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**Tracking the Rise of Robots:  
A Survey of the IFR Database and its Applications**

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**May 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 the 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 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 price indices. 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 that are not classified to any industry or application we find that their share in total robot stocks has sharply declined after 2005. The average value of 45% of unspecified industrial robots at country level is therefore likely to shrink in the future. We also compare IFR data with other data sources such as UN Comtrade data on net imports and unit prices 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 effect of robot adoption, (iii) its impact on employment and wages, and (iv) its influence on demographics, health, and politics.

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

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

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## 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 deals with labor productivity effects induced by increased robot adoption whereas the former investigates the labor market effects of robotization. Both papers as well as most others dealing with the impact of robotization base their empirical investigation on a special data set on industrial robots put together and published by the International Federation of Robots (IFR). Given the crucial role of the IFR data set in robot research we see the necessity for a detailed survey that presents the characteristics of IFR, the specifics of the data set and the major findings of its use in academic studies.

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. We identify four important strands of research on the rise of robots: (i) patterns of robot adoption and industrial organization, (ii) productivity and growth effect of robot adoption, (iii) its impact on employment and wages, and (iv) its influence on demographics, health, and politics. Finally, in Section 5 we are able to distinguish the revolutionary from the traditional aspects of the rise of robots.

## **2. The story of IFR**

### **2.1 Members of 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. 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. 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 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 IFR are today divided into three membership categories: i) industry associations, ii) R&D institutes, and iii) robot suppliers. From each geographical area only one association can be an industry association member. At present, 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 IFR. Table 1 lists all 16 national robotics associations.

<<< insert Table 1 here >>>

### **2.2 Organizational structure**

The organizational structure of IFR mirrors its historic evolution and is illustrated in Figure 1. The General Assembly (GA) is the main governing body of 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.

<<< insert Figure 1 here >>>

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 member, 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 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 IFR between meetings of the GA, directs the activities of the General Secretariat, and represents IFR externally.

The General Secretariat is responsible for the daily management of 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 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 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 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

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”. In order to serve its purpose, the activities of 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 that are commercially provided to researchers. Since 2009, 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. IFR defines robot density as the number of industrial robots in operation (i.e. operational stock) per 10,000 persons employed. Second, country/region 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.

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 closely collaborated with 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 was still published by UN-ECE. Since 2006, the IFR Statistical Department has published the World Robotics Statistics regularly.

2) 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 IFR, market expansion is supported through networking activities and exchange of experiences. Moreover, IFR helps in founding new robot associations in countries or regions where previously no appropriate association structures did exist.

3) 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.<sup>1</sup> 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, IFR also publishes position papers to convey its stance on topics related to robotics. Thereby, IFR advocates global, national, and local policies fostering robot adoption.

4) 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, 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 ISR in conjunction with its respective international robotics trade fair. Participants of 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. 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<sup>2</sup> award together with the IEEE Robotics and Automation Society (IEEE/RAS).<sup>3</sup> Firms with specific marketable innovations can apply for this award. Responsibility for the award ceremony alternates between IFR and IEEE/RAS.

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<sup>1</sup> 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.

<sup>2</sup> IERA stands for "Innovation and Entrepreneurship in Robotics and Automation".

<sup>3</sup> 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.



### 3. The IFR data base on industrial robots

#### 3.1 Installations and stock of robots

By documenting the number of robots newly installed worldwide per year as main indicator, 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). It 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 operations or processing (e.g. cutting or grinding). Single-purpose automation technology such as elevators, conveyors or weaving- and 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. Therefore, the IFR dataset only refers to a specific kind of industrial automation. Nevertheless, it covers more than 90% of the global market for industrial robots (Dauth et al. 2017, 9f.; Acemoglu/Restrepo 2020).

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.<sup>4</sup> 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 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 A.2 lists all geographical classes in the IFR data set.

Data processing includes two consistency checks: At first, the IFR checks if the total values by country in both questionnaires - for applications and for industries - match. Secondly, it is scrutinized if the IFR data are consistent with national associations’ data. 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

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<sup>4</sup> Classification by mechanical structure according to 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.

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 it 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 be not yet 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.

### **3.2 Robot prices**

The IFR provides both unit prices and price indices for robots. Unfortunately, both 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 has to 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.

Unit prices 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 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.<sup>5</sup> Currently, total market values for robots and thus unit prices are only available for 5 countries: China, North America<sup>6</sup>,

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<sup>5</sup> Only for some countries information on prices is available from 1985 onwards.

<sup>6</sup> 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

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 2008. Data on total market value for Italy are reported for the last time in 2006, and information on average unit prices stops there as well. The UK is covered until 2018.<sup>7</sup> 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 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. 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 lower priced 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 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 system. A way to resolve the issue of different sizes and complexities of robots delivered and furthermore to take into account 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 3a) and in fixed conversion rates against the US\$ (see Table 3b). 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.

<<< insert Tables 3a and 3b here >>>

In order to construct the quality-adjusted price index, the IFR resorts 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 ect.) and mechanical parts which are time-invariant (such as casings and steel structures). These components are 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 is measured via the US producer price for computers. For the mechanical parts it is more difficult. Therefore, changes in 4 characteristics<sup>8</sup> of the mechanical parts are monitored and it is assumed that costs would increase proportionally to the their improvements.<sup>9</sup> The IFR is then able to calculate what a robot would have cost in each year

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to report installations for the US, Canada and Mexico separately. However, information on prices is still for all of North America.

<sup>7</sup> 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.

<sup>8</sup> 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).

<sup>9</sup> A detailed account of this procedure can be found in the WRIR of 2006, Annex C.

of the time series with the characteristics of a robot in 2005.<sup>10</sup> The weighted price increases that are due to an increase in the characteristics are 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 has to 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.

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.<sup>11</sup> As the IFR points out in the WRIR of 2006, the price indices (not quality adjusted as well as quality adjusted, see Table 3c) with a fixed conversion rate against the 1990 US\$ can be viewed as a general price index since it lacks the exchange rate dimension whereas the price indices with current exchange rates are only applicable to the 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. 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.<sup>12</sup>

### 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). 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 (c.f. Figure 5b). The six non-manufacturing industries are solely at the two-digit-level. However, the IFR industry classes deviate from the classes in 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 a category "Rubber and plastic products (non-automotive)" and a separate category "Rubber and plastic (AutoParts)". The reason behind this procedure is the

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<sup>10</sup> There were actually 2 surveys, one running from 1990-1999 and one from 2001-2005. The resulting indices were chain linked.

<sup>11</sup> There are releases in earlier publications but the most up to date one can be found in the 2006 report.

<sup>12</sup> Until 2009 the IFR had also reported a price index with base year 1990 (up to 2005 with base year 1989). In contrast to the former producer price indices, this price index was based on average unit prices and did neither account for robot heterogeneity nor quality improvements. Together with the individual reporting of average unit prices, this index has ceased to be published after 2009.

high share of customers from the automotive sector in the robotics market. Table 4 serves as correspondence table between IFR classification and ISIC rev. 4 using basic set theory.

<<< insert Table 4 here >>>

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 by 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 “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”, “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 installation 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, 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 (Global Market Insights, 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. 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, 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)". The sub-class "Pharmaceuticals, cosmetics" is equivalent to ISIC division 21 ("Manufacture of pharmaceuticals, medicinal chemical and botanical products") plus ISIC class 203 ("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 203. 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 are instead 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 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 good 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 captured by “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” 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” 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 5 presents the different IFR application classes.

<<< insert Table 5 here >>>



### 3.5 Compliance rules

The IFR Statistical Department complies with 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 conclude 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 the number of reports underlying each data point is 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 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. One example may illustrate this: assume, 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 are revealed 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 2a and 2b show the re-classification procedure for all IFR industry and application classes according to compliance mechanism M1.

<<< insert Figures 2a and 2b here >>>

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 hierarchy level, i.e. a country group or geographical region. For instance, data reports for Bosnia-Herzegovina, 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 3 illustrates which compliance mechanism is applied to which geographical entity.

<<< insert Figure 3 here >>>

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" zeroes, 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 holds also 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 do 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 the various 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 stocks 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 robot with unspecified industry or application are mainly driven by smaller countries or countries that account for low shares of 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 6a und 6b).

<<< insert Tables 6a and 6b here >>>

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).<sup>13</sup> 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%).

<<< insert Figures 4a and 4b here >>>

Figures 4a and 4b 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 downwards trend for some countries and an upwards 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 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. Figures 4c and 4d) . 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 is only 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.

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, 758). Moreover, the IFR itself points out that the assumption of 12

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<sup>13</sup> 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).

years of service life is uncertain and needs further investigation.<sup>14</sup> The IFR depreciation procedure is associated with an implicit depreciation rate that fluctuates over time. This implicit depreciation rate can be calculated by re-arranging a standard capital accumulation equation:

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

$$\delta_t = 1 - \frac{R_t - I_t}{R_{t-1}}$$

$R_t$  is the stock of robots at year-end,  $I_t$  is the number of robots installed within a year, and  $\delta_t$  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 7a shows summary statistics for the implicit depreciation rate of total robot stocks by geographical class. At survey item level, the mean depreciate rate between 1993 and 2019 is equal to 4% per year. The global robot stock exhibits a mean implicit depreciation rate of about 7% per year.

To compute implicit depreciation rates also 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.

<<< insert Tables 7a, 7b and 7c here >>>

This explains why implicit depreciates 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 7b shows summary statistics for implicit depreciation rates by IFR industry classes that add up to aggregate (roughly two-digit level). Table 7c shows summary statistics for implicit depreciation rates by main IFR application classes.

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<sup>14</sup> 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).

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 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 5a 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 8a, robot stocks constructed using PIM with a depreciation rate of 5% most closely match the evolution of the respective IFR robot stocks. Figures 5b and 5c 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).

