What is driving robotisation in the automotive value chain? Empirical evidence on the role of FDIs and domestic capabilities in technology adoption

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Abstract

With a focus on a key production technology of the fourth industrial revolution, we look at the measurable impact of inward foreign direct investments (FDIs) and other host-country-specific factors on the adoption of industrial robots along two main segments of the automotive value chain. We find that FDIs *per se* do not have a significant effect on the adoption of industrial robots in the host country, but they become significant when interacted with proxies of host countries' innovation capabilities. Using disaggregated data on robotisation and controlling for endogeneity, we also find that the combination of FDIs and local innovation capacity only impact on robot adoption in the case of the automotive assembly segment. Instead, host-country-specific factors characterising the local industrial eco-system drive robotisation in the components supply segment of the automotive value chain more than in its assembly segment. This confirms the importance of domestic productive capabilities development in the process of manufacturing automation, but also reveals that remarkable heterogeneity exists within the automotive sectoral value chain in terms of drivers of technology adoption.

Keywords: *technology adoption; automotive; fourth industrial revolution; FDI and GVCs; local ecosystems*

1. Introduction

During the last decade, interest in the so-called 'fourth industrial revolution' (4IR) has exploded (Schwab 2016; OECD 2017; Hallward-Driemeier and Nayyar 2018; Sturgeon 2019; UNIDO 2020). An increasing number of interconnected digital technologies are expected to have a profound impact on different sectoral value chains, potentially reshaping the main channels through which technologies are adopted and diffused across advanced and emerging economies. Despite this mounting interest, most of research has been focusing on the impact that such new technologies may have on employment both within and across countries (Goos and Manning, 2007; Autor and Dorn, 2013; Graetz and Michael, 2018). On the contrary, research on the factors driving the adoption and diffusion of these technologies across countries has been limited.

Given the complexity of these technologies and their use in industries organised along global value chains, both country-specific and international factors are expected to play a role in their adoption and diffusion. Moreover, these processes of adoption and diffusion are expected to be highly heterogenous, because of diversities across 4IR technologies and their different potential applications across economic and industrial sectors (Andreoni et al, 2021). Innovation and – in several cases – production of these digital technologies and systems are still concentrated in a few industrialised countries. Multinational firms headquartered in these countries and their foreign investment decisions are among the key factors expected to play a role in this new digital industrial revolution. However available evidence on their actual role in the diffusion of digital technologies is limited.

This paper contributes filling this gap in the literature by providing new quantitative evidence on the measurable impact that inward foreign direct investments (FDIs), and other host-country-specific factors, have on the adoption of industrial robots, a key production technology of the 4IR, focusing on the global automotive value chain. The focus on a single technology and a specific sectoral value chain is aimed at providing robust cross-country evidence on a key technology dynamic of the fourth industrial revolution with both a sectoral and sub-sectoral focus. This quantitative cross-country evidence complements firm-level, sector and country specific studies of technology adoption and diffusion in which higher degrees of granularity and heterogeneity can be captured by adopting other research methods and opening the black-box of production.

We built our main research hypothesis around FDIs and their interaction with country-specific factors in driving adoption and diffusion of a complex and capital intensive technology like industrial robots. FDIs have long been considered a crucial channel for technology generation, transfer, and adoption (Cantwell 1989; see Papanastassiou et al., 2020 for a recent and comprehensive review). However, their role has been also problematised in the literature, especially with reference to countries across Africa, Asia and Latin America (Rasiah and Gachino, 2004).

This paper analyses two main sets of drivers of technology adoption and diffusion: the main determinant under scrutiny in this study, which is FDIs, and a series of country-specific factors that we use to proxy the level of development of the local ecosystem, i.e., its competitiveness and its innovativeness. Given that industrial robots are advanced technologies, we discuss and test the hypothesis that host economy characteristics play a significant role in technology adoption and diffusion alongside FDIs. More precisely, we analyse: (i) the measurable impact that FDIs exert *vis-à-vis* other country and sectoral specific variables for the adoption of industrial robots in the automotive sectoral value chain; (ii) whether the dynamics observed in the automotive sector as a whole tend to differ across two chain segments – namely automotive assembly and automotive components – thus capturing also the heterogeneity within the same sector.

To the best of our knowledge, this is the first time that a study on such a wide set of drivers of technology adoption has been performed with a focus on industrial robots and using evidence comparable across different countries. We built an *ad hoc* dataset covering 34 countries over 11 years. In our empirical analysis we define the dependent variable as the operational stock of industrial robots within the automotive sector, while our regressors include inward FDIs and a series of country- and sector-specific variables to proxy the readiness of the host-country's ecosystem (Moore, 1993), such as its innovativeness, export competitiveness, and level of industrial development. We use standard OLS estimations with fixed effects to study the main relationships between our dependent and independent variables. To control for endogeneity that could arise from both reverse-causality and omitted variables, we adopt an instrumental variable (IV) approach for the estimation of our model. The 2SLS estimation using our IV confirms our results.

We find that FDIs *per se* do not have an impact in the adoption of industrial robots, either considering the sector as a whole, nor disaggregating for the two segments of final assembling and automotive components. FDIs do have an impact when they are interacted with patents, which is our proxy for countries' innovativeness. When disaggregating for the two automotive segments, the interaction between FDIs and patents remain positive and statistically significant only for the final assembly segments. Robots' adoption in the component segments is also positively associated with the level of competitiveness of the host economy. This paper hence concludes that the host country competitiveness and innovativeness matter for the adoption of new technologies more than the mere existence of FDIs in the country.

The remainder of the paper is structured as follows. Section 2 presents a review of the literature on the impact of FDIs and the role played by other host-country-specific factors in technology adoption. From this perspective, we consider different strands of the literature on the impacts of

FDIs on receiving countries, with a specific focus on the role played by absorptive capacity and local capabilities in host countries. Given that this is a sector and technology-specific analysis, Section 3 introduces the main features of the automotive industry and of industrial robot technology. Section 4 presents the sources of our data, descriptive statistics and the main hypothesis of our econometric model. Section 5 presents the empirical strategy and our main econometric results. Section 6 discusses our main results and puts forward policy implications. Section 7 concludes.

2. Literature Review

The vital role of technology adoption for productivity and sectoral upgrading, have been widely recognised, especially for emerging and developing countries (Amsden 2001; Fu et al. 2011). Nonetheless, technological innovation and development are expensive, especially in terms of new digital technologies. As a result, they tend to be concentrated in large or specialised enterprises that have enough financial capabilities to invest (Gestrin and Staudt 2018). Thus, it is common to associate technological upgrading of countries and industries with the presence of large multi-national corporations (MNCs) (Søreide 2001), and to look at FDIs as one of the main channels through which technology diffuses internationally, combining with the characteristics of host economies. The role of local systems in shaping the impact of FDIs in technology adoption is often acknowledged especially in the case of emerging and developing countries (Crespo and Fontoura 2007; Glass and Saggi 2008; Narula and Driffield 2012; Amighini and Sanfilippo 2014).

To account for the special role of FDIs in technology adoption and for their interaction with host country characteristics, we briefly review below the two blocks of literature which we deem useful for the development of our research questions and methods.

2.1. Technology adoption mechanisms: the special role of FDIs

The links among FDIs, technology adoption and development have long received a wide attention in economic literature (Cantwell 1989; Caves 1996; Lall 2000). The issue has received mounting attention over the past three decades, mainly as a result of two increasingly acknowledged facts. First, the experiences of some developing countries, especially in East Asia, proved that if they were well managed, FDI could act as a trigger for industrialisation (Chang 1994; Lall, 2000; Lee

2013; Walheer and He 2020 for a recent contribution on China). Second, it has become apparent that MNCs are key spenders in research and development (R&D), decentralising a relatively large and increasing fraction of their R&D outside their home countries, and contributing to a high and growing share of R&D carried out in recipient countries, including emerging economies (Dachs et al. 2014, Papanastassiou et al., 2020).

Nonetheless, observed patterns of international technology transfer are extremely heterogeneous especially when emerging economies are considered as destination of FDIs. While some emerging countries are important recipient of MNCs also in high value-added activities (e.g., China, India, Singapore and Malaysia), other LDCs are much less involved in international production and innovation networks led by large MNCs (e.g., South Korea and Taiwan) (Rasiah, 1995). Moreover, while several scholars have emphasised the increase of technology sourcing and asset augmenting FDIs also in emerging regions (Laurence et al., 2015), some authors noted that R&D investments were limited to peripheral non-key R&D areas, distinguishing between frontier and supportive R&D (Rasiah and Yap, 2017).

