Who Is Afraid of Machines?*

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Abstract

We study how machines, embodied in various forms of capital such as ICT capital, software and 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, spanning roughly the entire economy, with annual observations over the period 1982–2005. We find that industries with faster capital growth reduced their demand for middle-educated workers and males, and also some evidence that their demand shifted in favor of middle-age workers. We investigate the robustness of the results across alternative identification strategies, various proxies for the use of machines, and different time periods, including an alternative sample from 2008 to 2015. Our evidence is consistent with the hypothesis that machines lower the demand for workers performing routine tasks, especially in routine-manual occupations. We also find evidence that at least some types of workers have shifted away from such tasks.

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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 and communication technologies cut the cost of distance dramatically, leading to new forms of production. More recently, the diffusion of computer technologies and artificial intelligence has fueled widespread fear that machines 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 lead to some workers losing their jobs to machines. On the other hand, other workers may benefit from the adoption of new technologies. It is therefore important to ask which types of workers are vulnerable to replacement, and how the labor market effect of new technologies differ by workers' backgrounds. At the same time, certain groups of workers may respond to the onset of machines by, for example, learning to acquire different types of skills.[2] The goal of this paper is exactly to identify such differences in the effects and responses across heterogeneous groups of workers. More precisely, we conduct one of the most comprehensive analyses of how machines, embodied in various forms of capital such as ICT capital, software and industrial robots, affect the demand for workers of different education, age and gender. To do so, we exploit differences across a large number of countries and industries over the past three decades. Ultimately, we intend to systematically scrutinize the recent past so as to be better prepared for the future, especially identifying the conditions under which machines may make workers redundant or complement them.

We start by formalizing in a simple model that the effect of new capital on the demand for labor generally depends both on worker characteristics and the tasks they perform. For instance, computers may complement highly-educated workers performing abstract tasks,

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

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

while robots may substitute less-educated workers performing routine, repetitive tasks (Autor and Dorn, 2013). This framework motivates our empirical investigation, for which we use data on value-added, inputs and factor payments for a sample of 10 developed countries and 30 industries over the period 1982–2005 from EU KLEMS. This dataset is unique in that it includes consistent industry-level information on wages and employment by workers' education, age and gender across a large sample of countries and a long time period; Equally important for our purposes, it also includes a breakdown of capital inputs into non-ICT, ICT net of software, and software capital by industry.

As a preliminary step, we describe some of the basic trends in the data. We first document the rise of ICT capital. While the stock of ICT relative to industrial output was minuscule in 1982, by 2005 it grew to more than 20% for ICT and almost 5% for software capital. It is this explosive growth, together with the simultaneous disappearance of some occupations, that triggered the fear that machines could ultimately replace workers. Indeed, over the same period, there have also been profound changes in the structure of wages and employment. In particular, the wage bill and employment shares of highly-educated workers, older workers and women increased significantly.

But did the advent of these new types of machine play a role in such labor market trends? And if so, which workers were the most affected? To shed some light on these questions, we follow the hypothesis of Autor et al. (2003) that new technologies substitute routine tasks. Using occupational data from the United States, we then show two patterns. First, middle-educated, young and female workers are more specialized in routine jobs. Second, there is a secular decline in routine jobs, which is especially strong for women.

Next, we perform our test. We show that industries and countries where capital grew faster shifted demand away from middle-educated workers and males. We also find some evidence that faster capital accumulation may have shifted demand in favor of middle-age workers. These results are consistent with the view that technological change has polarized the demand for skill, measured by education, but also that it has improved the employment opportunities for women. When breaking capital into its components, we find that both ICT and software contributed toward polarizing the demand for skill, but that the latter has become more important over time.

As a further step, we then look for heterogeneous effects. In particular, we test whether machines have differing effects on sectors that are more or less prone to automation. We find strong evidence of such heterogeneous effects: In general, changes in capital inputs tend to have *opposite* effects on the demand for labor in more routine-intensive industries compared to less routine-intensive ones. Moreover, changes in capital inputs (mostly software and ICT) are associated with negative changes in employment only in industries that are sufficiently routine-intensive.

Finally, we investigate the robustness of the results across various proxies for the use of machines, and also different time periods. Perhaps most interestingly, we examine an alternative identification strategy which helps isolate the effect of industrial robots from other forms of capital. We find that routine-intensive industries in countries where robot imports grew faster experienced a shift in demand toward middle-age workers and against men. Lastly, we confirm the main patterns in a sample with a limited industry coverage over the more recent period of 2008–2015.

Overall, our results provide support to the view that the workers who are most vulnerable to the rising use of machines are those specialized in routine tasks (e.g., middle-educated and younger workers), and especially in physical, or routine-manual, tasks (men). They are consistent with the hypothesis that machines may have replaced workers in medium-skill occupations. They also suggest that machines may have contributed toward improving the labor market outcomes for women, possibly by raising the demand for service occupations and lowering the need for physically demanding skills.

Before proceeding, we make two important remarks. First, although our evidence does suggest that machines are likely to have had different effects across workers, it does not necessarily imply job losses for some categories. When focusing on employment, we find only limited evidence of a negative association with growth in capital inputs. Even when we do, our estimation strategy only detects losses relative to other industries, which do not necessarily imply a fall in the absolute level of employment. Second, even though we use instruments to identify the effect of machines, there is still some remaining concern that our estimates may be affected by endogeneity. For instance, in industries that become more skill intensive, firms may have a stronger incentive to invest in ICT. Nevertheless, our results unveil interesting, useful and, in some cases, novel patterns, even if just interpreted as conditional correlations.

Related Literature The literature on how new technologies affect the relative demand for different types of workers goes at least as far back as Berman et al. (1994). Already then, they provided robust evidence that information and communication technologies (ICT) were boosting the relative demand for more skilled workers. This led to numerous studies further focusing on the different evolution of high- and 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-intensive occupations have declined (Autor et al., 2003), who happen to fall in the middle of the wage distribution (Autor and Dorn, 2013). Accordingly, they posit that ICT can be a main driver of "job polarization." Even more recent studies exploit newly-available data on industrial robots to study their potential impacts on the labor market (Acemoglu and Restrepo, 2017; Graetz and Michaels, 2018). The former finds that US commuting zones that were more exposed to robots during the period 1990–2007 experienced large and robust negative effects on employment and wages. However, the latter finds that, in a panel of 17 countries, robots only reduced the employment share of low-educated workers, with only small effects 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.[3] Other recent papers show that even when robots may seem to have no effect, it may be masking employment losses that are compensated for in other sectors. Using patents related to automation, Mann and Püttman (2017) find that although automation led to a decline in US manufacturing employment, this employment loss 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 positive spillovers to other industries more than offset the negative employment effect in aggregate.

The latter set of papers is related to our postulation that the effect of new technology on different types of workers are heterogeneous, and that worker responses may also be different. For instance, young workers or women may start working in different jobs or industries if employment is negatively affected by robots. In this vein, there is also a literature that

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

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).[4] Most recently, Acemoglu and Restrepo (2018) find that robots substitute for middle age workers, and also evidence for the reverse causal direction: aging is associated with more automation across countries and also U.S. commuting zones. But they do not focus on how the adoption of robots affects the relative demands for workers by age group.

To the best of our knowledge, little attention has been given to how technological change affects the relative demand for workers by gender, which we assess in conjunction with the demand for workers by education and age. Rendall (2017) and Juhn et al. (2014) have argued that new technologies have created jobs for women by lowering the demand for manual skill. Yet, systematic evidence is still missing. Furthermore, few have asked how the effect of new technology may differ by type of capital, such as ICT, software and robots. Our approach and methodology to answer these questions are closely related to Michaels et al. (2014); Graetz and Michaels (2018). They use the EU KLEMS data to examine how wage bill shares and labor productivity are affected by ICT and robots, respectively. In their analyses, however, they only consider different education levels, and not the age nor gender of workers. In addition, they do not consider non-ICT capital, distinguish between ICT and software, nor investigate years beyond 2007.

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 those found in Costinot and Vogel (2010); Goos et al. (2014), with additional consideration for capital as in (but not identical to) Acemoglu and Autor (2011). Let Y denote the output of a single industry.[5] Output Y is produced by combining capital (machines) with different

[4]On the other hand, there does seem to be a clear effect on older workers' retirement decisions: Bartel and Sicherman (1993) finds 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 less computer skills, but that those who do retire later.

[5]We focus on a single industry both to save on notation, and because the unit of observation in our empirical analysis is an industry. But it is straightforward to extend the analysis to a multi-industry economy.

types of workers. Denote by j the type of a worker (e.g., high-skill worker), and G the set of all types. Let Y_j denote the contribution of type j workers, which is combined across G to 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_i, workers and capital must perform a unit measure of different tasks:

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

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: tasks that cannot be automated are produced by one unit of type j labor, and those that can be are instead produced by one unit of capital.

Now let (K_j, L_j) denote the quantity of capital and labor used to produced Y_j. Since (K_j, L_j) are not differentiated by task z, $x_j(z) \equiv x_j$ for all z. Then, denoting by κ_j the share of tasks that can be automated, symmetry in how capital and type j labor are used to produced x_j implies

$$K_j = \kappa_j x_j, \; L_j = (1-\kappa_j) x_j$$

and substituting these in (1) yields:

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

Holding all else constant, an increase in machines, K_j, raises output of group j and the effect is stronger the higher the share of automated tasks:[6]

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

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

[6] An increase in automation, κ_j, raises group output as long as $\kappa_j < K_j/(K_j + L_j)$, a condition that we assume throughout. Automation, κ_j, can also be made endogenous, as in Acemoglu and Restrepo (2017) or Acemoglu et al. (2015).

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 labor of type j.[7] 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 type j labor only if $\epsilon < \alpha_j$.[8] Intuitively, when $\epsilon < \alpha_j$, it is easier to substitute type j workers for machines (high α_j) compared to other groups (low ϵ), so less workers of type j are needed. Conversely if $\epsilon > \alpha_j$, it is relatively harder to substitute type j workers, so the demand for them rises.

What is the effect an increase in industrial capital $K \equiv \sum_j K_j$ on the labor demand? To answer this question, assume for the moment that $K_j = \omega_j K$ with $\omega_j > 0$ for all $j \in G$. Then, it is immediate from (3)) 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. This is clearly unrealistic: some types of workers are likely more substitutable by machines than others. Moreover, even if the direction of the effects are the same, the magnitudes will also differ depending on differences in κ_j: Some tasks will be easier to automate for some groups than for others. 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 labor is more substitutable in group j relative to j', i.e., $\alpha_j > \alpha_{j'}$. Similarly, an increase in K will have stronger effect on workers of type j relative to j' if more tasks are automated in group j relative to j'.