<<< insert Figures 5a, 5b and 5c here >>>

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 for example installed 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 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).<sup>15</sup>

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 also included dedicated machinery 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 industry "Automotive parts" (IFR class 293) are not further disaggregated into the specific types of automotive parts. Data 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. 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 through 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 as well always equal to zero 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 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.

Seventh, data availability at industry-level is limited for most countries, especially in the initial years of the data set. Disaggregated industry data are available for eight countries only over the full period of the data set: 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 data set is available for ten countries – the same eight countries as for industry-level data plus Austria and Denmark.

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<sup>15</sup> It is questionable, however, whether these robots would occur at all in the WRIR dataset because the IFR classifies autonomous mobile robots with less than three axes and/ or without manipulation capabilities as service robots. And 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) and robotic devices (IFR 2020, 23-24).

### 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 using IFR data. They further use Comtrade data on robot exports to scrutinize the effect of aging demographics on the domestic development 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 little missing values. 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 litres, or no quantity is reported at all.

<<< insert Tables 8a and 8b here >>>

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 8a and 8b show the correlation between IFR installations and Comtrade data separately within each country, supplemented by 95% confidence intervals. Figures 6a and 6b 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.

<<< insert Figures 6a and 6b here >>>

Table 9 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. 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.<sup>16</sup> 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) and Italy (mean difference = -1,941.2), this outcome is not a big surprise as both 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. The finding is more surprising for New Zealand and the Republic of Korea as they do not host any of the major producers of industrial robots. According to IFR data, the Republic 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. Also for other important markets of industrial robots, the deviations between IFR and Comtrade figures are 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 also 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 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.<sup>17</sup>

<<< insert Table 9 here >>>

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<sup>16</sup> 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.

<sup>17</sup> 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 data set 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.

<<< insert Figure 7 here >>>

Comtrade also provides information on import market values. Using the quantity of imports less re-imports given by Comtrade one can easily calculate average unit prices. This has the advantage that prices 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. Monetary import values itself do not have many missings but the quantities reported by Comtrade have, so 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 7 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. 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 does not report UK prices after 2018 anymore. Strikingly, the unit prices based on IFR data are higher except for Korea. One can only speculate as why this is so. Bearing in mind that the Comtrade unit price is also an average price with no information to the size or the quality of the robot, 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 price 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 has to 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.

While IFR and Comtrade provide standardized and internationally comparable data for many countries the evolution of robot exposure within individual countries has also been studied and analyzed with data from particular firm-level surveys. An early example for this alternative empirical strategy is the investigation by Jäger et al. (2015). It is based on 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. In order 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 are able to 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.

Three more recent examples of the firm-level perspective that can be found in the studies by Cheng et al. (2019) for China, by Deng et al. (2020) for Germany and by Koch et al. (2021) for Spain 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 data set 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 data set 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.) Koch et al. (2021) work with a panel data set 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. The results that are derived with these firm-level data on the impact of robot exposure on employment and output are very similar, however, to those from studies 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.

## **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 data set 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 and 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 had become available as early as 2017. Graetz/Michaels (2018) are the authors of the second very influential paper with a major focus on the productivity effects of industrial robots.

In the following we aim at reviewing this very recent strand of robot research literature in four different, but closely related areas: robot adoption and industrial organization, productivity and growth, employment and wages as well as demographics, health and politics. Regarding the specific aspects of the use of the IFR data set in the different research papers we refer to the overview in Table 10 where we document the main specificities of the studies and point out in particular how the authors handled some of the difficult issues of the data.

<<<< insert Table 10 here >>>>

### **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. These aspects are treated in papers by OECD (2019), Keisner et al. (2016), Nuccio et al. (2020), López-Sánchez et al. (2020), Jungmittag (2020), Cséfalvay (2020), Cséfalvay/Gkotsis (2020), Faber (2018), Carbonero et al. (2018), Krenz et al. (2018), Fernández-Marcías et al. (2020) and Jung / Lim (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 the operational stock. 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 adoption, many other OECD countries even had negative rates. An extreme case is Russia being the only country where after the fall of 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." Keisner et al. (2016) looked at the robotics clusters in an even broader perspective, distinguishing between robot developers, robot manufacturers, intermediary companies and institutes as well as robot user manufacturers and in-house robotic development facilities of larger robot using firms. All parts of this "robotization" chain are characterized by strong geographical concentration and it is unclear how upgrading of other regions can take place and to what extent public policy measures could be helpful in this process.

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 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. 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 sparse regions in Spain, Italy and Scotland, which started from a very low provision of robots, show also 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 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 two sub-periods 1993-2005 and 2005-2015 that are divided by the large EU enlargement of May 1<sup>st</sup>, 2004. While in the first subperiod no convergence of robot densities could be identified, relatively fast conditional and unconditional convergence occurred in for 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 just one sector, namely 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 and in a case study for Mexico by Faber (2018). 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 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 the respective robot densities, they find evidence for a strong association between re-shoring and automation within countries as well as within sectors. Carbonero et al. (2018) who use IFR data for 41 countries and 15 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. Faber's (2018) study confirms the re-shoring result from investigating 1,806 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. e 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. And 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 the 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), building on the global robotization chain model by Keisner et al. (2016) and using IFR data for the period 1995-2016, point out the following

patterns in a global and intra-European perspective: Five countries - Japan, Korea, Germany, the US 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, Germany is very strong in robot manufacturing and robot deployment, the USA has its firm competitive advantages in robotics development, and at present China is a rival 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 the fact that they are equally strong 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 concerning the in-house robotics development, but they 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 where work is more routine and manual, where there are fewer highly educated workers and where wages and unionisation rates are higher. This seems to underline that robotization is not a revolutionary new phenomenon but a traditional response to increasing unit labor costs as it is known since the beginning of the industrial. 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. It is also positively related to the proportion of manufacturing workers in the total labor force and to the firms' capacity to adopt new technology.

### **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 data set with 17 countries and 14 industries 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 the “unspecified” category. They find a positive relationship between robot densification (expressed as 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 significantly. These baseline results are refined, discussed and qualified by CEBR (2017), Dauth et al. (2021), Jungmittag/Pesole (2019), Kromann et al. (2020) and Ghodsi et al. (2020). The growth effect of robots is particularly studied in a recent paper by Jurkat et al. (2021).

The study by CEBR (2017) that looks at 23 OECD countries, including the US and the UK, over the period 1993-2015 confirms the baseline result in all regards. Dauth et al. (2021) also confirm the positive impact of automation on labor productivity in Germany.<sup>18</sup> Kromann et al. (2020) use IFR data from IFR on the robot stock for the period 2004-2007 in 10 manufacturing industries of 9 countries in order 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 data set. 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 particular 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 value chains. Their results show that about 0.8 per cent 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. When considering value added growth, it becomes apparent that advanced economies - due to their higher share of value added in the world economy - provide the largest contribution.

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

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<sup>18</sup> 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. (2021) 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.

a robot and non-robot capital stock. This makes it necessary 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.

#### 4.4 Employment and wages

When the increase in the automation of industrial production by robots started, this immediately led to the question what effects this development might have on the industrial labor market in terms of employment and wages. From various perspectives, with various 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), Dahlin et al. (2019), Chiacchio et al. (2018), Giuntella /Wang (2019), Dauth et al. (2021), Aghion et al. (2019), Leigh et al. (2018), Carbonero et al. (2018), Anelli et al. (2019b), Aksoy et al. (2020) 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 and 19 industries in the US 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. This exposure is constructed as the sum of all increases in use of robots per thousand workers in the individual industries divided by the baseline value of employment within the respective industry and then summed up over all industries with employment shares as weights. The commuting zone 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. The following particularities in the use of robot data from IFR must be pointed out: Firstly, within the 11 industry sectors that 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 one thousand worker decreases the employment-to-population ratio by 0.39 percentage points and average wages by 0.77 % in a commuting zone relative to one without exposure to robots. These numbers imply that one robot per thousand workers would actually substitute for about six workers. 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.

Graetz/Michaels (2018) in contrast, did not find an overall employment effect of increased robot use within the same period in their cross-country, cross-industry study. However, they confirm the result that increased robot use lowers employment for low-skilled occupations. Dahlin (2019) also examines the effect of industrial robots on occupations in the United



States 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 an increased use of robots is associated with positive changes in the employment share of non-routine analytic jobs and negative changes in the share of routine manual jobs.

Borjas/Freeman (2019) compare the labor market effects of robots and of immigrants in the US. 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. As this 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 suggesting that one industrial robot is comparable to 2 to 3 human workers and even up to 3 to 4 in particular groups.

Chiacchio et al. (2018) apply the community zone approach for a study of 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 regional exposure of robots in industry  $j$  is proportional to the regional employment in the respective industry. The results support a negative impact of robots on employment. However, the effect is smaller than in the US. In the analyzed European countries one additional robot reduces the employment-to-population ratio only by 0.16-0.20 percentage points, thus by one half of the value for the US. One obvious explanation is the more liberalized labor market in the US and the much more active public labor market policy in the European countries. The authors find only mixed results for the impact of industrial robots on wages. Dauth et al. (2021) could not confirm that in Germany for the period 1994-2014 robots were major job killers. Rather they led to a change in the composition of employment, where a significant reduction in manufacturing job was offset or even slightly overcompensated 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. Aghion et al. (2019) investigate the effect of robotization on employment in France over the period 1994-2014. They show that robotization reduced aggregate employment at the regional employment zone level, but also that non-educated workers are more negatively affected by robotization than 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 initial 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 commuting zone approach as well as the exposure to robots measure. Exposure to robots in a commuting zone 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 commuting zones 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 commuting zone 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 in order 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 commuting zones. 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 US 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 of 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%. Third, robots in developed countries reduce off-shoring, which has depressed employment in emerging economies by 5% between 2005 and 2014.

