Tracking the rise of robots: A survey of the IFR database and its applications

Klump, Rainer and Jurkat, Anne and Schneider, Florian

Goethe University Frankfurt

2021

Tracking the Rise of Robots:

A Survey of the IFR Database and its Applications

Anne Jurkat (Goethe University Frankfurt),

Rainer Klump* (Goethe University Frankfurt) and

Florian Schneider (Goethe University Frankfurt and VDMA Frankfurt)

December 2021

Abstract

Robots are continuously transforming industrial production worldwide and thereby also inducing changes in a variety of production-related economic and social relations. While some observers call this transformation an unprecedented "revolution", others regard it as a common pattern of capitalist development. This paper contributes to the literature on effects of the rise of industrial robots in three ways. Firstly, we describe the historic evolution and organizational structure of the International Federation of Robotics (IFR), which collects data on the international distribution of industrial robots by country, industry, and application from industrial robot suppliers worldwide since 1993. Secondly, we extensively analyze this IFR dataset on industrial robots and point out its specificities and limitations. We develop a correspondence table between the IFR industry classification and the International Standard Industrial Classification (ISIC) Revision 4 and shed some light on the price development of industrial robots by compiling data on robot prices. We further compute implicit depreciation rates inherent to the operational stocks of robots in the IFR dataset and find an average depreciation rate of aggregate robot stocks between 4% and 7% per year between 1993 and 2019. Moreover, tracking the share of industrial robots not classified to any industry or application, we find that their share in total robot stocks has sharply declined since 2005. We also compare the IFR data with other data sources such as UN Comtrade data on net imports of industrial robots or data on robot adoption from firm-level surveys in selected countries. Thirdly, we provide a comprehensive overview of the empirical research on industrial robots that is based on the IFR dataset. We identify four important strands of research on the rise of robots: (i) patterns of robot adoption and industrial organization, (ii) productivity and growth effects, (iii) impacts on employment and wages, and (iv) links with demographics, health, and politics.

Keywords: Robots, productivity, growth, employment, industry classification, depreciation rates, IFR

JEL Classification: O4, O47, O33, J24, C23, E01

*Corresponding author: Faculty of Economics and Business, Goethe University Frankfurt, Theodor-W.-Adorno-Platz, 4, 60323 Frankfurt am Main, Germany; klump@wiwi.uni-frankfurt.de

We thank Susanne Bieller and Christopher Müller for valuable information on the organization of IFR and on details of the IFR Database. Research support by Daniel Kaiser is gratefully acknowledged. It goes without saying that the usual disclaimer applies.

List of content

1. Introduction

Robots are continuously transforming industrial production worldwide and thereby also inducing changes in a variety of production-related economic and social relations. While some observers call this transformation an unprecedented "revolution", others regard it as a common pattern of capitalist development. The academic research on the impact of robots on the economy and society has received a major boost by two seminal papers that have led methodical foundations for fruitful further studies: Acemoglu/Restrepo (2017; 2020) and Graetz/Michaels (2018). The latter focuses on productivity effects induced by increased robot adoption whereas the former investigates the labor market effects of robotization. In the following years, the literature on economic and social effects of automation has been a rapidly evolving field of research. The largest part of that literature deals with labor market related effects of automation on employment, wages, and the skill composition of the workforce, e.g. Dauth et al. (2020), De Vries et al. (2020), Caselli et al. (2021b), or Fu et al. (2021). Another important strand of literature scrutinizes the determinants (e.g. labor costs or firm characteristics) as well as temporal and geographical patterns of robot adoption and their relationship to industrial organization in terms of off- and re-shoring, for instance Cséfalvay (2020), Gentili et al. (2020), Jung/Lim (2020), and Faber (2020). Productivity and growth effects of industrial robots form a third focal point of research that can be found among others in Kromann et al. (2020) and Bekhtiar et al. (2021). The fourth crucial area of research examines links of robotization with demographics (e.g. Acemoglu/Restrepo (2021)), health (e.g. Gunadi/Ryu (2021) and Sedik/Yoo (2021)), and politics (e.g. Caselli et al. 2021a). The vast majority of this research bases its empirical investigation on a special dataset on industrial robots compiled and published by the International Federation of Robots (IFR) sine 1993. These data are collected from industrial robot suppliers worldwide and available by country, industry, and application

Given the crucial role of the IFR dataset in robot research we see the necessity for a detailed survey that presents the characteristics of the IFR, the specifics of the dataset and the major findings of its use in academic studies. Apart from identifying the main research applications of the IFR data, our contribution to the literature is twofold: firstly, we describe the historic evolution and organizational structure of the IFR. Secondly, we extensively analyze the IFR dataset on industrial robots and point out its specificities and limitations. In particular, we contribute to the literature by creating a correspondence table between the IFR industry classification and ISIC rev. 4. We further compute implicit depreciation rates inherent to the operational stocks of robots in the IFR dataset and find an average depreciation rate of aggregate robot stocks between 4% and 7% per year between 1993 and 2019. This is relevant as many authors employ the perpetual inventory method with a constant depreciation rate (typically 10% as baseline) from one period to the next to recalculate the robot stocks using the installation data of the IFR dataset. Moreover, tracking the share of industrial robots not classified to any industry or application, we find that their share in total robot stocks has sharply declined since 2005, indicating an improved availability of disaggregated data. We also compare the IFR data with UN Comtrade data on net imports of industrial robots or data on robot adoption from firm-level surveys in selected countries and observe a high degree of complementarity with those alternative data sources. Additionally, we shed some light on the price development of industrial robots by computing data on average robot prices using both the IFR and UN Comtrade as data sources.

We will proceed as follows: firstly, in Section 2 we describe the historical evolution and organizational structure of the IFR, which collects data on the international distribution of industrial robots by country, industry, and application from industrial robot suppliers worldwide since 1993. In Section 3, we extensively analyze this IFR dataset on industrial robots and point out its specificities and limitations. In Section 4, we provide a comprehensive overview of the empirical research on industrial robots that is based on the IFR dataset. Section 5 concludes.

2. The story of the IFR

2.1 Members of the IFR

The International Federation of Robotics (IFR) is the international association of the robotics industry and of selected research institutes in the field of robotics as well as an umbrella organization of all national robotics associations. The IFR was established as a non-profit organization in 1987. Initially, it started as the international association of several national robotics associations and its General Secretariat was hosted by the Swedish Industrial Robot Association (SWIRA), located at "Sveriges Mekanförbund" in Stockholm. In 2003, the General Secretariat was moved to the French Association for Manufacturing (SYMOP) in Paris. In the same year, the IFR Statistical Department moved to the German Mechanical Engineering Industry Association (VDMA) in Frankfurt am Main. Since March 2008 also the IFR General Secretariat is based in Frankfurt.

In 2006, apart from industry associations, R&D institutes with a major focus on robotics became eligible for membership according to the IFR constitution, and since 2013 also robot suppliers are full members of the IFR. Before 2013, robot manufacturers could only obtain the status of a "partner", just like universities and research centers not otherwise eligible for membership. Accordingly, participating members of the IFR are today divided into three membership categories: i) industry associations, ii) R&D institutes, and iii) robot suppliers. Only one association from each geographical area can be an industry association member. At present, the IFR counts 69 members from more than 20 countries, of which 16 are national industry associations, 9 are R&D institutes and the remaining 44 are robot suppliers. 20 of the robot suppliers produce industrial robots and the other 24 are either component suppliers, robot integrators or service robot suppliers. End users of robotics technologies, however, are not eligible for membership in the IFR. Table 1 lists all 16 national robotics associations.

Table 1: Overview of national robotics associations

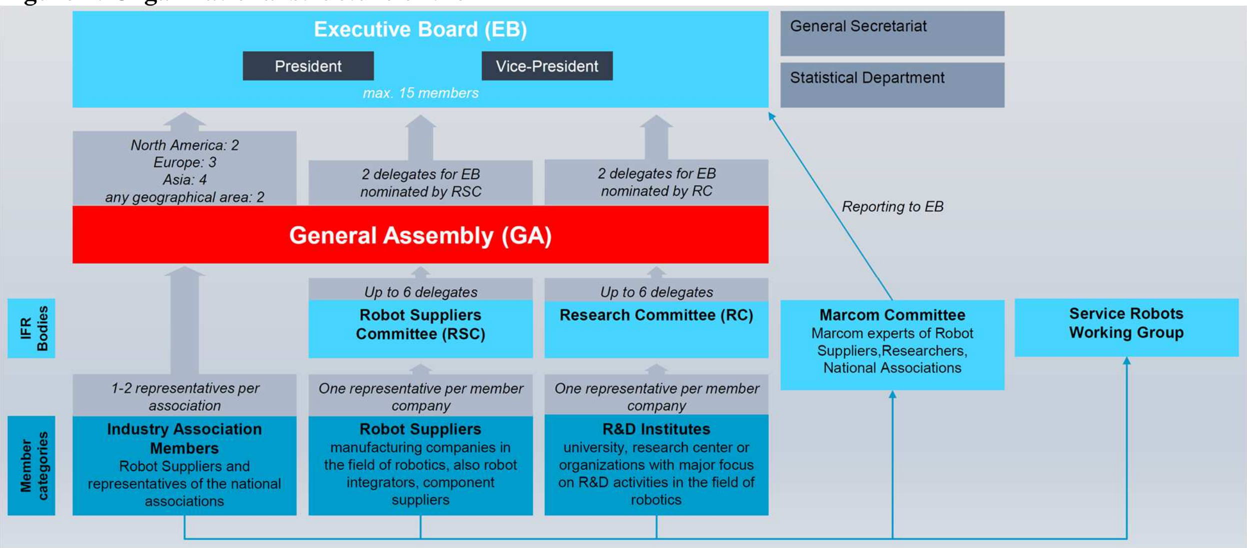
	Country	*Association*
1	China	China Robot Industry Alliance (CRIA)
2	Denmark	Danish Industrial Robot Association (DIRA)
3	France	Syndicat des Machines et Technologies de Production (SYMOP)
4	Germany	VDMA Robotics + Automation (VDMA R+A)
5	Italy	Associazione Italiana di Robotica e Automazione (SIRI)
6	Japan	Japan Robot Association (JARA)
7	Norway	Norwegian Society of Electrical and Automatica Control (NFEA)
8	Republic of Korea	Korea Association of Robot Industry (KAR)
9	Russia	Russian Association of Robotics (RAR)
10	Spain	Spanish Association of Robotics & Automation (AER)
11	Sweden	Swedish Industrial Robot Association (SWIRA)
12	Switzerland	Swiss Technology Network (swissRobotics.net)
13	Taiwan	Taiwan Automation Intelligence and Robotics Association (TAIROA)
14	Turkey	Industrial Automation Manufacturers Association (ENOSAD)
15	United Kingdom	British Automation & Robotics Association (BARA)
16	USA	Robotic Industries Association (RIA)

Source: IFR

2.2 Organizational structure

The organizational structure of the IFR mirrors its historic evolution and is illustrated in Figure 1. The General Assembly (GA) is the main governing body of the IFR. It decides on budgetary affairs as well as amendments of statutes and IFR services. Not all IFR members are represented in the GA. Each national industry association member sends one representative with voting rights to the GA, typically a director or board member of a robot manufacturing or integration company. Industry association members from a geographical area, in which more than 10,000 operational industrial robots are installed, can send a second representative with voting rights to the GA, who might be an employee of the respective association.

Figure 1: Organizational structure of the IFR



<u>Source:</u> IFR (internal document).

R&D institute members form the Research Committee (RC), which aims at stimulating research and development in the field of robotics. Each R&D institute member can send one representative to the RC, which in turn nominates six representatives (chairman + 5 members) with voting rights for the GA. Robot suppliers are organized in the Robot Suppliers Committee (RSC). Each robot supplier member is allowed to send one representative to the RSC, which in turn nominates six representatives (chairman + 5 members) with voting rights for the GA. The RSC mainly deals with statistics on the robotics market by deciding on structure and changes in the classification of the IFR robot data, while the IFR Statistical Department is the executive body that collects and analyses the data. The RSC is also responsible for forecasts of robot installations. Overall, the GA is composed of representatives of industry association members, delegates from the RSC and the RC, the IFR President and Vice President, the Secretary General (who does not have voting rights), and possibly additional observers that are appointed by the Executive Board (EB).

The EB is composed of a maximum of 15 voting members, including the IFR President, who represents the EB, the Vice President, the chairman and another nominated member of the RC, two elected RSC members, 11 representatives of industry association members, and the Secretary General, who is a member without voting rights. Except for the two members of the RC, all other EB members with voting rights are elected by the GA to serve for a term of two years. Of the 11 industry association representatives, two come from North America, three from Europe, four from Asia, and two further members from any geographical area. The IFR President and Vice President are to be elected among the EB members and should be representatives of well-known manufacturing companies in the field of robotics. The IFR President presides at all EB meetings that take place at least two times per year. The EB is responsible for the IFR's strategic orientation, which must be confirmed by the GA, and is supposed to assist all other IFR bodies so that their tasks and projects can be performed efficiently. It is empowered to manage the affairs of the IFR between meetings of the GA, directs the activities of the General Secretariat, and represents the IFR externally.

The General Secretariat is responsible for the daily management of the IFR, administration of its assets, and coordination of all major activities. It is established following an EB's decision for a minimum period of four years and is represented by the Secretary General, who is appointed by the EB. In more detail, the General Secretariat is supposed to act as a "service center" for the IFR members and a contact point for other international organizations. It manages the recruiting of new members, publishes a quarterly IFR robotics newsletter, and cooperates with the EB in developing an annual business plan and budget for the IFR. Admission to membership requires a written application to the General Secretariat, which is subsequently approved or rejected by the EB.

A further organizational structure enshrined in the constitution of the IFR are several Working Groups that perform sector and industry specific tasks related to robotics. Any IFR member can become a member of a Working Group. Each Working Group must report to the EB on its activities at least once per year. In October 2002, an IFR Service Robotics Group was founded. In subsequent years, planning of a formal Working Group on service robots started as the members recognized the growing market and the distinct properties of service robots in contrast to industrial robots. In 2006, the "Working Group Service Robots" was officially established and focuses on statistics and market development in the field of service robots.

A so-called "Marcom Committee" was established in 2015, on the initiative of the RSC. It gathers marketing and communication experts of national industry associations, robot suppliers, and R&D institutes and is responsible for marketing and PR activities. The "Marcom Committee" is not yet anchored in the constitution of the IFR because the latest version of the constitution is from 2013. With the next amendment of the statutes, it will be mentioned in the constitution and decided if it obtains the status of a committee or a working group.

2.3 Areas of activities

The IFR describes its operational framework in the following way: "The general purpose of the IFR is to promote research, development, use and international co-operation in the entire field of robotics, to act as a focal point for organizations and governmental representatives in activities related to robotics" (IFR 2021). Its self-defined aim consists in "promoting the positive benefits of robots for productivity, competitiveness, economic growth and quality of work and life". To serve its purpose, the activities of the IFR cover the following four areas: 1) statistics, 2) market analysis & market expansion, 3) positioning & communication, and 4) networking. These are all typical tasks for an association that represents members of an innovative industry cluster, reaches out to the various stakeholders and links them in joint activities such as trade fairs or conferences. As already investigated by Weder/Grubel (1993) or Klump (1996) for other industries, such activities lay the institutional foundations for further innovations and growth within the cluster.

1) The IFR Statistical Department, located at VDMA in Frankfurt, annually publishes data on the worldwide robotics market. As early as 1973 the United Nations Economic Commission for Europe (UN-ECE) had started with collecting, processing, and analyzing worldwide statistics on industrial robots. UN-ECE has closely collaborated with the IFR since the association was founded in 1987. The responsibility for the World Robotics Statistics was transferred to the IFR Statistical Department from 2003 onwards. In 2005, the IFR Statistical Department fully compiled the World Robotics Statistics for the first time but it was still published by UN-ECE. Since 2006, the IFR Statistical Department has published the World Robotics Statistics regularly. From 2009 on, data on industrial and service robots are analyzed in two separate reports. Previously, service robot data were examined within one chapter of the single World Robotics Report. Now they appear in a separate publication, the annual World Robotics Service Robots report. The main data source on industrial robots is the World Robotics Industrial Robots (WRIR) report that always contains five thematic blocks: first, the worldwide distribution of industrial robots is analyzed in terms of installations, stocks, and robot density. The IFR defines robot density as the number of industrial robots in operation (i.e. operational stock) per 10,000 persons employed. Second, country/regional reports explore the geographical distribution of industrial robots by analyzing their usage in single countries or regions. Third, installations of industrial robots for the current and the following two years are forecasted. Fourth, case studies illustrate the profitability and practical benefit of industrial robots. Fifth, the report is rounded off by special features summarizing topical issues in the field of robotics.

2) The IFR helps manufacturers and integrators of robots to enter new markets. For this purpose, the association serves as a platform for sharing information on current technological and economic trends in the global robot market. While being established in the robotics market is a prerequisite for companies to become a member of the IFR, market expansion is supported through networking activities and exchange of experiences. Moreover, the IFR helps in founding new robot associations in countries or regions where previously no appropriate association structures did exist.

3) The IFR represents the interests of its members in the public debate and, therefore, shapes and conveys the robotics industry's position on policy-relevant topics such as "collaborative robots, artificial intelligence and the workplace of the future" (IFR 2021). Press releases and regular IFR Executive Roundtable (ER) discussions that usually take place in conjunction with major international trade fairs are supposed to inform the public and policy makers on key topics.[1] The ER discussions are organized as panel discussions. Typically, prior to the ER discussions, the most recent World Robotics Statistics are presented. Media representatives are the main target group of the ER discussions, which are organized by the General Secretariat and the Marcom Committee that selects topics and speakers. Panelists are typically important CEOs of robot suppliers; depending on the topics, end users of robotic technologies and policy makers might also be invited. Apart from organizing ER discussions, the IFR also publishes position papers to convey its stance on topics related to robotics. Thereby, the IFR advocates global, national, and local policies fostering robot adoption.

[1] Major robotic trade fairs take place in Germany, the USA, Russia, China, and Japan: "automatica" in Munich taking place in even years and "AUTOMATE" in Detroit (until 2019 in Chicago) in uneven years; "INNOPROM" in Ekaterinburg; "China International Robot Show (CIROS)" in Shanghai and "Int'l Robotics & Automation Conference & Exhibition (iRACE)" in Shenzhen; the International Robot Exhibition "iREX" in Tokyo.

4) The IFR brings its members into contact with each other for exchanging opinions and ideas. Regular meeting points are the international trade fairs mentioned above. Thereby, the association aims to promote alliances and partnerships among its members, especially in research and development. For this end, the IFR also sponsors the International Symposium on Robotics (ISR), a conference on industrial and service robotics held since 1970. Always one of the national robot associations applies for organizing the ISR in conjunction with its respective international robotics trade fair. Participants of the ISR are typically R&D representatives of companies in the field of robotics and usually come from engineering or natural sciences. The focus is generally on application-oriented technological topics, but also key performance indicators of robots in the production process can be discussed. The IFR further enables networking activities by cooperating with other national and international robotics organizations as well as by interacting with international organizations such as the Organisation for Economic Co-operation and Development (OECD), the United Nations Industrial Development Organization (UNIDO), or the World Economic Forum (WEF). In order to stimulate robotics-related research and to support links between industry and science, the IFR sponsors the IERA[2] award together with the IEEE Robotics and Automation Society (IEEE/RAS).[3] Firms with specific marketable innovations can apply for this award. Responsibility for the award ceremony alternates between the IFR and IEEE/RAS.

3. The IFR database on industrial robots

3.1 Installations and stock of robots

By documenting the number of industrial robots newly installed worldwide per year as the main indicator, the IFR aims at giving a comprehensive overview on the global dissemination of industrial robots since 1993, the initial year of time series in the IFR dataset (IFR 2020, 21). Unlike an official statistics database, the IFR data is generated by voluntary contributions from individual producers or national sector associations and should mainly inform the members of the association about general sector and market trends. This explains not only the very rigid compliance rules (see section 3.5) but is also the reason why the automotive and electronics industries as the major users of industrial robots are observed in much more detail than many other industries. Although the data is today also commercially provided to researchers one should keep in mind that its use in academic research has always been of secondary importance to the provider. Even if the database is today the most important source of quantitative information on robot adoption worldwide the provider is not and does not feel responsible for making it better compatible with other research data. Responsibility for data collection was transferred to the IFR Statistical Department between 2003 and 2005. Since then, the IFR intensified the collaboration with robot suppliers and national associations and improved the harmonization of international classifications.

The IFR uses the term “industrial robot” based on the definition of the International Organization for Standardization (ISO). According to ISO standard 8373:2012 (§ 2.9), 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.” Thus, industrial robots are fully autonomous machines that do not require a human operator and can be re-programmed to perform several tasks such as welding and soldering, dispensing (e.g. painting/ enameling), (dis-) assembling, handling

[2] IERA stands for "Innovation and Entrepreneurship in Robotics and Automation".
[3] IEEE, the Institute of Electrical and Electronics Engineers, is the largest technical professional organization worldwide with more than 400.000 members. RAS is a society within IEEE with a special focus on robotics and automation, including theoretical and applied issues.

operations or processing (e.g. cutting or grinding). Single-purpose automation technology such as elevators, conveyors, and weaving or knitting machines are not covered by the above definition because they cannot be re-programmed to conduct other tasks, need a human operator, or both. Moreover, the IFR dataset excludes dedicated industrial robots specifically designed for and controlled by a special machine (e.g. automated storage and retrieval systems, integrated circuit handlers, or dedicated assembly equipment). Robotic devices as defined in ISO 8373:2012, §2.8 are also excluded (IFR 2020, 23-24). As mentioned in section 2.3, the IFR delimits industrial robots from service robots. The IFR database thereby generally follows the ISO criterion (8373:2012, §2.10) and views the application in industrial versus non-industrial automation as sufficient to distinguish industrial robots from service robots, whereas mechanical features (kinematics) are not a sufficient criterion. However, the IFR has also defined kinematic robot types mainly employed in industrial automation applications and includes those robots in its dataset on industrial robots. Consequently, robots with industrial robot kinematics employed in service applications are counted both, in the industrial robot statistics and the service robot statistics. Although autonomous mobile robots (AMR) are often used in industrial environments, they do not satisfy the definition of an industrial robot because they have less than three axes and lack manipulation capabilities. AMRs are thus classified as service robots. If the AMR is combined with a manipulator (e.g. an articulated robot), the IFR separately counts the manipulator as industrial robot and the platform as service robot. Therefore, the IFR dataset only refers to a specific kind of industrial automation and its counts of industrial robots should be understood as a proxy for automation in general. Nevertheless, it covers more than 90% of the global market for industrial robots (Dauth et al. 2020; Acemoglu/Restrepo 2020).

The IFR collects data on industrial robot installations for its annual WRIR statistics and report by means of two separate questionnaires from nearly all industrial robot suppliers worldwide: 1) annual installations by country and application; 2) annual installations by country and customer industry. Both questionnaires are composed of six separate sheets, one for each type of robots: Articulated robots, Cartesian robots, Cylindrical spherical robots, Parallel/ Delta robots, SCARA robots, and Others.[4] Primary data reported by industrial robot suppliers are supplemented by secondary data that have been collected by national robot associations on their national robot markets. On the one hand, these secondary data are used to validate the primary data. On the other hand, the secondary data are used to fill in missing information of companies not reporting to the IFR directly. Data are generally only published in aggregated form, by geographical entity, industry, or application. Company level data are not publicly available. The IFR dataset distinguishes five geographical entities (from lowest to highest hierarchy level): i) survey items, usually a single country, ii) country groups, iii) regions, iv) continents, and v) the whole world. Table A1 in the appendix lists all geographical classes in the IFR dataset and their availability of data on robot installations. Currently, 75 countries are covered by the dataset.

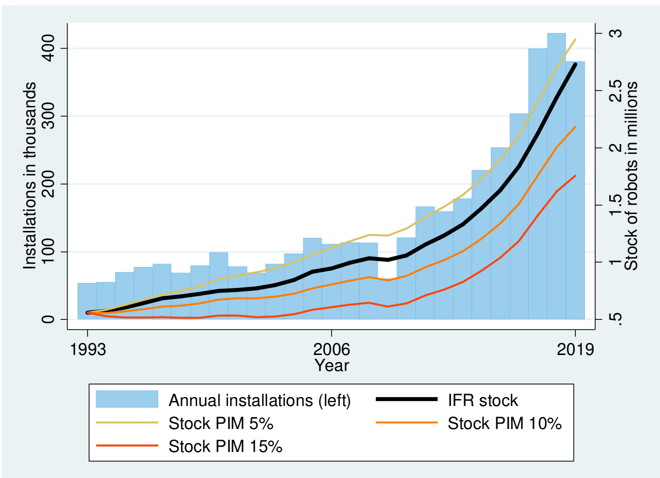
[4] Classification by mechanical structure according to the IFR (2020):

- Articulated robot: a robot whose arm has at least three rotary joints.
- Cartesian (linear/gantry) robot: a robot whose arm has three prismatic joints and whose axes are correlated with a cartesian coordinate system.
- Cylindrical robot: a robot whose axes form a cylindrical coordinate system.
- Parallel/ Delta robot: a robot whose arms have concurrent prismatic or rotary joints.
- SCARA (Selective Compliance Assembly Robot Arm) robot: a robot, which has two parallel rotary joints to provide compliance in a plane.
- Others: robots not covered by one of the above classes.

Data processing includes two consistency checks. First, the IFR checks if the total values by country in both questionnaires - for applications and for industries – match for each robot type. Secondly, whether the IFR data are consistent with national associations' data is scrutinized. Moreover, data processing involves the removal of double counting when secondary data are incorporated. Lastly, an automated compliance verification ensures adherence to compliance rules (see section 3.4 below). Sometimes, minor revisions occur in the dataset by updating the data on robot installations in previous years if new information becomes available.

Within the WRIR report the expressions "shipments" and "installations" of industrial robots are used interchangeably. Theoretically, the IFR statistics aim at counting the actual installation of robots at the customer's site. Practically, the available data, however, often refers to the shipment of robots. The IFR (2020, 22) points to the possibility that shipment and installation data might differ for two reasons: Geographical deviations can occur, if - without the knowledge of the supplier - a reseller installs robots in a different country than the supplier shipped them to (i.e. re-exports). Temporal deviations are possible as the time of installation might be significantly later than the shipment, e.g. because the robot is en route, is stored in an inventory or is work-in-progress at the robot integrator, such that a robot shipped might not yet be installed at year-end. This is also relevant since data on robot installations are used to construct estimates of the operational stock of industrial robots at the end of the year. While installations are flow values, the stock values are supposed to measure the number of robots currently deployed. The Japanese national robot association JARA calculates this figure for Japan. For all other countries, the IFR computes the operational stock of robots assuming an average service life of 12 years with immediate withdrawal from service afterwards (IFR 2020, 22). In other words, the IFR assumes that installed robots must be replaced by new robots after 12 years of usage. This corresponds to a one-hoss shay model of depreciation since the robots are assumed to exhibit no decay during their service life (Jungmittag 2020). This further implies that the operational stock in all IFR member countries except Japan equals the sum of robot installations over 12 years. Figure 2 illustrates the annual global installations of industrial robots as well as the global stock of robots according to the IFR database.

Figure 2: Annual global robot installations and stock development



In addition to IFR stock data, the robot stock is alternatively calculated based on the perpetual inventory method (PIM) with continuous depreciation (5%, 10%, or 15%) from one period to the next.
<u>Source:</u> Own calculations based on IFR data.