This extreme heterogeneity of FDI patterns makes it harder to explore the mechanisms through which FDIs actually contribute to the dissemination and adoption of technology. While case studies have shed light on some of these mechanisms, they can hardly produce generalisable evidence on the FDI-technology adoption links. Quantitative analyses have long relied on cross-sectional studies, generally pointing to a positive relationship between inward FDIs and domestic productivity (Blomstrom et al 2004, Globerman 1979), but raising substantial endogeneity problems. The increasing availability of longitudinal firm level data has helped address these estimation problems. However, it is widely acknowledged that even more sophisticated empirical studies exploiting the richness of micro-level data over relatively long time spans have led to mixed and inconclusive results (Gorg and Greenaway 2004; Castellani et al. 2015).

The literature has traditionally addressed the technological impact of FDIs in terms of the direct and indirect effects of MNCs on the efficiency of host economies (Barba Navaretti and Venables 2004; Castellani et al. 2015). *Direct effects* are mainly observed in terms of overall productivity increases and employment creation. There is a general agreement that productivity increases with

FDIs through MNCs' operations because their endowment with new technology as well as their managerial efficiency is superior (Torlak 2004; Proença et al. 2006; Sur and Nandy 2018). *Indirect effects* occur through the change in local firms' behaviour. The standard assumption is that MNCs can be a crucial pushing factor for technological upgrading due to their ability to inject substantial human and fixed capital, hence inducing technological change and knowledge spillovers (Hymer 1976; Blomstrom and Kokko 1996).

Extant literature has identified the following main channels though which knowledge spillovers accrue to local firms: demonstration/imitation effects, training of local workforce, improved competition, reinforced export, and backward and forward linkages with domestic firms (Kinoshita 1998; Crespo and Fontoura 2007; Wang and Blomstrom 1992; Markusen and Venables 1999, Zanfei, 2012). Barrios and Strobl (2002) suggested that the relevance of demonstration-imitation effects increases with the similarity of the goods produced by the two types of firms when considering spillovers related to product and process technology. In this sense, establishing procedures to imitate firms from other sectors that had already successfully implemented a specific type of technology is particularly relevant (Bruque and Moyano, 2007). Moreover, the imposition of higher standards to suppliers as an important indirect way of improving productivity has long been emphasised in the literature on the impact of MNC activity on host economies, since the seminal studies on linkages carried out by Hirschmann (1958). This aspect is relevant for our analysis on the automotive sector where increasing standards (in health and safety, for example) have important cascade effects on suppliers' productivity and overall performance (Bisztray 2016 for an example of AUDI in Hungary). As for the training of local workforce, Kinoshita (1998) highlighted the importance of developing absorption capacity for technological spillovers to materialise. In her work on China, she has shown that the arrival, through MNCs, of new technologies alone cannot create the expected positive results unless the labour force has the corresponding skills. Accordingly, 'the catch-up effect is important but not as much as the firm's costly effort to build a skill base for greater absorptive capacity, it is indispensable to create the corresponding skills' (Kinoshita 1998). These skills are not general but are specific to the technology and they imply an *adoption cost*, which is represented by the cost of training and by the effort of building up the firm-level capabilities in the host-country (Zanfei 2012).

2.2 Absorptive capacity and the role of the host-country's ecosystem

To explore under which circumstances FDIs can affect technology adoption, we will refer to four main streams of literature.

The first strand of contributions relies on the assumption that the larger the productivity gap between host country firms and foreign-owned firms, the larger the *potential for technology transfer* and for productivity spillovers to the former. This hypothesis stems from the classical work of Thorstein Veblen and Alexander Gerschenkron (the so-called Veblen-Gerschenkron effect), and it underpins early development models such as the ones of Rosenstein-Rodan, Albert Hirschman and Tibor Scitovsky emphasising inter-sectoral interdependencies and different (and related) types of external economies in backward regions. Findlay's contribution (1978) is the first attempt of formalising technological progress in relatively "backward" regions as an increasing function of the distance between their own level of technology and that of the "advanced regions", and of the degree to which they are open to FDIs. In Findlay's formalisation of a stylised dynamic model, structural features of the backward region determine technological progress and disproportional dynamics of growth across sectors result from different proportions of two types of capital stocks – foreign and domestic (more recent contributions in this stream include historical and country-specific analysis of catching up; see Abramovitz, 1989 and Rasiah and Yap, 2017).

Econometric studies within a more conventional international trade literature have also attempted to test sub-sets of hypotheses. Blomstrom and Wolff (1994) for example show that the growth of gross output per employee in 20 Mexican sectors in 1965-70 and in 1970-75, is positively related to a measure of FDIs and of initial labour productivity gap between local firms and multinationals. However, while this work opens the way to the empirical analysis of how the technological profile of local economies - as compared to foreign investors - affect technology transfer, it fails to account for issues of reverse causality as in the case of all cross-sectional studies. Driffield (2001) uses data at the 3-digit sectoral level over 4 years for the UK and finds that changes in productivity in the foreign sector, positively affect growth in productivity of domestic firms, and interprets this as evidence of catching up of local manufacturers stimulated by higher level competitors. Imbriani et al. (2014) estimate FDI spillovers in Italy and find that positive spillovers only occur in industries with a large technology gap.

A second and related stream of literature takes the opposite view that the lower the technological gap between domestic and foreign firms, the higher the *absorptive capacity* of the former, and thus the higher the expected benefits in terms of technology transfer to domestic (Cantwell, 1989)[1]. The first empirical test of this hypothesis was conducted by analysing how the entry of US multinationals in European markets over 1955–1975 affected the market shares of firms, as an indicator of economic performance. Cantwell (1989, p.86) suggests that the technological capacity of indigenous firms is the most important determinant of the European economy to what was then perceived as the "American challenge". Moreover, the most positive impact appears to have occurred in industries where the technological gap is small (Cantwell, 1989). In their work on Uruguayan manufacturing plants, Kokko et al. (1996) find positive and significant spill over effects only in the sub-sample of locally-owned plants with moderate technology gaps vis-a` -vis foreign firms. They argue that small or moderate gaps identify cases where foreign technologies are useful to local firms and where local firms possess the skills needed to apply or learn foreign technologies.

While other scholars find less clear-cut relations between technology gaps and FDI spillovers (Girma et al., 2005 for FDIs in the UK; Wang et al. 2016 for FDIs in China), it is worth observing that a mere identification of high (low) technology gaps with low (high) absorptive capacity might be misleading. In fact, in some sectors both domestic and foreign firms might well be above the average absorptive capacity, making it possible that large gaps co-exist with a relatively high levels of absorptive capacity for both foreign and domestic firms. Castellani and Zanfei (2003) adopt this perspective and use firm level data on Spain, Italy and France to show that it is the combination of relatively high technology gaps and relatively high local competencies that can be conducive to greater FDI spillovers. Quite similarly, Jordaan (2017) based on an extensive survey of FDI effects in Mexico, finds that a large technology gap fosters positive spillovers, especially among suppliers of foreign investors that are best suited to absorb new technologies.

[1] It is worth noting that the role of absorptive capacity is implicitly recognised also in the catching up tradition, when it is acknowledged that a sort of lower bound of local technological capabilities exists, below which foreign investment cannot be expected to have any positive effects on host economies (Findlay 1978 pp. 2-6).

A third stream of research that also has implications for the FDI-technology adoption nexus emphasises the importance of host-country "ecosystems" in shaping FDI effects. Ecosystems can be defined as "*evolving set(s) of actors, activities, and artifacts, and the institutions and relations, including complementary and substitute relations, that are important for the innovative performance of an actor or a population of actors*" (Granstrand and Holgersson, 2020:3). Such a set of factors characterising local contexts can be captured, at least partially, by different measures of technological capabilities and export competitiveness of local firms and institutions (Lall 1992; Meyer 2001; Andreoni 2018). The idea is that the quality of ecosystems helps discriminate host economies that are able to capture economic benefits from FDIs as opposed to those that are not.

The fourth, and final, strand of literature refers to studies that have emphasised the need for public policies aimed at firm-level productive, technological, and organisational capabilities development and industrial upgrading, to enable local economies to efficiently take advantage of technological expertise of foreign MNCs (Lall 2000; Cimoli et al. 2009)[2]. Rather than merely attracting foreign capital by means of standard promotion policies, such as tax benefits and the creation of export promoting zones, it is argued that the governments of FDI recipient countries should accumulate location-specific assets (Nordas 2000) and more directly address the impediments to technology transfer (Klein 2019). Like other streams of literature, these contributions emphasise the role of absorptive capacity as well, but also stresses the importance of undertaking policy measures to enable local actors to take advantage of MNCs' operations, by increasing both the 'social capability' and the 'technological congruence' of local economies (Abramovitz 1986; Fagerberg et al. 1994). The former concept relates to the capabilities to engage in innovation and organisational processes, while the latter refers to the capabilities to use and adapt new sources of knowledge that are closer to the technological frontier.