Three studies with a focus on Europe and the US, respectively, look in particular 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, and 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 US, 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 US, 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 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 Abeliasky/Prettner (2017), Abeliasky/Beulmann (2019), Acemoglu/Restrepo (2021), Anelli et al. (2019a; 2019b), Gihleb et al. (2020), Gunadi/Ryu (2020) and Frey et al. (2018).

The intensive use of robots in some highly industrialized countries might economically be seen as a promising strategy to face a long-term decline in population growth that sooner or later also transforms into a shrinking workforce. The fact that the robot adoption in the US 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. Abeliasky/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 are able to 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 commuting zones estimation. Middle-aged workers are identified as the most scarce 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 the US metropolitan areas Gunadi/Ryu (2020) 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 US 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 US. 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.

Anelli et al. (2019b) examine how exposure to robots and its consequences on job stability and economic uncertainty have affected individual demographic behavior such as marriages, divorces or fertility. Their empirical methodology for the US follows the commuting zone 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 increasing automation of production. Zones 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 outcome 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 community zone exposure 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. Frey et al. (2018) even make robots responsible for the victory of Donald Trump in the 2016 US presidential elections. Working again with the commuting zone 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 adaption 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 extreme socio-political impact of the robot revolution: if the exposure to robots had not increased in the immediate years before the 2016 presidential elections, 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 transmission 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 longer-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 the effects of the 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 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 robots. Moreover, availability of data disaggregated by industry and application has significantly improved since 2005, visible in a sharply declining share of robots with 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 necessarily easy but we believe that 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 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 EU KLEMS) would require, however, some kind of quality adjustment.

From the research results that are based on IFR data one learns that the effects of the rise of robots are multi-faceted. The patterns of adoption and the changes in industrial organization as well as the 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 US the rise of robots caused a significant reduction in industrial employment and wages, nothing comparable could be detected in Europe. The striking international differences to this ongoing development seem to indicate that economic policy measures as well as social institutions and traditions play a role in mitigating 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. 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. Kilic/Marin (2020) speculate that the era of "hyper-globalisation" had already come to an end after the global financial crisis and that this has also led to a reduction in global value chains that profited from cheap labor outside the industrialized countries. 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. Whether these trends characterize the coming decade and what this could mean for the economy, the society and for politics, will certainly become visible in the data provided by IFR.

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## Appendix

**Table 1: Overview of national robotics associations**

| <b>Table A1: National robotic associations</b> |                   |  |
|--|-------------------|--|
|  | <i>Country</i>    | <i>Association</i>   |
| 1  | China             | China Robot Industry Allinace (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

**Table 2: IFR Geographical classes and availability of installation data**

| <b>Table A2: IFR Geographical classes and data availability</b> |                 |                                   |                           |                             |                               |                                  |
|---|-----------------|-----------------------------------|---------------------------|-----------------------------|-------------------------------|----------------------------------|
| <i>Parent Class</i>   | <i>IFR Code</i> | <i>Geographic Entity</i>          | <i>Geographical level</i> | <i>Aggregate data since</i> | <i>Data by industry since</i> | <i>Data by application since</i> |
|   | 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 <sup>1</sup>                | Survey item               | 1999                        | 2004                          | 2004                             |
| RAM   | CO              | Colombia <sup>1</sup>             | Survey item               | 1999                        | 2004                          | 2004                             |
| RAM   | PE              | Peru <sup>1</sup>                 | Survey item               | 1999                        | 2004                          | 2004                             |
| RAM   | PR              | Puerto Rico <sup>1</sup>          | Survey item               | 1999                        | 2004                          | 2004                             |
| RAM   | VE              | Venezuela <sup>1</sup>            | 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 <sup>1</sup>            | Survey item               | 2004                        | 2004                          | 2004                             |
| OSAS  | KP              | North Korea <sup>1</sup>          | Survey item               | 2005                        | 2005                          | 2005                             |
| OSAS  | MO              | Macau <sup>1</sup>                | 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 <sup>1</sup>               | Survey item               | 2005                        | 2005                          | 2005                             |
| RAS   | OM              | Oman <sup>1</sup>                 | Survey item               | 2005                        | 2005                          | 2005                             |
| RAS   | PK              | Pakistan <sup>1</sup>             | Survey item               | 2005                        | 2005                          | 2005                             |
| RAS   | QA              | Qatar <sup>1</sup>                | Survey item               | 2005                        | 2005                          | 2005                             |
| RAS   | SA              | Saudi Arabia <sup>1</sup>         | Survey item               | 2005                        | 2005                          | 2005                             |
| RAS   | AE              | United Arab Emirates <sup>1</sup> | Survey item               | 2005                        | 2005                          | 2005                             |
| RAS   | UZ              | Uzbekistan <sup>1</sup>           | 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 <sup>1</sup> | Survey item   | 2005 | 2005 | 2005 |
| YUG | CR  | Croatia <sup>1</sup>            | Survey item   | 2005 | 2005 | 2005 |
| YUG | RS  | Serbia <sup>1</sup>             | 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 <sup>1</sup>            | Survey item   | 2005 | 2006 | 2006 |
| OEE | BG  | Bulgaria <sup>1</sup>           | Survey item   | 2005 | 2006 | 2005 |
| OEE | EE  | Estonia <sup>1</sup>            | Survey item   | 2003 | 2004 | 2004 |
| OEE | LV  | Latvia <sup>1</sup>             | Survey item   | 2005 | 2005 | 2005 |
| OEE | LT  | Lithuania <sup>1</sup>          | Survey item   | 2004 | 2006 | 2006 |
| OEE | MD  | Moldova <sup>1</sup>            | Survey item   | 2005 | 2005 | 2005 |
| OEE | UA  | Ukraine <sup>1</sup>            | 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 <sup>1</sup>            | Survey item   | 2004 | 2006 | 2005 |
| OEU | IE  | Ireland                         | Survey item   | 2002 | 2006 | 2005 |
| OEU | IL  | Israel                          | Survey item   | 1999 | 2005 | 2005 |
| OEU | MT  | Malta <sup>1</sup>              | Survey item   | 2005 | 2005 | 2005 |
| EU  | EUU | Europe unspecified              | Survey item   | 1993 | 2006 | 2006 |
| WR  | OT  | Others not specified            | Survey item   | 2006 | 2006 | 2006 |

Column about aggregate data availability indicate 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 <sup>1</sup> because no installations might be reported). <sup>1</sup>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 3a: Average unit prices of industrial robots in thousand US\$**

| 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 | 63.81 | 64.35 | 48.50  | 48.50  |

| 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              | na     | 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



**Table 3b: Price index for industrial robots at current prices in national currencies**

| year | USA                  |                  | Germany              |                  | France               |                  |
|------|----------------------|------------------|----------------------|------------------|----------------------|------------------|
|      | 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                | 61.30            | 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 | 46.50                | 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 | 34.30                | 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            |

| year | Italy                |                  | UK                   |                  | Sweden               |                  |
|------|----------------------|------------------|----------------------|------------------|----------------------|------------------|
|      | 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                | 81.40            |
| 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            | 58.90                | 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                | 25.20            | 44.30                | 18.40            | 56.20                | 23.30            |

**Source:** IFR

**Table 3c: Price indices for industrial robots at fixed conversion rates in US\$ 1990**

| year | USA                  |                  |
|------|----------------------|------------------|
|      | 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                | 24.40            |
| 2003 | 55.10                | 24.40            |
| 2004 | 54.40                | 23.10            |
| 2005 | 53.50                | 22.10            |