3.2 Robot prices

The IFR provides both average unit prices and price indices for robots (producer price indices and a price index for average unit prices). Unfortunately, both average unit prices and price indices are neither available for the entire time period of the IFR database nor for all countries. In addition, information on robot prices cannot be downloaded directly as a time series but must be gathered from the annual WRIR reports. Average unit prices are only provided until 2009 by the annual reports but can be easily calculated as they are turnover based. The producer price indices with base year in 1990 start in that same year but are only available until 2005.

Average unit prices (Table 2) are calculated through total market turnover divided by the number of robots delivered. Total turnover in current prices is expressed in historical local currency and then converted by the IFR into US Dollar at exchange rates that are taken from the Monthly Bulletin of the United Nations. Both values are published. The value of the market for robots can be found in Table 2.3 of the annual WRIR. Average unit prices are no longer published but can be found until 2009 in chapter 3 of the WRIR report, and since 2009 market values are still available in chapter 2. Data coverage for total market values begins in 1985 with prices for 6 countries and one country group: Japan, North America, Germany, Italy, France, UK, and Rep. of Korea. Some of the reports with historical data running to 1990 can only be found in print copies in the archives of the IFR at the VDMA headquarters in Frankfurt.[5] Currently, total market values for robots and thus average unit prices are only available for 5 countries: China, North America[6], Germany, Rep. of Korea, and Japan. Total market values for France have ceased to be published in 2006, the last year covered being 2005. However, in the case of France, average unit prices up to 2008 are available from the WRIR published in 2009. Data on total market value for Italy were reported for the last time in 2006, and information on average unit prices stops there as well. The UK is covered until 2018.[7] China appears first in the WRIR of 2013 and dates back to 2007. The Chinese values are solely based on IFR estimates, while for all other countries the market values are reported by the respective national robotics associations.

Calculating average unit prices through total market values has the disadvantage that it does not account for different qualities and sizes of robots: one only receives an average price across all robot types. This, however, is a drawback of the entire robotics database as each robot delivered is counted as one unit irrespective of its size or quality. Apparently, many robots sold in recent years are smaller sized robots and are therefore priced lower, causing the average robot price to decline (IFR 2020, 51). Also, a robot is not installed by itself but rather forms a system with computer technology, software, and peripherals. These costs are, however, not included in the market value and thus are not part of the average unit price. The IFR assumes that these additional components could increase the value of the installed robots significantly as the robot unit alone only constitutes roughly 1/3 of the cost of the whole

---

[5] Only for some countries information on prices is available from 1985 onwards. Please note that these archives are not publicly accessible. Table 2, however, covers the period from 1990 to 2019 which should be sufficient given that the actual data coverage for robots starts in 1993.

[6] Prior to the WRR 2011 North America was called US, but it contained price data on Canada and Mexico, just as the installations and the robot stock contained information on Canada and Mexico as well. As the IFR points out, this is due to the distributional structure of the North American robot market. All robots are shipped first to the US and are then exported to Canada and Mexico. After 2011 the North American Robotic Association began to report installations for the US, Canada and Mexico separately. However, information on prices is still for all of North America.

[7] The UK Robotic Association has ceased to report data on market values. For some time, the IFR estimated the market values but has ultimately discontinued the time series for the UK.

system. A way to resolve the issue of different sizes and complexities of robots delivered and furthermore to consider quality changes over time is to express robot prices as an index. Along these lines, the IFR has constructed two producer price indices, both with base year 1990, one without and one with quality changes. The price indices are reported from 1990-2005 and are expressed using both current exchange rates (see Table A2a in the appendix) and fixed conversion rates against the US Dollar (see Table A2b in the appendix). Due to the considerable effort involved and owing to compliance issues, the IFR no longer continues to construct such price indices. The information needed for constructing these price indices was provided by 5 multinational robot producing companies who reported list prices on 2 different, clearly defined robot models for each year. In addition, the firms reported also on several pre-specified electronic and mechanical characteristics shedding light on quality changes.

In order to construct the quality-adjusted price index, the IFR resorted to a producer price mark-up method. A robot is composed of three parts: a control unit (usually a computer), a mechanical unit with changing characteristics (such as arms, drives, sensors etc.) and mechanical parts which are time-invariant (such as casings and steel structures).
These components were assigned weights by which each component enters the overall price adjustment (20% control unit and 40% for each mechanical component). The price decline of the control unit was measured via the US producer price for computers. For the mechanical parts it was more difficult. Therefore, changes in 4 characteristics[8] of the mechanical parts were monitored and it was assumed that costs would increase proportionally to their improvements.[9] The IFR was then able to calculate what a robot would have cost in each year of the time series with the characteristics of a robot in 2005.[10] The weighted price increases that were due to an increase in the characteristics were added as a mark-up to the actual price of the robot in the respective year. The quality-induced price change is then the difference between this counterfactual price and the actual price. One must be aware, however, that this procedure does not yield a price index in the usual sense where the quality of a robot remains constant while the price changes. Instead, here quality evolves, and the price is corrected backwards. The price index provided by the IFR, therefore, measures what a robot with the characteristics of a robot in 2005 would have cost in previous years instead of asking how much a replacement robot would cost if the quality remained the same.

---

[8] These characteristics with their respective weights in brackets are: Total handling capacity in kg / maximum payload (0.2), repetition accuracy in mm (0.3), total aggregated speed of all six axes in degrees per second (0.3), total maximum reach in mm (0.2).

[9] A detailed account of this procedure can be found in the WRIR of 2006, Annex C.

[10] There were actually 2 surveys, one running from 1990-1999 and one from 2001-2005. The resulting indices were chain linked.

Table 2: Average unit prices of industrial robots in thousand US Dollars

Country	1990	1991	1992	1993	1994	1995
Germany	99.23	103.22	95.43	90.40	77.66	78.66
North America (USA)	112.09	105.24	99.98	106.56	103.06	89.73
Rep. of Korea	na	na	na	39.18	48.06	55.74
China						
UK	86.27	78.98	56.09	54.15	61.69	68.18
Italy	102.80	120.91	88.44	75.68	77.66	79.81
France	112.90	115.35	91.81	72.90	82.71	83.82

Country	1996	1997	1998	1999	2000	2001
Germany	71.08	61.77	60.07	55.27	49.45	46.51
North America (USA)	97.56	86.17	96.32	83.05	78.55	81.57
Rep. of Korea	44.30	19.45	41.23	38.75	27.69	23.04
China						
UK	76.16	60.83	56.94	63.22	53.97	47.91
Italy	76.55	63.11	67.34	65.85	63.42	65.59
France	65.41	56.94	59.89	64.04	47.46	47.07

Country	2002	2003	2004	2005	2006	2007
Germany	50.24	56.34	64.47	63.42	62.32	63.92
North America (USA)	74.84	70.04	68.03	60.00	67.00	66.02
Rep. of Korea	21.26	26.39	28.22	27.22	29.84	32.71
China						51.36
UK	46.67	57.61	50.96	46.22	46.72	46.67
Italy	71.12	85.42	95.26	91.61	121.77	137.02
France	48.14	56.46	63.70	61.30	60.20	67.20

Country	2008	2009	2010	2011	2012	2013
Germany	68.13	84.52	58.32	58.36	71.31	75.97
North America (USA)	74.01	64.04	62.00	61.01	62.01	61.01
Rep. of Korea	28.34	26.41	22.33	19.42	19.41	23.98
China	56.35	63.71	44.73	47.26	51.20	51.37
UK	36.21	37.80	37.59	40.95	57.08	55.51
Italy	173.37	na	na	na	na	na
France	68.40	na	na	na	na	na

Country	2014	2015	2016	2017	2018	2019
Germany	66.28	59.81	62.07	78.67	58.11	49.65
North America (USA)	58.01	56.99	58.71	57.67	50.53	52.81
Rep. of Korea	15.61	23.33	25.11	29.64	25.15	21.70
China	47.50	45.01	38.06	28.76	35.18	31.97
UK	53.01	50.46	41.97	45.80	43.06	na
Italy	na	na	na	na	na	na
France	na	na	na	na	na	na

Source: Own calculation based on IFR data.

The indices with current exchange rates are calculated for 6 countries - US, Italy, France, Germany, UK, and Sweden - and are published in the WRIR of 2006, chapter 3.[11] As the IFR points out in the WRIR of 2006, the price indices (not quality adjusted as well as quality adjusted, see Table A2b) with a fixed conversion rate against the 1990 USD can be viewed as a general price index as it lacks an exchange rate dimension, whereas the price indices with current exchange rates are only applicable to their respective countries. A substantial part of the price decline in current US$ is actually due to exchange rate fluctuations. This is not surprising as roughly 90% of the robot producing companies originate from Europe and Japan. The price decline without quality adjustment between 1990 and 2005 has been in the order of 40% to 60%, depending on the country. Accounting for quality changes leads to a more pronounced price decline: a robot installed in 2005 costs less than a quarter compared to one installed in 1990.[12]

3.3 Industry classification

Data on industrial robots are collected for 11 broad manufacturing categories, for six broad non-manufacturing categories, and for one category "Unspecified". The IFR industry classification is based on the International Standard Industrial Classification of All Economic Activities (ISIC) revision 4 (United Nations 2008). However, the IFR classification originally followed ISIC rev. 3 and did not adopt the structural changes that occurred with transition to ISIC rev. 4. Therefore, the IFR industry classification contains artefacts from ISIC rev. 3: for instance, the manufacturing sector is labelled as D as in ISIC rev. 3 instead of C as in ISIC rev. 4. Within manufacturing, industry disaggregation is available at the two- or three-digit level. Three-digit-level data are only reported for ISIC divisions 26, 27, and 29, i.e. electronics and automotive industries which are also the most important users of industrial robots. The six non-manufacturing industries are covered at the section-level.

The IFR industry classes partly deviate from ISIC rev. 4, making a perfect match between both classifications impossible. The most important complication for the matching process is created by the IFR's more detailed focus on the automotive industry: automotive parts are separated from all relevant ISIC categories and used for a finer granularity of the IFR industry class "Automotive parts". So, for instance the manufacture of rubber and plastics products (division 22 in ISIC rev. 4) that end up as automotive parts are taken out of that ISIC category and grouped as a subclass of "Automotive parts". Thus, the IFR industry classification contains the category "Rubber and plastic products (non-automotive)", and a separate category, "Rubber and plastic (AutoParts)". The reason behind this procedure is the high share of customers from the automotive sector in the robotics market. Table A3 in the appendix serves as correspondence table between IFR classification and ISIC rev. 4 using basic set theory.

The highest level of aggregation in the IFR dataset is obtained by the class "All industries" (code 0) and serves as parent class for all other IFR classes. The IFR classification is organized into eight broad classes (with parent code 0): "Agriculture, forestry, fishing", "Mining and quarrying", "Manufacturing", "Electricity, gas, water supply", "Construction", "Education/research/development", "All other non-manufacturing branches", and

[11] There are releases in earlier publications but the most up to date one can be found in the 2006 report.
[12] Until 2009 the IFR also reported an index of average robot prices with base year 1990 (up to 2005 with base year 1989) for the US, Germany, France, and the UK. In contrast to the former producer price indices, this price index was based on average unit prices in national currency and neither accounted for robot heterogeneity nor for quality improvements. Together with the individual reporting of average unit prices, this index ceased to be published after 2009.

“Unspecified”. Within the manufacturing sector, eleven classes of manufacturing activities are distinguished: “Food and beverages”, “Textiles”, “Wood and furniture”, “Paper”, “Plastic and chemical products”, “Glass, ceramics, stone, mineral products (non-auto)”, “Metal”, “Electrical/electronics”, “Automotive”, “Other vehicles” and “All other manufacturing branches”. Four of these manufacturing classes are further divided into sub-classes: “Plastic and chemical products”, “Metal”, “Electrical/electronics”, and “Automotive”. The number of robot installations in the dataset always results from summation of all the sub-classes of a branch, i.e. the number of robot installations at the level of “Plastic and chemical products” results from adding up all the robot installations in the sub-classes of that IFR class. The number of robots in the manufacturing sector is obtained from summation over all the manufacturing classes. Accordingly, the total number of robots in the economy across all industries (parent class “All industries”) is the sum of all 8 broad classes distinguished in the IFR dataset. The total number of robots can also be obtained from adding up the eleven manufacturing classes, the six non-manufacturing classes (“Agriculture, forestry fishing”, “Mining and quarrying”, “Electricity, gas, water supply”, “Construction”, “Education/research/development”, “All other non-manufacturing branches”) and the category “Unspecified”.

The first two IFR classes are equal to the first two ISIC sections: “Agriculture, forestry, fishing” has the same title as section A of ISIC rev. 4 and corresponds to ISIC divisions 01-03. “Mining and quarrying” has the same title as ISIC section B and corresponds to ISIC divisions 05-09. The third broad IFR class is “Manufacturing” and comprises 11 sub-classes, which in turn are partly divided into even more specific industrial categories. At aggregated level, the IFR class “Manufacturing” is equivalent to ISIC section C. The disaggregated manufacturing categories in the IFR classification, however, partially deviate from ISIC rev. 4. Either the IFR manufacturing categories combine several ISIC divisions and/or ISIC groups/ classes, or the IFR classes additionally include or exclude some single elements of ISIC categories. In the latter case, a perfect match between the IFR classification and ISIC rev. 4 is impossible. Nevertheless, even then we can at least approximately harmonize the two industry classifications.

The IFR class “Food and beverages” is equivalent to ISIC divisions 10-12 (“Manufacture of food products, beverages, tobacco products”). “Textiles” corresponds to ISIC divisions 13-15 (“Manufacture of textiles, wearing apparel, leather and related products”). “Wood and furniture” combines ISIC division 16 with a part of ISIC division 31, namely wood furniture. However, ISIC division 31 comprises furniture “of any material (except stone, concrete and ceramic)” (UN 2008, p. 155). Since wood furniture is the biggest component of ISIC division 31 (Pandey/Pulidindi, 2020), we suggest combining ISIC divisions 16 and 31 to get as close as possible to the IFR class “Wood and furniture".

"Paper" comprises ISIC divisions 17 and 18 (“Manufacture of paper and paper products”; “Printing and reproduction of recorded media”). The IFR class “Plastic and chemical products” is subdivided into four sub-categories and approximately corresponds to ISIC divisions 19-22 after adding IFR automotive sub-class “Rubber and plastic (AutoParts)”. An exact match is prevented by the exclusion of automotive parts in the IFR sub-class “Rubber and plastic products (non-automotive)”. Just as ISIC divisions 19-22 do, it includes rubber tires for bicycles or wheelbarrows but excludes car tires, which are contained in the IFR automotive sub-class “Rubber and plastic (AutoParts)”. However, “Rubber and plastic (AutoParts)” also includes bumpers, which are part of ISIC group 293. The sub-class “Pharmaceuticals, cosmetics” is equivalent to ISIC division 21 (“Manufacture of pharmaceuticals, medicinal chemical and botanical products") plus ISIC class 2023 ("Manufacture of soap and detergents, cleaning and polishing preparations, perfumes and toilet preparations"). Accordingly, sub-class "Other chemical products n.e.c" comprises ISIC divisions 19 and 20 ("Manufacture of coke and refined petroleum products"; "Manufacture of chemicals and chemical products") without ISIC group 2023. The IFR sub-class "Chemical products, unspecified" does not correspond to any ISIC class. It simply contains all data reports where the exact industrial category among "Plastic and chemical products", in which the robots are used, is either unknown (i.e. not specified by the reporting robot producer) or cannot be disclosed due to compliance rules.

Combining IFR-class "Glass, ceramics, stone, mineral products (non-automotive) with "Glass (AutoParts)" corresponds to ISIC division 23 ("Manufacture of other non-metallic mineral products"). IFR-class "Metal" comprises four sub-classes. The first one, "Basic metals" matches ISIC division 24 ("Manufacture of basic metals"). The second one, "Metal products (non-automotive)", is virtually equivalent to ISIC division 25 ("Manufacture of fabricated metal products, except machinery and equipment"). One limitation arises from the inclusion of metal furniture in the IFR subclass. The IFR-focus on non-automotive metal products seems to be a minor issue here, as all metal parts of motor vehicles mentioned in the IFR automotive sub-class "Metal (AutoParts)" are also contained in ISIC group 293 ("Manufacture of parts and accessories for motor vehicles"). Third, "Industrial machinery" corresponds to ISIC division 28 ("Manufacture of machinery and equipment n.e.c."), except for the exclusion of the manufacture of lawn mowers from the IFR sub-class. The fourth one, "Metal, unspecified" does not have any ISIC equivalent.

The next IFR-class, "Electrical/electronics", contains eight sub-classes. "Household/domestic appliances" approximates ISIC group 275 ("Manufacture of domestic appliances"). In contrast to ISIC group 275, the IFR sub-class, however, includes the manufacture of lawn mowers and lamps, which are part of ISIC classes 2821 ("Manufacture of agricultural and forestry machinery") and 2740 ("Manufacture of electric lighting equipment"), respectively. "Electrical machinery n.e.c. (non-automotive)" approximately is the union of ISIC groups 271, 272, 273 and 274 ("Manufacture of electric motors, generators, transformers, and electricity distribution and control apparatus"; "Manufacture of batteries and accumulators"; "Manufacture of wiring and wiring devices"; "Manufacture of electric lighting equipment", except for the exclusion of the manufacture of lamps from the IFR sub-class). A perfect match is not possible since electrical/electronic parts that end up in motor vehicles are taken out of this IFR subclass and subsumed under the automotive IFR sub-class "Electrical/electronics (AutoParts)". This automotive sub-class, however, contains elements that are also registered as parts of motor vehicles under ISIC group 293. Therefore, we cannot add "Electrical/electronics (AutoParts)" to "Electrical machinery n.e.c. (non-automotive)" as this would shift automotive parts according to ISIC definition that are not covered by ISIC groups 271, 272, 273 nor 274. Combining the IFR sub-classes "Electronic components/devices" and "Semiconductors, LCD, LED" is equivalent to ISIC group 261 ("Manufacture of electronic components and boards"). "Computers and peripheral equipment" correspond to the union of ISIC groups 262 and 268 ("Manufacture of computers and peripheral equipment"; "Manufacture of magnetic and optical media"). "Info communication equipment, domestic and professional (non-automotive)" can be approximated by the union of ISIC groups 263 and 264 ("Manufacture of communication equipment"; "Manufacture of consumer electronics"). An exact match is again prevented by the separation of communication equipment and consumer electronics that ends up in motor vehicles, in particular radios and hands-free systems. "Medical, precision, optical instruments” also comprises several ISIC groups: 265, 266 and 267 (“Manufacture of measuring, testing, navigating, and control equipment; watches and clocks”; “Manufacture of irradiation, electromedical and electrotherapeutic equipment”; “Manufacture of optical instruments and photographic equipment”). One limitation is that navigation systems used in motor vehicles are excluded from the IFR sub-class “Medical, precision, optical instruments”, and instead are registered in the sub-class “Electrical/electronics (AutoParts)”. The last “Electrical/electronics” sub-class is “Electrical/electronics, unspecified”, which again collects all data reports where the exact electrical/electronics industry is unknown or cannot be revealed due to compliance reasons, and thus does not have any ISIC equivalent.

The last disaggregated IFR industry class is the automotive sector (class “Automotive”). Its first sub-class “Motor vehicles, engines and bodies” is equivalent to the union of ISIC groups 291 and 292 (“Manufacture of motor vehicles”; “Manufacture of bodies (coachwork) for motor vehicles; manufacture of trailers and semi-trailers”). A specific peculiarity of the IFR industry classification consists in the fine granularity of the sub-class “Automotive parts”. Unlike ISIC, the IFR classification further divides parts and accessories of motor vehicles into “Metal (AutoParts)”, “Rubber and plastic (AutoParts)”, “Electrical/electronics (AutoParts)”, “Glass (AutoParts)” and “Other (AutoParts)”. These categories contain goods that have been separated out of the respective broader “non-automotive” IFR classes. Consequently, automotive parts in the IFR classification comprise significantly more elements than the corresponding ISIC group 293 (“Manufacture of parts and accessories for motor vehicles”). In detail, “Rubber and plastic (AutoParts)” includes tires of motor vehicles (part of ISIC class 2211), rubber hoses and belts (part of ISIC class 2219) as well as plastic hoses and belts (part of ISIC class 2220), which all are excluded from ISIC group 293. The only rubber/plastic products included in both IFR class “Rubber and plastic (AutoParts)” and ISIC group 293 seem to be bumpers. Similarly, “Electrical/electronic (AutoParts)” includes navigation systems (part of ISIC class 2651), communication equipment for motor vehicles (part of ISIC class 2630), electric motors, switchboard apparatus and relays (all part of ISIC class 2710) as well as batteries and accumulators (part of ISIC 2720). Generators, alternators, spark plugs, ignition wiring harnesses, power window and door systems, assembly of purchased gauges into instrument panels, and voltage regulators are contained in both IFR class “Rubber and plastic (AutoParts)” and ISIC group 293. Auto glass listed under “Glass (AutoParts)” in the IFR classification is no part of ISIC group 293 but included in ISIC group 231. In contrast, “Other (AutoParts)” encompasses car seats, safety belts and airbags, which are also part of ISIC group 293. As well, all metal parts of motor vehicles mentioned in the IFR definition of “Metal (AutoParts)”, namely brakes, gearboxes, axles, road wheels, suspension shock absorbers, radiators, silencers, exhaust pipes, catalytic converters, clutches, steering wheels, steering columns, and steering boxes, are also registered under ISIC group 293. To match IFR class “Automotive parts” as well as possible with ISIC group 293, “Metal products (AutoParts)”, “Electrical/electronic (AutoParts)” and “Other (AutoParts)” are to be combined while “Rubber and plastic (AutoParts)” and “Glass (AutoParts)” should be excluded.

Robots delivered to industries manufacturing automotive parts where the exact category is unclear were collected under “Automotive unspecified” (IFR code 299, sub-class of IFR class “Automotive”) until year 2017. Since 2018, these data reports are grouped into “Unspecified AutoParts” (IFR code 2999) as a subcategory of the IFR sub-class “Automotive parts” to improve the precision of IFR class “Automotive parts” because the number of robots delivered to industries manufacturing auto parts results from a summation of its sub-categories.

The IFR class “Other vehicles” is equivalent to ISIC division 30 (“Manufacture of other transport equipment”). The last IFR manufacturing class (91) is called “All other manufacturing branches” and unites ISIC divisions 32 and 33 (“Other manufacturing”; “Repair and installation of machinery and equipment”), but also contains data reports that were not allowed to appear in the more specific manufacturing industries for compliance reasons. Thus, a good match between IFR class 91 and ISIC is impossible.

The IFR dataset also covers some further broad non-manufacturing branches apart from “Agriculture, forestry, fishing” and “Mining and quarrying”: “Electricity, gas, water supply” corresponds to ISIC sections D and E, which entail the ISIC division 35 to 39; “Construction” matches ISIC section F (divisions 41 to 43) and “Education/research/development” is equivalent to the union of ISIC divisions 72 and 85 (“Scientific research and development”; “Education”). “All other non-manufacturing branches” (IFR class 90) comprises a large part of the service sector by including all the remaining ISIC divisions from 45 to 71, from 73 to 84 and from 86 to 99. However, the IFR class 90 also contains re-classified data from the non-manufacturing IFR classes (A-C, E-P), either due to compliance restrictions or because the specific branch is unknown. Finally, the IFR class “Unspecified” covers all data reports for which the robot applying industry is either unknown or cannot be shown in any of the aforementioned classes owing to compliance issues.

3.4 Classification of robot applications

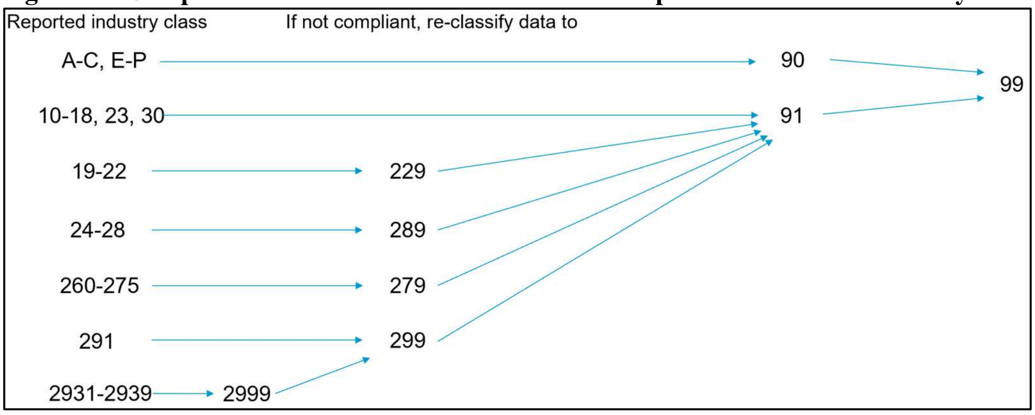
Apart from data collection by industrial classes, annual installations of industrial robots are also collected by application classes. The IFR distinguishes six broad application classes and one category “Unspecified” (class 999). “Unspecified” contains robots for which the application is either unknown or cannot be shown in any of the application classes due to compliance reasons. Each of the broad application classes also contains one “unspecified” sub-class for all data points where the exact application area within the broad category is either unknown or cannot be revealed due to compliance rules. The first broad application area is called “Handling operations/machine tending” (class 110) and comprises assistant processes, i.e. applications in which the robot does not process the primary operation directly. This class is the aggregate of ten sub-classes such as “Handling operations for metal casting” (class 111). The second broad application area is labelled “Welding and soldering (all materials)” (class 160) and is divided into six sub-classes, for instance “Arc welding” (class 161). “Dispensing” (class 170) is the third broad application class that encompasses four sub-classes, e.g. “Painting and enameling” (class 171). The fourth broad application area is “Processing” (class 190) and comprises five sub-classes such as “Laser cutting” (class 191). “Assembling and disassembling” (class 200) is the fifth broad application area, divided into three sub-classes, namely “Assembling” (class 201) and “Disassembling” (class 202) as well as “Assembling and disassembling unspecified” (class 209). The last broad application class is called “Others” (class 900) and comprises four sub-classes, for example “Cleanroom for semiconductors” (class 902). Table A4 in the appendix presents the different IFR application classes.

3.5 Compliance rules

The IFR is a private association that includes among its members the major robot producing firms. Thus, it is necessary that the Statistical Department complies with all antitrust and privacy protection rules. The fundamental principle behind these rules is to prevent users of the IFR data from retrieving information on an individual company: given that the data user has data on one company, it should not be possible to draw conclusions on another company's data. The compliance rules therefore require that each data point revealed must consist of data from at least four companies. This rule has been applied by the IFR from 2015 onwards and, therefore, affects installation data since year 2014. Earlier data points, however, were not adjusted retrospectively. Only since 2015 is the number of reports underlying each data point automatically checked. This iterative process is repeated until every single data point is compliant or until the most generic level is reached. Thereby, the IFR aspires to remove as little information as possible from the data but as much as is necessary to be compliant.