[2] Two streams of research are particularly relevant here, and set the context in which our analysis is cast, although their thorough consideration largely lays beyond the scope of this paper. The first one associated with development scholars focusing on learning in production, technological and organizational capabilities development at the sectoral and firm levels (Freeman, 1982; Amsden, 1989; see Andreoni and Chang, 2017 for a review). The second one rooted in the resource-based and capability theories of the firm, focuses on the interplay between production structures, organisations, and technology, and their integration into local and global production systems and the rise of industrial ecosystems in specific regions (Penrose, 1959; Rosenberg, 1970; Lazonick, 1990; Best, 1990 and 2018; Mudambi, 2009; Andreoni, 2018).

2.3 Hypotheses

Building on the streams of literature outlined above, we formulate and test two hypotheses regarding the impact of foreign direct investment and of country specific variables on the adoption of industrial robots.

> *Hypothesis 1. FDIs have an impact in the diffusion of technologies, but only when the host country is endowed with production capabilities.*

By formulating this hypothesis, we intend to problematise the role of FDIs in technology adoption. Indeed, our hypothesis incorporates insights from the strands of literature we have reviewed above. This is especially the case of firm-level studies stressing the role of firms' competencies and of local eco-system capabilities in the adoption of advanced technologies. We will test this hypothesis with reference to the adoption of industrial robots in the automotive industry, and utilise different proxies of the quality of local eco-systems as a key factor enabling technology adoption, both directly and in combination with FDIs.

Our study intends also to examine the heterogeneity of the FDI-technology adoption nexus along different segments of a given industry. We consider the automotive sector as paradigmatic of the variety of ways though which local eco-systems can affect technology adoption, once again both directly and in combination with FDIs. By so doing we connect to the literature reviewed in the previous section, which highlights that technology adoption reflects differences in technological capacities that can be observed at various levels. First, the diversity of technological capacities between the foreign and the domestic components of the economy (as in the case of technology gap approach); second, the differential abilities of local firms to absorb foreign technology (as in the case of the absorptive capacity literature); third the distinctive capacity of host economies to combine and leverage competencies of local firms and institutions (as in the case of local eco-system literature); fourth, the heterogeneity induced by national and regional policies aimed to the development of local capabilities (as in the case of contributions on industrial upgrading policies). We submit that the way in which all of these sources of heterogeneity will eventually affect the FDI-technology adoption nexus will not only be sector specific but will also reflect the technological and institutional specificities that can be observed within industries. This line of argument leads us to formulate Hypothesis 2 as follows:

> *Hypothesis 2. The impact of FDIs in the adoption of industrial robots is heterogeneous along different segments of the automotive value chain.*

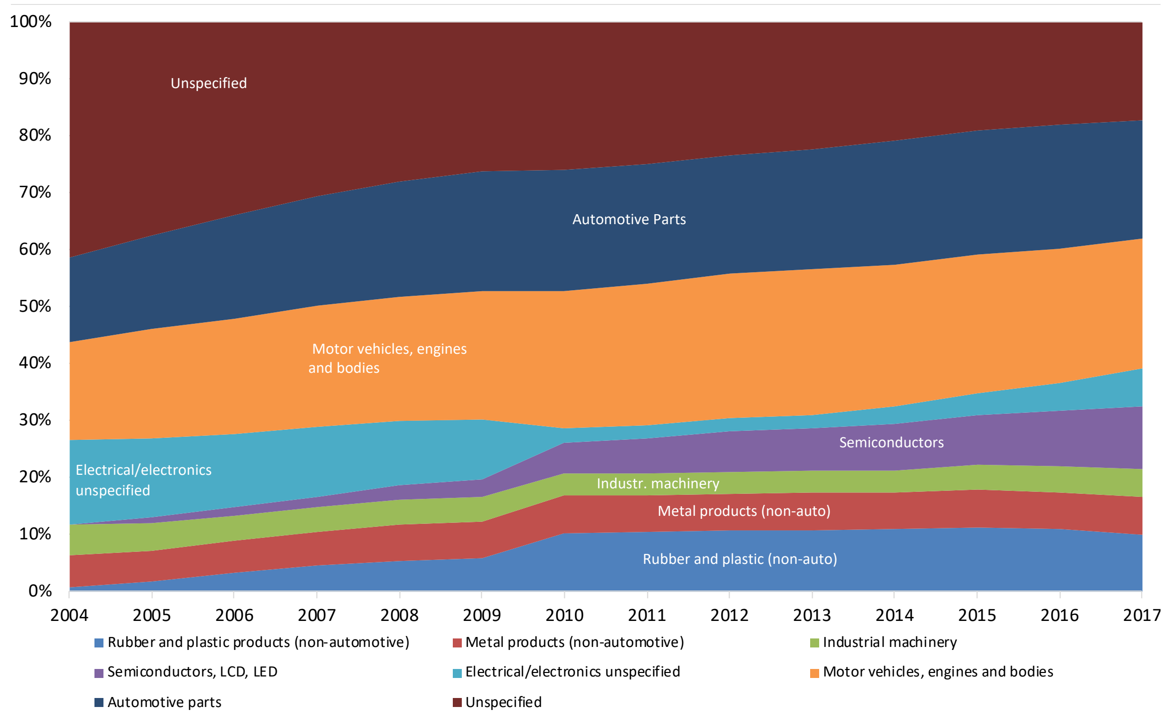
We will test this hypothesis with reference to two segments of automotive industry, namely final assembling and automotive components.

3. Industrial robots and the automotive sector

This paper focuses on the technological adoption of industrial robots, a specific technology that has been widely used in manufacturing since its first introduction in the automotive sector by Ford in the 1960s (Mehrabi et al. 2000; Michalos et al. 2010). Industrial robots have evolved significantly since then to become a key digital production technology of the 4IR (Andreoni and Anzolin 2020). Today, they are defined according to ISO 8373:2012 as '*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*'. Technological innovation in industrial robots has been mainly about increasing their ability to perform precision engineering complex tasks, connecting them into cyber-physical systems and use of industrial data for product and process improvements.

According to the International Federation of Robotics (IFR) data, there is a high sectoral concentration of industrial robots. A striking 99 per cent of industrial robots are used in the manufacturing sector and, within manufacturing, the automotive sector accounts for more than 36 per cent of total industrial robots, making it the most important sector for industrial robots' adoption (IFR 2018). The automotive sector, which is at the core of this study, has always been the bedrock of manufacturing automation advances due to its high-volume production, standardisation and modularisation, which allow the production of different parts to be assembled. Indeed, it is within downstream assembly operations, led by large OEMs specialising in final assembly, that the majority of robots can be found. Figure 1 shows industrial robots' distribution among manufacturing sub-sectors, including sub-sectors of the automotive sectoral value chain.

Figure 1. Industrial robots' distribution in the manufacturing industries (operational stock, 2004–2018)



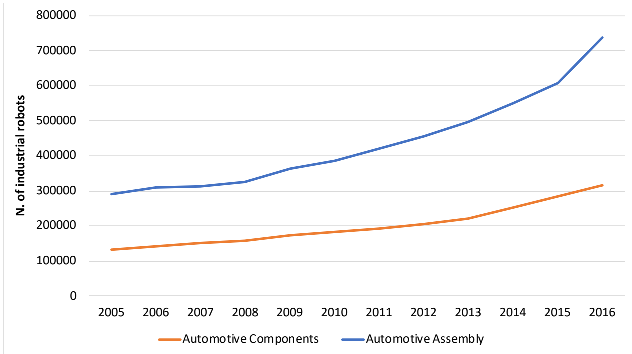
Source: Authors, based on IFR.

While the diffusion of robots has been facilitated by a gradual decline of prices of automation devices especially for automotive applications in OECD countries (OECD, 2019), the deployment of these highly sophisticated technologies is mostly associated with the increasing concentration of market power, technological and financial capabilities of final assembly OEMs that act at the global level and produce a high number of vehicles.

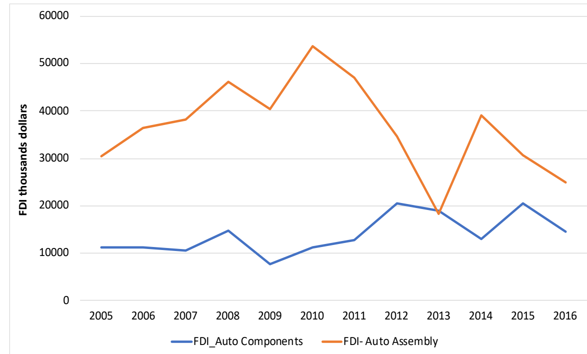
Figures 2 and 3 show the trend of FDI inflows and industrial robots' adoption for our two categories of Suppliers of Automotive Components and OEM[3] Automotive Assembly, aggregating the whole set of countries used for this analysis.

[3] In fDi market dataset Automotive OEMs is intended to be Automotive final assembly OEMs.

Industrial robots in the automotive sector 2005–2016



FDIs in the automotive sector (2005–2016)



Figures 2 and 3. Source: Authors, based on IFR and fDi Market dataset.

