1}$	0.67	-1.35**	-1.64**	-1.25*	0.24	0.45	-0.23	0.28
	[0.7]	[0.6]	[0.8]	[0.7]	[0.5]	[0.7]	[0.6]	[0.6]
Obs	7129	7200	7199	7189	7192	7133	7200	7129
R^2	0.991	0.994	0.989	0.989	0.992	0.988	0.992	0.991

Notes: Ordinary Least Squares (OLS) with clustered standard errors by country-industry pairs. Country-industry and country-year fixed effects included. All equations are weighted by the share of each industry's employment in country-wide employment in 1982. For a description of the variables, see Appendix Table B9. Asterisks denote significance at 1% (***), 5% (**), and 10% (*).

controlling for output implies that the coefficient estimates of the capital inputs are not spuriously driven by the expansion or contraction of industries.

The positive and statistically significant coefficient estimates of non-ICT capital in columns (3) and (8) imply that industries in which this type of capital grew faster also experienced an above-average increase in low-skill and female employment. Faster ICT growth is associated with higher employment for all worker types, as evidenced by the positive and statistically significant coefficient estimates of ICT in columns (1)–(8). In contrast, the negative and statistically significant coefficient estimates of software in columns (2)–(4) show that industries with above-average software growth experienced a decline in the medium- and low-skill employment, as well as a decline in young employment. Yet, since all regressions include country-year fixed effects, these negative correlations point to losses relative to other industries and not necessarily to a fall in the absolute level of employment of these workers.[34]

In Table 5.2, we study the association between changes in capital inputs and changes in employment across industries that differ in their exposure to automation. To this end, we interact each of the three types of capital with an industry-level index measuring the prevalence of routine tasks in 1980 (RSH_i), constructed by Autor et al. (2003).[35] Some clear patterns

[34] We also estimate the regressions of Table 5.1 by replacing the three capital inputs with aggregate capital. We find that aggregate capital increases the demand for low-skill, young, prime, and female workers (Appendix Table B1).

[35] This is a composite index comprising the five 1977 DOT broader-based measures of routine-cognitive, routine-manual, non-routine(-cognitive) analytical, non-routine(-cognitive) interpersonal and non-routine manual tasks. Autor et al. (2003) re-normalize each of the five measures into centiles of the 1960 occupation

emerge from this analysis. First, the coefficient estimate of each interaction term almost always has the opposite sign from the coefficient estimate of the respective non-interacted capital input. This suggests that the association of capital inputs with labor demand is systematically different in more routine-intensive industries compared to less routine-intensive ones. Hence, taking into consideration the reliance of industries on occupations vulnerable to automation is essential for assessing the labor market effects of machines. Most notably, the complementarities of ICT and software to female workers are weaker in more routine-intensive industries. One interpretation for these results is that women have exited routine occupations at a faster rate than men, and have transitioned toward occupations requiring intensive use of non-routine cognitive skills which are more complementary to these capital inputs. Consistent with this view, Acemoglu and Autor (2011) show that while employment in middle-wage jobs has fallen more among women than men, this has largely been offset by women's employment rising in professional, managerial and technical occupations.

Second, the routine-intensity of an industry plays a different role for each type of capital. Non-ICT capital is associated with higher employment growth in routine-intensive industries. This suggests that low-tech machines may complement jobs that require intensive use of routine skills. The opposite holds for high-tech capital: Both ICT and software are associated with employment losses (gains) in more (less) routine-intensive industries. The correlation with employment losses in routine-intensive industries is especially strong for software, where it is statistically significant for low and medium-skill workers, all age groups, and women. Independently of routine-intensity, industries in which software grew faster employed more high-skill workers and fewer medium-skill workers. But while high-ICT-growth industries employed more young and medium-skill workers, in less routine-intensive industries, higher ICT growth led to fewer low-skill and female workers.

Our results thus far point to important differences across different types of capital and industries. ICT growth is associated with employment growth, especially for low-skill, medium-skill and young workers. This is in line with the view that ICT makes workers more productive (Acemoglu and Restrepo, 2017, 2018). In contrast, software complements high-skill workers, but is associated with job losses for other workers, especially in routine-intensive industries. The result that machines may displace workers in routine occupations is known in the litera-

distribution, and compute the routine score as the ratio of the total score across all occupations within an industry, weighted by each occupation's within-industry employment share. RSH does not enter the specification individually as it is absorbed by the fixed effects.

Table 5.2: Capital inputs, routine intensity and labor demand, 1982–2005

Dep. var: $\ln E$	(1) HS	(2) MS	(3) LS	(4) Y	(5) P	(6) O	(7) M	(8) F
$\ln Y_t$	0.42***	0.32***	0.38***	0.49***	0.39***	0.40***	0.42***	0.38***
	[0.07]	[0.07]	[0.09]	[0.09]	[0.07]	[0.07]	[0.07]	[0.08]
K_{t-1}	-0.040*	-0.035*	-0.031	-0.029	-0.030	-0.039	-0.045	0.00093
	[0.02]	[0.02]	[0.02]	[0.02]	[0.03]	[0.04]	[0.03]	[0.03]
ICT_{t-1}	0.037	0.67*	1.65***	1.28**	0.38	0.67	0.60	1.26***
	[0.9]	[0.4]	[0.6]	[0.5]	[0.5]	[0.6]	[0.4]	[0.5]
$\mathrm{S/W}_{t-1}$	5.25*	2.57	0.23	4.03*	3.76**	5.74**	2.02	7.73***
	[2.9]	[1.7]	[2.7]	[2.4]	[1.8]	[2.3]	[2.0]	[2.3]
$\mathrm{RSH}\times\mathrm{K}_{t-1}$	0.12**	0.10**	0.11**	0.10*	0.11*	0.14*	0.14**	0.062
	[0.06]	[0.04]	[0.05]	[0.05]	[0.07]	[0.09]	[0.07]	[0.06]
$\mathrm{RSH}\times\mathrm{ICT}_{t-1}$	0.57	-0.77	-2.20*	-1.51	-0.033	-0.62	-0.44	-1.56*
	[1.5]	[0.7]	[1.1]	[1.0]	[0.9]	[1.2]	[0.8]	[0.9]
$\mathrm{RSH}\times\mathrm{S/W}_{t-1}$	-8.30	-7.03**	-3.29	-9.42**	-6.38**	-9.52**	-4.10	-13.3***
	[5.1]	[2.7]	[4.4]	[4.0]	[3.0]	[4.0]	[3.3]	[3.9]
Obs	7129	7200	7199	7189	7192	7133	7200	7129
R^2	0.991	0.994	0.990	0.989	0.992	0.989	0.992	0.991

Notes: Ordinary Least Squares (OLS) with clustered standard errors by country-industry pairs. Country-industry and country-year fixed effects included. All equations are weighted by the share of each industry's employment in country-wide employment in 1982. For a description of the variables, see Appendix Table B9. Asterisks denote significance at 1% (***), 5% (**), and 10% (*).

ture (e.g. Acemoglu and Autor, 2011). But the fact that we find evidence for job displacement only by software, arguably the most innovative form of capital in the sample period, is novel and interesting. In relation to Acemoglu and Restrepo (2017, 2018), this suggests that software is complementary to other automating technologies (e.g. robots). It also calls for the need to study the labor market effects of new technologies more specifically and in isolation, since their effects may differ from that of the technology embedded in other types of capital. Notwithstanding, the analysis so far only establishes conditional correlations, which do not necessarily imply causal relationships.

5.2 Industrial Robots and Labor Demand: 1996–2005

We now examine a new identification strategy that aims to isolate the effects of industrial robots on the demand for workers and their income shares from other forms of capital. There is a growing interest in understanding how automation affects the labor market, but its measurement has been one of the main challenges in the existing literature. Several influential papers have used data from the IFR. Graetz and Michaels (2018) were among the first to use this data source in order to build measures of robot density across countries, industries and years. However, once matched with the EU KLEMS data, robot density becomes available only for 14 industries and starts only in 1993. To have a sense of which type of capital is more likely to capture automation, we compute the correlations between the percentage change in robot intensity over 1993–2007 reported in Graetz and Michaels (2018), and the percentage changes in the capital-output ratios for capital of different types (k_{ict}) over 1993-2005, all averaged by country. This exercise reveals that robot intensity is highly correlated with non-ICT capital and software. This is intuitive, as automation is more common in heavy industries that use advanced machinery complemented with specialized software. Notwithstanding, we proceed to identify whether robotization had separate, independent effects on the employment and income shares of different worker types.

To overcome data limitations, we propose a novel approach that complements the analysis in Graetz and Michaels (2018). The basic idea is to build a proxy for a country's exposure to robotization and interact it with an industry-specific measure of exposure to automation. We do so using the UN COMTRADE data on bilateral trade in industrial robots, which starts in 1996.[36] For each country c in our sample, we collect annual data on total robot imports from 1996 to 2005, RI_{ct}. As long as robot imports are driven by exogenous shocks, such as global technological progress, they will be orthogonal to idiosyncratic shocks to any single industry in any individual country.

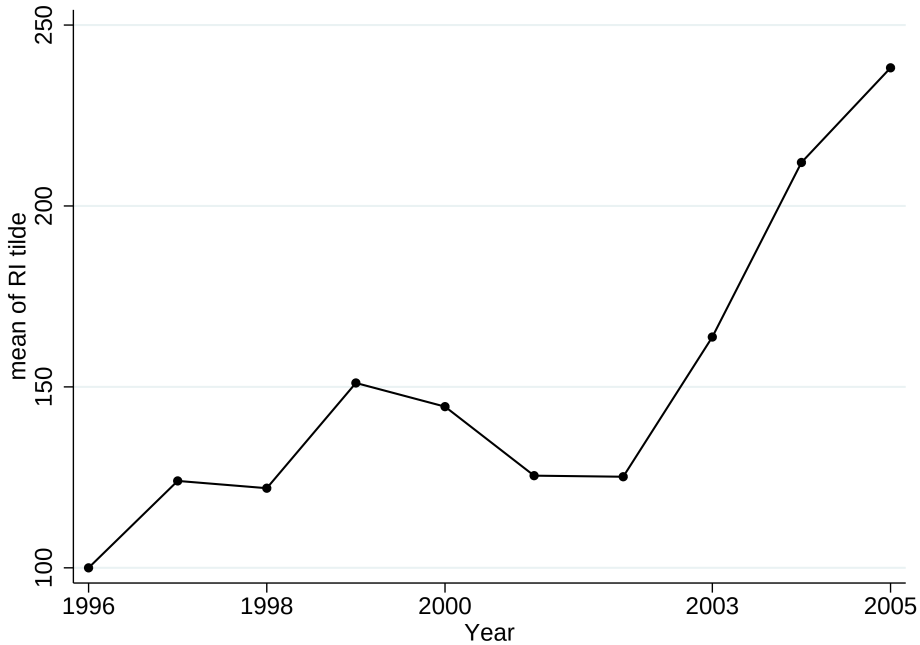
Nonetheless, we are still concerned that RI_{ct} may be endogenous. We alleviate this concern by replacing RI_{ct} with a measure of a country's exposure to the worldwide surge in industrial robots in the spirit of a Bartik instrument. Intuitively, a country is more exposed to robotization if it imports industrial robots from countries that experience relatively high growth rates in their robot exports. To capture this, for each country c, we first compute annual robot exports from each of its trade partners, indexed by p, to all destination countries in year t *except* for country c itself, RX_{pt-c}. We then compute the average across RX_{pt-c} weighted by country c's robot import dependence on country p in the initial year, 1996. We do this for all years in 1996–2005. More precisely, country c's exposure to robots, $\widetilde{RI}_{ct}$, is:

$$\widetilde{RI}_{ct} = \sum_{p} \left(\frac{RI_{cp,1996}}{RI_{c,1996}} \cdot RX_{pt-c} \right)$$

where $RI_{c,1996}$ is total robot imports of country c in 1996; $RI_{cp,1996}$ is robot imports of country

[36] Acemoglu and Restrepo (2018) use robot import data from the same source to measure the adoption of automation technologies across countries.

Figure 2: Exposure to robots



Notes: The normalised values of $\widetilde{RI}_{ct}$, measuring country c's exposure to robots, are averaged across countries by year. No country weights are used.
Source: Author's calculations based on UN COMTRADE.

c from country p in 1996, and the summation is over all countries exporting robots in the world. Since the weights used to compute $\widetilde{RI}_{ct}$ are fixed to the initial year of the sample period and are largely determined by geography, they are orthogonal to any other shocks. The values of $\widetilde{RI}_{ct}$ are normalized by the value in the initial year, 1996.

In order to have an idea of how the exposure of countries to robots evolved over 1996–2005, we plot in Figure 2 the year-by-year unweighted average of the normalized values of $\widetilde{RI}_{ct}$ across the 10 countries examined. Having in mind that the variable is constructed using data on trade flows of robots rather than stocks, the figure reveals an upward trend in countries' exposure to robotization, especially after 2002. This trend is comparable to the upward trends in the countries' exposure to ICT and software, documented in Section 3.2, albeit that analysis exploits data on capital stocks. In terms of magnitude, the figure indicates that the exposure of countries to robotization more than doubled between 1996 and 2005.[37]

Next, we capture the differential exposure of industries to robotization using the routine-share index RSH_i, which is meant to proxy for predetermined technological characteristics

[37] Appendix Figure A3 shows these trends by individual country.