Consider the following example. Workers differ in skill $j \in G = \{h, m, l\}$, where h, m, l denote high-, medium- and low-skill workers, respectively. In the data, medium-skill workers perform relatively more routine tasks, which are easier to automate (Autor and Dorn, 2013; Goos et al., 2014; Michaels et al., 2014). To capture this, suppose we make the extreme assumption that $\kappa_m > 0$ and $\kappa_h = \kappa_l = 0$. Then, if $\epsilon < \alpha_m$, more machines will substitute medium-skill workers and while complementing both high- and low-skill workers. That is, an increase in K polarizes the demand for skill.

[7]The model can also be used to study the effect of changes in automation, κ_j. However, in the empirical analysis we use observed changes in capital and hold constant measures of how difficult it is to replace workers.

[8]In the empirical analysis, we always control for output.

Table 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 Defence
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.

The model above assumes one type of capital for illustration.[9] In the empirical analysis, we proxy for K (for each industry) using different types of capital, which themselves would have differing levels of elasticity and ease of being used to automate tasks. In addition to analyzing the effect of technology on workers of different background, the other main goal of our analysis is to identify how different types of capital substitute or complement workers in different ways.

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 of 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 roughly span the entire economy of all countries (Table 1).

The EU KLEMS contains data on real gross value-added and different types of labor and capital by country, industry and year. The first advantage of EU KLEMS is this comparability across country-industry-year cells. The second advantage is that for each cell, it includes information on the wage bill and employment of workers by education level, age and gender,

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

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 education or no formal qualification.[10] There are three age groups, young (Y), prime (P) and old (O), comprising workers aged 15–29, 30–49 and 50+ years old, respectively.

The third and most important advantage is that for each country-industry-year cell, it also includes information on real fixed stocks of capital by type –most datasets do not include such a breakdown of capital, if they contain information on capital at all. Specifically for our purposes, we use data on non-ICT, ICT net of software, and software capital.[11] All real variables are computed in 1995 US dollars (USD) using real exchange rate data from the OECD.

3.2 The Rise of Machines

In Figure 1, we summarize the industrial capital-output ratio (K_i/Y_i) averaged over all countries in our sample by 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. We then average over countries using equal weights (Appendix Table A1 reports all within-country means for 1982 and 2005). In all countries, the share of ICT and especially software capital was minuscule in 1982. Averaged across all countries, the stocks of each were only less than 3% and 1% of GDP, respectively. But in the 23 years that followed, they grew by an order of magnitude, to more than 20% and almost 5%, respectively.[12]

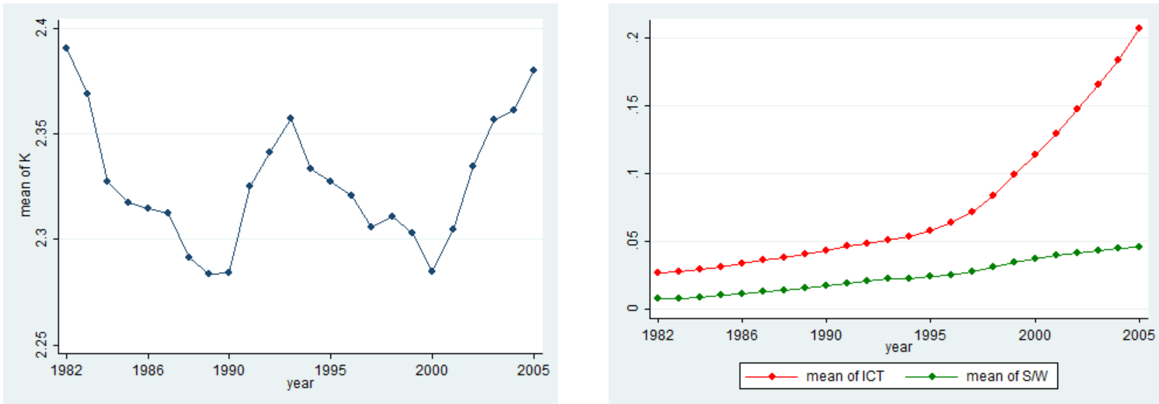
Presumably, the explosive growth in the latter two types of capital, in conjunction with the widespread disappearance of previously commonplace jobs such as factoryline workers, desk secretaries and bank tellers is what likely led to the fear that machines may ultimately replace at least certain types of workers altogether. At the same time, although the level

[10]For the purposes of this paper, levels of "skill" refer to these categories of education.

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

[12]We also calculate the capital-output ratios averaged across countries within each industry. The within-industry patterns and trends are very similar to those within each country and are shown in the Appendix Table A2.

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 average across countries by year using equal weights for each country.
Source: Authors' calculations based on EU KLEMS.

of non-ICT capital seems to fluctuate without a particular trend, and in fact even declined 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 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 into 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.[13] In particular, the latter 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 K.

Related, even if the relative size of ICT and software may seem still small 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

[13]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).

Table 2: Employment and wage bill shares

	1982 mean			2005 mean		
by Educ	HS	MS	LS	HS	MS	LS
Employment shares	0.094	0.521	0.385	0.177	0.618	0.205
Wage bill shares	0.137	0.527	0.337	0.244	0.594	0.162
by Age	Y	P	O	Y	P	O
Employment shares	0.336	0.472	0.191	0.246	0.521	0.233
Wage bill shares	0.282	0.521	0.196	0.185	0.566	0.249
by Gender	M		F	M		F
Employment shares	0.651		0.351	0.618		0.382
Wage bill shares	0.723		0.278	0.668		0.332

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 shares across industries within each country using as weights each industry's employment share in country-wide employment in 1982. We then average across countries by year using equal weights for each country.
Source: Authors' calculations based on EU KLEMS.

large impact on the labor market (Aum et al., 2018).

3.3 Employment and Wages by Worker Type

In Table 2, we summarize employment shares and wage bill shares by education level, age profile and gender, for 1982 and 2005, respectively. Similar to the production of statistics for the different types of capital, we first average the employment and wage bill shares across industries within each country using as weights each industry's employment share in country-wide employment in 1982 and we then average across countries by year using equal weights for each country.[14] Both in terms of employment and wage bills, the shares of highly educated workers rose significantly from 1982 to 2005, close to doubling. During the same time period, shares of low-educated workers dropped. Most interestingly, the shares of middle-educated workers rose, but the changes are much smaller in magnitude compared to both the high- and low-educated.

Since education levels rose in all countries in the sample, it is obvious that education levels

[14] The within-country and within-industry average shares by skill, by age, and by gender are shown in the Appendix Tables A3–A8. In the Appendix Tables A9 and A10, we also produce the country-wide employment and wage bill shares by age-skill and age-gender averaged across countries without using country weights.

would rise among the employed as well. In light of this, it is noticeable that middle-educated shares rose only as much as they did. Michaels et al. (2014) find, in fact, that the supply of this group of workers was mitigated by "the fall in the relative demand caused by technical change," as we also find later in our analysis. They also relate this to job polarization – the decline in the employment shares of jobs that fall in the middle of the wage distribution (Autor and Dorn, 2013; Goos et al., 2014)– since at least in the U.S., there is a tight correlation between the the education levels and mean wages across occupations.[15]

Novel to our analysis is the analyses of capital on workers by age and gender. What is immediately noticeable in the second panel of Table 2 is the rise in the shares of older workers, especially middle-aged, prime workers at the expense of young workers. Since younger workers tend to be more educated than their older counterparts, so this cannot be solely due to the supply factors –there must be an accompanying drop in the demand for younger workers.[16] Indeed, we will later see that younger workers tend to work in more routine jobs, at least in the U.S., and that they also seem to be more negatively affected by the rise of machines, although the exact results somewhat vary by the type of capital and the estimation strategy.

Last, the well-known improvement in women's status in the labor market is evident in the third panel of Table 2. Women's wage bill share rose by a significant amount, due to a rise in both their employment and wages relative to men's. It is important to keep this in mind as we proceed—in the following subsection, 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), potentially exposing them more to the threat of being replaced by machines. In many of our specifications, however, we find that women's employment are positively correlated with capital, *except when interacting capital with how routine an industry is.* This implies a shift in the jobs performed by women who supply their labor. In face of declining demand for jobs traditionally performed by women, it seems that women today have not only increased their education but have also prepared themselves for jobs that are less negatively affected by, or complementary with, the new types of capital.

[15] But they cannot decisively relate job polarization and ICT capital since the EU KLEMS, which we also rely on, lacks occupation data. Similarly as them, we choose to use the EU KLEMS due to its rich information on different types of capital, which is the driving force for our results.

[16] Such a change in the demand structure may also be forcing high-skill, younger individuals to continue in education rather than joining the workforce, which would also change the negatively select workers among the younger pool.

Table 3: Task scores by education, age and gender

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

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 already mentioned, we choose to work with the EU KLEMS data due to its rich information on various types of capital. But as implied by the model of Section 2, we believe that it is more likely that new types of capital substitute or complement specific tasks performed by workers, rather than directly affecting workers based on their characteristics (Michaels et al., 2014). Table 3 summarizes means of task scores by the different groups of workers we are interested in, similarly as Table 5 in Acemoglu and Autor (2011).[17]

The first five rows show the means of tasks scores used in Acemoglu and Autor (2011) by different groups of workers. These scores are constructed from the Occupational Information Network (O*NET), which contains scales on 400 different types of tasks for each occupation. Using this, they construct broader-based measures of routine-cognitive, routine-manual,

[17]However, they do not split workers by age, nor focus much on the differences between gender.

nonroutine(-cognitive) analytical, nonroutine(-cognitive) interpersonal and nonroutine manual tasks. Each of these are standardized to have a mean of zero and standard deviation of one, after which we compute the mean for each group of workers using hours-weighted employment weights from the 1980 U.S. IPUMS census. The routine-task intensity index (RTI) in the last row was used in Autor and Dorn (2013), which itself collapses five task measures extracted from the 1977 Dictionary of Occupational Titles (DOT), similar to the ones in the first five rows of Table 3.[18,19]

In the table, it is clear that the middle-educated, young and female workers work in more routine jobs than their respective counterparts. The table also makes it clear that, not surprisingly, the reason for which American women have such a high RTI in 1980 is not because they worked in routine-manual jobs, such as factoryline workers, but because they worked in routine-cognitive jobs, such as secretaries.[20]

Taken together, we can posit from Tables 2-3 that the demand for middle-educated and young workers may have dropped because those workers tended to work in routine jobs, which were replaced by new types of capital.[21] But such a line of reasoning is not obvious for women –even though they tend to work in routine jobs, recall from the previous subsection that women's employment and wages significantly rose relative to men's. As already mentioned, this leads to the conjecture that more than any other group of workers, women altered their labor supply toward cognitive jobs in response to the declining in demand for routine jobs.

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 nonroutine cognitive measures across the board. For middle-educated and young workers, there is noticeable drop in mean routine scores, indicating that as their employment fell, the content of their work also became less routine: the middle-educated now work in more manual jobs, and young workers in more cognitive jobs. But the changes are the most

[18] Specifically, RTI = log[R-cognitive + R-manual)/2] − log[NR-analytical + NR-interpersonal)/2] − log[NR-manual]. For how the five measures are extracted from the DOT, refer to Autor et al. (2003).