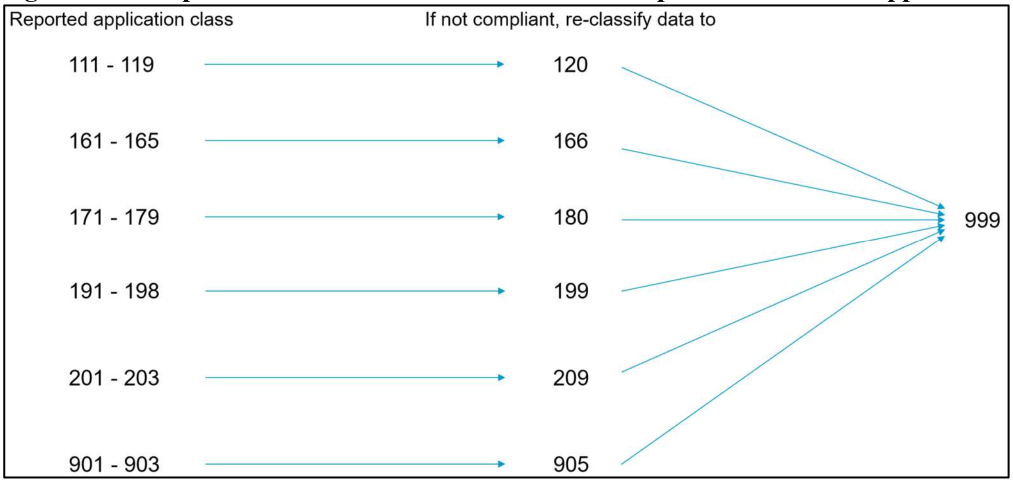
Two methods are applied upon compliance violation at the survey item or country group level. Higher levels of geographical aggregation (i.e. regions, continents, or world) are not subject to any compliance rules. Compliance mechanism M1 works as follows. Data are reclassified to an "unspecified"-class on the same level in the hierarchy of the IFR industry/application classification. Assume for example that data reports for IFR class 19 ("Pharmaceuticals, cosmetics") are non-compliant. Then, the data in class 19 are shifted to industry class 229 ("Chemical products, unspecified"). This results in 0 installations shown for industry class 19, as these data now appear in 229. If this is still non-compliant, the data are moved to a superior hierarchy level. In our example, this means that the data would be found under industry class 91 ("All other manufacturing branches"). This would result in 0 installations in industry classes 19 and 229 because data appears in class 91. If this is still non-compliant, the data will show up under the most generic IFR industry class, i.e. class 99 ("Unspecified"). M1 is applied to industry classes and application classes by country or country group. Figures 3a and 3b show the re-classification procedure for all IFR industry and application classes according to compliance mechanism M1.

Figure 3a: Compliance mechanism M1 – re-classification procedure for IFR industry classes



Source: IFR (internal document).

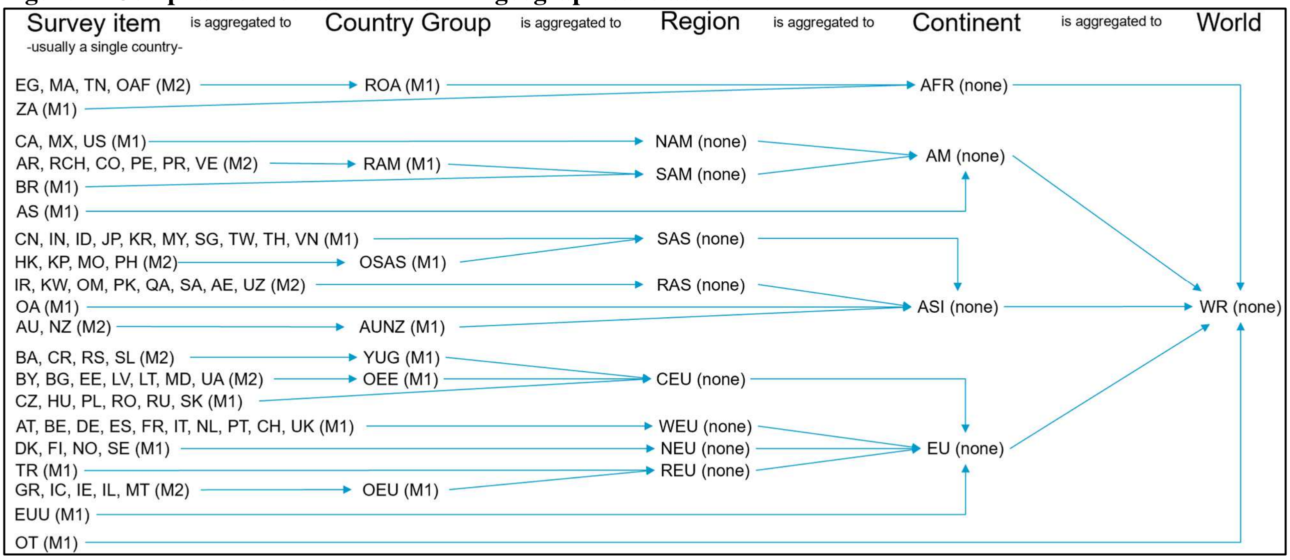
Figure 3b: Compliance mechanism M1 – re-classification procedure for IFR application classes



Source: IFR (internal document).

Compliance mechanism M2 may also be called geographical aggregation as this procedure stipulates that all data are hidden (i.e. no installations are shown) for a country and, instead, are added to the superior geographic level, i.e. a country group or geographical region. For instance, data reports for Bosnia-Herzegowina, Croatia, Serbia, and Slovenia are hidden and displayed only for Balkan Countries as a whole. Accordingly, M2 is applied to countries, at the discretion of the IFR Statistical Department. It is usually deployed for those countries with low installation figures. Figure 4 illustrates which compliance mechanism is applied to which geographical entity.

Figure 4: Compliance mechanisms for IFR geographical classes



The compliance mechanism applied to the respective geographical entity is shown in parentheses
Source: IFR (internal document).

The compliance mechanisms described above have several consequences for working with the IFR dataset. Data are seemingly inconsistent as a bottom-up summation of country-level data does not yield totals at higher hierarchy levels for data points since year 2014. This is obvious for M2: if data are hidden for some country, leading to “false” zeros, a summation over countries cannot add up to the country group-level values. Thus, the number of robot installations obtained from summing the country values within a country group or region will be lower than the number shown for the respective country group or region. This implies, that data for country groups, regions and continents usually cannot be obtained from adding up the values of the corresponding countries but must be retrieved from the data explicitly shown for the respective level of geographical aggregation. This also holds true for the highest level of geographical aggregation: data on robot installations for the whole world must be taken from the IFR geographical class “World” (WR) and are not equal to the sum over all countries in the dataset for data points since year 2014.

The complications created by M1 are less obvious. M1 shifts data to another industry class on the country or the country group level. In consequence, except for country (group) totals (i.e. values reported for the respective mother class “All industries” or “All applications”) not affected by M2, the sum of country (group)-level values will not match the reported region or continent value for the respective industrial categories. The bottom-up sum will be lower than the reported region or continent value for industry/application classes that are the origin of reclassified data, and it will be larger for “unspecified” classes which are the target of reclassification. For instance, the sum of robots employed in the manufacturing of “Household/domestic appliances” (IFR class 275) in Canada, Mexico and the USA will be smaller than the number of robots reported in the same industrial class for the region North America (NAM), if for at least one of the three countries the number was set to zero and shifted to IFR class 279 (“Electrical/electronics unspecified”) owing to the compliance rule. This would simultaneously imply a sum over Canada, Mexico, and the USA for IFR class 279 that is higher than reported for the region North America. The reason for this is that the compliance rules are not applied for regions, continents, and the world, such that there is no obstacle to revealing the true number of robots installed in all industrial classes.

In general, time series data for individual countries may seem incomplete, especially in small countries, because data can be published only in years without compliance violations. Moreover, inconsistencies between installations and robot stocks within a geographical entity can occur because robot stocks are not affected by the compliance mechanisms. Therefore, it can happen, that the robot stock increases from one year to the next, although the number of installations in the respective year is set to zero for compliance reasons. This may create consistency problems since 2014, in particular for all calculations of the robot stock based on perpetual inventory methods.

3.6 Data issues and limitations

The IFR dataset on industrial robots exhibits several data issues and limitations. We will explicitly discuss seven of them. First, a significant share of the robot data is not classified into any of the industrial categories or application areas and, therefore, appears under “Unspecified” (IFR industry class 99, or application class 999). On average, between 1993 and 2019 45.2% of the robot stocks at survey item level are not classified to a specific IFR industry class, while 27,7% are not classified to a specific IFR application class. However, these high shares of robots with unspecified industry or application are mainly driven by smaller countries or countries that account for low shares of the global market for industrial robots. Among Western and Northern European countries, including Germany and Italy as important markets for industrial robots, on average only 27.9% of the robot stocks are not classified to any IFR industry and 21.2% do not have a specified field of application. The average share of robots with unspecified industry or application in total robot stocks over the full period of the dataset decreases in the level of geographical aggregation (Tables 3a, 3b).

Table 3a: Share of robots with unspecified industry in total robot stocks

Geographical class	Obs	Mean	Std. Dev.	Min	Max
Survey item	1539	0.452	0.384	0	1
Country group	146	0.565	0.356	0.018	1
Region	196	0.391	0.376	0.035	1
Continent	102	0.369	0.338	0.043	1
World	27	0.197	0.040	0.133	0.275

Share of robots with unspecified industry in total robot stocks – Summary statistics by geographical class for the period 1993-2019. Japan, Russia, and Other Asia are removed from the survey item level due to data inconsistencies. **Source:** Own calculations based on IFR data.

Table 3b: Share of robots with unspecified application in total robot stocks

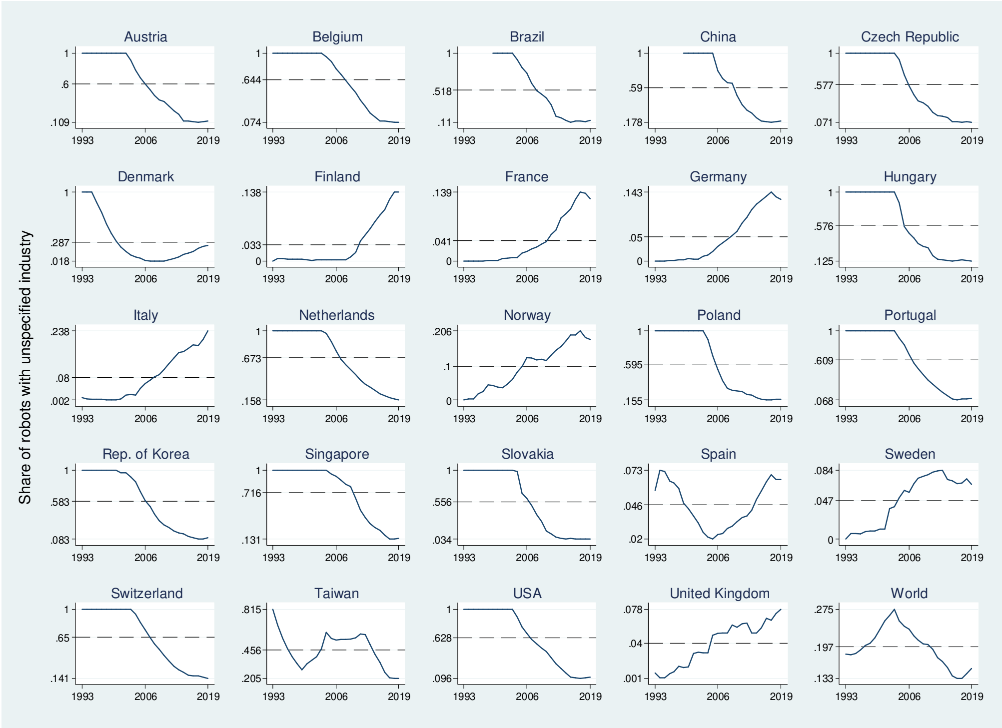
Geographical class	Obs	Mean	Std. Dev.	Min	Max
Survey item	1539	0.277	0.353	0	1
Country group	146	0.386	0.350	0	1
Region	196	0.261	0.348	0	1
Continent	102	0.147	0.251	0.006	1
World	27	0.070	0.030	0.032	0.186

Share of robots with unspecified application in total robot stocks – Summary statistics by geographical class for the period 1993-2019. Japan, Russia, and Other Asia are removed from the survey item level due to data inconsistencies. **Source:** Own calculations based on IFR data.

This can be explained by the fact that those countries with relatively high robot stocks and a low share of unspecified robots over the whole period of the dataset obtain more weight when climbing up the geographical hierarchy. In particular, the relative weight of Japan and Germany matters as these two countries have comparatively high robot stocks from the beginning, while the mean share of unspecified robots between 1993 and 2019 is very low (Japan: 0.04%, Germany: 5.0% for robots by industry; Japan: 0,2%, Germany: 5,4% for robots by application).[13] However, even at the global level still 19.7% of robots are not allocated to a specific industry class. For robot data by application area the picture is neater with only 7% of unspecified robots in the global robot stock. The pattern of a declining share of unspecified robots with a higher level of geographical aggregation seems to be disrupted by the relatively high unspecified shares at the country group level. Yet, this can be explained by the fact that country groups are formed via compliance mechanism M2 for countries with low installation figures and, thus, relatively low robot stocks. Moreover, some of the countries that form country groups have very high shares of unspecified robots. For example, country group "Australia/New Zealand" (AUNZ) exhibits a mean share of robots with unspecified industry of 90.1% (Australia: 92,2%, New Zealand: 87,4%).

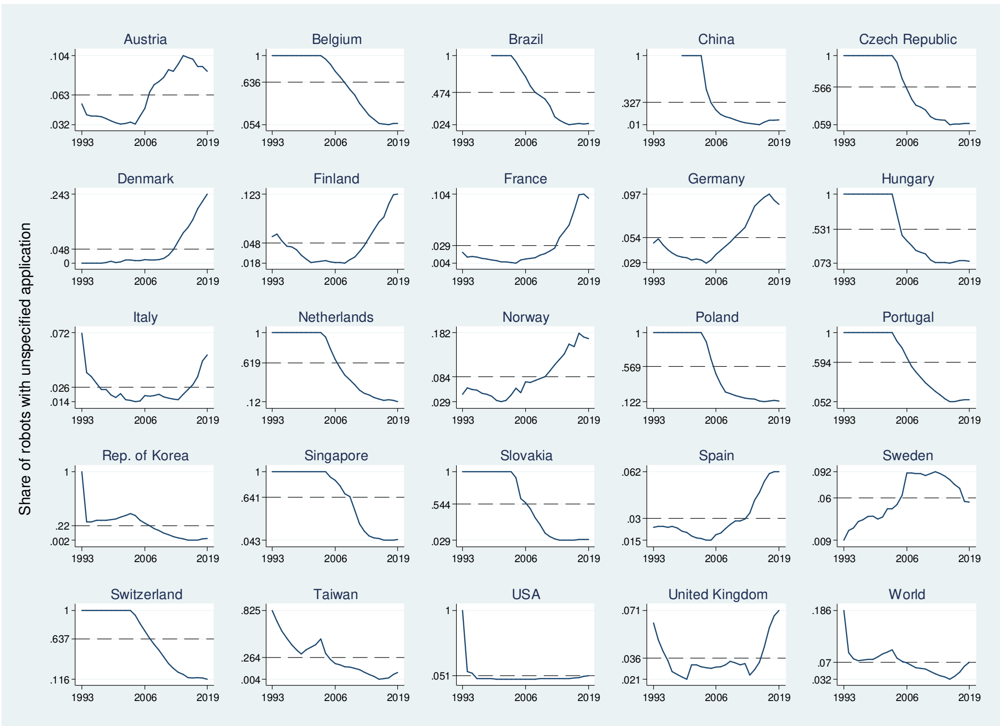
[13] Although Japan is excluded from the survey item level, Japanese data are still included in the respective region (South East Asia, SAS) and continent (Asia/ Australia, ASI) data as well as in the global robot stocks (World, WR).

Figure 5a: Share of robots with an unspecified industry in total robot stocks over time



<u>Source:</u> Own calculations based on IFR data.

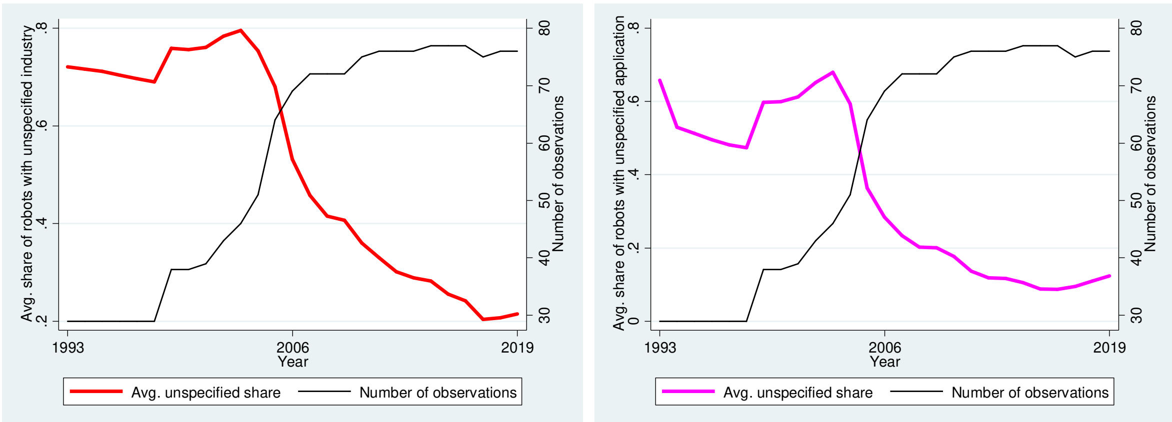
Figure 5b: Share of robots with an unspecified application in total robot stocks over time



<u>Source:</u> Own calculations based on IFR data.

Figures 5a and 5b illustrate the evolution of the share of robots with unspecified industry and unspecified application over time for 24 countries as well as for the global robot stock, where the dashed line indicates the respective mean of the unspecified share. The evolution of the unspecified share over time varies tremendously between these countries, showing a downward trend for some countries and an upward trend for others. Some countries start with an unspecified share of 1 (i.e. data are only available at the most aggregated industry/application level "All industries"/ "All applications") and exhibit an almost linear decay of the unspecified share until the end of the period (e.g. Belgium, Brazil, Netherlands, Switzerland). This phenomenon can be explained by progress in availability of disaggregated data. However, there are also some countries for which the share of unspecified robots starts at (or close to) 0 and increases over time. For instance, Germany, France, and Italy have shares of robots with an unspecified industry close to zero, which start to increase quite strongly around year 2005 up to approximately 13% for Germany and France, and even 24% for Italy, in year 2019. Nevertheless, in total the share of robots with unspecified industry or application sharply decreases since 2005, indicating a clear improvement in availability of disaggregated data (c.f. Figure 5c). Between 1993 and 2004, on average 74.3% of robots at survey item level are not classified to any industry, while 58.3% are not classified to any application. Between 2005 and 2019, the average share of robots with unspecified industry is only 33.9% and the average share of robots with unspecified application 15.9% at survey item level. Simultaneously, the number of observations (i.e. total robot stocks larger than zero) per year sharply increases over time, especially from 1998 to 2010.

Figure 5c: Average share of robots with an unspecified industry/application at survey item level over time



Japan, Russia, and Other Asia are excluded from the survey item level.
Source: Own calculations based on IFR data.

Second, the assumption of a one-hoss shay depreciation after 12 years in the IFR dataset is not in line with the mainstream literature on economic growth and productivity where capital equipment is usually subject to continuous depreciation from one time period to the next (Graetz/Michaels 2018). Moreover, the IFR itself points out that the assumption of 12 years of service life is uncertain and needs further investigation.[14] The IFR depreciation procedure is associated with an implicit depreciation rate that fluctuates over time. This implicit depreciation rate is calculated by rearranging a standard capital accumulation equation:

(1) $$R_t = (1 - \delta_t) R_{t-1} + I_t \quad \leftrightarrow \quad \delta_t = 1 - \frac{R_t - I_t}{R_{t-1}}$$

[14] The assumption was investigated in an UNECE/IFR pilot study, carried out as early as 2000 among some major robot suppliers (IFR/UN ECE 2001). This study suggested that 12 years of average service life might be too conservative and that the average service life was closer to 15 years. German and American tax authorities, however, assume in their standard depreciation schedules an average service life of 5 to 6 years for robots (Germany: 5 years for robots in the automotive industry and 6 years for robots in the mechanical engineering industry; USA: useful life of class 80.0C "Robotics" is 5 years in the American tax law). Such depreciation schedules however ignore possible refurbishments extending the actual service life (IFR 2020, 22-23).

R_t is the stock of robots at year-end, I_t is the number of robots installed within a year, and δ_t is the depreciation rate in period t. Since the stock of robots is valued at the end of a year, it is not appropriate to use the number of installations in t-1 as it is the case for investment in the capital accumulation equation of a standard neoclassical growth model. Table 4a shows summary statistics for the implicit depreciation rate of total robot stocks by geographical class. At survey item level, the mean depreciation rate between 1993 and 2019 is equal to 4% per year. The global robot stock has a mean implicit depreciation rate of about 7% per year.

Table 4a: Implicit depreciation rate by geographical class

Geographical class	Obs	Mean	Std. Dev.	Min	Max
Survey item	1454	0.040	0.079	0	1
Country group	139	0.024	0.032	0	0.239
Region	188	0.056	0.075	0	0.630
Continent	98	0.054	0.029	0	0.133
World	26	0.069	0.013	0.046	0.098

Implicit depreciation rate of total robot stocks between 1993 and 2019 – Summary statistics by geographical class. Japan, Russia, and Other Asia are removed from the survey item level due to data inconsistencies.
Source: Own calculations based on IFR data.

To also compute implicit depreciation rates at industry- and application-level, we impute such disaggregated data for countries and years where only aggregate data are available (i.e. all robots are reported as "Unspecified") by distributing robots to the respective industries based on country-specific average industry shares in the years where disaggregated data are non-missing. Simultaneously, for all countries and years with disaggregated data, unspecified robots are also distributed by adding them to the data reported under the individual industries based on the same country-specific average industry shares. After imputation, robot stocks are reconstructed according to the IFR methodology assuming a service life of 12 years. Thus, by construction at least 12 years of data must be available before any depreciation takes place.

This explains why implicit depreciation rates at industry- and application-level are lower than the mean depreciation rate of total robot stocks at survey item level, with values usually moving between 2% and 3% per year. While total robot stocks for countries with initial robot stocks in year 1993 larger than zero exhibit "historic" depreciations between 1993 and 2004 (i.e. cases where robot stocks grow by less than the number of robots newly installed), these "historic" depreciations cannot be preserved for imputed industry- and application-level data by construction. Table 4b shows summary statistics for implicit depreciation rates by IFR industry classes that add up to aggregate (roughly two-digit level). Table 4c shows summary statistics for implicit depreciation rates by main IFR application classes.

Table 4b: Implicit depreciation rates by industry

IFR code	Industry	Obs	Mean	Std. Dev.	Min	Max
10-12	Food and beverages	1173	0.021	0.043	0	0.571
13-15	Textiles	591	0.028	0.075	0	0.875
16	Wood and furniture	823	0.028	0.069	0	1
17-18	Paper	712	0.023	0.055	0	0.500
19-22	Plastic and chemical products	1309	0.027	0.061	0	0.852
23	Glass/ceramics/stone/mineral products	1003	0.027	0.085	0	1
24-28	Metal	1255	0.021	0.037	0	0.500
26-27	Electrical/electronics	1119	0.023	0.055	0	1
29	Automotive	1212	0.024	0.064	0	1
30	Other vehicles	984	0.021	0.054	0	0.571
91	All other manufacturing branches	1137	0.020	0.056	0	0.750
A-B	Agriculture/forestry/fishing	553	0.021	0.068	0	1
C	Mining and quarrying	348	0.021	0.083	0	1
E	Electricity/gas/water supply	314	0.018	0.095	0	1
F	Construction	856	0.023	0.073	0	1
P	Education/research/development	1057	0.025	0.053	0	1
90	All other non-manufacturing branches	626	0.009	0.029	0	0.235

Summary statistics for implicit depreciation rates of robot stocks by industry at survey-item level between 1993 and 2019. Japan, Russia, and Other Asia are removed from the survey item level due to data inconsistencies. **Source:** Own calculations based on IFR data.

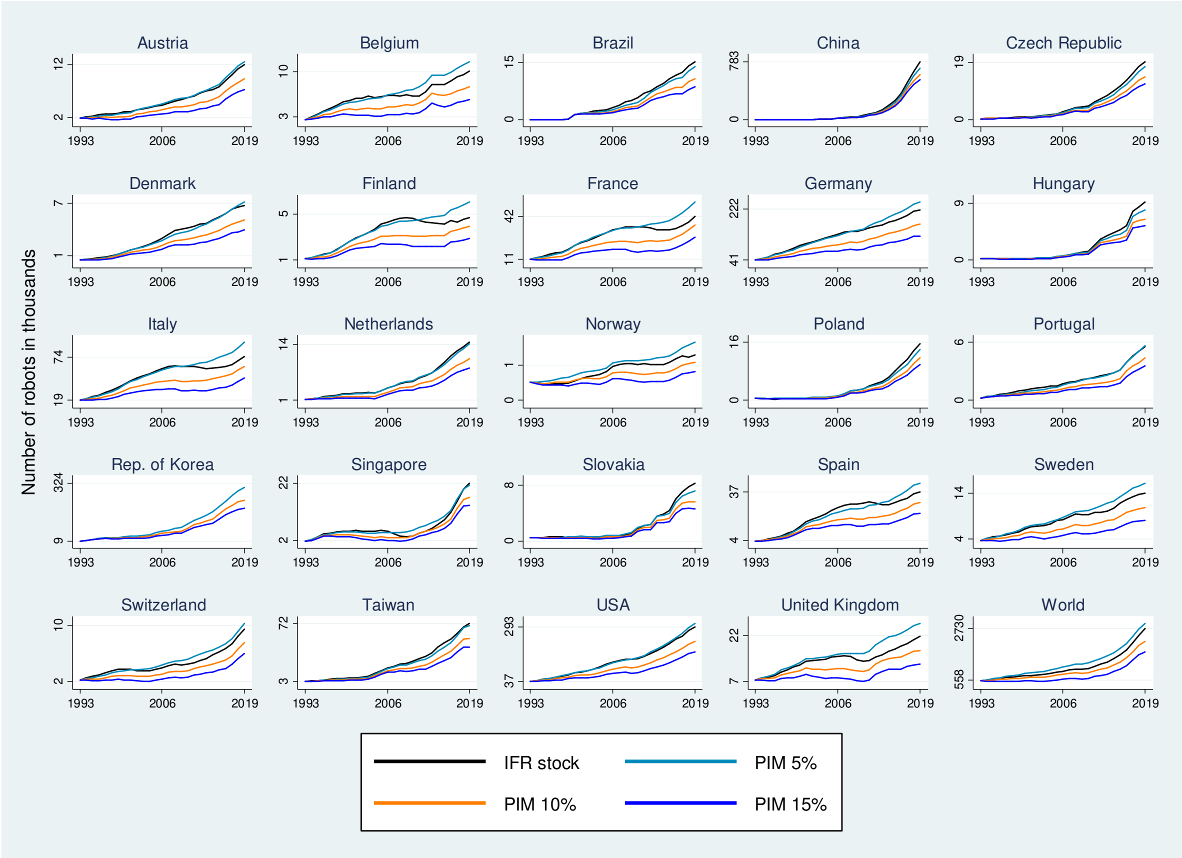
Table 4c: Implicit depreciation rates by application

IFR code	Application	Obs	Mean	Std. Dev.	Min	Max
110	Handling operations / Machine Tending	1409	0.024	0.067	0	1
160	Welding and soldering	1284	0.027	0.063	0	1
170	Dispensing	1107	0.025	0.059	0	1
190	Processing	1071	0.024	0.055	0	1
200	Assembling and disassembling	1069	0.021	0.046	0	0.714
900	Others	1105	0.019	0.056	0	1

Summary statistics for implicit depreciation rates of robot stocks by application at survey-item level between 1993 and 2019. Japan, Russia, and Other Asia are removed from the survey item level due to data inconsistencies. **Source:** Own calculations based on IFR data.

