

Fernández-Macías, Enrique; Klenert, David; Antón Pérez, José Ignacio

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Not so disruptive yet? Characteristics, distribution and determinants of robots in Europe

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JRC Technical Report

Not so disruptive yet?

Characteristics, distribution and determinants of robots in Europe

JRC Working Papers Series on
Labour, education and Technology
2020/03

Enrique Fernández-Macías, David Klenert, José-Ignacio Antón

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Contact information

Name: Enrique Fernández-Macías

Address: Joint Research Centre, European Commission (Seville, Spain)

Email: Enrique.FERNANDEZ-MACIAS@ec.europa.eu

Tel.: +34 9544-87114

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Not so disruptive yet? Characteristics, distribution and determinants of robots in Europe

Enrique Fernández-Macías, David Klenert(Joint Research Centre, European Commission, Seville, Spain), José-Ignacio Antón (University of Salamanca, Spain)

Abstract

This paper analyses data on industrial robots in European manufacturing sectors, focusing on their applications and characteristics, their distribution over countries and sectors and the main factors that are correlated with robot adoption such as wage levels and robot prices. We argue that, contrary to popular belief, the types of robots widely used in manufacturing today do not imply a discontinuity in terms of automation and labour replacement possibilities. Instead, current robot technology is better understood as the most recent iteration of industrial automation technologies that have existed for a very long time. In fact, these automation technologies arguably had their biggest employment impact generations ago, partially explaining changes in employment structures in agricultural and manufacturing sectors that go back to the Industrial Revolution. Thus, the potential employment effects of current robot technology are *a priori* limited.

Keywords: Robots, jobs, employment, low-skilled workers, inequality, European Union, economic activities

Authors: Enrique Fernández-Macías, David Klenert (Joint Research Centre, European Commission, Seville, Spain), José-Ignacio Antón (University of Salamanca, Spain)

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Introduction

In the aftermath of the global financial crisis of 2008, there has been a growing and often anxious debate about the impact of digital technologies on employment. The idea underlying this debate is that digital technologies are about to have a highly disruptive impact on the economy, making many current forms of employment obsolete. There are several factors behind this idea: from the allegedly exponential nature of technical change in the digital economy (Pratt 2015) to the anxiety provoked by the dramatic employment effects of the crisis itself, not to mention the impact on public imagination of recent breakthroughs in artificial intelligence (such as when the Alpha Go machine learning system beat the human champion of Go in 2016; Silver et al 2018). Perhaps Social Sciences have also contributed to this anxiety by producing some sweeping projections of the potential employment effects of existing or emerging digital technologies, projections that get frequently reported in mass media and discussed at the dinner table.¹ The obvious contrast between these projections and the real employment figures (which suggest continuity rather than disruption, and slightly growing rather than dramatically declining general employment trends) seems surprisingly unnoticed in these debates.

Better than any other concept or technology, robots embody fears of technological unemployment and human obsolescence (Mokyr, Vickers & Ziebarth 2015). Therefore, it should be no surprise that in the context of the current debates on technology and employment there has been a renewed interest on the deployment of robots and their effect on employment. Robots (understood as machines that can perform productive tasks with some degree of autonomy) have existed for some time now, and are widely used for many industrial applications. The digital revolution has had an important impact on robot technology too: in particular, the use of algorithmic control and digital sensors allow for a significant increase in the flexibility and autonomy of robots (Fernández-Macías et al. 2018). It is a very pertinent question, therefore, to what extent current robot technologies have *already* had a significant effect on employment, and of what kind. The interest of such a question is further increased by the fact that the addition of AI capabilities may in the near future further expand the capability range of robots, thus potentially expanding their employment effects as well.²

Is there any empirical evidence on the impact of robots on employment so far? As we shall see later in this paper, modern robot technology has been applied in industry since the 1980s, and the addition of digital capabilities goes back to the 1990s at least. If advanced industrial robotics would have had a disruptive effect in manufacturing, we should be able to identify such an effect in terms of employment already. Until recently, there was no standardized data on the adoption of industrial robots in the different countries and sectors, and therefore it was extremely difficult to identify this effect or disentangle it from other factors such as offshoring. It is only in the last few years that detailed data on robot adoption has become available to the research community, through the World Robotics Survey provided by the International Federation of Robotics (IFR, 2017).

1 The most widely known study of this type is the one by Frey and Osborne (2017, first published as a working paper in 2013), which alerted that automation could put at risk almost half of current jobs by 2030. For a survey of this body of literature (and a much less dismal projection), see Nedelkoska and Quintini (2018).

2 On the future potential of AI and machine learning see the excellent discussions in Pratt (2015) and Brynjolfsson and Mitchell (2017), also Tolan et al. 2020. In this paper we restrict the analysis to one particular robot technology – industrial robots. The use of industrial robots is well documented since the mid 1990s and their characteristics are well defined. This provides a good basis for econometric analysis. We refrain from analysing other robot technologies such as service robots, which fall into a less clearly defined category and their use is not well documented yet beyond experimental applications.

Thus, several papers have been published using this data to discuss the impact of robots on employment, in most cases finding a negative impact either on overall employment or specifically for the low-skilled (Acemoglu & Restrepo, 2019; Chiacchio, Petropoulos & Pichler, 2018; Graetz & Michaels 2018). In a recent paper, we relax some of the assumptions of this earlier literature and find no evidence that robots reduce low-skill employment in the European context (Klenert, Fernández-Macías and Antón 2020). In fact, our results show a small positive correlation between robot use and total employment in Europe between 1995 and 2015.

This paper uses the same data and aims at contributing to the same debate, but takes a step back to better understand the phenomenon at stake. First, it looks carefully at the types of robots that are widely used in industry and are included in the IFR database, discussing their characteristics and the types of tasks that they can perform. Second, it discusses the recent evolution of the distribution of robots across Europe by country and sector. And third, it explores the factors that are associated with the more or less intense deployment of robots across countries and sectors, such as robot prices and workers' wages.

A key argument of this paper is that, contrary to what is generally assumed (though not always explicitly stated), the types of robots widely used in European industry (and across the world) do not imply a discontinuity or disruption in terms of automation and labour replacement possibilities. Instead, currently existing robots are better understood as the most recent iteration of industrial automation technologies that have existed for a very long time, and which in fact had their biggest employment impact generations ago (explaining changes in the employment structure in agricultural and manufacturing that go back to the Industrial Revolution). Thus, the potential employment effects of current robotic technology are *a priori* limited. Of course, this does not preclude the possibility that a future breakthrough in AI or any other field leads to an abrupt disruption in automation potential. But the existing empirical evidence on industrial robots provided by the IFR shows that so far, this has simply not happened. Another contribution of this paper is the analysis of the different drivers of robotisation in Europe. Of all independent variables we analyse, only a handful have a significant positive correlation with robotisation: the initial wage level and the routine content of work, while net imports and offshorability exhibit a negative correlation.

Most of the recent Social Science literature using IFR data has focused on the relationship between robots and employment.³ The discussion of the characteristics of these robots is in most cases marginal, although there is a more or less general assumption that they imply a major breakthrough in automation possibilities. For instance, one of the most cited papers in this literature states that “creating robots that are autonomous, flexible, and versatile was a major engineering challenge, but remarkable progress has been made. Robots can now perform a fairly wide range of tasks, including welding, painting, and packaging with very little human intervention. These capabilities set robots apart from earlier waves of automation and more conventional information and communication technologies (ICT), which left flexible movement in three dimensions firmly in human hands” (Graetz & Michaels, 2018). Another highly cited paper states that “robots, and automation technologies more generally, displace workers from tasks they were previously performing and should thus have very different labor market effects than overall capital deepening and other types of technological changes” (Acemoglu & Restrepo, 2019). These are perfectly valid hypotheses whose consequences can be empirically tested by linking data on robots and employment, but they are also assertions with respect to what currently existing robots can and cannot do that can be directly discussed by looking at the characteristics and applications of these robots, which is what we will do in this paper.

3 Some articles also look at the impact of robots on productivity (Graetz & Michaels, 2018; Jungmittag & Pesole, 2019; Kromann, Malchow-Møller, Skaksen & Sørensen, 2019) and trade and offshoring (Carbonero et al., 2018; de Backer et al. 2018; Krenz et al., 2018).

Similarly, previous papers using IFR data pay little attention to the extraordinarily and persistently concentrated distribution of industrial robots, which necessarily limits the relevance of their evolution in terms of overall employment. These robots are almost exclusively present in manufacturing, a sector that accounts for a small fraction of employment in Europe nowadays (between 10 and 20% in most countries); but even within manufacturing, most robots are concentrated in just two or three subsectors. As we will discuss in detail later, around three quarters of all the robot stocks in Europe in 2016 were concentrated in just three manufacturing subsectors: automotive (sector 29 - with more than 50% of all robots), rubber and plastic (sectors 19-22) , and metal products (sectors 24, 25 and 28).⁴

Finally, only a limited number of studies analyse the determinants of robot adoption using IFR data. For instance, Presidente (2017), finds a positive relationship between Employment Protection Legislation (EPL) and investment in industrial robots, which is interpreted as evidence that “with strict regulation firms have the incentive to substitute human labour with machines providing services more flexibly” (Presidente 2017). Graetz & Michaels (2018) speculate that falling robot prices drive robot adoption, but do not provide a formal analysis. In our analysis, institutional factors play a smaller role as drivers of robot adoption compared to more traditional drivers of industrial mechanisation such as the intensity of routine and manual task content in the sector.

The paper unfolds as follows. Section 2 discusses data and methods, focusing on the strengths and limitations of the IFR data and our strategies to deal with them. In section 3, we discuss the characteristics and applications of industrial robots as measured in the IFR database, assessing to what extent they involve a breakthrough with respect to previous automation technologies. In section 4, we present some figures on the distribution of robots in Europe, emphasising their extraordinary concentration. In section 5 we link the IFR database with external sources to explore the factors that explain the variations in robot stocks in Europe in the last couple of decades. Section 6 concludes.

4 Outside of Europe, the electrical/electronic manufacturing sub-sectors (26-27) also account for a very large share of robot stocks (nearly a third of the global total). Worldwide, around 80% of robots are concentrated in just three groups of manufacturing industries (transport equipment, electrical/electronic [26-27] and rubber/plastic [19-22], OECD, 2019).

Data and methods

In order to explore the distribution and determinants of robot adoption, we make use of several databases with information on the deployment of robots across Europe in the last couple of decades and the macroeconomic and sector-level features that might affect this process.

The main data input in our analysis comes from the World Robotics Database (IFR 2019). It contains information on deliveries and stocks of robots from 1993 to 2018 by sector of activity (roughly based on ISIC rev. 4, the international version of NACE rev. 2). In most of the cases, stocks are estimated from the robots sent by manufacturers under the assumption of 12 years of average service life (that is, each robot is fully functional over that lifespan and then it depreciates to zero). The database presents several measurement problems and inconsistencies, with serious potential implications on data analysis. First of all there is a relevant share of robot stocks and deliveries each year which is classified as *unspecified*, that is there is no information on country or industry available. This issue is especially pronounced in earlier years. Secondly, even for countries with detailed information on the number of robots stocks and deliveries by year and industry, there can be a part of the stocks and deliveries that is classified as *unspecified*. In this case *unspecified* only refers to the industry classification. The latter problem is not negligible as long as the percentage of unspecified robots can go beyond 20% in some (few) cases. A third problem has to do with the different degree of detail of stocks and deliveries by country and year. Many industries include a subsector (in the jargon of the survey, a “class”) with unspecified deliveries and stocks and it is unclear in several cases to which level of aggregation they belong (in the database, referred as “divisions” or “classes”, equivalent to one- and two-digit sectors of activity). In this respect, the wording of the branch is not always consistent with the pattern observed over time.⁵

Aiming to employ as many sectors as possible, given that they directly determine the degrees of freedom—and, therefore, the statistical power—in our analysis, we proceeded to re-estimate the stock of robots under the premise that robot deliveries (which is the magnitude actually controlled by the manufacturers) are more reliable than the reported stocks, based on estimations with the exception of Japan. We follow a procedure very similar to the one proposed by Graetz and Michaels (2018), imputing unspecified deliveries to the different sectors on the basis of the specified deliveries. Our procedure is a bit more detailed, since we employ the information of the three closest years with specified deliveries for imputation purposes (instead of the average of the whole period). Also, we re-estimate the initial stocks imputing the unspecified initial ones, we preserve the rate of depreciation of the initial amount of robots implied by the data and we apply the 12-year assumption onwards. Graetz and Michaels (2018) take the initial stock as fully new and re-calculate all the series from data on deliveries using the so-called perpetual inventory method of depreciation. Instead, we maintain the robot-specific depreciation rate advised by the IFR and we are consistent with the initial information on stocks in the survey.