According to data from the International Organization of Motor Vehicle Manufacturers (OICA), the top ten final assembly automotive companies produced around 70 per cent of all cars globally commercialised in 2018.[4] In recent decades, this concentration phenomenon has been accompanied by the rise of large components' suppliers as a result of a number of mergers and acquisitions (Wong 2017). It is less clear what happened to other parts of the supply chain. As pointed out by Sturgeon et al. (2008), 'with consolidation, we must question the staying power of smaller, lower tier, local suppliers' and, thus, the increasing 'endogenous asymmetries' along the value chain (Milberg and Winkler 2013). Looking at some successful experiences of technology adoption and expansion of automotive national production, as in the case of Eastern European countries or Thailand (see Barnes et al. 2017 for Thailand; O'Shaughnessy 2007 for Czech Republic), it is evident how the importance of attracting big MNCs investments runs in parallel with the urgency to develop local suppliers that are capable of dealing with and responding to final assembly OEMs' requirements (Anzolin et al. 2020[5]).

4. Data and Methods

[4] http://www.oica.net/category/production-statistics/

[5] Anzolin at al. (2020) uses the same sources of data as we are using in the present work, but it undertakes a descriptive statistic regarding only the role of FDIs for robots' adoption. In the current paper, we perform an econometric study in the attempt to provide evidence of causality links and we add yet another set of independent variables, which represent the local ecosystem (i.e., patents and exports).

This section provides information on (i) the two main datasets and (ii) the key variables used in our analysis and some descriptive statistics

4.1 Sources of data

We used two main sources of data: the International Federation of Robotics (IFR) and fDi Markets. The former collects data on industrial robots; precisely, it reports the number of industrial robots' applications from nearly all industrial robot suppliers in the world (IFR 2018). The IFR dataset provides insights on the number of robots per industry, country and year. The two main pieces of information provided by IFR are (i) the number of robots (both in operational stock and in market delivery value) by sector and segment (that is, further classification within the sector) up to three digits in ISIC rev. 4 classification; and (ii) the type of application and sub-application (for example, the welding category includes laser welding, arc welding, spot welding, etc.). We will use the details offered by the first set of information on the automotive sector. This new dataset is the only available source regarding industrial robots and has been used recently in a number of publications, mainly focusing on the impact of robots on labour and at a higher level of sectoral aggregation (Acemoglu and Rastrepo 2019; Graetz and Michael, 2018).

fDi Market is an online dataset built and maintained by the Intelligent Unit of the *Financial Times*. It compiles data on cross-border investment projects covering all sectors, specified in NAICS 07 classification,[6] and countries worldwide. Out of more than 142,000 observations of investment projects registered in 2003–2014, we use investments in the automotive sector, considering the two *industry sectors* Automotive OEM and Automotive Components. Among the numerous information that fDi Markets offers, we use *destination_country*, *year*, *business_activity* (intended as the functional activity) and *sub_sector*. Out of all business activities we used only *Manufacturing*, in order to provide further consistency with the first dataset where there are—by definition—only industrial robots applied in manufacturing activities. The rich information on *business_activities* (including R&D, Design Development and Testing, Sales and Marketing; see below for full array of functional activities used) is further used to build the instrumental variable technique in order to correct for endogeneity as explained below. The fDi market dataset has been

[6] https://www.fdimarkets.com/faqs/

used by UNCTAD to compile data on greenfield FDIs in the World Investment Report series and in a number of academic publications (Castellani et al. 2013, Crescenzi et al. 2014; Amoroso et Müller 2017).

We focus on two specific segments of the automotive sectoral value chain. Through a matching table,[7] we were able to combine data on robot adoption and inward FDIs in 34 countries with reference to the following two sectoral classes:
(i) *Automotive Assembly*, which matches Motor Vehicle (291 in IFR) and Automotive OEM (in the fDi market dataset). We refer to this as **class 2910**.
(ii) *Automotive Components*, which matches Auto parts (293 in IFR) and Automotive Components (in the fDi market dataset). We refer to this as **class 2930**.

We restrict our analysis to the 34 countries that have more than 500 industrial robots within their entire automotive sector (see Tables A1 and A2 for a list of these countries). We built a unique country-level panel dataset on the automotive sector by matching our sources of data, covering the period from 2005 to 2016 for which data are available. Thus, the time span for data on robot adoption largely overlaps with the coverage of FDI data (2003–2017). Lags between the two data series will be utilised to reduce endogeneity problems[8] (which are further dealt with by introducing an appropriate instrumental variable as specified below).

Although the two datasets are extremely rich in detailed information, they present some limitations. First, within the automotive classification of IFR data on industrial robots there are two unspecified classes: Unspecified AutoParts (class 2999) and Automotive Unspecified (class 299).[9] While we were able to insert the former in our Automotive Components final class, the latter remains excluded from our model because we are not able to check whether they belong to

[7] https://www.census.gov › naics › concordances › 2007_NAICS_to_ISIC_4
[8] Endogeneity problems are not the only reasons why FDIs are lagged, rather there is a logic related to the way in which the dataset is built. Within fDi market dataset, FDI are inserted into the database once they are publicly announced. Although some controls take place afterwards to check the FDI has been actually put in place, the announcement date is likely to be sooner than the actual plant-based investment (we are looking only at investments in the manufacturing).
[9] We triangulated our information interviewing people responsible for the IFR in Germany. According to what they mentioned, we decided that the choice most pertinent to the data was not to include the 299 class in our specifications.

Auto Components or Auto Assembly.[10] A second limitation is due to the fact that, up until 2010, the United States, Mexico and Canada were classified together as a single geographic aggregate by the IFR database; therefore, in order to have an 11-year panel we used aggregate data for North America, thus encompassing the three countries for the entire period. Accordingly, our final sample is of 32 countries.[11] A third limitation refers to the nature of FDI data. On one hand, fDiMarkets collects data on FDI projects monitored through press information and company reports. A possible source of bias is that a fraction of announced FDI projects may not take place, but this drawback is partially dealt with by means of periodic checks by the FT unit in charge of double-checking the information provided and of removing information on projects that are not realised. On the other hand, as mentioned earlier, the dataset reports only greenfield investment projects, which impedes monitoring of international investment operations that take the form of mergers and acquisitions.

4.2 Main variables

The purpose of this paper is twofold. First, we intend to observe whether, and to what extent, FDIs drive the adoption of industrial robots in the automotive sectoral value chain with a focus on its two main segments. Our observations include the number of robots adopted by each country in the relevant sectors in each year of our panel, and the FDI flow measured in millions of dollars.[12] Second, we want to provide further information on other possible drivers that lead to industrial robots' adoption and are related to other sectoral- and country-level characteristics that lead to the adoption of industrial robots. In this sense, we use the following variables to proxy the readiness level of adopting industrial robots across different countries.

Patents. We use patents as a proxy for the innovativeness level of the destination country. Although patents could present some criticalities (Arundel and Kabla 1998; OECD 2009), they are widely used in the literature as a proxy for innovation (Acs et al. 2002; Dosi et al. 2015). Our source of data in this respect is the OECD Patent Statistics (Science Technology and Patents section) and the method used to link IPC[13] classes on the basis of an 'Algorithmic Links with

[10] We opted for this approach after email correspondence with IFR personnel in Germany.
[11] Thirty-two countries, excluding Mexico, US, and Canada, but including North America.
[12] UNCTAD uses the same dataset and the same unit of measure (UNCTAD, 2019).
[13] International Patent Classification.

Probabilities' approach developed by Lybbert and Zolas (2014). With the use of table concordances, we were able to match patents classification with our two industrial classes: Automotive Assembly and Automotive Components.

Export data. We use the UN Comtrade dataset, which provides detailed information about exports following HS classification. We used data on exports to proxy countries' competitiveness in the automotive sector; exports are one of the most used proxy to study country competitiveness, both in relation to indexes such as the Global Competitiveness Index or the World Competitiveness Index and in academic contributions (Doner et al. 2006; Hudakova 2016; Brancati et al., 2018; Ruzekova et al., 2020). We followed Jetin's (2018) contribution to detect HS classes that are relevant for our analysis and we extended his classification in order to properly match our sources of data. The classes we used are: 8703 (motor cars and vehicle for transport of persons); 8706 (chassis fitted with engines); 870710 (bodies including cabs), which make up for class *2910 Automotive Assembly*; 8708 (motor vehicles parts and accessories); and 940120 (seats), which make up for class *2930 Automotive Components*.

We include time and country fixed effects and a series of control variables that account for structural characteristics at the country level. We use OICA[14] data to control for ***volume***, intended as the number of cars produced in each country of our dataset, as an indicator of industry size. Being characterised by high economies of scale, the number of cars produced gives an indication of the productivity level of the country and could possibly inform the intensity of its local value chain (OECD 2009). Production volumes in fact are a crucial element as they have direct consequences on the suppliers and the different ways of production (see Mayes 1996). An important additional control concerns the level of industrial development of each country, which we proxy by the ***Employment share in manufacturing*** and ***Gross capital formation*** based on World Bank data.