[19] These are the same five measures used in Autor et al. (2003), which they also use to construct industry-specific routine measures which we exploit in our analysis.

[20] Lee and Shin (2017) document that secretaries was among the jobs that declined the most in terms of employment shares, although not by gender.

[21] 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 A11.

stark for women, and furthermore, this is despite their having a larger employment share. American women not only work much more than before, but also in much more cognitive jobs than their predecessors.

4 Econometric model and estimation strategy

Our main empirical specification is a wage bill share equation that is derived from the cost-minimization problem of the representative firm of an industry. The representative firm employs different types of workers and also different types of capital, namely, non-ICT, ICT net of software, and software. Assuming a translog cost function while treating all types of capital as quasi-fixed factors (Berman et al., 1994), the estimating equation is as follows:[22]

$$\mathrm{Wsh}^j_{ict} = \alpha_{ct} + \alpha_{ic} + \beta^j_y \cdot \ln Y_{ict} + \boldsymbol{\beta}^j_k \cdot \mathbf{K}_{ict} + \epsilon^j_{ict}, \tag{4}$$

where the dependent variable, Wsh^j_{ict}, is the wage bill share 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 at year t. Country-year fixed effects, α_{ct}, capture time-varying country characteristics, such as 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). Country-industry fixed effects, α_{ic}, capture time-invariant unobserved country and industry characteristics, such as the initial level of technology and the pattern of specialization.[23]

In what follows, we drop the $_{ict}$ subscript unless necessary. Y is real gross value-added, capturing industry scale, and enters the model in logs. The main explanatory variables are the different types of capital included in the vector $\mathbf{K}$: namely, the ratios of real non-ICT, ICT net of software, and software capital stocks to real gross value-added.[24] The coefficient vector $\boldsymbol{\beta}^j_k$ captures the change in the *relative* demand for worker group j induced by these types of capital. Any unobserved factors impacting wage bill shares are incorporated in the error term, ϵ^j.

[22] A detailed description of the derivation of the empirical specification and the estimation strategy is relegated to the Appendix B of the Appendix.

[23] Country-industry fixed effects are included in the model by deviating all variables from their country-industry means.

[24] While the model-based derivation would dictate that variables in K should enter in logs, 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.

The error terms of the system are likely to be correlated, because they have an identical set of explanatory variables across different j's in a group G, and also because the underlying model implies cross-equation constraints. Firms' investment decisions over each of the different types of capital and labor can be made simultaneously, so there is also potential for a simultaneity bias. Moreover, in any given year, our unit of observation is a country-industry cell, while industries and even countries are not independent (Egger and Egger, 2005; Goos et al., 2014). For all these reasons, we estimate the equations of the system simultaneously by Iterated Three-Stage Least Squares (I3SLS), while treating all explanatory variables as endogenous and instrumenting each with its first and second lags. All equations are 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).

In order to study the effects of capital on the *absolute* demand for workers in levels, we estimate a version of equation (4) in which the dependent variable is the logged employment level of worker group j, $\ln \mathrm{E}_{cit}^{j}$, where E is measured in hours of work. The absolute labor demand equations are estimated individually by Two-Stage Least Squares (2SLS), with all explanatory variables treated as endogenous and instrumented with their first and second lags. All equations are weighted using the same weights as in the estimations of the wage bill share equations.

5 Econometric Results

5.1 Baseline Results: 1982–2005

We first estimate the effects of industrial capital on the demand for different types of workers for the sample period 1982–2005. In Table 4, Panel A, the dependent variable in each column is the wage bill *share* of a worker type, while in Panel B the dependent variables are employment *levels in logs*.[25] In columns (1)–(3), (4)–(6), and (7)–(8) of each panel, workers differ by education, age, and gender, respectively.

In Panel A, columns (1)-(3), the coefficient estimates of output and capital are highly statistically significant, suggesting that industries that grew faster and accumulated more

[25]The first-stage results of the I3SLS and 2SLS estimations of this table and of all subsequent tables that include instruments were all satisfactory: the F-statistic is above 10, the R-squared is relatively high, and the coefficient estimates of the instruments are highly statistically significant. Results available upon request.

Table 4: Industrial capital and labor demand

Panel A: Relative labor demand by skill, by age, and by gender								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. var: Wsh	HS	MS	LS	Y	P	O	M	F
ln Y	0.038***	-0.089***	0.051***	0.0059*	0.0053	-0.011***	-0.013***	0.013***
	[0.004]	[0.005]	[0.004]	[0.004]	[0.004]	[0.003]	[0.004]	[0.004]
K (total)	0.0049***	-0.013***	0.0084***	-0.0013	0.0031*	-0.0019	-0.012***	0.012***
	[0.002]	[0.002]	[0.002]	[0.001]	[0.002]	[0.001]	[0.002]	[0.002]
Obs		7001			7001		7001	
R^2	0.650	0.530	0.820	0.692	0.530	0.715	0.443	0.443
Hansen J statistic		833.0			649.5		713.1	
Instruments	First and second lags of instrumented variables							

Panel B: Absolute labor demand 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
ln Y	0.54***	0.47***	0.60***	0.70***	0.66***	0.66***	0.63***	0.71***
	[0.05]	[0.05]	[0.06]	[0.06]	[0.06]	[0.05]	[0.05]	[0.06]
K (total)	0.055**	0.048*	0.094***	0.089***	0.11***	0.11***	0.085***	0.15***
	[0.03]	[0.03]	[0.03]	[0.03]	[0.04]	[0.03]	[0.03]	[0.04]
Obs	7001	7001	7001	7001	7001	7001	7001	7001
R^2	0.718	0.678	0.769	0.462	0.469	0.455	0.286	0.423
Instruments	First and second lags of instrumented variables							

Notes: Iterated Three-Stages Least Squares (I3SLS) with asymptotic standard errors in square brackets in Panel A. Two-Stages Least Squares (2SLS) with robust standard errors in Panel B. 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 Table C4. Asterisks denote significance at 1% (***), 5% (**), and 10% (*).

capital experienced demand shifts in favor of high- and low-skill workers at the expense of medium-skill workers. These results are consistent with the view that technological change has polarized the demand for skill (.e.g. Michaels et al., 2014). They are also consistent with the evidence on capital-skill complementarity (e.g. Griliches, 1969; Krusell et al., 2003), and on skill-biased scale effects (e.g. Berman et al., 2005; Epifani and Gancia, 2006, 2008).

The significance levels of the coefficient estimates are lower when workers are divided into age groups in Panel A, columns (4)–(6). There is some evidence that capital has a positive impact on the relative demand for middle-age workers, possibly because machines and experience are at least weakly complementary. There is also some evidence that fast-growing industries demand relatively younger workers, which could reflect an increase in hiring but at the same time as they shift away from older workers.

When we split workers by gender in columns Panel A, (7)–(8), the coefficient estimates of output and capital are highly significant, and positive for females. This suggests that female workers have been moving toward expanding industries at a faster rate than men. Possible explanations for this finding are the fast growth of industries in which women traditionally have a comparative advantage, such as services, and the rise in women's average education levels. It could also be that machines are better substitutes for physical (routine-manual) jobs, which are predominantly done by men, than routine-cognitive jobs, which are oriented more toward women (as we saw in Table 3).

Next consider Panel B, in which the dependent variable is the employment level. Their magnitudes vary, but the coefficient estimates of output and capital are positive and highly significant in all columns, suggesting that output growth and capital accumulation are associated with employment gains for all worker types. So if we take total capital aggregated at the industry level as a proxy for machines, there is no evidence that machines replace workers to the point of generating employment losses relative to other industries. Yet, it could still be that a specific type of capital input displaces certain types of workers, and that this effect is present in only some industries. To shed light on this and gain a better understanding what is driving the results behind Table 4, we now dig deeper into the analysis by decomposing capital into different categories.

In Table 5, Panels A and B display the effects of non-ICT, ICT net of software, and software capital on the relative and absolute demands for different types of workers, respectively. Columns (1)–(3) of Panel A show that both ICT and software are complementary to high-skill workers, while all capital inputs are biased against medium-skill but advantage low-skill workers. The effects on the age composition of labor demand in columns (4)–(6) are more nuanced. Non-ICT capital and software seem to be biased in favor of middle-aged workers, while ICT is biased against them. In columns (7)–(8), which show the effects on the gender composition of labor demand, non-ICT capital and software complement female workers.

In contrast to Table 4, Panel B of Table 5 displays some negatively significant coefficient estimates. In particular, industries with higher software growth registered job losses for medium-skill, low-skill and young workers. Keep in mind that these results indicate losses relative to other industries and do not necessarily imply a fall in the absolute level of employment, since all regressions include country-time fixed effects.

Tables 6-7 test the robustness of the results found in Table 5. In Table 6, all explanatory variables are treated as exogenous. Even without instruments, the results are very similar to the baseline ones, suggesting that endogeneity may not be a serious problem.

Another concern could be that annual data may be too noisy to identify the effects of

Table 5: Capital inputs and labor demand

Panel A: Relative labor demand by skill, by age, and by gender								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. var: Wsh	HS	MS	LS	Y	P	O	M	F
ln Y	0.033***	-0.081***	0.048***	0.0048	0.0097**	-0.014***	-0.014***	0.014***
	[0.004]	[0.005]	[0.005]	[0.004]	[0.004]	[0.003]	[0.005]	[0.005]
K	0.0018	-0.0089***	0.0071***	-0.0011	0.0040**	-0.0029**	-0.012***	0.012***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.001]	[0.002]	[0.002]
ICT	0.017**	-0.044***	0.027***	0.030***	-0.044***	0.015**	0.0016	-0.0016
	[0.009]	[0.01]	[0.010]	[0.008]	[0.009]	[0.006]	[0.009]	[0.009]
S/W	0.43***	-0.48***	0.056*	-0.21***	0.22***	-0.015	-0.062**	0.062**
	[0.03]	[0.04]	[0.03]	[0.03]	[0.03]	[0.02]	[0.03]	[0.03]
Obs		7001			7001		7001	
R^2	0.668	0.554	0.821	0.694	0.535	0.716	0.443	0.443
Hansen J statistic		2205.2			750.8		901.0	
Instruments	First and second lags of instrumented variables							