Specifically, our re-estimation procedure consists of the following four steps:

- 1) We compute the country- and sector-specific depreciation rates of initial stock embedded in the evolution of stocks during the first 11 years (the initial stock minus deliveries in the

⁵ For instance, according to its wording class 229 (chemical products unspecified) is just a residual category of class 22 (Rubber and plastic products excluding automotive parts). Nevertheless, the distribution of the data itself suggests that it is a residual class of the whole division 19-22.

initial year have to disappear after 11 years). This implies making decisions about what to do when depreciation is negative or when depreciated stock exceeds the initial stock. When there is no stock in the sector, but the sector can receive later some initial stock through imputation of unspecified initial stocks, we use the depreciation path of unspecified stocks. The total yearly deliveries include the sum of the original value plus the imputed unspecified figure.

- 2) We impute unspecified deliveries to a sector at time t using the share of deliveries in the sector (out of total specified deliveries in the country) during the 3 nearest years ($t-1$, t and $t+1$, with proper adjustments for the first and the last year). The total initial stock in a certain sector includes the sum of the original value plus the imputed unspecified figure.
- 3) We impute initial unspecified stocks using the share of deliveries in the sector s (out of total specified deliveries in the country) during the 3 nearest years (t , $t+1$ and $t+2$, as, overall, this year is the first in the series).
- 4) We recalculate stocks employing initial stocks (including imputed values), deliveries (including imputed values), depreciation rates of the initial stocks (obtained in step 1) and the 12-year depreciation assumption for deliveries.

Some countries required some ad-hoc additional adjustments (for instance, for taking into account that the initial stock cannot be lower than the number of deliveries in the first year). Moreover, we explored the evolution of the deliveries and stocks in each one of the residual classes and, coherently with the data structure, we consider that they represent a residual category of the respective division.

For the econometric analysis, we needed to link the previously described data on industrial robots with other data sources. This is complicated by the fact that there were very relevant changes in the industry classification throughout the period of our analysis. Specifically, ISIC rev. 4 replaced ISIC rev. 3 in the late 2000s, and the same applies to the European taxonomy, with NACE rev. 2 substituting NACE rev. 1.1. The correspondence between the old and the new taxonomies is not perfect, but fortunately, this issue is less problematic when considering only manufacturing or industrial activities as is mostly the case in this paper, especially if it is possible to aggregate some sub-sectors. In principle, for each country included in the database, we obtained an estimate of robot stocks from 1995 to 2015 for the following sectors of activity (expressed for convenience in terms of NACE rev. 1.1):

- A. Agriculture, hunting, forestry; fishing.
- B. Mining and quarrying.
- C10–12. Food products and beverages; tobacco products.
- C13–15. Textiles, leather, wearing apparel.
- C16. Wood and wood products (including furniture).
- C17–18. Paper and paper products, publishing and printing.
- C19–22. Plastic, rubber and chemical products.
- C23. Glass, ceramics, stone, mineral products not elsewhere classified. (without automotive parts).
- C24–28. Metal.
- C26–27. Electrical/electronics.
- C29. Automotive.
- C30. Other transport equipment.
- C32. All other manufacturing branches.

- D–E. Electricity, gas and water supply.
- F. Construction.
- P. Education.
- Other non-manufacturing activities.

We choose to restrict the analysis to manufacturing sectors only, for the following reasons: It makes the database used in the analysis more homogenous and consistent, thus reducing the risk of omitting relevant variables. In this respect, one should take into account that this database includes only *industrial* robots, which, in practice, refer to a very specific type of capital, as we argue in Section 3. On the downside, limiting ourselves to manufacturing sectors reduces the degrees of freedom in the analysis, which is marked by the combination of sectors and countries. Ultimately, the decision of focusing exclusively on manufacturing sectors is driven by the fact that the International Federation of Robotics Database only covers manufacturing sectors with the necessary precision, while the coverage of other sectors is extremely limited and often problematic. This reflects the fact that industrial robots are predominately used in manufacturing activities so far.

Apart from the IFR database, in this paper we make use of several additional databases. The first one is the European Jobs Monitor (EJM) database, administered by the European Foundation for the Improvement of Living and Working Conditions (Eurofound, 2019). The EJM database includes basic labour market information (mainly, employment figures by 2-digit sector of activity, 2-digit occupational level, sex, age group and level of education) based on ad hoc extractions from the European Labour Force Survey provided by Eurostat. A second database used in this paper is the European Working Conditions Survey (Eurofound, 2018), complemented by the European Jobs Monitor Task Indicator dataset (Eurofound, 2016) from which we obtain information on the routine-task contents of European jobs, a potential determinant of robotization. Thirdly, we exploit the European Union Capital, Labour Energy, Materials and Services database (EU KLEMS), an ambitious Framework Programme research project that collects information, among others, on capital stocks and wages (European Union Capital, Labour, Energy, Materials and Services Consortium, 2018; Jäger, 2018). Fourthly, we retrieve information on labour market institutions from the database on Institutional Characteristics of Trade Unions, Wage Setting, State Intervention and Social Pacts, 1960-2014 (ICTWSS), provided by Visser (2016). Particularly, we focus on country-level union density and the type of collective bargaining regime. We complement this information with sector-level union densities from the European Social Survey (ESS) for 2005 and 2010 (ESS European Research Infrastructure Consortium, 2018a and 2018b). In the sixth place, the United Nations International Trade Statistics Database (UN Comtrade, 2019) allows exploring the trade shocks during the analysed period, which can potentially affect the process of robot adoption if they have a relevant effect on the performance and evolution of some sectors of activity. We also use this source in order to estimate robot prices in Section 6. A seventh resource used is the United States census data accessed through the Integrated Public Use Microdata Series (IPUMS) initiative (Ruggles et al., 2019) in order to construct alternative measures of the jobs potentially replaceable by industrial robots following the strategy proposed by Graetz and Michaels (2018). Finally, we also used the database of the Organisation for Economic Co-operation and Development, OECD.Stat (OECD, 2019), from which we obtain some basic macroeconomic information on European Union countries and Employment Protection Legislation (EPL version 1), a measure of labour market rigidity, complemented by the database collected by Avdagic (2012) for Eastern Europe on this same measure.

With the exception of the EJM, employed through all the paper and the Comtrade database—an input for estimating robot prices—the use of these data sources is mainly restricted to the fifth section, where we carry out an econometric analysis of the determinants of robot adoption. We provide more details on the specific indicators used in the respective sections.

Characteristics and applications of industrial robots

The term robot originates from the science fiction literature, not from science or engineering. In science fiction, robots often embody fears about uncontrolled technology, but also sublimated anxiety about working class revolt and revolution. In the 1920 Czech play “R.U.R.” from Karel Čapek that coined the term *robot* (derived from the Czech “robota”, meaning “forced labour”), robots are humanoid machine servants that increasingly do all manual labour in a future society, and eventually revolt and destroy humanity. The term immediately caught the popular imagination, being widely used not only in science fiction literature but also in public debates about the implications of technical change and the future of work. But the industrial robots we will be discussing in this report are, in fact, very different from the robots of science fiction literature. Industrial robots have to be put in the context of the very long history of mechanisation and automation of industry, that goes back even further than the industrial revolution.

Both mechanisation and automation refer to the replacement of human labour by machines (Wallén, 2008). But mechanisation, which started much earlier, requires direct human operation to function (and it is thus closer to the simple use of tools to expand the productive power of human labour), whereas automation implies some degree of autonomy in the functioning of machines (and it comes therefore closer to the literary concept of robots). However, the difference between mechanisation and automation is not clear-cut but a matter of degree: full automation (fully autonomous machinery) is impossible in strict terms, since there is always some human intervention in the design, programming or repairing of machines. As of today, fully autonomous machines only exist in science fiction.

Even before the Industrial Revolution, windmills and watermills harnessed the energy of wind and water currents to power mechanisms that could replace human labour for tasks that essentially involved physical strength, such as grinding or hammering. The refining of mechanical transmission systems such as wheels, axles and gears allowed an increasing precision in the application of strength to the manipulation of objects, thus opening the door for the replacement of some manual dexterity tasks, such as spinning or knitting. But the big leap in the mechanisation of industrial processes came in the 18th and 19th Century with the discovery of more flexible, controllable and portable sources of energy, such as steam or electricity (Mumford, 2010). In parallel, there was an equally important progress in mechanical, electrical and electronic mechanisms of control, allowing increasing levels of precision and flexibility, and expanding the range of physical tasks that could be performed with machines. Already in the early 20th Century, these developments had allowed the mechanisation or even partial automation of key manufacturing operations such as weaving or iron and glass making, among many others (More, 2014).

Perhaps the next big leap in industrial automation comes with the digital control of machinery in the second half of the 20th Century. The main advantage of digital compared to mechanical forms of controlling machinery is in terms of flexibility. Whereas mechanical control is generally embedded in the physical configuration of the machine, digital control allows a differentiation between the physical machine (hardware) and the control routines (software) that facilitates not

only more precise control of complex operations, but also the possibility of redeployment or adaptation of the machine to different tasks without physically reconfiguring it. Even though the types of tasks performed by digitally controlled machinery in manufacturing are still mostly those involving strength and dexterity, the possibilities for automation in those domains are considerably expanded with the use of digital control (Wallén, 2008).

At this point of our discussion, it is important to note that the increasing mechanisation and automation of industry of the last two centuries is not only the result of technological developments, but also of a large-scale reorganisation of the industrial production process that took place in parallel. Technical and organisational change are two processes which are endogenously related, and which feed each other. The availability of automation technologies stimulated the reorganisation of production to make use of the new possibilities, and the reorganisation of production stimulated the development of new automation technologies. Historically, the forms of work organisation associated with Taylorism/Fordism (detailed division of labour, standardisation of processes, centralisation of control, etc), which were themselves an application of principles of mechanical engineering to management, expanded very significantly the range of tasks that could be automated in the first half of the 20th Century (Braverman 1998). Early mechanization and automation technologies were mostly applicable to highly standardized mass production, and thus they contributed to not only the standardisation of industrial processes, but even of industrial products and society itself (mass standardised production required mass standardised consumption).

In any case, the industrial robots we will analyse in this report should be understood within the context of this long history of mechanisation and automation of industry, rather than as a sharp rupture in that history as sometimes they are implicitly understood. The first patents and prototypes of digitally controlled machines using the term “industrial robot” (which incidentally, was proposed by an engineer who was also a big science fiction fan, Joseph Engelberger) go back to the 1960s, and the first real applications to the 1970s for hazardous manual tasks such as spray painting or material handling (Wallén 2008). The industrial application of the kinds of industrial robots we will analyse in this report really takes off in the late 1980s and early 1990s, approaching the period that we will analyse in this report (1995 onwards).

The definition of industrial robots used in the IFR database follows the International Standards Organisation 8373:2012 norm. According to this definition, an industrial robot is “an automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications” (International Standards Organisation 2012). Essentially, this refers to digitally controlled industrial machinery, whose purpose is the physical manipulation of things, that operates in three axes or more, and whose programmed function or motions can be changed without physical alteration, or even adapted to different applications (with or without physical alteration).

