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DETERMINANTS AND IMPACT OF AUTOMATION
AN ANALYSIS OF ROBOTS' ADOPTION IN OECD COUNTRIES

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Foreword

This report was prepared by the Working Party on Measurement and Analysis of the Digital Economy (MADE). The report analyses the diffusion of robots by industry and their effects on the demand for skills.

This paper was approved and declassified by written procedure by the Committee on Digital Economy Policy on 19 May 2017 and was prepared for publication by the OECD Secretariat.

This report was drafted by Giorgio Presidente from the OECD Secretariat.

This publication is a contribution to the OECD Going Digital project, which aims to provide policymakers with the tools they need to help their economies and societies prosper in an increasingly digital and data-driven world.

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Executive Summary

Dramatic improvements in technology allow automating an increasing number of tasks and occupations. For this reason, there is a widespread concern that new technologies might destroy a large number of jobs and cause "technological unemployment". The threat of displacement is believed to be particularly strong with industrial robots, because they are explicitly designed to perform tasks that would otherwise be performed by humans.

This report sheds light on automation trends and their effect on employment. A better understanding of what robots actually do and to what extent they are used across countries and sectors can help policy makers to design policies aimed at smoothing the transition towards industry 4.0.

The data used in this report reveal that robots are disproportionally in use in advanced economies, which suggests that the issue of automation is particularly relevant for the OECD.

The report finds that different categories of robots are differently correlated to employment in different occupations. In addition, the sign and magnitude of these correlations vary across countries.

On average, robots are found to be associated with a reduction in elementary occupations – those requiring the lowest levels of skills – and an increase of professionals and technicians, high skill professions. For occupations in the middle of the skill distribution the correlation is strong and negative.

In general, therefore, the estimates presented in this report do not support the hypothesis of labour market polarisation, which would imply an increase in both high-skill and low-skill employment. However, some country-specific results – most notably for the United States – can be interpreted as evidence in support of this hypothesis.

Introduction

Continuous improvements in technology have made it possible to automate an increasing number of tasks. For this reason, there is a widespread concern that new technologies might destroy a large number of jobs and cause “technological unemployment”. The threat of displacement is believed to be particularly strong with industrial robots, because they are explicitly designed to perform tasks that would otherwise be performed by humans. The analysis in this paper is meant to shed light on trends of automation as measured by investment in industrial robots, and their effect on employment. A better understanding of what robots actually do and to what extent they are used across countries and sectors can help policy makers to design policies aimed at smoothing the transition towards industry 4.0. The data used in this paper reveal that robots are disproportionally in use in advanced economies, which suggests that the issue of robotisation is particularly relevant for the OECD.

Despite being extensively debated, the impact of robots on the labour market has rarely been subject of empirical analysis. To date, Michael and Graetz (2015) and Acemoglu and Restrepo (2016) are the only notable exception. However, by focusing on highly aggregated measures of labour inputs, the literature has produced mixed results. Indeed, the first authors find a positive impact of robots on productivity, but only marginal effects on hours worked. On the contrary, Acemoglu and Restrepo (2016) do find a negative impact of robots on employment and wages.

Instead of relying on aggregate measures of labour, this paper exploits specific fields of application of industrial robots and links them to employment data by detailed occupation. The methodology adopted by this paper has the advantage of minimising the bias in measuring the potentially disruptive effect of technology on labour. Different categories of robots are found to have heterogeneous impacts on different occupations, and those impacts vary by country. Robots are found on average to be biased against elementary occupations - those requiring the lowest levels of skills – and biased in favour of professional and technicians, high skill professions. For occupations in the middle of the skill distribution the correlation is strong and negative. Thus, while the estimates presented in this study do not support the hypothesis of *polarisation of the labour market* – which would require an increase of both skilled and unskilled employment - at least for the European countries considered in the analysis they do suggest that technology can be biased against mid-skill occupations.

The rest of the paper is organised as follows. Section 2 defines the main characteristics of robots; Section 3 reviews the literature on technology and labour that is most relevant to this paper; Section 4 introduces the data; Sections 5 to 10 describe the data on robots; Sections 11 to 14 present a novel analysis of the impact of industrial robots on employment by detailed occupation; Section 15 concludes.

Characteristics of robots

An industrial robot is defined as an automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which may be either fixed in place or mobile for use in industrial automation applications.[1] Robots are by no means the only form of automation. Technologies such as Computer Numerical Control (CNC) were introduced in the early 1960s and they allowed the automation of machine tools, reducing drastically the need for human operators. But machines tools are designed to perform very specific tasks and even if numerically controlled, they lack in flexibility as compared to robots.

As emphasised by the definition, robots differ from other technologies in that they are *reprogrammable*, *autonomous* and characterised by a high degree of *dexterity*. As such, they are rightly considered labour saving technologies: they can mimic many of the manual operations otherwise performed by humans. Moreover, once instructed through computer code they can perform several different tasks and they can do so autonomously, *i.e.* without the active involvement of a human operator.

These characteristics make robots particularly well-suited to accomplishing manual, routine tasks. These kinds of tasks are widespread in manufacturing industries, which are also the most intensely automated, but also in construction, mining and agriculture. Although featuring a much lower share of total number of robots, the latter sectors feature a non-negligible number of operational robots. The large employment losses experienced by these sectors over the last decades – manufacturing and non – are likely to have contributed to generating concerns about automation.

In addition, as technology evolves, artificial intelligence and machine learning are increasingly embedded in robots. New generations of robots are increasingly autonomous and able to take independent decisions. While early CNC performed tasks by following instructions that were hard-wired through computer code, new generations of robots receive feedback from external inputs, process information, and update the rules they follow. Thus, technological process makes robots able to perform tasks that are increasingly "non-routine".[2] As a consequence, an increasing number of occupations could become prone to automation, even in non-manufacturing sectors, where non-manual, non-routine tasks are somewhat more abundant.

Thus, given their intrinsic characteristics but also the potential for future applications, it is not surprising that among other technologies, robots are seen as particularly threatening for human workers.

Literature review

This is the first paper attempting a systematic assessment of the impact of robots by industrial application on employment by occupation. Descriptive statistics on industrial robots are published annually by the International Federation of Robotics (IFR)[3]. However, such reports have not reached the attention of research institutions and are mainly used for business purposes.

To date, the only research paper exploiting data on robots is Michael and Graetz (2015). The authors focus on the impact of robots by industrial sector on highly aggregated measures of labour inputs. They find a positive impact of robots on productivity, but only marginal effects on hours worked.

Autor, Katz, and Krueger (1998) are one example of study focusing on a specific technology class, *i.e.* computers. They use data on computer adoption to shed light on the skill-bias component of US inequality. However, computers can be considered general purpose technologies and they could *a-priori* complement or substitute human labour, depending on the field of application and the category of labour under scrutiny.

For this reason, after Autor and Dorn (2013), the literature seems to have given up on measuring technology and instead uses an index of "routine task intensity" (RTI). The rationale of using RTI as a proxy for technology can be found in the theory developed by Autor, Levy, and Murnane, (2003). According to the authors, jobs that are rich in routine tasks are those which are most readily automated, as they tend to be easily codified and executed by computer programmes.

Autor, Levy, and Murnane (2003) is also the first paper putting forward the "polarisation hypothesis", stating that mid-skill jobs are inherently easier to automate (because rich in routine tasks), and the authors use it to explain the hollowing-out in the middle of the earning distribution. According to some authors, the pattern is not unique to the United States. These broad findings of the growth of non-routine jobs and the decline of routine work has also been documented for many other OECD countries (*e.g.* Spitz-Oener, 2006; Dustmann *et al.*, 2009; Firpo, Fortin and Lemieux, 2009; Goos, Manning and Salomons, 2009).

But evidence on market polarisation is mixed. Lefter and Sand (2011) argue that the increase in job polarisation in the United States in the 1990s relative to the 1980s is due to a change in the occupational classification that leads to systematic occupational mismatch. When correcting for this problem, their findings show a long-term upward trend in high-skill jobs and a downward trend in some middle-skill jobs, with no major differences between the 1980s and the 1990s.

According to the view put forward by Autor, Levy, and Murnane (2003), despite requiring a substantial amount of post-secondary education, routine abstract occupations, such as tellers and book keepers, are also easy to automate. However, this paper only addresses substitution of routine-manual jobs, as industrial robots are designed to perform manual tasks.[4]

Related, but conceptually different, theories on skill-biased technical change (*e.g.* Acemoglu, 1998) try to explain the contemporaneous increase in the supply of college graduates and their wages during the 1980s. The common theme of these theories is that some technologies such as computers are complementary to educated workers and substitute for less educated ones. This is because sophisticated machinery can replace workers performing "simple tasks", but at the same time they require engineers in order to be set up and operated. These theories predict that technology should increase demand for high skill workers and reduce it for unskilled ones, without having an impact on mid-skill jobs.[5]

Data description

This paper presents and uses a largely unexploited database by the International Federation of Robotics (IFR), which collects information on shipment of industrial robots from almost all existing robot suppliers worldwide.

IFR data are organised in two datasets. The first dataset contains shipment by country and economic sector, from 1993 to 2014. The second dataset covers, over the same time span, shipments by country and robots' field of application, such as "fixing, press-fitting" , "painting", handling materials, *etc.* Data on shipments are used to estimate the stock of operational robots, namely the number of units in use. Details on the construction of the stocks are provided in the Annex.

Data on robots have been matched to 3-digit level occupation data. These are collected by the OECD from national labour force surveys. Employment data are classified according to the latest version of the International Standard Classification of Occupation (ISCO-08). Data on employment and compensation by industry, according to the latest version International Standard Industry Classification (ISIC rev.4) are from the OECD STAN database. Finally, data on the user cost of ICT capital are from the OECD Productivity Database. Further details are provided in the Annex.

Geographical distribution of industrial robots

Over the last two decades, the operational stock of robots has grown considerably. Figure 1 shows the growth in the number of operational robots for several countries over three periods: 1993-2000; 2001-07; and 2008-14. These periods reflect the two peaks of the economy cycle before the dot.com bubble and the subprime crisis.

The average growth from 1993 to 2000 was about 78%. Adoption of industrial robots was still in an early stage in 1993, which explains the strong growth in the operational stock. Growth was even stronger from 2000 to 2007, with a country average of above 80%. Growth continued from 2007 to 2014 but at a slower pace, *i.e.* 38%. The impact of the financial crisis and the exhaustion of economies of scale produced by decreasing returns to capital are likely to have contributed to the observed slowdown.