Panel B: Absolute labor demand 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
ln Y	0.50***	0.44***	0.55***	0.65***	0.62***	0.61***	0.59***	0.66***
	[0.06]	[0.05]	[0.06]	[0.07]	[0.06]	[0.06]	[0.06]	[0.07]
K	0.040	0.042	0.081***	0.074**	0.094**	0.096***	0.070**	0.13***
	[0.03]	[0.03]	[0.03]	[0.04]	[0.04]	[0.03]	[0.03]	[0.04]
ICT	0.41***	0.32***	0.59***	0.60***	0.35***	0.39***	0.41***	0.50***
	[0.1]	[0.07]	[0.10]	[0.10]	[0.09]	[0.1]	[0.08]	[0.09]
S/W	0.77***	-1.16***	-1.52***	-1.03***	0.49***	0.53**	-0.13	0.53**
	[0.3]	[0.2]	[0.3]	[0.2]	[0.2]	[0.2]	[0.2]	[0.2]
Obs	7001	7001	7001	7001	7001	7001	7001	7001
R^2	0.721	0.685	0.775	0.474	0.484	0.470	0.303	0.442
Instruments	First and second lags of instrumented variables							

Notes: Iterated Three-Stages Least Squares (I3SLS) with asymptotic standard errors in square brackets in Panel A. Two-Stages Least Squares (2SLS) with robust standard errors in Panel B. 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 Table C4. Asterisks denote significance at 1% (***), 5% (**), and 10% (*).

variables that change slowly over time. Our estimation method, which uses the first and second lag of the independent variable as instrument, already allows for some sluggishness in the response of the wage bill shares and employment levels. Moreover, focusing on the short run helps identifying changes in the demand for labor, rather than secular trends in supply.[26] Nevertheless, as an additional check, in Table 7 we re-estimate the baseline model on a sample with biannual frequency, where the start period is 1982 and the end year is 2004. The results are qualitatively very similar, albeit some coefficient estimates, such as that of ICT (net of software), are less significant.[27] We have also performed several other robustness checks which are no included in the text. In particular, the results are very similar when we

[26] Trends in supply at the country level are also absorbed by country-year fixed effects.

[27] In the Appendix, we show that the results remain largely unchanged also when the start year is 1983 and the end year 2005 (Table C1).

Table 6: Capital inputs and labor demand, non-IV

Panel A: Relative labor demand by skill, by age, and by gender

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. var: Wsh	HS	MS	LS	Y	P	O	M	F
ln Y	0.025***	-0.053***	0.027***	0.014***	0.000018	-0.014***	0.0025	-0.0025
	[0.002]	[0.003]	[0.003]	[0.002]	[0.003]	[0.002]	[0.003]	[0.003]
K	-0.00075	-0.0048***	0.0055***	0.000084	0.0013	-0.0014**	-0.0054***	0.0054***
	[0.0008]	[0.0010]	[0.0009]	[0.0007]	[0.0008]	[0.0006]	[0.0008]	[0.0008]
ICT	0.024***	-0.075***	0.051***	0.014**	-0.044***	0.030***	-0.011	0.011
	[0.007]	[0.009]	[0.008]	[0.006]	[0.007]	[0.005]	[0.007]	[0.007]
S/W	0.41***	-0.41***	0.0076	-0.18***	0.22***	-0.037*	-0.052*	0.052*
	[0.03]	[0.03]	[0.03]	[0.02]	[0.03]	[0.02]	[0.03]	[0.03]
Obs		7001			7001		7001	
R^2	0.669	0.560	0.823	0.695	0.536	0.717	0.449	0.449

Panel B: Absolute labor demand 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
ln Y	0.48***	0.33***	0.45***	0.56***	0.46***	0.46***	0.48***	0.48***
	[0.03]	[0.02]	[0.03]	[0.03]	[0.02]	[0.03]	[0.02]	[0.03]
K	0.039***	0.027***	0.068***	0.064***	0.067***	0.071***	0.059***	0.086***
	[0.01]	[0.009]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]
ICT	0.30***	0.45***	0.71***	0.68***	0.55***	0.64***	0.56***	0.67***
	[0.09]	[0.05]	[0.07]	[0.07]	[0.06]	[0.08]	[0.06]	[0.06]
S/W	1.01***	-1.20***	-1.58***	-1.06***	0.24	0.23	-0.30*	0.36*
	[0.2]	[0.2]	[0.2]	[0.2]	[0.2]	[0.2]	[0.2]	[0.2]
Obs	7001	7001	7001	7001	7001	7001	7001	7001
R^2	0.721	0.688	0.776	0.476	0.496	0.478	0.310	0.455

Notes: Iterated Seemingly Unrelated Regressions (ISUR) with asymptotic standard errors in square brackets in Panel A. Ordinary Least Squares (OLS) with robust standard errors in Panel B. 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 Table C4. Asterisks denote significance at 1% (***), 5% (**), and 10% (*).

control for relative wages in the model, as well as when output is not accounted for.[28]

As an additional exercise, we check whether capital (machines) had disproportionate effects on industries more prone to automation. To do so, we add interaction terms between the three types of capital and an industry-level index measuring the prevalence of routine tasks (RSH), computed in Autor et al. (2003). This index is constructed from the same five 1977 DOT measures used to construct the RTI index in Autor and Dorn (2013), which we also used in Section 3.4.[29] The RSH index is treated as exogenous and is thus not instrumented in the I3SLS and 2SLS estimations. The results are reported in Table 8.

The Table reveals some strong patterns. First, in most cases in Panel A, the coefficient estimate of the interaction term has the opposite sign of the coefficient on the corresponding,

[28]For the results of the latter exercise, see Appendix Table C2.

[29]Specifically, they re-normalize each of the five indices into centiles of the 1960 occupation distribution, and compute the routine score as a ratio of the total score across all occupations within an industry, weighted by each occupation's within-industry employment share.

Table 7: Capital inputs and labor demand, biannual frequency (1982–2004)

Panel A: Relative labor demand by skill, by age, and by gender								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. var: Wsh	HS	MS	LS	Y	P	O	M	F
ln Y	0.037***	-0.12***	0.080***	-0.0046	0.015*	-0.011	-0.022**	0.022**
	[0.009]	[0.01]	[0.01]	[0.008]	[0.009]	[0.006]	[0.009]	[0.009]
K	0.0036	-0.019***	0.016***	-0.0030	0.0058	-0.0028	-0.017***	0.017***
	[0.004]	[0.006]	[0.005]	[0.004]	[0.004]	[0.003]	[0.005]	[0.005]
ICT	0.017	-0.0037	-0.013	0.054***	-0.044**	-0.0095	0.0049	-0.0049
	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]	[0.01]	[0.02]	[0.02]
S/W	0.44***	-0.56***	0.12**	-0.25***	0.22***	0.027	-0.076	0.076
	[0.05]	[0.06]	[0.05]	[0.04]	[0.05]	[0.03]	[0.05]	[0.05]
Obs		3501			3501		3501	
R^2	0.670	0.544	0.814	0.693	0.551	0.706	0.434	0.434
Hansen J statistic		365.8			378.1		148.7	
Instruments	First and second lags of instrumented variables							

Panel B: Absolute labor demand 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
ln Y	0.62***	0.56***	0.68***	0.78***	0.84***	0.82***	0.76***	0.84***
	[0.1]	[0.1]	[0.1]	[0.1]	[0.1]	[0.1]	[0.1]	[0.1]
K	0.090	0.086	0.13*	0.12	0.17*	0.17**	0.13	0.20**
	[0.07]	[0.07]	[0.08]	[0.09]	[0.09]	[0.08]	[0.08]	[0.1]
ICT	0.52*	0.13	0.47**	0.47**	0.056	0.018	0.16	0.30
	[0.3]	[0.2]	[0.2]	[0.2]	[0.2]	[0.2]	[0.2]	[0.2]
S/W	0.49	-1.12***	-1.39***	-0.92**	0.88**	1.01**	0.17	0.86**
	[0.5]	[0.3]	[0.4]	[0.4]	[0.4]	[0.5]	[0.4]	[0.4]
Obs	3501	3501	3501	3501	3501	3501	3501	3501
R^2	0.725	0.673	0.766	0.458	0.421	0.410	0.246	0.395
Instruments	First and second lags of instrumented variables							

Notes: Iterated Three-Stages Least Squares (I3SLS) with asymptotic standard errors in square brackets in Panel A. Two-Stages Least Squares (2SLS) with robust standard errors in Panel B. 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 Table C4. Asterisks denote significance at 1% (***), 5% (**), and 10% (*).

non-interacted type of capital.[30] This suggests that machines have a very different effect—even *opposite* effects—in more routine-intensive industries compared to less routine-intensive ones. In other words, industries that are more reliant on occupations prone to automation are critical for assessing the labor market impact of machines. Second, in Panel B, coefficient estimates are negative only among the set of interaction terms. This means that the increasing use of machines had adverse employment effects only in industries that are sufficiently routine-intensive. More precisely, software seems to have reduced the employment of all types of workers, while ICT the employment of low-skill, young and female workers.

[30]Note that the direct effect of RSH is absorbed by the fixed effects.

Table 8: Capital inputs, routine intensity and labor demand

Panel A: Relative labor demand by skill, by age, and by gender

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. var: Wsh	HS	MS	LS	Y	P	O	M	F
ln Y	0.027***	-0.083***	0.056***	-0.0020	0.015***	-0.013***	0.0024	-0.0024
	[0.005]	[0.006]	[0.005]	[0.004]	[0.005]	[0.003]	[0.005]	[0.005]
K	0.014***	0.0026	-0.017***	0.0095***	0.0030	-0.013***	-0.024***	0.024***
	[0.004]	[0.005]	[0.004]	[0.004]	[0.004]	[0.003]	[0.004]	[0.004]
ICT	-0.056**	-0.053	0.11***	0.13***	-0.14***	0.012	-0.087***	0.087***
	[0.03]	[0.03]	[0.03]	[0.02]	[0.03]	[0.02]	[0.03]	[0.03]
S/W	0.51***	-0.37***	-0.14	-0.038	-0.19*	0.23***	-1.27***	1.27***
	[0.1]	[0.1]	[0.1]	[0.10]	[0.1]	[0.08]	[0.1]	[0.1]
K * RSH	-0.034***	-0.025**	0.059***	-0.028***	0.0046	0.024***	0.037***	-0.037***
	[0.009]	[0.01]	[0.01]	[0.009]	[0.010]	[0.007]	[0.010]	[0.010]
ICT * RSH	0.15***	0.014	-0.17***	-0.19***	0.20***	-0.0044	0.20***	-0.20***
	[0.05]	[0.06]	[0.06]	[0.05]	[0.05]	[0.04]	[0.05]	[0.05]
S/W * RSH	-0.16	-0.19	0.35*	-0.29*	0.74***	-0.44***	2.15***	-2.15***
	[0.2]	[0.2]	[0.2]	[0.2]	[0.2]	[0.1]	[0.2]	[0.2]
Obs		7001			7001		7001	
R^2	0.672	0.552	0.820	0.695	0.541	0.717	0.483	0.483
Hansen J statistic		2447.4			849.3		762.7	
Instruments	First and second lags of instrumented variables							