Table 5.3: Capital inputs and labor demand, 1996–2005

Dep. var: $\ln E$	(1) HS	(2) MS	(3) LS	(4) Y	(5) P	(6) O	(7) M	(8) F
$\ln Y_t$	0.37***	0.34***	0.40***	0.46***	0.43***	0.42***	0.44***	0.42***
	[0.07]	[0.08]	[0.08]	[0.1]	[0.07]	[0.07]	[0.08]	[0.09]
K_{t-1}	0.0049	0.000045	-0.0015	-0.00042	-0.00015	0.00022	0.00047	0.0025
	[0.004]	[0.003]	[0.003]	[0.004]	[0.003]	[0.003]	[0.003]	[0.002]
ICT_{t-1}	0.035	0.16**	0.32***	0.27***	0.18**	0.15*	0.17**	0.21***
	[0.1]	[0.07]	[0.10]	[0.09]	[0.07]	[0.09]	[0.07]	[0.07]
S/W_{t-1}	0.36	-0.53*	-0.66	-0.26	-0.044	0.11	0.0089	-0.13
	[0.3]	[0.3]	[0.4]	[0.4]	[0.3]	[0.3]	[0.3]	[0.3]
Obs	2989	3000	2999	2998	3000	2989	3000	2989
R^2	0.997	0.998	0.997	0.997	0.998	0.997	0.998	0.998

Notes: Ordinary Least Squares (OLS) with clustered standard errors by country-industry pairs. Country-industry and country-year fixed effects included. All equations are weighted by the share of each industry's employment in country-wide employment in 1996. For a description of the variables, see Appendix Table B9. Asterisks denote significance at 1% (***), 5% (**), and 10% (*).

of an industry. The final "robot shock" variable is the interaction $\text{RSH}_i \times \widetilde{RI}_{ct}$. In words, this variable captures the effect of industrial robots comparing industries that differ in their (exogenous) potential for automation in countries that differ in their (pre-determined) exposure to the worldwide surge in robots. Augmented with our newly-constructed variable, our baseline specification is modified as:

$$\ln E_{ict}^j = \alpha_{ct} + \alpha_{ic} + \beta_y^j \cdot \ln Y_{ict} + \boldsymbol{\beta}_k^j \cdot \mathbf{k}'_{ict-1} + \beta_r^j \cdot [\text{RSH}_i \times \widetilde{RI}_{ct-1}] + \epsilon_{ict}^j. \quad (5)$$

By keeping the country-year and country-industry fixed effects, this identification strategy compares industries that exogenously differ in routine-intensity *within countries* experiencing exogenously differential exposure to changes in the supply of robots. To further alleviate simultaneity bias concerns, we continue to use the first lag of the key explanatory variables, including our new interaction term between robots and RSH.

Before presenting the estimation results from our augmented version with robot exposure, we re-estimate equation (4) on the restricted sample starting in 1996, the year in which data on trade in robots became available. In addition to allowing us to directly compare the coefficient estimates with and without the robot proxy, this exercise is interesting in its own right as technology has changed dramatically since 1982. For instance, the first IBM Personal Computer was released in 1982, the World Wide Web was invented in 1989, and the dot-com boom occurred roughly from 1995 to 2000. It is therefore interesting to examine how the labor

Table 5.4: Capital inputs, robots and labor demand, 1996–2005

Panel A: Employment by skill, by age, and by gender

Dep. var: $\ln E$	(1) HS	(2) MS	(3) LS	(4) Y	(5) P	(6) O	(7) M	(8) F
$\ln Y_t$	0.37***	0.34***	0.40***	0.46***	0.43***	0.42***	0.44***	0.42***
	[0.07]	[0.08]	[0.08]	[0.10]	[0.07]	[0.07]	[0.08]	[0.09]
K_{t-1}	0.0036	-0.00064	-0.0036	-0.0022	-0.00051	0.00082	0.00063	0.0010
	[0.004]	[0.003]	[0.004]	[0.004]	[0.003]	[0.003]	[0.003]	[0.002]
ICT_{t-1}	0.029	0.16**	0.31***	0.26***	0.17**	0.15*	0.17**	0.20***
	[0.1]	[0.07]	[0.09]	[0.09]	[0.07]	[0.09]	[0.07]	[0.07]
S/W_{t-1}	0.40	-0.51*	-0.60	-0.21	-0.034	0.097	0.0045	-0.095
	[0.3]	[0.3]	[0.4]	[0.4]	[0.3]	[0.3]	[0.3]	[0.3]
$\text{RSH}\times\widetilde{RI}_{t-1}$	-0.065	-0.035	-0.11**	-0.090	-0.018	0.031	0.0082	-0.073
	[0.07]	[0.04]	[0.04]	[0.06]	[0.04]	[0.05]	[0.04]	[0.05]
Obs	2989	3000	2999	2998	3000	2989	3000	2989
R^2	0.997	0.998	0.997	0.997	0.998	0.997	0.998	0.998

Panel B: Income share by skill, by age, and by gender

Dep. var: Lsh	(1) HS	(2) MS	(3) LS	(4) Y	(5) P	(6) O	(7) M	(8) F
$\ln Y_t$	-0.014	-0.11***	-0.0070	-0.015**	-0.068***	-0.050***	-0.085***	-0.048***
	[0.01]	[0.02]	[0.007]	[0.006]	[0.02]	[0.01]	[0.02]	[0.009]
K_{t-1}	0.00055	0.000027	-0.00015	0.00047	0.00024	-0.00039	0.00069	-0.00033
	[0.0007]	[0.0008]	[0.0004]	[0.0003]	[0.0005]	[0.0004]	[0.0007]	[0.0002]
ICT_{t-1}	0.0042	0.028	0.019**	0.011*	0.023	0.014	0.033	0.016*
	[0.01]	[0.02]	[0.009]	[0.007]	[0.02]	[0.01]	[0.02]	[0.010]
S/W_{t-1}	0.18***	-0.041	0.049	0.037	0.17	-0.016	0.18*	0.011
	[0.06]	[0.10]	[0.04]	[0.04]	[0.1]	[0.05]	[0.09]	[0.04]
$\text{RSH}\times\widetilde{RI}_{t-1}$	0.013**	0.019*	-0.0064	-0.0037	0.014	0.015*	0.033***	-0.0080
	[0.007]	[0.01]	[0.008]	[0.005]	[0.01]	[0.009]	[0.01]	[0.006]
Obs	2989	3000	2999	2998	3000	2989	3000	2989
R^2	0.991	0.983	0.989	0.973	0.957	0.974	0.974	0.995

Notes: Ordinary Least Squares (OLS) with clustered standard errors by country-industry pairs in both panels. Country-industry and country-year fixed effects included. All equations are weighted by the share of each industry's employment in country-wide employment in 1996. For a description of the variables, see Appendix Table B9. Asterisks denote significance at 1% (***), 5% (**), and 10% (*).

market effects of technology may have changed before and after computer-related technologies became widespread. These results are presented in Table 5.3 and bear a close resemblance to those for the sample period 1982–2005. ICT is associated with employment gains for workers of all ages, both genders, as well as for the less-skilled. Software, instead, is associated with employment losses for medium-skill workers. There are no statistically significant associations between non-ICT capital and labor demand.

In Panel A of Table 5.4, we estimate the baseline specification augmented with our robot exposure variable. The associations of non-robot capital inputs with employment are qualitatively identical to Table 5.3. But in addition, we find that robots decrease the demand for low-skill workers. Hence, only software and robots exert negative effects on employment, which are concentrated among the less-skilled, suggesting that both capture automating technologies. The displacement effect of robots on low-skill workers is in line with Graetz and Michaels (2018) who find that robots decrease the employment share of this worker type. But relative to their finding, we show that low-skill workers incur employment losses due to robots even in *absolute* terms.

In Panel B we complement the results on employment with an analysis of the effects of capital inputs and robots on the income shares of different worker types. To do so, we re-estimate the augmented version of the baseline specification using the income share of each group as the dependent variable. The results of this panel suggest that ICT growth is associated with an increase in the income shares of low-skill, young, and female workers, while software growth is associated with higher income shares for high-skill and male workers. Robots also have positive effects: They increase the income shares of high and medium-skill workers, older workers and men. The results from this panel confirm that robots and software are skill-biased, but do not support the view that machines are responsible for falling income shares within industries.

In Appendix B, we conduct a number of robustness checks for Table 5.4. We first check the exogeneity of our robot variable by removing all other explanatory variables and running an OLS of employment levels and income shares only on $\mathrm{RSH}_i \times \widetilde{RI}_{ct-1}$ (Appendix Table B2). The coefficients are nearly identical to the benchmark, lending credibility to our constructed robot exposure variable.[38] For the rest of our analysis, we continue to include the other controls so that we can compare the effect of robots against the reduced form effect of other types of capital.

Second, we re-estimate (5) by Two-Stage Least Squares (2SLS) replacing $\mathrm{RSH}_i \times \widetilde{RI}_{ct-1}$ with $\mathrm{RSH}_i \times RI_{ct}$, and instead instrumenting the latter with $\mathrm{RSH}_i \times \widetilde{RI}_{ct-1}$ and $\mathrm{RSH}_i \times \widetilde{RI}_{ct-2}$ (Appendix Table B3). All other variables are treated as exogenous and are thus not instrumented. The results remain largely unchanged.[39] In addition, we ensure that the effects of robots identified in Table 5.4 are not sensitive to alternative ways of computing the weights

[38]Keeping only $\ln Y$ as a control variable also produces virtually the same coefficients. These results are available upon request.

[39]The missing values of the first- and second-lagged "robot shock" variable are replaced with zeros (Arellano and Bond, 1991). The first-stage statistics suggest that our IV strategy is valid. The p-values of the under-identification test are below 10%, so we cannot reject the null hypothesis that the model is identified. Also, the weak identification tests suggest that the instruments are relevant and strongly correlated with the instrumented variable. Finally, the p-values for the Hansen J-statistic are all above 10% except in Panel B(6), rejecting the null of over-identifying restrictions.

used to construct countries' exposure to robots. As an alternative, rather than using the initial year 1996, we compute country c's average robot imports from country p over 1996–2005, divided by country c's average robot imports from all countries over the same period. Estimating (5) by OLS, or by 2SLS instrumenting $\text{RSH}_i \times RI_{ct}$ with the first and second lags of the interaction term between RSH_i and the alternative $\widetilde{RI}$, we obtain very similar results to the benchmark ones. (Appendix Tables B4 and B5). The results are also very similar when we exclude Japan, which uses mostly domestically-produced robots, from the sample (Acemoglu and Restrepo, 2018, Appendix Table B6).[40]

Last, in the baseline specification, we assume that wages are set at the national level and are thus accounted for by the country-year fixed effects. To allow for the possibility that the wage-setting process takes place at the industry level, we incorporate the log of real hourly wages and replace dummies for country-year pairs with year dummies. OLS estimations of this specification yield very similar results to the main ones (Appendix Tables B7 and B8).

5.3 Digging Deeper

We now explore the findings obtained so far in more depth. We start by differentiating the effects between manufacturing and services. These sectors are of particular interest because they account for a high fraction of country-wide employment, make intensive use of robotic technologies, but have experienced very different employment trends. Manufacturing industries were among the first to automate production processes. For instance, Ford's car production assembly line introduced in 1913 was a pioneer of modern automation. In most advanced countries, manufacturing employment shares continued to grow until the 1960s, after which it started to decline. In contrast, the service sector continues to grow in national employment shares, but is also being profoundly transformed by the advent of new technologies. For instance, while advances in ICT largely explain the wide diffusion of call centers in the 1990s, many companies started to locate call centers overseas in the 2000s. Even more recently, speech recognition software, the Internet and AI have been reducing or even eliminating the need for human operators.

In Panel A of Tables **??** and **??**, we estimate the augmented employment and income share equations, respectively, on the sample of manufacturing industries.[41] Among manufacturing

[40] Japan is the world's largest producer of robots, and relies little on imports of these. This is also evident in Figure A3: Japan's robot exposure is more or less flat over time, except for the initial year.