To obtain a robot stock that is in line with capital accumulation of a standard neoclassical growth model, Graetz/Michaels (2018) applied the perpetual inventory method (PIM) with a constant depreciation rate from one period to the next. Thereby, the initial robot stock indicated in the IFR dataset is taken as a given and installations in the subsequent years are used to construct robot stocks according to equation (1), however with a constant depreciation rate of either 5%, 10%, or 15%. Figure 6a plots the IFR robot stocks and the different PIM robot stocks over time for 24 selected countries and the global robot stock. As can be expected from the mean of the implicit depreciation rate shown in Table 4a, robot stocks constructed using PIM with a depreciation rate of 5% most closely match the evolution of the respective IFR robot stocks. Figures 6b and 6c plot the evolution of imputed robot stocks, summed over survey items, by IFR industry and application classes respectively, either constructed according to IFR methodology or employing PIM. Again, robot stocks obtained from PIM with a depreciation rate of 5% most closely track the respective IFR stocks. The most important robot-adopting industry is IFR class 29 (“Automotive”), followed by 26-27 (“Electrical/electronics”), and 24-28 (“Metal”). Largest part of the operational stock of industrial robots is involved in “Handling operations/ machine tending” (application class 110), followed by “Welding and soldering” (application class 160), and “Assembling and disassembling” (application class 200).

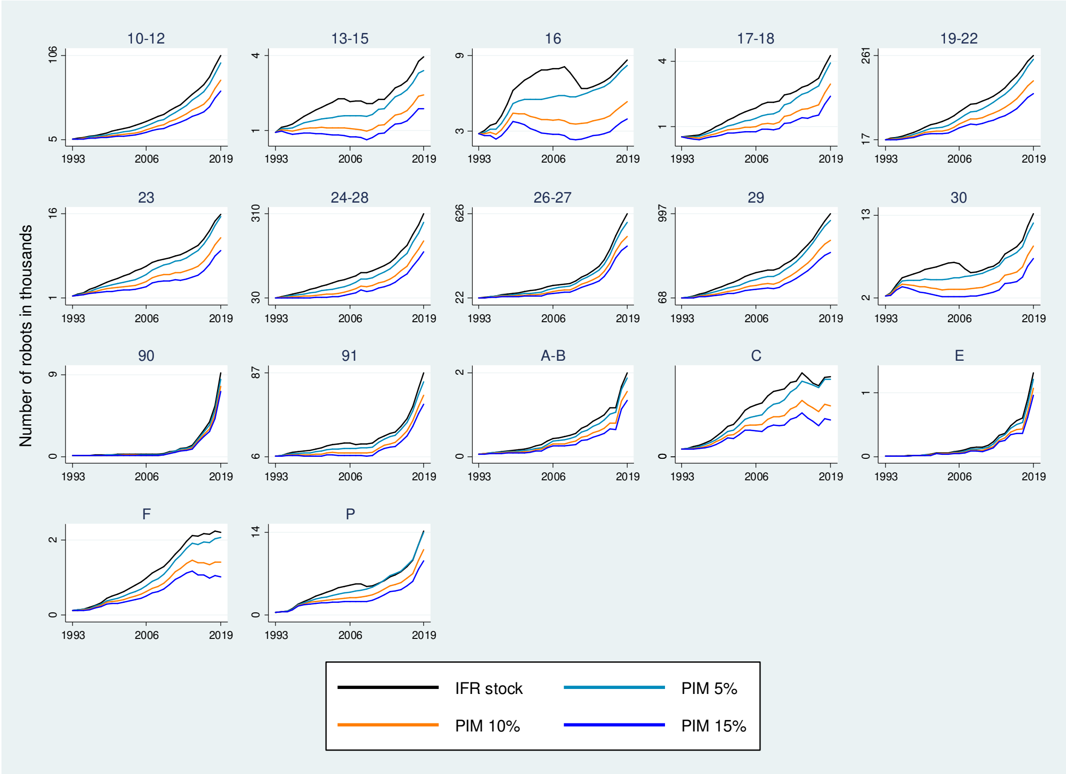
Figure 6a: Evolution of total robot stocks over time according to IFR method and to PIM



The perpetual inventory method (PIM) is applied with three different depreciation rates: 5%, 10%, 15%. Own calculations based on IFR data. Since data for the US is equal to North American (NAM) data until 2011 (i.e. includes Canada and Mexico), the US stock is adjusted before 2011 according to the average US share in robot installations between 2011 and 2013 among NAM countries. After 2011, the US stock was continued according to IFR methodology to obtain the IFR stock for this country.

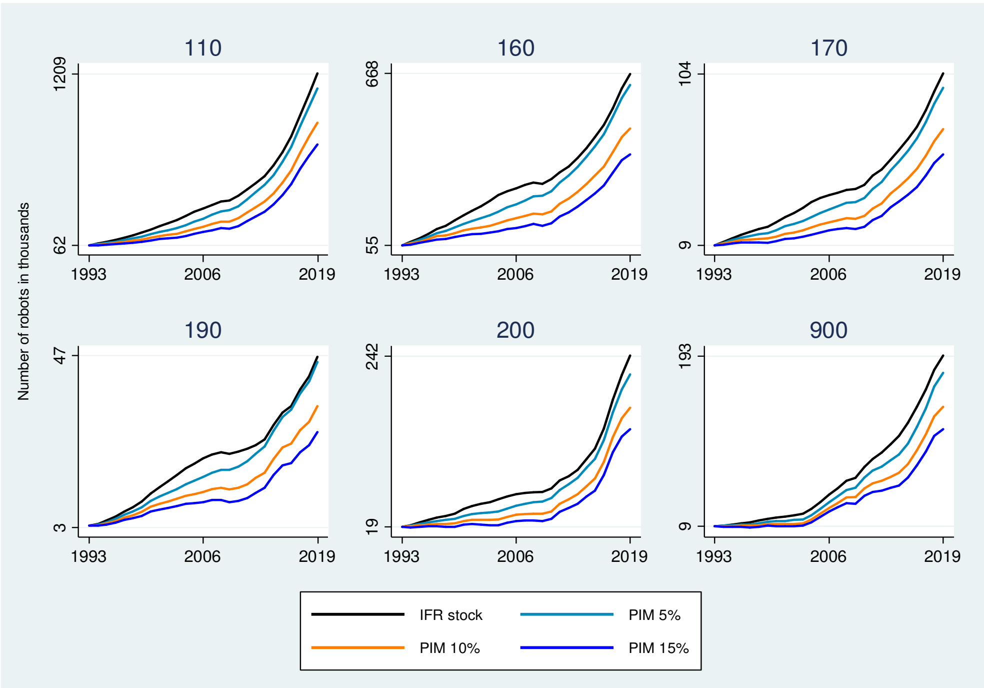
<u>Source:</u> IFR data and own calculations.

Figure 6b: Evolution of aggregated robot stocks for IFR industry classes over time according to IFR method and to PIM



The perpetual inventory method (PIM) is applied with three different depreciation rates: 5%, 10%, 15%. Own calculations based on IFR data. Imputed industry robot stocks are aggregated over survey items excluding Japan, Russia, and Other Asia. **Source:** IFR data and own calculations.

Figure 6c: Evolution of aggregated robot stocks for main IFR application classes over time according to IFR method and to PIM



The perpetual inventory method (PIM) is applied with three different depreciation rates: 5%, 10%, 15%. Own calculations based on IFR data. Imputed industry robot stocks are aggregated over survey items excluding Japan, Russia, and Other Asia. **Source:** IFR data and own calculations.

Third, the IFR's construction of the operational stock of robots does not involve any quality adjustment due to embodied technological change. Thus, a robot installed for example in 2019 is assumed to have the same quality as a robot installed in 1993, as both robots are simply counted as one unit installed in the respective year, thereby ignoring the technological progress between these two points in time. For instance, a single robot installed in 2019 might be able to perform production tasks that required a number of different robots in previous times, i.e. technological progress led to a more complex, integrated robot with higher capacity, which however is still registered as one unit (Kromann et al. 2020). This also implies that the number of robots reported by the IFR underestimates the actual (quality-adjusted) stock of robots in countries and industries in which robot investments have increased in recent years and overestimate the stock in countries and industries where investments in recent years have been relatively low. Assuming that technological progress improves the quality of robots over time, a quality-adjusted measure of the number of robots would ceteris paribus grow faster than the number of units presented by the IFR (Borjas and Freeman 2019). Moreover, although the IFR collects data for different robot types, the varying quality attributes and complexity of these robot types are not further quantified – all robots installed are simply counted as one additional unit.

Fourth, as the IFR dataset counts industrial robots that are sold on the open market, it does not cover robots that are used within the producing firm. A popular example of criticism in this respect is online retailer Amazon's purchase of warehouse robots provider Kiva Systems in 2012 (Estolatan et al. 2018). Since then, this market-leading company in the field of warehouse automation has been called "Amazon Robotics" and is solely intended for Amazon's exclusive use to improve the productivity of its own warehouse processes (Leigh et al. 2020). Because Amazon does not sell these robots, they are also not included in WRIR. And their number is not small: at the end of year 2019, more than 200,000 mobile robots were working inside Amazon's warehouse network (Del Rey 2019). This example, however, is misplaced, as these robots would not occur in the WRIR dataset anyway because the IFR classifies autonomous mobile robots as service robots, not as industrial robots. As mentioned in section 2.3, the IFR collects service robot data in a separate publication, the annual World Robotics Service Robots Report.

Fifth, data for some survey items suffer from inconsistencies that cannot be explained by the compliance mechanisms. There is a break in the time series for Japanese data between 2000 and 2001 due to international harmonization of definitions and coverage of statistics. Prior to year 2001, Japanese data included dedicated industrial robots on top of multipurpose industrial robots and thus are overstated. Another peculiarity of the Japanese data refers to robot stocks: they are estimated by JARA and deviate from the IFR methodology because they are approximately defined as the sum of installations over ten years. Moreover, Japanese data reported under the industry "Automotive parts" (IFR class 293) are not further disaggregated into the specific types of automotive parts. Data from the former USSR contained in the time series for Russia also underwent major reclassifications. In consequence, robot figures reported for Japan and Russia are not consistent over time and difficult to include in econometric analyses. Since 2001 Japanese robot installations should only comprise multipurpose industrial robots, while Japanese robot stocks continue to include previously counted dedicated robots until they are fully depreciated. At least since 2010, the international comparability of Japanese data should have improved.
Industry-level data for Austria exhibit an inconsistency in 2003, as robot stocks are always equal to zero even if installations in the same year are larger than zero. Similarly, robot stocks at industry level for Taiwan are always equal to zero between 1993 and 1999 even if

installations are larger than zero. The same holds true for Taiwanese application-level data. The Republic of Korea likewise exhibits stocks at industry level equal to zero between 2001 and 2003, even though installations in the respective industries are larger than zero in 2001 and 2003. Between 1993 and 1998, robot stocks at application-level for Australia are always equal to zero as well, even if installations are strictly positive. Only after correcting these issues, data for Austria, Australia, the Republic of Korea, and Taiwan can be included in econometric analyses. Furthermore, data collected under the survey item "Other Asia" (OA) exhibit an aggregate robot stock that increases by much more than the number of robots installed between 1999 and 2000. We decided to drop Japan, Russia, and Other Asia from all our calculations at survey item level, whereas Austria, Australia, the Republic of Korea, and Taiwan are included.

Sixth, data for the USA and Australia are partly impaired through geographical aggregation. Data for the USA includes Mexico and Canada before 2011 and is therefore equal to data for the region North America (NAM) up to this year. Similarly, Australian data include New Zealand before year 2005 and are thus equal to data for country group AUNZ up to this year. This data issue can be solved by adjusting data for the USA, Canada, and Mexico as well as Australia and New Zealand according to their country shares in the available geographically disaggregated data. This approach relies on the assumption that the country shares did not significantly change over time.

Seventh, data availability at industry level is limited for most countries, especially in the initial years of the dataset. Disaggregated industry data are available for only eight countries over the full period of the dataset: Germany, Spain, France, Italy, United Kingdom, Sweden, Finland, and Norway. Similarly, availability of application-level data is limited: data disaggregated by the six broad application classes over the full period of the dataset is available for ten countries – the same eight countries as for industry-level data plus Austria and Denmark.

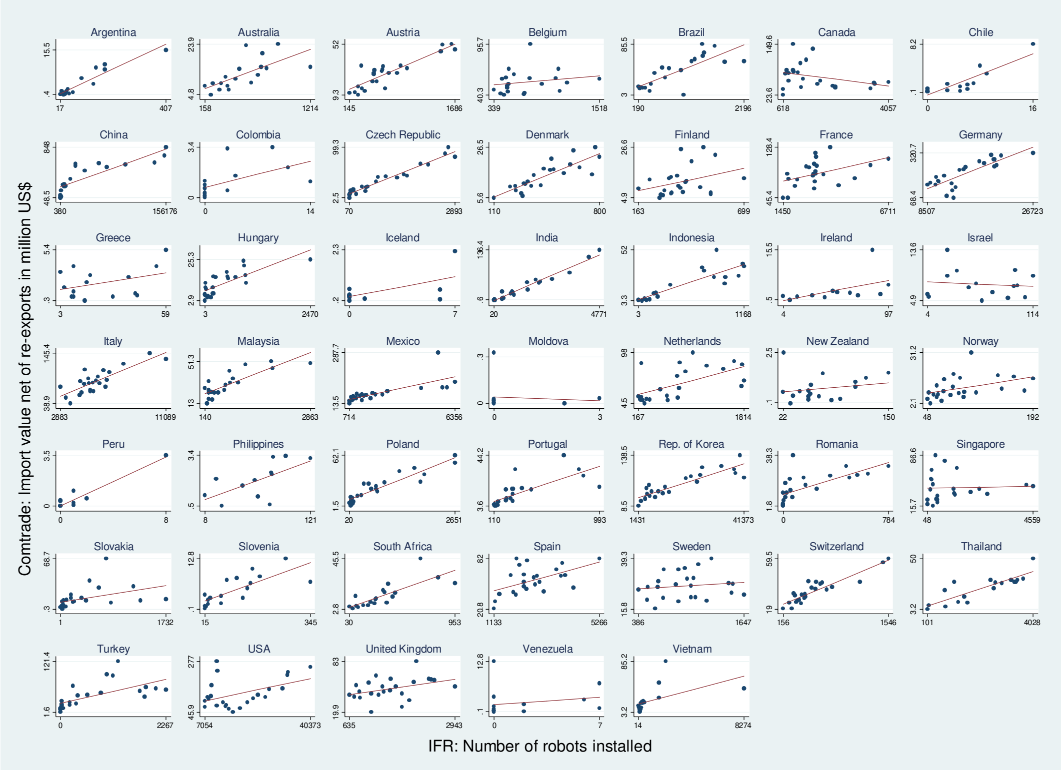
3.7 Alternative data sources

An alternative data source for the usage of industrial robots is the UN Comtrade database, where industrial robots are counted under HS6 commodity code 847950. Time series that track international trade of industrial robots start in 1996. Acemoglu/Restrepo (2021) use robot imports from Comtrade to confirm their results on the effect of an aging demography on robot adoption obtained from IFR data. They further use Comtrade data on robot exports to scrutinize the effect of aging demographics on the domestic development of industrial robots. Blanas et al. (2019) construct a measure of a country's exposure to industrial robots from Comtrade data to study employment effects of industrial robots. Thus, Comtrade data on trade of industrial robots might be an attractive alternative or complementary data source for future research in the field of robotics. In contrast to IFR data, these data, however, are not disaggregated by customer industry or field of application. Comtrade distinguishes four types of trade flows: imports and exports as well as re-imports and re-exports. Units of measurement used to quantify these trade flows are trade values in current US-Dollars, net weight in kilograms, and varying quantity units. The most reliable data from Comtrade appear to be monetary import values, as there are few missing. Quantity units reported in the Comtrade database suffer from a significant number of missing values even if monetary trade values are non-missing. Moreover, quantities in the Comtrade database exhibit varying units of measurement. Most frequently, the number of items is reported, but some quantities (even within the same country) are measured by weight in kilograms or volumes in liters, or no quantity is reported at all.

We analyze the correlation between robot installations according to the IFR dataset and Comtrade import data on industrial robots. To obtain comparable indicators for domestic robot installations from Comtrade, we compute import values and import quantities net of re-exports. Import values are converted to constant US Dollars with base year 1996 using data on the US consumer price index from the World Bank (2021). Comtrade quantity data are restricted to data points measuring the number of items. For both Comtrade import values and quantities, we only keep country-years with positive imports net of re-exports to compute Pearson correlation coefficients with IFR installations. For pooled cross-country times series data, the correlation coefficient between IFR installations and Comtrade import values in constant US Dollars (1996 = 100) is equal to roughly 0.81. The correlation between IFR installations and Comtrade import quantities measured as the number of items imported net of re-exports is much weaker, with a value of only 0.29.

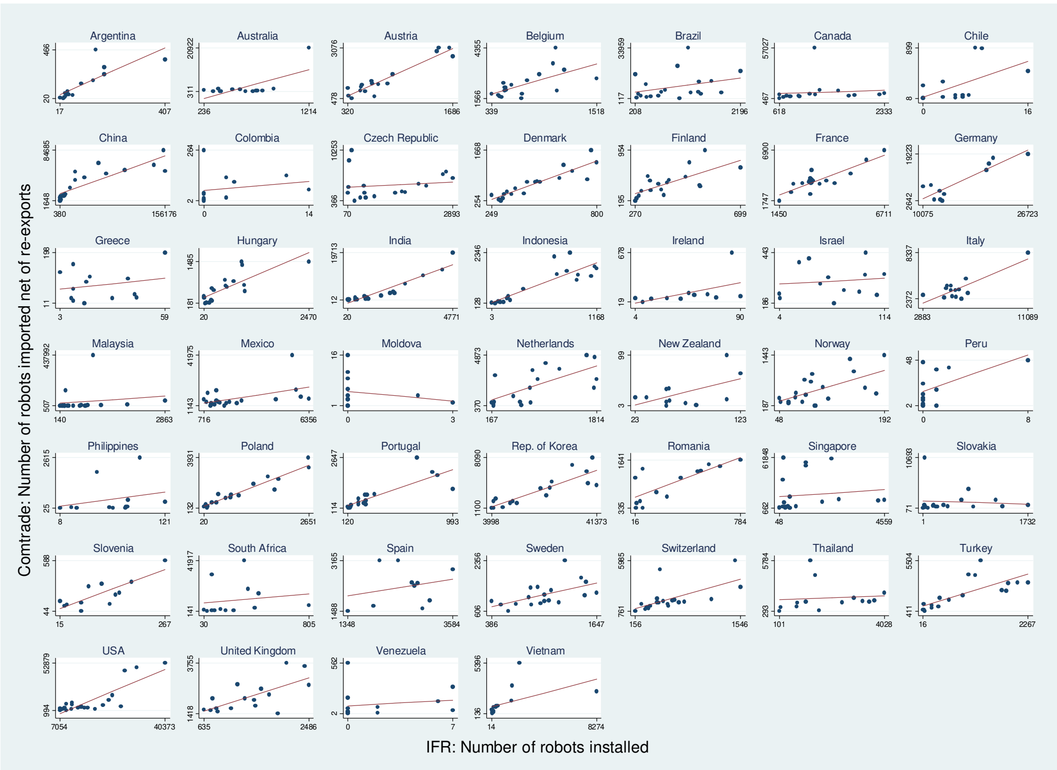
Considering the panel data structure, Tables A5a and A5b in the appendix show the correlation between IFR installations and Comtrade data separately within each country, supplemented by 95% confidence intervals. Figures 7a and 7b visualize the relationship between IFR and Comtrade data using scatter plots with a fitted line. The highest correlation coefficients between IFR installations and Comtrade import values among countries with at least 20 observations are observed for India (0.98), the Czech Republic (0.97), Poland (0.93), and Switzerland (0.91). Except for Canada, Moldova, and Israel, all correlation coefficients are strictly positive. Between IFR installations and Comtrade import quantities, the highest correlations are observed for Poland (0.96), Austria (0.95), India (0.94), and Denmark (0.91). Except for Moldova and Slovakia, again all correlation coefficients are larger than zero. Due to missing values for import quantities in the Comtrade database, we lose observations for almost all countries. In total the number of observations is reduced by 200, compared to the correlation analysis using monetary import values.

Figure 7a: Scatter plot of IFR installations and Comtrade import values



Country-years with negative import values net of re-exports are excluded. Country-years with IFR installations equal to zero only for compliance reasons are removed as well. Only countries with at least ten observations are included. **Source:** Own calculations based on IFR and Comtrade data.

Figure 7b: Scatter plot of IFR installations and Comtrade import quantities



Country-years with negative import quantities net of re-exports are excluded. Country-years with IFR installations equal to zero only for compliance reasons are removed as well. Only countries with at least ten observations are included. **Source:** Own calculations based on IFR and Comtrade data.

Table A6 in the appendix takes a closer look at the similarity of robot quantities according to IFR and Comtrade. Optimally, Comtrade data reporting the annual number of robots imported net of re-exports should be close to robot installations in the same year, according to the IFR dataset. Deviations should mainly arise for countries which use a significant number of robots that were produced domestically. However, robot quantities reported in the two datasets differ substantially. The most extreme difference is observed for Malaysia, with Comtrade net imports being on average almost 50 times as high as IFR installations: while IFR robot installations between 1996 and 2019 are roughly 684 per year on average, Comtrade net imports amount to roughly 33,676 robots per year on average. The highest difference is also observed for Malaysia: in year 2015, 436,994 units more are reported in Comtrade compared to IFR, a deviation that is hard to explain and almost twice as high as global robot installations according to IFR data. In general, Comtrade data exhibit higher numbers compared to IFR data. On average across all countries, annual robot installations equal 3,028 according to IFR data, while Comtrade net imports suggest a number of 4,407. This is equivalent to a mean difference of 1379.1, which is statistically significant at the 5% level.[15] The mean difference is defined as Comtrade net imports minus IFR installations. Out of 46 countries analyzed, only eight have a negative mean difference. Four of these eight countries exhibit negative differences for all observed data points: Germany, Italy, New Zealand, and the Republic of Korea. For Germany (mean difference = -6,492.5), Italy (mean difference = -1,941.2), and the Rep. of Korea (mean difference = -16,126.8) this outcome is not a big surprise as these countries are important producers of industrial robots (Estolatan et al. 2018), and robots domestically produced and installed do not show up in the Comtrade database. According to IFR data, the Rep. of Korea installed 19,517 robots per year on average and has the second highest robot density (measured as the number of industrial robots per 10,000 persons employed) in manufacturing worldwide (IFR 2020, 55), while Comtrade net imports only indicate an average number of 3,391. The finding is more surprising for New Zealand, as it does not host any of the major producers of industrial robots.

For other important markets of industrial robots, the deviations between IFR and Comtrade figures are also substantial. For Singapore, the country with the most automated manufacturing industry in the world (IFR 2020, 55), IFR data indicate average annual installations of 1,081, whereas Comtrade net imports suggest average annual installations as high as 16,581, which corresponds to a mean difference of 15,500. China has a mean difference of -10,300 and exhibits the highest negative difference among all paired data points, with 106,637 units less reported in Comtrade compared to IFR in year 2017. From 1998 (initial reporting year for China in the IFR dataset) to 2015, Comtrade quantities are always larger than IFR quantities. That relation is reversed from 2015 onwards with constantly highly negative differences, possibly indicating China's growing ability and importance in the domestic production of industrial robots as documented in Cheng et al. (2019). The inverse pattern is found for the USA with a mean difference of -5,238: until 2014, all observed differences are clearly negative but become highly positive afterwards.[16]

[15] Ignoring the panel data structure, a simple paired t-test delivers a t-statistic of $t(754) = 1.995$, with $\Pr(T < t) = 0.977$, $\Pr(|T| > |t|) = 0.046$, and $\Pr(T > t) = 0.023$. Considering the panel data structure, we can fit a fixed-effects model with the paired difference as outcome variable and a constant term only (i.e. $y - x = a$). Using Stata command "xtreg, fe", the estimated intercept of 1379.1 represents the average value of the fixed effects, with $t = 2.08$ and $p = 0.038$. The F-test that all country-specific fixed effects are equal to zero generates a F-statistic $F(45, 709) = 2.47$, suggesting that estimating the fixed effects model is more appropriate than conducting a paired t-test on pooled data.

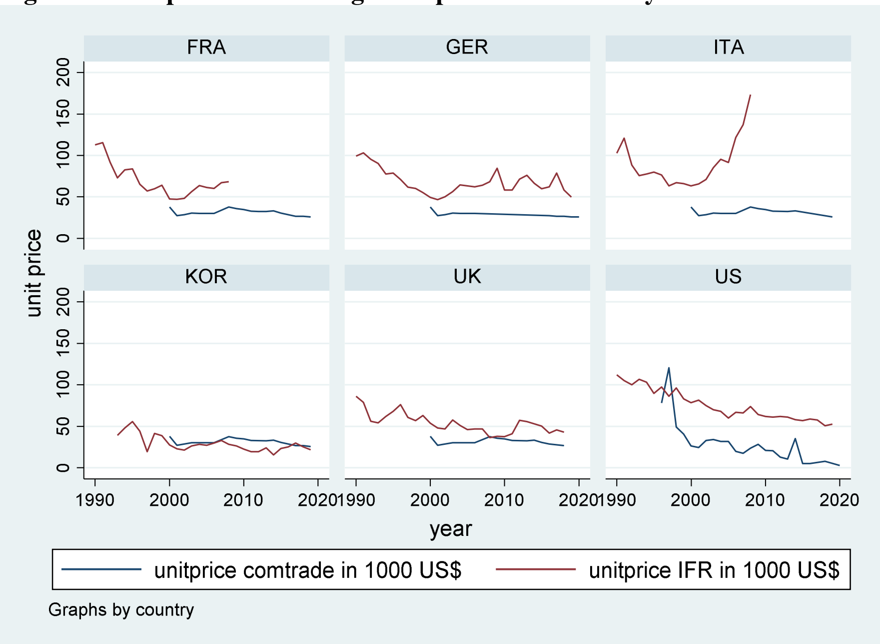
[16] After 2014, only the years 2015, 2016 and 2018 are covered for the US due to non-availability of quantity data in 2017 and 2019 in the Comtrade database.

Summing up, the high correlation between IFR installations and monetary Comtrade import values make it attractive to cross-check analytical results obtained from either dataset by means of robustness checks. However, one needs to keep in mind that robots domestically produced and installed do not show up in Comtrade data, leading to downward-biased installation values based on Comtrade for important robot producing countries. More caution is needed when complementing IFR installations with Comtrade import quantities measured as "Number of items" since the correlation between both data sources is much weaker compared to monetary Comtrade import values, and the quantities reported in both datasets differ substantially. One major reason for the significant differences in reported quantities is likely a diverging definition of industrial robots between the two datasets. The scope of that definition is likely broader in the Comtrade database because it does not follow (or even refine) the ISO definition as closely as the IFR does.