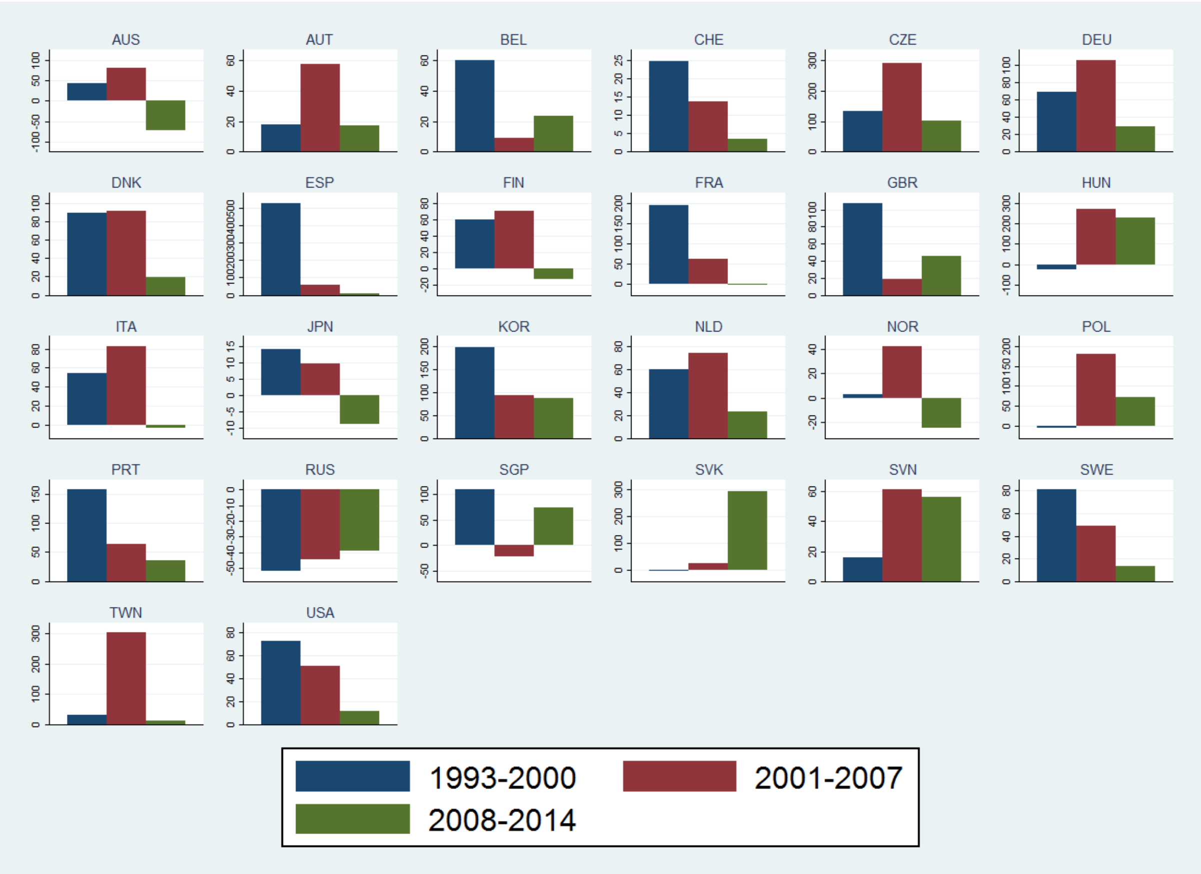
In the first period (1993-2000), Spain increased its stock of operational robots by a factor of five, mainly due to an explosion of automation in the automotive sector. Some East European countries, on the contrary, registered negative growth rates, ranging from -27% in Hungary to -5% in Slovak Republic.

In the second period (2001-07), most countries increased considerably their stock of operational robots. Five countries showed three-digit growth rates: Germany (106%), Poland (180%), Hungary (273%), Czech Republic (291%), and Chinese Taipei (301%). Poland, Hungary and, to a lesser extent, the Slovak Republic "caught up" with automation after negative growth rates in the first period.

The last period (2008 to 2014) is characterised by large cross-country differences. Several advanced economies showed a decrease in the number of operational robots (Norway, -25%; Finland, -12%; Japan, -8.9%; Italy, -3.3%; and France, -1.7%), whereas some countries, particularly Korea and Singapore, registered three-digit growth rates.[6]

Russia is the only country where the number of operational robots decreased over the three periods, possibly due to a decline in industrialisation after the fall of the Soviet Union.

Figure 1. Growth of stock of operational robots by country (1993-2014). Average yearly growth rates (%)



Source: Author's calculations, based on IFR.

Figure 2 shows the number of operational robots in all countries for which data are available. The country with the lowest number of units in 2014 was Lithuania (fewer than 20 units) and the country with the highest number was Japan (250 000 units). By 2014, the last year for which information is available, roughly 750 000 industrial robots were estimated to be operational in OECD countries, constituting more than 80% of the world-stock. Germany, Korea, USA and Japan are the most robotised countries in the OECD region and account together for almost 70% of the total number of operational robots. Robots, therefore, are highly concentrated in advanced economies. Among partner economies, Chinese Taipei and the People’s Republic of China lead in the adoption of robots, with an operational stock of over 19 000 and 86 000 units, respectively.

Figure 2. Stock of operational robots by country (1993-2014)

Source: Author's calculations, based on IFR.

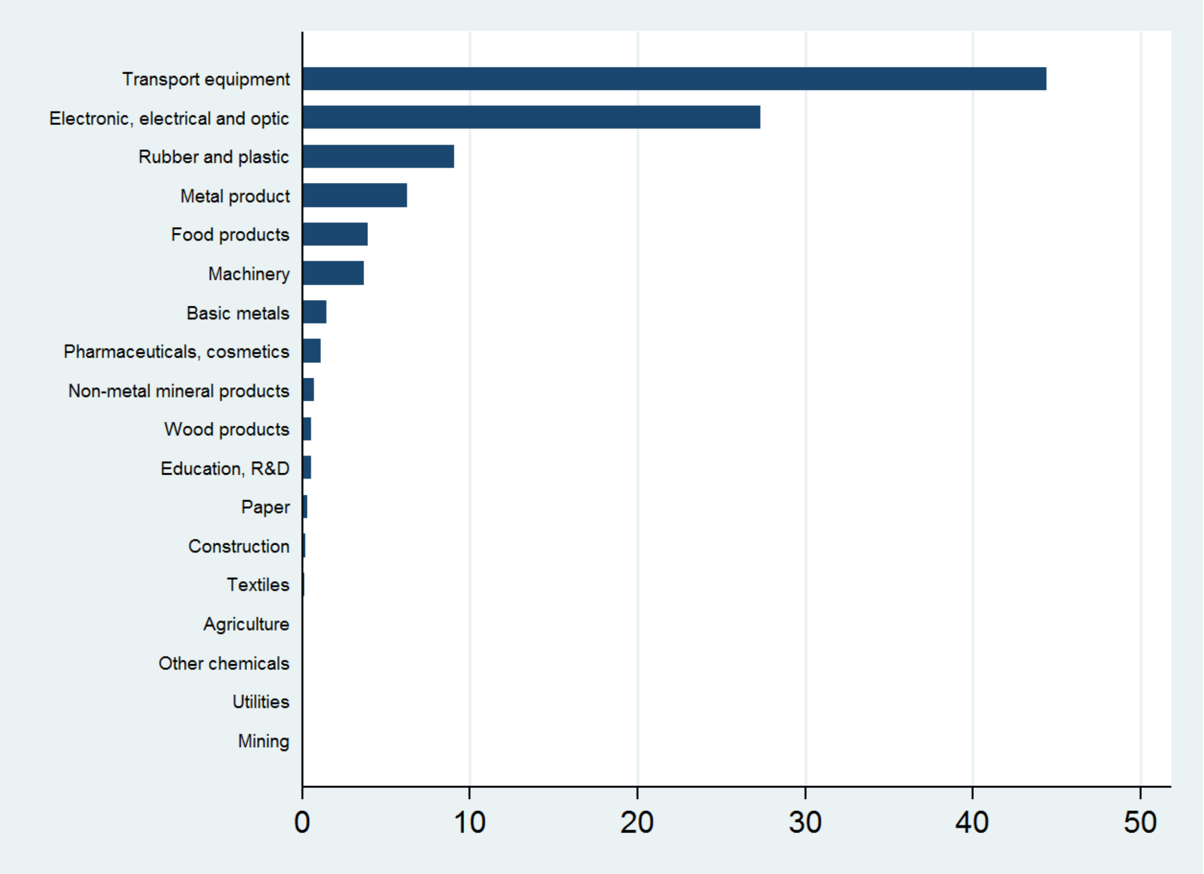
Sectorial distribution of industrial robots

Robots are highly concentrated in a few industrial sectors (Figure 3).[7] Transport equipment leads with almost 45% of the total stock of robots in 2014. Being characterised by large production volumes and relatively standardised products, the automotive sector is historically more prone to automation and accounts for the lion's share of robotisation.

Almost 30% of robots can be found in "Electronic, electrical and optical equipment". While the goods produced in this sector have a high level of technological content, their production is fairly standardised. Large R&D investments and highly skilled labour are needed for the creation of blueprints in the industry but their *reproduction* in large stocks is easily automatable (*e.g.* microprocessors). Rubber and plastic as well as metal products account for between 5% and 10% of the worldwide stock.

Figure 3. Worldwide stock of robots by industry (2014)

As a percentage of all robots

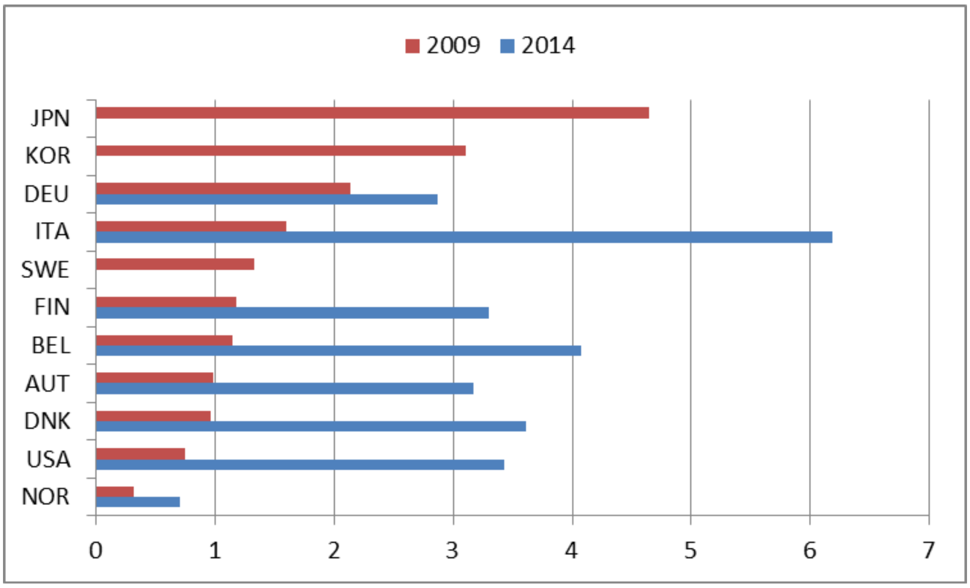


Source: Author's calculations, based on IFR.