[41] All equations estimated on the manufacturing sample are weighted by the share of each manufacturing

Table 5.5: Capital inputs, robots and labor demand, manufacturing vs services

Panel A: Manufacturing

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. var: $\ln E$	HS	MS	LS	Y	P	O	M	F
$\ln Y_t$	0.27***	0.26***	0.26***	0.32***	0.35***	0.31***	0.32***	0.30***
	[0.06]	[0.08]	[0.09]	[0.09]	[0.08]	[0.07]	[0.07]	[0.09]
K_{t-1}	0.0044	0.0042	-0.00020	-0.0017	-0.0015	-0.0039	0.0057	-0.0080
	[0.01]	[0.01]	[0.02]	[0.01]	[0.01]	[0.01]	[0.01]	[0.02]
ICT_{t-1}	-0.23*	-0.018	0.072	0.027	-0.015	-0.042	-0.043	-0.045
	[0.1]	[0.1]	[0.1]	[0.1]	[0.1]	[0.1]	[0.1]	[0.1]
$\mathrm{S/W}_{t-1}$	0.78	-0.14	-0.35	0.063	0.18	0.27	0.021	0.40
	[0.6]	[0.5]	[0.6]	[0.5]	[0.5]	[0.5]	[0.4]	[0.5]
$\mathrm{RSH}\times\widetilde{RI}_{t-1}$	0.024	-0.16	-0.23**	-0.32***	-0.15	-0.053	-0.12	-0.27**
	[0.10]	[0.10]	[0.1]	[0.1]	[0.09]	[0.10]	[0.09]	[0.1]
Obs	1289	1300	1299	1298	1300	1289	1300	1289
R^2	0.998	0.998	0.998	0.998	0.998	0.998	0.999	0.998

Panel B: Services

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. var: $\ln E$	HS	MS	LS	Y	P	O	M	F
$\ln Y_t$	0.34***	0.26***	0.37***	0.26**	0.32***	0.26**	0.34***	0.21**
	[0.1]	[0.10]	[0.1]	[0.1]	[0.1]	[0.1]	[0.1]	[0.09]
K_{t-1}	0.0054	0.0028	0.00039	0.0031	0.0034*	0.0040**	0.0049**	0.0043***
	[0.003]	[0.002]	[0.003]	[0.003]	[0.002]	[0.002]	[0.002]	[0.001]
ICT_{t-1}	0.091	0.092	0.23**	0.13*	0.099	-0.0072	0.076	0.11**
	[0.1]	[0.06]	[0.09]	[0.07]	[0.06]	[0.08]	[0.06]	[0.06]
$\mathrm{S/W}_{t-1}$	0.55*	-0.46	-0.36	0.045	0.0060	0.029	0.16	-0.12
	[0.3]	[0.4]	[0.5]	[0.4]	[0.4]	[0.3]	[0.3]	[0.3]
$\mathrm{RSH}\times\widetilde{RI}_{t-1}$	0.053	0.078*	-0.074	0.11**	0.077**	0.20***	0.14***	0.045
	[0.07]	[0.04]	[0.07]	[0.05]	[0.04]	[0.06]	[0.03]	[0.04]
Obs	1300	1300	1300	1300	1300	1300	1300	1300
R^2	0.998	0.999	0.997	0.998	0.999	0.998	0.999	0.999

Notes: Ordinary Least Squares (OLS) with clustered standard errors by country-industry pairs in both panels. Country-industry and country-year fixed effects included. All equations in Panel A are weighted by the share of each manufacturing industry's employment in total manufacturing employment in 1996. All equations in Panel B are weighted by the share of each service industry's employment in total services employment in 1996. For a description of the variables, see Appendix Table B9. Asterisks denote significance at 1% (***), 5% (**), and 10% (*).

industries, those that are more exposed to robots experienced a decline in their employment of low-skill, young and female workers. Robots also reduced the income share of the young, while they increased the income share of high-skill, older and male workers. ICT is associated with both employment and income share losses for high-skill workers, while non-ICT capital is associated with income share increases for the medium-skill, young and male workers. Software is not found to be statistically significant for employment levels or income shares.

industry's employment in total manufacturing employment in 1996. Similarly, all equations estimated on the services sample are weighted by the share of each service industry's employment in total services employment in 1996.

Service industries are quite different, as seen in Panel B of Tables **??** and **??**: Those more exposed to robots experienced an *increase* in their employment of medium-skill workers, all age groups, and men. Robots also increased the income shares of high-skill, young, old and male workers. Similarly, capital inputs are mostly positively associated with employment and income shares, but these associations differ across types of capital and worker groups. Software is associated with employment gains for high-skill workers, and ICT is associated with employment gains for the low-skill, young and female workers. Similarly, software is associated with larger income shares for high-skill and also young workers, while ICT is associated with higher income shares for low-skill and female workers.[42]

Taking stock, our evidence suggests that while robots may have destroyed jobs in manufacturing industries, they may have created jobs in service industries. These findings can be interpreted in light of the model in Section 2, which shows that automation has both a displacement and a productivity effect, so that its net impact on labor demand is ambiguous. Through the lenses of the model, the displacement effect seems to dominate when automation is already widely adopted, as in manufacturing industries, while the productivity effect seems to dominate when automation is at an earlier stage, as is likely the case for service industries in the period of our analysis.

Second, robots complement high-skill, old and male workers. This effect seems to be stronger for income shares, suggesting that robots may replace existing jobs with better jobs. This may be because automation requires highly specialized workers, such as engineers, and raises the productivity of managerial tasks. Moreover, industries more prone to automation tend to be those where male workers have a comparative advantage. At the same time, as noted in Section 3.4, women are exiting from routine and manual occupations faster than men. Consistently with this interpretation, our results also suggest that ICT, which is more complementary to cognitive and possibly interpersonal tasks, may have increased the demand for female workers, especially in service industries.

To shed more light on the gender and skill bias of new technologies, and especially robots, we re-estimate our main specifications by further stratifying the male and female groups by their level of skill (education). The results are presented in Table 5.7, both for employment (Panel A) and income shares (Panel B). The equations in columns (1)–(3) and (4)–(6) cor-

[42]We obtain very similar results to those in Tables **??** and **??** from 2SLS estimations where the key explanatory variable, $\text{RSH}_i \times RI_{ct}$, is instrumented with the first two lags of $\text{RSH}_i \times \widetilde{RI}_{ct}$. The results are available upon request.

Table 5.6: Capital inputs, robots and income shares, manufacturing vs services

Panel A: Manufacturing

Dep. var: Lsh	(1) HS	(2) MS	(3) LS	(4) Y	(5) P	(6) O	(7) M	(8) F
$\ln Y_t$	-0.017	-0.079***	-0.0034	-0.0087*	-0.046***	-0.044**	-0.070**	-0.029***
	[0.01]	[0.02]	[0.005]	[0.005]	[0.02]	[0.02]	[0.03]	[0.010]
K_{t-1}	0.0019	0.012*	0.00081	0.0020**	0.0065	0.0063	0.011*	0.0030
	[0.003]	[0.006]	[0.001]	[0.0010]	[0.005]	[0.004]	[0.007]	[0.002]
ICT_{t-1}	-0.029*	-0.012	0.0060	-0.0042	-0.0038	-0.039	-0.021	-0.018
	[0.02]	[0.07]	[0.01]	[0.01]	[0.06]	[0.02]	[0.07]	[0.02]
S/W_{t-1}	0.14	0.13	0.018	0.0092	0.24	0.047	0.25	0.036
	[0.1]	[0.4]	[0.03]	[0.05]	[0.3]	[0.1]	[0.4]	[0.07]
$RSH \times \widetilde{RI}_{t-1}$	0.047***	0.032	-0.017	-0.026***	0.037*	0.050***	0.059**	0.0024
	[0.01]	[0.03]	[0.01]	[0.009]	[0.02]	[0.02]	[0.03]	[0.01]
Obs	1289	1300	1299	1298	1300	1289	1300	1289
R^2	0.981	0.982	0.994	0.973	0.941	0.978	0.951	0.989

Panel B: Services

Dep. var: Lsh	(1) HS	(2) MS	(3) LS	(4) Y	(5) P	(6) O	(7) M	(8) F
$\ln Y_t$	-0.025	-0.098***	-0.0054	-0.026**	-0.043*	-0.059***	-0.043*	-0.085***
	[0.02]	[0.03]	[0.010]	[0.01]	[0.02]	[0.02]	[0.03]	[0.02]
K_{t-1}	0.00071	-0.00077	0.00014	0.00063**	-0.000077	-0.00048	0.00054	-0.00046*
	[0.0008]	[0.0005]	[0.0004]	[0.0003]	[0.0005]	[0.0004]	[0.0006]	[0.0002]
ICT_{t-1}	0.0015	0.031	0.014*	0.0097	0.032	0.0044	0.024	0.022*
	[0.01]	[0.02]	[0.008]	[0.007]	[0.02]	[0.01]	[0.02]	[0.01]
S/W_{t-1}	0.18***	-0.094	0.052	0.076*	0.11	-0.042	0.14	0.0021
	[0.07]	[0.08]	[0.05]	[0.04]	[0.1]	[0.05]	[0.09]	[0.05]
$RSH \times \widetilde{RI}_{t-1}$	0.030**	0.026	0.0020	0.013*	0.0056	0.040***	0.051***	0.0076
	[0.01]	[0.02]	[0.01]	[0.008]	[0.02]	[0.01]	[0.01]	[0.01]
Obs	1300	1300	1300	1300	1300	1300	1300	1300
R^2	0.992	0.986	0.989	0.980	0.966	0.978	0.979	0.995

Notes: Ordinary Least Squares (OLS) with clustered standard errors by country-industry pairs in both panels. Country-industry and country-year fixed effects included. All equations in Panel A are weighted by the share of each manufacturing industry's employment in total manufacturing employment in 1996. All equations in Panel B are weighted by the share of each service industry's employment in total services employment in 1996. For a description of the variables, see Appendix Table B9. Asterisks denote significance at 1% (***), 5% (**), and 10% (*).

respond to male and female workers of high, medium, and low-skill, respectively. The main result emerging from the two panels is that robots displace low and medium-skill women, but raise the income share of high and medium-skill men.[43]

[43] In tables that are available upon request, we show that 2SLS estimations where the key explanatory variable, $RSH_i \times RI_{ct}$, is instrumented with the first two lags of $RSH_i \times \widetilde{RI}_{ct}$, produce very similar results to those in Tables **??** and **??**.

Table 5.7: Capital inputs, robots and labor demand by gender-skill

Panel A: Employment by gender-skill

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var: $\ln E$		M			F	
	HS	MS	LS	HS	MS	LS
$\ln Y_t$	0.37***	0.35***	0.43***	0.34***	0.28***	0.38***
	[0.08]	[0.08]	[0.09]	[0.1]	[0.08]	[0.09]
K_{t-1}	0.0032	0.00089	-0.0045	0.013	-0.0018	-0.00070
	[0.004]	[0.003]	[0.005]	[0.01]	[0.003]	[0.003]
ICT_{t-1}	-0.0036	0.14**	0.38***	-0.061	0.17***	0.25**
	[0.1]	[0.07]	[0.1]	[0.2]	[0.06]	[0.10]
$\mathrm{S/W}_{t-1}$	0.61*	-0.28	-0.86*	-0.30	-0.60**	-0.084
	[0.3]	[0.3]	[0.5]	[0.9]	[0.3]	[0.4]
$\mathrm{RSH}\times\widetilde{RI}_{t-1}$	-0.073	0.017	-0.062	-0.15	-0.10**	-0.13***
	[0.07]	[0.04]	[0.05]	[0.2]	[0.05]	[0.05]
Obs	3000	3000	3000	2989	3000	2999
R^2	0.997	0.998	0.997	0.979	0.998	0.989

Panel B: Income share by gender-skill

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var: Lsh		M			F	
	HS	MS	LS	HS	MS	LS
$\ln Y_t$	-0.0097	-0.069***	-0.0065	-0.0041	-0.043***	-0.00054
	[0.010]	[0.01]	[0.007]	[0.005]	[0.010]	[0.003]
K_{t-1}	0.00059	0.00044	-0.00034	-0.000048	-0.00041	0.00019
	[0.0005]	[0.0005]	[0.0003]	[0.0003]	[0.0004]	[0.0001]
ICT_{t-1}	0.0023	0.012	0.018**	0.0017	0.016*	0.00094
	[0.008]	[0.02]	[0.007]	[0.005]	[0.008]	[0.005]
$\mathrm{S/W}_{t-1}$	0.12***	0.034	0.024	0.064***	-0.075*	0.025
	[0.04]	[0.07]	[0.03]	[0.02]	[0.04]	[0.04]
$\mathrm{RSH}\times\widetilde{RI}_{t-1}$	0.014***	0.020***	-0.00067	-0.00046	-0.0016	-0.0058
	[0.005]	[0.008]	[0.007]	[0.005]	[0.007]	[0.005]
Obs	3000	3000	3000	2989	3000	2999
R^2	0.983	0.987	0.988	0.994	0.992	0.986

Notes: Ordinary Least Squares (OLS) with clustered standard errors by country-industry pairs in both panels. Country-industry and country-year fixed effects included. All equations are weighted by the share of each industry's employment in country-wide employment in 1996. For a description of the variables, see Appendix Table B9. Asterisks denote significance at 1% (***), 5% (**), and 10% (*).

This could be due to both demand and supply factors. On the demand-side, it may be the case that only less-skilled female workers found it more difficult to shift from routine-cognitive occupations (e.g. clerical and administrative) toward non-routine-cognitive occupations (e.g. managerial and technical), making them vulnerable to automation. On the supply-side, any aggregate changes in female labor force participation would be absorbed by the country-year fixed effects. Nonetheless, the negative employment effects of robots on low-skill women may still be because fewer of these women sought employment in routine occupations, or any employment at all, compared to their higher-skilled counterparts.

Finally, robots are likely to complement engineers, product designers and managers, all occupations that are still dominated by (high-skill) men, raising their income shares. Similar patterns hold for software, although it is associated with an increase in the demand for high-skill male and female workers. In contrast, ICT capital seems to complement medium and low-skill workers of both genders.

5.4 Machines and Labor Demand after the Crisis: 2008–2015

The benchmark sample used in the analysis of Section 5.1 is long enough to cover several technological innovations which have transformed labor markets. But does it contain useful lessons for the future? A host of new technologies have arrived since 2005, the end of our benchmark sample, but little is known about their labor market effects. To shed some light on these important questions, we extend our analysis to the period 2008–2015. Unfortunately, this comes at a cost. For the variables of interest, the coverage of countries and industries in EU KLEMS becomes much more limited after 2008. In particular, the number of industries falls to 13 (from 30) and the number of countries to 7 (from 10).[44] These limitations, especially the coarse definition of industries, preclude us from following the empirical strategy used in Section 5.2. Nevertheless, we can have a sense of which results still hold by comparing the correlations between capital inputs and employment across the two sample periods.