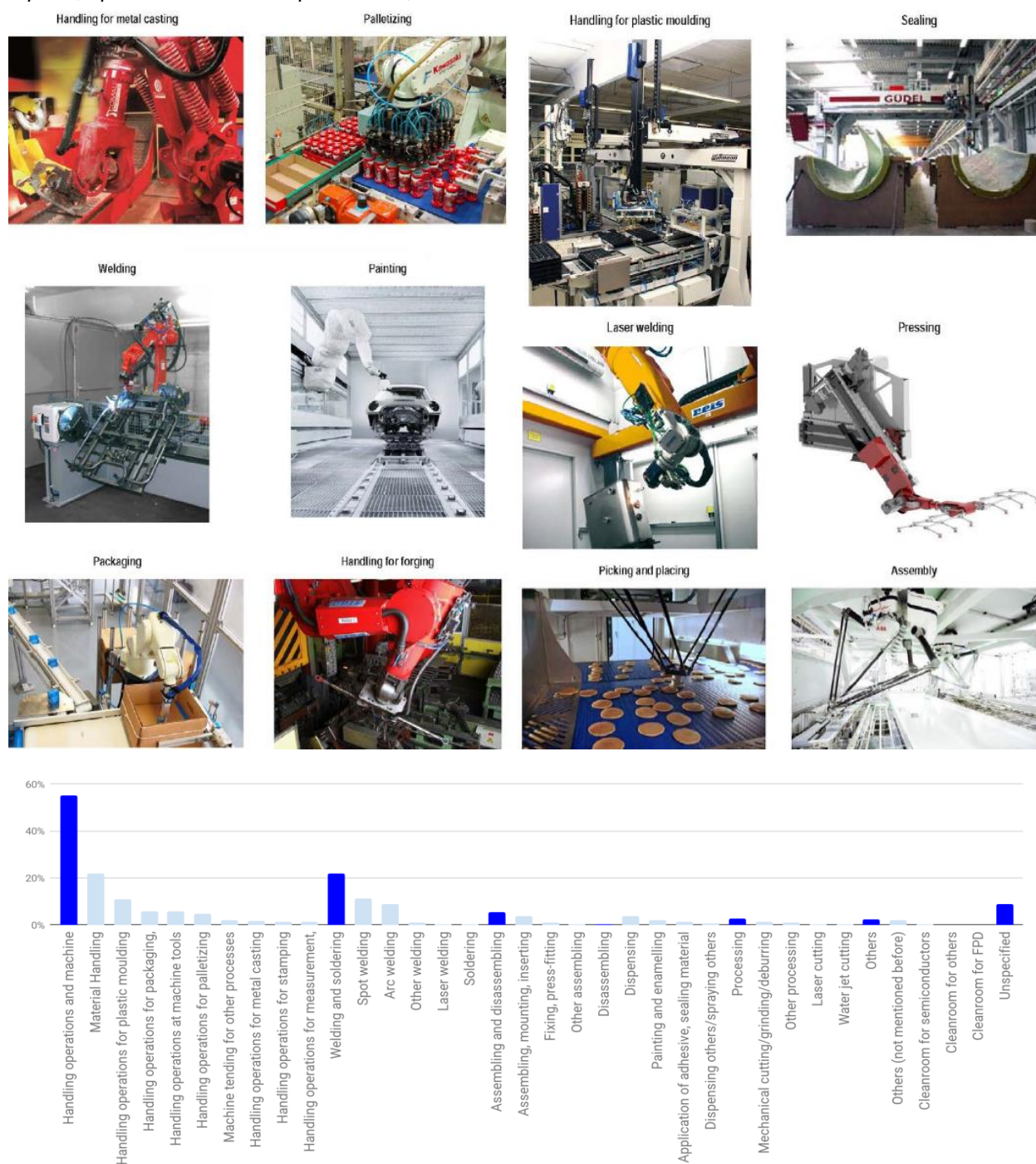
But what do these robots do? In what ways are they different from previous waves of mechanisation and automation in industry? To get a better idea of what kinds of robots we are talking about, Figure 1 shows the distribution of industrial robots in Europe in 2017 by application (what are they used for), including some pictures from IFR (2017) to illustrate the kinds of robots we are talking about.

The main category of robot applications in Europe is *handling operations and machine tending* (55% of all European robots fall in this category), which essentially involves moving things from

one place to another with a certain degree of precision. The second category is *welding and soldering* (22%), which involves joining materials or items together by using high heat to melt the joining parts or by putting some filler metal into the joint. The third category is *assembling and disassembling* (5%), which refers to the sequential addition of standardised interchangeable parts to a complex product (such as a car, an electric appliance or electronic goods). Other significant (but much less prevalent) applications of robots in Europe involve painting, cutting, etc.

Figure 1 shows that what current industrial robots do is essentially *physical tasks that involve the moving and precise manipulation of objects within industrial processes*. As can be seen in the pictures also shown in Figure 1, these robots are not even remotely anthropomorphic: in most cases, they resemble arms at most, ending in an effector which may (or may not) resemble a human hand and which typically performs the precise manipulation task. Although they typically have axes that enable them to move in all directions, they generally remain within a predefined and rather limited space. And even though they can be reprogrammed to change the specific tasks they do, in the vast majority of cases they remain physically constrained to performing a very particular application.

Figure 1: Robot applications in Europe, 2016 (source: IFR [2019]). Pictures World Robotics 2017 report (reproduced here with permission)

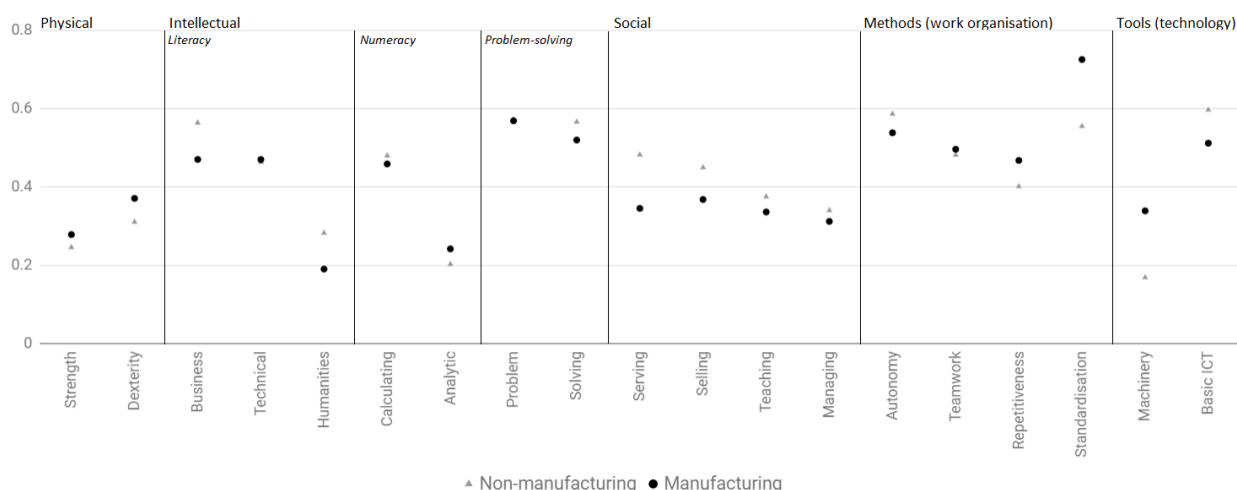


In other words, Figure 1 shows that the industrial robots widely used in European industry and which we will analyse in detail in this report are, indeed, the latest iteration of the very long-term process of industrial mechanisation and automation rather than a radical departure from this process. The vast majority of European (and worldwide) industrial robots perform essentially the same type of operations as previous mechanisation and automation technologies, replacing labour input in routine tasks that involve physical strength and dexterity. Compared to previous automation technologies, they may be able to perform these tasks more flexibly and precisely, they

may do more complex operations in a slightly more autonomous way, but the difference with previous automation technologies is one of degree rather than of a qualitative nature.

This has important implications for any assessment of the potential effect of industrial robots on employment, that we can formulate even before doing any empirical analysis. Figure 2 below shows the distribution of labour input by different categories of tasks for the working population in manufacturing and services, according to a recent estimation carried out by Eurofound (Fernández-Macías, Hurley and Bisello 2016). The horizontal axis shows the different task categories, ranging from physical tasks (strength and dexterity) to use of technology (Information and Communication Technologies, ICT), and the vertical axis reflects the relative intensity of the average task input for each category, for the average European worker. To a large extent because of the impact of previous waves of automation, the amount of labour input spent on physical strength and dexterity tasks in Europe is already quite marginal, *even in manufacturing*. In fact, employment in manufacturing itself is rather small in Europe nowadays, between 10 and 20% in most European countries (it is only above 20% in the Visegrad region), which is again largely a result of previous waves of automation. Thus, the potential for labour replacement of the types of robots we are talking about seems *a priori* rather limited.

Figure 2: Average task profile of manufacturing and non-manufacturing workers in EU15, 2012 (source: Fernández-Macías, Hurley & Bisello [2016]).



A much more disruptive development would be the large-scale automation of service sector employment. The vast majority of workers in Europe work in services, in occupations and tasks that involve social interaction, information processing and problem-solving (Fernández-Macías, Hurley & Bisello 2016). There has been significant automation for some of these tasks too, mostly involving computers: information processing tasks of a routine nature (administrative and bureaucratic work) used to rely mostly on human labour, whereas today they are performed by relatively few human operators and massive amounts of computing power. It is social interaction tasks, and tasks requiring physical or intellectual capabilities of a non-structured and non-standardised nature that remain beyond the possibilities of existing automation technologies, and where most human labour is currently concentrated. AI, according to some, may in the near future facilitate also the automation of some of these tasks, since it may under certain conditions operate in unstructured environments with a higher level of autonomy (Pratt, 2015; Brynjolfsson & Mitchell 2017). Maybe robots with AI capabilities will eventually replace human labour in service activities to a similar extent as in manufacturing. But so far, this remains a possibility rather than an observable fact: there is no evidence of large-scale (or even moderate scale) robot-based automation of the kind of

social interaction or non-structured physical or intellectual tasks typical of service sector employment (see, for instance, Autor & Dorn 2013).⁶

In any case, this article remains focused on industrial robots that operate mostly in the manufacturing sector, a sector where large-scale automation is indeed an incontrovertible fact. But as we have emphasized in this section, such large-scale automation is by no means a new phenomenon, but something that started more than a century ago. And whereas today's robots are extremely sophisticated automation technologies if we compare them with their predecessors (such as Jacquard's loom or Arkwright's spinning mill), they are remarkably similar in terms of the kind of labour they can replace (routine tasks involving strength and dexterity). The main difference between the robots we will analyse in this report and earlier automation technologies probably lies in their higher flexibility and precision, and perhaps also lower relative prices. These are probably the factors behind their increasing take up in the last couple of decades in Europe, which we will study in the following sections.

The distribution of industrial robots in Europe

According to the data provided by IFR, in the last two decades there has been a sharp increase in the number of industrial robots operating in European manufacturing. This is illustrated by Figure 3, which shows that the total stock of robots in Europe went from slightly more than 100,000 units in 1995 to almost 400,000 in 2015, an increase of 350% over a twenty-year period. Figure 3 also shows how that increase is distributed by country, and although the growth is more or less generalised, there are very significant differences that merit a detailed discussion.

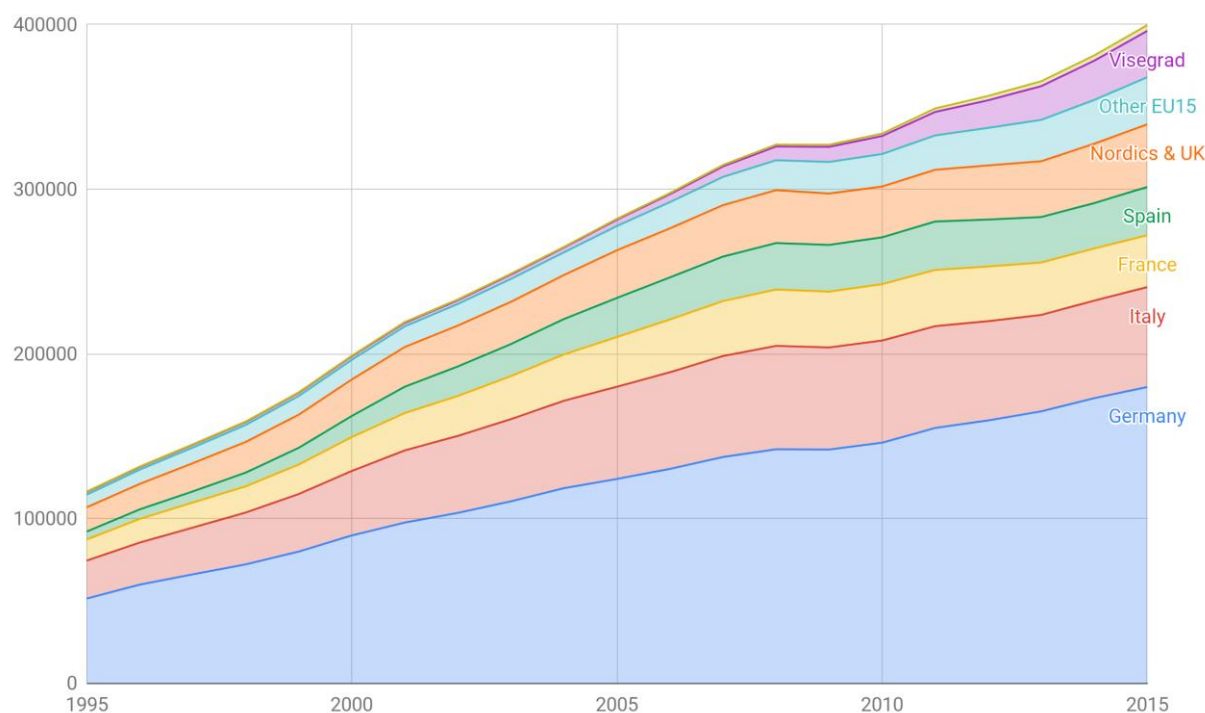
Germany is by far the country with the largest stock of robots (nearly 200,000 units, which amount to almost half of the total in the EU), and has been for the last 20 years. Despite starting at a very high level already in 1995, the stock of robots in Germany grew even faster than for the EU as a whole, so that its dominant position was actually reinforced. This contrasts starkly with Italy and France, the second and third countries in terms of robot stocks throughout the period: even though they also expanded in terms of the absolute number of units, their rate of growth was lower than for the EU as a whole and thus reduced their relative share. In fact, the stock of robots in Italy and France declined even in absolute terms in the second half of the period. The absolute number of robots in Spanish manufacturing started low in 1995 but expanded very fast, much faster than the EU as a whole, until it stalled after the crisis hit in 2008. In the Nordic countries (Denmark, Sweden and Finland) and the UK, the expansion was relatively mild, similar to that of France and Italy, whereas in other Continental European economies (as the Netherlands, Belgium or Austria, included in the aggregate category of "Other EU15" in the chart) the expansion in the number of robots was similar to the EU average.