Robots' penetration

Figure 4 shows the number of robots per thousand employees in use in selected countries for 2009 and 2014.[8] Japan had by far the highest density in the sample in 2009 - roughly five units per thousand employees. Korea followed with three units per thousand employees. Italy is the country with the highest density in 2014, which increased by a factor of more than three in five years. The figure also shows that Norway is the country with the lowest density, both in 2009 and 2014.

Figure 4. Number of robots per 1 000 employees by country



Source: Author's calculations, based on IFR.

Price of robots

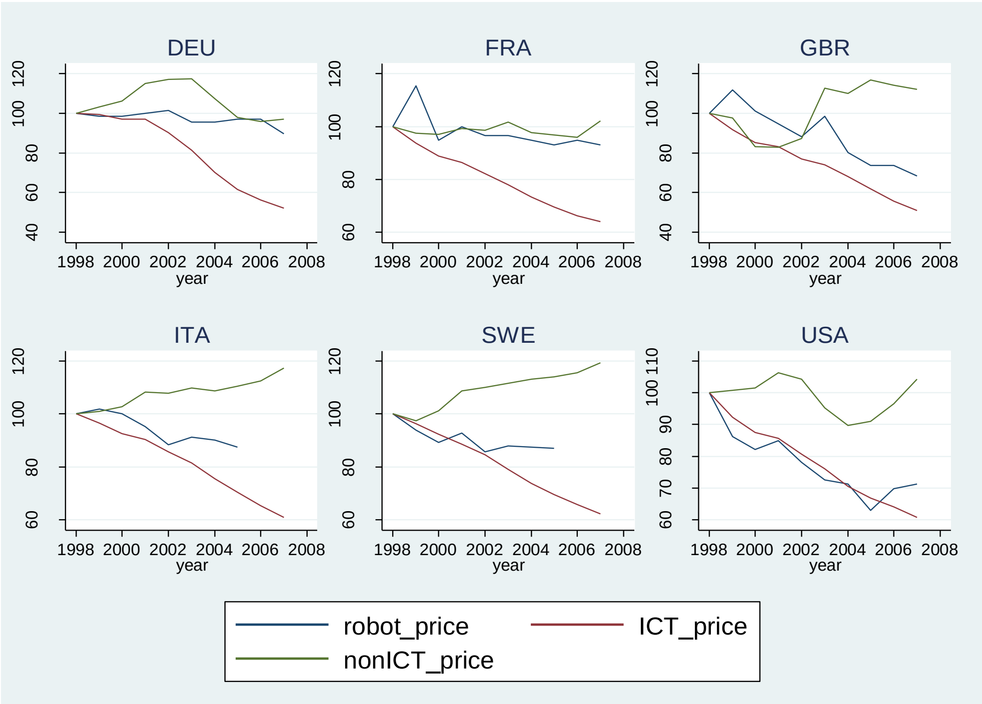
A robot unit is usually included in a wider system composed of other robots, software, computer-controlled machine tools and other numerically controlled equipment. Even when a robot unit is the central piece of equipment in a system, its cost usually accounts for one-third or one-quarter of the total cost of the system. Other main cost entries are peripherals, software and system engineering.

The unit price of a robot, therefore, can be measured both as the cost of a unit in isolation (robot *list price*) or as the total cost of a system divided by the number of robot units included in the system (*average unit price*). List price data are not available and only average unit prices are considered in this study.[9]

Figure 5 compares the current prices of robots, ICT capital and non-ICT capital over 1993-2008 in a subsample of countries where all sets of data are available. Robots are combination of hardware and software, and they are usually included in robot systems that are themselves constituted by computers, peripheral and possibly machine tools and other equipment. Figure 5 shows that the decline of robot prices was mostly driven by improvements in ICT, rather than that of mechanical equipment. Although purely speculative, this evidence suggests that movement in robot prices would result from a combination of trends in ICT and non-ICT capital prices.

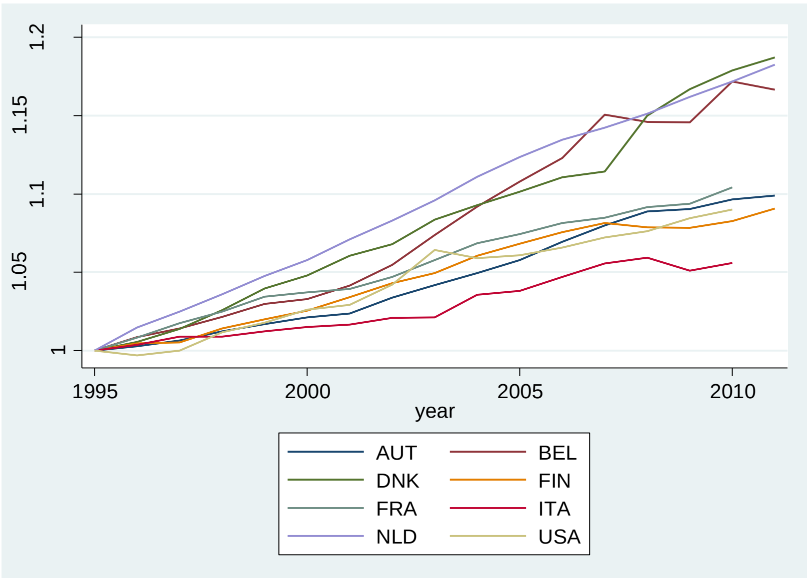
For the United States, the decline in robots' prices was even faster than the fall in the price of ICT capital. The faster decline in the price of robots *vis-à-vis* their components points toward an exceptional higher productivity growth in the robot-producing sector.

Figure 5. Price of robots, ICT and non-ICT capital (index 1998=100)



Source: Author's calculations, based on IFR and Schreyer (2003).

Figure 6. Labour costs per employee relative to ICT prices in transport equipment



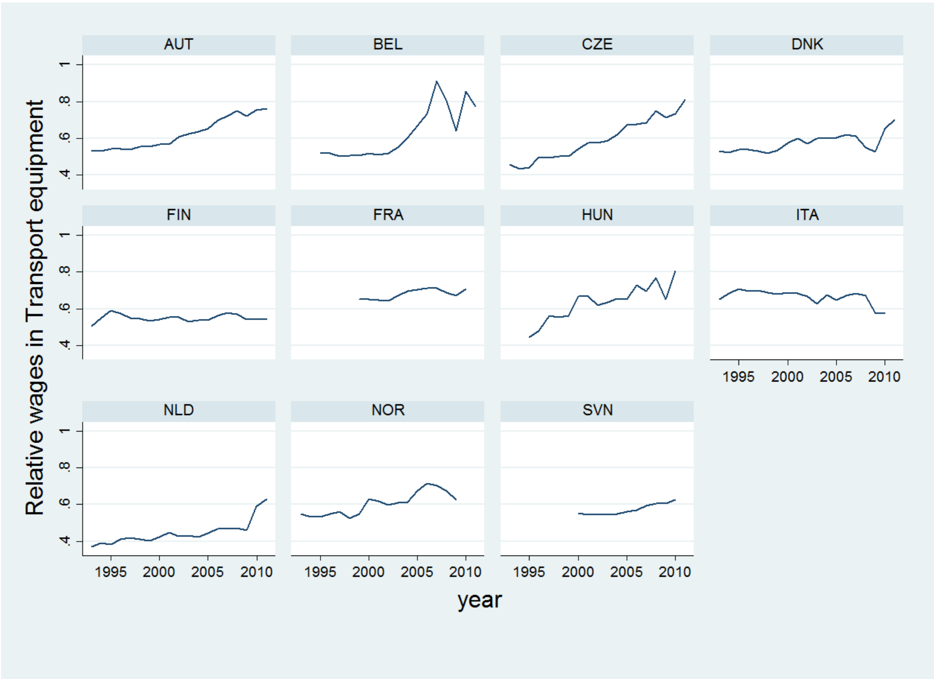
Source: Author's calculation, based on IFR and STAN.

Real wages: the relative price of labour *vis-à-vis* the price of robots

Economic theory suggests that with substitute production factors, when the cost of an input decreases relative to another, firms will use more of the former and less of the latter. This could imply that a fast decline in the price of robots may have led to lower employment and/or lower wages.

Higher relative prices might contribute to explain why some sectors invest more in robots than others. Figure 6 shows that the cost of labour relative to the ICT capital prices[10] in Transport equipment has been increasing in all countries for which data were available. Figure 7 shows that indeed real wages in transport equipment grew faster than the average wage in other sectors. However, the figure should be interpreted with caution as robots have probably increased labour productivity and therefore wages.

Figure 7. Real wage in transport equipment, relative to average wages in other sectors



Source: Author's calculation, based on STAN.

Fields of application of industrial robots

Robots are classified by the IFR according to their field of application, *i.e.* the type of tasks they perform. Table 1 show that some robots perform general tasks, such as “material handling”, “picking”, or “placing”. Other categories of robots perform more specific tasks, such as “painting”, or “welding”. Among the latter, there are robots that are dedicated to the production of semiconductors, which requires operating in cleanrooms.