[44] The exact coverage of countries and industries is listed in the Appendix Table A11. The descriptive statistics for the main capital and labor variables by type of capital and type of worker, respectively, reveal similar patterns and trends as the descriptive statistics covering the period 1982–2005 (Appendix Tables A12 and A13). ICT and software continued to grow over the more recent period, but at lower rates compared to 1982–2005. The main difference in the labor statistics is the decline in the employment shares of middle-aged, male and female workers between 2008 and 2015. Importantly, note that the statistics for the more recent period do not exactly overlap with the statistics for the older period because of the different composition of countries and industries. Most notably, the 2008–2015 sample includes the manufacturing sector as a whole, rather than a set of two-digit manufacturing industries as is the case in the 1982–2005 sample.

Table 5.8: **Capital inputs and labor demand, 2008–2015**

Dep. var: $\ln E$	(1) HS	(2) MS	(3) LS	(4) Y	(5) P	(6) O	(7) M	(8) F
$\ln Y_t$	0.48***	0.64***	0.67***	1.04***	0.53***	0.58***	0.63***	0.63***
	[0.1]	[0.2]	[0.2]	[0.3]	[0.2]	[0.1]	[0.2]	[0.2]
K_{t-1}	-0.0062	-0.0066	-0.0069	-0.015**	-0.010**	-0.0046	-0.0086**	-0.0077*
	[0.004]	[0.004]	[0.004]	[0.006]	[0.004]	[0.004]	[0.004]	[0.004]
ICT_{t-1}	-0.096	0.13	0.24*	-0.062	0.048	0.35***	0.13	-0.028
	[0.2]	[0.10]	[0.1]	[0.2]	[0.09]	[0.1]	[0.09]	[0.08]
S/W_{t-1}	0.22	-0.63***	-0.54**	-0.58**	0.093	0.10	-0.080	-0.20
	[0.3]	[0.2]	[0.3]	[0.3]	[0.2]	[0.2]	[0.2]	[0.2]
Obs	728	728	728	728	728	728	728	728
R^2	0.996	0.998	0.998	0.996	0.999	0.998	0.999	0.999

Notes: Ordinary Least Squares (OLS) with clustered standard errors by country-industry pairs. Country-industry and country-year fixed effects included. All equations are weighted by the share of each industry's employment in country-wide employment in 2008. For a description of the variables, see Appendix Table B9. Asterisks denote significance at 1% (***), 5% (**), and 10% (*).

Table 5.8 confirms the qualitative difference between ICT and software in the most recent period. In particular, ICT is still associated with *increases* in employment (for low-skill and old workers), suggesting a complementarity with humans. At the same time, software, like automation in the earlier period, is associated with *decreases* in the employment of medium-skill, low-skill, and young workers.

6 Conclusion

Around the world, and especially in advanced countries, there is a growing concern over the labor market impact of new technologies. ICT, robotics and artificial intelligence continue to improve, permeating and taking over parts of the production process previously performed by humans. Such is the scale of this phenomenon that many fear that machines may render certain types of workers redundant, justifiably so. Under such circumstances, it is paramount to identify which segments of the population have been more vulnerable, and conversely, what kind of worker characteristics have been in higher demand.

In this paper, we conducted a comprehensive analysis of how new technologies, embodied in various forms of capital inputs, have affected the demand for workers of different education, age and gender. Our main analysis uses high-quality, comparable data for 10 advanced countries and 30 industries from 1982 to 2005, spanning roughly their entire economies, as well as a more restricted sample of countries and industries from 2008 to 2015. We find that the most advanced types of capital inputs, namely software and industrial robots, are associated with a decline in employment for low- and medium-skill workers, young workers and women, especially in vulnerable sectors such as manufacturing. On the other hand, these capital inputs are associated with higher employment levels of high- and medium-skill workers, and men, especially in service industries. These results are consistent with the view that software and robots replace humans in routine tasks, while other forms of capital increase their productivity. We also find that robots raised the income shares of high-skill, old and male workers, which suggests an increase in the demand for engineers, product developers and managers.

While some of our results may raise concern, there are encouraging messages as well. First, while robots do seem to destroy jobs in manufacturing, they can create new employment opportunities in growing service industries. Whether the service sector is ultimately doomed to follow the same fate as manufacturing due to further automation is an open question. A simple theoretical model shows that this may be the case: The job displacement effect becomes stronger with the expansion of automation. Indeed, digital technology is allowing "white-collar robots" to substitute for service-sector workers and professionals. Nonetheless, service industries may be different: New technologies may have the potential to create new professions at a faster rate than they make existing ones obsolete.

Moreover, our results suggest that new technologies displace routine jobs, not skilled jobs. This implies that workers *can* still escape the threat of automation by adapting and acquiring new skills. Women are a case in point. Despite the fact that robots seem to be biased against them, women's employment and income shares still rose dramatically overall, indicating that they were able to upgrade their skills and switch toward occupations that were less exposed to robots. Related, it is also important to bear in mind that our empirical strategy can only detect employment losses relative to other industries. So, if spillover effects are strong enough across industries, the aggregate effects of automation can still be positive even if its effects are negative at the industry level (Autor and Salomons, 2017).

Finally, judging by the current pace of technological progress and that of the recent past, we believe that changes in the future are likely to be fast. Hence, it is essential to implement policies that can help workers to cope with the continuously and rapidly changing labor market. Reflecting on the recent developments in the manufacturing sector, we speculate that promoting employment in industries and occupations that are declining is likely to fail. Instead, useful policy insights could be drawn from our evidence showing that women have been able to adapt to the changing environment, likely by acquiring the skills that allow them to change the types of tasks that they perform. By studying this process thoroughly, we may be able to design and implement policies that can guide other groups as well through a faster and smoother transition, and thus avoid an employment "race" against machines.

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Appendices

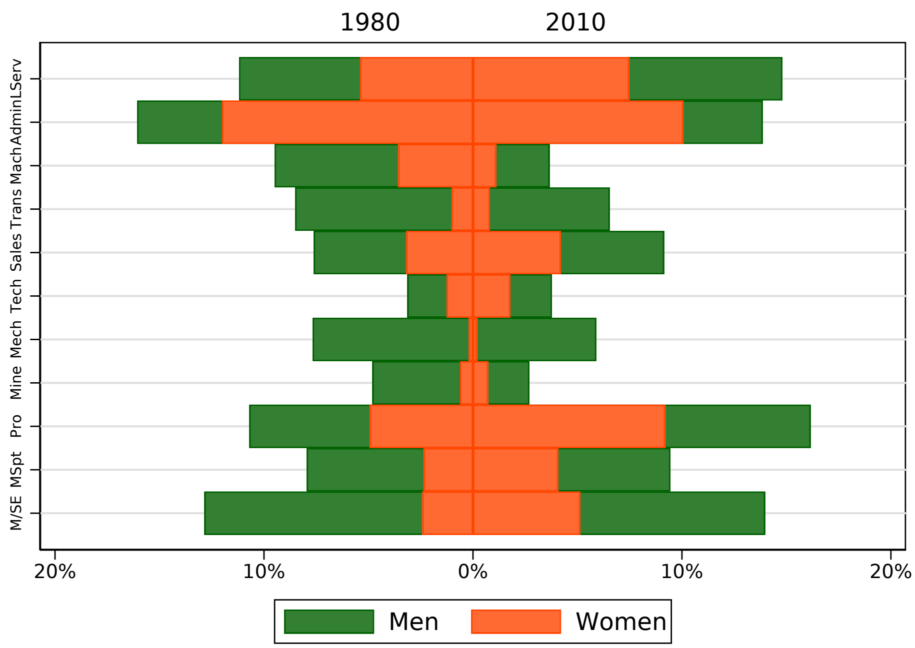
A Additional Figures and Tables

Figure A1: Change in Employment Shares by Gender from 1980 to 2010

Notes: Change in within-gender employment shares between 1980 and 2010 in the U.S., across 11 1-digit occupations: Managers+Self-employed (M/SE), Managerial Support (MSpt), Professionals (Pro), Mining Occupations (Mine), Mechanics (Mech), Technicians (Tech), Sales, Transportation (Trans), Machine Operators (Mach), Administrative Occupations (Admin), and Low-skill Services (LServ). Occupations are ordered in descending order of their occupation mean wages from left to right, not differentiating by gender. For more details see Lee and Shin (2017).

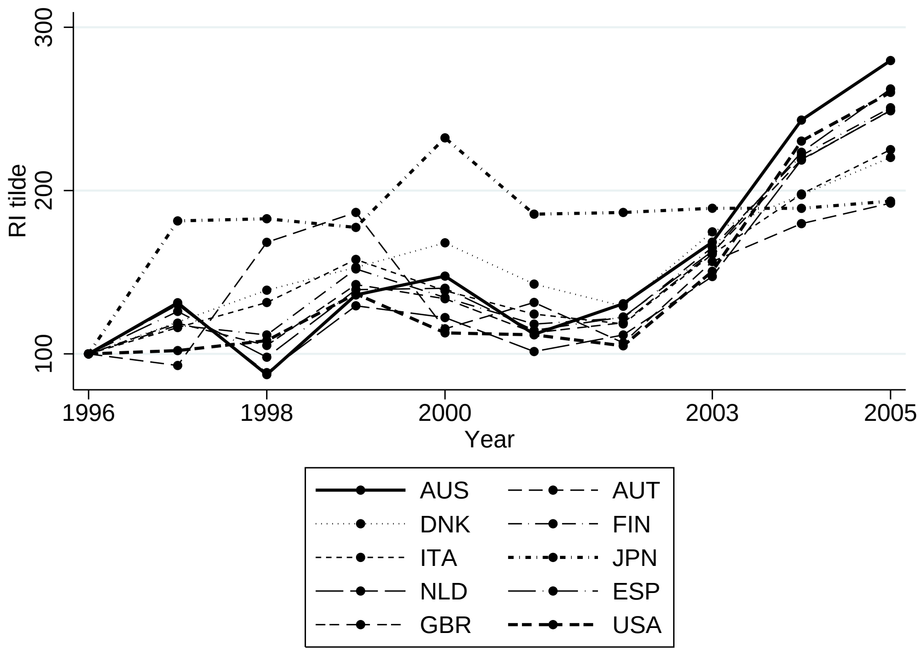
Source: U.S. IPUMS Census.

Figure A2: Employment Shares by Gender and Occupation, 1980 and 2010



Notes: 1980 and 2010 employment shares across 11 1-digit occupations: Managers+Self-employed (M/SE), Managerial Support (MSpt), Professionals (Pro), Mining Occupations (Mine), Mechanics (Mech), Technicians (Tech), Sales, Transportation (Trans), Machine Operators (Mach), Administrative Occupations (Admin), and Low-skill Services (LServ). Occupations are ordered in descending order of their occupation mean wages from bottom to top, not differentiating by gender. For more details see Lee and Shin (2017).
Source: U.S. IPUMS Census.

Figure A3: Exposure to robots by country



Notes: Normalized values of $\widetilde{RI}_{ct}$, measuring country c's exposure to robots, by year. AUS: Australia, AUT: Austria, DNK: Denmark, FIN: Finland, ITA: Italy, JPN: Japan, NLD: Netherlands, ESP: Spain, GBR: United Kingdom, USA: United States of America.

Source: Author's calculations based on UN COMTRADE.

Table A1: Capital inputs by country

Country	1982 mean			2005 mean		
	K	ICT	S/W	K	ICT	S/W
Australia	2.656	0.044	0.003	1.978	0.374	0.066
Austria	3.256	0.037	0.002	2.861	0.165	0.023
Denmark	2.490	0.008	0.006	2.272	0.328	0.076
Finland	2.317	0.008	0.015	2.341	0.145	0.042
Italy	3.128	0.039	0.004	3.180	0.158	0.022
Japan	2.104	0.019	0.008	3.282	0.086	0.037
Netherlands	2.798	0.032	0.005	2.427	0.238	0.048
Spain	1.892	0.040	0.003	2.337	0.157	0.025
United Kingdom	1.551	0.008	0.022	1.619	0.221	0.052
United States	1.713	0.029	0.006	1.504	0.203	0.068
Unweighted mean	2.390	0.027	0.008	2.380	0.207	0.046

Notes: K: ratio of non-ICT capital stock to real gross value-added; ICT: ratio of real ICT capital stock net of software capital stock to real gross value-added; S/W: ratio of real software capital stock to real gross value-added. The ratios are averaged across industries within each country using as weights each industry's employment share in country-wide employment in 1982.
Source: Authors' calculations based on EU KLEMS.

Table A2: Capital inputs by industry

NACE Rev. 1.1	1982 mean			2005 mean		
	K	ICT	S/W	K	ICT	S/W
15T16	1.708	0.012	0.005	1.867	0.156	0.039
17T19	1.333	0.007	0.002	2.116	0.143	0.039
20	1.711	0.017	0.006	1.819	0.103	0.024
21T22	1.352	0.014	0.006	1.465	0.282	0.057
23	8.057	0.038	0.027	17.439	1.656	0.405
24	2.912	0.025	0.010	1.919	0.123	0.046
25	1.690	0.010	0.006	1.674	0.100	0.033
26	1.768	0.013	0.006	1.655	0.156	0.034
27T28	2.182	0.015	0.006	1.738	0.104	0.031
29	1.202	0.010	0.009	1.143	0.163	0.055
30T33	1.789	0.046	0.025	1.078	0.196	0.070
34T35	1.713	0.015	0.009	1.884	0.136	0.063
36T37	1.177	0.011	0.003	1.364	0.151	0.038
50	1.163	0.013	0.006	1.169	0.167	0.046
51	1.198	0.017	0.011	0.928	0.225	0.045
52	1.194	0.014	0.009	1.229	0.209	0.037
60T63	4.577	0.105	0.007	4.130	0.376	0.062
64	3.054	0.544	0.016	1.658	0.825	0.102
70	17.068	0.002	0.002	18.084	0.058	0.010
71T74	3.385	0.018	0.022	2.607	0.469	0.100
ATB	5.312	0.012	0.001	4.637	0.046	0.011
C	4.938	0.019	0.004	4.697	0.148	0.029
E	7.568	0.046	0.006	6.312	0.224	0.055
F	0.662	0.005	0.002	0.703	0.079	0.022
H	1.230	0.008	0.002	1.797	0.124	0.017
J	1.192	0.019	0.025	0.652	0.353	0.160
L	3.855	0.016	0.012	4.551	0.311	0.068
M	1.790	0.005	0.005	1.924	0.192	0.041
N	0.992	0.006	0.004	1.196	0.138	0.025
O	1.688	0.036	0.007	2.269	0.368	0.052

Notes: K: ratio of non-ICT capital stock to real gross value-added; ICT: ratio of real ICT capital stock net of software capital stock to real gross value-added; S/W: ratio of real software capital stock to real gross value-added. The ratios are averaged across countries within each industry. No country weights are used. *Source*: Authors' calculations based on EU KLEMS.