**Source:** IFR

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

| IFR                 |                 |  | ISIC Rev. 4    |                            |  |
|---------------------|-----------------|--|----------------|----------------------------|--|
| <i>Parent class</i> | <i>IFR Code</i> | <i>Title</i>   | <i>Section</i> | <i>Divisions or Groups</i> | <i>Description</i>   |
| -                   | 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 U Manufacture of beverages<br>U Manufacture tobacco products  |
| D                   | 13-15           | Textiles   | C              | 13-15                      | Manufacture of textiles U Manufacture of wearing apparel<br>U Manufacture of leather and related products  |
| D                   | 16              | Wood and furniture   | C              | 16 U 31                    | Manufacture of wood and of products of wood and cork, except furniture;<br>manufacture of articles of straw and plaiting materials<br>U Manufacture of furniture   |
| D                   | 17-18           | Paper  | C              | 17-18                      | Manufacture of paper and paper products<br>U Printing and reproduction of recorded media   |
| D                   | 19-22           | Plastic and chemical products  | C              | 19-22                      | Manufacture of coke and refined petroleum products<br>U Manufacture of chemicals and chemical products<br>U Manufacture of pharmaceuticals, medicinal chemical and botanical<br>products U Manufacture of rubber and plastics products |
| 19-22               | 19              | Pharmaceuticals, cosmetics   | C              | 21 U 2023                  | Manufacture of pharmaceuticals, medicinal chemical and botanical products<br>U Manufacture of soap and detergents, cleaning and polishing preparations,<br>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<br>U Manufacture of chemicals and chemical products (without class 2023)  |
| 19-22               | 22 U 2932       | Rubber and plastic products (non-automotive)<br>U Rubber and plastic (AutoParts) | C              | 22                         | Manufacture of rubber and plastics products  |
| 19-22               | 229             | Chemical products, unspecified   | C              | xxx                        | xxx  |
| D                   | 23 U 2934       | Glass, ceramics, stone, mineral products (non-automotive)<br>U Glass (AutoParts) | C              | 23                         | Manufacture of other non-metallic mineral products   |
| D                   | 24-28           | Metal  | C              | 24<br>U 25<br>U 28         | Manufacture of basic metals<br>U Manufacture of fabricated metal products, except machinery and<br>equipment U 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 U 27                        | Manufacture of computer, electronic and optical products   |
| 26-27 | 275                               | Household/domestic appliances   | C | 275                            | Manufacture of domestic appliances   |
| 26-27 | 271                               | Electrical machinery n.e.c. (non-automotive)  | C | 271<br>U 272<br>U 273<br>U 274 | Manufacture of electric motors, generators, transformers and electricity distribution and control apparatus<br>U Manufacture of batteries and accumulators<br>U Manufacture of wiring and wiring devices<br>U Manufacture of electric lighting equipment |
| 26-27 | 260<br>U 261                      | Electronic components/devices<br>U Semiconductors, LCD, LED   | C | 261                            | Manufacture of electronic components and boards  |
| 26-27 | 262                               | Computers and peripheral equipment  | C | 262<br>U 268                   | Manufacture of computers and peripheral equipment<br>U Manufacture of magnetic and optical media   |
| 26-27 | 263                               | Info communication equipment domestic and professional (non-automotive)   | C | 263<br>U 264                   | Manufacture of communication equipment<br>U Manufacture of consumer electronics  |
| 26-27 | 265                               | Medical, precision, optical instruments   | C | 265<br>U 266<br>U 267          | Manufacture of measuring, testing, navigating and control equipment; watches and clocks<br>U Manufacture of irradiation, electromedical and electrotherapeutic equipment<br>U 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<br>U 2931<br>U 2933<br>U 2939 | Motor vehicles, engines and bodies<br>U Metal (AutoParts)<br>U Electrical/electronic (AutoParts)<br>U Other (AutoParts) | C | 29                             | Manufacture of motor vehicles, trailers and semi-trailers  |
| 29    | 291                               | Motor vehicles, engines and bodies  | C | 291<br>U 292                   | Manufacture of motor vehicles<br>U Manufacture of bodies (coachwork) for motor vehicles; manufacture of trailers and semi-trailers   |
| 29    | 293                               | Automotive parts  | C | xxx                            | xxx  |
| 293   | 2931<br>U 2933<br>U 2939          | Metal (AutoParts)<br>U Electrical/electronic (AutoParts)<br>U 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 U Repair and installation of machinery and equipment   |
| 0   | E    | Electricity, gas, water supply       | D U E                | 35-39                       | Electricity, gas, steam and air conditioning supply<br>U Water collection, treatment and supply U Sewerage<br>U Waste Collection, treatment and disposal activities; materials recovery<br>U Remediation activities and other waste management services  |
| 0   | F    | Construction                         | F                    | 41-43                       | Construction of buildings U Civil engineering<br>U Specialized construction activities   |
| 0   | P    | Education/reserach/development       | P U M                | 85 U 72                     | Education U Scientific research and development  |
| 0   | 90   | All other non-manufacturing branches | G-O<br>\ 72<br>U Q-U | 45-71<br>U 73-84<br>U 86-99 | Wholesale and retail trade; repair of motor vehicles and motorcycles<br>U Transportation and storage<br>U Accommodation and food service activities<br>U Information and communication<br>U Financial and insurance activities U Real estate activities<br>U Professional, scientific and technical activities (without Scientific research and development)<br>U Administrative and support service activities<br>U Public administration and defence; compulsory social security<br>U Human health and social work activities<br>U Arts, entertainment and recreation<br>U Other service activities<br>U Activities of households as employers; undifferentiated goods- and services producing activities of households for own use<br>U Activities of extraterritorial organizations and bodies |
| 0   | 99   | Unspecified                          | xxx                  | xxx                         | xxx  |

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

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

**Table 5: IFR application classes**

| <b>IFR class</b> | <b>Application area</b>                                       | <b>Definitions/ Notes</b>  |
|------------------|---|--|
| <b>110</b>       | <b>Handling operations/ machine tending</b>                   | 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;<br>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  |
| <b>160</b>       | <b>Welding and soldering (all materials)</b>                  |  |
| 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  |
| <b>170</b>       | <b>Dispensing</b>   |  |
| 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  |
| <b>190</b>       | <b>Processing</b>   | 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  |
| <b>200</b>       | <b>Assembling and disassembling</b>                           | 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  |
| <b>900</b>       | <b>Others</b>   |  |
| 901              | Cleanroom for flat-panel display (FPD)                        |  |
| 902              | Cleanroom for semiconductors                                  |  |
| 903              | Cleanroom for others  |  |
| 905              | Others  | Applications not mentioned before  |
| <b>999</b>       | <b>Unspecified</b>  | Application is unknown or hidden for compliance reasons  |

**Source:** IFR (2020)

**Table 6a: 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 6b: 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

**Table 7a: 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

**Table 7b: 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 7c: 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



**Table 8a: 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 8b: 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 9: Comparison between IFR and Comtrade quantities**

| Country       | Obs | IFR installations |         |       |        | Comtrade imports |         |      |        | Difference |         |         |        |
|---------------|-----|-------------------|---------|-------|--------|------------------|---------|------|--------|------------|---------|---------|--------|
|               |     | 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  | -10300.0   | 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   | -16100.0   | 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 10: Overview of research papers using IFR industrial robot data**

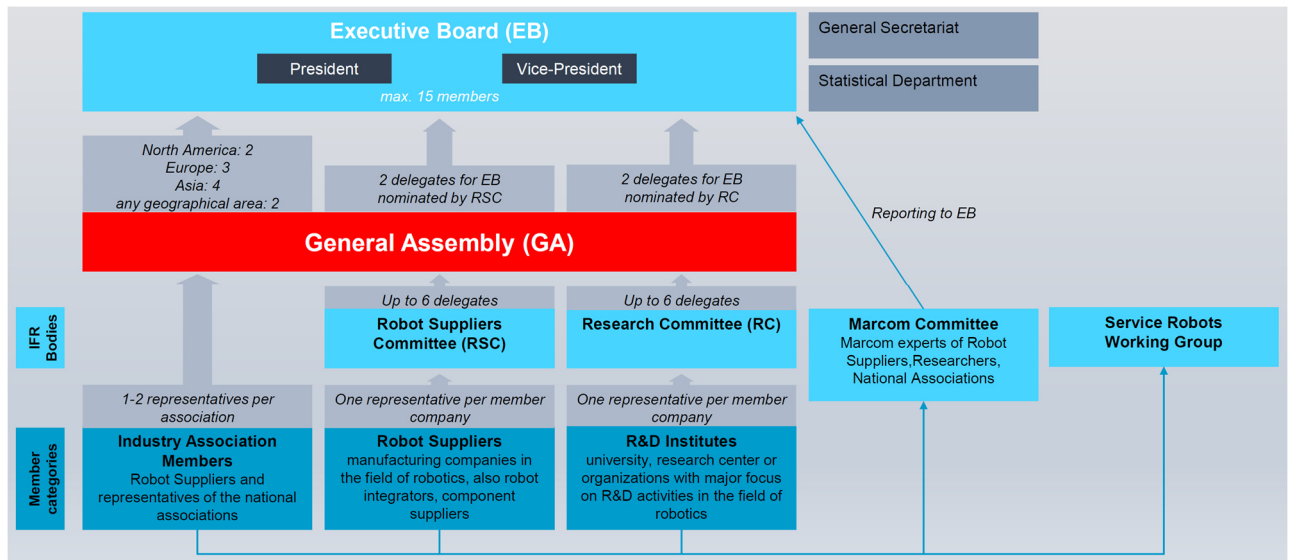
| Paper                      | Period/ Years    | Countries                     | Regions                    | Industries (Manuf. + Non-Manuf.) | Calculation of robot stock  | Definiton of robot intensity  | Robot prices   | Treatment of unspecified robots*  |
|----------------------------|------------------|-------------------------------|----------------------------|----------------------------------|---|---|--|---|
| Abeliansky/Beulmann (2019) | 2002-2014        | Germany                       | /                          | 17 (15+2)                        | PIM 10% (5%, 15% as robustness checks)                              | Robot stock per 1,000 employees (logged)  |  | Omitted   |
| Abeliansky/Prettner (2017) | 1993-2013        | 60 countries                  | /                          | 13 (13+0)                        | PIM 10% (5%, 15% as robustness checks)                              | Robot stock per capita/ Robot stock per 10,000 employees in manufacturing   |  | Omitted   |
| Acemoglu/Restrepo (2020)   | 1993-2007        | USA                           | 722 CZ                     | 19 (13+6)                        | IFR stocks  | Robot stock 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 (allocated to industries in the same proportions as in the classified data) |
| Aghion et al. (2019)       | 1994-2014        | France                        | 297 local employment zones | 19 (13+6)                        | IFR stocks  | Robot stock per 1,000 workers   |  | Omitted   |
| Aksoy et al. (2020)        | 2006, 2010, 2014 | 20 EU countries               | /                          | 12 (8+4)                         | IFR stocks  | Robot stock per 10,000 workers  |  | Omitted   |
| Anelli et al. (2019a)      | 1993-2016        | 14 Western European countries | 192 NUTS-2 regions         | 11 (11+0)                        | IFR stocks  | Robot stock per 100,000 workers   |  | Omitted   |
| Anelli et al. (2019b)      | 2005-2016        | USA                           | 741 CZ                     | 19 (13+6)                        | IFR stocks  | Robot stock per 1,000 workers   |  | Redistributed   |
| Borjas/Freeman (2019)      | 2004-2016        | USA                           | /                          | 26 (20+6)                        | Simple sum of installations over time (PIM 10% as robustness check) | Robot stock per worker  |  | Unspecified shipments prior to 2004 are allocated according to the 2004 industry share    |
| Carbonero et al. (2018)    | 2005-2014        | 41 countries                  | /                          | 14 (9+5)                         | IFR stocks  | Robot stock per 10,000 workers  |  | Omitted   |
| CEBR (2017)                | 1993-2015        | 23 OECD                       | /                          | /                                | Monetary value of IFR stocks in 2010 US\$ PPP                       | Ratio of the monetary value of robot installations to GDP, or in 2010 US\$ PPP & robot stock per million hours worked | Price indices 1993-2015  | N/A   |
| Chiacchio et al. (2018)    | 1995-2007        | 6 EU countries                | 116 NUT2 regions           | 18 (13+5)                        | IFR stocks  | Robot stock per 1,000 workers   | IFR price indices (w & w/o quality adjustment)   | Redistributed   |