But the really spectacular increase in robot stocks actually took place in the Visegrad countries (Hungary, Poland, Czech Republic and Slovakia). Even though it cannot be fully appreciated in the chart because compared to other countries the values remain relatively low, the expansion for those countries went from close to no industrial robots in 1995 (less than 2,000 according to the estimation based on IFR data) to 30,000 in 2015, a near 17-fold increase. This increase is more

⁶ This statement refers mainly to robots in the sense of physical machines and not to software such as chat-bots or automated journalism, which have made notable progress in recent years.

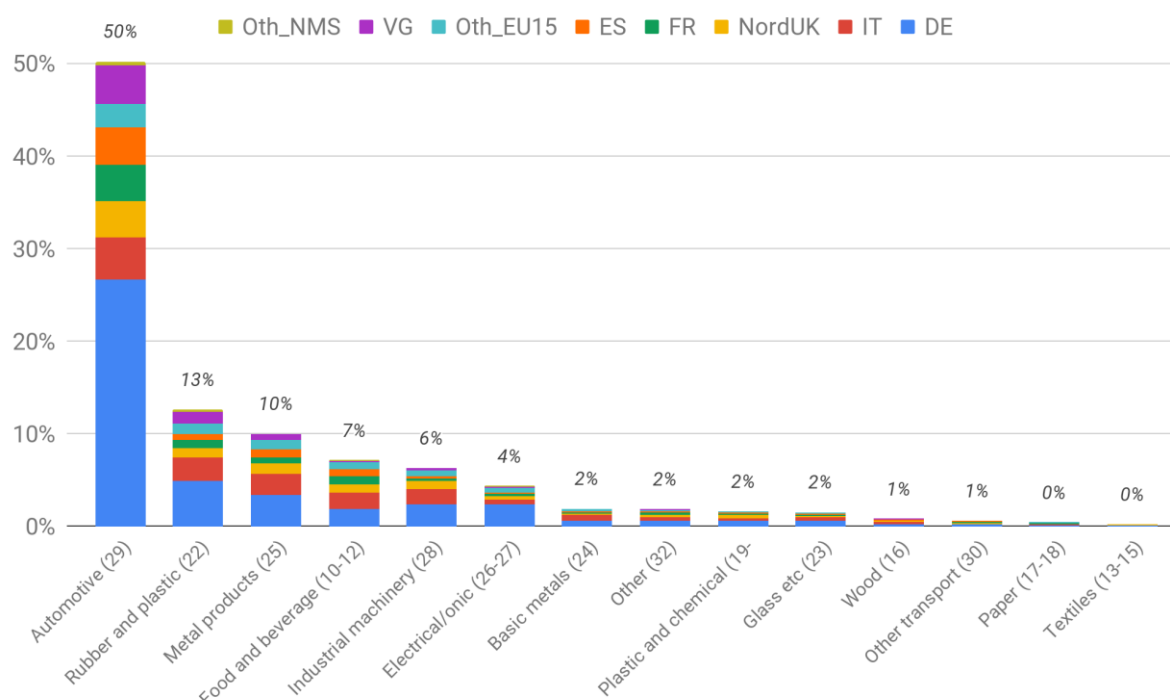
remarkable because, as can be seen in the chart, most of it actually took place after 2005, in a period of barely 10 years.

Figure 3: Evolution of industrial robot stocks by country, absolute figures (source: authors' analysis from IFR [2019]).



In short, the evolution of industrial robot stocks in Europe in the last 20 years shows a very significant increase, but also a large concentration across countries with very different rates of growth, with Germany holding an increasingly dominant position and the Visegrad countries expanding very rapidly in recent years. But the concentration of robots is even more striking if we look at the distribution of robot stocks in 2015 for different sub-sectors within manufacturing, as shown in Figure 4. More than 50% of all European robots are installed in the automotive sector [code 29]. In fact, automotive plus the following two main robot-using sectors (rubber and plastic [code 22] and metal products [code 25]) account for three quarters of all robots, and if we add the following three sub-sectors (food and beverage, industrial machinery and electronics), we can see that 6 of the 14 sub-sectors of manufacturing hold more than 90% of all the robots installed in Europe. Sectors as important as textiles, paper, wood, or even plastics and chemicals (see Figure 4 for codes) have close to no robots according to the figures provided by the IFR.

Figure 4: Distribution of industrial robot stocks by sector and country, EU 2016 (source: authors' analysis from IFR [2019])



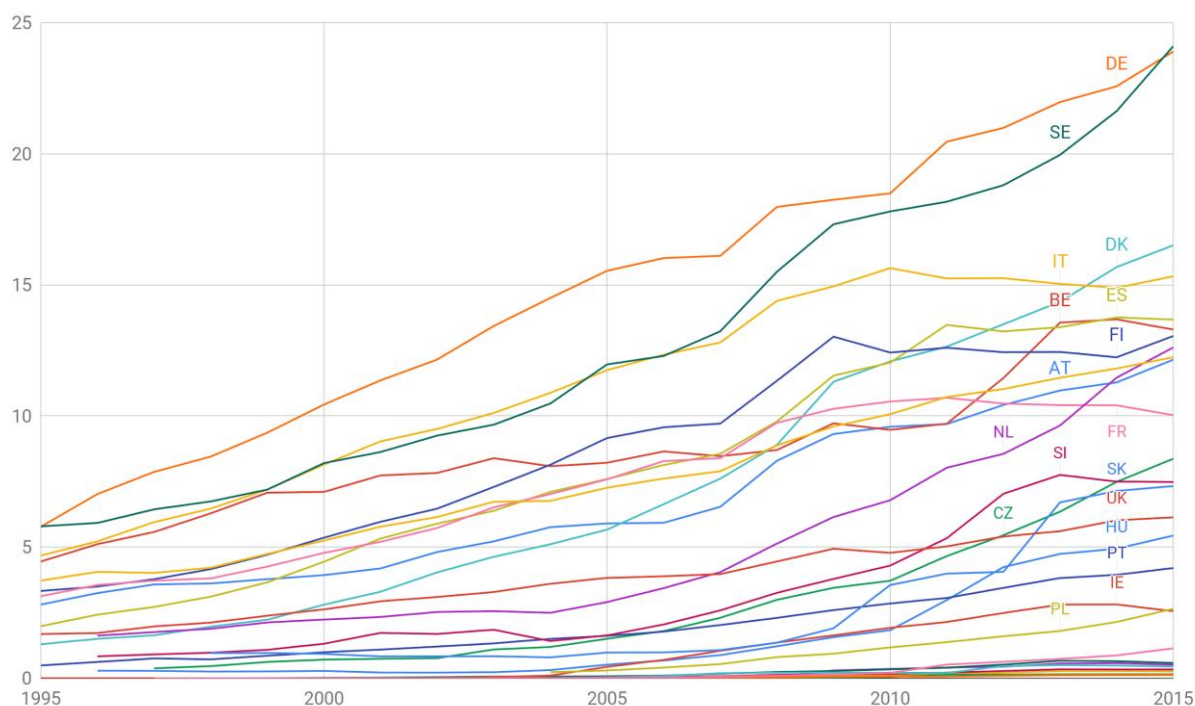
In fact, the distributions of industrial robots by country and sector combine in a way that exacerbates the extreme concentration previously mentioned. The most striking fact in this respect is the fact that 27% of all European robots are concentrated in German car manufacturing. German car manufacturing, for reference, accounts today for less than 1% of total employment in the EU, and for less than 4% of all employment in manufacturing in the EU: yet it accounts for more than 1 in every four industrial robots operating in Europe. This extraordinary concentration of European robots in German car manufacturing has, in fact, become stronger over time (the value was less than 20% in 1995).

Therefore, an important fact about industrial robots in Europe is that they are extraordinarily concentrated in a few countries, sectors and country-sector combinations, something which has not significantly changed in the last two decades. This has important implications. First, it suggests that industrial robots (at least, the types of industrial robots captured in the IFR statistics) are to some extent a specialised technology, with limited applicability even within manufacturing. Eight out of the fourteen manufacturing subsectors identified in Figure 4 have essentially no robots in operation. Second, this delimits very significantly the potential role that robots may have played in recent employment trends in Europe. And third, from a more operational perspective, this extraordinary concentration of robots means that any significant result of the analysis of IFR data is likely to be driven by very few data points.

So far, we have only discussed the growth and distribution of industrial robots in absolute and relative terms, without having a point of reference to evaluate how significant these numbers actually are. The IFR data shows that there are around 400,000 industrial robots currently in operation in Europe, a number that has grown considerably in the last 20 years: but is that really a big number? With respect to what? Since robots are often discussed in terms of automation of human labour, the most obvious point of reference for evaluating the number of robots is the

number of workers in the same industries and countries. On this basis, we can create an index of *robot density* defined as number of robots per thousand workers in each industry-country combination. Figure 5 and Figure 6 show the evolution of robot density by country and sector.

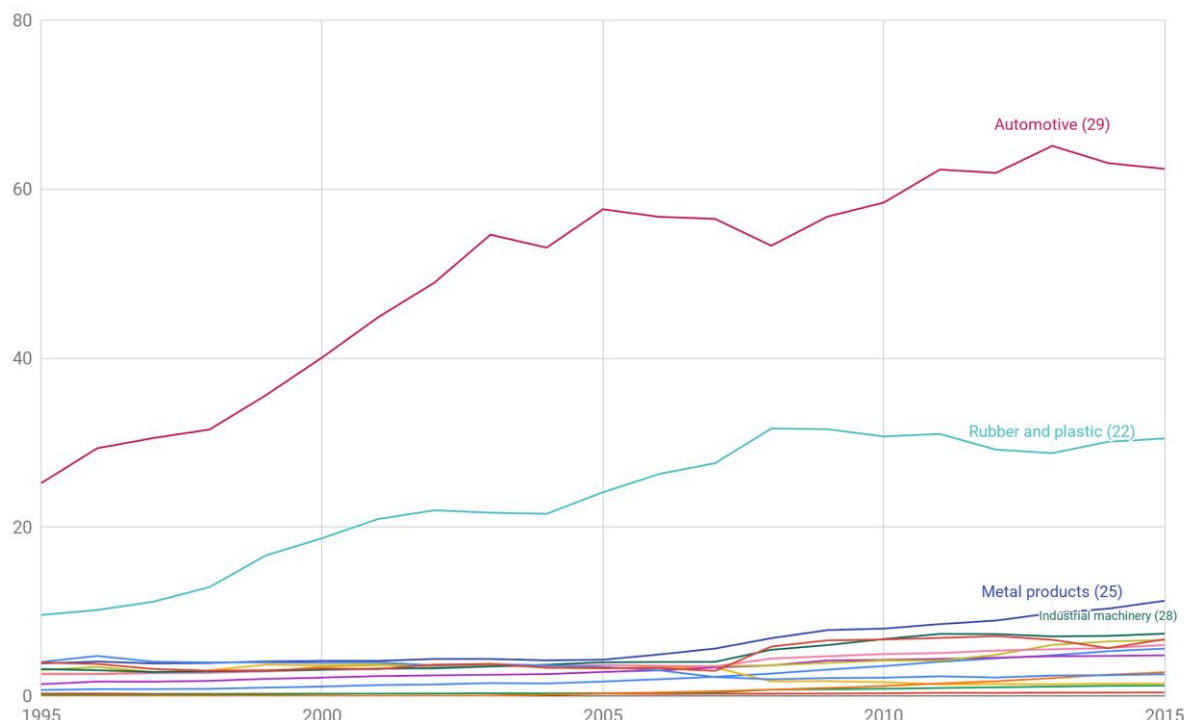
Figure 5: Robot density by country, 1995-2015 (source: authors' analysis from IFR and EJM database).