Using import market values and the quantity of net imports given by Comtrade one can easily calculate average unit prices, which are then available for more countries than the IFR-based prices. Comtrade-based unit prices are available from 1996 onwards; however, data coverage is incomplete due to many missing import quantities. As a result, unit prices are not available throughout the sample. Moreover, the Comtrade average unit prices are import prices only. These prices cannot reflect the entire market for robots as domestically produced and installed robots do not appear in this database.

Figure 8 compares the average unit prices of the IFR database with Comtrade. The average unit price calculated through the IFR database differs in countries with a smaller share of imported robots (e.g. Germany, France, Italy) substantially. One would expect countries with a high share of imported robots to display a similar price in Comtrade- as in IFR-based calculations. Yet, the US, a massive importer of robots, also displays a considerable difference in unit prices, while the Rep. of Korea does fit the picture and the UK price difference is rather small. Here it seems that the Comtrade unit price represents a good alternative for the IFR unit prices, especially because the IFR no longer reports UK prices after 2018. Strikingly, the unit prices based on IFR data are higher except for in Korea. One can only speculate about the reasons for this. Bearing in mind that the Comtrade unit price is also an average price with no information on size or quality of robots, it could well be that on average, smaller and, therefore, lower-priced robots have been imported into Europe and the US. Moreover, the price development based on Comtrade data is much smoother than the IFR-based prices, which display more volatility. Only for the US one can observe a similar trend in the import-based price development as in the IFR-based prices. For Italy, the IFR prices show an increase from 2000 onwards whereas Comtrade prices report a strikingly smooth price behavior (IFR prices are not available from 2008 onwards). Comtrade as an alternative data source for unit prices on robots can therefore complement the IFR data especially for those countries where price information has ceased to be reported by the IFR. But it must be treated cautiously, as it reflects import prices only. It also suffers from the same shortcomings as the IFR-based unit prices regarding quality and size.

Figure 8: Comparison of average unit prices for robots by IFR and Comtrade



Source: Own calculations based on IFR and Comtrade data.

While IFR and Comtrade provide standardized and internationally comparable data for many countries, robotization within individual countries has also been analyzed with data from firm-level surveys or customs data. An early example for this alternative empirical strategy is the investigation by Jäger et al. (2015). It uses firm data from the European Manufacturing Survey (EMS) 2009 to study the impact of robots on employment and productivity. EMS was carried out for 10 European countries and covers data from around 3,700 companies of European manufacturing; the study concentrates on a sub-sample of 7 countries (Germany, Austria, France, Spain, Denmark, the Netherlands, and Switzerland) with more than 3,200 manufacturing companies with at least 20 employees. With regard to industrial robots, EMS provides the actual number of firms using robots as well as the intensity of their robot usage related to the economically rational maximum in the own firm. By using this variable, EMS data differs from IFR data in the WRIR. While the latter refers to the installed base within a certain country, the EMS variable is targeted towards the broader economic diffusion of robots in terms of using firms.

To get a better understanding of the "robotics ecosystem" in a sub-national perspective Leigh/Kraft (2018) performed a survey of the US industrial robotics industry in 2015. The industry consisting of both robot suppliers and service providers (called integrators) shows a very uneven geographical clustering. While the authors can show that robotics-related employment is geographically correlated with the manufacturing sector, the actual use of robots cannot be determined from their data. Neither can causal links between robots and employment, wages or productivity be confirmed.

Some more recent examples of the firm-level perspective that can be found in the studies by Cheng et al. (2019) for China, by Zator (2019) and Deng et al. (2020) for Germany, by Humlum (2019) for Denmark, by Koch et al. (2021) for Spain and by Barth et al. (2020) for Norway show a high degree of complementarity to the IFR data base. Cheng et al. (2019) investigate firms' robot adoption behaviors with data from the China Employer-Employee Survey (CEES). This dataset is considered representative of the entire Chinese manufacturing sector. Data for 2015 cover 1,115 firms in the Chinese provinces of Guangdong and Hubei.

Interestingly, the share of robot units across industries in the WRIR dataset versus the probability of using robots by industries in the CEES data have a correlation coefficient of 0.97. Similar results are reported by Deng et al. (2020) who analyze firm-level data for Germany during the period 2014-2018 from the IAB Establishment Panel, an annual survey of nearly 16,000 plants, sampled from around 2 million German employers. Comparing data from IFR and IAB for the robot density, defined as the number of robots per 1,000 employees, in 2018 they find a correlation coefficient across all industries of 0.84. If only manufacturing industries are considered, the correlation coefficient rises to a value of 0.96 (Deng et al. 2020, 25, Figure A1.).[17] However, the authors also show that the use of robots is not yet very diffused and the distribution of robots is highly skewed among robot users: in 2018, only 1.55% of German plants are robot users (8.22% in the manufacturing sector) and more than half of the total robot stock is owned by the top 5% of robot using plants, just as the robot density (robots per 1,000 employees) is significantly higher among the top users. Moreover, robot users are significantly larger in terms of employment, have higher labor productivity, pay higher wages, make more investments, and are more likely to export and adopt the most updated technology than non-users.

In a Danish case study, Humlum (2019) compares IFR data with two micro data to measure robot adoption at firm level, one being a firm survey conducted by Statistics Denmark in 2018 called VITA and the other consisting of data for the import of robots as measured in the Danish Foreign Trade Statistics Register (UDHI) in the period 1993-2015. In cross-sectional comparisons all three data sets give a similar figure, and in a time series perspective data from UDHI follow very well the development described by the IFR data.[18] Koch et al. (2021) work with a panel dataset of Spanish manufacturing firms from Encuesta Sobre Estrategias Empresariales (ESEE) for the period 1990-2016. The paper uses explicit information on robot use in the production process of individual firms and is able to differentiate between "robot adopting" and "non-adopting" firms. They identify positive effects of robots on employment and output for robot-adopting firms but negative impacts for non-adopters. Interestingly, the results derived with ESEE firm-level data are very similar, when using the stock of robots within industries from the IFR data. This is remarkable because the IFR measure captures the intensive margin of robot diffusion, regardless of how many firms use this technology, whereas the ESEE measure reflects the share of firms using robots and thus the extensive margin of robot use. Barth et al. (2020) study the effects of automation on wages in Norway for the period 1999-2016 working with firm-level data on robot adoption that come from the Norwegian Trade Statistics Register. They find on average a positive effect of robots on wages with a higher benefit for better educated workers leading to an increase in the skill-premium. Comparing their dataset with IFR statistics on the number of imported robots in Norway it becomes evident that both show equal trends in the aggregate but on a different level, pointing to the different way how they are generated. As the authors conclude: "The data from the IFR on newly installed robots are potentially lower as the robotics federation obtains most of its information from a survey of industry experts. The survey data is likely to

[17] Adachi et al. (2020) compare data on robot aboption from the Japan Robot Association (JARA) and from Japan's Census of Manufacture (CoM) for the period 1978-2017. They find a high correlation in the aggregate value and point out that since 1993 JARA data, being its main source, are almost identical with the IFR country statistics for industrial robots.

[18] Fan et al. (2020) investigate the impact of higher labor costs on the speed of robot adoption among Chinese firms over the period 2008-2012 on the basis of data from the Chinese General Administration of Customs (CGAS). A comparison of customs data with IFR statistics shows a parallel trend in the aggregate with a constantly lower level of robot installations for the IFR survey data.

include a less than 100% response rate and therefore underestimate the number of yearly new robots installed in Norway." (Barth et al. 2020, 15).[19]

4. Data applications and findings

4.1 Overview

The study by Gorle/Clive (2013) is an example for the early use of IFR data on industrial robots in business research documenting the rise of automated production in selected countries, including China and Korea. High-level academic research based on the IFR dataset on industrial robots is a more recent phenomenon. It benefited enormously from two research papers that have set important standards for further studies investigating more aspects of robot exposure and its impact on economic and social life. The mostly cited paper by far is the study by Acemoglu/Restrepo (2020) on the impact of robots on the US labor market in a very decentralized perspective. It is based on a working paper version (Acemoglu/Restrepo 2017) that first became available in 2017. Graetz/Michaels (2018) contributed the second very influential paper with a major focus on the productivity effects of industrial robots.

In the following we review this very recent strand of robot research literature in four different, but closely related areas: (i) robot adoption and industrial organization, (ii) productivity and growth, (iii) employment and wages, (iv) demographics, health and politics. Table A7 in the appendix provides an overview of research papers whose results mainly rely on the IFR dataset. There, we document the main specifics of the studies and point out how the authors handled some of the data issues.

4.2 Patterns of robot adoption and industrial organization

The impact of robots on industrial organization depends on where and in what way robots are adopted by firms and how this adoption changes the organizational structure of production within the particular industry and within global value chains (GVC). These aspects are treated by OECD (2019), Nuccio et al. (2020), López-Sánchez et al. (2020), Jungmittag (2020), Cséfalvay (2020), Cséfalvay/Gkotsis (2020), De Backer et al. (2018), Faber (2020), Carbonero et al. (2018), Compagnucci et al. (2019), Krenz et al. (2018), Fernández-Marcías et al. (2020), Jung/Lim (2020), Stiebale et al. (2020), and Gentili et al. (2020).

OECD (2019, 9 f.) gives a first overview over the worldwide patterns of robotization since 1993. Three subperiods are distinguished: 1993-2000, 2001-07 and 2008-14. The average growth during the first subperiod was about 78%. Adoption of industrial robots was still in an early stage in 1993, which explains the strong growth in operational stocks. Growth was even stronger in the second subperiod with an average of above 80%. It continued after the financial crises but at a much slower pace of 38% on average. Two sectors stand out by far in the adoption of robots: "Transport equipment" (including automotive industry) with a share of almost 45% in the total stock of robots in 2014 and “Electronic, electrical and optical equipment” with almost 30% due to the large production volumes and the high degree of standardization in mass production. While Spain (with its growing automotive industry) had a very fast increase during the first subperiod, some Central European countries and Germany grew with a three-digit rate during the second subperiod. The last subperiod saw extremely different developments: while Singapore and Korea showed three-digit growth rates of robot

[19] Further firm-level analyses on robot adoption that do not make use of the IFR data can be found in Acemoglu et al. (2020) and Bonfiglioli et al. (2020) for France, Bessen et al. (2020) for the Netherlands, Dixon et al. (2021) for Canada, and Fan et al. (2021) for China.

adoption, many other OECD countries even had negative rates. An extreme case is Russia being the only country where after the fall of the Soviet Union the number of operational robots decreased over all three subperiods. Looking at the robot density, measured by the number of robots per thousand employees, OECD (2019, 129) summarizes: "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. ... Norway is the country with the lowest density, both in 2009 and 2014."

López-Sánchez et al. (2020) investigate the global pattern of robot adoption, defined as the change in the operational stock of robots per 10,000 people of the active population in the period 1993-2016. Looking at a sample of 71 countries - with North America covering Canada, Mexico, and the US - and applying a time-series clustering algorithm with an adaptive dissimilarity index they are able to identify similar and dissimilar robotization trajectories. These can be clustered in 4 groups and one outlier. Cluster 1 consists of 40 countries including the Russian Federation, Argentina or Pakistan that started late with robotization and had a rather low growth or even an erratic development in robot intensity. Cluster 4 brings together the "leaders" of robotization: Germany, Singapore and Korea that have even increasing growth in robot adoption from 2010 onwards. Cluster 3 contains 6 other industrialized countries like France, Italy or Sweden that have grown less than the "leaders" and showed a relative stagnation in robot adoption since 2007. In Cluster 2 one finds 21 countries including North America, China and the UK that show a lower rate of robotization over the whole period than Cluster 3 but have accelerated in recent years. Japan is the outlier whose behavior is rather unique.

Nuccio et al. (2020) investigate the regional clustering of robots in the five largest European countries (France, Germany, Italy, Spain, and the UK). For the period 1993-2015, they compute the annual national stock of robots for 15 industries (using the PIM 10% approach) and distribute it to the 137 NUTS 2 regions according to the regional share in the national number of firms in the respective industries. They find a very uneven regional development with some pronounced clustering of robot adoption in traditional manufacturing areas. Southern Germany with its variety of integrated manufacturing industries, namely in car production, is the only region with advanced automation and dynamic growth of robot stocks. Northern Italy has accumulated a good robot stock, but shows a declining growth rate, while manufacturing French regions appear to lack stock and not to increase the existing levels. The English Midlands and Eastern Germany, the capital cities-regions and some regions in Spain, Italy, and Scotland started from a very low provision of robots but catch up with steady growth rates, while the other regions lag behind. A related study by Jungmittag (2020) looks at the patterns of convergence or divergence for the robot densities in 9 manufacturing industries of 24 EU countries for the period 1993-2015. The annual data from the IFR are used for the calculation of robot stocks with a PIM 5%, 10% and 15% approach, respectively. Testing for unconditional as well as for conditional convergence taking country-specific effects into account, the authors find completely different patterns for European manufacturing industries in the two sub-periods 1993-2005 and 2005-2015 that are divided by the large EU enlargement of May 1st, 2004. While in the first subperiod no convergence of robot densities could be identified, relatively fast conditional and unconditional convergence occurred in the second sub-period, mainly driven by the increased growth of robot densities in some Central and Eastern European countries. Cséfalvay (2020) looks also at the global as well as the intra-European convergence of robot densities during the period 1995-2013. Over the whole period Germany was able to keep its dominant position with a steady growth rate.

Until 2005 the deployment of robots appeared at large scale in the large industrial countries of Western Europe (Italy, France, Spain) while after the EU enlargement of 2004 it happened mainly in Eastern and Central Europe, where robots were rarely to be found at the beginning of the period. In addition, the robot deployment in Eastern and Central Europe is highly concentrated in the automotive sector while Western European countries show a more diversified sectoral pattern of automation in manufacturing. The author concludes that this "dependent robotization" concerns Eastern and Central Europa in two ways: first by a sectoral dependence from car manufacturing, with few spill-over effects to other industries, and second by a dependence from localization decisions of global car producing firms, both leading to a potentially high economic vulnerability.

One source of this vulnerability might be re-shoring activities by globally active firms. This phenomenon is studied in a theoretical and empirical perspective by Krenz et al. (2018), by Carbonero et al. (2018) with a special focus on developing countries, by De Backer et al. for developed and emerging economies, and in a case study for Mexico by Faber (2020). The theoretical model developed by Krenz et al. (2018) suggests that initially, when industrial robots are not very productive, firms facing low costs of distance save on the wage bill by offshoring production to low-wage countries. As the productivity of industrial robots increases, the incentive to re-shore increases, because firms with high productivity in automation produce more efficiently at home with robots than they do abroad. In a panel analysis for 43 countries (including all EU members) with 9 manufacturing industries over the years 2000-2014, using IFR data for the calculation of robot densities, evidence for a strong association between re-shoring and automation within countries as well as within sectors was found. Carbonero et al. (2018) who use IFR data for 41 countries and 14 sectors during 2005-2014 find significant evidence that the use of robots had induced certain industries in developed countries to reduce the amount of inputs produced in developing and emerging economies. Scrutinizing the transfer of productive resources in groups of multinational enterprises, De Backer et al. (2018) do not find any effects of robots on reshoring. However, they provide some evidence that growth in robot stocks is associated with reduced growth in offshoring for developed economies between 2010-2014, while no significant effect is found for emerging economies. They further find a positive relationship between robot investment and GVC upgrading as well as forward participation in GVCs for developed economies, but not (yet) for emerging countries. Faber's (2018) study confirms the re-shoring result of Krenz et al. (2018) and Carbonero et al. (2018) by investigating 1,805 regional labor markets in Mexico, defined according to a commuting zone approach in the spirit of Acemoglu/Restrepo (2020). Working with IFR data for 1993-2015 (where Mexico is treated as a part of North America until 2000 so that national data have to be extrapolated) he looks at the exposure of local employment to both domestic and foreign robots. He finds a robust and negative impact of automation in the US to Mexican exports and employment, in particular for the later time period 2000-2015. The strongest negative effects of such re-shoring activities occurred in manufacturing industries that were highly exposed to US robots (i.e. automotive, electronics, metal products and minerals) and in services. The most affected Mexican employees were low-educated machine operators and technicians in manufacturing as well as highly educated service workers in managerial and professional occupations. The results should be considered as a warning that ongoing automation in highly industrialized countries may induce a radical transformation in the patterns of globalization that have characterized the past three decades.

In a recent study Cséfalvay/Gkotsis (2020, 3f.) build a theoretical and analytical framework of the “robotization chain”, which applies the GVC concept to robotization but also points out differences to traditional GVCs. Their framework distinguishes between robot developers, robot manufacturers, and robot user manufacturers, as well as intermediary companies and institutions (e.g. “robot integrators” with expertise in installing and customizing robots) and in-house robotics development facilities of larger robot using firms. Using IFR, PATSTAT, and ORBIS data for the period 1995-2016, they point out the following patterns in a global and intra-European perspective. All parts of the "robotization chain” are characterized by strong geographical concentration. Five countries - Japan, Korea, Germany, the USA, and China - dominate the global robotization landscape, but none of them possesses an equally strong position across the whole chain. Japan and Korea are robustly engaged in every part of the robotization chain and thus the global leaders in the “robotization chain”. Germany is very strong in robot manufacturing (including patent filing of robot manufacturers) and robot deployment, the USA has firm competitive advantages in robotics development, and at present China is a rival only in the industrial deployment of robots. Within Europe one can identify three main groups of countries with significantly different positions. The countries of the first group – Sweden, Germany, Austria, Denmark, and France – have densities in every part of the robotization chain which are mostly well above the European average values. Their leadership is based on their strong position in robotics development – though with differences regarding robotics developers, robot manufacturers and in-house robotics developers – as well as in robot deployment. The countries of the second group – Spain, Italy, Belgium, the Netherlands, and Finland – do not participate in every part of the robotization chain. Many of them lack robot manufacturing and are weak in-house robotics development but have relatively well performing robotics developers and also deploy industrial robots intensively. Finally, the countries of the third group, all Central and Eastern European countries and Portugal, have only recently started to converge with their European counterparts, in particular by the deployment of industrial robots. However, this development is often almost exclusively limited to the automotive industry. These countries are still very far behind in robotics development, and, according to patent data at present, robot manufacturing and in-house robotics development are non-existent in this group. This makes them particularly vulnerable to re-shoring activities of multinational firms.

Fernández-Marcías et al. (2020) and Jung/Lim (2020) provide explanations for the patterns of robot adoption in Europa and beyond. Fernández-Marcías et al. (2020) study determinants of increased automation in European countries in the period 1995-2015 and conclude that industrial robots have grown more in those sectors with more routine and manual work, fewer highly educated workers, and higher wages and unionization rates. This seems to underline that robotization is not a revolutionary new phenomenon but a traditional response to increasing unit labor costs as known since the beginning of the industrialization. Jung/Lim (2020) who analyze 42 countries worldwide for the years 2001-2017 in a simultaneous estimation model come to similar results. Major determinants of the expansion of industrial robots are increases in unit labor costs and hourly compensation levels, a result supported by Compagnucci et al. (2019). Robot adoption is also positively related to the proportion of manufacturing workers in the total labor force and to the firms' capacity to adopt new technology.

Gentili et al. (2020), studying the dynamics in six major OECD countries (Denmark, France, Germany, Italy, UK, and USA), distinguish in a cluster analysis for the period 2000-2015 industry- and country-sensitive differences in the process of robotization. There are some country-sector pairs that combine a high robot density with increasing productivity, declining output prices, higher employment, and growing wages. But at the same time there are also country-sector clusters characterized by stagnant productivity and ongoing labor dislocation. This coexistence may explain why positive and negative views on the impact of robots on employment and wages (c.f. 4.4) can be found at the same time. Moreover, Stiebale et al. (2020) show for 6 EU countries between 2004 and 2013 that productivity gains due to robotization at country-industry level are concentrated solely on firms with the highest initial productivity. Their results further reveal that robot adoption is linked with rising markups, sales, and profitability of firms with the highest initial markups, sales, and profitability, respectively, while many other firms face shrinking markups, sales, and profits. These findings imply that robotization shifts market power to the top performing firms within a certain country and industry and substantially contributes to industry concentration. Stiebale et al. (2020, 21) therefore conclude that robotization drives the emergence of "superstar firms" in the European manufacturing sector as robot adopting firms expand their market shares at the expense of non-adopters. Their findings are also consistent with the theory of endogenous technology adoption: a firm will invest in a productivity-enhancing technology, such as industrial robots, if the expected gains from reduced marginal costs are greater than the fixed costs of adoption. Since large firms with higher initial output and sales tend to benefit more, they might be more willing to incur the fixed costs of investment. Koch et al.'s (2021) firm-level analysis establishes robust evidence for such positive selection of ex-ante better performing firms into robot adoption.

4.3 Productivity and growth

The seminal paper by Graetz/Michaels (2018) studies the effects of automation on both labor productivity and total factor productivity (TFP), implying that robot adoption should not only influence the development of employment but also the long-run growth of output. The authors construct a novel panel dataset with 17 countries and 14 industries (9 manufacturing and 5 non-manufacturing sectors) ranging from 1993-2007 using the IFR data on robotics and data from EUKLEMS for output, labor, and capital. Their robot stock measure is built on the perpetual-inventory method (PIM) with a depreciation rate of 10%. Whenever needed, they impute initial stocks for 1993. However, they refrain from allocating "unspecified" robots to the specified industries. They find a positive relationship between robot densification (expressed as the percentile of changes in robots per million hours worked) and labor productivity growth that is driven by an increase in value added and not by a significant reduction in hours worked. The estimated labor productivity growth of 0.36 percentage points that can be attributed to robots is comparable to the effect of the steam engine as a driver of economic growth in the 19th century and only a little lower than the growth effect of highways in the middle of the 20th century or that of ICT in recent decades. In addition, the study shows that robot densification also increased TFP and lowered output prices. These baseline results are refined, discussed, and qualified by Bekhtiar et al. (2021), CEBR (2017), Dauth et al. (2018), Jungmittag/Pesole (2019), Kromann et al. (2020), Ghodsi et al. (2020), Fu et al. (2021), Stiebale et al. (2020), and in a recent paper by Jurkat et al. (2021).

Bekhtiar et al. (2021) critically examine the methodology of Graetz/Michaels (2018) and question the reliability of their results. They illustrate that the largest part of country-industry observations does not exhibit relevant changes in robot density between 1993 and 2007. Especially, notable robotization is almost completely concentrated on manufacturing industries. Excluding non-manufacturing sectors from the analysis, they are not able to replicate the results of Graetz/Michaels (2018), i.e. they do not find any productivity effects of robotization and no significant decline of output prices in manufacturing sectors. However, they are able to re-establish a positive effect of robot densification on labor productivity and TFP when additionally (unlike Graetz/Michaels (2018)) controlling for demographic characteristics of the workforce (i.e. initial period employment shares of middle aged workers (age 30 to 49), and of old workers (age 50 plus), as well as the change in the share of female workers).[20] Based on these results, Bekhtiar et al. (2021) caution that the highly skewed distribution of changes in robot densities is a general threat to the econometric validity of results obtained from country-industry level research on robotization using the IFR dataset. Moreover, they provide evidence that the economic effects of robotization might weaken over time. By repeating the analysis of Graetz/Michaels for the more recent period 2008-2015, they do not find any significant productivity effects of robotization, neither in the full sample nor in the sample solely comprising manufacturing sectors.

In contrast, the study by CEBR (2017) looks at 23 OECD countries, including the US and the UK, over the period 1993-2015 and confirms the baseline result of Graetz/Michaels (2018) in all regards. Dauth et al. (2018) also confirm the positive impact of automation on labor productivity in Germany.[21] Kromann et al. (2020) use data from the IFR on the robot stock for the period 2004-2007 in 10 manufacturing industries of 9 countries to investigate the effect of automation on total factor productivity. They estimate production functions at the industry level making a distinction between ICT and non-ICT capital and including a robot-intensity index, calculated as the number of robots relative to non-ICT capital in the industry. They find that a more intensive use of industrial robots has a significantly positive effect on TFP. In particular, an increase of one standard deviation in the robot intensity is associated with more than 6% higher TFP. Jungmittag/Pesole (2019) extend this approach to a much broader dataset. They work with a panel of 9 industries for 12 EU countries in the period 1995-2015 using 5%, 10%, and 15% annual depreciation for the calculation of the annual stock of robots with PIM. Since the robot stock of an industry is part of its non-ICT capital, it is assumed that non-ICT capital has a quality and a quantity dimension. The quality of non-ICT capital is assumed to be positively influenced by the number of industrial robots used in an industry relative to the total non-ICT capital input. The estimation of industrial Cobb-Douglas production functions then shows that this quality variable - stocks of robots per 1 million Euros non-ICT capital - had a significant effect on TFP growth and via this channel also increased labor productivity. The substantial effects on productivity are, however, limited to a few industries with an already large deployment of robots, notably transport equipment, including car manufacturing.

Ghodsi et al. (2020) match IFR data on operational robot stocks with data from the World Input-Output Database (WIOD) for 56 industries in 43 countries over the period 2000-2014 to investigate the impact of automation on value added. Their particular focus is on the inter-industry linkages within global values chains. Their results show that about 0.8% of the growth in global real value-added is explained by the increase in the number of robots. The main positive impact comes from international forward linkages. Advanced economies provide the largest contribution due to their higher share of value added in the world economy.

[20] Their inclusion of demographic controls for the sectoral workforce is motivated by the findings of Acemoglu/Restrepo (2021), c.f. section 4.5.

[21] Koch et al. (2021) speculate from their analysis of Spanish firm panel data that the the productivity gains documented in Graetz/Michaels (2018) or Dauth et al. (2018) might be partly explained by a reallocation of workers from low-productivity non-adopting firms to high-productivity robot adopters. In other words, with the selection of more productive firms into robot adoption, increased exposure to robots reduces market shares of non-adopters and forces the least productive firms to exit.

Jurkat et al. (2021) analyze the growth effects of robots by estimating the parameters of a normalized CES production function from a panel of 9 industries in 10 countries for the period 1993-2007. Unlike Kromann et al. (2020) or Jungmittag/Pesole (2019), they do not treat the robot stock as an indicator of the quality of non-ICT capital but distinguish between a robot and non-robot capital stock. This requires to calculate values of robot capital using IFR data on the number of robot shipments and also user costs of robots. Their results from a system approach estimation show a high elasticity of substitution between human labor and the robot stock and a generally lower elasticity of traditional capital with the composite labor service that is constructed from the joint input of human labor and robots. Substitutability between human labor and robots but at the same time complementarity between human labor and other capital goods was already supported by Compagnucci et al. (2019) in a panel VAR analysis for 16 countries over the period 2011-2016.

In sum, the picture of the robot-productivity nexus is much clearer than findings in the other strands of literature (c.f. 4.2, 4.4, 4.5). Positive effects of robotization on labor productivity and TFP can be found in all studies. In Fu et al. (2021), however, the positive effect on labor productivity is limited to developed countries and non-existent in developing economies. Bekhtiar et al. (2021) also do not find any productivity effects of robotization between 2008 and 2015. And as Stiebale et al. (2020, 1) show, robotization at the industry-level increases productivity, markups, and overall profits of firms with the highest initial productivity, markups, and profitability, respectively, but has insignificant or negative effects on the other firms in the industry, thereby possibly driving the emergence of "superstar firms".