|  |                                      |                                     |  |  |   |   |  |  |
|--|--------------------------------------|-------------------------------------|--|--|---|---|--|--|
| <b>Cséfalvay (2020)</b>                | 1995-2013                            | 18 EU countries                     | /  | Automotive industries (Automotive + Other vehicles) vs. Non-automotive industries (all other industries incl. unspecified) | IFR stocks  | Robot stock per 10,000 employees in manufacturing     |  | Unspecified robots are treated as robots which do not belong to manufacturing or automotive industries |
| <b>Cséfalvay/Gkotsis (2020)</b>        | 1995-2016                            | 43 countries                        | /  | /  | IFR stocks  | Robot stock per 10,000 employees in manufacturing     |  | N/A  |
| <b>Dahlin et al. (2019)</b>            | 2010, 2015                           | USA                                 | 327 metropolitan areas                     | /  | Muro (2017)   | Robot stock (logged)                                  |  | N/A  |
| <b>Dauth et al. (2020)</b>             | 1994-2014                            | Germany                             | 402 local labour markets                   | 25 (20+5)  | IFR stocks  | Robot stock per 1,000 workers (full-time equivalents) |  | Omitted  |
| <b>De Vries et al. (2020)</b>          | 2005-2015                            | 37 countries                        | /  | 19 (14+5)  | PIM 10% (5%, 15% as robustness checks)                                      | Robot stock per 1,000 persons employed                | Turnover-based prices of robots for the US   | Omitted  |
| <b>Faber (2018)</b>                    | 1993-2015                            | Mexico                              | 1,806 CZ                                   | 19 (13+6)  | IFR stocks  | Robot stock per worker                                |  | Omitted  |
| <b>Fernández-Marcías et al. (2020)</b> | 1995-2005, 2005-2015                 | European countries                  | /  | 9 (9+0)  | Own method of re-estimation maintaining the 12-year service life assumption | Robot stock per 1,000 workers                         | Estimation of robot prices based on Comtrade data & comparison with IFR price data | Redistributed within own re-estimation method  |
| <b>Frey et al. (2018)</b>              | 2011, 2015                           | USA                                 | 722 CZ                                     | 19 (13+6)  | IFR stocks  | Robot stock per 1,000 workers                         |  | Redistributed  |
| <b>Fu et al. (2021)</b>                | 2004-2016                            | 74 (45 developed, 29 developing c.) | /  | /  | IFR stocks  | Robot stock over total labor force                    |  | N/A  |
| <b>Ge &amp; Zhou (2020)</b>            | 1993-2015                            | USA                                 | 722 CZ                                     | 19 (13+6)  | IFR stocks  | Robot stock per 1,000 workers                         |  | Redistributed  |
| <b>Ghaleb et al. (2020)</b>            | 2005-2011 (USA), 1994-2016 (Germany) | USA, Germany                        | 596 CZ                                     | 19 (13+6)  | IFR stocks  | Robot stock per 1,000 workers                         |  | Redistributed  |
| <b>Ghodsí et al. (2020).</b>           | 2000-2014                            | 43 countries                        | /  | 17 (11+6)  | IFR stocks  | Robot stock   |  | Omitted  |
| <b>Giuntella / Wang (2019)</b>         | 2000-2016                            | China                               | 261 prefectural level cities; 31 provinces | 18 (12+6)  | IFR stocks  | Robot stock per 1,000 workers                         |  | Omitted  |
| <b>Graetz/Michaels (2018)</b>          | 1993-2007                            | 17 countries                        | /  | 14 (9+5)   | PIM 10% (5%, 15% as robustness check)                                       | Robot stock per million hours worked                  |  | Omitted  |
| <b>Gunadi/Ryu (2020)</b>               | 2006-2017                            | USA                                 | 93 metropolitan areas                      | 17 (11+6)  | IFR stocks  | Robot stock per 1,000 workers (logged)                |  | Redistributed  |
| <b>Jung/Lim (2020)</b>                 | 2001-2017                            | 42 countries                        | /  | /  | IFR stocks  | Annual shipment of robots per 10,000                  |  | N/A  |

|                                    |                                 |                 |  |           |                                       |  |  |               |
|------------------------------------|---------------------------------|-----------------|--|-----------|---------------------------------------|--|--|---------------|
|                                    |                                 |                 |  |           |                                       | manufacturing workers  |  |               |
| <b>Jungmittag (2020)</b>           | 1995-2015                       | 24 EU countries | /  | 9 (9+0)   | PIM 5%, 10%, 15%                      | Robot stock per 1,000 workers  |  | Redistributed |
| <b>Jungmittag/Pesole (2019)</b>    | 1995-2015                       | 12 EU countries | /  | 9 (9+0)   | PIM 5%, 10%, 15%                      | Robot stock per million Euros non-ICT capital input                  |  | Redistributed |
| <b>Jurkat et al. (2021)</b>        | 1993-2007                       | 10 countries    | /  | 9 (9+0)   | PIM 10% (5%,15% as robustness checks) | Value of robot stocks in 1995 US\$                                   | User costs                                     | Redistributed |
| <b>Krenz et al. (2018)</b>         | 2000-2014                       | 43 countries    | /  | 9 (9+0)   | IFR stocks                            | Robot stock per 1,000 workers & robot stock per million hours worked |  | Omitted       |
| <b>Kromann et al. (2020)</b>       | 2004-2007                       | 9 countries     | /  | 10 (10+0) | IFR stocks                            | Robot stock per million Euros non-ICT capital                        | IFR price indices (w & w/o quality adjustment) | Omitted       |
| <b>Leigh et al. (2020)</b>         | 2010-2015                       | USA             | 352 core-based statistical areas (CBSAs) | 13 (13+0) | IFR stocks                            | Robot stock per 1,000 workers  |  | Redistributed |
| <b>López-Sánchez et al. (2020)</b> | 1993-2016                       | 71 countries    | /  | /         | IFR stocks                            | Robot stock per 10,000 people of active population                   |  | N/A           |
| <b>Nuccio et al. (2020)</b>        | 1993-2015                       | 5 EU countries  | 137 NUTS-2 regions                       | 15 (11+4) | PIM 10%                               | Robot stock per 1,000 inhabitants                                    |  | Omitted       |
| <b>OECD (2019)</b>                 | 1993-2000, 2001-2007, 2008-2014 |                 | /  | 18 (13+5) | PIM 10%                               | Stock of robots  | Average unit prices 1998-2008                  | Omitted       |

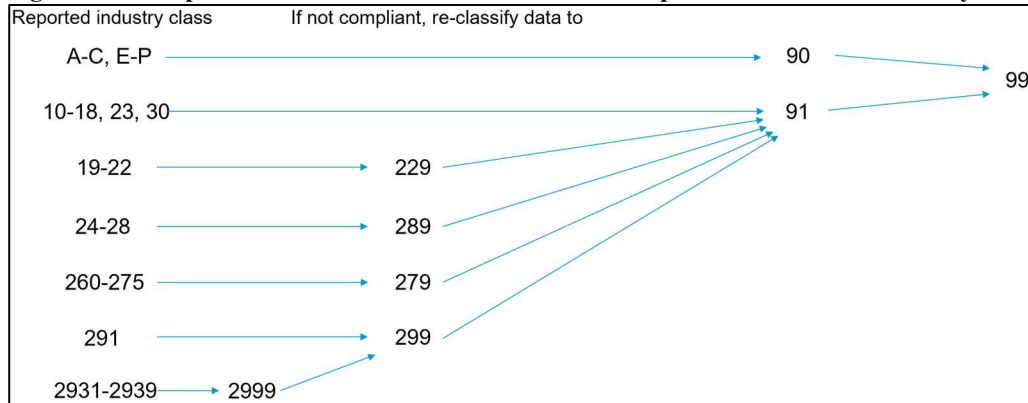
\*Treatment of unspecified robots is not relevant for analyses based on aggregate robot data at country-level instead of country-industry level. Therefore, for the respective papers this column is labelled by “not applicable” (N/A). Redistribution of unspecified robots indicates that unspecified robots are allocated to industries based on industry shares in specified data, 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.

**Figure 1: Organizational structure of IFR**



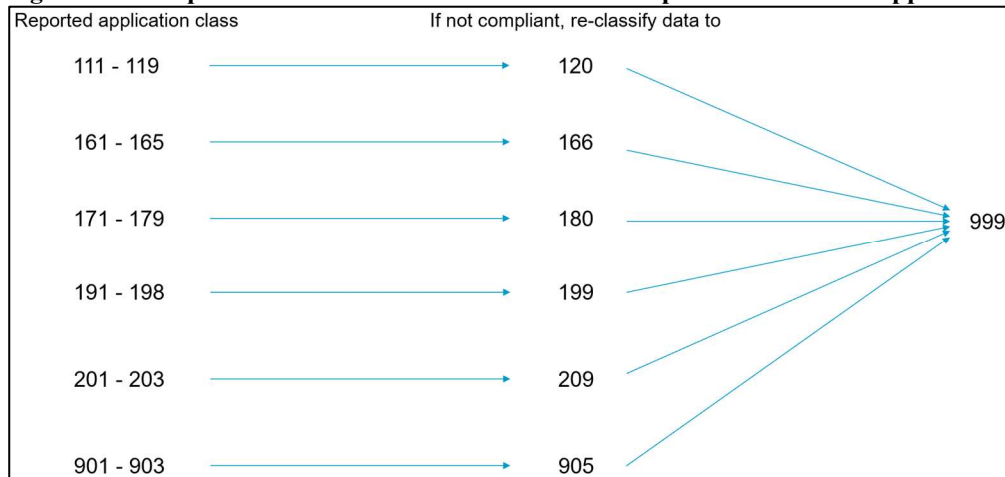
**Source:** IFR (internal document)