In the overall EU, there were about 12 industrial robots per thousand workers in manufacturing in 2015, up from almost 4 in 1995. Although this is still a threefold increase, the number sounds considerably less impressive than what the absolute trends suggested earlier: the proportion of industrial robots to workers overall in European manufacturing is around one (robot) to one hundred (workers).

The average robot density varies considerably by country and sector. The highest robot density is, as could be expected, found in Germany (see Figure 5), with more than 20 robots per thousand manufacturing workers. Italy, Spain and France are around or slightly above the European average, with 10 to 15 robots per thousand workers. Using robot density rather than the absolute number of robots make some of the small countries emerge as important users of industrial robots, most importantly the Nordics (Sweden actually overtakes Germany in 2015, whereas Denmark and Finland are slightly above the average), as well as Belgium and Austria.

Figure 6: Robot density by sector in the EU, 1995-2015 (source: authors' analysis from IFR[2019] and Eurofound [2019]).



But the biggest variation in robot density is by sub-sectors within manufacturing. Here robot density actually sharpens the divide between the two or three most robot-intensive sectors and the rest. In car manufacturing, there are more than 60 robots per thousand workers, a value that certainly implies a significantly more intense use of robots and a more plausible case for significant labour replacement. Rubber and plastic also shows rather high values (30 robots per thousand workers in 2015), whereas metal products and industrial machinery (the following most robot-intensive sectors) are actually below the average of 12. These results imply an extremely polarised distribution of robot density by sector: only two of the 14 sectors are above the average, and the other twelve are all below, in most cases far below with values of 1 or 2 robots per thousand workers. These results reinforce the impression that industrial robots (as measured in the IFR database) are a specialised technology, mostly relevant in car manufacturing and to some extent in rubber and plastics (sector 22)⁷, but marginal in other sectors.

In sum, the limited scope of applicability of current industrial robots (in terms of sectors and applications) and the resulting concentration of industrial robots in a small subset of sectors and countries suggest a limited role of industrial robots in recent employment trends in Europe, at least from an economy-wide perspective. Industrial robots are certainly labour-saving devices in the tradition of previous automation technologies, and thus may have replaced labour input to some extent. But industrial automation has been going on for centuries and thus most of the replaceable labour input was already gone twenty years ago. Furthermore, as we saw in the previous section the types of robots we are talking about do not involve a significant departure from previous

⁷ Not to be confused with sector 19-21 plastics and chemicals.

automation technologies but a refinement of those, and thus we should not expect any major discontinuity in terms of their employment effects.

The determinants of robot density in Europe. An econometric approach

What factors could explain the wide diversity in the rates of adoption of industrial robots in different manufacturing subsectors and countries in Europe? If we recall the detailed description of industrial robots and what they can actually do (essentially, physical tasks involving strength and dexterity, and which are of a standardised and repetitive nature), the most obvious factor to consider is the degree of routine of labour in the different sector-country combinations. But whereas the degree of routine in tasks can determine the technological feasibility of replacing human by machine input in different productive processes, wage levels are surely an important additional determinant because they can directly affect the relative cost of human compared to robotic input in carrying out those tasks. And there are other variables that in principle could affect robot adoption too. In particular, international trade and the offshoring of specific parts (or all) of the production process can be an alternative to robotisation in the context of increasingly global markets for manufactured goods. Typically, production is offshored to developing economies with cheap labour, but it could also be offshored to third countries with even more automated productive technologies. Since we adopt a European perspective, for our purposes what matters is that offshoring can be considered as a third alternative in addition to the two primary options of using human or machine input for carrying out specific tasks, and in this case the main underlying factor would be the relative cost of offshoring production to global value chains. Finally, there may also be institutional factors driving robot adoption in specific sectors and countries. For instance, if firms use robots as a way to circumvent the constraints imposed by employment protection legislation on their capacity to adjust labour input “at will” (Presidente 2017).

To assess the relative importance of each of these factors, we use an econometric approach with multiple independent and control variables, and the increase in robot density as the dependent variable. In this analysis, *increase in robot density* (the dependent variable) is defined as the ratio of the increase in the number of robots in each sector to the *initial* number of workers (in thousands) in that industry and country. The reason why the denominator (number of workers) is kept fixed at the initial level (1995) rather than changing as the numerator (number of robots) is because employment can be itself affected by robot adoption and other factors, and thus would introduce variability in the dependent variable which is not related to robot adoption as such. The period of analysis covers the last two decades (1995 to 2015). Looking at change over the entire period may obscure changes in the trend, but looking at change on a yearly basis would be too biased by errors in the measurement of robot stocks. Therefore, we opted for splitting the period in two sub-periods of ten years each (1995-2005 and 2005-2015) as a compromise to minimise problems of measurement error. The analysis is restricted to sectors within manufacturing, since the IFR data for non-manufacturing sectors is sparse and unreliable, and the large majority of industrial robots included in the database (far above 90% in 2015, see Figure 12 in the appendix) are installed in manufacturing sectors.

As for the independent variables, according to the previous considerations we introduce the following at the industry-country level:

- Different measures of routine task content.
- Wages (in natural logs).

- Increase in net imports with respect to initial employment.
- Offshorability risk.
- Share of workers with high education.
- Share of workers aged 50 years and above.
- Union density.
- Employment Protection Legislation (version 1)
- Collective bargaining coverage.
- Level of centralisation of collective bargaining,
- Coordination of wage setting

With the exception of net imports, we include only the value of the variable of interest at the beginning of the period because of endogeneity concerns (e.g., the amount of high-routine jobs can shrink because of robotisation). In the case of net imports, we decided to use its change over time in the model since it could act as an alternative or functional equivalent to robotisation, and in that respect the initial level is not very informative. However, this could lead to endogeneity problems that must be taken into account.

The logic of introducing wages in the analysis is to see if robotisation tends to be more intense in those sectors where the cost of labour is higher. A more comprehensive analysis would require exploring the change in wages (which, unfortunately, is plagued by endogeneity concerns since pay can be affected by automation) and the cost of not only robots but also other types of capital. Nevertheless, the price of robots and capital across sectors and countries can differ and our databases do not allow us to explore this issue in an appropriate way (apart from endogeneity concerns, capital-related variables are only available for a reduced set of countries and years).⁸

Regarding international trade, if there is a big increase in net imports in a certain industry, we should expect a lower integration of robots in production processes. As mentioned above, the inclusion of this variable might raise endogeneity concerns given that it is likely that the process of robotisation and international competitiveness are jointly determined.

The degree of routinisation of work might in principle be a key variable for understanding to which extent robots can be used in production. In principle, the literature highlights that the feasibility of automation is linked to processes that involve routine tasks and do not require human interaction (Autor, Levy & Murnane, 2003; Goos & Manning, 2007; Spitz-Oener, 2006). We employ three different measures here. The first one draws from the proposal of Autor and Dorn (2013) for the US, based on the American Dictionary of Occupational Titles, adapted by Goos, Manning and Salomons (2014) to the ISCO-88 occupational classification employed in European countries. The construction of this measure (Routine Task Intensity, RTI) only considers occupational categories at 2 digits and is 0/1 standardized. Fernández-Macías, Hurley and Bisello (2016) suggest an alternative measure based on the observed tasks in the European Union 15 at cells defined by 2-digit-level sectors and occupations exploiting the European Working Conditions Survey 2010. This second index is continuous and normalised to a 0-1 range. We also compute an additional measure

⁸ From a theoretical point of view, the role of capital other than robots (which can be considered as a specific type of non-ICT capital with a small fraction of ICT capital, given by the attached software) is of more interest for the discussion of the effects of robots on employment.

inspired by one of the instrumental variables proposed by Graetz and Michaels (2018), which aim to capture in more detail the kinds of tasks and jobs robots can perform. It tries to measure the share of replaceable employment, which is derived from the share of employment in each sector that corresponds to occupations matched to the IFR data on robot applications (the mapping is done following Graetz and Michaels proposal applied to the 1990 US Census classification, then translated to ISCO-88 and assigned to the relevant employment figures of Eurofound's European Jobs Monitor database).⁹

Offshorability is related to the degree to which a job can be done at a different location without losing quality (Blinder & Krueger, 2013), and it can also be expressed as a 0/1 standardised index. Offshorability may also be linked to robot installation because as previously mentioned they can be substitutes. For the offshorability measures we draw upon the work of Mahutga, Curran and Roberts (2018), adapting the indices originally designed for American data to the European classifications.

To assess the potential impact of industrial relations on the installation of robots, we look at the effect of union density at the industry level, obtained from ESS micro-data. This data should be taken with caution given the low number of observations by industry. In principle, it is difficult to establish a clear hypothesis about the possible effects of unionisation on the rise of robots, given that the responses to automation of unions might differ across countries. To avoid employment losses, unions may try to somehow limit the installation of robots, and it is also possible that employers try to use robots to reduce the influence of unions in the workforce (replacing workers by machines).

Finally, we include two indicators of the composition of the initial labour force: the share of workers with high education and the share of workers aged 50 years or above. We try to see if the introduction of robots might be related to complementarities with the former or a process of replacement of the latter group. It could be that a larger share of highly educated workers facilitates the introduction of robots (as they are not as replaceable as other types of employees) or that the presence of this sort of workforce favours robot adoption as long as they are more likely to be complementary. In the case of workers aged 50 and above, the expected sign is not clear. A higher share of workers close to retirement can facilitate their replacement by robots but their presence could also negatively affect the adoption of new technology.

In the model, we also include several indicators of labour market institutions. Unfortunately, they are only available at the national level, which does not only reduce the variability of the indicators of interest but also poses econometric problems due to the low number of countries for which we have information on all variables (12, which implies a problem for using clustered standard errors in the regression analysis with a reduced number of clusters). Specifically, we consider the

⁹ Graetz and Michaels (2018) propose a second instrumental variable based on the prevalence of reaching and handling tasks. It combines information on the relative importance of reaching and handling relative to other physical demands making use of the Dictionary of Occupational Titles and an analogous procedure as the above in order to obtain a 0-1 industry-level measure. While the bivariate correlation between this measure and the increase in the robot stock per worker is positive, it becomes negative when controlling for other variables, so we decided to remove it from the main analysis given that it is based on American data on task content and we already have other alternative indexes for approaching this issue. These results are available upon request.

following indicators: Employment Protection Legislation index (version 1, computed from OECD.Stat and Avdagic, 2012), collective bargaining coverage (from OECD.Stat), wage bargaining centralization (an index ranging from 1 to 5) and two indicators of wage coordination. The first measure of wage coordination looks at the likely degree of coordination of bargaining (from 1 to 5), while the second one is behavioural, aiming at capturing the modes and efforts of coordination (resulting in an index from 1 to 6).¹⁰ The impact of these national features is quite unpredictable *ex ante*, since labour market institutions may either act as a constraint to robot installation or as an incentive (to use robots to overcome the constraints imposed by regulation on the management of labour).¹¹ Employment protection can raise the part of the cost of labour not captured by the wage but also can introduce difficulties for replacing workers by robots, while the impact of union density and collective bargaining might be related to union power, in the sense explained above. In principle, companies have a limited ability to modify collective bargaining centralisation and coordination as long as they depend on the national legal frameworks, and robotisation can be a way to reduce the impact of that constraint as argued by Presidente (2017).

Figures *Figure 7* depict the correlation between the above-mentioned factors and the increase in robots by sector normalised by the initial number of employees. The analysis is carried out at the country-sector level (although some variables are only available at the national level) and each observation is weighted by the proportion of total employment considered in the analysis in the country in the initial year. An alternative weighting procedure based on absolute employment figures yields very similar results.

The first salient—but not surprising—feature is that, given that the robots are very concentrated in a few sectors of activity, the correlations between the increase in robot density (defined as the ratio of the increase of robots to the initial level of employment) and most of the variables shown are at best quite weak. Secondly, we can highlight the slightly positive correlation between the increase in the robot stock per worker and the initial wage level and two of the three measures of routine. Conversely, the graphs suggest the existence of a negative correlation between robot adoption, net imports at the sectoral level and the offshorability index. The rest of relationships are basically null.