Panel B: Absolute labor demand 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
ln Y	0.56*	0.051	0.21	0.41	0.16	0.031	0.22	0.080
	[0.3]	[0.2]	[0.2]	[0.3]	[0.3]	[0.2]	[0.3]	[0.2]
K	-0.11	-0.071	-0.045	-0.055	-0.046	-0.054	-0.093	0.074
	[0.07]	[0.05]	[0.05]	[0.07]	[0.07]	[0.07]	[0.07]	[0.07]
ICT	-0.039	0.81***	1.71***	1.31***	0.53*	0.87***	0.71**	1.42***
	[0.4]	[0.2]	[0.3]	[0.3]	[0.3]	[0.3]	[0.3]	[0.3]
S/W	5.07***	2.52***	0.16	3.64***	3.88***	5.75***	1.88**	7.93***
	[1.2]	[0.7]	[0.9]	[0.9]	[0.8]	[0.9]	[0.8]	[0.8]
K * RSH	0.37	0.10	0.15	0.20	0.12	0.098	0.23	-0.12
	[0.3]	[0.2]	[0.2]	[0.3]	[0.2]	[0.2]	[0.2]	[0.2]
ICT * RSH	0.71	-0.54	-1.80***	-1.23***	0.23	-0.27	-0.091	-1.27***
	[0.6]	[0.4]	[0.5]	[0.4]	[0.4]	[0.5]	[0.4]	[0.4]
S/W * RSH	-7.78***	-7.09***	-3.38**	-8.65***	-6.73***	-10.1***	-4.14***	-13.9***
	[2.2]	[1.3]	[1.7]	[1.7]	[1.4]	[1.6]	[1.4]	[1.5]
Obs	7001	7001	7001	7001	7001	7001	7001	7001
R^2	0.722	0.671	0.773	0.484	0.457	0.430	0.267	0.444
Instruments	First and second lags of instrumented variables							

Notes: Iterated Three-Stages Least Squares (I3SLS) with asymptotic standard errors in square brackets in Panel A. Two-Stages Least Squares (2SLS) with robust standard errors in Panel B. 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 Table C4. Asterisks denote significance at 1% (***), 5% (**), and 10% (*).

We can also discern soe more nuanced results. Among these, the bias of software in favor of high-skill and against medium-skill workers appears to be independent of how routine-intensive an industry is. This suggests that software may complement skilled labor more than it may substitute routine tasks. All types of capital tend to be more biased against young workers in more routine-intensive industries, likely reflecting the fact that workers at the beginning of their career tend to be assigned more routine tasks. Last, the complementarity between machines and women is weaker in more routine-intensive industries. One interpretation is that women are exiting routine occupations at a faster rate than men, and are transitioning toward non-routine cognitive tasks of which the complementarity with capital goods is stronger. Consistent with this view, Acemoglu and Autor (2011) show that while employment in middle-wage jobs has fallen more among females than males, this largely offset by women's employment rising in professional, managerial and technical occupations.

5.2 Industrial Robots and Labor Demand: 1996–2005

We now examine an alternative identification strategy which may help us isolate the effect of industrial robots from other forms of capital. There is a growing interest in understanding how automation affects the labor market, but one of the main challenges faced by the literature has been measurement. Several influential papers have used data from the International Federation of Robotics:Graetz and Michaels (2018) were among the first to use this source to build measures of robot density across countries, industries and time. However, once matched with the EU KLEMS data, robot density is available for only 14 industries starting in 1993. To have a sense of which type of capital is more likely to capture automation, we have computed the correlations between the percentage change in robot intensity over 1993–2007 averaged by country reported in Graetz and Michaels (2018), and the percentage changes in the ratios of the different stocks of capital to industrial value added over 1982–2005 averaged by country. Somewhat expectedly, this exercise shows that robot intensity is highly correlated with non-ICT capital and software. Nonetheless, we proceed to identify whether robotization has had separate effects on wage bill shares and employment.

To overcome data limitations, we propose a novel approach that complements the analysis in Graetz and Michaels (2018). First, we use the changes in import of industrial robots by country (from COMTRADE, available from 1996) as a proxy for supply shocks.[31] To

[31] Acemoglu and Restrepo (2018) also use data on imports of robots to measure the adoption of automation

the extent that these changes are driven by exogenous shocks, such as global technological progress, they will be orthogonal to idiosyncratic shocks to any single industry in an individual country. Second, we capture the exposure of industries to robotization using the routine-intensity index, RSH, which is meant to capture predetermined technological characteristics. Then, we identify the effects of robots at the country-industry level by interacting robot imports with RSH. This yields a "difference-in-difference" specification in which the effect of robot adoption is identified by the differential impact of supply shocks across industries that differ in their exposure to automation.

While not entirely immune to endogeneity concerns, this identification strategy has the advantage of allowing us to keep all the country-year and country-industry fixed effects. Moreover, to further alleviate simultaneity bias concerns, we still use the first and second lags as instruments for all the explanatory variables, including the interaction term between robot imports and the routine-intensity index.

Before presenting the results with the proxy for robot adoption, we re-estimate the baseline model (Table 5) on the restricted sample starting in 1996, the year in which data on robot imports became available. In addition to allowing us to directly compare the coefficient estimates from including a proxy for robots to our baseline approach, this exercise is interesting in its own right since 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 market effects of technology may have changed before and after computer-related technologies became more widespread.

The results are presented in Table 9. Looking at Panel A, one striking result is that the polarizing effect of ICT on the relative demand for skill seems to be entirely driven by software, which is also biased against old workers. This is possibly related to the fact that investment in software outpaced investment in hardware from the 1990s and onward, at least in the U.S. (e.g. Aum et al., 2018). To the extent that investment in software is a good proxy for innovation during this latter period, these results are also consistent with Aubert et al. (2006) who find that the wage bill share of older workers is lower in more innovative firms. Panel B also confirms the negative effects of software on the employment levels of medium- and low-skill workers. Only non-ICT capital is still complementary to females, suggesting

technologies across countries.

Table 9: Capital inputs and labor demand (1996–2005)

Panel A: Relative labor demand by skill, by age, and by gender								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. var: Wsh	HS	MS	LS	Y	P	O	M	F
ln Y	-0.017	-0.051***	0.068***	0.0064	-0.0065	0.00014	-0.0031	0.0031
	[0.01]	[0.01]	[0.009]	[0.008]	[0.01]	[0.008]	[0.007]	[0.007]
K	-0.044***	0.040***	0.0042	-0.0058*	0.0056	0.00021	-0.0065**	0.0065**
	[0.005]	[0.006]	[0.003]	[0.003]	[0.005]	[0.003]	[0.003]	[0.003]
ICT	-0.010	-0.0029	0.013	0.011	-0.028**	0.017**	0.0030	-0.0030
	[0.01]	[0.01]	[0.008]	[0.007]	[0.01]	[0.008]	[0.007]	[0.007]
S/W	0.49***	-0.57***	0.087**	-0.024	0.16***	-0.14***	0.035	-0.035
	[0.06]	[0.06]	[0.04]	[0.03]	[0.05]	[0.04]	[0.03]	[0.03]
Obs		2911			2911		2911	
R^2	0.541	0.363	0.747	0.626	0.433	0.743	0.498	0.498
Hansen J statistic		7509.4			997.9		759.2	
Instruments	First and second lags of instrumented variables							
Panel B: Absolute labor demand 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
ln Y	0.51***	0.65***	0.79***	0.87***	0.76***	0.84***	0.77***	0.76***
	[0.1]	[0.1]	[0.1]	[0.1]	[0.09]	[0.1]	[0.1]	[0.08]
K	0.0099	0.100	0.11	0.066	0.051	0.043	0.047	0.046
	[0.08]	[0.06]	[0.08]	[0.08]	[0.05]	[0.04]	[0.06]	[0.04]
ICT	-0.17*	0.19**	0.42***	0.34***	0.18**	0.21**	0.21**	0.22***
	[0.10]	[0.08]	[0.1]	[0.1]	[0.09]	[0.09]	[0.08]	[0.08]
S/W	1.13***	-0.87**	-1.08**	-0.63	0.29	0.23	0.079	0.099
	[0.4]	[0.4]	[0.5]	[0.4]	[0.3]	[0.4]	[0.3]	[0.3]
Obs	2911	2911	2911	2911	2911	2911	2911	2911
R^2	0.568	0.522	0.672	0.390	0.378	0.650	0.326	0.481
Instruments	First and second lags of instrumented variables							

Notes: Iterated Three-Stages Least Squares (I3SLS) with asymptotic standard errors in square brackets in Panel A. Two-Stages Least Squares (2SLS) with robust standard errors in Panel B. 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 Table C4. Asterisks denote significance at 1% (***), 5% (**), and 10% (*).

that the disproportionate shift of women into more high-tech occupations has waned since the late 1990s.

In Table 10 we add the new proxy for robot adoption to the baseline specification. Panel A shows that the adoption of robots was advantageous for middle-age workers and disadvantageous for older workers, while Panel B shows that it had a negative impact on the employment levels of older workers and men. These results are consistent with the view that industrial robots displace mature workers (e.g. Acemoglu and Restrepo, 2017, 2018), thereby limiting their employment opportunities. They are also consistent with the view that industrial robots replace workers in physical (routine-manual) tasks, which are predominantly performed by medium- to low-skill men. The absence of significant effects on men's wage bill

Table 10: Capital inputs, robots and labor demand (1996–2005)

Panel A: Relative labor demand by skill, by age, and by gender								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. var: Wsh	HS	MS	LS	Y	P	O	M	F
ln Y	-0.0012	-0.023***	0.024***	0.0050	-0.0048	-0.00022	-0.0025	0.0025
	[0.008]	[0.008]	[0.005]	[0.004]	[0.007]	[0.006]	[0.004]	[0.004]
K	-0.028***	0.030***	-0.0026*	-0.0029**	0.0023	0.00065	-0.011***	0.011***
	[0.002]	[0.002]	[0.002]	[0.001]	[0.002]	[0.002]	[0.001]	[0.001]
ICT	-0.022*	-0.013	0.036***	0.0058	-0.023**	0.017*	-0.00091	0.00091
	[0.01]	[0.01]	[0.008]	[0.007]	[0.01]	[0.009]	[0.007]	[0.007]
S/W	0.49***	-0.52***	0.032	0.022	0.15***	-0.17***	0.11***	-0.11***
	[0.06]	[0.06]	[0.04]	[0.03]	[0.06]	[0.05]	[0.03]	[0.03]
robots * RSH	0.0025	0.0068	-0.0093	0.0029	0.027**	-0.030***	-0.0059	0.0059
	[0.01]	[0.01]	[0.008]	[0.007]	[0.01]	[0.01]	[0.007]	[0.007]
Obs		2297			2297		2297	
R^2	0.465	0.353	0.696	0.551	0.219	0.440	0.428	0.428
Hansen J statistic		4376.9			506.6		2780	
Instruments	First and second lags of instrumented variables							