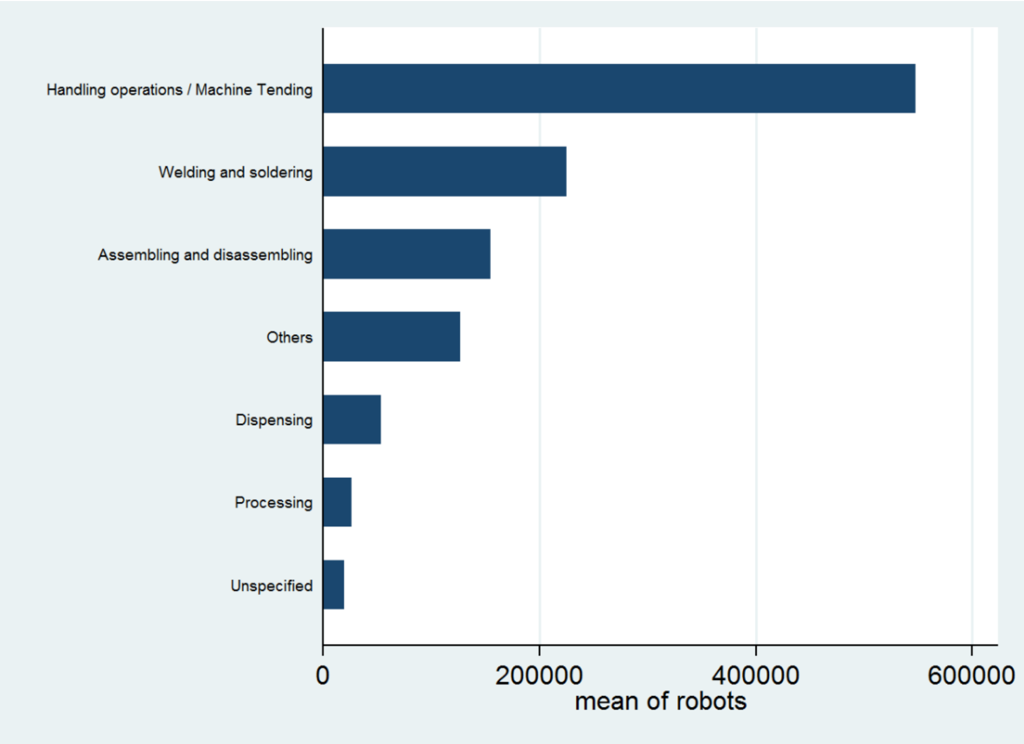
Figure 8 shows the worldwide distribution of robots by field of application in 2014. The main field of application was “handling operations/machine tending”, with almost six hundred thousand units operational worldwide, representing almost 50% of the total stock. Handling operations are widespread in all industries and are relatively easy to automate, as they mostly consist in bundles of routine tasks.

Table 1. Classification of robots by field of application

Handling operations / machine tending
Metal casting
Plastic moulding
Stamping forging, bending
Handling operations at machine tools
Machine tending for other processes
Measurement, inspection, testing
Palletizing
Packaging, picking, placing
Material handling
Handling operations unspecified
Processing
Laser cutting
Water jet cutting
Mechanical cutting/grinding/deburring
Other processing
Processing unspecified
Welding and soldering
Arc welding
Spot welding
Laser welding
Other welding
Soldering
Welding unspecified
Assembling and disassembling
Fixing, press-fitting
Assembling, mounting, inserting
Disassembling
Other assembling
Assembling unspecified
Dispensing
Painting and enamelling
Application of adhesive, sealing material
Others dispensing/spraying
Dispensing unspecified
Others
Cleanroom for FPD (flat-panel display)
Cleanroom for others
Cleanroom for semiconductors
Others unspecified
Unspecified

Source: IFR.

Figure 8. Number of robots by macro-field of application in 2014



Source: Author's calculations, based on IFR.

What is the relationship between robots and human labour?

In this section, a simple econometric model is used to compute correlations between the stock of robots in each country and the evolution of employment by detailed occupations. The data and methodology used here help to mitigate the bias affecting some previous studies, due to omitted variables and aggregation over different categories of technologies and occupations.

While the analysis falls short of establishing a causal relationship between robots and employment, it provides new evidence on the potential displacing effect of robots on employment.

The ISCO-08 documentation[11] describes the task content of each detailed occupation. Occupations have then been matched to one or more categories of robots through a text mining algorithm, based on the occupation's tasks and the robots' field of application (Tables 1 and 2). For instance, the occupation "physical and earth science professionals" (ISCO 211) includes the tasks "measurement, inspection, testing", which are included in the wider category "handling", that can be performed by a robot in the field of application "handling operations / machine tending". Following the same logic,, the task description for the occupation "building finishers and related trade workers" (712) includes "handling", "processing", "welding", "assembling" and "dispensing", *i.e.* all robot application fields. As employment data are generally not available below the ISCO 3 digit level, occupations and robots' applications have been matched at that level. Only occupations matched to at least one field of robots application, forty-seven as listed in Table 2, have been kept for further analysis.

This approach looks at the *direct* relationship between robots and employment in each occupation. However, it does not account for the *indirect* effects stemming from the reorganisation of production associated to the diffusion of robots. For instance, robots used for painting automobiles might increase productivity, reduce prices and raise final demand for transport equipment. As a consequence, employment in the industry might increase, including in some occupations that are not directly related with painting.

The structure of the robot data, organised either by country and sector, or by country and application, does not allow controlling for the potential heterogeneous effect of a particular category of robots on the same occupation in different sectors. However, the empirical specification discussed below will take in take into account occupation-specific factors (such as concentration in some sector of the economy) and therefore it will be able to alleviate the problem.

Another important factor to take into account is the potential quality change of robots over the sample period. One common method uses quality-adjusted price deflators in order to capture different vintages of capital. However, the available robot data already refer to quantities and they do not provide detailed price data. For that reason, in the empirical specification it will be included a common time trend which at least partially accounts for potential changes in quality.

Table 2. Matching between occupations and industrial robots

ISCO-08 3 digits	Occupation	Handling	Processing	Welding	Assembling	Dispensing
211	Physical and earth science professionals	yes				
214	Engineering professionals (excluding electrotechnology)	yes				
225	Veterinarians	yes				
226	Other health professionals	yes				
311	Physical and engineering science technicians	yes			yes	
313	Process control technicians	yes				
314	Life science technicians and related associate professionals	yes	yes			
315	Ship and aircraft controllers and technicians	yes				
321	Medical and pharmaceutical technicians	yes				
324	Veterinary technicians and assistants	yes				
325	Other health associate professionals				yes	
343	Artistic, cultural and culinary associate professionals					yes
352	Telecommunications and broadcasting technicians	yes				
611	Market gardeners and crop growers	yes	yes			
612	Animal producers	yes				
711	Building frame and related trades workers	yes	yes		yes	yes
712	Building finishers and related trades workers	yes	yes	yes	yes	yes
713	Painters, building structure cleaners and related trades workers					yes
721	Sheet and structural metal workers, moulders and welders, and related workers	yes	yes	yes	yes	
722	Blacksmiths, toolmakers and related trades workers	yes	yes		yes	
723	Machinery mechanics and repairers	yes			yes	yes
731	Handicraft workers	yes	yes		yes	yes
732	Printing trades workers		yes			
741	Electrical equipment installers and repairers	yes	yes		yes	
742	Electronics and telecommunications installers and repairers	yes		yes	yes	yes
751	Food processing and related trades workers	yes	yes			
752	Wood treaters, cabinet-makers and related trades workers	yes			yes	
753	Garment and related trades workers	yes	yes		yes	
754	Other craft and related workers	yes	yes		yes	yes

811	Mining and mineral processing plant operators	yes	yes		yes	yes
812	Metal processing and finishing plant operators	yes				yes
813	Chemical and photographic products plant and machine operators	yes				
814	Rubber, plastic and paper products machine operators	yes	yes			
815	Textile, fur and leather products machine operators	yes				
816	Food and related products machine operators		yes			
817	Wood processing and papermaking plant operators	yes	yes		yes	
818	Other stationary plant and machine operators	yes				yes
821	Assemblers	yes		yes	yes	
835	Ships' deck crews and related workers	yes				yes
912	Vehicle, window, laundry and other hand cleaning workers	yes				
921	Agricultural, forestry and fishery labourers	yes	yes			
931	Mining and construction labourers		yes		yes	
932	Manufacturing labourers					yes
933	Transport and storage labourers	yes				
941	Food preparation assistants		yes			
961	Refuse workers	yes				
962	Other elementary workers	yes	yes			yes

Source: Author's compilation (2016).

Robots and employment: results from regression analysis

This part presents the results obtained following the methodology outlined in the previous section. Figure 8 summarises the regression results, reported in the Annex. For sake of simplicity, estimates for detailed occupations have been aggregated into five groups, according to the ISCO-08 definition of "major occupational groups". For each group, the horizontal bars represent the estimated correlation between employment and the stock of robots used for a specific application, *e.g.* handling, welding, *etc.*

Two main messages emerge from Figure 9. The first is that even narrowly defined technologies can have different impacts on different occupations. The second is that the same occupational group can be affected differently from different categories of robots. The findings suggest that results based on highly aggregated variables, such as total employment or aggregate capital stocks should be interpreted with caution.[12] Research should be undertaken on data about detailed occupations and detailed technologies, which are rarely found in existing studies.[13] Results also suggest that the impact of automation (introduction of robots in production processes in this case) will change the nature of work (the tasks performed by workers within each occupation) without necessarily displacing employment in those occupations.

Given that robots are explicitly designed to perform tasks otherwise accomplished by humans, one could expect a negative correlation between the number of robots performing a given task and the level of employment in occupations including those tasks. Figure 9, however, shows that it is not the case.

A potential explanation for this result is that automation changes the task composition of occupations but it does not necessarily result in a decrease of employment in those same occupations. In an often-cited article, James Bessen (2015) argues that the introduction of ATMs in the United States resulted in a change in the tasks of bank tellers. Instead of distributing cash, bank tellers took up tasks that could not be automated, like customer services. The provision of these new services made it possible for banks to open new branches, so that the number of bank tellers following the introduction of ATMs increased.

This argument is also supported by a recent study by Arntz *et al.* (2016), which argues that occupations are actually bundles of tasks. In their study, the authors find that considering specific tasks rather than occupations, reduces considerably the estimated risk of automation. Moreover, Arntz *et al.* (2016) find also a substantial heterogeneity across countries, which is consistent with the country-specific results presented below.

Robots can be *skill-biased*, *i.e.* they complement skilled workers and substitute for unskilled ones. Figure 9 provides evidence for skill bias. For instance, processing robots are positively correlated with professional occupations and negatively correlated with elementary occupations (although results are mixed for technicians and other mid-skill occupations).