The case of RTI (an index based on the proposal by Autor and Dorn 2013, as implemented by Goos, Manning and Salomons 2014) is particularly striking, because it shows a negative correlation with robot adoption which is not only inconsistent with the other two routine indices used (based on Eurofound 2016 and Gratz and Michaels 2018) but also with the theory and even common sense (robots should be more frequently used where work is more routine and not the opposite). In fact, the same RTI indicator has the expected positive correlation with robot density if we include the non-manufacturing sectors in the analysis (available on request); but as previously mentioned, the IFR data on robots is not very adequate for the very few non-manufacturing sectors available (which all have extremely low values of robot adoption), and the result should not change if we restrict the analysis to manufacturing (more routine manufacturing sectors should install more robots). The fact that the RTI indicator is based on a relatively rough adaptation to Europe using

¹⁰ See Kenworthy (2001) and Visser (2015) for further details.

¹¹ This issue definitely deserves a more detailed and specific analysis, covering the underlying theoretical mechanisms explaining how certain labour market institutions can shape the adoption of technology, particularly robots. Such an analysis would go beyond the scope of the current paper.

only ISCO at the two digit level suggests that it may not be a very adequate measure of routine, and thus we will use it only for comparison.

Figure 7: Correlation between 10-year changes in robots and several variables (I), 1995-2015 (source: authors' analysis from EU KLEMS Consortium [2018], Eurofound [2018, 2019], IFR [2019], OECD [2019] and UN Comtrade [2019])

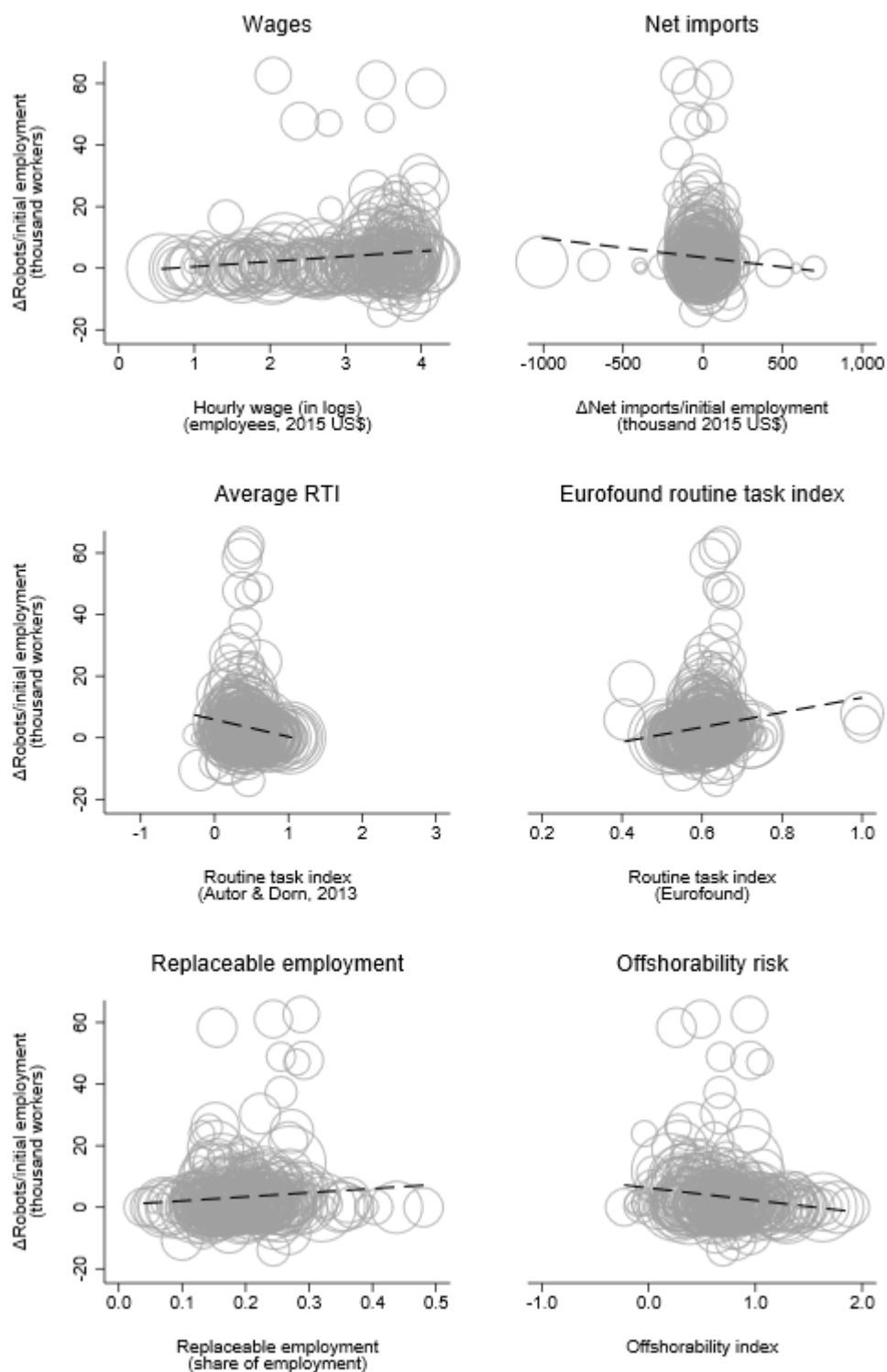


Figure 8: Correlation between 10-year changes in robots and several variables (II), 1995-2015 (source: authors' analysis from Avdagic[2012], ESS European Research Infrastructure Consortium [2018a, 2018b], Eurofound [2019], IFR [2019], OECD [2019] and Visser [2016])

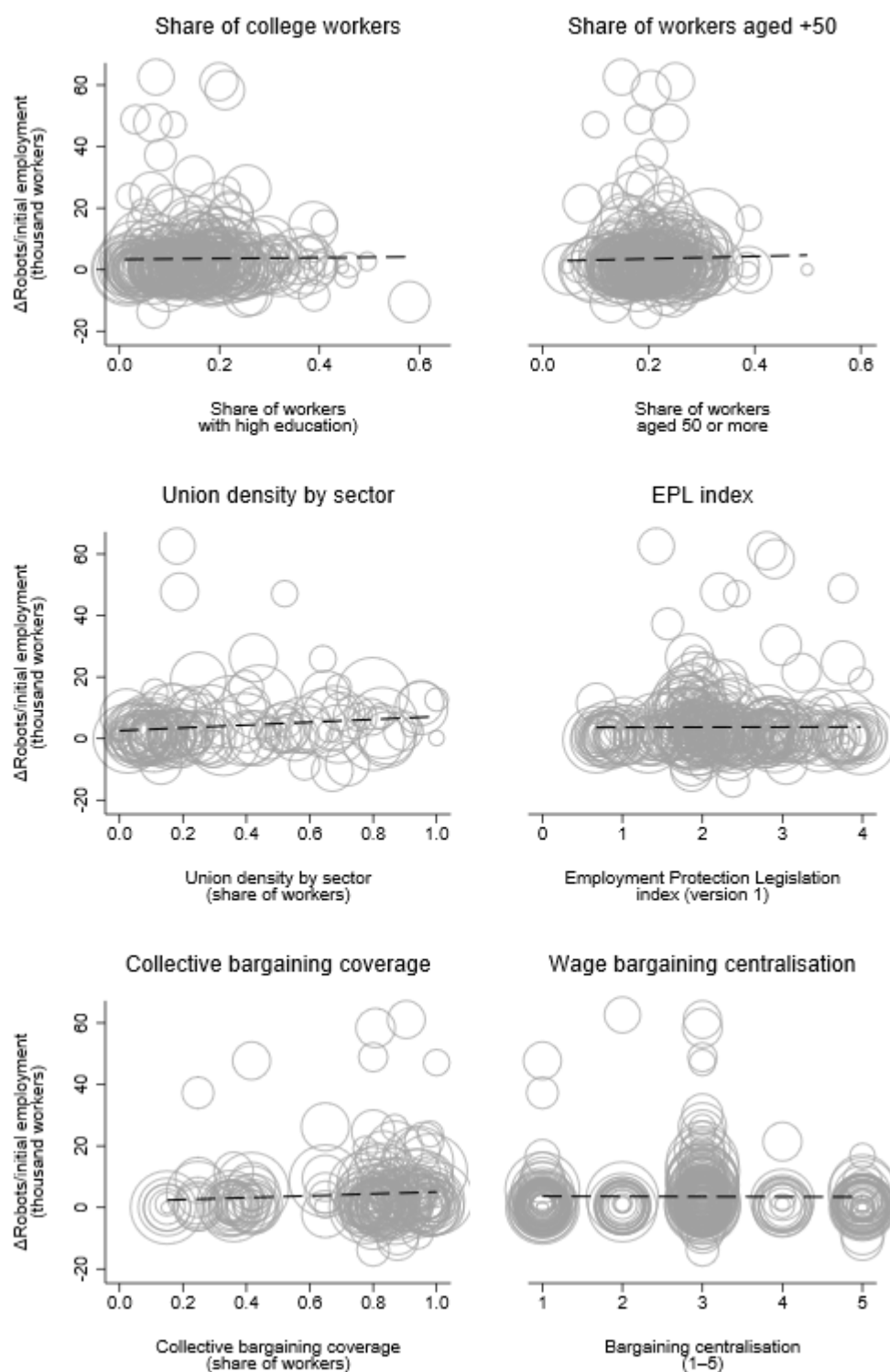
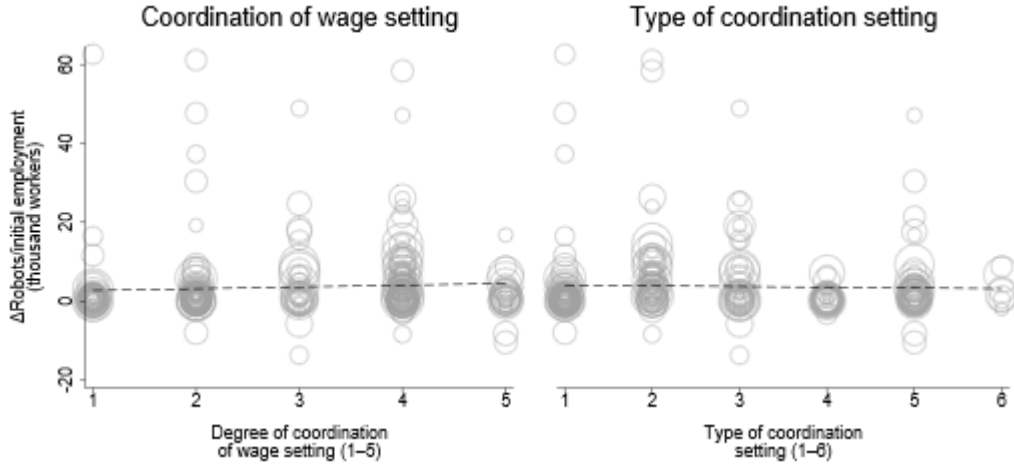


Figure 9: Correlation between 10-year changes in robots and several variables (III), 1995-2015 (source: authors analysis from Eurofound [2018], IFR [2019], OECD [2019] and Visser [2016])



After presenting the relationship between the change in the stock of robots per worker and each of the variables of interest described above, we perform a multivariate analysis trying to isolate the influence of each of the factors discussed above. Even though this exercise is an approximation to the causal effect of those variables, one should bear in mind that the analysis is still likely to present endogeneity problems. First of all, we look at the initial level of most of the variables. If there is a relevant change during the periods of analysis in the factors of interest which is correlated with the observable variables, we could have endogeneity problems. This applies particularly to wages or labour market institutions. Secondly, the variable capturing the influence of international trade is expressed in changes, given that the initial level does not provide any insight in this context. Lastly, the model's statistical power is rather limited given the size of the total sample (below 300 industry-country-year cells). This particularly applies to inference when including national-level variables, given that the amount of clusters in this case is well below 50.

Our econometric analysis follows the equation:

$$\frac{\Delta Robots_{it}}{L_{it-1}} = \alpha + \beta \frac{\Delta(M_{it}-X_{it})}{L_{it-1}} + \delta Z_{it-1} + \varepsilon_{it} \quad , \quad (1)$$

where i refers to the sector, t to the current time period and $t-1$ to the initial time period. That is, the increase in the number of robots with respect to initial employment is regressed on the change in net imports $M-X$ per initial employment in the sector and the initial value of a set of covariates Z that includes hourly wages (in logs), a measure of routine task content, the average value of the offshorability index in the sector, the share of college workers and the share of workers aged 50 or more. Furthermore, we carry out additional regressions including union density at the sector level and national-level variables related to labour market institutions. We explore the sensitivity of results to the inclusion of different measures of wage setting coordination.