Panel B: Absolute labor demand 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
ln Y	0.44***	0.44***	0.49***	0.57***	0.52***	0.53***	0.52***	0.56***
	[0.06]	[0.05]	[0.06]	[0.06]	[0.05]	[0.06]	[0.05]	[0.06]
K	-0.021	0.029**	0.013	0.0066	0.0019	0.0088	-0.00035	0.026
	[0.02]	[0.01]	[0.02]	[0.02]	[0.01]	[0.01]	[0.01]	[0.02]
ICT	-0.17	0.25***	0.47***	0.36***	0.27***	0.31***	0.28***	0.25***
	[0.1]	[0.06]	[0.08]	[0.07]	[0.06]	[0.09]	[0.06]	[0.07]
S/W	1.52***	-0.68***	-0.70*	-0.40	0.24	-0.43	0.051	-0.13
	[0.5]	[0.3]	[0.4]	[0.4]	[0.3]	[0.4]	[0.3]	[0.3]
robots * RHS	0.073	-0.064	0.016	-0.068	-0.085	-0.27**	-0.13**	-0.11
	[0.3]	[0.06]	[0.1]	[0.09]	[0.06]	[0.1]	[0.06]	[0.07]
Obs	2297	2297	2297	2297	2297	2297	2297	2297
R^2	0.423	0.461	0.679	0.388	0.263	0.094	0.073	0.317
Instruments	First and second lags of instrumented variables							

Notes: Iterated Three-Stages Least Squares (I3SLS) with asymptotic standard errors in square brackets in Panel A. Two-Stages Least Squares (2SLS) with robust standard errors in Panel B. 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 Table C4. Asterisks denote significance at 1% (***), 5% (**), and 10% (*).

shares may suggest that such male workers who earn lower wages were partly replaced by better-paid male workers.

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

The sample used so far is long enough to capture several technological innovations which may have had important effects on labor market outcomes. But does it contain useful lessons for the future? To address this question, we now extend the analysis to the period 2008–2015. Unfortunately, this comes at a cost. For the variables of interest, the coverage of countries

Table 11: Capital inputs and labor demand (2008–2015)

Panel A: Relative labor demand by skill, by age, and by gender								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. var: Wsh	HS	MS	LS	Y	P	O	M	F
ln Y	0.32*	-0.68**	0.36**	-0.26*	-0.031	0.29*	-0.017	0.017
	[0.2]	[0.3]	[0.2]	[0.1]	[0.1]	[0.2]	[0.10]	[0.10]
K	0.047**	-0.067*	0.020	-0.031*	0.011	0.021	-0.0090	0.0090
	[0.02]	[0.04]	[0.02]	[0.02]	[0.02]	[0.02]	[0.01]	[0.01]
ICT	0.37*	-0.45	0.075	-0.14	0.11	0.022	-0.19*	0.19*
	[0.2]	[0.3]	[0.2]	[0.2]	[0.1]	[0.2]	[0.1]	[0.1]
S/W	1.14**	-2.14**	1.00**	-0.38	0.24	0.14	-0.43	0.43
	[0.6]	[0.9]	[0.5]	[0.4]	[0.4]	[0.5]	[0.3]	[0.3]
Obs		707			707		707	
R^2	0.365	-0.752	0.438	-0.224	0.451	0.244	0.198	0.198
Hansen J statistic		223.5			198.7		186.2	
Instruments	First and second lags of instrumented variables							

Panel B: Absolute labor demand 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
ln Y	1.02	-1.04	-0.64	-1.81	0.45	1.60	-0.40	0.44
	[0.9]	[0.8]	[0.8]	[1.6]	[0.6]	[1.0]	[0.8]	[0.6]
K	0.0058	-0.22*	-0.16	-0.37	-0.12	-0.033	-0.21*	-0.071
	[0.1]	[0.1]	[0.1]	[0.2]	[0.10]	[0.1]	[0.1]	[0.09]
ICT	0.89	-0.89	-1.45*	-0.45	-0.15	-1.18	-1.00	0.36
	[0.9]	[0.8]	[0.8]	[1.4]	[0.5]	[0.8]	[0.7]	[0.5]
S/W	4.48*	-4.83	-3.79	-3.50	0.99	0.55	-1.97	1.09
	[2.6]	[3.2]	[3.1]	[6.1]	[1.6]	[3.3]	[2.4]	[1.8]
Obs	707	707	707	707	707	707	707	707
R^2	0.669	-0.031	0.604	0.246	0.546	0.065	0.207	0.531
Instruments	First and second lags of instrumented variables							

Notes: Iterated Three-Stages Least Squares (I3SLS) with asymptotic standard errors in square brackets in Panel A. Two-Stages Least Squares (2SLS) with robust standard errors in Panel B. 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 Table C4. Asterisks denote significance at 1% (***), 5% (**), and 10% (*).

and industries in EU KLEMS becomes much more limited after 2008. Specifically, the number of industries falls to 13 (from 30) and the number of countries to 7 (from 10). With these limitations in mind, we now estimate our baseline specifications on the more recent, albeit restricted, sample 2008–2015. The exact coverage of industries and countries is listed in the Appendix (Table A12), which also includes descriptive statistics.

Some of the trends found during the baseline sample period are still present. In particular, the fractions of ICT and software in industrial production, and the wage bill and employment shares of high-skill and older workers increase even further over this period. However, the closing of the gender gap ceased or even reversed after 2008 (Appendix Tables A13-A14).

Table 11 displays the results of the baseline model, in which we include traditional capital, ICT net of software, and software as independent variables, on the post-2008 sample.[32] Although many estimates are insignificant, which could be due to the smaller sample size (both because of the data limitations, and shorter time span), the patterns are broadly consistent with the evidence so far. Starting with Panel A, industries where software grew faster experienced polarization in their demand for skill, and all types of capital are found to complement high-skill workers. There is some evidence of non-ICT capital being biased against young workers and ICT capital being complementary to females. Panel B shows that medium- and low-skill workers, and males may suffer from job losses in industries where capital accumulation is faster. In sum, the analysis from the post-crisis period confirms that the categories most vulnerable to the increasing use of machines coincide with workers that tend to be specialized in routine tasks (medium-skill workers), and especially in routine-manual occupations (low-skill and male 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 steadily, and are permeating and taking over parts of the production process previously performed by humans. The scale of the phenomenon is such to justify the fear that machines may render certain types of workers redundant. In such a scenario, it is of utmost importance to identify which worker characteristics have been in high demand and subsequently, which segments of the population have instead been more vulnerable.

In this paper, we have 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 or gender. Our main analysis uses high-quality, comparable data for 10 advanced countries and 30 industries, spanning roughly their entire economies, from 1982 to 2005, as well as a more restricted sample of countries and industries from 2008 to 2015. There is some evidence that investment in the most advanced types of capital inputs, such as software and industrial robots, was accompanied by employment contractions for low- and

[32]Appendix Table C3 shows results from including only total capital (all categories aggregated at the industrial level) using the new sample, but most of the coefficient estimates are statistically insignificant.

middle-educated workers, and men. In more routine-intensive industries, more software seems to have reduced employment regardless of workers' education, age or gender. Our findings confirm previous studies showing that new technologies might have polarized the demand for skill during the 1980s and 1990s, and suggest that this process continued into more recent years.

But while these results may raise some concerns, it is important to bear in mind that our empirical strategy cannot detect whether employment losses in some industries are compensated by employment gains in other industries (Autor and Salomons, 2017). Moreover, tasks performed by humans are also changing in repsonse to the rise of machines. We find strong evidence that new technologies created more opportunities for women, possibly by lowering the demand for physically demanding skills. Women have also moved on to expanding industries and less routine-intensive industries at a faster rate than men, indicating that they were able to adapt and acquire new skills that were either impervious to, or even complementary with, machines.[33]

So overall, we remain cautiously optimistic that humans are not in a direct confrontation with machines. While new technologies do seem to substitute certain groups of workers that focus on particular types of tasks, they also complement large segments of the labor force performing other types of tasks. Evidence shows that at least some subgroups of workers have been able to adapt to the changing environment, likely by changing the types of tasks they perform and acquiring the required skills. By studying this process, we may be able to design and implement policies that can guide other groups through a faster and smoother transition as well, and avoid an employment "race" against machines.

[33] American women have transitioned from working primarily in administrative and clerical occupations toward professional, managerial and technical occupations (Acemoglu and Autor, 2011).

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Appendix

A Additional descriptive statistics

Table A1: Non-ICT, ICT net of Software, and Software capital 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: Non-ICT, ICT net of Software, and Software capital 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: Wage bill shares by skill

Panel A: Averaged by country						
Country	1982 mean			2005 mean		
	HS	MS	LS	HS	MS	LS
Australia	0.093	0.426	0.481	0.235	0.398	0.367
Austria	0.085	0.608	0.307	0.148	0.687	0.165
Denmark	0.062	0.534	0.409	0.103	0.678	0.219
Finland	0.271	0.301	0.428	0.419	0.414	0.168
Italy	0.049	0.886	0.065	0.096	0.900	0.004
Japan	0.195	0.509	0.297	0.320	0.598	0.082
Netherlands	0.080	0.780	0.140	0.168	0.792	0.040
Spain	0.130	0.109	0.761	0.262	0.310	0.428
United Kingdom	0.105	0.555	0.340	0.259	0.657	0.085
United States	0.301	0.561	0.138	0.428	0.510	0.062
Panel B: Averaged by industry						
NACE Rev. 1.1	1982 mean			2005 mean		
	HS	MS	LS	HS	MS	LS
15T16	0.067	0.507	0.427	0.157	0.631	0.212
17T19	0.056	0.484	0.464	0.145	0.630	0.225
20	0.076	0.500	0.430	0.177	0.638	0.200
21T22	0.104	0.544	0.352	0.207	0.634	0.159
23	0.126	0.551	0.330	0.227	0.620	0.152
24	0.135	0.518	0.347	0.272	0.577	0.150
25	0.094	0.522	0.392	0.188	0.632	0.180
26	0.080	0.504	0.416	0.179	0.628	0.193
27T28	0.080	0.531	0.388	0.176	0.646	0.179
29	0.093	0.585	0.322	0.213	0.646	0.141
30T33	0.120	0.573	0.307	0.265	0.607	0.128
34T35	0.109	0.572	0.328	0.218	0.634	0.148
36T37	0.084	0.508	0.415	0.176	0.622	0.203
50	0.073	0.593	0.341	0.138	0.684	0.178
51	0.112	0.559	0.329	0.206	0.629	0.164
52	0.086	0.576	0.338	0.165	0.657	0.178
60T63	0.061	0.539	0.401	0.123	0.665	0.212
64	0.080	0.599	0.325	0.247	0.607	0.146
70	0.257	0.514	0.229	0.391	0.514	0.095
71T74	0.288	0.503	0.209	0.482	0.429	0.089
ATB	0.064	0.411	0.524	0.139	0.582	0.279
C	0.109	0.526	0.370	0.205	0.624	0.171
E	0.118	0.598	0.284	0.232	0.656	0.112
F	0.074	0.545	0.381	0.111	0.693	0.196
H	0.062	0.535	0.402	0.138	0.651	0.211
J	0.207	0.609	0.184	0.422	0.511	0.067
L	0.202	0.573	0.226	0.376	0.555	0.069
M	0.481	0.396	0.124	0.622	0.335	0.044
N	0.259	0.540	0.201	0.398	0.532	0.070
O	0.179	0.537	0.285	0.303	0.572	0.125

Notes: HS: tertiary degree or above; MS: upper-secondary degree or equivalent; LS: the rest. In Panel A, wage bill 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, wage bill shares are averaged across countries within each industry. No country weights are used.
Source: Authors' calculations based on EU KLEMS.