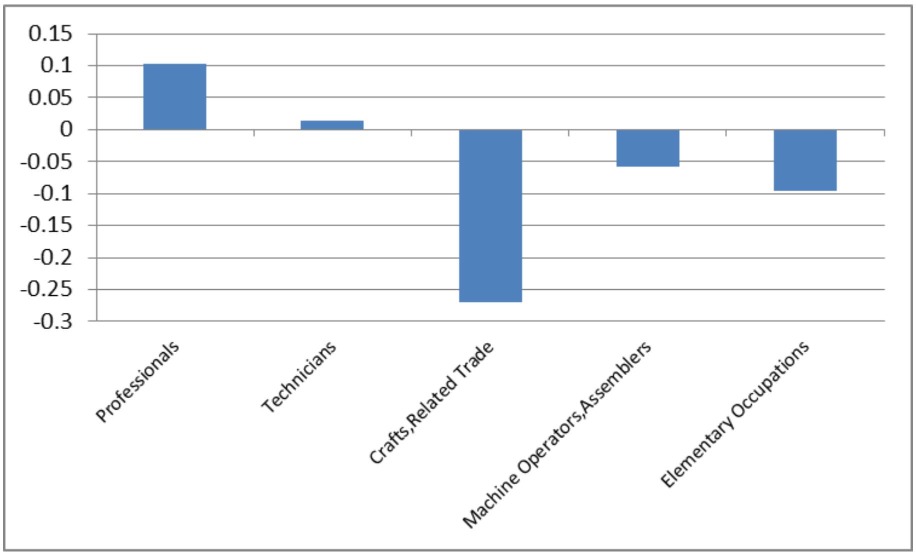
Some categories of robots appear to have a negative impact even on skilled occupations. For example, this is the case for assembling robots on professionals' occupations. The IFR includes in "processing" all robots performing tasks such as cutting, grinding, and deburring (Table 1). These robots can substitute for production workers performing routine tasks, which would explain the negative correlation with elementary occupations. When robots substitute professionals' occupations, a major group composed of skilled, non-routine occupations (*e.g.* engineers), they are likely to do so by making redundant their *supervisory* or co-ordinating role. That happens because using robots can increase the quality of the goods produced and the overall efficiency of the workflows.

Figure 9. Estimated correlation between robots (by application) and employment (by occupation)

Source: Author's calculations (2016).

Figure 10 presents the total effect of all categories of robots taken together, on the five occupational groups.[14] Robots are positively correlated to employment of professionals and technicians occupations, and negatively related to all other occupations, although to a different extent. In particular, the occupational group crafts and related trade workers shows the largest negative elasticity (0.25). This means that a 1% increase in the number of robots is associated with a 25% decline in employment.

Figure 10. Estimated correlation between total stock of robots and employment (by occupation)



Source: Author's calculations (2016).

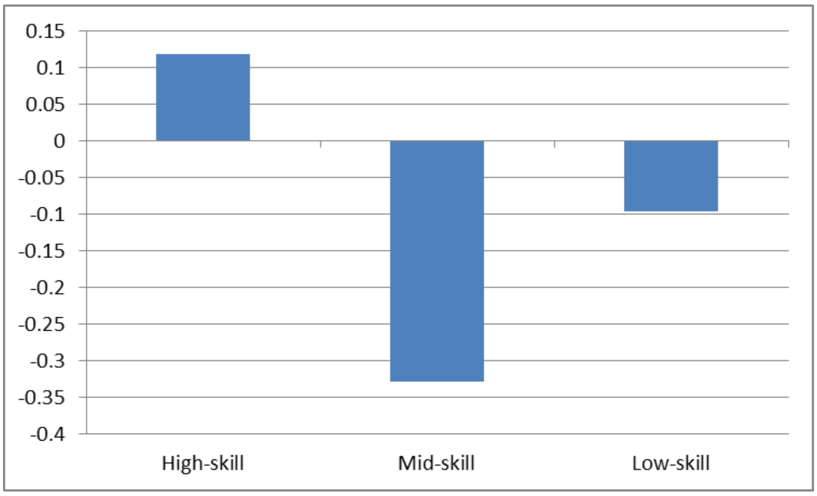
As most literature has focused on the impact of technology on skill groups, it is useful to show the above estimates by high, medium and low skills, based on the correspondence in Table 3. Coding accordingly the occupational groups used in this study, reveals a familiar picture: robots are positively correlated to high-skill occupations and negatively correlated to low-skill ones (Figure 11). The correlation is negative for mid-skill occupations, but the overall pattern, calculated for the manufacturing sector only, does not support the job polarisation hypothesis by Autor *et al.* (2003), according to which technology tends to displace mid-skill occupations and increase demand for occupations at the extremes of the skill distribution.[15]

Table 3. Mapping of ISCO-08 major groups to skill levels

ISCO-08 major groups	Skill level
1 Managers	3 + 4
2 Professionals	4
3 Technicians and associate professionals	3
4 Clerical support workers	
5 Services and sales workers	
6 Skilled agricultural, forestry and fishery workers	2
7 Craft and related trades workers	
8 Plant and machine operators, and assemblers	
9 Elementary occupations	1
0 Armed forces occupations	1+2+4

Source: ILO (2012).

Figure 11. Estimated correlation between total stock of robots and employment (by skill level)



Source: Authors' calculations (2016).

Estimated change in employment associated to the diffusion of robots

The values displayed in Figure 10 are the estimated elasticities of employment by occupation to robots, *i.e.* the change in employment in a given occupation following a 1% increase in the total number of robots.

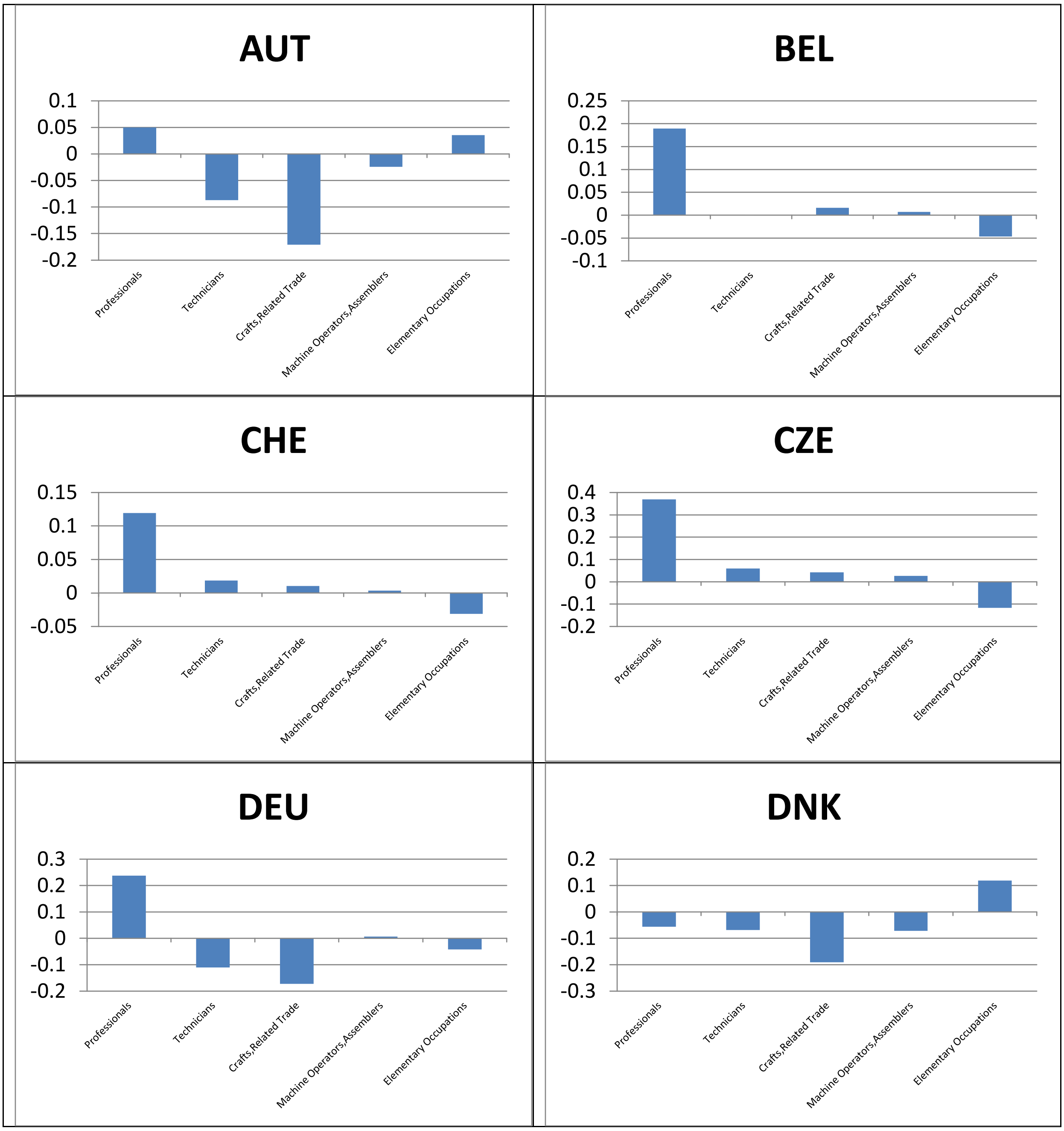
In order to estimate the change in employment associated to the diffusion of robots, the above elasticities have been multiplied by the growth in the stock of robots over the whole sample period (1993-2014).[16] Clearly, investment in different categories of robots has been different over time and across countries. In addition, some categories of robots are positively related with some occupations, but negatively with others. Therefore, in order to estimate the change in employment accounted for by robots, it is necessary to compute the actual change in robot stock.