4.4 Employment and wages

When the increase in the automation of industrial production by robots started, this immediately raised the question about implications for the (industrial) labor market in terms of employment and wages. From various perspectives, with varying methodologies and for different countries, these issues were tackled by Acemoglu/Restrepo (2017; 2020), Graetz/Michaels (2018), Borjas/Freeman (2019), De Vries et al. (2020), Klenert et al. (2020), Dahlin et al. (2019), Chiacchio et al. (2018), Giuntella /Wang (2019), Dauth et al. (2021), Dottori (2020), Aghion et al. (2019), Leigh et al. (2018), Carbonero et al. (2018), Compagnucci et al. (2019), Anelli et al. (2019b), Aksoy et al. (2020), Fu et al. (2021), OECD (2019), and Ge/Zhou (2020).

The paper by Acemoglu/Restrepo (2017; 2020) studying US local labor market effects of increased robot exposure has become the central reference for this field of research. The authors use micro level data for 722 commuting zones (CZs) and 19 industries in the USA for the period 1990 to 2007 and match these with a novel measure for the exposure to robots using IFR data on robot stocks for the period 1993 to 2007. The exposure to robots of a CZ depends on its industrial composition. It is constructed as the sum of all changes in national robot stocks in the individual industries, divided by the base year employment level (in thousands of workers) within the respective industry, over all industries where the employment shares of all industries in the respective CZ serve as weights.[22] Intuitively, CZs with high employment shares of industries strongly investing in robots, especially the automotive industry, will be assigned a higher exposure to robots. The CZ approach enables the authors to closely investigate the effects a higher exposure to robots has on local labor markets rather than studying cross-country and cross-industry effects. Following

[22] Different to the working paper (Acemoglu/Restrepo, 2017), the penetration of robots is also adjusted for the growth rate of output of the respective industry during the period of analysis in Acemoglu/Restrepo (2020).

particularities in their use of IFR data must be pointed out: firstly, within the 11 industry sectors that the IFR distinguishes for the manufacturing industry, Acemoglu/Restrepo (2017; 2020) split up the category "Metal" into the three categories "Basic Metals“ (IFR class 24), „Metal products“ (IFR class 25) und „Industrial machinery“ (IFR class 28) so that they can work with 13 manufacturing industries. Secondly, the "Unspecified" data category on robot installations is allocated to the 19 industries according to the respective industry’s share in the classified data. Thirdly, as the IFR data for the US with industry breakdown is only available from 2004 onwards and to mitigate endogeneity concerns, exposure to robots in European countries between 1993 and 2007 is used as an instrument for the US exposure between 2004 and 2007. The authors find that one robot per thousand workers reduces wages by 0.42%, the employment-to-population ratio by 0.2 percentage points, and substitutes for 3.3 workers.[23] These strong labor market effects are robust to including exposure to imports from China, to excluding the automobile industry as a heavy user of robots, or to including IT or other types of capital. The employment effects are more pronounced in manufacturing as well as in routine and manual tasks.

Chiacchio et al. (2018) apply the CZ approach to study the employment and wage effects of robots in Europe. Their analysis covers six EU countries (Finland, France, Germany, Italy, Spain, and Sweden) with 116 NUTS2 regions and 18 industries for the period 1995-2007. The results support a negative impact of robots on employment. In the analyzed European countries one additional robot reduces the employment-to-population ratio only by 0.16-0.20 percentage points, thus one half of the value for the USA according to Acemoglu/Restrepo (2017) but comparable to the results of Acemoglu/Restrepo (2020). One obvious explanation for a stronger employment reduction in the USA is the more liberalized US labor market and the much more active public labor market policy in EU countries. The authors find only non-robust evidence for reduced growth of hourly wages due to industrial robots. Compagnucci et al. (2019) observe labor dislocation in OECD countries, measured as reduced growth rates of hours worked and real wages, when the number of robots at industry-level grows.

Borjas/Freeman (2019) compare the labor market effects of robots and immigrants in the USA. Working with IFR data for robot shipments between 2001-2016 they construct the stock of robots by simply summing up annual shipments assuming that depreciation (i.e. obsolescence) and appreciation (i.e. quality improvements due to technological change) balance each other out (PIM with a net depreciation rate of 10% is used as a robustness check). They define robot intensity for each industry-year as the stock of robots per workers in the respective industry assuming that robots are distributed across geographic areas within an industry proportional to employment in that industry. Thereby, they solely rely on variation in robot intensity across industries instead of modelling the robot shock in local labor markets according to their local industry mix like Acemoglu/Restrepo (2017, 2020) do by means of commuting zones. Nevertheless, they obtain the same qualitative and even similar quantitative results as Acemoglu/Restrepo (2017, 2020): their study confirms the negative impact of industrial robots on employment and earnings, concentrated on lower educated workers and those in automatable occupations. As the least educated group is also the most challenged by the influx of migrants, they compare the respective effects and find robust evidence that the entry of an additional immigrant has a much less negative effect: one

[23] The working paper version Acemoglu/Restrepo (2017) found higher effects: one robot per 1,000 workers decreases the employment-to-population ratio by 0.37 percentage points and average wages by 0.73% in a commuting zone with average robot exposure relative to one without exposure to robots. These numbers imply that one robot per thousand workers would substitute for about six workers.

industrial robot is comparable to 2 to 3 human workers and even up to 3 to 4 for occupations with a high degree of automation and workers with lower levels of education.

Graetz/Michaels (2018) in contrast, did not find an overall employment effect of increased robot use between 1993-2007 and even report a positive effect on mean hourly wages (albeit with a magnitude of only 10% of the estimated labor productivity gains) in their country-industry level study. However, they confirm the result that increased robot use lowers employment for low-skilled occupations. In conflict with these findings, Bekhtari et al. (2021) do not find robust support for positive wages effects and a decline in the share of hours worked by low-skilled workers associated with robotization when replicating the analysis of Graetz/Michaels(2018) while excluding non-manufacturing sectors. Instead, their estimates, although not robustly across different specifications, swing towards negative wage effects and job polarization (i.e. employment shrinks in the middle of the skill distribution). Bekhtari et al. (2021) also cannot identify a clear impact of robotization on wages in the more recent period from 2008 to 2015. In a study on robot adoption in 14 EU countries for the period 1995-2015 with a focus on manufacturing sectors, Klenert et al. (2020) find a positive effect on total employment and even no robust, negative effect on low-skilled occupations. They conclude that industrial robots should at present not be regarded as a major disruption regarding employment in Europe.

Dahlin (2019) examines the effect of industrial robots on occupations in the USA in 2010 and 2015 and finds that an increase in industrial robots is associated with increases in high-skill and some middle-skill occupations but not for other types of occupations. De Vries et al. (2020) had a closer look at the relationship between industrial robots and occupational shifts by task content. Using a panel of 19 industries in 37 high-income as well as emerging market and transition economies from 2005-2015, they find that robotization is associated with positive changes in the employment share of non-routine analytic jobs and negative changes in the share of routine manual jobs.

Dauth et al. (2021) confirm that in Germany for the period 1994-2014 robots were no major job killers. Rather they led to a change in the composition of employment, where a significant reduction in manufacturing jobs was offset or even slightly overcompensated for by a job increase in the service sector. At the level of individual workers robots did not raise the displacement risk for incumbent manufacturing workers but rather reduced the availability of those jobs for young labor market entrants. Similar results are reported from local labor market studies in other European countries, reflecting the structural differences in labor market conditions compared to the USA. Dottori (2020) could not find an overall negative impact of robot adoption in a study on local labor markets in Italy combined with an analysis on the level of individual workers over the period 1991-2016. The adjustment to robots seems to have rather occurred through a lower likelihood of entering manufacturing for new workers. Caselli et al. (2021b) come to a qualitatively similar result by investigating the effect of robot adoption on employment in 377 local Italian labor markets between 2011 and 2018. By a manual match of data on occupations' activities and robots' applications, they differentiate between workers who operate robots and those who are exposed to being replaced by them. While the empirical results see rising employment opportunities for robot operators no significant negative effect on the exposed workers could be found. OECD (2019) also links occupational activities with robot applications for 20 OECD countries (no local labor markets approach) between 1993 and 2014 but finds negative employment effects for middle- and low-skilled occupations (crafts and related trade workers, machine operators, assemblers, and elementary occupations), while high-skilled occupations (technicians and professionals) benefit. Aghion et al. (2019) show that robotization reduced aggregate employment at the regional employment zone level in France over the period 1994-2014, while this effect is concentrated on less-educated workers. Giuntella/Wang (2019) apply the same framework to China. In both aggregate- and individual-level analyses, they find large negative effects of robot exposure on employment and wages. For 261 prefecture-level cities they show that an increase by 1 standard deviation in robot exposure lowers an individual's probability of being employed by 5% with respect to the mean and reduces hourly wages by 7%. In addition, they find evidence that the negative effects on employments are largely driven by the state-owned sector and that these effects are concentrated among low-skilled workers, older workers, and men. Furthermore, cities with an initially higher specialization in manufacturing seem to suffer significantly higher losses in terms of workers' employment and wages.

The methodological approach by Acemoglu/Restrepo (2017; 2020) has been criticized, however, for exaggerating the impact that robots have on employment. Leigh et al. (2020) question both the CZ approach as well as the exposure to robots measure. Exposure to robots in a CZ assumes that all firms of one industry use robots in the same way regardless of geographical location and firm size. Firms are therefore assumed to be identical over CZs and to employ robots in the same fashion. These are strong assumptions which are not necessarily true. Outside of manufacturing, the number of robots installed is often very low. It is not realistic to assume that a small number of robots would impact labor markets on such a large scale as implied in the CZ approach, especially if this small number is then allocated to over 700 small regions. Actually, some firms will use these robots while a majority of firms will not. Moreover, results from manufacturing might not be applicable to other sectors. Industry specific use in e.g. education is entirely different from manufacturing. Leigh et al. (2020) therefore pursue a different strategy to quantify the robot related impact on the US labor market. Firstly, they modify the exposure to robots based on IFR data so that it applies to manufacturing only and use 352 metropolitan areas as defined by the US Census - the so-called "core-based statistical areas (CBSA)" - instead of CZs. Secondly, they use real time data on job postings to calculate a robotics skill demand index (RSDI). This index accounts for the skills required to operate a robot, calculated as the number of job postings with at least one robot related skill cluster divided by the total number of job postings in manufacturing. Job postings indicate that robot related work is indeed concentrated in the US Midwest and Southeast regions reflecting the overall higher manufacturing intensity of labor markets there. The authors find that for the period 2010-2016 one robot per thousand workers more or an RSDI of 1% above average has boosted manufacturing employment by 0.2 percent, while no statistically significant effect on wages is found. This translates according to Leigh et al. (2020) into an increase of 900 manufacturing employees over these six years and thus, a positive employment effect in the USA after the Great Recession.

Carbonero et al. (2018) link the national employment effects of robot adoption to the re-shoring activities of globally active firms. Their results for a panel of 41 countries point to a long-run decline of worldwide employment of about 1.3% due to an increase in the number of robots by 24% between 2005 and 2014. In developed countries, this decline of employment amounts to slightly over 0.5%, while in emerging economies it reaches almost 14%. Moreover, robots in developed countries reduced offshoring and thereby depressed employment in emerging economies by 5% between 2005 and 2014, i.e. the negative effect of robots is present within countries and through the global supply chain.

Three studies with a focus on Europe and the USA, respectively, look specifically at the impact of increasing automation on the gender pay gap and come to strikingly different conclusions. Aksoy et al. (2020), building on IFR data for 20 European countries, 12 industries, and the years 2006, 2010, and 2014, find that robot adoption increased both male and female earnings, but also increased the gender pay gap. This is due to a larger positive effect on male earnings, especially in medium- and high-skilled occupations, where women are underrepresented, in countries with low levels of initial gender equality, and outsourcing destination countries. Different findings are reported by Anelli et al. (2019b) as well as by Ge/Zhou (2020) in their studies of the American labor market over the period 2005-2016 and 1990-2015, respectively. In the USA, an increase in robot exposure has reduced the gender income gap significantly. According to the findings of Ge/Zhou (2020) one more robot per thousand workers decreased the gender wage gap by 0.3 log points, and the increase in robots accounts for 6% of the total reduction in the gender wage gap between 1990 and 2015. In general, earnings for both groups decreased in the USA, but male income fell at substantially higher rate than female income, lowering the gender income gap at a reduced income level.

4.5 Demographics, health, and politics

The adoption of robots in industrial production is not only influenced by major demographic factors such as growth or the age structure of a given population. It may also influence itself important social and political trends such as changes in demographic behavior, physical and mental health of workers or the voting patterns of citizens. This is the outcome of papers by Abeliansky/Prettner (2017), Abeliansky/Beulmann (2019), Acemoglu/Restrepo (2021), Anelli et al. (2019a; 2019b), Gihleb et al. (2020), Gunadi/Ryu (2021), Frey et al. (2018), and Caselli et al. (2021a).

The intensive use of robots in some highly industrialized countries might be seen as an economically promising strategy to face a long-term decline in population growth that eventually also transforms into a shrinking workforce. The fact that the robot adoption in the USA is so much lower than in countries like Germany, Japan or South Korea would thus be the outcome of the pronounced differences in population growth. Abeliansky/Prettner (2017) treat robots as a perfect substitute for human labor and investigate the effects of a declining population growth on the robot density, defined as automation capital per capita, between 1993 and 2013 in a sample of 60 countries. Their dependent variable is the growth rate in the stock of robots, constructed from IFR data following the PIM approach under the assumption of a 10% depreciation rate. The main explanatory variable is population growth from UN data sources, lagged by 1 and 2 periods. Estimations (over 3-year-averages) in various empirical models show a robust negative relationship between (lagged) population growth and the increase in robot density. These findings are complemented and deepened by the study of Acemoglu/Restrepo (2021) who analyze theoretically and empirically the effects of an aging population on the use of robots. Looking at a sample of 52 countries over the period 1993-2014 they calculate the change in the stock of robots relative to industry employment in 1990. The main explanatory variable is the change in the age composition of the workforce measured by UN data for the rate of older (56 years or more) to middle-aged workers (21-55 years old) between 1990 and the expected level in 2025. They find a robust positive effect of aging on the adoption of robots, meaning that an expected future decline in the middle-aged population and an expected increase in the older population are associated with faster present robot adoption. The future demographic shifts alone explain 35% of the variation in robot adoption across all countries of the sample. The same finding can also be derived when looking at differences among US local labor markets via a CZ estimation. Middle-aged workers are identified as the most scare resource in industrial production. If their share relative to old workers declines, the higher cost of the most productive workforce directs technical change into the direction of faster automation. When looking at the sectoral dynamics, robot adoption responds positively to aging precisely in those industries that rely more on middle-aged workers and that have greater opportunities for automation.

Looking at the immediate effects on the workplace, it is not surprising that more automation should impact on the physical and mental health of workers. In a study for US metropolitan areas, Gunadi/Ryu (2021) find that higher exposure to industrial robots is positively associated with the self-reported health of the low-skilled population. This might be explained by a reduction of unhealthy behavior in industrial production when robots take over the most burdensome tasks. Gihleb et al. (2020) analyze the relationship between robot adoption and workplace injuries in the USA and Germany. They show that higher robot exposure reduces workplace-related injuries in manufacturing firms in both countries. However, the US counties that are more exposed to robot penetration experience a significant increase in drug- or alcohol-related deaths and mental health problems, consistent with the evidence of negative effects on labor market outcomes in the USA. The German case, where data from the SOEP panel on physical and mental health are used, is completely different. There seems to be no evidence of significant effects on the mental health of workers. This result is in line with the insignificant impact of automation on labor market outcomes in Germany. At first glance this result contradicts the findings by Abelansky/Beulmann (2019) who investigate in-depth the effect of automation on the mental health of German employees across 21 manufacturing sectors in the period 2002-2014. Their main regressor is sector- and year-specific robot intensity (i.e. stock of robots divided by employment in thousands of employees in the respective sector) calculated on the basis of IFR data with a PIM approach and a rate of depreciation of 10%. The dependent variable is a mental health index score of individual i, measured at time t, who works in sector s that is taken from bi-annual SOEP panel data. It is constructed from various mental health related survey questions that can be divided into four subcategories. The estimation results indicate that an increase in robot intensity is associated with a decrease of mental health, that men - and in particular young men aged 20-29 - are more affected than women and that workers in medium-level jobs are affected the most. The main drivers of a decline in mental health seem to be worries about job security and the economic situation in general. In a decomposition of the mental health index, the authors find evidence that automation does not affect vitality, social functioning nor the emotional state of individual, but mainly the "mental work ability". An increased robot exposure leads to individuals feeling less productive, which in turn affects their overall mental health negatively. Therefore, the difference to the results by Gihleb et al. (2020) can be explained by the use of a different measure for mental health.

Further, a higher robot density could lower the risk of contagion in the workplace and thus contribute to a greater industrial resilience in terms of future pandemics. Using IFR data for Italy, Caselli et al. (2020) show that industries with a higher use of robots face a lower risk of contagion with COVID-19. In the future these industries might therefore be excluded from lockdowns, even if they are not essential. Sedik/Yoo (2021) use IFR data to analyze the past patterns of robot adoption in 18 industries of 40 countries after pandemic events between 2000 and 2014. They find an accelerated use of robots after pandemics leading to a rise in productivity, but also an increase in inequality by displacing low-skilled workers.

Anelli et al. (2019b) examine how exposure to robots and its consequences for job stability and economic uncertainty affects individual demographic behavior such as marriages, divorces, or fertility. Their empirical methodology for the USA follows the CZ approach by

Acemoglu/Restrepo (2017; 2020) applied to 741 zones for the period 2005-2016. The results of the analysis indicate some significant social costs of automation. CZs with higher robot penetration experienced a decrease in new marriages, and an increase in both divorce and cohabitation. While the overall fertility rate did not change, marital fertility declined, and out-of-wedlock births increased. Speculating about the causal links, the authors point out that a more intensive robot adoption may not only have increased the uncertainty of all traditional labor relations but may in particular have deteriorated the relative marriage-market value of male industrial workers.

Anelli et al. (2019a) investigate with the same empirical methodology also the impact of robot adoption on electoral outcomes in 14 Western European countries between 1993 and 2016. Their findings have a highly political relevance because they indicate that higher local exposure to robots, measured by IFR data, increases the political support for nationalist and radical-right parties. The study is based on two different empirical strategies, one relying again on the CZ approach. The other approach tries to identify the individual exposure to robots measured by individual i's probability of working in occupation j, that can be predicted according to age, gender, educational attainment and region of residence and then multiplied by an estimate of the automation threat for occupation j. The second approach makes the transmission channels between automation and voting results more transparent: higher robot exposure at the individual level leads to poorer perceived economic conditions and well-being, lower satisfaction with the government and democracy, and a reduction in perceived political self-efficacy. Caselli et al (2021a) studying the effects of immigration, imports from China and robot adoption on the results of general elections in Italy 2001, 2008 and 2013 find evidence that robotization "... turns out to be positively associated with a rise in the support to far-right parties ..." (Caselli et al. 2021a, 16). Frey et al. (2018) see robots in some sense responsible for the victory of Donald Trump in the 2016 US presidential elections. Working again with the CZ approach, their dependent variable is the percentage point difference in the Republican party vote share between the 2016 and 2012 presidential elections. As explanatory variable they make use of the change in robot adoption in the immediate years before these elections. They find a positive link between changes in robot exposure and changes in the share of votes in favor of the Republican candidate and finish with a very interesting counterfactual exercise that demonstrates the potentially extreme socio-political impact of the robot revolution: if the exposure to robots had not increased in the immediate years before the 2016 presidential election, the major swing states Michigan, Pennsylvania and Wisconsin would have swung in favor of Hillary Clinton leaving the Democrats with a majority in the Electoral College. Even if the authors do not identify the direct transmissions channels there is no doubt that the political impact of increasing automation stems from the major structural changes that the traditional human industrial labor force had to face. Instead of riots against machines as in the days of the Industrial Revolution the Robot Revolution seems to lead to riots against politicians that are held responsible for job losses.

We are thus confronted with significant socio-demographic and political side effects of robot adoption that may even promote a vicious circle: Lower population growth and aging promote a higher rate of automation that via its short-term negative labor market effects increases overall economic uncertainty, destroys traditional family patterns, and promotes the rise of nationalist and radical-right parties. If these parties and politicians promise a return to safer economic and social conditions, this would only prevent the substitution of scare labor by robots and thus lower income and wealth in the long-run. The challenge for economic policy is thus straightforward. As Abelansky/Prettner (2017, 16) summarize: "Of course, the transition to automation technologies might not be all that smooth because automation capital competes with labor and therefore could act so as to depress wages. If this concern is valid and widespread, it might lead to resistance against automation from labor unions and the population at large. Altogether, it might therefore be in everybody's interest if governments enact policies that alleviate the burden of those who suffer because of automation."

5. Conclusions and outlook

As our survey shows, the IFR database on industrial robots has been a valuable tool for a growing body of academic research on the patterns and effects of rising robot adoption. So far it remains the only reliable data source that covers the development of the exposure to robots in internationally comparable format and over a long period of time for a broad range of countries. Alternative data sources, such as the UN Comtrade Database or firm-level surveys for individual countries, can complement data from the IFR but will by no means replace it. As a dataset that is provided by a private association representing the interest of the global robotic industry, it needs to meet high standards of compliance while maintaining all professional standards for presenting a realistic picture of the development on the world markets for industrial robots. Moreover, availability of data disaggregated by industry and application has significantly improved since 2005, visible in a sharply-declining share of robots with an unspecified industry or application in total robot stocks.

Nevertheless, we are aware of several shortcomings in the data, which are partly due to the strict compliance guidelines. Matching the data with widely-used databases such as EUKLEMS or WIOD is not easy but our paper, by making the difficulties explicit, aids those who wish to work with it in the future. In addition, we see an increasing need to develop means of quality adjustments when it comes to robot prices. Robot prices are only provided by the IFR as average unit prices, and the only quality adjusted price index ends in 2005. Constructing robot stocks in the same fashion as other capital stocks are calculated (e.g. in EUKLEMS) would require, however, some kind of quality adjustment.

Studies based on IFR data reveal that the rise of robots has multi-faceted effects that should differentiate between occupations, skill levels, gender, and developed and developing countries. Patterns of robot adoption and changes in industrial organization as well as effects on productivity and growth are in line with long-term trends in capitalist development where rising wages induce labor-augmenting technical change. Whether the structural transformation in the organization of work means a revolutionary change in industrial production that leads to a general reduction in employment and wages seems, however, to depend very much on the institutional, political, and social framework conditions. While in the USA the rise of robots caused a significant reduction in industrial employment and wages, less evidence in that direction could be detected in Europe. The striking international differences to this ongoing development seem to indicate that economic policy measures as well a social institutions and traditions play a role in mitigating the negative effects of industrial robots on employment and wages so that the positive effects on productivity and growth can dominate. Nevertheless, the social costs of structural change may induce vicious cycles in politics that prevent necessary policy reforms.

The most controversial debate in that context has started on the pros and cons of a particular "robot tax" (Kovacev 2020) that should redistribute income from non-routine workers who benefit from increasing automation to routine workers who lose their jobs. As Guerreiro et al. (2020) point out in a theoretical model context, an economic justification for such a tax can only be given in the short-run and as a reaction to the extreme high speed in robot adoption that leaves too little time for an adequate adaption of the workers' skills on a very broad level. Humlum (2019, 39ff.) has simulated the effects of the introduction of both a temporary and a permanent tax of 30% for the use of robots in Denmark. He concluded that the temporary tax can achieve the goal of delaying the diffusion of industrial robots, but that it is also an ineffective and relatively costly way to redistribute income to production workers employed in manufacturing. Korea, the country with the second highest robot density in the world in 2019 (IFR 2020), could become an interesting case for studying the impact of changing tax regimes on robot adoption and labor market conditions. In 2017, a reform of the Korean tax law introduced a reduction of the automation tax credit that had before subsidized the firms' investment in new robots. A rigorous empirical assessment of this reform will certainly become an innovative contribution to this debate.

There are no signs that the rise of robots has already come to an end. On the contrary, there are indications that it will proceed at an even higher speed after the end of the COVID-19 pandemic since robots can also help to mitigate the effects of future global diseases (Caselli et al., 2020, Sedik/Yoo, 2021). De Backer et al. (2018) have already pointed out the negative effect that robotics may have on the offshoring activities from developed countries. Robotics seem to decrease the need for relocating activities away from developed economies. Kilic/Marin (2020) speculate that the era of "hyper-globalisation", when GVCs profited from cheap labor outside industrialized countries, already came to an end after the global financial crisis. Using IFR data for robot intensity they show that before 2007 industries with higher robot exposure were also importing more from developing countries while this pattern was completely reversed after 2010. For the post-pandemic era one could therefore expect that the growing risks of global sourcing and trading, together with rapidly falling robot prices, will induce a massive reshoring of firm activities. Atkinson (2021) foresees a particular pressure on developing countries to keep up with the further boom of robotization that he expects in the developed world. How much these trends will indeed characterize the coming decade and shape the economic, social and political dimensions of robotization will certainly become visible in the data provided by the IFR.

References

Abeliansky, A. & Beulmann, M. (2019). Are They Coming for Us? Industrial Robots and the Mental Health of Workers. *cege Discussion Papers 379*.

Abeliansky, A. & Prettner, K. (2017). Automation and Demographic Change. *cege Discussion Papers 310*.

Acemoglu, D., Lelarge, C. & Restrepo, P. (2020). Competing with Robots: Firm-Level Evidence from France, *AEA Papers and Proceedings*, 110, 383-388.

Acemoglu, D. & Restrepo, P. (2017). Robots and Jobs: Evidence from US Labor Markets. *NBER Working Paper 23285*.

Acemoglu, D. & Restrepo, P. (2020). Robots and Jobs: Evidence from US Labor Markets. *Journal of Political Economy, 128*(6), 2188-2244.

Acemoglu, D. & Restrepo, P. (2021). Demographics and Automation. *Review of Economic Studies*, forthcoming.

Adachi, D., Kawaguchi, D. & Saito, Y. D. (2020). Robots and Employment: Evidence from Japan, 1978-2017. *RIETI Discussion Paper Series 20-E-051*, Tokyo.

Aghion, P., Antonin, C. & Bunel, S. (2019). Artificial Intelligence, Growth and Employment: The Role of Policy. *Economie et Statistique / Economics and Statistics*, 510-511-512, 149–164. Doi: 10.24187/ecostat.2019.510t.1994

Aksoy, C., Özcan, B. and Philipp, J. (2020). Robots and the Gender Pay Gap in Europe. *QPE Working Paper*.

Anelli, M., Colantone, I. & Stanig, P. (2019a). We Were the Robots: Automation and Voting Behavior in Western Europe. *IZA Discussion Papers* 12485.

Anelli, M., Giuntella, O. & Stella, L. (2019b). Robots, Labor Markets, and Family Behavior. *IZA Discussion Papers* 12820.

Atkinson, R. D. (2021). Robots and International Economic Development. Information Technology & Innovation Foundation, Washington, D.C.

Barth, E., Roed, M., Schone, P. & Umblijs, J. (2020). How Robots Change within-firm Wage Inequality. *IZA Discussion Papers 13605*.

Bekhtiar, K., Bittschi, B. and Sellner, R. (2021) Robots at work? Pitfalls of industry level data, Munich: ifo Institute - Leibniz Institute for Economic Research at the University of Munich, EconPol Working Paper 58.