Tables 1 and 2 present the results of six different models. All the models are estimated using standard errors clustered at the relevant level (country-sector or country) in order to control for serial correlation and heteroskedasticity—and, eventually, within-country correlation. Observations are weighted by the proportion of total employment in the country in the sectors included in the analysis in the initial time period. When pooling the changes of two time intervals (1995-2005 and

2005-2015), we include a time dummy. The first model in the table only comprises sector-level variables and includes the routine task index proposed by Autor and Dorn (2013). The second one employs instead the routine indicator proposed by Eurofound (Fernández-Macías, Hurley and Bisello 2016), whereas the third one tests the measure based on one of the instruments proposed by Graetz and Michaels (2018), the share of potentially replaceable employment by robots. In the fourth model (Table 2), we include the sector-level unionisation variable derived from the ESS. This is a quite noisy and imprecise variable given the low number of observations in some sectors and countries. Furthermore, given the years for which the ESS is available, we can only exploit the 10-year change corresponding to 2005-2015 in this specification. The last two models assess the effect of a more complete set of national-level variables, including the effect of two different sorts of measures of wage coordination. It is convenient to keep in mind that in the last three models we face a significant reduction in statistical power due to not only a lower sample size (because of the limited availability of some variables in a non-negligible number countries) but also a smaller number of clusters (12, given by the number of countries).¹²

Despite the limitations previously mentioned, there are several findings that can be highlighted:

- First, the initial wage level seems to be positively correlated with the rise of robots even when we control for other variables.
- Second, the relationship between robot adoption and the increase of net imports is seldom statistically significant, even though it shows the expected negative sign.
- Third, the coefficients for the routine indicators in the sector are significant, although not consistent across the three variables used. As we already observed in the simple bivariate correlation using scatterplots, the first routine task index (RTI) shows a surprising but statistically significant negative association with the increase in robot density, even after controlling for the other variables in the model. This result is counterintuitive and goes against theoretical expectations: a possible explanation is that the variable, based on occupational shares at the two digit level, is already biased by previous waves of automation. In other words, the industrial subsectors with higher shares of workers in occupations defined as routine are precisely those less previously affected by automation, and thus where less robots are installed. Of course, this means that this variable does not capture well routine content at the task level, but occupational groups within manufacturing which are likely to have more routine jobs. In any case, this is a surprising result, given that this measure of routinization has been widely used in Social Sciences for predicting the impact of technological change. It seems that it does not perform so well as a direct predictor of robot adoption, which represent, as mentioned, only a specific dimension of technical change. The other two variables measuring routine content show more plausible results, since both are positively associated with the increase in robot density and significant.
- Fourth, the risk of offshorability seems to be negatively correlated with robot adoption, which is in line with our initial expectations and may support the idea that robotisation and offshoring can be alternative business strategies.
- Fifth, the coefficient for the (initial) share of workers with high education is negative in all cases, which is not consistent with the idea that robots are complementary with high-

¹² We also implemented an alternative weighting scheme (based on total figures of employment) and perform the same regressions considering only the countries with the highest number of robots per worker at the end of the period of analysis (2015). These results (available upon request) are qualitatively similar to the ones shown here.

skilled labour. The proportion of workers over 50 exerts an effect not significantly different from zero in most of the specifications.

- Sixth, sector-level union density is positively associated with the increase in the stock of robots, but this effect is not robust to the inclusion of other variables capturing the impact of labour market institutions. The degree of centralisation of wage bargaining and the degree of wage coordination exhibit statistically significant negative and positive coefficients, respectively, in model V. But when we include the mechanism/mode of coordination instead of the degree of coordination, those effects vanish. Employment Protection Legislation is not significant in any of the models. However, models V and VI should be considered as mere exploratory models, since data limitations force a drastic reduction in the number of observations and thus in the robustness and reliability of the analysis. It is worth noting that the effect of sector-level union density remains of a similar size even in models V and VI, so the loss of statistical significance for this variable may just be the result of a less adequate specification.

Overall, and with all the limitations and qualifications previously discussed, the results of this econometric analysis of the factors behind robot adoption in European industries seem very much in line with the ideas presented in previous sections, with some interesting complementary details. Our analysis shows that in Europe, industrial robots have grown more in those sectors where work is more routine and manual, where there are fewer highly educated workers and where wages and unionisation rates are higher. As we have repeatedly argued, this suggests a rather traditional industrial automation story: probably, a similar set of factors could be identified in previous rates of automation technology throughout at least most of the 20th Century. Perhaps less traditional is the possible role played by the offshoring of parts of the production process as an alternative strategy to automation. Although the evidence in this respect is less robust, it suggests that offshoring may have reduced the extent of robotisation of some of the European industry in the last couple of decades, a period of rapidly expanding international trade and increasingly deep global value chains. Finally, we could not say much about the potential role of institutions either as drivers or barriers to robotisation, probably because of data limitations (although if the effect was strong enough we may have been able to observe it). The only suggestive result in this case is the significant positive association between unionisation rate and robot adoption, which can be understood as reflecting a possible causal link (an interpretation advanced by Presidente [2017] concerning the use of robots as a way to circumvent labour regulation) or perhaps more plausibly as reflecting a simple correlation driven by other factors (the sectors that have installed more robots in Europe in recent years have traditionally had higher unionisation rates and also a more advanced technological profile).

Table 1: Determinants of the change in the stock of robots (I) (10-year changes at the sector level, stacked differences, 1995–2015) (source: IFR, EU KLEMS, EJM, EWCS, UN Comtrade, OECD.Stat, own elaboration).

	I	II	III
Hourly wage (in logs)	0.150 *** (0.039)	0.166 *** (0.041)	0.151 *** (0.039)
Increase in net import exposure	-0.227 (0.185)	-0.205 (0.175)	-0.202 (0.176)
RTI	-0.196 ***		

	(0.073)		
Eurofound routine task index		0.206 ***	
	(0.047)		
Share of replaceable employment		0.208 ***	
	(0.056)		
Offshorability index	-0.057	-0.085 *	-0.215 ***
	(0.061)	(0.047)	(0.047)
Share of workers with high education	-0.239 ***	-0.120 ***	-0.143 ***
	(0.069)	(0.044)	(0.044)
Share of workers aged 50 or more	-0.010	0.022	-0.011
	(0.060)	(0.057)	(0.056)
Observations	224	224	224
R ²	0.11	0.14	0.14

Table 2: Determinants of the change in the stock of robots (II) (10-year changes at the sector level, stacked differences, 1995-2015) (source: IFR, EU KLEMS, EJM, EWCS, UN Comtrade, OECD.Stat, ESS, ICTWSS, Avdagic [2012], own elaboration).

	IV	V	VI
Hourly wage (in logs)	0.091 (0.067)	0.348 ** (0.146)	0.237 (0.150)
Increase in net import exposure	-0.342 * (0.204)	-0.232 (0.147)	-0.262 * (0.159)
Eurofound routine task index	0.218 *** (0.059)	0.270 *** (0.074)	0.282 *** (0.073)
Offshorability index	-0.136 ** (0.066)	-0.162 ** (0.079)	-0.157 * (0.089)
Share of workers with high education	-0.201 *** (0.073)	-0.444 *** (0.125)	-0.315 *** (0.116)
Share of workers aged 50 or more	-0.030 (0.072)	-0.168 (0.114)	-0.160 (0.118)
Sector-level union density	0.158 ** (0.062)	0.170 (0.108)	0.185 (0.117)
EPL index (version 1)		0.142 (0.139)	0.002 (0.131)
Collective bargaining coverage		-0.236 (0.176)	-0.037 (0.152)
Wage bargaining centralisation		-0.427 *** (0.136)	-0.058 (0.128)
Degree of bargaining coordination		0.424 *** (0.128)	
Type of bargaining coordination			-0.109 (0.139)
Observations	123	81	81
R ²	0.25	0.39	0.34

BOX: Robot prices: two estimations

The aim of this box is to estimate the average prices of industrial robots.¹³ For that purpose, we average the prices of exported robots in the top 5 robot-exporting countries and the prices of imported robots in the top 5 robot-using countries.¹⁴ We obtain these prices by looking at trade data from the UN Comtrade database in the top 5 importing countries over the period 1996-2018. One caveat here is that some top robot exporters are top robot users as well. Hence we do not get the prices of robots produced and used within the same country, which might distort the prices to some extent. We will compare our estimates to estimates based on IFR data (IFR, 2019) to see if this has an impact.

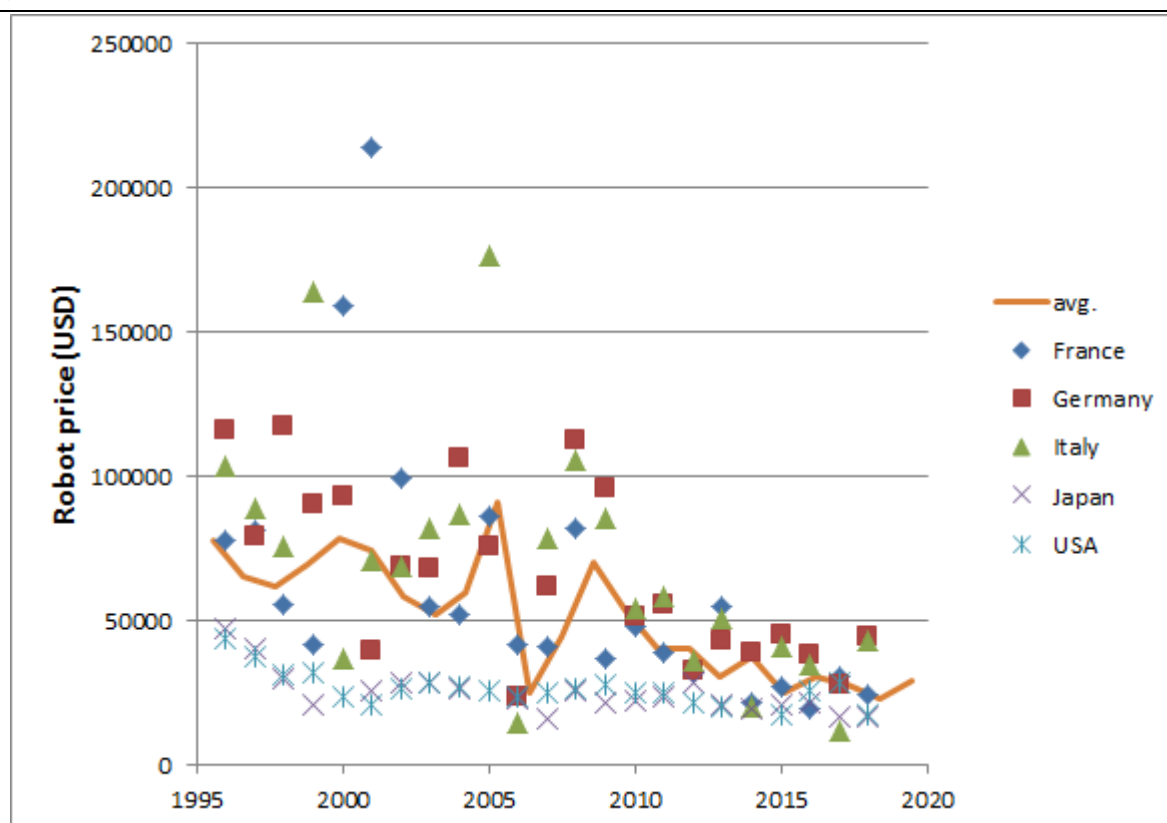
For Japan and the US it is straightforward to derive the price of one robot unit that was either exported or imported. We average over the two different sets of prices (imports and exports) to get a price estimate for one robot unit in the respective country. France, Germany and Italy report the value of all robot exports and imports but not the units. To obtain price estimates for these countries we rely on import reports from China, Japan, the Rep. of Korea and the US. We then average over the prices reported by the different countries to get the robot price estimates for France, Germany and Italy.

The price estimates based on Comtrade data are shown in Figure 10. There is a clearly visible downward trend in the robot price in all countries since the mid-1990s. The variation between countries is relatively large, although this might be in part due to the fact that the estimation is somewhat rough. Especially when the value of imports or exports is small, small errors in the trade values can be amplified by dividing by a small number of robots. This is the case for France and Italy in earlier years, where often exports in the single or double digits are reported. Excluding these countries would lead to a somewhat smoother average price.