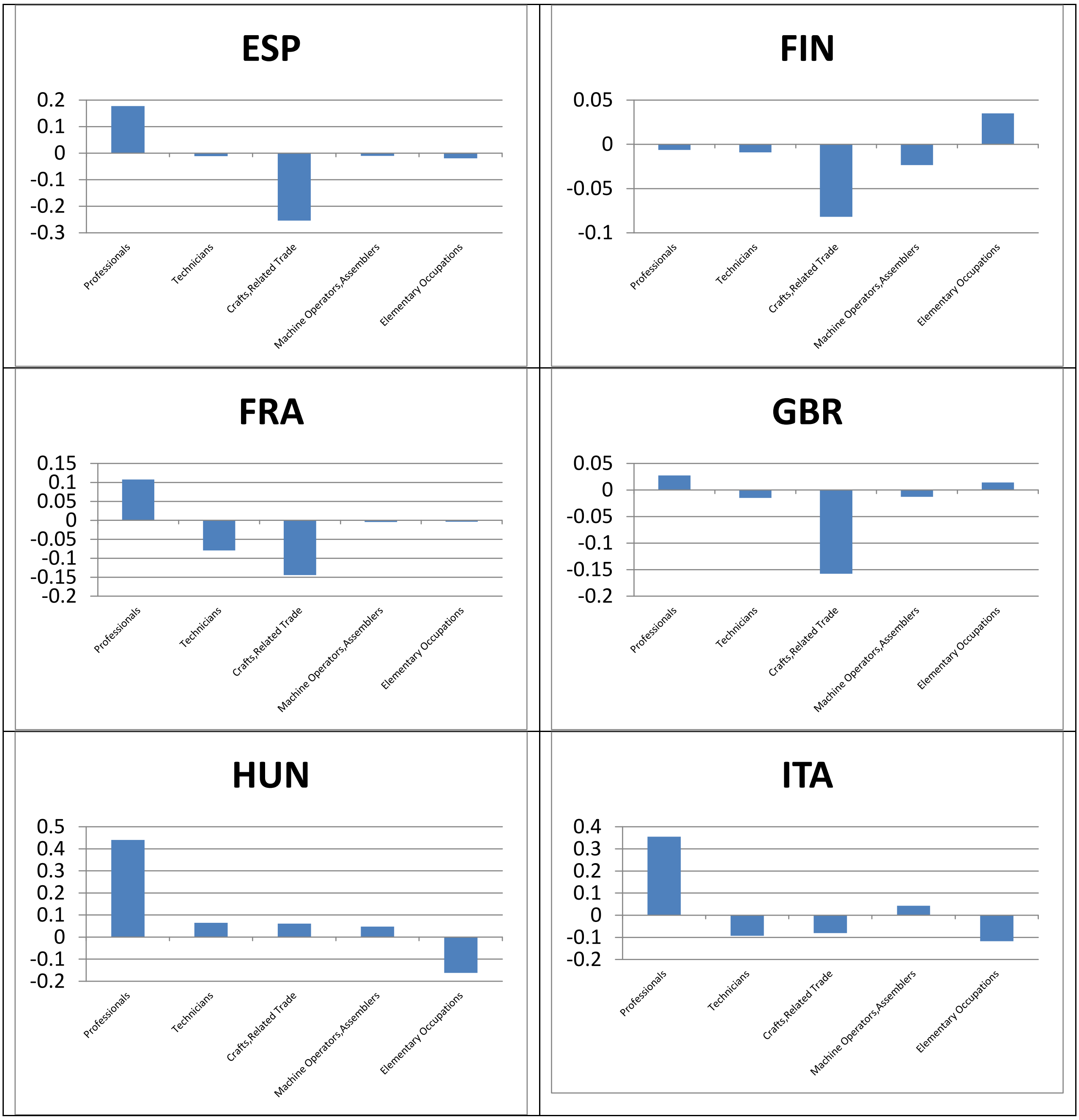
Figure 12 shows the estimated changes in employment by country and by occupational group. In some countries, most notably the United States, it can be seen that the estimated change in employment associated to the diffusion of robots is compatible with the polarisation hypothesis, with the exception of a negative correlation between robots and professionals occupations. However, robots are associated to an increase in the number of professionals in most countries. The change is largest for Turkey (60%) and Hungary (40%), and the lowest in Norway (1.2%). Robots are negatively correlated with professionals in some countries, especially Denmark (-5%). Overall, the mean change in employment of professionals is positive (about 21%). For technicians, the mean change in employment is estimated to be negative (about -1.5%).

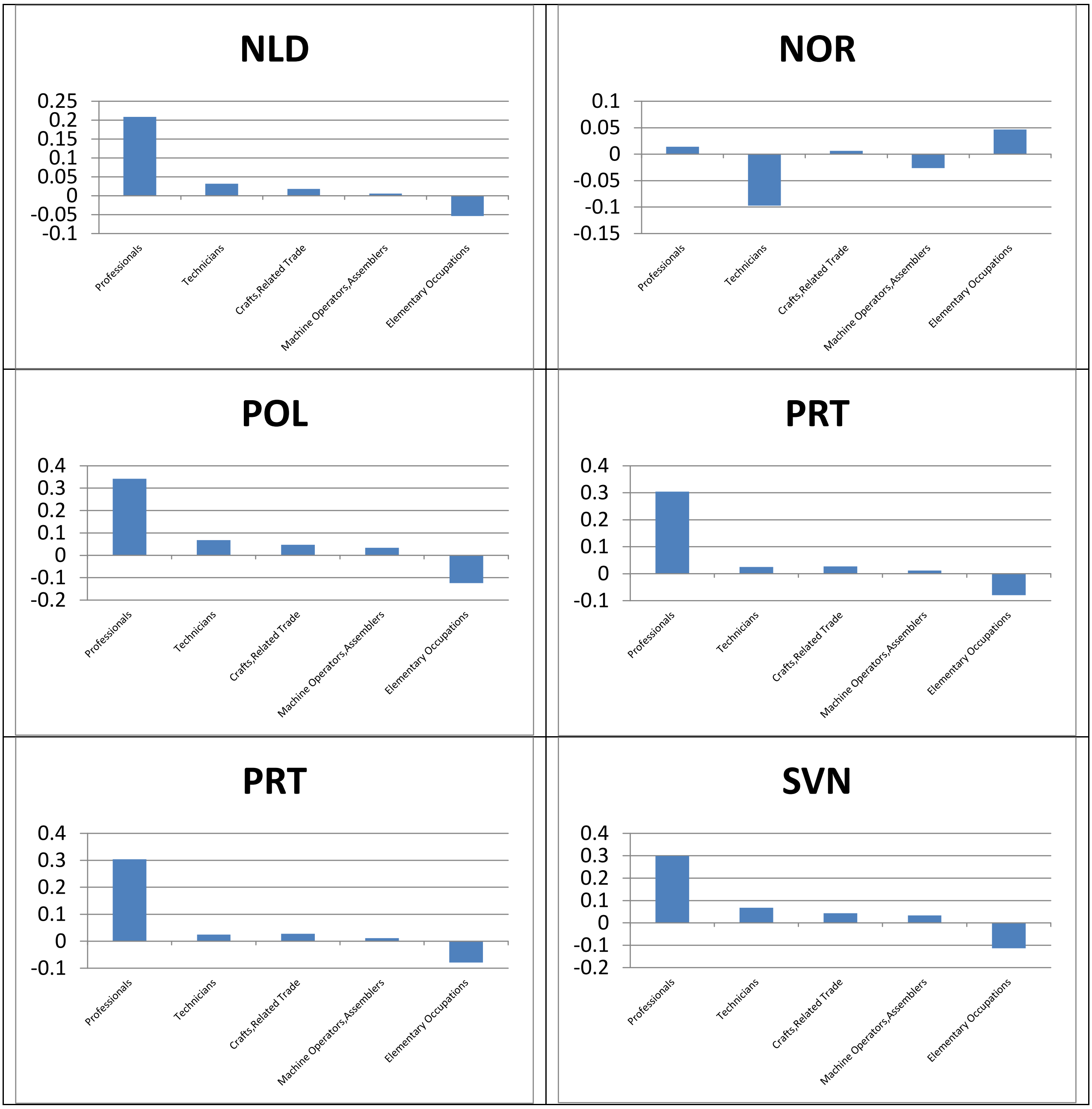
Robots are associated to a decrease of elementary occupations employment in most countries, the mean change being -5.1%. The largest decrease is in Turkey (-20%) while the correlation is positive in some countries, *e.g.* Denmark (10%), Austria (4%) and Norway (5%).

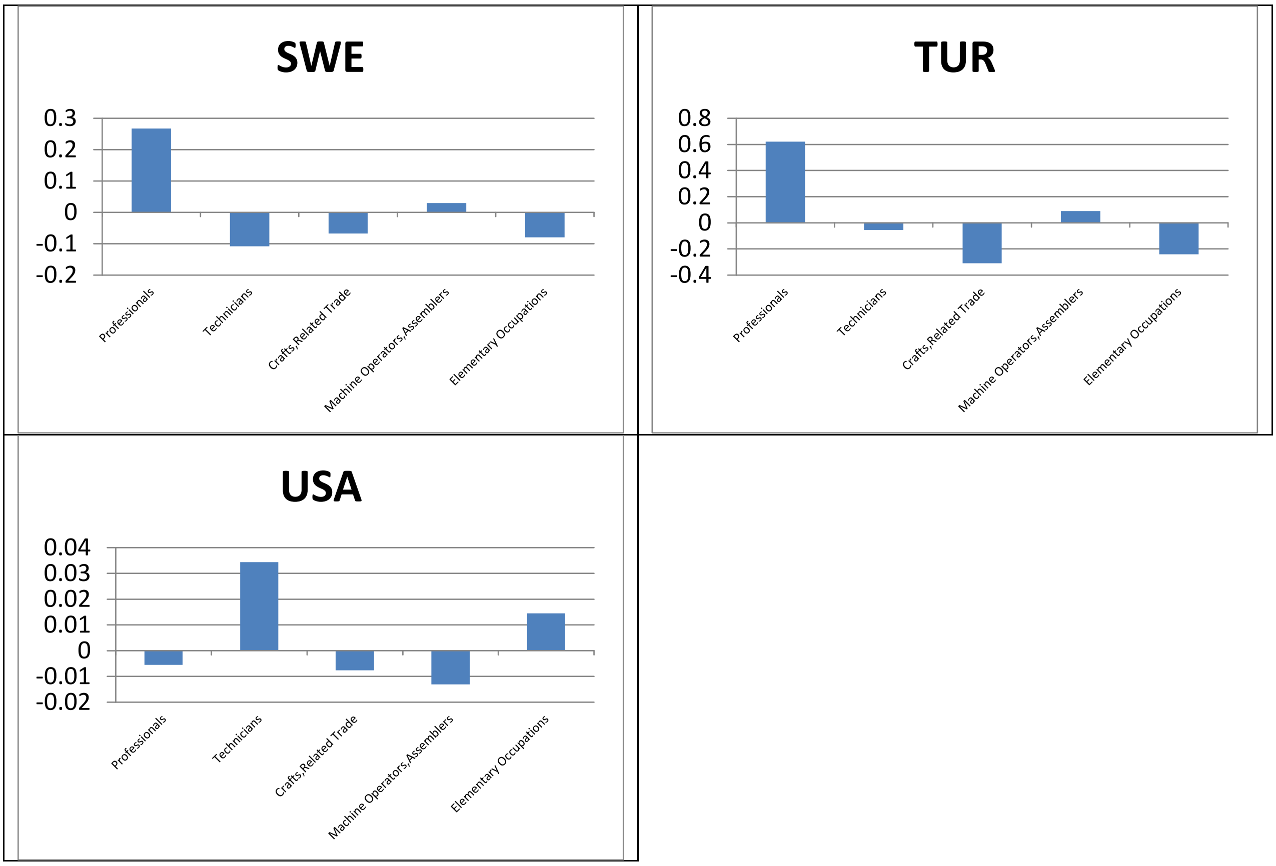
Depending on the country, robots have a different impact on occupations in the middle of the skill distribution. However, the estimated decline in employment of crafts and related trade workers due to robots is on average -6%. The average change for machine operators and assemblers is positive but less than 1%.