All variables are summarised in Table 1, with further specifications provided in the Appendix. Table 2 provides summary statistics of our main variables. The variable ***volume*** presents fewer

[14] International Organisation of Motor Vehicles Manufacturers, http://www.oica.net/production-statistics/

observations because Switzerland does not produce any motor vehicles (as it does not have any final assembly OEMs operating in the country) and is therefore not listed in the OICA dataset.

Table 1: List of Variables

Variable Name	Description	Source	Classification
N_Rob	Number of industrial robots in the Automotive Sectors divided into Automotive Motor Vehicle and Automotive Components.	International Federation of Robotics	ISIC rev. 4
FDI	Foreign direct investments measured in inflow FDI in million $US. FDI are divided in Automotive Final Assembly OEM and Automotive Components.	fDi market dataset, Financial Times.	NAICS 07
Pat	Number of patents, whose IPC classes are matched with the two automotive segments through 'Algorithmic Links with Probabilities' approach (Lybbert and Zolas 2014)	OECD Patents statistics – Triadic Patent families	ISIC rev.4
Exports	Export of different HS classes that relates to automotive bodies and components measured in millions of $US.	UN Comtrade	HS classification
Gross Fixed Capital Formation	Measured in millions of $US.	World Bank Data	n/a
Employment in Manufacturing	Share of people employed in the manufacturing sector out of the total amount of working population.	World Bank Data	n/a
Volume (produced)	Number of motor vehicles produced in each country	OICA	n/a

Table 2: Descriptive Statistics

	Observations	**Mean**	**Standard Dev.**	**Min**	**Max**
N_Rob	769	6057.046	13796.44	0	75924
FDI	769	1103.986	2087.179	0	14665.31
Pat	763	9.16452	27.94249	0	293.219

Exp_MillUS	769	14083.85	26010.67	108.231	161186.7
Gross Fixed Cap_Form	769	440850.2	871613.5	7834.047	4841477
Employm_share_manuf	769	2523502	4393846	16.227	40.526
Volume of cars produced	744	25.9541	4.991809	2631	2.81e+07

5. Empirical strategy and results

5.1 Empirical strategy

OLS estimation

To investigate the impact of FDIs and other contextual variables (such as patents and exports) on the adoption of industrial robots, we first of all used a standard OLS model and regressed the number of industrial robots on FDI, patents, export, and a vector of control variables. The econometric analysis consists in a standard OLS regression with time and country fixed effects, where the dependent variable is the number of robots' applications per country, sub-sector and year. Normalisation effects come from control variables in the model. The empirical fixed effects model is as follows:

$$IFR_{tcs} = \alpha + \beta FDI_{(t-1)\ cs} + \varphi Pat_{(t-1)\ cs} + \gamma Exp_{tcs} + \eta X_{tc} + \delta_t + \delta_c + \varepsilon$$

As mentioned, IFR corresponds to the number of industrial robots, *FDI* corresponds to inflow of FDI accounted in million dollars, and *Pat* and *Exp* respectively correspond to the number of patents and the value of export in million dollars. All these variables regard the automotive sector and specifically observations in a country *c*, at time *t*, in a segment *s.* We then introduced a vector of control variables, among which we include *Volume* of cars produced in each country, *Employment share in manufacturing* and *Gross Fixed Capital formation*. With the two latter variables we controlled for elements related to the industrialization and investment level of each country. In order to limit possible endogeneity due to reverse causality, in our baseline model we adopt the standard procedure of lagging the main independent variables (FDI and patents). We included time fixed effects to absorb the time variations and country fixed effects to control for unobserved heterogeneity across countries. Regressions that did not have country fixed effects but included individual country dummies and other controls for industrialisation levels are reported in Appendix as robustness checks, yielding no substantial differences in results.

IV estimation

Although we lagged FDIs by one year, endogeneity could still arise from potential reverse causality and due to omitted variables, which could lead to biased results of the FDI coefficient undermining the causal relation we intend to test between FDIs and industrial robots. On one hand, reverse causality could arise due to the effects that industrial robot adoption may have on inward FDIs, by increasing the attractiveness of local industry for foreign investors. On the other hand, other country-specific elements that cannot be captured with existing data may have an important role in our model, thus causing omitted variable issues. We account for this issue by adopting an instrumental variable (IV) approach that corrects for potential endogeneity bias.

We exploit the high level of granularity present in our dataset to develop an original sector specific IV. Our endogenous variable is FDI, which corresponds to all FDIs in the automotive sector regarding manufacturing activities. The information provided by the fDiMarkets dataset allows us to identify several business activities other than manufacturing, which we used to build our IV.[15] We use FDIs in other activities (named *FDI_other_activity*) that are essentially pre and post-production within the two automotive segments: Automotive Assembly and Automotive Components.

The intuition behind the construction of our IV is that *FDI_other_activity* (e.g. logistics) influence FDIs in manufacturing directly since FDIs are quite likely to co-occur and often co-locate in different business functions that complement one-another, and in fact they are highly correlated (see the first-stage regression reported in the Appendix). Instead, they can be expected to have virtually no impact on the adoption of industrial robots, our dependent variable. A direct link between our IV and our dependent variable is prevented by the fact that industrial robots are used

[15] The other activities are: Business Services Construction, Customer Contact Centre, Design, Development & Testing, Education & Training, Headquarters, ICT & Internet Infrastructure, Logistics, Distribution & Transportation, Maintenance & Servicing, Recycling, Research & Development, Sales, Marketing & Support, Shared Services Centre, Technical Support Centre.

exclusively in manufacturing activities, unlike other types of service robots (logistics, distribution, sales, training, R&D, etc.)[16] that are used in pre and post-production activities. It is possible that, for example, BMW would invest in an industrial robot for R&D purposes but, since we are considering greenfield investments, this would necessarily pass through an investment in the shop floor; thus, in manufacturing, our endogenous variable. Indeed, it is highly unlikely that a company would decide to undertake a greenfield investment in R&D (or any pre and post-production activities) that includes an industrial robot without the manufacturing plant being located nearby. To reinforce our hypothesis, we analysed the 'description' category of fDiMarket for FDI_other_activity, which provided an explanation of the type of investment. Descriptions are available for 77 per cent of the FDI_other_activity recorded (of which are 3720) and none make any reference to an investment in robots. A final note about the case in which a company producing robot technologies, such as KUKA, invests in an industrial robot for R&D: the sectoral classification of the FDI would be different; that is, it would not enter the Automotive class but rather the Industrial Machinery, Equipment & Tools class.

5.2 Results

We present two levels of analysis. The first part considers the automotive sector as a whole, without disaggregating by sub-sectors (that is, Automotive Assembly and Automotive Components).

In Table 3 we estimate different models in order to see how our main variables change when more elements are considered. The first important result is that one-year lagged FDIs do not have a significant impact in robots' adoption in all estimation results. Our IV technique (as reported in column 7) confirms these findings. Columns 2–5 report the estimated regression coefficients of simple specifications where we progressively added our main independent variables in order to observe how coefficients change. Specifically, column 5 displays the regression coefficients from a full specification that considers the effects of our main independent variables and the full vector of control variables.

[16] The International Federation of Robotics developed a different dataset for service robots where other types of activities are involved.

Lagged patents are positive and statistically significant. An increase of one patent corresponds to 42 more industrial robots and, similarly, US$1 million more in automotive exports leads to 0.2 more industrial robots. Moreover, in columns 3 and 5 we included the interaction between FDI and patent variables in order to shed further light on the relationship that FDIs may have when undertaken in the presence of innovation capacity. The results are strong and significant, pointing in the direction of a positive relationship between FDIs interacted with patents and the adoption of industrial robots. Interestingly, if we consider column (3) and assume a value of 10 for patents, the marginal effect of FDIs would be positive. In all specifications with the interacted term, this is highly statistically significant, confirming what had already been found in the literature regarding the importance of absorptive capacity in order to technologically benefit from FDIs (Zanfei 2012; Pavlinek and Zizalova 2014 on the automotive sector). The positive effect of patents and export on the adoption of industrial robots could indicate that the gap between the ecosystem of the host country and foreign investors is less significant—which is consistent with Glass and Saggi (2002) and Kokko et al. (2001)—and the idea that higher levels of human capital in the host country are associated with larger spillovers (Iršová and Havránek 2013).

We repeated our estimation with the IV technique. Using the 2SLS approach, the results are confirmed, showing positive and statistical values of patents and export, thus providing evidence on the key role played by the industrial ecosystem of the host country. Lagged patents were confirmed to be high, positive and statistically significant, making them the most relevant indicator for the adoption of industrial robots in the automotive sector. In all our specifications we kept country and year dummies with standard errors clustered at the sectoral (for example, the two segments of the automotive industry) and country level.