Bessen, J., Goos, M., Salomons, A. &van den Berge, W. (2020). Firm-Level Automation: Evidence from the Netherlands. *AEA Papers and Proceedings*, *110*, 389–393.

Blanas, S., Gancia, G. & Lee, S. Y. (2019). Who is Afraid of Machines? *Economic Policy*, *34*, 627–690.

Bonfiglioli, A., Crinò, R., Fadinger, H. & Gancia, G. (2020). Robot Imports and Firm-Level Outcomes. *CEPR Discussion Papers 14593*.

Borjas, G. & Freeman, R. (2019). From Immigrants to Robots: The Changing Locus of Substitutes for Workers. *RSF: The Russell Sage Foundation Journal of the Social Sciences, 5*(5), 22–42.

Carbonero, F. Ernst, E. & Weber, E. (2018). Robots Worldwide: The Impact of Automation on Employment and Trade. *ILO Working Papers 36, Geneva.*

Caselli, M., Fracasso, A. & Traverso, S. (2020). Mitigation of Risks of Covid-19 Contagion and Robotisation: Evidence from Italy. *Covid Economics. Vetted and Real-Time Papers*, 17, May 2020, 174-188.

Caselli, M., Fracasso, A. & Traverso, S. (2021a). Globalization, Robotization and Electoral Outcomes: Evidence form Spatial Regressions for Italy. *Journal of Regional Science*, 61, 86-111.

Caselli, M., Fracasso, A, Scicchitano, S., Traverso, S. & Tundis, E. (2021b). Stop Worrying and Love the Robot: An Activity-Based Approach to Assess the Impact of Robotization on Employment Dynamics. *GLO Discussion Papers No. 802,* Essen.

CEBR (2017). The Impact of Automation: A Report for Redwood. *Centre for Economics and Business Research*, London.

Cheng, H., Jia, R., Li, D. & and Hongbin, TL. (2019). The Rise of Robots in China. *Journal of Economic Perspectives*, 33 (2), 71–88. Doi: 10.1257/jep.33.2.71

Chiacchio, F., Petropoulos, G. & Pichler, D. (2018). The Impact of Industrial Robots on EU Employment and Wages - A Local Labour Market Approach. *Bruegel Working Papers 02-2018,* Bruessels.

Cho, J. & Kim, J. (2018). Identifying Factors Reinforcing Robotization: Interactive Forces of Employment, Working Hour and Wage, *Sustainability*, 10(2), 1-21.

Compagnucci, F., Gentili, A., Valentini, E. & Gallegati, M. (2019). Robotization and Labour Dislocation in the Manufacturing Sectors of OECD Countries: A Panel VAR Approach. *Applied Economics*, 51, 6127-6138.

Cséfalvay, Z. (2020). Robotization in Central and Eastern Europe: Catching Up or Dependence? *European Planning Studies, 2*, 1534–1553.

Cséfalvay, Z. & Gkotsis, P. (2020). Robotisation Race in Europe: the Robotisation Chain Approach. *Economics of Innovation and New Technology*.

Dahlin, E. (2019). Are Robots Stealing Our Jobs? *Socius: Sociological Research for a Dynamic World, 5*, 1-14.

Dauth, W., Findeisen, S., Südekum, J., & Wössner, N. (2021). The Adjustment of Labor Markets to Robots: Revised version. *Journal of the European Economic Association*, forthcoming.

Dauth, W., Findeisen, S., Südekum, J. & Wössner, N. (2018). Adjusting to Robots: Worker-Level Evidence. *Opportunity and Inclusive Growth Institute Working Paper 13*.

De Backer, K., DeStefano, T., Menon, C. & Suh, J. R. (2018). Industrial Robotics and the Global Organisation of Production. *OECD Science, Technology and Industry Working Paper 2018/03, Paris.*

Del Rey, J. (2019, Dec 11). How Robots are Transforming Amazon Warehouse Jobs — for Better and Worse. *Vox*. Retrieved from https://www.vox.com/recode/2019/12/11/20982652/robots-amazon-warehouse-jobs-automation, accessed January 16, 2021.

Deng, L., Plümpe, V. & Stegmaier, J. (2021). Robot Adoption at German Plants, IWH Discussion Papers, No. 19/2020, *Leibniz-Institut für Wirtschaftsforschung Halle (IWH)*, Halle (Saale).

De Vries, G. J., Gentile, E., Miroudot, S. & Wacker, K. M. (2020). The Rise of Robots and the Fall of Routine Jobs. *Labor Economics, 66*.

Dixon, J., Hong, B. & Wu, L. (2021). The Robot Revolution: Managerial and Employment Consequences for Firms. *Management Science*, forthcoming.

Dottori, D. (2020). Robots and Employment: Evidence from Italy. *Banca d'Italia Occasional Papers No. 572*, Rome.

Estolatan, E., Geuna, A., Guerzino, M. & Nuccio, M. (2018). Mapping the Evolution of the Robotics Industry: A Cross Country Comparison. *Innovation Policy White Paper Series, 2018-02, Munk School of Global Affairs & Public Policy,* Toronto.

Faber, M. (2020). Robots and Reshoring: Evidence from Mexican Labor Markets. *Journal of International Economics, 127*.

Fan, H., Hu, Y. & Tang, L. (2021). Labor Costs and the Adoption of Robots in China. *Journal of Economic Behavior and Organization*, 186, 608-631.

Fernández-Macías, E., Klenert, D. & Antón, J.-I. (2020). Not so Disruptive Yet? Characteristics, Distribution and Determinants of Robots in Europe, *European Commission JRC120611*, Seville.

Frey, C., Berger, T. & Chen, C. (2018). Political Machinery: Did Robots Swing the 2016 US Presidential Election? *Oxford Review of Economic Policy, 34*, 418-442.

Fu, X., Qun, B., Xie, H. & Fu, X. (2021). Diffusion of Industrial Robotics and Inclusive Growth: Labour market Evidence from Cross Country Data. *Journal of Business Research*, 122, 670-684.

Ge, S. & Zhou, Y., (2020). Robots, Computers, and the Gender Wage Gap, *Journal of Economic Behavior & Organization*, 178, 194-222.

Gentili, A., Compagnucci, F., Gallegati, M. & Valentini, E. (2020). Are Machines Stealing our Jobs? *Cambridge Journal of Regions, Economy and Society*, 13, 153-173.

Ghodsi, M., Reiter, O., Stehrer, R. & Stöllinger, R. (2020). Robotisation, Employment and Industrial Growth Intertwined Across Global Value Chains. *The Vienna Institute for International Economic Studies Working Paper 177*.

Gihleb, R. / Giuntella, O. / Stella, L. / Wang, T. (2020). Industrial Robots, Workers' Safety, and Health. *IZA Discussion Papers 13672*.

Giuntella, O. & Wang, T. (2019) Is an Army of Robots Marching on Chinese Jobs?. *IZA Discussion Paper 12281.*

Gorle, P. & Clive, A. (2013). Positive Impact of Industrial Robots on Employment: Updated in January 2013 to Take Account of More Recent Data. *IFR/Metra Martech*, London.

Graetz, G. & Michaels, G. (2018). Robots at Work. *The Review of Economics and Statistics, 100*(5), 753-768.

Guerreiro, J., Rebelo, S. & Teles, P. (2020). Should Robots Be Taxed?" *NBER Working Paper 23806*.

Gunadi, C. and Ryu, H. (2021) 'Does the rise of robotic technology make people healthier?', Health Economics, vol. 30, no. 9, pp. 2047–2062.

Humlum, A. (2019). Robot Adoption and Labor Market Dynamics, *Unpublished Working Paper*.

IFR (2020). World Robotics 2020: Industrial Robots. *VDMA Services GmbH*, Frankfurt am Main.

IFR (2021), International Federation of Robotics Homepage, https://ifr.org, accessed March 03, 2021.

IFR & UN ECE (2001). World robotics 2001 – Annex B: Measuring Service Lives of Industrial Robots – Pilot Study, *United Nations*, New York-Geneva.

Jäger, A., Moll, C., Som, O. & Zanker, C. (2015). Analysis of the Impact of Robotic Systems on Employment in the European Union: Final report. *Publications Office of the EU*, Luxembourg.

Jungmittag, A. (2020). Robotisation of the Manufacturing Industries in the EU: Convergence or Divergence? *The Journal of Technology Transfer*, 1–22.

Jungmittag, A. & Pesole, A. (2019). The Impacts of Robots on Labour Productivity: A Panel Data Approach Covering 9 Industries and 12 Countries. *JRC Working Papers Series on Labour, Education and Technology 2019/08.*

Jung, J. H. & Lim, D.-G. (2020). Industrial Robots, Employment Growth, and Labor Cost: A Simultaneous Equation Analysis. *Technological Forecasting and Social Change*, 159, 120202, 1-11. Doi.org/10.1016/j.techfore.2020.120202.

Jurkat, A., Saam, M. & Salg, J. (2021). The Substitutability of Robots and Human Labor - A CES Estimation Approach, *Unpublished Draft*.

Kilic, K. & Marin, D. (2020). How COVID-19 is transforming the world economy. *Vox EU*. Retrieved from https://voxeu.org/article/how-covid-19-transforming-world-economy, accessed May 20, 2020.

Klenert, D., Fernandez-Macias, E., Anton, J.-I. (2020). Do Robots Really Destroy Jobs? Evidence from Europe. *European Commission JRC118393*, Seville.

Koch, M., Manuylov, I. & Smolka, M. (2021). Robots and Firms. *The Economic Journal*, forthcoming.

Kovacev, R. J. (2020). A Taxing Dilemma: Robot Taxes and the Challenges of Effective Taxation of AI, Automation and Robotics in the Fourth Industrial Revolution. *The Contemporary Tax Journal*, 9(2), Article 4. Available at: https://scholarworks.sjsu.edu/sjsumstjournal/vol9/iss2/4.

Krenz, A., Prettner, K. & Strulik, H. (2018). Robots, Reshoring, and the Lot of Low-Skilled Workers. *cege Discussion Papers 351*.

Kromann, L., Malchow-Møller, N., Skaksen, J. & Sørensen, A. (2020). Automation and Productivity – A Cross-Country, Cross-Industry Comparison. *Industrial and Corporate Change, 29*(2), 265–287.

Leigh, N. G.& Kraft, B. (2018). Emerging Robotic Regions in the United States: Insights for Regional Economic Evolution. *Regional Studies*, 52(6), 804–815.

Leigh, N. G., Kraft, B. & Lee, H. (2020). Robots, Skill Demand and Manufacturing in US Regional Labour Markets. *Cambridge Journal of Regions, Economy and Society, 13*(1), 77–97.

López-Sánchez, J. I., Arroyo-Barriguete, J. L. & Morales-Contreras, M. (2020). The Industrial Robot Evolution in the World. A First Dendrogram for a Cluster Analysis. In Pons, J. (Ed.), *Inclusive Robotics for a Better Society, INBOTS 2018. Biosystems & Biorobotics, 25*, 31-36. *Springer,* Cham.

Muro, M. (2017). Where the Robots Are. *The Avenue*. (https://www.brookings.edu/blog/the-avenue/2017/08/14/where-the-robots-are/, accessed 19.04.21).

Nuccio, M. / Guerzoni, M. / Cappelli, R. / Geuna, A. (2020). Industrial Pattern and Robot Adoption in European Regions. *Department of Management, Università Ca'Foscari Venezia Working Paper Series 3*.

OECD (2019). Determinants and Impact of Automation: An Analysis of Robots' Adoption in OECD Countries. *OECD Digital Economy Papers 277*.

Pandey, H. & Pulidindi, K. (2020, Oct 14). Furniture Market size worth over $750 Bn by 2026. *Global Market Insights*. Retrieved from https://www.gminsights.com/pressrelease/furniture-market, accessed March 21, 2021.

Sedik, T. S. & Yoo, J. (2021). Pandemics and Automation: Will the Lost Jobs Come Back? *IMF Working Papers 21/11*, Washington, D.C.

Stiebale, J., Südekum, J., and Woessner, N. (2020). Robots and the Rise of European Superstar Firms. *DICE Discussion Paper 347*.

United Nations (2008). International Standard Industrial Classification of All Economic Activities (ISIC), Revision 4. *Statistical Papers, Series M* (4), Rev.4.

United Nations, UN Comtrade Database (https://comtrade.un.org)

World Bank (2021), Consumer Price Index (2010 = 100) - United States. (https://data.worldbank.org/indicator/FP.CPI.TOTL?locations=US, accessed April 27, 2021)

Zator, M. (2019). Digitization and Automation: Firm Investment and Labor Outcomes. *Unpublished Working Paper*.

Appendix

Table A1: IFR Geographical classes and availability of installation data

Parent Class	*IFR Code*	*Geographic Entity*	*Geographical level*	*Aggregate data since*	*Data by industry since*	*Data by application since*
	WR	WORLD	Global	1993	1993	1993
WR	AFR	AFRICA	Continent	1999	2005	2005
AFR	ZA	South Africa	Survey item	1999	2005	2005
AFR	ROA	Rest of Africa	Country group	2005	2005	2005
ROA	EG	Egypt	Survey item	2005	2005	2005
ROA	MA	Morocco	Survey item	2005	2005	2005
ROA	TN	Tunisia	Survey item	2005	2005	2005
ROA	OAF	Other Africa	Survey item	2005	2005	2007
WR	AM	AMERICA	Continent	1993	2004	1993
AM	NAM	North America	Region	1993	2004	1993
NAM	CA	Canada	Survey item	2011	2011	2011
NAM	MX	Mexico	Survey item	2011	2011	2011
NAM	US	United States	Survey item	1993	2004	1993
AM	SAM	South America	Region	1993	2004	2004
SAM	BR	Brazil	Survey item	1999	2004	2004
SAM	RAM	Rest of South America	Country group	1999	2004	2004
RAM	AR	Argentina	Survey item	1999	2004	2004
RAM	RCH	Chile#	Survey item	1999	2004	2004
RAM	CO	Colombia#	Survey item	1999	2004	2004
RAM	PE	Peru#	Survey item	1999	2004	2004
RAM	PR	Puerto Rico#	Survey item	1999	2004	2004
RAM	VE	Venezuela#	Survey item	1999	2004	2004
AM	AS	America, not specified	Survey item	1993	2006	2006
WR	ASI	ASIA/AUSTRALIA	Continent	1993	1993	1993
ASI	SAS	South East Asia	Region	1993	1993	1993
SAS	CN	China	Survey item	1999	2006	2004
SAS	IN	India	Survey item	1999	2006	2005
SAS	ID	Indonesia	Survey item	2002	2006	2005
SAS	JP	Japan	Survey item	1993	1996	1995
SAS	KR	Rep. of Korea	Survey item	1993	2001*	1993
SAS	MY	Malaysia	Survey item	1999	2006	2004
SAS	SG	Singapore	Survey item	1993	2005	2005
SAS	TW	Taiwan	Survey item	1993	1993*	1993*
SAS	TH	Thailand	Survey item	2002	2005	2004
SAS	VN	Vietnam	Survey item	2004	2005	2005
SAS	OSAS	other South/East Asia	Country group	2002	2006	2005
OSAS	HK	Hong Kong#	Survey item	2004	2004	2004
OSAS	KP	North Korea#	Survey item	2005	2005	2005
OSAS	MO	Macau#	Survey item	2005	2005	2005
OSAS	PH	Philippines	Survey item	2002	2006	2005
ASI	RAS	Rest of Asia	Region	2001	2005	2004
RAS	IR	Iran	Survey item	2001	2005	2004
RAS	KW	Kuwait#	Survey item	2005	2005	2005
RAS	OM	Oman#	Survey item	2005	2005	2005
RAS	PK	Pakistan#	Survey item	2005	2005	2005
RAS	QA	Quatar#	Survey item	2005	2005	2005
RAS	SA	Saudi Arabia#	Survey item	2005	2005	2005
RAS	AE	United Arab Emirates#	Survey item	2005	2005	2005
RAS	UZ	Uzbekistan#	Survey item	2005	2005	2005
ASI	OA	Other Asia	Survey item	1993	2006	2006
ASI	AUNZ	Australia/New Zealand	Country group	1993	2006	1993*
AUNZ	AU	Australia	Survey item	1993	2006	1993*
AUNZ	NZ	New Zealand	Survey item	2005	2006	2005
WR	EU	EUROPE	Continent	1993	1993	1993
EU	CEU	Central/Eastern Europe	Region	1993	2004	2004
CEU	YUG	Balkan Countries	Country group	1993	2005	2005
CEU	CZ	Czech Republic	Survey item	1993	2004	2004

CEU	HU	Hungary	Survey item	1993	2004	2004
CEU	PL	Poland	Survey item	1993	2004	2004
CEU	RO	Romania	Survey item	2003	2004	2004
CEU	RU	Russian Federation	Survey item	1995	2004	2004
CEU	SK	Slovakia	Survey item	1993	2004	2004
YUG	BA	Bosnia-Herzegowina#	Survey item	2005	2005	2005
YUG	CR	Croatia#	Survey item	2005	2005	2005
YUG	RS	Serbia#	Survey item	2005	2005	2005
YUG	SL	Slovenia	Survey item	1993	2005	2005
CEU	OEE	Other Eastern Europe	Country group	2003	2004	2004
OEE	BY	Belarus#	Survey item	2005	2006	2006
OEE	BG	Bulgaria#	Survey item	2005	2006	2005
OEE	EE	Estonia#	Survey item	2003	2004	2004
OEE	LV	Latvia#	Survey item	2005	2005	2005
OEE	LT	Lithuania#	Survey item	2004	2006	2006
OEE	MD	Moldova#	Survey item	2005	2005	2005
OEE	UA	Ukraine#	Survey item	2003	2004	2004
EU	WEU	Western Europe	Region	1993	1993	1993
WEU	AT	Austria	Survey item	1993	2003	1993
WEU	BE	Belgium	Survey item	1993	2004	2004
WEU	DE	Germany	Survey item	1993	1993	1993
WEU	ES	Spain	Survey item	1993	1993	1993
WEU	FR	France	Survey item	1993	1993	1993
WEU	IT	Italy	Survey item	1993	1993	1993
WEU	NL	Netherlands	Survey item	1993	2004	2004
WEU	PT	Portugal	Survey item	1993	2004	2004
WEU	CH	Switzerland	Survey item	1993	2004	2004
WEU	UK	United Kingdom	Survey item	1993	1993	1993
EU	NEU	Nordic Countries	Region	1993	1993	1993
NEU	DK	Denmark	Survey item	1993	1996	1993
NEU	FI	Finland	Survey item	1993	1993	1993
NEU	NO	Norway	Survey item	1993	1993	1993
NEU	SE	Sweden	Survey item	1993	1993	1993
EU	REU	Rest of Europe	Region	1993	2005	2005
REU	TR	Turkey	Survey item	1993	2005	2005
REU	OEU	all other European countries	Survey item	1998	2005	2005
OEU	GR	Greece	Survey item	1999	2006	2005
OEU	IC	Iceland#	Survey item	2004	2006	2005
OEU	IE	Ireland	Survey item	2002	2006	2005
OEU	IL	Israel	Survey item	1999	2005	2005
OEU	MT	Malta#	Survey item	2005	2005	2005
EU	EUU	Europe unspecified	Survey item	1993	2006	2006
WR	OT	Others not specified	Survey item	2006	2006	2006

The column about aggregate data availability indicates in which year the respective data were first surveyed; for some entities, the first strictly positive data entry is observed several years later. Columns about data availability by industry and application indicate the first year in which not all reported installations are unspecified (this does not hold true for all countries labelled by # because no installations might be reported). # Surveyed, but no or very few installations reported; data usually hidden due to compliance mechanisms from year 2014 onwards. * Australia and Australia/New Zealand: No disaggregation by application between 1999 and 2003. * Rep. of Korea: No disaggregation by industry in year 2002. * Taiwan: No disaggregation by industry between 2000 and 2003; no disaggregation by application between 2000 and 2003.
Source: IFR

Table A2a: Price indices for industrial robots at current exchange rates in US Dollars

	USA		Germany		France	
year	not quality adjusted	quality adjusted	not quality adjusted	quality adjusted	not quality adjusted	quality adjusted
1990	100.00	100.00	100.00	100.00	100.00	100.00
1991	95.70	94.20	97.10	95.50	96.60	95.10
1992	69.50	58.60	75.10	63.30	74.60	62.90
1993	53.10	36.30	61.30	42.00	61.00	41.70
1994	56.90	41.40	59.00	43.00	59.30	43.20
1995	59.70	45.30	57.30	43.50	57.00	43.30
1996	55.90	40.20	58.20	41.80	57.10	41.00
1997	46.30	27.10	55.60	32.50	54.10	31.70
1998	45.70	26.20	51.20	29.40	50.10	28.80
1999	40.90	19.70	51.90	25.10	50.70	24.50
2000	37.30	17.90	51.10	24.50	50.00	23.90
2001	31.50	15.10	48.60	23.40	47.50	22.80
2002	34.40	16.60	45.10	21.70	44.00	21.20
2003	40.40	18.10	46.60	20.90	45.50	20.40
2004	42.80	18.30	46.00	19.70	44.90	19.20
2005	41.10	17.00	44.60	18.50	43.60	18.10

	Italy		UK		Sweden	
year	not quality adjusted	quality adjusted	not quality adjusted	quality adjusted	not quality adjusted	quality adjusted
1990	100.00	100.00	100.00	100.00	100.00	100.00
1991	97.50	95.90	98.60	97.10	92.90	91.40
1992	90.50	76.30	88.50	74.60	85.90	72.40
1993	80.10	54.80	69.10	47.20	77.40	52.90
1994	82.00	59.80	70.10	51.10	74.50	54.30
1995	83.70	63.50	74.20	56.30	69.80	52.90
1996	75.70	54.40	63.50	45.60	67.40	48.40
1997	72.10	42.20	54.00	31.60	64.00	37.50
1998	66.80	38.40	52.90	30.40	64.60	37.10
1999	68.00	32.80	49.60	24.00	60.70	29.30
2000	66.90	32.00	47.60	22.80	57.70	27.60
2001	63.60	30.60	43.20	20.80	59.90	28.80
2002	59.00	28.40	43.10	20.80	55.40	26.70
2003	61.00	27.30	47.50	21.30	56.80	25.40
2004	60.20	25.80	45.40	19.40	56.50	24.20
2005	58.40	24.20	44.30	18.40	56.20	23.30

Source: IFR

Table A2b: Price indices for industrial robots at fixed conversion rates in US Dollars 1990

	USA	
year	not quality adjusted	quality adjusted
1990	100.00	100.00
1991	95.30	91.60
1992	83.90	71.60
1993	73.80	53.80
1994	71.60	49.80
1995	67.90	43.20
1996	66.30	40.50
1997	63.20	34.90
1998	61.30	31.60
1999	59.30	28.00
2000	57.10	26.80
2001	57.10	26.90
2002	53.40	25.40
2003	55.10	24.40
2004	54.40	23.10
2005	53.50	22.10

Source: IFR

Table A3: Correspondence table between IFR and ISIC Rev. 4 classifications

IFR			ISIC Rev. 4		
Parent class	*IFR Code*	*Title*	*Section*	*Divisions or Groups*	*Description*
-	0	All industries	xxx	xxx	xxx
0	A-B	Agriculture, forestry, fishing	A	01-03	Agriculture, forestry, fishing
0	C	Mining and quarrying	B	05-09	Mining and quarrying
0	D	Manufacturing	C	10-33	Manufacturing
D	10-12	Food and beverages	C	10-12	Manufacture of food products ∪ Manufacture of beverages ∪ Manufacture tobacco products
D	13-15	Textiles	C	13-15	Manufacture of textiles ∪ Manufacture of wearing apparel ∪ Manufacture of leather and related products
D	16	Wood and furniture	C	16 ∪ 31	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials ∪ Manufacture of furniture
D	17-18	Paper	C	17-18	Manufacture of paper and paper products ∪ Printing and reproduction of recorded media
D	19-22 ∪ 2932	Plastic and chemical products ∪ Rubber and plastic (AutoParts)	C	19-22	Manufacture of coke and refined petroleum products ∪ Manufacture of chemicals and chemical products ∪ Manufacture of pharmaceuticals, medicinal chemical and botanical products ∪ Manufacture of rubber and plastics products
19-22	19	Pharmaceuticals, cosmetics	C	21 ∪ 2023	Manufacture of pharmaceuticals, medicinal chemical and botanical products ∪ Manufacture of soap and detergents, cleaning and polishing preparations, perfumes and toilet paper
19-22	20-21	Other chemical products n.e.c	C	19-20 \ 2023	Manufacture of coke and refined petroleum products ∪ Manufacture of chemicals and chemical products (without class 2023)
19-22	22 ∪ 2932	Rubber and plastic products (non-automotive) ∪ Rubber and plastic (AutoParts)	C	22	Manufacture of rubber and plastics products
19-22	229	Chemical products, unspecified	C	xxx	xxx
D	23 ∪ 2934	Glass, ceramics, stone, mineral products (non-automotive) ∪ Glass (AutoParts)	C	23	Manufacture of other non-metallic mineral products
D	24-28	Metal	C	24 ∪ 25 ∪ 28	Manufacture of basic metals ∪ Manufacture of fabricated metal products, except machinery and equipment ∪ Manufacture of machinery and equipment n.e.c.