Table A3: Employment share by skill

Panel A: Averaged by country

Country	1982 mean			2005 mean		
	HS	MS	LS	HS	MS	LS
Australia	0.060	0.383	0.556	0.168	0.394	0.438
Austria	0.055	0.569	0.376	0.105	0.676	0.219
Denmark	0.034	0.470	0.498	0.074	0.633	0.294
Finland	0.187	0.340	0.473	0.320	0.471	0.209
Italy	0.050	0.883	0.067	0.085	0.897	0.018
Japan	0.140	0.529	0.331	0.252	0.659	0.089
Netherlands	0.047	0.785	0.168	0.112	0.831	0.057
Spain	0.088	0.088	0.825	0.185	0.309	0.505
United Kingdom	0.060	0.558	0.382	0.166	0.711	0.123
United States	0.223	0.607	0.170	0.301	0.598	0.101
Unweighted mean	0.094	0.521	0.385	0.177	0.618	0.205

Panel B: Averaged by industry

NACE Rev. 1.1	1982 mean			2005 mean		
	HS	MS	LS	HS	MS	LS
15T16	0.041	0.483	0.476	0.098	0.635	0.267
17T19	0.028	0.462	0.510	0.086	0.634	0.280
20	0.048	0.484	0.472	0.116	0.645	0.248
21T22	0.070	0.528	0.402	0.149	0.647	0.204
23	0.089	0.547	0.369	0.162	0.644	0.193
24	0.091	0.517	0.392	0.202	0.607	0.191
25	0.059	0.508	0.438	0.125	0.648	0.227
26	0.051	0.491	0.458	0.120	0.643	0.238
27T28	0.051	0.513	0.435	0.118	0.658	0.225
29	0.062	0.566	0.371	0.148	0.672	0.180
30T33	0.078	0.560	0.362	0.187	0.645	0.168
34T35	0.075	0.557	0.375	0.154	0.660	0.186
36T37	0.049	0.488	0.463	0.116	0.636	0.248
50	0.048	0.564	0.393	0.090	0.678	0.231
51	0.078	0.542	0.380	0.142	0.649	0.209
52	0.057	0.549	0.394	0.109	0.655	0.236
60T63	0.044	0.521	0.436	0.088	0.665	0.247
64	0.056	0.571	0.374	0.176	0.632	0.193
70	0.171	0.523	0.306	0.288	0.562	0.150
71T74	0.208	0.508	0.284	0.350	0.505	0.144
ATB	0.037	0.399	0.564	0.089	0.574	0.337
C	0.072	0.514	0.419	0.138	0.646	0.216
E	0.085	0.591	0.324	0.179	0.680	0.141
F	0.051	0.530	0.419	0.078	0.683	0.240
H	0.040	0.512	0.447	0.090	0.646	0.265
J	0.149	0.628	0.224	0.333	0.573	0.093
L	0.146	0.582	0.272	0.297	0.605	0.099
M	0.384	0.432	0.185	0.530	0.402	0.068
N	0.176	0.566	0.258	0.292	0.606	0.101
O	0.110	0.530	0.359	0.213	0.613	0.174

Notes: HS: tertiary degree or above; MS: upper-secondary degree or equivalent; LS: the rest. In Panel A, employment shares are averaged across industries within each country using as weights each industry's employment share in country-wide employment in 1982. In Panel B, employment shares are averaged across countries within each industry. No country weights are used.
Source: Authors' calculations based on EU KLEMS.

Table A4: Income share by skill

Panel A: Averaged by country

Country	1982 mean			2005 mean		
	HS	MS	LS	HS	MS	LS
Australia	0.075	0.346	0.383	0.175	0.272	0.243
Austria	0.068	0.459	0.235	0.113	0.490	0.128
Denmark	0.050	0.416	0.310	0.084	0.548	0.175
Finland	0.224	0.243	0.339	0.325	0.317	0.125
Italy	0.041	0.742	0.061	0.076	0.684	0.003
Japan	0.138	0.367	0.215	0.206	0.402	0.055
Netherlands	0.067	0.647	0.115	0.127	0.609	0.030
Spain	0.100	0.078	0.540	0.182	0.201	0.260
United Kingdom	0.086	0.444	0.267	0.211	0.527	0.068
United States	0.225	0.419	0.103	0.296	0.344	0.042
Unweighted mean	0.107	0.416	0.257	0.179	0.439	0.113

Panel B: Averaged by industry

NACE Rev. 1.1	1982 mean			2005 mean		
	HS	MS	LS	HS	MS	LS
15T16	0.040	0.317	0.264	0.094	0.392	0.134
17T19	0.045	0.402	0.357	0.130	0.540	0.190
20	0.059	0.389	0.320	0.127	0.461	0.146
21T22	0.074	0.413	0.253	0.131	0.420	0.099
23	0.041	0.222	0.139	0.102	0.402	0.077
24	0.077	0.330	0.213	0.130	0.292	0.080
25	0.070	0.420	0.300	0.131	0.445	0.122
26	0.054	0.349	0.287	0.113	0.401	0.121
27T28	0.056	0.397	0.271	0.117	0.440	0.119
29	0.070	0.464	0.250	0.160	0.486	0.112
30T33	0.092	0.455	0.245	0.180	0.460	0.090
34T35	0.090	0.476	0.279	0.155	0.462	0.104
36T37	0.066	0.422	0.334	0.136	0.485	0.150
50	0.058	0.495	0.268	0.101	0.517	0.132
51	0.076	0.389	0.218	0.124	0.400	0.101
52	0.076	0.512	0.311	0.129	0.550	0.143
60T63	0.045	0.439	0.307	0.077	0.444	0.128
64	0.045	0.376	0.197	0.096	0.253	0.064
70	0.026	0.048	0.020	0.039	0.043	0.009
71T74	0.227	0.395	0.170	0.386	0.351	0.076
ATB	0.042	0.300	0.352	0.095	0.460	0.189
C	0.047	0.138	0.161	0.069	0.155	0.057
E	0.042	0.242	0.107	0.059	0.170	0.029
F	0.062	0.454	0.319	0.091	0.540	0.145
H	0.054	0.454	0.338	0.110	0.503	0.154
J	0.135	0.381	0.111	0.216	0.270	0.037
L	0.169	0.470	0.184	0.299	0.440	0.057
M	0.428	0.350	0.111	0.542	0.299	0.039
N	0.215	0.458	0.170	0.341	0.449	0.062
O	0.146	0.453	0.209	0.235	0.438	0.096

Notes: HS: tertiary degree or above; MS: upper-secondary degree or equivalent; LS: the rest. In Panel A, income shares are averaged across industries within each country using as weights each industry's employment share in country-wide employment in 1982. In Panel B, income shares are averaged across countries within each industry. No country weights are used.
Source: Authors' calculations based on EU KLEMS.

Table A5: Employment share by age

Panel A: Averaged by country

Country	1982 mean			2005 mean		
	Y	P	O	Y	P	O
Australia	0.394	0.409	0.197	0.278	0.462	0.260
Austria	0.331	0.466	0.203	0.218	0.573	0.209
Denmark	0.289	0.467	0.241	0.239	0.479	0.283
Finland	0.351	0.490	0.158	0.214	0.496	0.290
Italy	0.265	0.614	0.121	0.251	0.635	0.115
Japan	0.292	0.498	0.210	0.218	0.476	0.306
Netherlands	0.353	0.476	0.171	0.221	0.544	0.235
Spain	0.267	0.442	0.291	0.242	0.539	0.218
United Kingdom	0.359	0.464	0.178	0.255	0.495	0.250
United States	0.462	0.395	0.142	0.327	0.512	0.162
Unweighted mean	0.336	0.472	0.191	0.246	0.521	0.233

Panel B: Averaged by industry

NACE Rev. 1.1	1982 mean			2005 mean		
	Y	P	O	Y	P	O
15T16	0.350	0.464	0.186	0.247	0.533	0.220
17T19	0.376	0.444	0.180	0.227	0.535	0.238
20	0.316	0.475	0.207	0.228	0.526	0.244
21T22	0.332	0.483	0.185	0.237	0.537	0.227
23	0.318	0.501	0.181	0.194	0.584	0.222
24	0.310	0.506	0.184	0.218	0.566	0.216
25	0.323	0.497	0.177	0.242	0.540	0.218
26	0.307	0.496	0.197	0.215	0.550	0.235
27T28	0.325	0.488	0.187	0.229	0.544	0.227
29	0.349	0.487	0.165	0.226	0.557	0.217
30T33	0.355	0.490	0.154	0.239	0.565	0.196
34T35	0.325	0.513	0.159	0.220	0.564	0.216
36T37	0.360	0.462	0.178	0.245	0.533	0.222
50	0.400	0.450	0.149	0.319	0.493	0.187
51	0.367	0.462	0.171	0.302	0.503	0.195
52	0.378	0.446	0.176	0.351	0.462	0.187
60T63	0.286	0.517	0.197	0.210	0.553	0.237
64	0.308	0.505	0.188	0.260	0.550	0.191
70	0.330	0.471	0.199	0.246	0.500	0.254
71T74	0.360	0.479	0.161	0.273	0.528	0.199
ATB	0.251	0.431	0.318	0.195	0.456	0.349
C	0.276	0.520	0.200	0.177	0.562	0.261
E	0.256	0.523	0.221	0.175	0.567	0.258
F	0.324	0.492	0.184	0.276	0.513	0.212
H	0.403	0.432	0.164	0.374	0.453	0.174
J	0.396	0.467	0.137	0.227	0.575	0.199
L	0.322	0.481	0.197	0.187	0.568	0.245
M	0.251	0.554	0.195	0.148	0.579	0.273
N	0.384	0.468	0.148	0.203	0.564	0.233
O	0.353	0.454	0.193	0.281	0.494	0.225

Notes: Y: 15–29 years old; P: 30–49 years old; O: 50+ years old. In Panel A, employment shares are averaged across industries within each country using as weights each industry's employment share in country-wide employment in 1982. In Panel B, employment shares are averaged across countries within each industry. No country weights are used.
Source: Authors' calculations based on EU KLEMS.

Table A6: Income share by age

Panel A: Averaged by country

Country	1982 mean			2005 mean		
	Y	P	O	Y	P	O
Australia	0.249	0.374	0.180	0.146	0.354	0.191
Austria	0.218	0.371	0.173	0.128	0.423	0.180
Denmark	0.198	0.410	0.160	0.138	0.443	0.226
Finland	0.206	0.454	0.146	0.105	0.414	0.247
Italy	0.243	0.533	0.068	0.185	0.538	0.040
Japan	0.153	0.410	0.158	0.105	0.334	0.224
Netherlands	0.220	0.442	0.168	0.122	0.435	0.209
Spain	0.167	0.347	0.204	0.113	0.361	0.169
United Kingdom	0.261	0.407	0.128	0.147	0.452	0.207
United States	0.291	0.332	0.124	0.167	0.381	0.134
Unweighted mean	0.221	0.408	0.151	0.136	0.413	0.183

Panel B: Averaged by industry

NACE Rev. 1.1	1982 mean			2005 mean		
	Y	P	O	Y	P	O
15T16	0.179	0.319	0.123	0.115	0.363	0.142
17T19	0.254	0.395	0.150	0.145	0.485	0.230
20	0.213	0.393	0.157	0.129	0.408	0.186
21T22	0.199	0.397	0.144	0.111	0.379	0.161
23	0.128	0.223	0.082	0.071	0.366	0.143
24	0.162	0.339	0.119	0.079	0.304	0.119
25	0.218	0.422	0.145	0.125	0.402	0.170
26	0.182	0.369	0.139	0.101	0.373	0.162
27T28	0.208	0.381	0.135	0.116	0.393	0.166
29	0.223	0.422	0.139	0.126	0.450	0.182
30T33	0.224	0.434	0.134	0.128	0.443	0.159
34T35	0.220	0.471	0.141	0.113	0.438	0.169
36T37	0.245	0.418	0.153	0.149	0.442	0.180
50	0.286	0.399	0.127	0.173	0.418	0.159
51	0.199	0.363	0.122	0.134	0.356	0.135
52	0.299	0.448	0.151	0.224	0.433	0.164
60T63	0.187	0.438	0.166	0.102	0.387	0.160
64	0.144	0.332	0.116	0.071	0.257	0.085
70	0.026	0.051	0.017	0.016	0.051	0.025
71T74	0.230	0.432	0.131	0.162	0.475	0.177
ATB	0.161	0.337	0.196	0.124	0.390	0.230
C	0.076	0.195	0.076	0.032	0.163	0.087
E	0.079	0.226	0.085	0.031	0.156	0.072
F	0.229	0.447	0.160	0.163	0.427	0.186
H	0.294	0.411	0.142	0.221	0.401	0.144
J	0.183	0.345	0.099	0.078	0.333	0.111
L	0.216	0.434	0.173	0.115	0.464	0.218
M	0.176	0.525	0.188	0.091	0.512	0.277
N	0.272	0.434	0.137	0.126	0.499	0.227
O	0.219	0.417	0.172	0.154	0.418	0.197

Notes: Y: 15–29 years old; P: 30–49 years old; O: 50+ years old. In Panel A, income shares are averaged across industries within each country using as weights each industry's employment share in country-wide employment in 1982. In Panel B, income shares are averaged across countries within each industry. No country weights are used.
Source: Authors' calculations based on EU KLEMS.