Table 3. Determinants of robot adoption in automotive industry

	Y =N_Rob OLS	Y =N_Rob OLS	Y =N_Rob OLS	Y =N_Rob OLS	Y =N_Rob OLS	Y =N_Rob OLS	Y =N_Rob IV	Y =N_Rob IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FDI_t-1	-0.056 *(0.134)*	-0.050 (0.138)	-0.222 (0.133)	-0.117 (0.105)	0.004 (0.121)	-0.107 (0.102)	0.194 (0.213)	0.147 (0.224)
Pat_t-1		38.239* (22.119)	39.857 (27.143)	36.717 (29.425)	42.117** (21.702)	36.502 (28.118)	45.096** (23.042)	42.528** (20.817)
FDI*Pat			0.021*** (0.006)	0.018*** (0.005)		0.015*** (0.005)		
Exp_MillUS				0.195*** (0.036)	0.136* (0.076)	0.191*** (0.037)	0.15** (0.073)	0.137* (0.073)
Gross Fixed Cap_Form					0.007*** (0.002)	0.005** (0.002)		0.007*** (0.002)
Employm_share_manuf					-141.511 (170.781)	-102.227 (162.749)		-148.33 (164.423)
Volume_lead					0.0002 (0.0008)	0.00003 (0.0001)		0.0002 (0.0007)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R squared	0.82	0.82	0.80	0.84	0.86	0.88	0.86	0.88
F value							20.47	17.35
N. observations	768	761	541	541	736	535	736	736

*Standard errors in parentheses *** p < 0.01, ** p < 0.05, * p < 0.1. The F values for the validity of the instrument are the Kleibergen-Paap rk Wald F statistics and the values are above the 10 per cent critical value.*

The second part of our analysis, displayed in Table 4, presents similar estimation models performed with a further level of disaggregation of our variables. The high disaggregation of our data allows us to take a further step in trying to analyse if, and to what extent, there are any differences across segments of the value chain of the automotive industry. We disaggregated FDIs, patents and export in two classes: 2910, which corresponds to Automotive Assembly, and 2930, which corresponds to Automotive Components.

Our estimation results are mixed at the sub-sectoral level. Columns 1 to 4 of Table 4 present OLS estimations following the same procedure as in Table 3. The impact of FDIs on Automotive final assembly is positive in all specifications, while they are negative for the Automotive Component segment; however, in none of the segments are their effects significant for the adoption of industrial robots. Patents are not significant for Automotive Assembly, while they are highly significant in the case of Automotive Components. FDIs have a measurable impact only when companies in the host country are involved themselves in technology and innovation efforts. The level of automotive export of the host country has a positive and significant impact for the adoption of industrial robots in both segments, being higher in the case of Automotive Components.

In column 4, we repeated the full specification, adding the variable constructed by interacting FDIs and patents as above, maintaining the disaggregation for the two automotive segments. Interestingly, FDIs have an impact when interacted with patents only in the case of Automotive Assembly, while the interaction creates a composite effect for Automotive Components, cancelling out both the effects of patents and FDI interacted with patents. This finding confirms our hypothesis that patents, which better reflect the technological capabilities of each country, are the crucial variable for the adoption of industrial robots.

When we turned to our 2SLS estimation model, we could use the same type of IV, disaggregated for our two segments, which confirm our OLS results. Even at the disaggregated level, we find that patents and exports—that is, the innovativeness and export competitiveness of countries in the automotive sector—have a stronger impact for technology adoption. FDIs appear to have a positive and significant impact on robot adoption in the assembly stage of automotive value chain, but only when combined with sufficiently high technological competencies held by local suppliers in the host country.

As we shall argue in the discussion section below, this heterogeneity in the results reflects differences in technology adoption patterns across different segments of the automotive value chain (Banga 2014; Andreoni and Tregenna 2020).

Table 4. Determinants of FDIs in two segments of the automotive industry

	Y =N_Rob OLS	Y =N_Rob OLS	Y =N_Rob OLS	Y =N_Rob OLS	Y =N_Rob IV
	(1)	(2)	(3)	(4)	(5)
FDI_t-1 ***2910***	0.069 *(0.206)*	0.140 (0.183)	0.143 (0.168)	0.020 (0.137)	0.359 (0.351)
FDI_t-1 ***2930***	-0.115 (0.154)	-0.045 (0.137)	-0.073 (0.142)	-0.183 (0.139)	0.035 (0.302)
Pat_t-1 **2910**		28.624 (24.046)	29.835 (22.053)	18.654 (15.917)	30.439 (21.200)
Pat_t-1 **2930**		49.150** (22.887)	46.634** (21.908)	75.292 (60.461)	46.755** (21.102)
FDI*PAT **2910**				0.017*** (0.003)	
FDI*PAT **2930**				0.005 (0.014)	
Exp_MillUS **2910**		0.226*** (0.045)	0.192*** (0.045)	0.224*** (0.048)	0.193*** (0.044)
Exp_MillUS **2930**		0.381*** (0.119)	0.296** (0.119)	0.260* (0.140)	0.300*** (0.115)
Gross Fixed Cap_Form			0.006*** (0.001)	0.005*** (0.001)	0.006*** (0.011)
Employm_share_manuf			-148.206 (459.669)	-92.538 (101.597)	-152.245* (89.235)
Volume_lead			0.0003 (0.0001)	0.0003 (0.0001)	0.0003 (0.0001)
Dummy_sector2	-807.87* (451.858)	-386.447 (516.550)	-146.029 (459.699)	-51.08 (460.40)	-75.028 (540.215)
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes
R squared	0.82	0.84	0.86	0.88	0.88
F value					5.608
N. of observations	768	761	736	535	736

*Standard errors in parentheses *** p < 0.01, ** p < 0.05, * p < 0.1. Legend: 2910 = Automotive assembly; 2930 = Automotive components. The F value for the validity of the instrument is the Kleibergen-Paap rk Wald F statistic and the value is above the 15 per cent critical value.*

6. Discussion

FDI is an essential part of international economic system and potentially a crucial catalyst for economic growth. This is related to the fact that MNCs play a key role in the transfer of knowledge and technology (Dunning 1996; Cantwell 2017; Papanastassiou et al. 2020). As discussed in section 2.1, the literature on the effects of FDIs does emphasise the impact on the host country technology adoption both via the demand for robots exerted by subsidiaries of MNCs, and via changes in robot adoption by local firms, that may be induced by the multinational presence though different channels such as voluntary and involuntary technology transfer, linkage creation and competitive pressures. However, we find evidence that, in the case of automotive industry, FDIs alone do not affect the adoption of industrial robots. Hence, we find support in the data to our first hypothesis is that FDIs per se do not appear to have any significant impact on robot adoption in the automotive sector; however, the impact of other country and sector specific factors – namely technological and exporting capacity of local economies - is crucial in explaining robot adoption. We use the level of exports and the number of patents to proxy the competitiveness and innovativeness of host countries. These local country factors appear to affect robot adoption both in isolation from FDI and when combined with FDIs; they are positive and statistically significant, pointing to the fact that absorptive capacity is crucial for technological change in 4IR technologies as well (Cohen and Levinthal, 1990).

Going into greater details, our second hypothesis is supported by the following findings: (1) FDIs *per se* do not significantly impact on robot adoption in either the assembly nor the component segments of the automotive industry; (2) *FDIs* have a positive and significant impact when *combined with high innovative capacity* in the host economy, but *only in the assembly segment of the industry*; (3) other factors characterising the local eco-system, such as innovation capacity and export competitiveness (for any given level of FDIs), play *a greater role in the component segment of the industry*.

These results reflect the different structural and behavioural characteristics of these two segments of the industry, which in turn affect the impact that FDIs and the local eco-system have on technology adoption.

In the *automotive assembly segment*, which is dominated by large MNCs, FDI is directed to support production operations such as welding, pressing and painting. In most of the cases, such operations cannot be performed competitively without high levels of robotisation. This implies that MNCs active in automotive assembly rely heavily on fully automated production processes, and hence exert a direct positive effect on robot adoption in the countries where their plants are located (Castellani et al., 2015; Sur and Nandy, 2018). This positive impact of FDIs in the assembly segments can be reinforced by the competitive pressure on local automotive manufacturers (if present), which may be induced to respond by purchasing the same cutting-edge robot technology (indirect positive effect via competitive pressure on local automotive makers to innovate). A further reinforcing mechanism is the creation of backward linkages by MNCs active in the assembly segment, which may resort to local suppliers of parts and components, often requiring them to meet high-level technical and production standards (see Freyssenet and Lung 2000 for the effect of standardisation process on developing countries). Meeting these standards may well drive robotisation among local firms. This indirect positive effect of FDIs (via induced robot adoption by local suppliers) is highly demanding in terms of the technological and organisational competencies of local firms.