Table A4: Employment shares 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
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 A5: Wage bill shares by age

Panel A: Averaged by country						
Country	1982 mean			2005 mean		
	Y	P	O	Y	P	O
Australia	0.310	0.463	0.226	0.212	0.510	0.278
Austria	0.286	0.490	0.225	0.186	0.584	0.230
Denmark	0.264	0.524	0.207	0.165	0.553	0.281
Finland	0.255	0.564	0.181	0.137	0.543	0.321
Italy	0.289	0.632	0.078	0.238	0.709	0.053
Japan	0.210	0.570	0.220	0.155	0.508	0.337
Netherlands	0.265	0.531	0.204	0.159	0.570	0.270
Spain	0.228	0.482	0.290	0.174	0.558	0.267
United Kingdom	0.329	0.511	0.160	0.185	0.562	0.253
United States	0.387	0.446	0.167	0.242	0.560	0.197

Panel B: Averaged by industry						
NACE Rev. 1.1	1982 mean			2005 mean		
	Y	P	O	Y	P	O
15T16	0.283	0.519	0.197	0.185	0.579	0.236
17T19	0.319	0.490	0.189	0.176	0.574	0.251
20	0.284	0.510	0.206	0.177	0.564	0.258
21T22	0.268	0.537	0.196	0.171	0.578	0.251
23	0.260	0.548	0.192	0.137	0.618	0.246
24	0.253	0.553	0.194	0.154	0.601	0.245
25	0.274	0.544	0.182	0.180	0.575	0.245
26	0.261	0.538	0.201	0.159	0.583	0.258
27T28	0.277	0.532	0.191	0.172	0.577	0.251
29	0.281	0.544	0.175	0.166	0.594	0.240
30T33	0.284	0.552	0.164	0.176	0.606	0.219
34T35	0.259	0.568	0.168	0.160	0.601	0.239
36T37	0.302	0.515	0.182	0.195	0.572	0.233
50	0.342	0.492	0.158	0.229	0.561	0.210
51	0.292	0.528	0.180	0.213	0.568	0.219
52	0.335	0.498	0.168	0.270	0.527	0.203
60T63	0.237	0.552	0.211	0.157	0.595	0.248
64	0.246	0.555	0.198	0.172	0.618	0.210
70	0.266	0.537	0.196	0.195	0.547	0.258
71T74	0.294	0.542	0.164	0.205	0.584	0.211
ATB	0.251	0.467	0.282	0.171	0.513	0.316
C	0.226	0.574	0.205	0.126	0.595	0.280
E	0.199	0.567	0.234	0.118	0.599	0.283
F	0.274	0.535	0.190	0.215	0.553	0.232
H	0.349	0.485	0.166	0.288	0.523	0.189
J	0.298	0.545	0.158	0.150	0.637	0.213
L	0.265	0.524	0.211	0.143	0.586	0.272
M	0.197	0.589	0.214	0.103	0.580	0.317
N	0.323	0.512	0.165	0.152	0.586	0.262
O	0.271	0.512	0.217	0.200	0.545	0.256

Notes: Y: 15–29 years old; P: 30–49 years old; O: 50+ years old. In Panel A, wage bill 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, wage bill shares are averaged across countries within each industry. No country weights are used.
Source: Authors' calculations based on EU KLEMS.

Table A6: Employment shares 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
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 A7: Wage bill shares by gender

Panel A: Averaged by country				
Country	1982 mean		2005 mean	
	M	F	M	F
Australia	0.770	0.230	0.683	0.317
Austria	0.617	0.383	0.627	0.373
Denmark	0.641	0.374	0.604	0.397
Finland	0.645	0.355	0.637	0.363
Italy	0.687	0.313	0.563	0.437
Japan	0.787	0.213	0.757	0.243
Netherlands	0.805	0.195	0.710	0.290
Spain	0.801	0.199	0.714	0.286
United Kingdom	0.764	0.236	0.700	0.300
United States	0.715	0.285	0.686	0.314
Panel B: Averaged by industry				
NACE Rev. 1.1	1982 mean		2005 mean	
	M	F	M	F
15T16	0.720	0.280	0.707	0.293
17T19	0.575	0.407	0.610	0.390
20	0.850	0.156	0.821	0.180
21T22	0.821	0.179	0.766	0.234
23	0.875	0.132	0.828	0.172
24	0.825	0.175	0.762	0.238
25	0.820	0.173	0.769	0.231
26	0.845	0.155	0.811	0.189
27T28	0.858	0.142	0.820	0.180
29	0.868	0.132	0.839	0.161
30T33	0.804	0.196	0.785	0.215
34T35	0.883	0.126	0.848	0.152
36T37	0.773	0.232	0.767	0.233
50	0.766	0.248	0.706	0.294
51	0.713	0.287	0.669	0.331
52	0.643	0.357	0.584	0.416
60T63	0.885	0.115	0.810	0.190
64	0.760	0.236	0.716	0.284
70	0.699	0.301	0.632	0.368
71T74	0.702	0.298	0.679	0.321
ATB	0.800	0.200	0.731	0.269
C	0.913	0.087	0.864	0.136
E	0.903	0.097	0.831	0.169
F	0.943	0.057	0.924	0.076
H	0.623	0.377	0.580	0.420
J	0.644	0.356	0.610	0.390
L	0.764	0.236	0.625	0.375
M	0.537	0.463	0.417	0.583
N	0.393	0.607	0.322	0.678
O	0.609	0.391	0.570	0.430

Notes: M: male; F: female. In Panel A, wage bill 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, wage bill shares are averaged across countries within each industry. No country weights are used.
Source: Authors' calculations based on EU KLEMS.

Table A8: Employment shares by gender

Panel A: Averaged by country

Country	1982 mean M	1982 mean F	2005 mean M	2005 mean 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

Panel B: Averaged by industry

NACE Rev. 1.1	1982 mean M	1982 mean F	2005 mean M	2005 mean 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 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: Wage bill 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	0.184	0.610	0.207	0.330	0.517	0.153	0.223	0.516	0.261
2005	0.136	0.626	0.238	0.202	0.573	0.225	0.171	0.445	0.384

	HS		MS		LS	
by Gender	M	F	M	F	M	F
1982	0.782	0.218	0.719	0.281	0.714	0.286
2005	0.647	0.353	0.646	0.354	0.690	0.310

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 A11: U.S. employment shares

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

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: US IPUMS Census.

Table A12: 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 Defence; 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 A13: Non-ICT, ICT net of Software, and Software capital by country and by industry, 2008–2015

Panel A: Averaged by country

Country	2008 mean			2015 mean		
	K	ICT	S/W	K	ICT	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
NACE Rev. 1.1	2008 mean			2015 mean		
	K	ICT	S/W	K	ICT	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 A14: **Employment and wage bill shares, 2008–2015**

	2008			2015		
by Educ	HS	MS	LS	HS	MS	LS
Employment shares	0.247	0.452	0.301	0.309	0.440	0.251
Wage bill shares	0.315	0.434	0.251	0.357	0.446	0.197
by Age	Y	P	O	Y	P	O
Employment shares	0.228	0.517	0.255	0.199	0.493	0.308
Wage bill shares	0.168	0.552	0.281	0.154	0.526	0.320
by Gender	M		F	M		F
Employment shares	0.576		0.424	0.582		0.418
Wage bill shares	0.615		0.385	0.617		0.383

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 ratios 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 Econometric model and estimation strategy

B.1 Econometric model

Assume that a representative firm within in each industry, and that labor supply is perfectly inelastic. The representative firm hires different types of workers, and invests in three types of capital: non-ICT, ICT net of software, and software. Hence, the three types of capital can be viewed as labor demand shifters that induce an increase or a decrease in the *relative* demands for workers who differ either by education, age or gender.

By treating the different types of capital as quasi-fixed factors (Berman et al., 1994), we consider the cost function of the representative firm to be of the short-run form:

$$C_{SR}(W, Y, K, ICT, S/W) = \{\min W \cdot E' \quad s.t. \quad Y = f(E, K', \mathrm{ICT}', S/W')\} \tag{B1}$$

The short-run cost of the firm (C_{SR}) only includes the total wage bill. W and E are vectors of hourly wages and total hours worked, respectively, of workers who differ either by education, age or gender. Y stands for output, while K, ICT and S/W stand for non-ICT, ICT net of software, and software capital, respectively.

The cost function is also assumed to be translog (Berman et al., 1994).[B1] Total differentiation of (B1) with respect to wages yields a system of wage bill share equations for each type of worker:

$$\mathrm{Wsh}^j_{ict} = \sum_{j \in G} \beta^j_w * \ln W^j_{ict} + \beta^j_y \cdot \ln Y_{ict} + \boldsymbol{\beta}^j_k \cdot \mathbf{K}_{ict} + \epsilon^j_{ict}, \tag{B2}$$

The dependent variable, Wsh^j_{cit}, is the wage bill share of worker group $j \in G$, where $G = \{\mathrm{HS}, \mathrm{MS}, \mathrm{LS}\}$ or $\{\mathrm{Y}, \mathrm{P}, \mathrm{O}\}$ or $\{\mathrm{M}, \mathrm{F}\}$, in industry i in country c at year t. W^j is the relative wage of worker group j, which enters the model in logs. Y is real value-added, capturing industry scale, and also enters the model in logs. The main explanatory variables are the different types of capital and are included in the vector K. In particular, this vector comprises the ratios of real non-ICT, ICT net of software and software capital stocks to real value-added in industry i. We use the actual ratio rather than logs, because the ratios of ICT and software to value-added for some country-industry pairs are very close to zero in early years of the sample, leading to extremely negative values (Michaels et al., 2014). The coefficient estimates of vector $\boldsymbol{\beta}^j_k$ capture the change in the *relative* demand for worker group j induced by each types of capital. Any unobserved factors that affect the wage bill shares are absorbed into the error term, ϵ^j.