Table A7: Employment share by gender

Panel A: Averaged by country

Country	1982 mean		2005 mean	
	M	F	M	F
Australia	0.671	0.329	0.608	0.392
Austria	0.598	0.402	0.613	0.387
Denmark	0.571	0.444	0.564	0.437
Finland	0.564	0.436	0.575	0.425
Italy	0.688	0.312	0.615	0.385
Japan	0.689	0.311	0.675	0.325
Netherlands	0.752	0.248	0.674	0.326
Spain	0.739	0.261	0.651	0.349
United Kingdom	0.597	0.403	0.600	0.400
United States	0.637	0.363	0.608	0.392
Unweighted mean	0.651	0.351	0.618	0.382

Panel B: Averaged by industry

NACE Rev. 1.1	1982 mean		2005 mean	
	M	F	M	F
15T16	0.634	0.366	0.643	0.357
17T19	0.484	0.516	0.541	0.459
20	0.799	0.206	0.793	0.208
21T22	0.756	0.244	0.726	0.274
23	0.821	0.186	0.794	0.206
24	0.765	0.235	0.724	0.276
25	0.751	0.240	0.725	0.275
26	0.785	0.215	0.778	0.222
27T28	0.802	0.198	0.789	0.211
29	0.819	0.181	0.805	0.195
30T33	0.734	0.266	0.739	0.261
34T35	0.833	0.176	0.813	0.187
36T37	0.707	0.293	0.728	0.272
50	0.692	0.325	0.650	0.350
51	0.624	0.376	0.604	0.396
52	0.556	0.444	0.521	0.479
60T63	0.847	0.153	0.783	0.217
64	0.704	0.296	0.670	0.330
70	0.610	0.390	0.573	0.427
71T74	0.613	0.387	0.600	0.400
ATB	0.741	0.259	0.708	0.292
C	0.873	0.126	0.835	0.165
E	0.861	0.139	0.795	0.205
F	0.924	0.076	0.912	0.088
H	0.527	0.473	0.515	0.485
J	0.530	0.470	0.507	0.493
L	0.702	0.298	0.572	0.428
M	0.454	0.546	0.369	0.631
N	0.307	0.693	0.256	0.744
O	0.483	0.517	0.485	0.515

Notes: M: male; F: female. In Panel A, employment shares are averaged across industries within each country using as weights each industry's employment share in country-wide employment in 1982. In Panel B, employment shares are averaged across countries within each industry. No country weights are used.
Source: Authors' calculations based on EU KLEMS.

Table A8: Income share by gender

Panel A: Averaged by country

Country	1982 mean		2005 mean	
	M	F	M	F
Australia	0.619	0.184	0.458	0.232
Austria	0.463	0.299	0.442	0.289
Denmark	0.484	0.301	0.477	0.331
Finland	0.510	0.296	0.476	0.290
Italy	0.569	0.275	0.416	0.347
Japan	0.566	0.154	0.499	0.164
Netherlands	0.665	0.164	0.544	0.223
Spain	0.568	0.151	0.448	0.194
United Kingdom	0.606	0.190	0.557	0.249
United States	0.528	0.218	0.459	0.223
Unweighted mean	0.558	0.223	0.478	0.254

Panel B: Averaged by industry

NACE Rev. 1.1	1982 mean		2005 mean	
	M	F	M	F
15T16	0.445	0.176	0.438	0.183
17T19	0.466	0.321	0.526	0.334
20	0.645	0.122	0.595	0.129
21T22	0.607	0.133	0.495	0.156
23	0.347	0.057	0.473	0.106
24	0.510	0.110	0.380	0.122
25	0.644	0.135	0.537	0.161
26	0.583	0.107	0.515	0.121
27T28	0.620	0.105	0.553	0.123
29	0.680	0.104	0.635	0.122
30T33	0.639	0.153	0.575	0.154
34T35	0.740	0.104	0.611	0.110
36T37	0.631	0.190	0.593	0.178
50	0.633	0.194	0.536	0.214
51	0.491	0.192	0.419	0.205
52	0.585	0.314	0.476	0.345
60T63	0.701	0.089	0.527	0.123
64	0.464	0.143	0.295	0.119
70	0.066	0.028	0.060	0.031
71T74	0.556	0.237	0.552	0.262
ATB	0.546	0.148	0.533	0.211
C	0.312	0.032	0.246	0.035
E	0.352	0.039	0.215	0.044
F	0.788	0.048	0.719	0.058
H	0.524	0.323	0.443	0.324
J	0.402	0.225	0.315	0.207
L	0.627	0.195	0.490	0.307
M	0.475	0.414	0.360	0.520
N	0.323	0.519	0.270	0.582
O	0.489	0.320	0.440	0.328

Notes: M: male; F: female. In Panel A, income shares are averaged across industries within each country using as weights each industry's employment share in country-wide employment in 1982. In Panel B, income shares are averaged across countries within each industry. No country weights are used. *Source*: Authors' calculations based on EU KLEMS.

Table A9: Employment shares by skill-age and skill-gender, 1982 and 2005

	HS			MS			LS		
by Age	Y	P	O	Y	P	O	Y	P	O
1982	0.257	0.572	0.171	0.393	0.468	0.140	0.260	0.466	0.274
2005	0.202	0.596	0.202	0.265	0.530	0.204	0.228	0.413	0.359

	HS		MS		LS	
by Gender	M	F	M	F	M	F
1982	0.733	0.267	0.651	0.349	0.626	0.374
2005	0.588	0.412	0.587	0.413	0.615	0.385

Notes: HS: tertiary degree or above; MS: upper-secondary degree or equivalent; LS: the rest. Y: 15–29 years old; P: 30–49 years old; O: 50+ years old. M: male; F: female. The figures represent country-wide employment shares averaged across countries in 1982 and 2005. No country weights are used.
Source: Authors' calculations based on EU KLEMS.

Table A10: U.S. employment shares

	HS	MS	LS	M	W	Y	P	O
1980	0.215	0.585	0.200	0.630	0.370	0.323	0.451	0.226
2010	0.075	0.581	0.344	0.552	0.448	0.198	0.497	0.305
1980	-0.072	0.085	-0.172	-0.176	0.299	0.093	-0.049	-0.036
2010	-0.080	-0.036	-0.169	-0.209	0.068	-0.003	-0.112	-0.094

Notes: HS: tertiary degree or above; MS: upper-secondary degree or equivalent; LS: the rest. Y: age 16–29, P: age 30–49, O: age 50–65. M: Male, F: Female. Employment shares are computed within each year by education, age or gender.
Source: U.S. IPUMS Census.

Table A11: Countries and industries, 2008–2015

Panel A: Countries			
No.	Country Name	No.	Country Name
1	Austria	5	Netherlands
2	Denmark	6	Spain
3	Finland	7	United Kingdom
4	Italy		

Panel B: Industries			
NACE Rev. 2	Industry Name	NACE Rev. 2	Industry Name
A	Agriculture, Forestry and Fishing	J	Information and Communication
B	Mining and Quarrying	K	Financial Intermediation
C	Manufacturing	L	Real Estate
F	Construction	O	Public Administration and Defense; Compulsory Social Security
G	Wholesale and Retail trade	P	Education
H	Transport and Storage	Q	Health and Social Work
I	Hotels and Catering		

Source: EU KLEMS.

Table A12: Capital inputs by country and by industry, 2008–2015

Panel A: Averaged by country

Country	2008 mean K	2008 mean ICT	2008 mean S/W	2015 mean K	2015 mean ICT	2015 mean S/W
Austria	2.893	0.059	0.040	3.066	0.061	0.051
Denmark	2.066	0.035	0.040	1.903	0.049	0.042
Finland	1.743	0.019	0.025	1.838	0.027	0.030
Italy	2.160	0.026	0.035	2.240	0.025	0.036
Netherlands	2.075	0.019	0.052	2.039	0.025	0.064
Spain	2.176	0.046	0.028	2.626	0.060	0.030
United Kingdom	1.801	0.020	0.049	1.845	0.024	0.050
Unweighted mean	2.131	0.032	0.038	2.219	0.041	0.044

Panel B: Averaged by Industry

NACE Rev. 1.1	2008 mean K	2008 mean ICT	2008 mean S/W	2015 mean K	2015 mean ICT	2015 mean S/W
A	5.784	0.022	0.012	4.969	0.031	0.012
B	2.139	0.017	0.013	3.331	0.041	0.024
C	1.474	0.025	0.041	1.409	0.036	0.050
F	1.673	0.008	0.013	2.343	0.018	0.019
G	0.929	0.025	0.041	0.901	0.030	0.051
H	3.396	0.050	0.038	3.588	0.077	0.048
I	1.285	0.025	0.013	1.213	0.025	0.015
J	1.041	0.269	0.197	0.806	0.248	0.177
K	0.826	0.033	0.109	0.932	0.038	0.151
L	17.777	0.007	0.006	17.939	0.010	0.012
O	4.541	0.035	0.069	4.648	0.045	0.067
P	1.181	0.016	0.018	1.333	0.024	0.021
Q	1.097	0.029	0.014	1.211	0.046	0.017

Notes: K: ratio of non-ICT capital stock to real gross value-added; ICT: ratio of real ICT capital stock net of software capital stock to real gross value-added; S/W: ratio of real software capital stock to real gross value-added. In Panel A, the ratios are averaged across industries within each country using as weights each industry's employment share in country-wide employment in 2008. In Panel B, wage bill shares are averaged across countries within each industry. No country weights are used.
Source: Authors' calculations based on EU KLEMS.

Table A13: **Employment and income shares, 2008–2015**

	2008 mean			2015 mean		
by Educ	HS	MS	LS	HS	MS	LS
Employment share	0.247	0.452	0.301	0.309	0.440	0.251
Income share	0.233	0.318	0.181	0.263	0.329	0.141
by Age	Y	P	O	Y	P	O
Employment share	0.228	0.517	0.255	0.199	0.493	0.308
Income share	0.122	0.400	0.211	0.113	0.381	0.239
by Gender	M		F	M		F
Employment share	0.576		0.424	0.582		0.418
Income share	0.438		0.295	0.44		0.294

Notes: HS: tertiary degree or above; MS:upper-secondary degree or equivalent; LS: the rest. Y: 15–29 years old, P: 30–49 years old, O: 50+ years old. M: Male, F: Female. We first average the employment and income shares across industries within each country using as weights each industry's employment share in country-wide employment in 2008. We then average across countries by year using equal weights for each country.
Source: Authors' calculations based on EU KLEMS.

B Additional empirical results

Table B1: Industrial capital and labor demand, 1982–2005

Dep. var: $\ln E$	(1) HS	(2) MS	(3) LS	(4) Y	(5) P	(6) O	(7) M	(8) F
$\ln Y_t$	0.45***	0.34***	0.42***	0.54***	0.42***	0.43***	0.44***	0.44***
	[0.07]	[0.07]	[0.09]	[0.10]	[0.07]	[0.08]	[0.07]	[0.09]
K_{t-1} (total)	0.011	0.0080	0.019**	0.020**	0.021**	0.023	0.016	0.035***
	[0.009]	[0.007]	[0.008]	[0.010]	[0.010]	[0.01]	[0.01]	[0.01]
Obs	7129	7200	7199	7189	7192	7133	7200	7129
R^2	0.991	0.994	0.989	0.988	0.992	0.988	0.992	0.990

Notes: Ordinary Least Squares (OLS) with clustered standard errors by country-industry pairs. Country-industry and country-year fixed effects included. All equations are weighted by the share of each industry's employment in country-wide employment in 1982. For a description of the variables, see Appendix Table B9. Asterisks denote significance at 1% (***), 5% (**), and 10% (*).

Table B2: Robots and labor demand, OLS, no controls

Panel A: Employment by skill, by age, and by gender

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. var: $\ln E$	HS	MS	LS	Y	P	O	M	F
RSH$\times\widetilde{RI}_{t-1}$	-0.074	-0.044	-0.11**	-0.097	-0.025	0.022	-0.00094	-0.084
	[0.07]	[0.04]	[0.05]	[0.06]	[0.04]	[0.06]	[0.04]	[0.05]
Obs	2989	3000	2999	2998	3000	2989	3000	2989
R^2	0.997	0.998	0.997	0.997	0.998	0.997	0.998	0.998

Panel B: Income share by skill, by age, and by gender

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. var: Lsh	HS	MS	LS	Y	P	O	M	F
RSH$\times\widetilde{RI}_{t-1}$	0.013**	0.019	-0.0062	-0.0046	0.014	0.016*	0.033**	-0.0072
	[0.007]	[0.01]	[0.008]	[0.005]	[0.01]	[0.009]	[0.01]	[0.006]
Obs	2989	3000	2999	2998	3000	2989	3000	2989
R^2	0.991	0.981	0.988	0.973	0.954	0.972	0.972	0.995

Notes: Ordinary Least Squares (OLS) with clustered standard errors by country-industry pairs in both panels. Country-industry and country-year fixed effects included. All equations are weighted by the share of each industry's employment in country-wide employment in 1996. For a description of the variables, see Appendix Table B9. Asterisks denote significance at 1% (***), 5% (**), and 10% (*).