These positive (direct and indirect) impacts of FDIs in the assembly segment on robot adoption in recipient countries can be compensated, at least partially, by crowding-out effects, hence reducing the demand for robots by outplacing local car makers and other automotive manufacturers (if present). In addition, FDIs in the assembly segment may be accompanied by a substantial increase in the imports of automotive parts and components and may even attract foreign first-tier investors active in the automotive component segment (through a follow the leader mechanism), thus crowding out local suppliers if not qualified. This negative indirect effect (via market stealing and outplacing of local competitors and suppliers) is most likely to occur if FDIs mainly pursue market seeking objectives and if local suppliers compete on price rather than on innovation (Sturgeon et al. 2008; see Barnes et al. 2017 for evidence on these patterns in the South African case).

Consistent with this line of argument, our results suggest that the positive effects prevail in the case of FDIs in the assembly segment, with particular importance given to the indirect impact via competitive pressure on local automotive manufacturers and via the creation of backward linkages and demand of high-quality components. Both of these indirect effects are likely to take place only in the presence of a lively local eco-system that is characterised by dynamic and innovative firms and institutions. In fact, the impact that the combination of FDI effects and local innovation capacity have, is broadly confirmed by our findings in Table 4, showing that robot adoption is positively and significantly affected by the interacted term FDI*patents in the assembly segment.

If we now turn to the upstream segment of the automotive value chain, it is worth mentioning that *component manufacturers* (ranging from large first-tier international suppliers to lower-level tiers of domestic suppliers) are highly heterogeneous players. Their outlets range from hyper-specialised worldwide quasi-monopolistic niches to national and regional markets for broader varieties and variants of automotive components, wherein oligopolistic rivalry prevails. Such suppliers make their decisions to automate production processes according to a number of parameters, including capital expenditure considerations, the organisational pressures to adopt a new technology, and the specific production requirements and product standards they have to comply with. Hence, robot adoption in the case of component suppliers is highly dependent on innovation capacity and on the competitive pressures in both domestic and international markets. This is consistent with our results in Table 4, which show that robot adoption in the component segment is positively and significantly affected by host countries' patents and by exporting, as measures of local innovativeness and competitiveness. This interpretation is also in line with the recent GVC literature (Kano et al. 2020) that sheds light on the importance of local capabilities to be able not only to link up to GVCs, but also to increase the value-added content of what is produced (Andreoni and Tregenna 2020).

By contrast, FDIs in the automotive component segments are most likely to be associated with heavy market-stealing effects. In fact, international suppliers investing in a country might easily crowd out national suppliers that are competing in the same market, at least for low and intermediate levels of innovativeness of the local eco-system. Hence, the positive direct effect of FDIs in this segment, determined by the purchase of robot by MNCs specialised in component manufacturing, will probably be compensated by the indirect negative effect due to the exit of local suppliers. This interpretive line is broadly consistent with our results, as the interactive term FDI*Patents turns out to be not significant in the automotive component segments in Table 4.

To conclude, by narrowing down our analysis to a specific industrial sector and a specific type of technology, we found that FDIs are not a determinant of this type of technology adoption *per se*; rather, they become significant only when interacted with our proxy for innovation capacity. This confirms what has already found in the literature: that effect of FDIs on technological upgrading is considerably stronger among those endowed with higher levels of capabilities and absorptive capacity (Kemeny 2010). This is consistent with other studies in similar technologies, that report how the acquisition of new technologies is determined by absorptive capacity and a series of organisational activities that imply pre-existing capabilities (see Zhao et al., 2020 for a case on 3D printing)[17]. We also contribute to extant literature by showing how different segments of the automotive value chains are characterised by distinctive technology adoption patterns. Our findings reveal that FDIs, which are considered a major source of economic growth opportunity, could actually trigger local industrial robots' adoption, but only when there is already an existing set of elements such as innovation capacity and export competitiveness. Export competitiveness creates more demand and higher economies of scale, which in turn generate better productivity and trigger the adoption of new industrial robots due to the increase in volumes.

We performed a series of robustness checks that are reported in the Appendix, Tables A5 through A9. First, we controlled for the level of countries' industrialisation in tables A5 and A6. Specifically, instead of controlling for country fixed effect, we divided the countries into four categories: emerging, industrialised, Eastern Europe and China. These four categories are motivated by the level of industrial development of different countries, considering the specificities of Eastern European countries and their integration in the European market and the special role of China as a recent, highly successful, player in the automotive industry. Main results remain unchanged when controlling for these different levels of industrialisation of recipient countries.

[17] It is interesting to note how some mechanisms would allow the adoption of industrial robots through other channels. For instance, in the case of South Africa the presence of MNCs has been crucial for the adoption of industrial robots, and this started well before the turn of the millennium. In fact, plants in South Africa often replicate robot adoption strategies that are quite similar to the ones of mother or sister plants in other parts of the world. However, it is important to consider that without the development of local innovative capabilities, this replication mechanism could also have a negative impact: South Africa has become a technology colony "capable of introducing and industrialising selected multinational technologies, but largely incapable of contributing to processes of global innovation" (Barnes et al., 2018: 32; see also Barnes and Morris, 2004).

Second, we controlled for those countries that have a significant indigenous production of motor vehicle units, listed in table A7. In table A8 we perform an analysis where we use the number of motor vehicles produced, which takes value 1 if the units produced number is higher than one million, 0 otherwise. The latter variable is positive and statistically significant. This robustness checks also confirms our main findings.

As a final robustness check we ran regressions controlling for another characteristic of countries' robot manufacturing industry, i.e., the level of export of industrial robots, using UN Comtrade data class 847950: "industrial robots, not elsewhere specified or included". The latter is a residual class including machinery broadly corresponding to the definition of industrial robot, which is important for consistency purposes of our analysis. The export of commodities is often used as a proxy to analyze the competitiveness level of a specific industry, also giving a sense of the technological content of such sector. As expected, the impact of this variable on robot adoption is always positive, albeit not statistically significant, while leaving the measured impact of our focal variables unaltered (see Table A9 in Appendix).

7. Conclusion

In this paper we have presented new evidence on the impact of FDIs in the adoption of industrial robots in the automotive sector. We have also considered other factors whose presence in conjunction with FDIs is responsible for industrial robots' adoption, namely the innovativeness and competitiveness of the country's industrial ecosystem. Due to the high-level disaggregation of our data, we presented results on how these mechanisms work along both final assembly and components segments of the value chain.

Consistent with an extensive body of empirical literature that links FDIs effects with local capabilities (Meyer and Sinani 2009; Castellani et al. 2016), we find that FDIs in the automotive sector do not have a significant effect *per se*, and their impact is positive only if combined with sufficient innovation capacity in the host economy. When disaggregating at different segments of the value chain, the combination of FDIs and local innovativeness has a positive and significant impact only in the case of automotive final assembly. Other context-specific factors that reflect the

level of innovativeness and competitiveness of the local eco-system have a greater impact in the case of component manufacturing than in the automotive assembly segment.
From this perspective, our paper adds to extant literature in at least two crucial respects: first, it contributes to a better understanding of whether and how FDIs may shape the adoption of industrial robots, as part of a more general discourse on technology adoption. As shown, this implies a reconsideration of the role played by MNCs and by local capabilities in this process. Secondly, our paper helps explore the high heterogeneity of technology adoption even within the same sector, thus paving the way to more detailed analyses and policies.

However, our study also presents some limitations. First, the automotive sector conceals much more within-industry heterogeneity than we are able to capture. Other segments of the automotive industry, e.g., different component parts, might be worth analysing. Moreover, within the two segments we have examined, one might observe different business models and ways in which companies adopt industrial robots. Further empirical analysis is needed in this respect. Second, our findings highlight that technological change is a complex, highly heterogenous phenomenon that can hardly be captured by means of purely quantitative analysis, and calls for a combination of disciplinary approaches, also beyond economics, to include institutional and socio-political aspects. Third, while the automotive sector is a key user of robots, our findings can hardly be generalised to interpret the FDI-technology adoption nexus in the case of other sectors. More research ought to be carried out in different sectors and application domains to obtain a broader and richer picture of the interplay between foreign investment and local innovation eco-systems in the case of robot adoption. Finally, empirical models will have to be extended to include other context specific factors such as labour market institutions, market structure, as well as industrial policy and specific skill sets which may heavily affect the adoption of industrial robots.

To conclude, at the policy level, an increasing number of countries are focusing on the adoption and implementation of innovation policies to adopt and foster new technologies. Our paper points to the need to build up local basic productive capabilities that serve as a key factor for the adoption and use of new technologies (UNIDO 2020; Andreoni et al. 2021). This is likely to be particularly important and demanding for emerging countries as a key to the adoption of new digital technologies and to upgrade their role in GVCs. Further sectoral and technology-specific research is needed to disentangle technology adoption dynamics, as a crucial aspect for the future, and to explore national and regional patterns of digital transformation in greater detail.