Figure 12. Estimated changes in employment associated to the diffusion of robots (by country)




ESP
0.2
0.1
0
-0.1
-0.2
-0.3
Professionals
Technicians
Crafts,Related Trade
Machine Operators,Assemblers
Elementary Occupations
FIN
0.05
0
-0.05
-0.1
Professionals
Technicians
Crafts,Related Trade
Machine Operators,Assemblers
Elementary Occupations
FRA
0.15
0.1
0.05
0
-0.05
-0.1
-0.15
-0.2
Professionals
Technicians
Crafts,Related Trade
Machine Operators,Assemblers
Elementary Occupations
GBR
0.05
0
-0.05
-0.1
-0.15
-0.2
Professionals
Technicians
Crafts,Related Trade
Machine Operators,Assemblers
Elementary Occupations
HUN
0.5
0.4
0.3
0.2
0.1
0
-0.1
-0.2
Professionals
Technicians
Crafts,Related Trade
Machine Operators,Assemblers
Elementary Occupations
ITA
0.4
0.3
0.2
0.1
0
-0.1
-0.2
Professionals
Technicians
Crafts,Related Trade
Machine Operators,Assemblers
Elementary Occupations


NLD
0.25
0.2
0.15
0.1
0.05
0
-0.05
-0.1
Professionals
Technicians
Crafts,Related Trade
Machine Operators,Assemblers
Elementary Occupations
NOR
0.1
0.05
0
-0.05
-0.1
-0.15
Professionals
Technicians
Crafts,Related Trade
Machine Operators,Assemblers
Elementary Occupations
POL
0.4
0.3
0.2
0.1
0
-0.1
-0.2
Professionals
Technicians
Crafts,Related Trade
Machine Operators,Assemblers
Elementary Occupations
PRT
0.4
0.3
0.2
0.1
0
-0.1
Professionals
Technicians
Crafts,Related Trade
Machine Operators,Assemblers
Elementary Occupations
PRT
0.4
0.3
0.2
0.1
0
-0.1
Professionals
Technicians
Crafts,Related Trade
Machine Operators,Assemblers
Elementary Occupations
SVN
0.4
0.3
0.2
0.1
0
-0.1
-0.2
Professionals
Technicians
Crafts,Related Trade
Machine Operators,Assemblers
Elementary Occupations



Source: Authors' calculations (2016).

Conclusions

Dramatic improvements in technology allow automating an increasing number of tasks and occupations. For this reason, there is a widespread concern that new technologies might destroy a large number of jobs and cause "technological unemployment". The threat of displacement is believed to be particularly strong with industrial robots, because they are explicitly designed to perform tasks that would otherwise be performed by humans.

The analysis in this paper is meant to shed light on automation trends and their effect on employment. A better understanding of what robots actually do and to what extent they are used across countries and sectors can help policy makers to design policies aimed at smoothing the transition towards industry 4.0. Moreover, the data used in this paper reveal that robots are disproportionally in use in advanced economies, which suggests that the issue of robotisation is particularly relevant for the OECD.

In this paper, different categories of robots are found to be differently correlated to employment of different occupations. Moreover, the sign and magnitude of such correlations are heterogeneous across countries. On average, robots are found to be associated with a reduction in elementary occupations, those requiring the lowest levels of skills, and an increase of professionals and technicians, high skill professions. For occupations in the middle of the skill distribution the correlation is strong and negative. Thus, on the one hand, estimates presented in this study do not support in general the hypothesis of *polarisation of the labour market*, which would require an increase of both skilled and unskilled employment. On the other hand, however, country-specific results – most notably for the United States – can be interpreted as evidence in support of the hypothesis.

References

Acemoglu, Daron (1998), "Why Do New Technologies Complement Skills? Directed Technical Change and Wage Inequality." *The Quarterly Journal of Economics*, Vol. 113, no. 4, pp. 1055-089, http://www.jstor.org/stable/2586974.

Acemoglu, Daron, and Pascual Restrepo (2016), "The Race between Machine and Man: Implications of Technology for Growth, Factor Shares and Employment", NBER Working Paper No. 22252, Cambridge, MA, *National Bureau of Economic Research*, http://dx.doi.org/10.3386/w22252.

Arntz, M., T. Gregory and U. Zierahn (2016), "The Risk of Automation for Jobs in OECD Countries: A Comparative Analysis", *OECD Social, Employment and Migration Working Papers*, No. 189, OECD Publishing, Paris, https://doi.org/10.1787/5jlz9h56dvq7-en.

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

Autor, David H. and David Dorn (2013) "The Growth of Low-Skill Service Jobs and the Polarization of the U.S. Labour Market", *American Economic Review*, Vol. 103, Issue 5, pp. 1553–1597.

Autor, David H., Frank Levy, and Richard J. Murnane (June 2001), "The Skill Content of Recent Technological Change: An Empirical Exploration, NBER Working Paper No. w8337, *National Bureau of Economic Research*, https://papers.ssrn.com/sol3/papers.cfm?abstract_id=273705.

Autor, David H., Lawrence F. Katz, and Alan B. Krueger (1998), "Computing Inequality. Have Computers Changed the Labor Market?", *Quarterly Journal of Economics*, Vol. 113, Issue 4, pp. 1169-1213.

Bessen, James E. (2016), "How Computer Automation Affects Occupations: Technology, Jobs, and Skills", Boston Univ. School of Law, *Law and Economics Research Paper*, Vol. No. 15, Issue 49, https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2690435

Dustmann, Christian, Johannes Ludsteck and Uta Schönberg (2009) "Revisiting the German Wage Structure", *Quarterly Journal of Economics*, Vol. 124, Issue 2, pp. 843-881, https://doi.org/10.1162/qjec.2009.124.2.843.

Firpo, Sergio, Nicole M. Fortin and Thomas Lemieux (2011) "Occupational Tasks and Changes in the Wage Structure", *IZA Discussion Papers*, No. 5542, Institute of Labor Economics, http://ftp.iza.org/dp5542.pdf.

Goos, Maarten, Alan Manning and Anna Salomons (2009) "Job Polarization in Europe", *American Economic Review*, Vol. 99, Issue 2, pp. 58–63, https://doi.org/10.1257.aer.99.2.58

Graetz, Georg, and Guy Michaels (2015), "Robots at work", *IZA Discussion Papers*, No. 8938, Institute of Labor Economics, http://ftp.iza.org/dp8938.pdf.

Lefter, M. Alexandru and Benjamin M. Sand (2011) "Job Polarization in the U.S.: A Reassessment of the Evidence from the 1980s and 1990s", *Working Paper Series*, 2011-

03, School of Economics and Political Science, Department of Economics, University of St. Gallen, http://ux-tauri.unisg.ch/RePEc/usg/econwp/EWP-1103.pdf .

Schreyer, P., P. Bignon and J. Dupont (2003), "OECD Capital Services Estimates: Methodology and a First Set of Results", *OECD Statistics Working Papers*, 2003/06, OECD Publishing, Paris, http://dx.doi.org/10.1787/658687860232

Schreyer, Paul (2010), "Measuring Multi-Factor Productivity when Rates of Return Are exogenous," Chapter 2, pp. 13-40 in W.E. Diewert, B.M. Balk, D. Fixler, K.J. Fox and A.O. Nakamura (eds.), *Price and Productivity Measurement*, Volume 6 -- Index Number Theory, Trafford Press.

Spitz-Oener, Alexandra (2006) "Technical Change, Job Tasks and Rising Educational Demand: Looking Outside the Wage Structure", *Journal of Labour Economics*, Vol. 24, Issue 2, pp. 235–70, https://www.journals.uchicago.edu/doi/pdfplus/10.1086/499972.

Annex

Construction of robot stocks

The IFR data do not provide a breakdown of deliveries by industries for the early years in the sample, when all delivered units are reported under the "unspecified" category. To circumvent the problem, the average share of an industry shipment (computed from all the years for which the breakdown is available) is multiplied by the number of robots reported as "unspecified", for each country.

A perpetual inventory method is then applied to shipments in order to construct the stock of robots by country, industry and year. IFR estimates for the first year of the sample (1993) is used as initial stock. A 10% annual depreciation rate is applied for the construction of the capital series. The number is borrowed from Graetz and Michael (2015), which also experiment with other depreciation schedules that do not alter their results.

Occupation data

Data by detailed occupation are obtained by harmonising information from three different sources. For European data, standard conversion tables are used to convert data up to 2010 from ISCO88 to ISCO08. Data on the US are translated from SOC 2010 into ISCO08, and then appended to the other series.

The most problematic aspect is the conversion from ISCO88 to ISCO08, since even with 3-digits level data it is not possible to perfectly execute the conversion described in the tables. However, possible incongruences disappear when aggregating occupations into macro-occupational groups. Visual inspection of the obtained series excludes the presence of breaks and outliers.

The Model

Define the indicator function $1_{\{o \in a\}}$, which takes the value 1 if an occupation o is related to a field of application a, and zero otherwise. There are five fields of application, *i.e.*

$$a \in \{\text{handling; processing; welding; assembling; dispensing}\}$$

The analysis is based on the following model,

$$\ln(EMP_{oct}) = \beta_0 + \sum_a \beta_a \ln(R_{act}) + \sum_a 1_{\{o \in a\}} \delta_a \ln(R_{act}) + u_c + u_o + t_0 + u_t + \epsilon_{oct} \quad (1)$$