**Figure 2a: Compliance mechanism M1 – re-classification procedure for IFR industry classes**



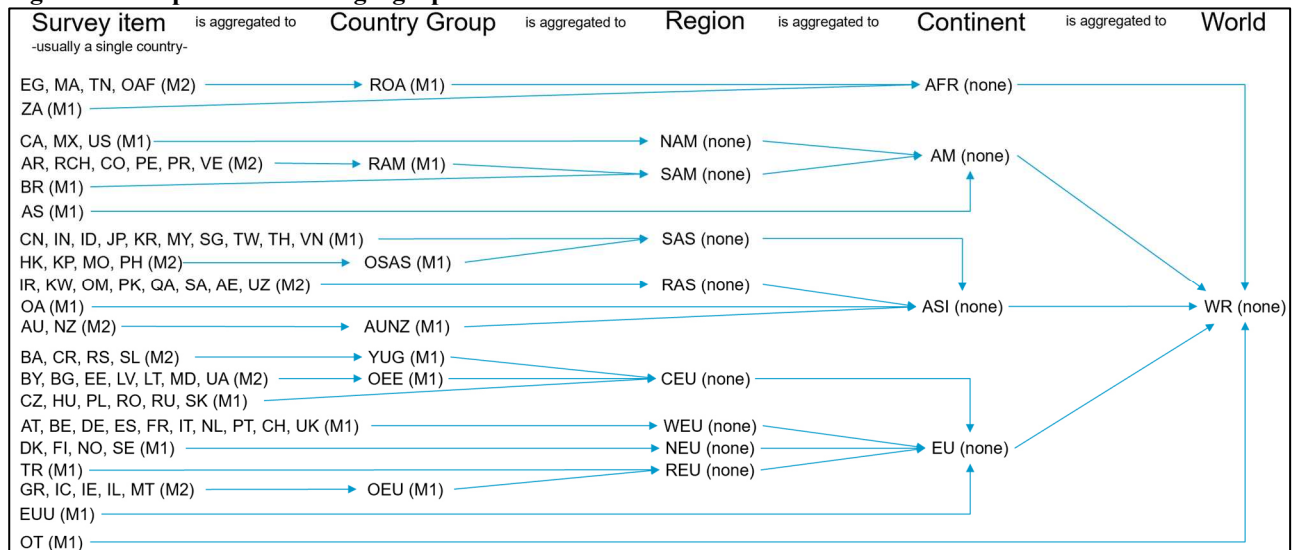
**Source:** IFR (internal document)

**Figure 2b: Compliance mechanism M1 – re-classification procedure for IFR application classes**



**Source:** IFR (internal document)

**Figure 3: Compliance for IFR geographical classes**

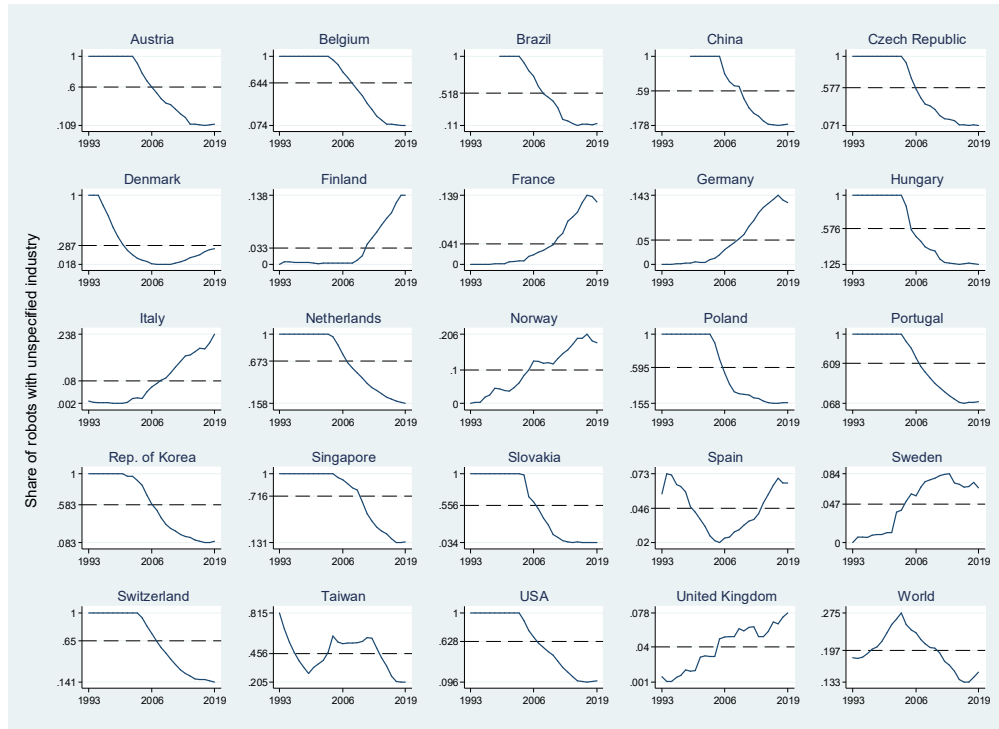


The compliance mechanism applied to the respective geographical entity is shown in parentheses

**Source:** IFR (internal document)

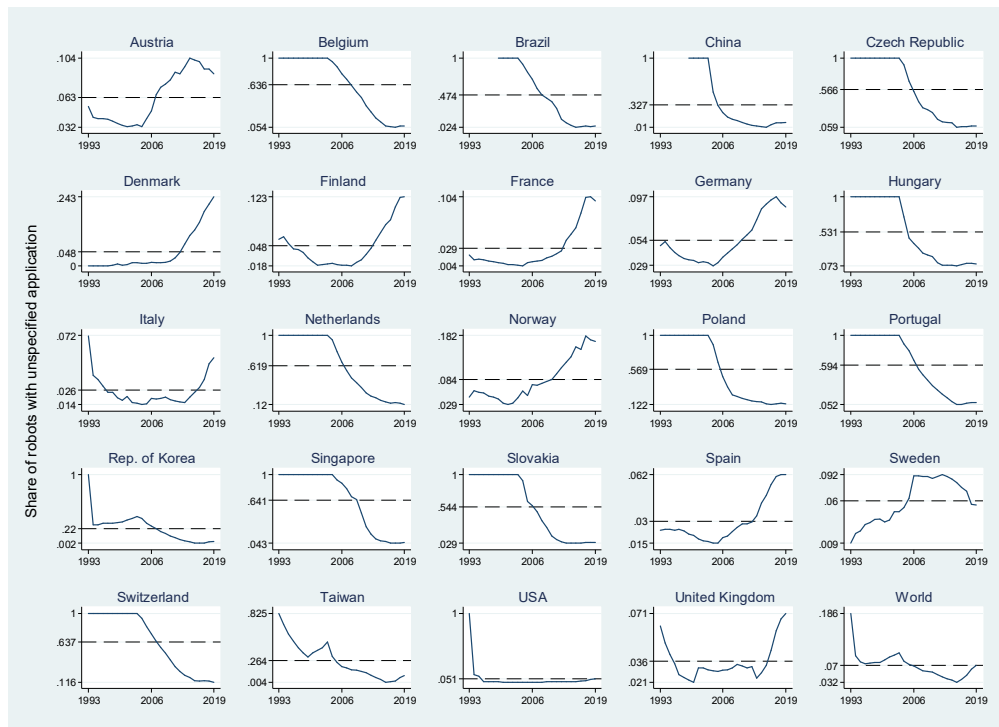


**Figure 4a: Share of robots with unspecified industry in total robot stocks over time**



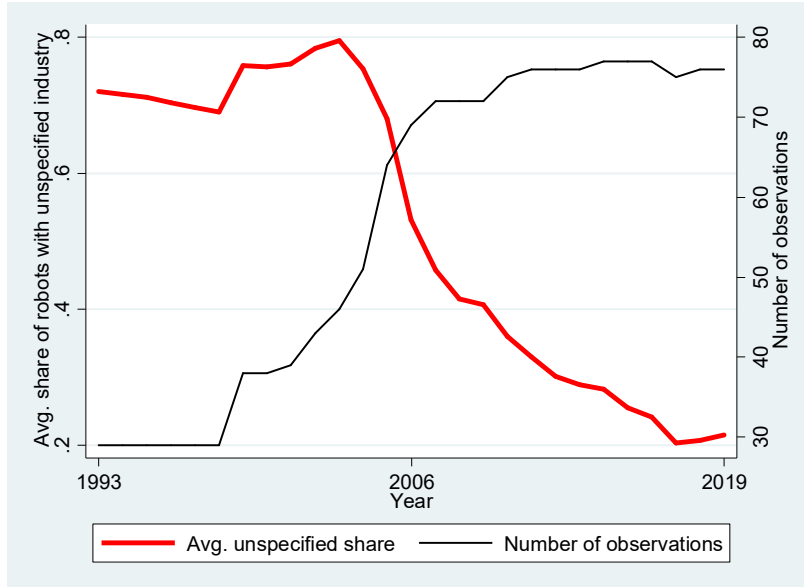
**Source:** Own calculations based on IFR data

**Figure 4b: Share of robots with unspecified application in total robot stocks over time**



**Source:** Own calculations based on IFR data

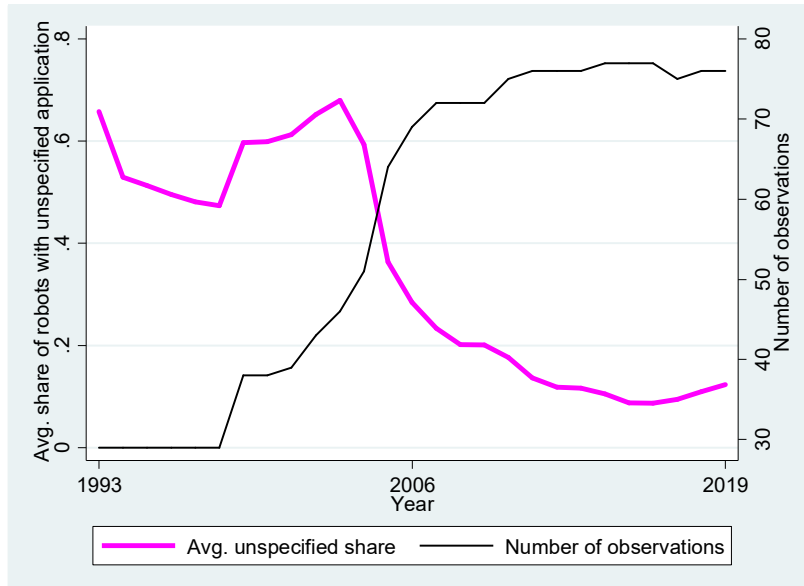
**Figure 4c: Average share of robots with unspecified industry at survey item level over time**



Japan, Russia, and Other Asia are excluded from the survey item level.