Table B3: Capital inputs, robots and labor demand, 2SLS

Panel A: Employment by skill, by age, and by gender

Dep. var: $\ln E$	(1) HS	(2) MS	(3) LS	(4) Y	(5) P	(6) O	(7) M	(8) F
$\ln Y_t$	0.37***	0.34***	0.41***	0.46***	0.43***	0.42***	0.44***	0.42***
	[0.07]	[0.07]	[0.08]	[0.09]	[0.07]	[0.07]	[0.07]	[0.08]
K_{t-1}	0.0034	-0.00065	-0.0037	-0.0022	-0.00070	0.00093	0.00070	0.00070
	[0.004]	[0.002]	[0.004]	[0.004]	[0.003]	[0.003]	[0.003]	[0.002]
ICT_{t-1}	0.013	0.15**	0.29***	0.24***	0.16**	0.15*	0.16***	0.18***
	[0.1]	[0.06]	[0.08]	[0.08]	[0.06]	[0.08]	[0.06]	[0.06]
S/W_{t-1}	0.44	-0.48*	-0.54	-0.14	-0.0023	0.097	0.011	-0.023
	[0.3]	[0.3]	[0.4]	[0.4]	[0.3]	[0.3]	[0.2]	[0.2]
$RSH \times RI_t$	-0.084	-0.037	-0.12**	-0.096	-0.028	0.040	0.014	-0.092*
	[0.07]	[0.05]	[0.05]	[0.06]	[0.04]	[0.06]	[0.04]	[0.05]
Obs	2961	2970	2969	2968	2970	2961	2970	2961
R^2	0.041	0.130	0.051	0.113	0.227	0.161	0.236	0.088
Kleibergen-Paap rk LM	88.76	88.75	88.75	88.75	88.75	88.76	88.75	88.76
Kleibergen-Paap rk LM (p-value)	5.33e-20	5.34e-20	5.35e-20	5.35e-20	5.34e-20	5.33e-20	5.34e-20	5.33e-20
Kleibergen-Paap Wald rk F	87.34	87.35	87.35	87.34	87.35	87.34	87.35	87.34
Hansen J	0.211	1.424	1.366	2.014	1.018	0.540	0.765	0.549
Hansen J (p-value)	0.646	0.233	0.242	0.156	0.313	0.462	0.382	0.459
Instruments for $RSH \times RI$	First- and second-lags of $RSH \times \widetilde{RI}$							
$\ln Y$, K, ICT, S/W	Treated as exogenous							

Panel B: Income share by skill, by age, and by gender

Dep. var: Lsh	(1) HS	(2) MS	(3) LS	(4) Y	(5) P	(6) O	(7) M	(8) F
$\ln Y_t$	-0.015	-0.11***	-0.0065	-0.015***	-0.069***	-0.051***	-0.088***	-0.048***
	[0.01]	[0.02]	[0.006]	[0.006]	[0.01]	[0.01]	[0.02]	[0.009]
K_{t-1}	0.00056	0.00017	-0.00012	0.00052**	0.00027	-0.00030	0.00087	-0.00035
	[0.0007]	[0.0007]	[0.0003]	[0.0003]	[0.0005]	[0.0004]	[0.0006]	[0.0002]
ICT_{t-1}	0.0055	0.031	0.018**	0.011*	0.023	0.017	0.038*	0.014
	[0.01]	[0.02]	[0.009]	[0.006]	[0.02]	[0.01]	[0.02]	[0.009]
S/W_{t-1}	0.18***	-0.058	0.051	0.039	0.15	-0.025	0.15*	0.016
	[0.05]	[0.09]	[0.04]	[0.03]	[0.09]	[0.05]	[0.08]	[0.04]
$RSH \times RI_t$	0.014**	0.027**	-0.0066	-0.0025	0.016	0.021**	0.044***	-0.0098
	[0.007]	[0.01]	[0.009]	[0.006]	[0.01]	[0.010]	[0.01]	[0.007]
Obs	2961	2970	2969	2968	2970	2961	2970	2961
R^2	-0.033	0.022	0.003	0.024	0.020	-0.095	-0.145	0.042
Kleibergen-Paap rk LM	88.76	88.75	88.75	88.75	88.75	88.76	88.75	88.76
Kleibergen-Paap rk LM (p-value)	5.33e-20	5.34e-20	5.35e-20	5.35e-20	5.34e-20	5.33e-20	5.34e-20	5.33e-20
Kleibergen-Paap Wald rk F	87.34	87.35	87.35	87.34	87.35	87.34	87.35	87.34
Hansen J	2.052	2.437	0.490	1.836	0.221	3.111	1.629	0.177
Hansen J (p-value)	0.152	0.118	0.484	0.175	0.638	0.0777	0.202	0.674
Instruments for $RSH \times RI$	First- and second-lags of $RSH \times \widetilde{RI}$							
$\ln Y$, K, ICT, S/W	Treated as exogenous							

Notes: Two-Stage Least Squares (2SLS) with clustered standard errors by country-industry pairs in both panels. Country-industry and country-year fixed effects included. All equations are weighted by the share of each industry's employment in country-wide employment in 1996. For a description of the variables, see Appendix Table B9. Asterisks denote significance at 1% (***), 5% (**), and 10% (*).

Table B4: Capital inputs, robots and labor demand, alternative robot variable, OLS

Panel A: Employment by skill, by age, and by gender

Dep. var: $\ln E$	(1) HS	(2) MS	(3) LS	(4) Y	(5) P	(6) O	(7) M	(8) F
$\ln Y_t$	0.37***	0.34***	0.40***	0.46***	0.43***	0.42***	0.44***	0.42***
	[0.07]	[0.08]	[0.08]	[0.10]	[0.07]	[0.07]	[0.08]	[0.09]
K_{t-1}	0.0036	-0.00066	-0.0036	-0.0021	-0.00054	0.00070	0.00057	0.0010
	[0.004]	[0.003]	[0.004]	[0.004]	[0.003]	[0.003]	[0.003]	[0.002]
ICT_{t-1}	0.028	0.16**	0.31***	0.26***	0.17**	0.15*	0.17**	0.20***
	[0.1]	[0.07]	[0.09]	[0.09]	[0.07]	[0.09]	[0.07]	[0.07]
S/W_{t-1}	0.40	-0.51*	-0.60	-0.21	-0.033	0.100	0.0059	-0.093
	[0.3]	[0.3]	[0.4]	[0.4]	[0.3]	[0.3]	[0.3]	[0.3]
RSH$\times\widetilde{RI}_{t-1}$, alt	-0.064	-0.037	-0.11**	-0.087	-0.020	0.025	0.0055	-0.074
	[0.07]	[0.04]	[0.05]	[0.06]	[0.04]	[0.05]	[0.04]	[0.05]
Obs	2989	3000	2999	2998	3000	2989	3000	2989
R^2	0.997	0.998	0.997	0.997	0.998	0.997	0.998	0.998

Panel B: Income share by skill, by age, and by gender

Dep. var: Lsh	(1) HS	(2) MS	(3) LS	(4) Y	(5) P	(6) O	(7) M	(8) F
$\ln Y_t$	-0.014	-0.11***	-0.0070	-0.015**	-0.068***	-0.050***	-0.085***	-0.048***
	[0.01]	[0.02]	[0.007]	[0.006]	[0.02]	[0.01]	[0.02]	[0.009]
K_{t-1}	0.00055	0.0000036	-0.00014	0.00048*	0.00023	-0.00042	0.00065	-0.00031
	[0.0007]	[0.0008]	[0.0004]	[0.0003]	[0.0005]	[0.0004]	[0.0007]	[0.0002]
ICT_{t-1}	0.0043	0.028	0.019**	0.012*	0.023	0.014	0.033	0.016*
	[0.01]	[0.02]	[0.009]	[0.007]	[0.02]	[0.01]	[0.02]	[0.010]
S/W_{t-1}	0.18***	-0.040	0.049	0.037	0.17	-0.016	0.18*	0.011
	[0.06]	[0.10]	[0.04]	[0.04]	[0.1]	[0.05]	[0.09]	[0.04]
RSH$\times\widetilde{RI}_{t-1}$, alt	0.014**	0.018	-0.0063	-0.0028	0.014	0.014	0.032**	-0.0069
	[0.007]	[0.01]	[0.008]	[0.005]	[0.01]	[0.009]	[0.01]	[0.006]
Obs	2989	3000	2999	2998	3000	2989	3000	2989
R^2	0.991	0.983	0.989	0.973	0.957	0.974	0.974	0.995

Notes: Ordinary Least Squares (OLS) with clustered standard errors by country-industry pairs in both panels. Country-industry and country-year fixed effects included. All equations are weighted by the share of each industry's employment in country-wide employment in 1996. For a description of the variables, see Appendix Table B9. Asterisks denote significance at 1% (***), 5% (**), and 10% (*).

Table B5: Capital inputs, robots and labor demand, alternative robot variable, 2SLS

Panel A: Employment by skill, by age, and by gender

Dep. var: $\ln E$	(1) HS	(2) MS	(3) LS	(4) Y	(5) P	(6) O	(7) M	(8) F
$\ln Y_t$	0.37***	0.34***	0.41***	0.46***	0.43***	0.42***	0.44***	0.42***
	[0.07]	[0.07]	[0.08]	[0.09]	[0.07]	[0.07]	[0.07]	[0.08]
K_{t-1}	0.0035	-0.00069	-0.0038	-0.0021	-0.00074	0.00080	0.00064	0.00072
	[0.004]	[0.002]	[0.004]	[0.004]	[0.003]	[0.003]	[0.003]	[0.002]
ICT_{t-1}	0.014	0.15**	0.29***	0.24***	0.16**	0.15*	0.16***	0.18***
	[0.1]	[0.06]	[0.08]	[0.08]	[0.06]	[0.08]	[0.06]	[0.06]
S/W_{t-1}	0.43	-0.47*	-0.54	-0.15	-0.00022	0.10	0.015	-0.024
	[0.3]	[0.3]	[0.4]	[0.4]	[0.3]	[0.3]	[0.2]	[0.2]
$RSH \times RI_t$	-0.080	-0.039	-0.12**	-0.092	-0.030	0.034	0.010	-0.091*
	[0.07]	[0.05]	[0.05]	[0.06]	[0.04]	[0.06]	[0.04]	[0.05]
Obs	2961	2970	2969	2968	2970	2961	2970	2961
R^2	0.044	0.127	0.046	0.117	0.226	0.164	0.237	0.091
Kleibergen-Paap rk LM	89.73	89.71	89.71	89.71	89.71	89.73	89.71	89.73
Kleibergen-Paap rk LM (p-value)	3.28e-20	3.30e-20	3.30e-20	3.30e-20	3.30e-20	3.28e-20	3.30e-20	3.28e-20
Kleibergen-Paap Wald rk F	106.4	106.4	106.4	106.4	106.4	106.4	106.4	106.4
Hansen J	0.0443	0.899	1.705	1.689	0.688	0.544	0.497	0.0636
Hansen J (p-value)	0.833	0.343	0.192	0.194	0.407	0.461	0.481	0.801
Instruments for $RSH \times RI$	First- and second-lags of $RSH \times \widetilde{RI}, alt$							
$\ln Y$, K, ICT, S/W	Treated as exogenous							

Panel B: Income share by skill, by age, and by gender

Dep. var: Lsh	(1) HS	(2) MS	(3) LS	(4) Y	(5) P	(6) O	(7) M	(8) F
$\ln Y_t$	-0.015	-0.11***	-0.0065	-0.015***	-0.069***	-0.051***	-0.088***	-0.048***
	[0.01]	[0.02]	[0.006]	[0.006]	[0.01]	[0.01]	[0.02]	[0.009]
K_{t-1}	0.00055	0.00013	-0.00011	0.00053**	0.00027	-0.00033	0.00083	-0.00033
	[0.0007]	[0.0007]	[0.0003]	[0.0003]	[0.0005]	[0.0004]	[0.0007]	[0.0002]
ICT_{t-1}	0.0054	0.030	0.018**	0.011*	0.023	0.017	0.037*	0.015*
	[0.01]	[0.02]	[0.009]	[0.006]	[0.02]	[0.01]	[0.02]	[0.009]
S/W_{t-1}	0.18***	-0.056	0.051	0.038	0.15	-0.023	0.15*	0.015
	[0.05]	[0.09]	[0.04]	[0.03]	[0.09]	[0.05]	[0.08]	[0.04]
$RSH \times RI_t$	0.014*	0.025*	-0.0059	-0.0017	0.016	0.019**	0.042***	-0.0090
	[0.007]	[0.01]	[0.009]	[0.006]	[0.01]	[0.009]	[0.01]	[0.007]
Obs	2961	2970	2969	2968	2970	2961	2970	2961
R^2	-0.031	0.032	0.006	0.025	0.023	-0.068	-0.124	0.049
Kleibergen-Paap rk LM	89.73	89.71	89.71	89.71	89.71	89.73	89.71	89.73
Kleibergen-Paap rk LM (p-value)	3.28e-20	3.30e-20	3.30e-20	3.30e-20	3.30e-20	3.28e-20	3.30e-20	3.28e-20
Kleibergen-Paap Wald rk F	106.4	106.4	106.4	106.4	106.4	106.4	106.4	106.4
Hansen J	2.359	1.604	1.267	1.115	0.184	2.098	1.229	0.439
Hansen J (p-value)	0.125	0.205	0.260	0.291	0.668	0.147	0.268	0.508
Instruments for $RSH \times RI$	First- and second-lags of $RSH \times \widetilde{RI}, alt$							
$\ln Y$, K, ICT, S/W	Treated as exogenous							

Notes: Two-Stage Least Squares (2SLS) with clustered standard errors by country-industry pairs in both panels. Country-industry and country-year fixed effects included. All equations are weighted by the share of each industry's employment in country-wide employment in 1996. For a description of the variables, see Appendix Table B9. Asterisks denote significance at 1% (***), 5% (**), and 10% (*).