13 We are aware that there is a wide price range for industrial robots, but it is helpful to estimate the average price to get an idea in which direction prices are moving. The estimates of robot prices are not used in the previous econometric analysis for the following reasons. First, our econometric analysis estimates a demand equation for robots: since robot prices and quantities are jointly determined by supply and demand forces, the inclusion of this variable would lead to simultaneity bias. Second, since it is necessary to use UN Comtrade data, we can solely retrieve prices at the country level, which would reduce the degrees of freedom in any analysis. Third, for a similar type of robot, the variation across countries is likely to be driven by different transportation costs and tariffs, but this variability is limited. Finally, and linked to the latter factor, differences in prices across countries might also respond to heterogeneity in the robot stock (e.g., robots in different sectors and/or with different impact on productivity). This issue can be interpreted as a source of measurement error or a form of omitted variable in a right-hand-side variable, with negative implications on the consistency and efficiency of estimates. For all these reasons, we decided to omit this variable from the previous econometric analysis.

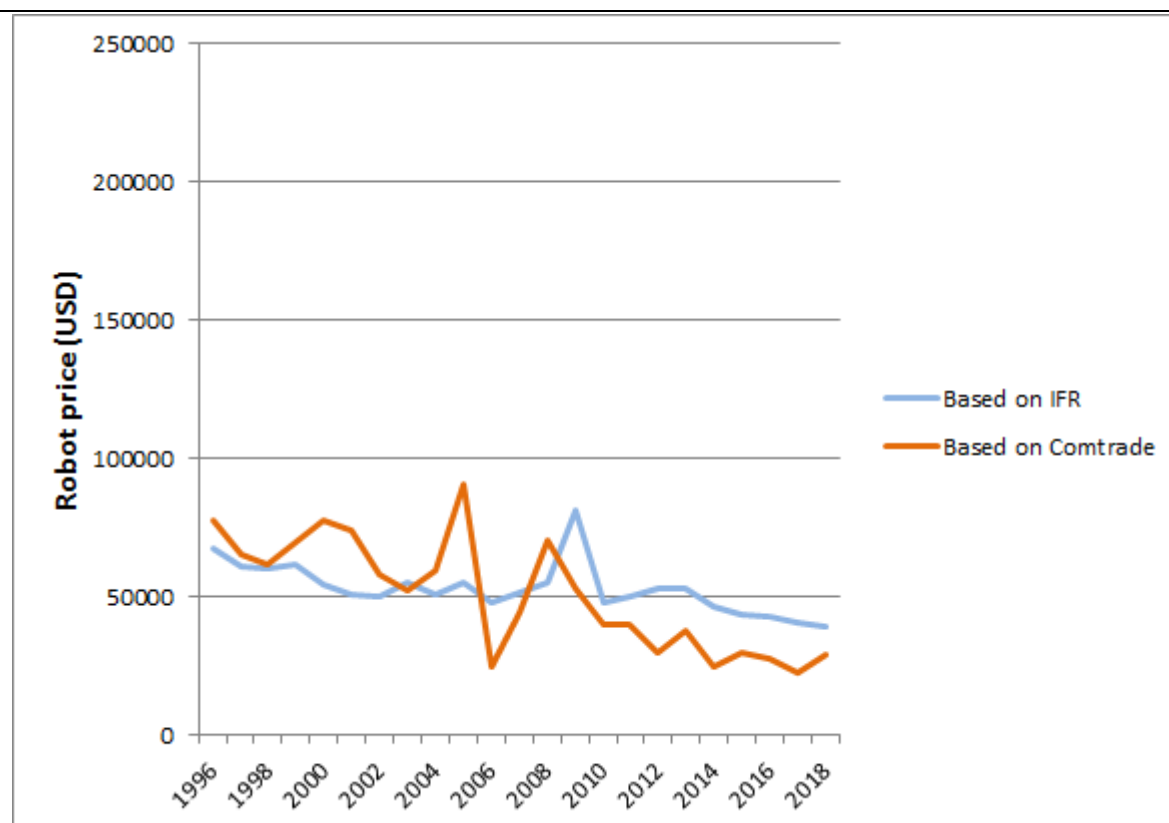
14 In 2018, 74% of all global robot installation took place in 5 countries: China, Japan, the US, the Republic of Korea and Germany (IFR, 2019). In 2017, Japan, Germany, Italy, France and the US accounted for 67% of all robot exports (own calculations based on UN Comtrade [2019]).

Figure 10: Robot price estimates for France, Germany, Italy, Japan and the US based on trade data from the Comtrade database (source: UN Comtrade, own elaboration).



The IFR uses a different approach for estimating robot prices. Until 2005, they collected price information directly from robot producers and national robot federations, which they used for estimating the average price of one robot (see IFR, 2006). Since 2006 they estimate the total value of the industrial robots market (given the information they have from robot producers and national robot federations) and then divide this number by the robot deliveries in a given year. We reproduce these numbers for comparison below. As can be seen in Figure 11, the estimates do not differ too much, considering the approximate nature of the two approaches.

Figure 11: Global robot price estimates: estimation based on UN Comtrade data versus estimation based on IFR data (source: IFR, UN Comtrade, own elaboration).



Both estimations show robot prices declining, but it is important to note that in both cases the biggest declines in average robot prices takes place in the first decade of data (up to 2006), whereas in the second half of the period the decline is less rapid. In fact, the Comtrade-based estimation suggests no significant decline after 2006 (although there is an abrupt increase between 2006 and 2007-8 that makes the post-2008 period look like a decline; but a running average would show a leveling after 2005-6); the IFR's own estimation, on the other hand, suggests stagnating robot prices between 2000 and 2014, only starting to fall again in the last 4 years shown.

Conclusions

In recent years, the debate on the impact of robots on employment has reached truly surprising dimensions. For instance, a 2017 Eurobarometer survey found that 72% of Europeans believe that *robots and artificial intelligence steal people's jobs*, a concern that is frequently also present in policy debates and backed by some highly cited research findings. The current article contributes to this debate by analysing existing data on industrial robots over the last two and a half decades. Our analysis provides a radically different perspective suggesting much more caution in this matter.

In this paper, we carefully look at the characteristics and distribution of actually existing robots in Europe (and their recent trends). We could identify three key facts that we believe are missing in current debates but have great significance. They invite skepticism towards any claim that robots have had or are having any significant employment effects in Europe, even if the link between robots and employment has not been explicitly analysed in this paper (for a detailed discussion of that relationship that also invites skepticism, see Klenert, Fernández-Macías and Antón 2020).

First, in this paper we argue that the kinds of industrial robots used in European manufacturing are essentially more sophisticated versions of previous existing automation technologies. Most importantly, they do not imply any significant discontinuity or disruption in terms of the types of tasks they can do (they still mostly perform physical tasks involving strength and dexterity, moving and manipulating physical objects), or in terms of the nature of the tasks (they still have to be relatively routinised, standardised and encapsulated - although the addition of algorithmic control and sensor devices has marginally increased their flexibility in this respect in recent years). Not only are most currently used robots only an incremental improvement in terms of the types of task they can do with respect to previous automation technologies, but they remain circumscribed to physical tasks which are already marginal in terms of labour input in most advanced economies. Partly because of the effect of previous waves of automation (going back decades or even centuries), the amount of purely physical labour used in production is already quite small, even in manufacturing. Most labour input goes to tasks involving problem solving, information processing or social interaction (Fernández-Macías, Hurley and Bisello 2016), which are completely beyond the capabilities of the types of robots used in European industry today.

Second, we show that the distribution of industrial robots is extremely concentrated by economic activity and country. In most manufacturing subsectors, the number of robots per thousand workers is very close to zero; only in 3 subsectors this number is significant (i.e. above 10 robots per thousand workers). This suggests that robots are largely a specialised technology, mostly used in car manufacturing (60 robots per thousand workers) and in the production of plastic (30) and metal products (11). In fact, this concentration has increased over the analysed period (1995-2016). There is a similarly growing geographic concentration of robots, with nearly one of every two robots in Europe installed in a single country (Germany). German car manufacturing, therefore, accounts for one fourth of all industrial robots in Europe, despite employing less than 1% of all European workers.

Third, using econometric techniques, we identify which sector-country variables are associated with the variation in robot stocks in Europe in the analysed period (1995-2016). Industrial robots grew more in sectors with higher labour input in routine and manual tasks, with fewer highly educated workers and with higher wages and unionisation rates.

Taken together, these three facts suggest a rather traditional automation story (that would probably fit previous waves of automation), rather than the kind of paradigm change often suggested by the literature and the popular press on this matter. In terms of policy implications, these simple descriptive facts should bring a healthy dose of skepticism and caution to the debate on the employment effects of robots. Robots currently in operation in Europe are simply too concentrated and specialised, limited to sectors already employing too few people and to the performance of tasks that are already too marginal, to have large employment effects. Current robot technologies included in the IFR database explored in this paper are more advanced and flexible than previous automation technologies, and they appear to contribute to productivity growth in European manufacturing (see Graetz and Michaels 2018 and Jungmittag and Pesole 2019). But they involve no radical disruption or discontinuity that could suggest the possibility of large employment effects. These robots are more likely to replace less sophisticated robots than human workers.

The statements made in this paper concern mainly the manufacturing sector, not the rest of the economy. Does this limit the validity or generality of our findings? In our opinion it does not, because as of today robots are only having a discernible economic impact in manufacturing. Robots in services may be a very exciting possibility, but they are still not used widely enough to have a significant economic effect (Müller et al. 2019). Beyond experimental and laboratory applications, robots in services are mostly used for recreational purposes (toys) or for very narrow domestic services (vacuum cleaning). This may change in the future (perhaps with the addition of AI capabilities to existing robot technologies), and that could certainly lead to the type of disruptive employment effects that are often discussed in the popular press. But so far, this remains just a possibility. Robots are not so disruptive yet.

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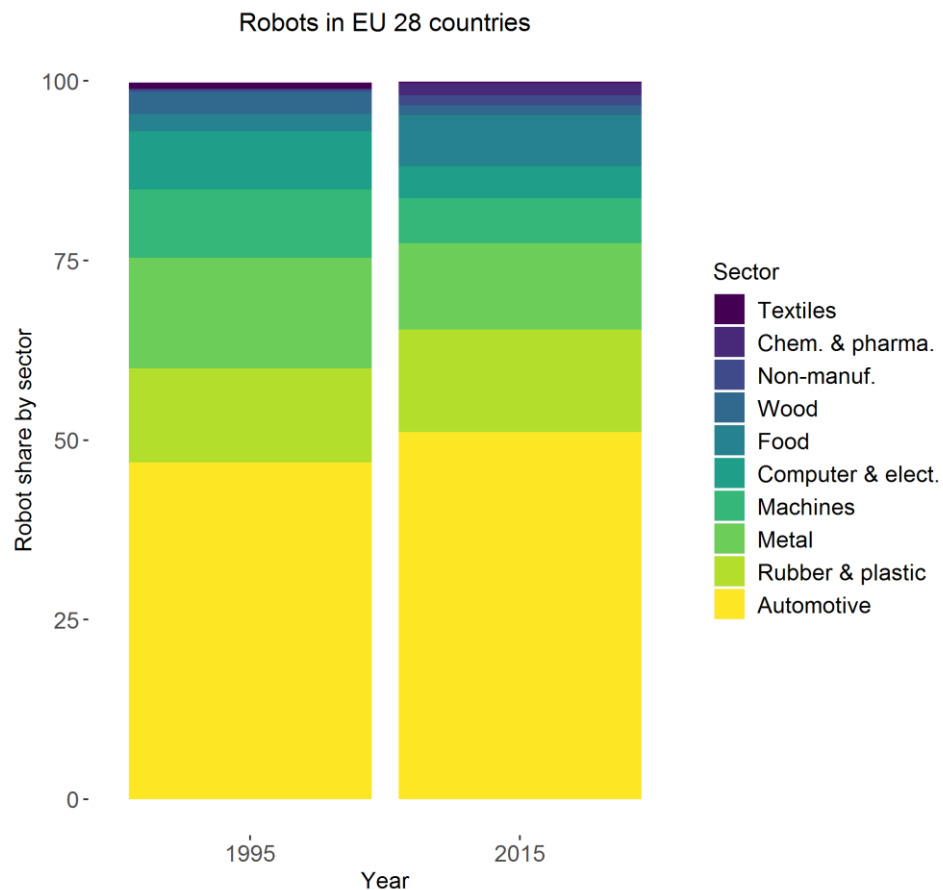
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Annex A: Distributional of robots by sector (including non-manufacturing)

Figure 12: Distribution of industrial robot stocks by sector and country, including non-manufacturing sectors, EU 2015 (source: authors' analysis from IFR [2019])



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