**Source:** Own calculations based on IFR data

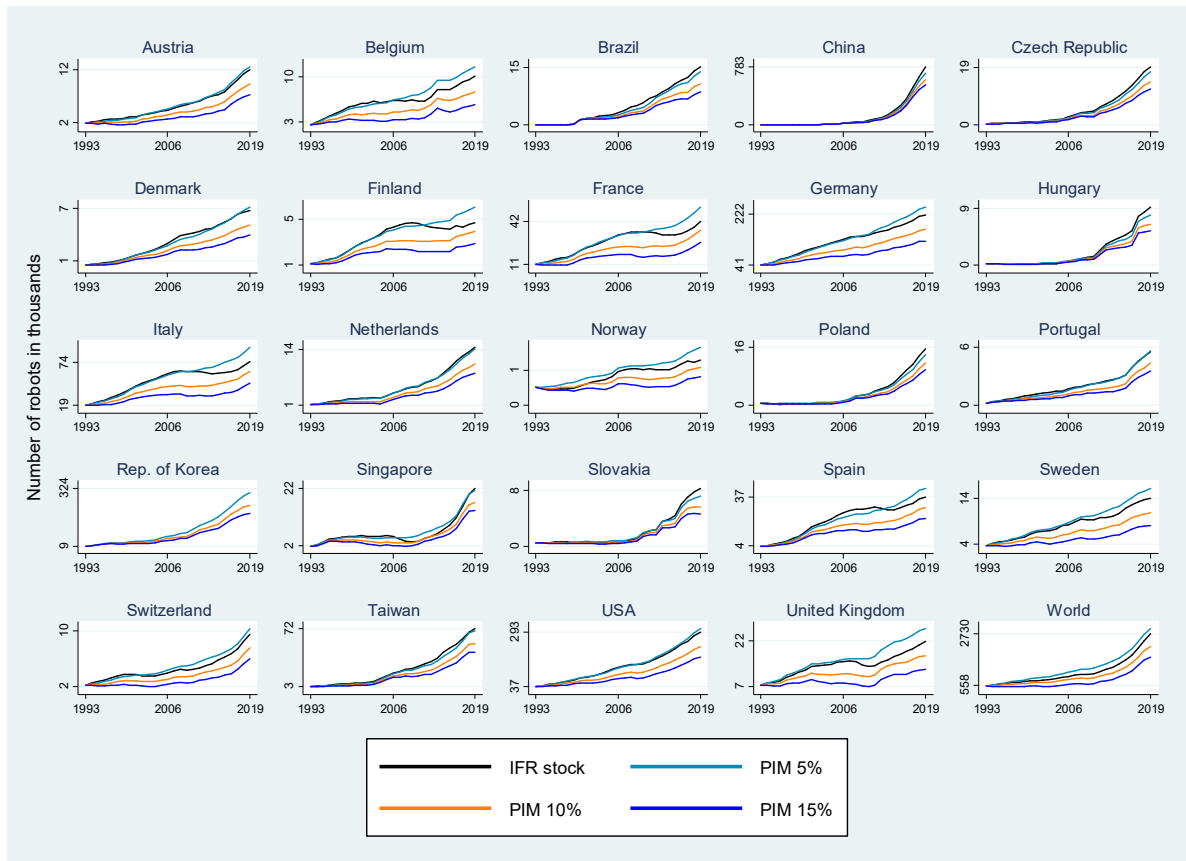
**Figure 4d: Average share of robots with unspecified application at survey item level over time**



Japan, Russia, and Other Asia are excluded from the survey item level.

**Source:** Own calculations based on IFR data

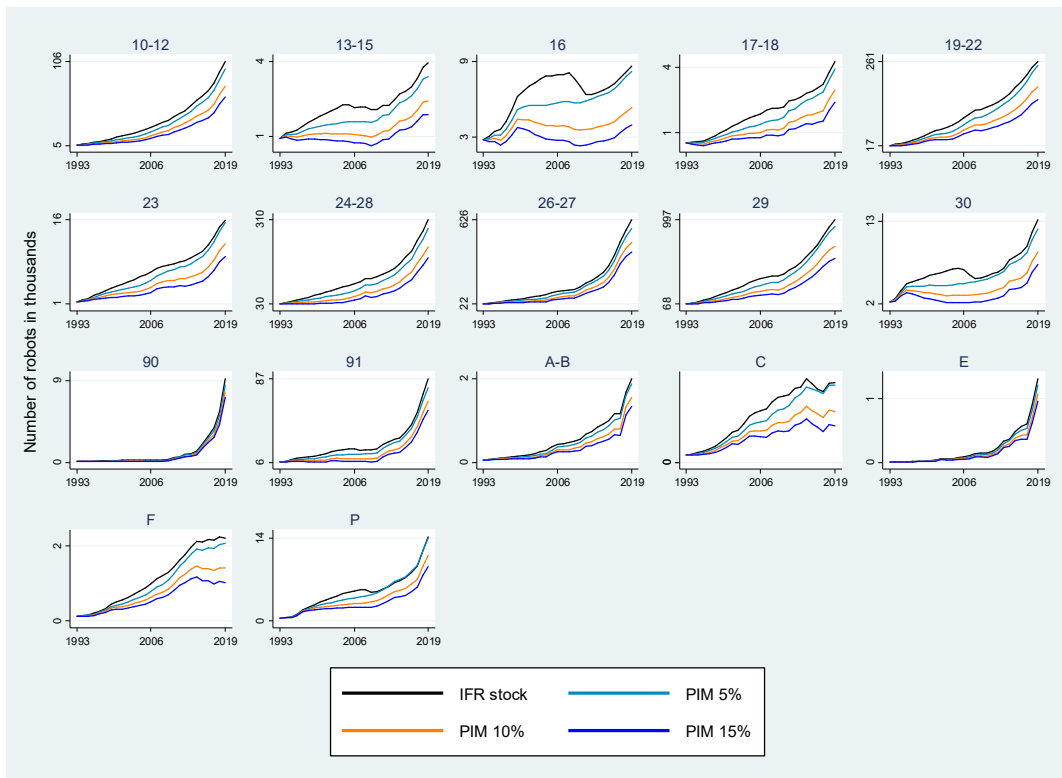
**Figure 5a: Evolution of total robot stocks over time according to IFR method and to PIM**



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.

**Source:** IFR data and own calculations

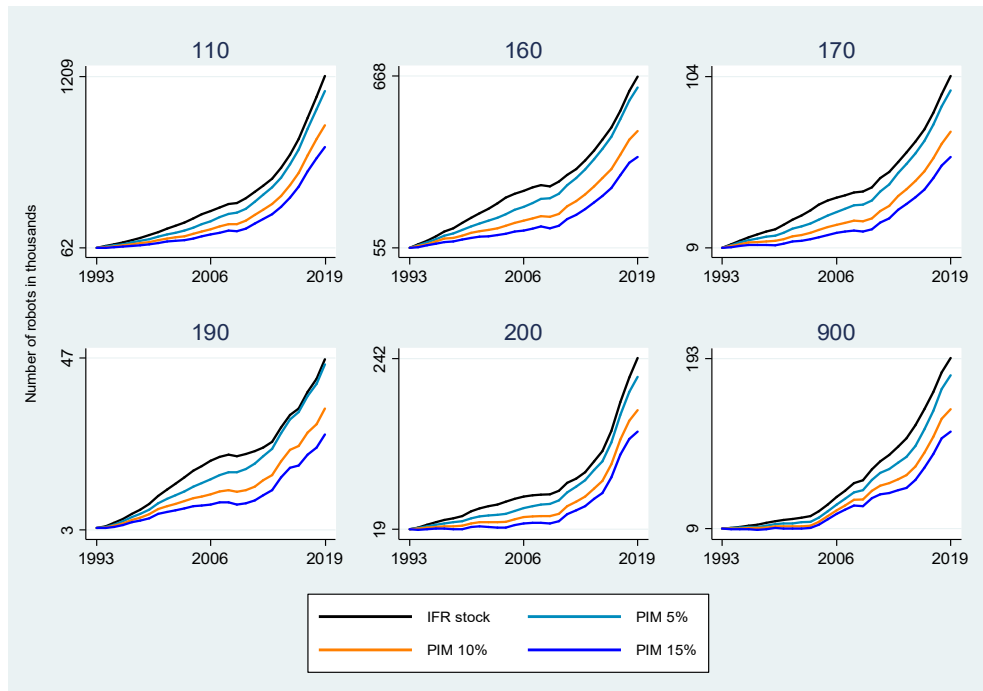
**Figure 5b: Evolution of aggregated robot stocks for IFR industry classes over time according to IFR method and to PIM**