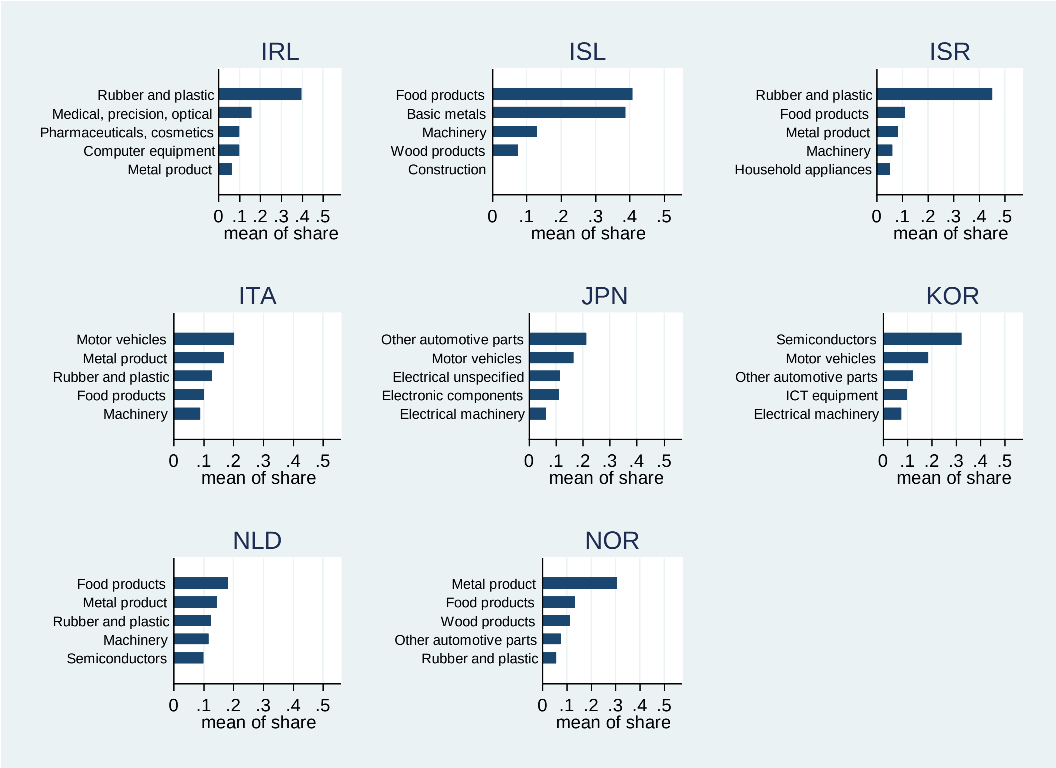
The dependent variable is the logarithm of employment in occupation o in country c at time t. The main independent variable is $\ln(R_{act})$, the logarithm of the stock of robots performing application a in each country and year. The coefficients of interest are β_a and δ_a , $\forall\, a$. The former measures the average impact of a category of robots on all occupations (but related to at least one category of robots), while the latter measures the impact on specific occupations. The cumulative impact on an occupation is the sum of the two coefficients. Positive values of the coefficient indicate that, within a country, there is a positive correlation between the stock of robots employed for application a and employment in the occupations related to a .

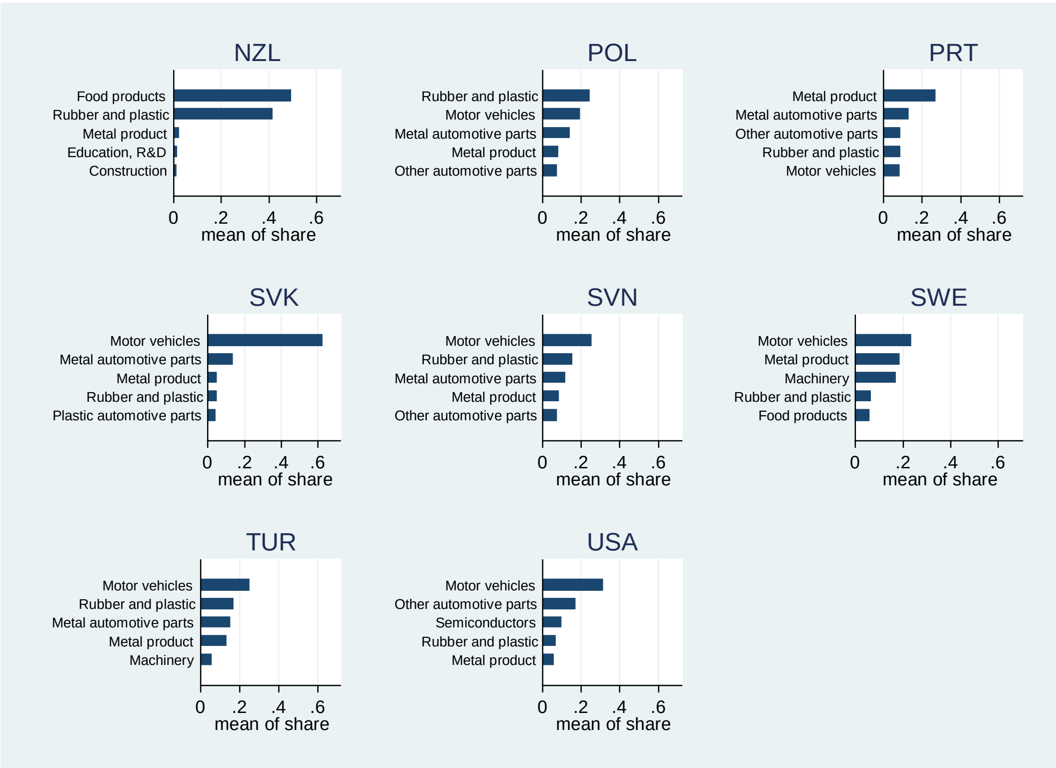
Equation (1) comprises occupation-specific fixed effects and time trends $(u_o + t_0)$. Occupation-specific time trends are included to control for wage growth, which is a main determinants of employment changes and may be correlated with robots' adoption.[17] Robots are disproportionally concentrated in some industries, such as transport equipment. Therefore, the relative weight of a sector in a given country could be correlated to both the stock of robots and the composition of employment by occupation. The existence of systematic cross-country differences in robotisation and employment are controlled for by the inclusion of country fixed effects (u_c). Finally, year dummies (u_t) are used to control for common shocks that would create correlation across units in the sample.

Regression results

	Robots' field of application				
VARIABLES	**Assembling**	**Dispensing**	**Handling**	**Processing**	**Welding**
Average effect	-0.0646**	-0.0075	-0.2333***	0.1749***	0.1622***
	(0.0318)	(0.0268)	(0.0338)	(0.0329)	(0.0316)
Professionals	-	-	0.2267***	-	-
	-	-	(0.0364)	-	-
Technicians	0.1594***	0.0575	0.1786***	-0.2005***	-
	(0.0401)	(0.0371)	(0.0343)	(0.0428)	-
Crafts, related trade workers	0.0465	0.0349	0.2103***	-0.1404***	-0.2172***
	(0.0393)	(0.0292)	(0.0447)	(0.0351)	(0.0364)
Machine operators, Assemblers	0.0199	-0.0248	0.2030***	-0.1378***	-
	(0.0387)	(0.0330)	(0.0349)	(0.0369)	-
Elementary occupations	-	-	0.2840***	-0.2574***	-
	-	-	(0.0374)	(0.0390)	-
Observations	8,527	8,528	8,529	8,530	8,531
R-squared	0.7986	0.7986	0.7986	0.7986	0.7986
r2_a	0.795	0.795	0.795	0.795	0.795
Standard errors in parentheses					
*** p<0.01, ** p<0.05, * p<0.1					

Figure A1. Share of operational robots by country: top five sectors, 2014


IRL
Rubber and plastic
Medical, precision, optical
Pharmaceuticals, cosmetics
Computer equipment
Metal product
0 .1 .2 .3 .4 .5
mean of share
ISL
Food products
Basic metals
Machinery
Wood products
Construction
0 .1 .2 .3 .4 .5
mean of share
ISR
Rubber and plastic
Food products
Metal product
Machinery
Household appliances
0 .1 .2 .3 .4 .5
mean of share
ITA
Motor vehicles
Metal product
Rubber and plastic
Food products
Machinery
0 .1 .2 .3 .4 .5
mean of share
JPN
Other automotive parts
Motor vehicles
Electrical unspecified
Electronic components
Electrical machinery
0 .1 .2 .3 .4 .5
mean of share
KOR
Semiconductors
Motor vehicles
Other automotive parts
ICT equipment
Electrical machinery
0 .1 .2 .3 .4 .5
mean of share
NLD
Food products
Metal product
Rubber and plastic
Machinery
Semiconductors
0 .1 .2 .3 .4 .5
mean of share
NOR
Metal product
Food products
Wood products
Other automotive parts
Rubber and plastic
0 .1 .2 .3 .4 .5
mean of share


NZL
Food products
Rubber and plastic
Metal product
Education, R&D
Construction
0 .2 .4 .6
mean of share
POL
Rubber and plastic
Motor vehicles
Metal automotive parts
Metal product
Other automotive parts
0 .2 .4 .6
mean of share
PRT
Metal product
Metal automotive parts
Other automotive parts
Rubber and plastic
Motor vehicles
0 .2 .4 .6
mean of share
SVK
Motor vehicles
Metal automotive parts
Metal product
Rubber and plastic
Plastic automotive parts
0 .2 .4 .6
mean of share
SVN
Motor vehicles
Rubber and plastic
Metal automotive parts
Metal product
Other automotive parts
0 .2 .4 .6
mean of share
SWE
Motor vehicles
Metal product
Machinery
Rubber and plastic
Food products
0 .2 .4 .6
mean of share
TUR
Motor vehicles
Rubber and plastic
Metal automotive parts
Metal product
Machinery
0 .2 .4 .6
mean of share
USA
Motor vehicles
Other automotive parts
Semiconductors
Rubber and plastic
Metal product
0 .2 .4 .6
mean of share

End Notes

[1]. Definition ISO 8373, as reported by the IFR.

2. Although detailed robot-price data are not available, the empirical section will try to account for quality improvements.

3. The OECD would like to thank IFR for granting access to the robot data used in this paper.

[4]. The IFR defines service robot as a robot that performs useful tasks for humans or equipment excluding industrial automation application. The classification of a robot into industrial robot or service robot is done according to its intended application.

[5]. Clearly, the two theories of technical change do are not mutually exclusive, but they rather complement each other, as discussed in David (2015).

[6]. The adoption of a cross-countries common protocol to collect robots data ensures that such differences are not due to different methodological choices.

[7]. The Annex presents data on the share of operational robots by country and economic sector.

[8]. Employment data for Japan and Korea are available until 2009 only.

[9]. Additional measurement issues are caused by the fact that the concept of system is not unambiguously defined.

[10]. ICT capital prices are used as a proxy for robot prices due to data coverage limitations.

[11]. http://www.ilo.org/public/english/bureau/stat/isco/docs/groupdefn08.pdf

[12]. Most existing studies attempt to identify elasticities of various aggregate measures of labour to changes in measures of technology. But “labour” and “technology” are very broad categories. For instance, the same technology (*e.g.* computers) can complement labour in some occupations (*e.g.* designers), but substitute it in others (*e.g.* book keepers). Similarly, two distinct technologies might have a different impact on the same occupation.

[13]. Clearly, the main reason for that is data availability.

[14]. Shedding light on the specific channels through which different categories of robots affect the employment in specific occupation, would require more detailed information on what each occupation does on the workplace. Some progress in this direction could be made by exploiting ONET data. However, this would severely limit the size of the sample as ONET data refer to the United States only.

[15]. It should be noticed, however, that unlike in Autor *et al.* (2003) the present analysis is limited to manufacturing.

[16]. Due to data constraints, for some countries the change in the stock of robots can be computed over different periods.

[17]. Data on wages at the 3-digits level of detailed are not available.