24-28	24	Basic metals	C	24	Manufacture of basic metals
24-28	25	Metal products (non-automotive)	C	25	Manufacture of fabricated metal products, except machinery and equipment
24-28	28	Industrial machinery	C	28	Manufacture of machinery and equipment n.e.c
24-28	289	Metal, unspecified	C	xxx	xxx
D	26-27	Electrical/electronics	C	26 ∪ 27	Manufacture of computer, electronic and optical products ∪ Manufacture of electrical equipment
26-27	275	Household/domestic appliances	C	275	Manufacture of domestic appliances
26-27	271	Electrical machinery n.e.c. (non-automotive)	C	271 ∪ 272 ∪ 273 ∪ 274	Manufacture of electric motors, generators, transformers and electricity distribution and control apparatus ∪ Manufacture of batteries and accumulators ∪ Manufacture of wiring and wiring devices ∪ Manufacture of electric lighting equipment
26-27	260 ∪ 261	Electronic components/devices ∪ Semiconductors, LCD, LED	C	261	Manufacture of electronic components and boards
26-27	262	Computers and peripheral equipment	C	262 ∪ 268	Manufacture of computers and peripheral equipment ∪ Manufacture of magnetic and optical media
26-27	263	Info communication equipment domestic and professional (non-automotive)	C	263 ∪ 264	Manufacture of communication equipment ∪ Manufacture of consumer electronics
26-27	265	Medical, precision, optical instruments	C	265 ∪ 266 ∪ 267	Manufacture of measuring, testing, navigating and control equipment; watches and clocks ∪ Manufacture of irradiation, electromedical and electrotherapeutic equipment ∪ Manufacture of optical instruments and photographic equipment
26-27	279	Electrical/electronics, unspecified	C	279	Manufacture of other electrical equipment
D	29	Automotive	C	xxx	xxx
D	291 ∪ 2931 ∪ 2933 ∪ 2939	Motor vehicles, engines and bodies ∪ Metal (AutoParts) ∪ Electrical/electronic (AutoParts) ∪ Other (AutoParts)	C	29	Manufacture of motor vehicles, trailers and semi-trailers
29	291	Motor vehicles, engines and bodies	C	291 ∪ 292	Manufacture of motor vehicles ∪ Manufacture of bodies (coachwork) for motor vehicles; manufacture of trailers and semi-trailers
29	293	Automotive parts	C	xxx	xxx
293	2931 ∪ 2933 ∪ 2939	Metal (AutoParts) ∪ Electrical/electronic (AutoParts) ∪ Other (AutoParts)	C	293	Manufacture of parts and accessories for motor vehicles
293	2931	Metal (AutoParts)	C	xxx	xxx

293	2932	Rubber and plastic (AutoParts)	C	xxx	xxx
293	2933	Electrical/electronic (AutoParts)	C	xxx	xxx
293	2934	Glass (AutoParts)	C	xxx	xxx
293	2939	Other (AutoParts)	C	xxx	xxx
293	2999	Unspecified AutoParts	C	xxx	xxx
29	299	Automotive unspecified	C	xxx	xxx
D	30	Other vehicles	C	30	Manufacture of other transport equipment
D	91	All other manufacturing branches	C	32-33	Other manufacturing ∪ Repair and installation of machinery and equipment
0	E	Electricity, gas, water supply	D ∪ E	35-39	Electricity, gas, steam and air conditioning supply ∪ Water collection, treatment and supply ∪ Sewerage ∪ Waste Collection, treatment and disposal activities; materials recovery ∪ Remediation activities and other waste management services
0	F	Construction	F	41-43	Construction of buildings ∪ Civil engineering ∪ Specialized construction activities
0	P	Education/research/development	P ∪ M	85 ∪ 72	Education ∪ Scientific research and development
0	90	All other non-manufacturing branches	G-O \ 72 ∪ Q-U	45-71 ∪ 73-84 ∪ 86-99	Wholesale and retail trade; repair of motor vehicles and motorcycles ∪ Transportation and storage ∪ Accommodation and food service activities ∪ Information and communication ∪ Financial and insurance activities ∪ Real estate activities ∪ Professional, scientific and technical activities (without Scientific research and development) ∪ Administrative and support service activities ∪ Public administration and defence; compulsory social security ∪ Human health and social work activities ∪ Arts, entertainment and recreation ∪ Other service activities ∪ Activities of households as employers; undifferentiated goods- and services producing activities of households for own use ∪ Activities of extraterritorial organizations and bodies
0	99	Unspecified	xxx	xxx	xxx

Symbol ∪ serves as logical join operator, while quantity operator \ indicates a difference quantity.

Sources: Own research based on IFR (2020) and United Nations (2008).

Table A4: IFR application classes

IFR class	Application area	Definitions/ Notes
110	**Handling operations/ machine tending**	Assistant processes for the primary operation (the robot does not process the main operation directly)
111	Handling operations for metal casting	Incl. die-casting
112	Handling operations for plastic moulding	Incl. inserting operations for injection moulding
113	Handling operations for stamping/ forging/ bending	
114	Handling operations at machine tools	
115	Machine tending for other processes	e.g. handling during assembly, handling operations during glass or ceramics production or food production; Robots that handle workpieces at an external welding tool centre point (TCP) (i.e. MIG/MAG torch or spot gun) need to be reported in the appropriate welding classification (i.e. 161 for arc welding or 162 for spot welding) and are not counted under handling operations
116	Handling operations for measurement, inspection, testing	Triage, quality inspection, calibration
117	Handling operations for palletizing	All sectors, all kinds and sizes of pallets
118	Handling operations for packaging, picking and placing	e.g. operations during primary and secondary packaging
119	Material handling n.e.c.	e.g. transposing, handling during sandcasting
120	Handling operations/ machine tending unspecified	Exact IFR 11X class is unknown or hidden for compliance reasons
160	**Welding and soldering (all materials)**	
161	Arc welding	
162	Spot welding	
163	Laser welding	
164	Other welding	e.g. ultrasonic welding, gas welding, plasma welding
165	Soldering	
166	Welding and soldering unspecified	Exact IFR 16X class is unknown or hidden for compliance reasons
170	**Dispensing**	
171	Painting and enamelling	Area-measured application of lacquer (surface coat)
172	Application of adhesive, sealing material or similar material	Spot-wise and line-wise application
179	Dispensing others/ Spraying others	e.g. powder coating, application of mould release agent, area-measured application of adhesive, spraying of wax to conserve
180	Dispensing unspecified	Exact IFR 17X class is unknown or hidden for compliance reasons
190	**Processing**	Enduring changing: the robot leads the workpiece or the tool, incl. material removal
191	Laser cutting	
192	Water jet cutting	
193	Mechanical cutting/ grinding/ deburring/ milling/ polishing	
198	Other processing	e.g. gas/ plasma cutting, drilling, bending, punching, shearing
199	Processing unspecified	Exact IFR 19X class is unknown or hidden for compliance reasons
200	**Assembling and disassembling**	Enduring positioning of elements
201	Assembling	Assembling, mounting, screw/ nut-driving, clinching, riveting, bonding
202	Disassembling	Recycling, removal of cover after processing
209	Assembling and disassembling unspecified	Exact IFR 20X class is unknown or hidden for compliance reasons
900	**Others**	
901	Cleanroom for flat-panel display (FPD)	
902	Cleanroom for semiconductors	
903	Cleanroom for others	
905	Others	Applications not mentioned before
999	**Unspecified**	Application is unknown or hidden for compliance reasons

Source: IFR (2020)

Table A5a: Correlation between IFR installations and Comtrade import values

Country	Corr	Obs	95% Confidence interval	
Argentina	0.935	15	0.812	0.979
Australia	0.677	18	0.307	0.869
Austria	0.883	24	0.746	0.949
Belgium	0.211	21	-0.243	0.589
Brazil	0.789	21	0.541	0.910
Canada	-0.318	24	-0.639	0.098
Chile	0.876	15	0.659	0.958
China	0.848	21	0.657	0.937
Colombia	0.549	15	0.052	0.829
Czech Rep.	0.974	23	0.938	0.989
Denmark	0.845	23	0.664	0.932
Finland	0.337	24	-0.077	0.651
France	0.445	24	0.051	0.719
Germany	0.820	24	0.622	0.919
Greece	0.374	15	-0.171	0.744
Hungary	0.777	24	0.544	0.899
Iceland	0.598	11	-0.003	0.882
India	0.979	21	0.948	0.992
Indonesia	0.853	18	0.642	0.944
Ireland	0.508	12	-0.093	0.838
Israel	-0.117	15	-0.594	0.421
Italy	0.815	24	0.614	0.917
Malaysia	0.827	21	0.615	0.928
Mexico	0.737	24	0.476	0.879
Moldova	-0.094	13	-0.614	0.482
Netherlands	0.601	24	0.262	0.809
New Zealand	0.203	18	-0.291	0.612
Norway	0.425	24	0.026	0.707
Peru	0.948	15	0.848	0.983
Philippines	0.631	12	0.090	0.885
Poland	0.931	24	0.846	0.970
Portugal	0.748	24	0.493	0.884
Rep. of Korea	0.887	24	0.753	0.950
Romania	0.672	23	0.359	0.849
Singapore	0.038	23	-0.380	0.443
Slovakia	0.406	23	-0.008	0.701
Slovenia	0.766	18	0.466	0.908
South Africa	0.788	20	0.530	0.912
Spain	0.519	24	0.146	0.763
Sweden	0.134	24	-0.285	0.510
Switzerland	0.905	24	0.790	0.958
Thailand	0.849	18	0.633	0.942
Turkey	0.634	24	0.310	0.826
USA	0.445	24	0.051	0.720
United Kingdom	0.383	24	-0.024	0.681
Venezuela	0.198	15	-0.350	0.645
Vietnam	0.515	16	0.026	0.805
Pooled data	0.808	955	0.785	0.829

Country-years with negative import values net of re-exports are excluded. Country-years with IFR installations equal to zero only for compliance reasons are removed as well. Only countries with at least ten observations are included. Corr refers to Pearson correlation coefficients.

Source: Own calculations based on IFR and Comtrade data.

Table A5b: Correlation between IFR installations and Comtrade import quantities

Country	Corr	Obs	95% Confidence interval	
Argentina	0.799	14	0.467	0.934
Australia	0.674	14	0.224	0.887
Austria	0.949	18	0.866	0.981
Belgium	0.629	19	0.245	0.843
Brazil	0.312	20	-0.151	0.663
Canada	0.087	18	-0.396	0.532
Chile	0.560	14	0.042	0.841
China	0.858	21	0.676	0.941
Colombia	0.195	13	-0.399	0.674
Czech Rep.	0.135	18	-0.354	0.566
Denmark	0.906	19	0.767	0.964
Finland	0.694	18	0.336	0.877
France	0.859	19	0.664	0.945
Germany	0.899	11	0.648	0.974
Greece	0.219	13	-0.378	0.687
Hungary	0.793	19	0.530	0.917
India	0.936	21	0.845	0.974
Indonesia	0.864	18	0.666	0.948
Ireland	0.510	11	-0.130	0.850
Israel	0.121	13	-0.460	0.630
Italy	0.827	14	0.529	0.944
Malaysia	0.153	20	-0.310	0.558
Mexico	0.475	20	0.041	0.758
Moldova	-0.204	13	-0.679	0.391
Netherlands	0.680	18	0.312	0.870
New Zealand	0.547	12	-0.039	0.853
Norway	0.622	20	0.248	0.835
Peru	0.551	14	0.029	0.837
Philippines	0.249	12	-0.379	0.720
Poland	0.958	18	0.889	0.985
Portugal	0.820	18	0.571	0.930
Rep. of Korea	0.881	18	0.704	0.955
Romania	0.774	14	0.412	0.925
Singapore	0.122	21	-0.327	0.526
Slovakia	-0.068	18	-0.518	0.412
Slovenia	0.814	12	0.450	0.946
South Africa	0.149	13	-0.438	0.647
Spain	0.253	10	-0.448	0.761
Sweden	0.557	19	0.138	0.807
Switzerland	0.636	20	0.269	0.842
Thailand	0.095	14	-0.458	0.596
Turkey	0.747	19	0.444	0.897
USA	0.831	22	0.630	0.928
United Kingdom	0.678	16	0.275	0.878
Venezuela	0.147	14	-0.416	0.629
Vietnam	0.514	15	0.003	0.813
Pooled data	0.293	755	0.227	0.357

Country-years with negative import values net of re-exports are excluded. Country-years with IFR installations equal to zero only for compliance reasons are removed as well. Only countries with at least ten observations are included. Corr refers to Pearson correlation coefficients.

Source: Own calculations based on IFR and Comtrade data.

Table A6: Comparison between IFR and Comtrade quantities

		IFR installations				Comtrade imports				Difference			
Country	Obs	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
Argentina	14	105	104.5	17	407	150.1	144.8	20	466	45.1	87.7	-32	316
Australia	14	602.3	262.5	236	1214	2300.1	5379.8	311	20922	1697.8	5206.5	-232	19708
Austria	18	791.2	460.5	320	1686	1450.1	863.7	478	3076	658.8	450.5	-88	1572
Belgium	19	706.4	323.9	339	1518	2329.7	725.5	1566	4355	1623.4	579.2	894	3297
Brazil	20	945.9	585.3	208	2196	7799.8	8831.3	117	33959	6853.9	8666.6	-923	32752
Canada	18	1203.1	539.6	618	2333	6955.8	12701.6	467	57027	5752.7	12666.0	-151	55831
Chile	14	4.9	4.5	0	16	220	315.9	8	899	215.1	313.4	5	891
China	21	38411.1	53277.4	380	156176	28113.9	24630.6	1648	84685	-10297.2	34558.1	-106637	25747
Colombia	13	2.7	4.6	0	14	64.4	73.8	2	264	61.7	73.1	2	264
Czech Rep.	18	1129.6	997.0	70	2893	3374.6	2657.7	366	10253	2244.9	2709.2	109	10090
Denmark	19	477.1	178.7	249	800	727	385.8	254	1668	249.9	236.5	-42	896
Finland	18	407.7	117.7	270	699	461.2	195.6	195	954	53.4	141.9	-124	398
France	19	3400.9	1277.2	1450	6711	3825.1	1151.7	1747	6900	424.2	655.4	-753	1814
Germany	11	15809	5374.5	10075	26723	9316.5	6243.9	2642	19223	-6492.5	2750.5	-10439	-2465
Greece	13	23.8	17.4	3	59	77.5	57.7	11	198	53.7	56.5	-12	146
Hungary	19	513.5	588.4	20	2470	646.3	420.1	181	1485	132.7	361.5	-994	573
India	21	1387.6	1414.0	20	4771	3169.2	5101.4	12	19713	1781.6	3811.2	-515	14942
Indonesia	18	542.8	434.7	3	1168	961.1	751.8	128	2346	418.3	435.2	45	1477
Ireland	11	46.2	29.0	4	90	134.5	183.3	19	678	88.4	170.3	3	595
Israel	13	61.6	37.1	4	114	297.6	81.7	186	443	236	85.5	122	379
Italy	14	5602.8	1795.8	2883	11089	3661.6	1521.1	2372	8337	-1941.2	1009.8	-3525	-54
Malaysia	20	683.9	670.3	140	2863	33675.6	99772.3	507	437992	32991.7	99671.7	316	436994
Mexico	20	2545.9	1904.6	716	6356	7561.1	8876.8	1143	41975	5015.1	8146.3	-498	36509
Moldova	13	0.4	1.0	0	3	4.9	4.5	1	16	4.5	4.8	-1	16
Netherlands	18	849	586.8	167	1814	2152.6	1574.6	370	4873	1303.6	1251.9	-216	3215
New Zealand	12	68.5	31.5	23	123	27.3	28.4	3	99	-41.3	28.6	-95	-4
Norway	20	102.2	43.0	48	192	588.3	369.1	187	1443	486.1	344.0	90	1251
Peru	14	1	2.1	0	8	21.1	17.5	2	48	20.1	16.4	1	46
Philippines	12	63.4	32.9	8	121	484.7	850.5	25	2615	421.3	842.9	-53	2521
Poland	18	890.6	881.5	20	2651	1298.4	1086.4	132	3931	407.8	349.8	-255	1289
Portugal	18	351.9	282.1	120	993	743.6	703.3	114	2647	391.7	499.0	-10	1951
Rep. of Korea	18	19517.3	13871.9	3998	41373	3390.5	2131.7	1100	8090	-16126.8	12035.3	-37024	-2525
Romania	14	283.1	262.3	16	784	1011.4	472.2	335	1641	728.3	316.4	265	1321
Singapore	21	1080.9	1326.2	48	4559	16581.1	21758.3	662	61848	15500.2	21637.1	162	61615
Slovakia	18	458.6	514.9	1	1732	1406.8	2503.5	71	10693	948.3	2589.9	-945	10658
Slovenia	12	108.1	75.2	15	267	224.4	153.2	44	588	116.3	101.9	-21	321
South Africa	13	253.2	214.8	30	805	8984.5	13525.6	141	41917	8731.3	13495.4	86	41590
Spain	10	2561.1	651.3	1348	3584	2290.6	636.7	1488	3165	-270.5	787.5	-1368	1134
Sweden	19	1021.8	352.8	386	1647	1173.2	413.8	606	2356	151.4	364.7	-402	1093
Switzerland	20	613.4	381.8	156	1546	1992.7	1327.1	761	5985	1379.3	1123.7	605	4574
Thailand	14	1919.8	1337.0	101	4028	1696.3	1521.5	293	5784	-223.5	1927.4	-2239	4532
Turkey	19	830.7	783.2	16	2267	2048.6	1503.2	411	5504	1217.9	1055.2	357	4258
USA	22	16443.7	8925.5	7054	40373	11205.4	15623.6	994	52879	-5238.3	9590.7	-21362	17143
UK	16	1438.6	592.9	635	2486	2195.9	725.2	1418	3755	757.3	542.6	-523	1661
Venezuela	14	1.7	2.8	0	7	102.7	156.2	2	562	101	155.8	2	562
Vietnam	15	1058.1	2110.6	14	8274	1193.7	1434.8	136	5396	135.6	1843.3	-5831	3220
Pooled data	755	3028.1	11701.5	0	156176	4407.1	18782.2	1	437992	1379.1	18994.5	-106637	436994

Comparison between the number of robots installed/ imported according to IFR and Comtrade, respectively. Country-years with negative import values net of re-exports are excluded. Country-years with IFR installations equal to zero only for compliance reasons are removed as well. Only countries with at least ten observations are included. Difference is defined as Comtrade quantity (number of industrial robots imported net of re-exports) minus IFR installations. **Source:** Own calculations based on IFR and Comtrade data.

Table A7: Overview of research papers using IFR industrial robot data

Paper	Period/ Years	Countries	Regions	Industries (Manuf. + Non-Manuf.)	Calculation of robot stock	Definition of robot intensity	Robot prices	Treatment of unspecified robots*
Abeliansky/Beulmann (2019)	2002-2014	Germany	/	17 (15+2)	PIM 10% (5%, 15% as robustness checks)	Stock of robots per 1,000 employees	/	Omitted
Abeliansky/Prettner (2017)	1993-2013	60 countries	/	Manufacturing sector (no distinction of sub-industries)	PIM 10% (5%, 15% as robustness checks)	3-year average growth rates of the stock of robots (either manufacturing robots, or all robots)	/	Omitted; imputation
Acemoglu/Restrepo (2020)	1993-2007	USA	722 CZ	19 (13+6)	IFR stocks	Stock of robots per 1,000 workers	Robustness check: adjustment for variation in the average price of a robot across industries (data on robot prices from RIA)	Redistributed
Acemoglu/Restrepo (2021)	1993-2014	60 countries in country-level analysis; 58 countries in country-industry-level analysis; USA for analysis at CZ-level	722 CZ	19 (13+6)	IFR stocks	Stock of robots per 1,000 industrial workers (adjusted for hours per worker) in country-level analysis; Annual installations of robots per 1,000 workers in country-industry-level analysis; Stock of robots per 1,000 workers in CZ-level analysis	/	Redistributed
Aghion et al. (2019)	1994-2014	France	297 local employment zones	19 (13+6)	IFR stocks	Stock of robots per 1,000 workers	/	Redistributed
Aksoy et al. (2020)	2006, 2010, 2014	20 EU countries	/	12 (8+4)	IFR stocks	Stock of robots per 10,000 workers	/	Omitted
Anelli et al. (2019a)	1993-2016	14 Western European countries	192 NUTS-2 regions	11 (11+0)	IFR stocks	Stock of robots per 100,000 workers	/	Imputation
Anelli et al. (2019b)	2005-2016	USA	741 CZ	19 (13+6)	IFR stocks	Stock of robots per 1,000 workers	/	Redistributed
Bekhtiar et al. (2021)	1993-2007 & 2008-2015	17 countries	/	14 (9+5) & 9 (9+0)	PIM 10%	Stock of robots per million hours worked	/	Omitted; imputation
Borjas/Freeman (2019)	2004-2016	USA	/	26 (20+6)	Simple sum of installations over time (PIM 10% as robustness check)	Stock of robots per worker	/	Imputation
Carbonero et al. (2018)	2005-2014	41 countries	/	14 (9+5)	IFR stocks	Stock of robots per 10,000 workers	/	Omitted
Caselli et al. (2020)	2017	Italy	/	27 (22+5)	IFR stocks	Stock of robots per 1,000 workers	/	Redistributed

Caselli et al. (2021a)	2001-2008 & 2008-2013	Italy	684 local labor market areas	27 (22+5)	IFR stocks	Stock of robots per 1,000 workers	/	Redistributed
Caselli et al. (2021b)	2011-2018	Italy	377 local labor market areas	Instead of industries, 13 robot application categories are distinguished	IFR stocks (PIM 10% as robustness check)	Stock of robots per worker	/	Redistributed
CEBR (2017)	1993-2015	23 OECD	/	/	Monetary value of IFR stocks in 2010 US$ PPP	Robotics automation investment expressed as either the ratio of the monetary value of robot installations to GDP or in 2010 US$ PPP; Robotics density defined as robot stock per million hours worked	Price indices 1993-2015	N/A
Chiacchio et al. (2018)	1995-2007	6 EU countries	116 NUTS-2 regions	18 (13+5)	IFR stocks	Stock of robots per 1,000 workers	IFR price indices (w & w/o quality adjustment)	Redistributed
Compagnucci et al. (2019)	2001-2016	16 OECD countries	/	9 (8+1)	IFR stocks	Yearly growth rate of the stock of robots		Redistributed
Cséfalvay (2020)	1995-2013	18 EU countries	/	Automotive industries (Automotive + Other vehicles) vs. Non-automotive industries (all other industries incl. unspecified)	IFR stocks	Stock of robots per 10,000 employees in manufacturing	/	Unspecified robots are treated as robots which do not belong to manufacturing or automotive industries
Cséfalvay/Gkotsis (2020)	1995-2016	43 countries	/	/	IFR stocks	Stock of robots per 10,000 employees in manufacturing	/	N/A
Dahlin et al. (2019)	2010, 2015	USA	327 metropolitan areas	/	Muro (2017)	Stock of robots	/	N/A
Dauth et al. (2020)	1994-2014	Germany	402 local labour markets	25 (20+5)	IFR stocks	Stock of robots per 1,000 workers (full-time equivalents)	/	Omitted
De Backer et al. (2018)	2000-2014	40 countries	/	Unclear**	PIM 10%	Annual growth of robot stocks	/	Redistributed; imputation
De Vries et al. (2020)	2005-2015	37 countries	/	19 (14+5)	PIM 10% (5%, 15% as robustness checks)	Stock of robots per 1,000 persons employed	Turnover-based prices of robots for the US	Omitted; imputation
Dottori (2020)	1993-2016	Italy	784 local labor market areas	15 (11+4)	IFR stocks	Stock of robots per 1,000 workers	/	Redistributed
Faber (2020)	1993-2015	Mexico	1,805 CZ	19 (13+6)	IFR stocks	Stock of robots per worker	/	Redistributed; imputation
Fernández-Marcías et al. (2020)	1995-2005, 2005-2015	European countries	/	9 (9+0)	Own method of re-estimation maintaining the	Stock of robots per 1,000 workers	Estimation of robot prices based on Comtrade data & comparison	Redistributed within own re-estimation method

					12-year service life assumption		with IFR price data	
Frey et a.l. (2018)	2011, 2015	USA	722 CZ	19 (13+6)	IFR stocks	Stock of robots per 1,000 workers	/	Redistributed
Fu et al. (2021)	2004-2016	74 (45 developed, 29 developing)	/	/	IFR stocks	Stock of robots	/	N/A
Ge & Zhou (2020)	1993-2015	USA	722 CZ	19 (13+6)	IFR stocks	Stock of robots per 1,000 workers	/	Redistributed
Gentili et al. (2020)	2011-2015	6 OECD countries	/	11 (8+3)	IFR stocks	Stock of robots per 1,000 employees; Average growth rates of robot stocks	/	Redistributed
Ghodsi et al. (2020)	2000-2014	43 countries	/	Unclear**	IFR stocks	Stock of robots	/	Unclear**
Gihleb et al. (2020)	2005-2011 (USA), 1994-2016 (Germany)	USA, Germany	596 CZ	19 (13+6)	IFR stocks	Stock of robots per 1,000 workers	/	Redistributed
Giuntella/Wang (2019)	2000-2016	China	261 prefecturial level cities; 31 provinces	18 (12+6)	IFR stocks	Stock of robots per 1,000 workers	/	Redistributed
Graetz/Michaels (2018)	1993-2007	17 countries	/	14 (9+5)	PIM 10% (5%, 15% as robustness check)	Stock of robots per million hours worked	IFR price indices (w & w/o quality adjustment)	Omitted; imputation
Gunadi/Ryu (2021)	2006-2017	USA	105 metropolitan areas	17 (11+6)	IFR stocks	Stock of robots per 1,000 workers	/	Redistributed
Jung/Lim (2020)	2001-2017	42 countries	/	/	IFR stocks	Annual shipment of robots per 10,000 manufacturing workers	/	N/A
Jungmittag (2020)	1995-2015	24 EU countries	/	9 (9+0)	PIM 5%, 10%, 15%	Stock of robots per 1,000 workers	/	Redistributed; imputation
Jungmittag/Pesole (2019)	1995-2015	12 EU countries	/	9 (9+0)	PIM 5%, 10%, 15%	Stock of robots per million Euros non-ICT capital input	/	Redistributed; imputation
Jurkat et al. (2021)	1993-2007	10 countries	/	9 (8+1)	PIM 10% (5%, 15% as robustness checks)	Value of robot stocks in 1995 US$	User costs	Redistributed; imputation
Klenert et al. (2020)	1995-2007 & 1995-2015	14 EU countries	/	14 (9+5)	PIM 10% (5%, 15%, and assuming full depreciation after 12 years as robustness checks)	Stock of robots per 1,000 employees; Stock of robots	/	Redistributed; imputation
Krenz et al. (2018)	2000-2014	43 countries	/	9 (9+0)	IFR stocks	Stock of robots per 1,000 workers; Stock of robots per million hours worked	/	Omitted
Kromann et al. (2020)	2004-2007	9 countries	/	10 (10+0)	IFR stocks	Stock of robots per million Euros non-ICT capital (measured in 1997 German prices using PPPs)	IFR price indices (w & w/o quality adjustment)	Unclear **

Leigh et al. (2020)	2010-2015	USA	352 core-based statistical areas (CBSAs)	13 (13+0)	IFR stocks	Stock of robots per 1,000 workers	/	Redistributed
López-Sánchez et al. (2020)	1993-2016	71 countries	/	/	IFR stocks	Stock of robots per 10,000 people of active population	/	N/A
Nuccio et al. (2020)	1993-2015	5 EU countries	137 NUTS-2 regions	15 (11+4)	PIM 10%	Stock of robots per 1,000 inhabitants	/	Omitted
OECD (2019)	1993-2014	20 OECD countries	/	Instead of industries, 5 robot application categories are distinguished (assembling, dispensing, handling, processing, welding)	PIM 10%	Stock of robots by application category	Average unit prices 1998-2008 (defined as the total cost of a system divided by the number of robot units included in the system)	Imputation
Sedik/ Yoo (2021)	2000-2018	40 countries	/	18 (13+5)	IFR stocks	Robot adoption defined as cumulative sum of installations per 1,000 workers; robot density defined as stock of robots per 1,000 workers	/	Omitted
Stiebale et al. (2020)	2004-2013	6 EU countries	/	14 (14+0)	IFR stocks	Stock of robots; Stock of robots per 1,000 workers as robustness check	/	Omitted

* Treatment of unspecified robots is not relevant for analyses based on aggregate robot data at country-level instead of country-industry level (total national robot stocks comprise all robots, incl. unspecified ones). Therefore, for the respective papers this column is labelled by "not applicable" (N/A). Redistribution of unspecified robots indicates that unspecified robots are allocated to industries based on industry shares in specified data for all years (i.e. category "Unspecified" is broken up), while the detailed method of redistribution might slightly differ from one paper to the next. "Omitted" indicates that unspecified robots are excluded from the analysis. "Imputation" means that robot data for years with missing industry disaggregation (i.e. all robots "unspecified") are imputed based on industry shares in years when disaggregated data are available.

**Authors were asked about their industry disaggregation and treatment of unspecified data, but either did not respond or could not clarify.

The period as well as the number of countries, regions, and industries mentioned in the overview table refer to the number included in the authors' econometric analyses using IFR data, while more or less countries might be analyzed in other descriptive or analytical parts of the papers.