The perpetual inventory method (PIM) is applied with three different depreciation rate: 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

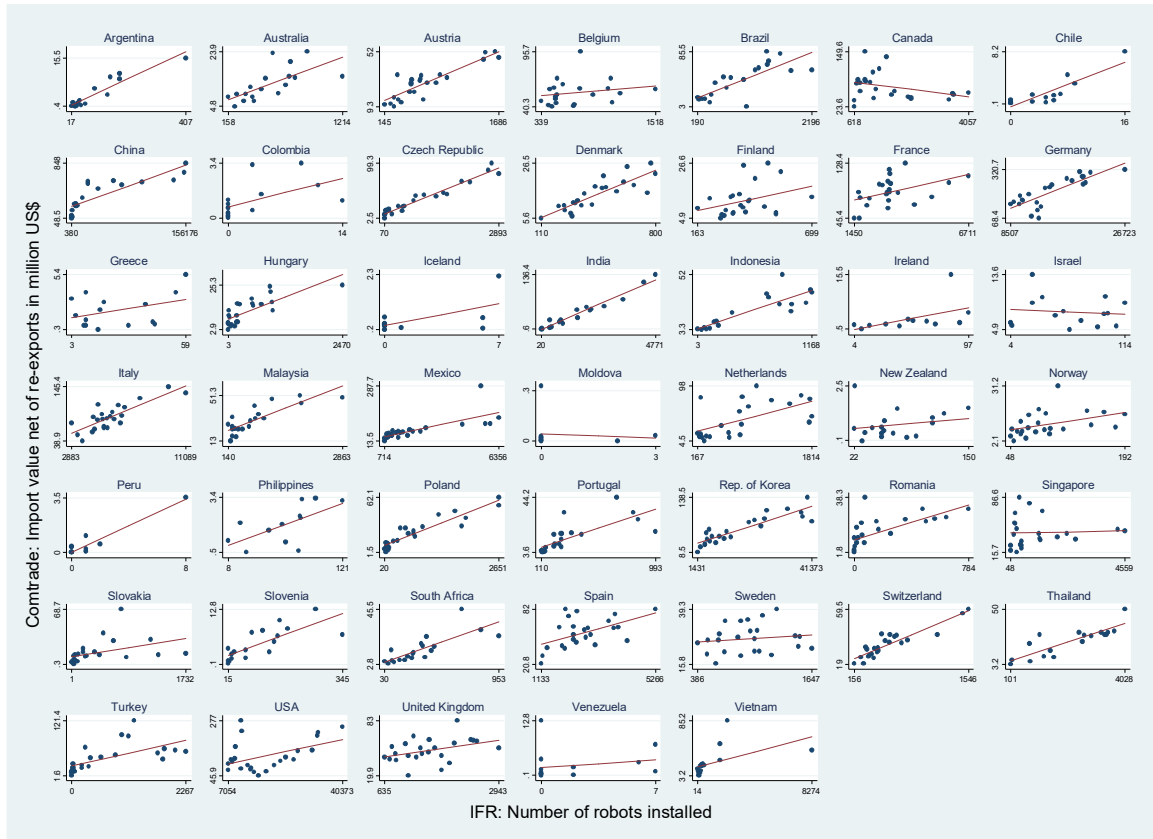
**Figure 5c: Evolution of aggregated robot stocks for main IFR application classes over time according to IFR method and to PIM**



The perpetual inventory method (PIM) is applied with three different depreciation rate: 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

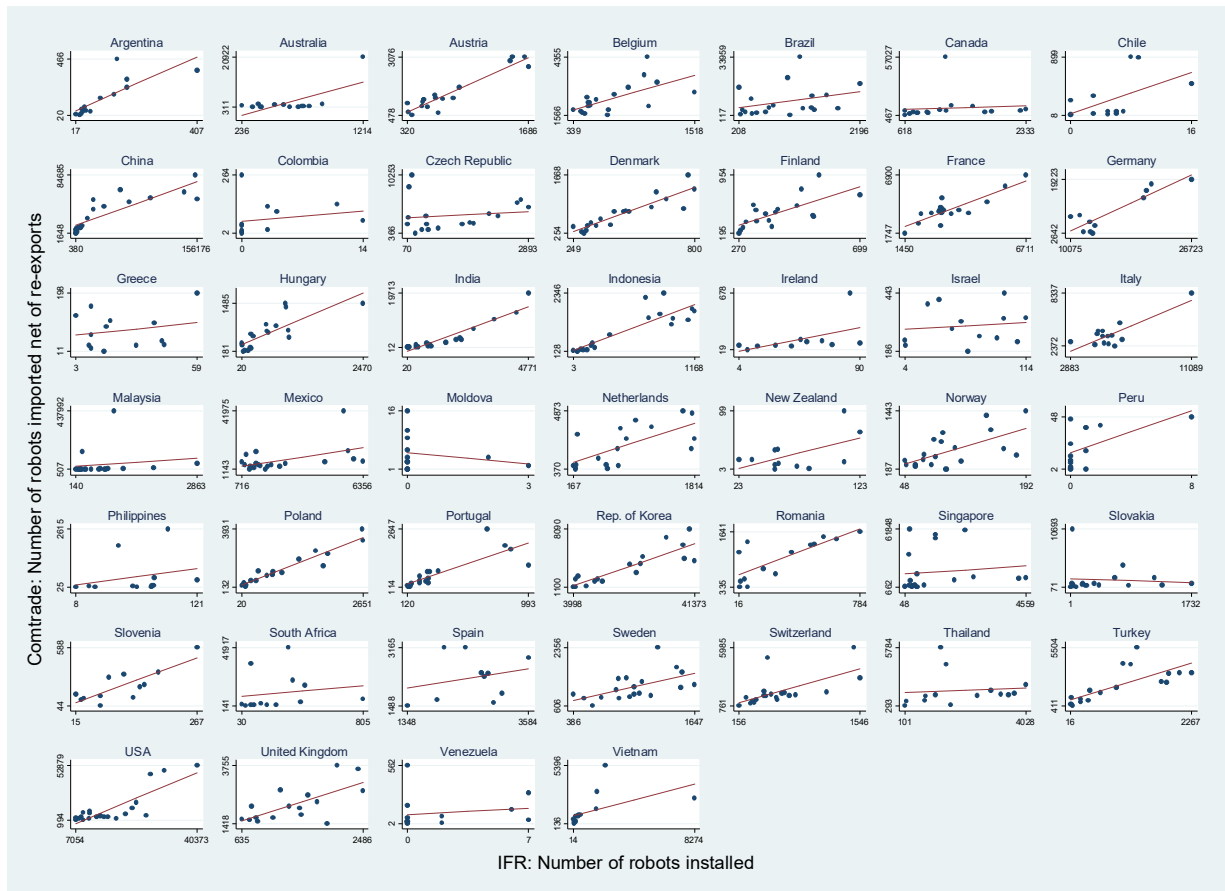
**Figure 6a: Scatter plot of IFR installations and Comtrade import values**



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

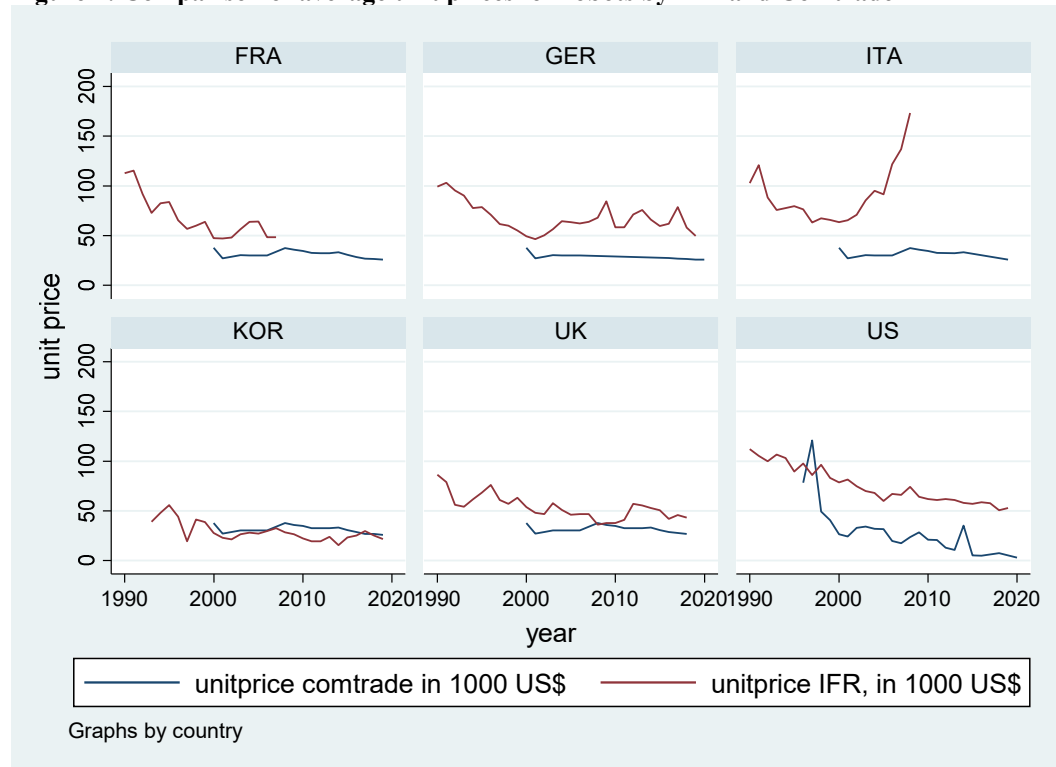
**Figure 6b: Scatter plot of IFR installations and Comtrade import quantities**



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

**Figure 7: Comparison of average unit prices for robots by IFR and Comtrade**



**Source:** Own calculations based on IFR and Comtrade data