Table B6: Capital inputs, robots and labor demand, OLS, Japan excluded

Panel A: Employment by skill, by age, and by gender

Dep. var: $\ln E$	(1) HS	(2) MS	(3) LS	(4) Y	(5) P	(6) O	(7) M	(8) F
$\ln Y_t$	0.37***	0.34***	0.44***	0.47***	0.41***	0.42***	0.43***	0.43***
	[0.08]	[0.09]	[0.09]	[0.1]	[0.08]	[0.08]	[0.09]	[0.09]
K_{t-1}	0.0048	-0.00066	-0.0033	-0.0021	0.00076	0.0023	0.0015	0.0018
	[0.004]	[0.003]	[0.004]	[0.005]	[0.003]	[0.002]	[0.003]	[0.002]
ICT_{t-1}	0.0071	0.15**	0.33***	0.26***	0.17**	0.15	0.16**	0.20***
	[0.1]	[0.07]	[0.1]	[0.09]	[0.07]	[0.09]	[0.07]	[0.07]
S/W_{t-1}	0.48	-0.43	-0.62	-0.15	-0.011	0.11	0.063	-0.083
	[0.3]	[0.3]	[0.4]	[0.4]	[0.3]	[0.3]	[0.3]	[0.3]
$RSH \times \widetilde{RI}_{t-1}$	-0.068	-0.050	-0.13***	-0.10	-0.018	0.033	-0.000073	-0.062
	[0.08]	[0.05]	[0.05]	[0.06]	[0.04]	[0.06]	[0.04]	[0.05]
Obs	2689	2700	2699	2698	2700	2689	2700	2689
R^2	0.996	0.998	0.997	0.997	0.998	0.997	0.998	0.998

Panel B: Income share by skill, by age, and by gender

Dep. var: Lsh	(1) HS	(2) MS	(3) LS	(4) Y	(5) P	(6) O	(7) M	(8) F
$\ln Y_t$	-0.0071	-0.11***	-0.013	-0.013*	-0.071***	-0.041***	-0.080***	-0.045***
	[0.01]	[0.02]	[0.008]	[0.007]	[0.02]	[0.009]	[0.02]	[0.01]
K_{t-1}	0.00080	-0.00027	0.000015	0.00036	0.00031	-0.00024	0.00088	-0.00041
	[0.0007]	[0.0008]	[0.0003]	[0.0003]	[0.0006]	[0.0003]	[0.0007]	[0.0003]
ICT_{t-1}	-0.0011	0.023	0.020**	0.010	0.018	0.011	0.026	0.014
	[0.01]	[0.02]	[0.010]	[0.007]	[0.02]	[0.01]	[0.02]	[0.01]
S/W_{t-1}	0.20***	-0.017	0.039	0.045	0.18*	-0.0093	0.20**	0.015
	[0.06]	[0.10]	[0.04]	[0.04]	[0.1]	[0.05]	[0.09]	[0.04]
$RSH \times \widetilde{RI}_{t-1}$	0.013*	0.0087	-0.0072	-0.0063	0.010	0.010	0.024*	-0.010
	[0.007]	[0.01]	[0.009]	[0.006]	[0.01]	[0.009]	[0.01]	[0.007]
Obs	2689	2700	2699	2698	2700	2689	2700	2689
R^2	0.992	0.983	0.989	0.972	0.953	0.974	0.973	0.995

Notes: Ordinary Least Squares (OLS) with clustered standard by country-industry pairs in both panels. Japan is excluded from the sample. Country-industry and country-year fixed effects included. All equations are weighted by the share of each industry's employment in country-wide employment in 1996. For a description of the variables, see Appendix Table B9. Asterisks denote significance at 1% (***), 5% (**), and 10% (*).

Table B7: Capital inputs, robots and labor demand, OLS with wages as controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. var: $\ln E$	HS	MS	LS	Y	P	O	M	F
$\ln W_t^{HS}$	-0.26	-0.22***	-0.18**					
	[0.2]	[0.07]	[0.09]					
$\ln W_t^{MS}$	-0.20	-0.52***	-0.61***					
	[0.2]	[0.08]	[0.1]					
$\ln W_t^{LS}$	-0.046	0.053	0.088*					
	[0.10]	[0.04]	[0.05]					
$\ln W_t^{29}$				-0.37***	-0.17*	0.13		
				[0.1]	[0.09]	[0.1]		
$\ln W_t^{49}$				-0.20	-0.40***	-0.58***		
				[0.1]	[0.08]	[0.1]		
$\ln W_t^{50}$				-0.20*	-0.040	-0.18		
				[0.1]	[0.09]	[0.1]		
$\ln W_t^{M}$							-0.46***	-0.33***
							[0.1]	[0.09]
$\ln W_t^{F}$							-0.15	-0.41***
							[0.1]	[0.09]
$\ln Y_t$	0.58***	0.68***	0.74***	0.84***	0.64***	0.70***	0.67***	0.73***
	[0.09]	[0.07]	[0.06]	[0.06]	[0.04]	[0.05]	[0.04]	[0.06]
K_{t-1}	0.0041	-0.00018	-0.0076*	-0.0018	-0.00071	-0.0034	-0.000046	0.0015
	[0.003]	[0.002]	[0.004]	[0.003]	[0.002]	[0.003]	[0.002]	[0.002]
ICT_{t-1}	0.077	0.12**	0.39***	0.18***	0.12**	0.11	0.12***	0.15***
	[0.1]	[0.06]	[0.1]	[0.06]	[0.05]	[0.08]	[0.05]	[0.05]
$\mathrm{S/W}_{t-1}$	0.0049	-0.59**	-0.15	-0.26	-0.058	0.90***	0.23	-0.30
	[0.4]	[0.3]	[0.4]	[0.4]	[0.2]	[0.3]	[0.2]	[0.2]
$\mathrm{RSH}\times\widetilde{RI}_{t-1}$	-0.011	0.016	-0.075***	-0.015	-0.022*	0.065***	0.026**	-0.033**
	[0.04]	[0.02]	[0.03]	[0.02]	[0.01]	[0.02]	[0.01]	[0.01]
Obs	2989	2989	2989	2989	2989	2989	2989	2989
R^2	0.996	0.998	0.996	0.998	0.999	0.997	0.999	0.999

Notes: Ordinary Least Squares (OLS) with clustered standard errors by country-industry pairs. Country-industry and year fixed effects included. All equations are weighted by the share of each industry's employment in country-wide employment in 1996. For a description of the variables, see Appendix Table B9. Asterisks denote significance at 1% (***), 5% (**), and 10% (*).

Table B8: Capital inputs, robots and income shares, OLS with wages as controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. var: Lsh	HS	MS	LS	Y	P	O	M	F
$\ln W_t^{HS}$	0.11***	-0.076***	0.00049					
	[0.03]	[0.03]	[0.02]					
$\ln W_t^{MS}$	-0.072**	0.19***	0.086***					
	[0.03]	[0.03]	[0.02]					
$\ln W_t^{LS}$	-0.013	0.016	-0.023**					
	[0.02]	[0.02]	[0.010]					
$\ln W_t^{29}$				0.078***	-0.075**	0.056***		
				[0.02]	[0.03]	[0.02]		
$\ln W_t^{49}$				-0.019	0.26***	-0.099***		
				[0.02]	[0.04]	[0.02]		
$\ln W_t^{50}$				-0.026	-0.033	0.094***		
				[0.02]	[0.03]	[0.02]		
$\ln W_t^{M}$							0.23***	-0.090***
							[0.05]	[0.03]
$\ln W_t^{F}$							-0.046	0.13***
							[0.05]	[0.03]
$\ln Y_t$	-0.020*	-0.13***	-0.050***	-0.020**	-0.13***	-0.059***	-0.16***	-0.055***
	[0.01]	[0.02]	[0.01]	[0.009]	[0.02]	[0.01]	[0.02]	[0.010]
K_{t-1}	0.000072	0.000016	-0.00036	0.00049*	0.000042	-0.00076*	-0.00022	-0.00012
	[0.0003]	[0.0006]	[0.0006]	[0.0003]	[0.0007]	[0.0005]	[0.0010]	[0.0003]
ICT_{t-1}	0.0015	0.046**	0.037***	0.021***	0.042**	0.024*	0.056**	0.031***
	[0.01]	[0.02]	[0.01]	[0.008]	[0.02]	[0.01]	[0.02]	[0.01]
$\mathrm{S/W}_{t-1}$	0.14***	-0.071	0.047	-0.033	0.016	0.091*	0.14*	-0.067
	[0.05]	[0.10]	[0.05]	[0.04]	[0.1]	[0.05]	[0.08]	[0.05]
$\mathrm{RSH}\times\widetilde{RI}_{t-1}$	0.0067*	0.010	-0.013***	-0.0028	-0.0072	0.013***	0.0094*	-0.0072**
	[0.004]	[0.007]	[0.004]	[0.003]	[0.006]	[0.005]	[0.005]	[0.003]
Obs	2989	2989	2989	2989	2989	2989	2989	2989
R^2	0.992	0.984	0.985	0.969	0.962	0.969	0.980	0.995

Notes: Ordinary Least Squares (OLS) with clustered standard by country-industry pairs. Country-industry and year fixed effects included. All equations are weighted by the share of each industry's employment in country-wide employment in 1996. For a description of the variables, see Appendix Table B9. Asterisks denote significance at 1% (***), 5% (**), and 10% (*).

Table B9: Description of variables

Variable	Description	Source
E^{HS}	Hours worked by high-skill workers	EU KLEMS
E^{MS}	Hours worked by medium-skill workers	EU KLEMS
E^{LS}	Hours worked by low-skill workers	EU KLEMS
E^{15-29}	Hours worked by workers aged 15–29	EU KLEMS
E^{30-49}	Hours worked by workers aged 30–49	EU KLEMS
E^{50+}	Hours worked by workers aged 50 and over	EU KLEMS
E^{M}	Hours worked by male workers	EU KLEMS
E^{F}	Hours worked by female workers	EU KLEMS
$E^{M,HS}$	Hours worked by high-skill male workers	EU KLEMS
$E^{M,MS}$	Hours worked by medium-skill male workers	EU KLEMS
$E^{M,LS}$	Hours worked by low-skill male workers	EU KLEMS
$E^{F,HS}$	Hours worked by high-skill female workers	EU KLEMS
$E^{F,MS}$	Hours worked by medium-skill female workers	EU KLEMS
$E^{F,LS}$	Hours worked by low-skill female workers	EU KLEMS
Lsh^{HS}	Income share of high-skill workers	EU KLEMS
Lsh^{MS}	Income share of medium-skill workers	EU KLEMS
Lsh^{LS}	Income share of low-skill workers	EU KLEMS
Lsh^{15-29}	Income share of workers aged 15–29	EU KLEMS
Lsh^{30-49}	Income share of workers aged 30–49	EU KLEMS
Lsh^{50+}	Income share of workers aged 50+	EU KLEMS
Lsh^{M}	Income share of male workers	EU KLEMS
Lsh^{F}	Income share of female workers	EU KLEMS
W^{HS}	Hourly wage for high-skill workers	EU KLEMS
W^{MS}	Hourly wage for medium-skill workers	EU KLEMS
W^{LS}	Hourly wage for low-skill workers	EU KLEMS
W^{15-29}	Hourly wage for workers aged 15–29	EU KLEMS
W^{30-49}	Hourly wage for workers aged 30–49	EU KLEMS
W^{50+}	Hourly wage for workers aged 50+	EU KLEMS
W^{M}	Hourly wage for male workers	EU KLEMS
W^{F}	Hourly wage for female workers	EU KLEMS
Y	Real gross value-added	EU KLEMS
K	Ratio of non-ICT capital to real gross value-added	EU KLEMS
ICT	Ratio of ICT (net of software) capital stock to real gross value-added	EU KLEMS
S/W	Ratio of software capital stock to real gross value-added	EU KLEMS
RSH	Mean value of the ratio of routine task input to total (routine and non-routine) task input measured in centiles of the 1960 task input distribution	ALM (2003)
RSH$\times RI$	imports of robots of country c from all its trade partners	UN COMTRADE
RSH$\times \widetilde{RI}$	average robot exports from country c's trade partner p to all destination countries *except* for country c itself, weighted by country c's robot import dependence on trade partner p in 1996	UN COMTRADE
RSH$\times \widetilde{RI}$, alt	average robot exports from country c's trade partner p to all destination countries *except* for country c itself, weighted by country c's average robot import dependence on trade partner p over 1996–2005	UN COMTRADE

Notes: Authors' notation.