Accounting for unobserved time-varying country characteristics, such as relative wages and changes in the aggregate supply of production factors, as well as industrial heterogeneity

[B1] The translog form is preferred to other functional forms such as the CES, as it imposes no *a priori* restrictions on the substitutability between inputs.

within each country, (B2) becomes:

$$\text{Wsh}^j_{ict} = \alpha_{ct} + \alpha_{ic} + \beta^j_y \cdot \ln Y_{ict} + \boldsymbol{\beta}^j_k \cdot \mathbf{K}_{ict} + \epsilon^j_{ict}, \tag{B3}$$

where α_{ct} is a country-year fixed effect and α_{ic} a country-industry fixed effect.[B2]

Linear price homogeneity and symmetry imply that the parameters of (B3) are subject to the following constraints:

$$\sum_j \beta^j_Y = \sum_j \beta^j_K = 0. \tag{B4}$$

B.2 Estimation strategy

The cross-equation constraints in (B4) and the fact that the regression would use an identical set of explanatory variables for groups within the same industry imply that the error terms are likely to be correlated (Berndt, 1991). In this case, simultaneous estimation of the equations produces more efficient coefficient estimates than estimating each equation individually. Assuming that all explanatory variables are exogenous, the system is estimated by Iterated Seemingly Unrelated Regressions (ISUR). The iteration of this method allows us to obtain estimates that are insensitive to the equation dropped from the system.[B3]

When $j \in \{\text{HS}, \text{MS}, \text{LS}\}$, $\{\text{Y}, \text{P}, \text{O}\}$ or $\{\text{M}, \text{F}\}$, we choose to drop the equation corresponding to low-skill workers (LS), the oldest workers (50+), and female workers (F), respectively. Using the constraints in (B4), we then estimate the parameters that are not directly estimated. Their asymptotic standard errors are obtained by the delta method. All equations are weighted by the share of each industry's employment in country-wide employment in 1982, the first year of the benchmark sample (Michaels et al., 2014).

For the baseline results, we treat all explanatory variables as endogenous and estimate the system of equations by Iterated Three-Stage Least Squares (I3SLS). Each explanatory variable is instrumented with its first and second lags. Missing values for the first- and second-lagged instrumented variables are replaced with zeros (Arellano and Bond, 1991).

In order to study the effects of the same types of capital on the *absolute* demand for workers of different groups, we estimate a version of equation (B3) in which the dependent variable is the logged employment level of worker group j, ln E^j_{cit}, where E is measured in hours of work:

$$\log \text{E}^j_{ict} = \alpha_{ct} + \alpha_{ic} + \beta^j_y \cdot \ln Y_{ict} + \boldsymbol{\beta}^j_k \cdot \mathbf{K}_{ict} + \epsilon^j_{ict}, \tag{B5}$$

[B2] We incorporate country-industry fixed effects by deviating all variables from their country-industry means.

[B3] As the wage bill shares on the left-hand side of the system add up to 1, the variance-covariance matrix is singular and thus, the estimation of the system is not feasible unless one equation is dropped (Berndt and Wood, 1975; Hijzen et al., 2005).

For the baseline results, equation (B5) is estimated by Two-Stage Least Squares (2SLS), with all explanatory variables treated as endogenous and instrumented with their first and second lags. When all explanatory variables are treated as exogenous, equation (B5) is estimated by Ordinary Least Squares (OLS). Weighted estimations are implemented using the same weights as in the estimations of wage bill share equations.

C Additional empirical results

Table C1: Capital inputs and labor demand, biannual frequency (1983–2005)

Panel A: Relative labor demand by skill, by age, and by gender								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. var: Wsh	HS	MS	LS	Y	P	O	M	F
ln Y	0.041***	-0.12***	0.078***	-0.0084	0.018*	-0.0094	-0.031***	0.031***
	[0.009]	[0.01]	[0.01]	[0.008]	[0.009]	[0.007]	[0.010]	[0.010]
K	0.0035	-0.019***	0.015***	-0.0046	0.0039	0.00065	-0.023***	0.023***
	[0.005]	[0.006]	[0.005]	[0.004]	[0.005]	[0.003]	[0.005]	[0.005]
ICT	0.012	-0.015	0.0032	0.037***	-0.046***	0.0086	0.019	-0.019
	[0.01]	[0.02]	[0.02]	[0.01]	[0.02]	[0.01]	[0.02]	[0.02]
S/W	0.44***	-0.52***	0.076	-0.21***	0.24***	-0.024	-0.067	0.067
	[0.04]	[0.05]	[0.05]	[0.04]	[0.04]	[0.03]	[0.05]	[0.05]
Obs		3500			3500		3500	
R^2	0.664	0.514	0.812	0.689	0.514	0.726	0.412	0.412
Hansen J statistic		1428.0			425.1		729.9	
Instruments	First and second lags of instrumented variables							
Panel B: Absolute labor demand 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
ln Y	0.57***	0.56***	0.70***	0.76***	0.84***	0.86***	0.74***	0.90***
	[0.1]	[0.1]	[0.1]	[0.1]	[0.1]	[0.1]	[0.1]	[0.2]
K	0.064	0.090	0.13*	0.11	0.17*	0.19**	0.12	0.23**
	[0.07]	[0.08]	[0.08]	[0.09]	[0.10]	[0.10]	[0.09]	[0.1]
ICT	0.34	0.17	0.43**	0.45***	0.14	0.17	0.24	0.26
	[0.2]	[0.1]	[0.2]	[0.2]	[0.2]	[0.2]	[0.2]	[0.2]
S/W	0.70	-1.06***	-1.53***	-0.93***	0.65**	0.65	0.0046	0.66*
	[0.5]	[0.3]	[0.4]	[0.3]	[0.3]	[0.4]	[0.3]	[0.4]
Obs	3500	3500	3500	3500	3500	3500	3500	3500
R^2	0.714	0.666	0.770	0.467	0.423	0.429	0.277	0.374
Instruments	First and second lags of instrumented variables							

Notes: Iterated Three-Stages Least Squares (I3SLS) with asymptotic standard errors in square brackets in Panel A. Two-Stages Least Squares (2SLS) with robust standard errors in Panel B. 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 Table C4. Asterisks denote significance at 1% (***), 5% (**), and 10% (*).

Table C2: Capital inputs and labor demand, output excluded

Panel A: Relative labor demand by skill, by age, and by gender								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. var: Wsh	HS	MS	LS	Y	P	O	M	F
K	-0.0043***	0.0065***	-0.0023	-0.0019	0.0019	-0.000048	-0.010***	0.010***
	[0.001]	[0.002]	[0.002]	[0.001]	[0.001]	[0.0010]	[0.001]	[0.001]
ICT	0.042***	-0.11***	0.064***	0.034***	-0.037***	0.0033	-0.0084	0.0084
	[0.008]	[0.01]	[0.009]	[0.007]	[0.008]	[0.006]	[0.008]	[0.008]
S/W	0.40***	-0.42***	0.020	-0.21***	0.22***	-0.0037	-0.052*	0.052*
	[0.03]	[0.04]	[0.03]	[0.03]	[0.03]	[0.02]	[0.03]	[0.03]
Obs		7001			7001		7001	
R^2	0.664	0.540	0.819	0.693	0.536	0.714	0.446	0.446
Hansen J statistic		1463.8			744.8		791.9	
Instruments	First and second lags of instrumented variables							
Panel B: Absolute labor demand 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
K	-0.054***	-0.036**	-0.019	-0.044**	-0.020	-0.015	-0.037*	0.012
	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]
ICT	0.80***	0.65***	1.01***	1.09***	0.82***	0.86***	0.86***	1.00***
	[0.1]	[0.06]	[0.08]	[0.09]	[0.07]	[0.08]	[0.07]	[0.07]
S/W	0.37	-1.49***	-1.94***	-1.53***	0.017	0.070	-0.58***	0.031
	[0.3]	[0.2]	[0.3]	[0.3]	[0.2]	[0.2]	[0.2]	[0.2]
Obs	7001	7001	7001	7001	7001	7001	7001	7001
R^2	0.694	0.655	0.751	0.386	0.403	0.411	0.177	0.378
Instruments	First and second lags of instrumented variables							

Notes: Iterated Three-Stages Least Squares (I3SLS) with asymptotic standard errors in square brackets in Panel A. Two-Stages Least Squares (2SLS) with robust standard errors in Panel B. 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 Table C4. Asterisks denote significance at 1% (***), 5% (**), and 10% (*).

Table C3: Industrial capital and labor demand (2008–2015)

Panel A: Relative labor demand by skill, by age, and by gender								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. var: Wsh	HS	MS	LS	Y	P	O	M	F
ln Y	0.60	-1.05	0.45	-0.23	0.20	0.033	-0.21	0.21
	[0.4]	[0.6]	[0.3]	[0.2]	[0.2]	[0.2]	[0.2]	[0.2]
K (total)	0.057	-0.079	0.022	-0.029	0.019	0.0100	-0.016	0.016
	[0.04]	[0.06]	[0.03]	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]
Obs		707			707		707	
R^2	-0.541	-3.211	0.137	-0.112	0.063	0.569	-0.180	-0.180
Hansen J statistic		233.2			233.1		96.01	
Instruments	First and second lags of instrumented variables							

Panel B: Absolute labor demand 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
ln Y	2.14	-0.94	-0.92	-0.38	0.89	0.63	-0.65	1.56
	[2.0]	[1.2]	[1.3]	[1.9]	[1.1]	[1.0]	[1.2]	[1.4]
K (total)	0.046	-0.21*	-0.17	-0.29	-0.10	-0.076	-0.22*	-0.025
	[0.2]	[0.1]	[0.1]	[0.2]	[0.1]	[0.10]	[0.1]	[0.1]
Obs	707	707	707	707	707	707	707	707
R^2	0.326	0.058	0.545	0.614	0.357	0.554	0.056	0.064
Instruments	First and second lags of instrumented variables							

Notes: Iterated Three-Stages Least Squares (I3SLS) with asymptotic standard errors in square brackets in Panel A. Two-Stages Least Squares (2SLS) with robust standard errors in Panel B. 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 Table C4. Asterisks denote significance at 1% (***), 5% (**), and 10% (*).

Table C4: Description of variables

Variable	Description	Source
Wsh^{HS}	Wage bill share of high-skill workers	EU KLEMS
Wsh^{MS}	Wage bill share of medium-skill workers	EU KLEMS
Wsh^{LS}	Wage bill share of low-skill workers	EU KLEMS
Wsh^{15-29}	Wage bill share of workers aged 15–29	EU KLEMS
Wsh^{30-49}	Wage bill share of workers aged 30–49	EU KLEMS
Wsh^{50+}	Wage bill share of workers aged 50+	EU KLEMS
Wsh^{M}	Wage bill share of male workers	EU KLEMS
Wsh^{F}	Wage bill share of female workers	EU KLEMS
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
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)
robots	Imports of industrial robots (HS 1996 code: 847950) from the "World" normalized with the value of the initial year	UN Comtrade

Notes: Authors' notation.