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Appendix

1. On the data

Table. A1. FDIs in thousands of US dollars for two segments of the automotive value chain.

Country	FDI_Automotive Components	FDI_Automotive Assembly
Argentina	1,240.52	7,838.55
Austria	1,148.76	1,272.57
Belgium	200.760	4,036.12
Brazil	5,538.31	38,359.10
China	29,419.83	102,516.38
Czech Republic	5,365.29	3,869.7
Finland	74.3	0.53
France	1,892.15	983.58
Germany	2,699.63	3,817.17
Hungary	5,637.48	6,031.66
India	12,746.89	39,659.91
Indonesia	1,654.22	8439.9
Italy	169.35	2,384.89
Japan	242.43	348.83
Malaysia	576.96	1773
Netherlands	69.84	1076.8
North America	55,638.74	92,338.11
Poland	9,485.28	6,127.62
Portugal	235.45	1,644.1
Romania	7,494.44	3,059.6
Russia	5,692.70	31,721.26
Slovakia	2,420.04	10,448.36
Slovenia	n/a	358.07
South Africa	275.06	7,224.38
South Korea	4,054.40	1,720.48
Spain	1,304.27	20,947.99
Sweden	75	1,027.2
Switzerland	23.3	343.9497
Taiwan	31.1	940.1
Thailand	5,257.01	12,684.37
Turkey	2,181.89	12,431.86
United Kingdom	3,609.27	14,207.51

Table A2. Number of robots adopted in two segments of the automotive value chain

Country	N_robots Automotive Components	N_robots Automotive Assembly
Argentina	1,312	5,112
Austria	12,636	4,359
Belgium	8,192	19,178
Brazil	10,018	25,246
China	51,121	157,531
Czech Republic	18,641	17,569
Finland	3,249	819
France	78,792	138,895
Germany	328,890	563,755
Hungary	2,973	7,654
India	7,281	23,425
Indonesia	492	155
Italy	98,378	125,865
Japan	794,381	527,497
Malaysia	894	409
Netherlands	6,163	1,498
North America	331,119	435,488
Poland	10,457	8,505
Portugal	6,639	1,944
Romania	1,257	3,586
Russia	2,080	4,615
Slovakia	5,748	14,242
Slovenia	3,479	1,659
South Africa	2,181	7,822
South Korea	185,087	221,759
Spain	99,254	94,396
Sweden	15,215	22,094
Switzerland	4,878	223
Taiwan	4,461	1,186
Thailand	1,677	82
Turkey	8,318	9,158
United Kingdom	44,539	62,340

2. On the 2SLS.

Table A3. First-stage regressions of IV models reported in Table 3.

Y: FDI t-1	***First stage***	***First stage***
	(1)	*(2)*
FDI_other_activity	*6.256****	*6.294****
	(1.382)	*(1.511)*
Pat_t-1	-2.302	-2.373*
	(1.180)	*(1.231)*
Exp_MillUS	-0.003	-0.003
	(0.003)	*(0.003)*
Gross Fixed Cap_Form		0.0003
		(0.000)
Employm_share_manuf		4.00
		(39.531)
Volume_lead		-3.42
		(0.799)
Time fixed effects	Yes	Yes
Country fixed effects	Yes	Yes
R squared	0.34	0.34

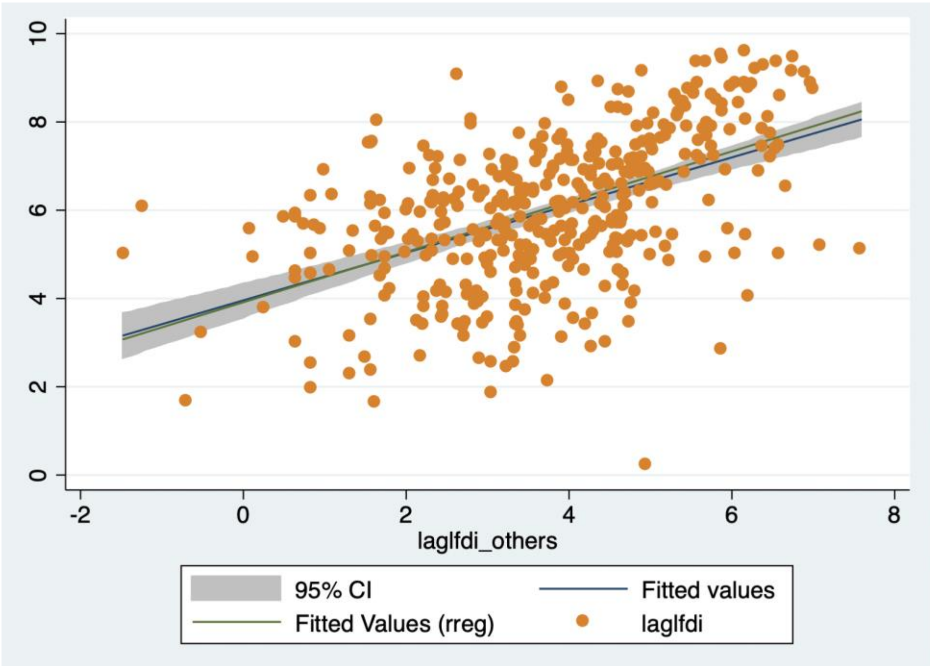
Standard errors in parentheses *** p < 0.01, ** p < 0.05, * p < 0.1

Table A4. First-stage regressions of IV models reported in Table 4.

Y: FDI t-1	*First stage*	*First stage*	*First stage*	*First stage*
	(1)	*(1)*	*(3)*	*(4)*
	2910	***2910***	***2930***	***2930***
FDI_other_activity	*9.656****	*9.145****	*5.757****	*5.750****
	(1.611)	*(1.6040)*	*(1.499)*	*(1.613)*
Pat_t-1	-1.50	-2.286	-1.961	-2.377
	(1.315)	*(1.324)*	*(1.643)*	*(1.630)*
Exp_MillUS	0.003*	0.0001	0.132**	0.136**
	(0.001)	*(0.001)*	*(0.005)*	(0.000)
Gross Fixed Cap_Form		-0.00005		-0.00004
		(0.00008)		*(0.000008)*
Employm_share_manuf		12.097		4.149
		(29.294)		(35.463)
Volume_lead		-2.28		-2.24
		(0.00001)		(0.00001)
Time fixed effects	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes
R squared	0.44	0.45	0.38	0.37

Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Figure A1: Scatterplot correlation of first-stage regression.



Lines are fitted by OLS regression. Vertical axes: lagged FDI in automotive manufacturing activities. The slope coefficient is 0.5 with robust standard error 0.05; the *t*-statistic, *F*-statistic and R-squared are 10.66, 113.65, and 0.24, respectively.

3. Robustness checks.

We conducted a robustness check, controlling for the level of countries' industrialisation. Specifically, instead of controlling for country fixed effect, we divided the countries into four categories: emerging, industrialised, Eastern Europe and China. In doing so, we adopted a revised UNIDO classification of industrialised and emerging economies, which considers China as a category in itself (see Teng and Lo 2019[18]). Moreover, due to specificities related to the automotive sector, we decided to isolate the Eastern Europe category.

TABLE A5. Robustness check – countries' level of industrialization

	Y =N_Rob	*Y =N_Rob*	*Y =N_Rob*

[18] *"Determinants of Developing Countries' Export Upgrading: The Role of China and Productive Investment", Working Paper No. 227/2019 SOAS Department of Economics,* https://www.soas.ac.uk/economics/research/workingpapers/file142705.pdf

	OLS	OLS	IV
	(1)	(2)	(3)
FDI_t-1	-0.98	-0.087	0.519
	(0.221)	(0.100)	(0.427)
Pat_t-1	199.34**	63.725	124.687*
	(68.828)	(41.859)	(66.452)
FDI*Pat		0.0073	
		(0.007)	
Exp_MillUS		0.312***	0.301***
		(0.029)	(0.037)
Gross Fixed Cap_Form		0.0009	0.002
		(0.001)	(0.001)
Employm_ share_manuf		282.974*	382.948**
		(113.257)	(150.571)
Volume_lead		0.0002*	0.0003*
		(0.0001)	(0.0001)
Emerging	1467.144*	3706.637***	4520.099**
	805.3781	(1384.468)	(1822.032)
Industrialised	7872.169***	4940.061 ***	5642.212***
	3690.908	(1469.493)	(2095.563)
dummy_China	8043.545 *	3028.607	-1725.137
	2103.426	(4723.087)	(5659.732)
Time fixed effects	Yes	Yes	Yes
Country fixed effects	No	No	No
R squared	0.26	0.77	0.74
F value			16.73

Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. *The F value for the validity of the instrument is the Kleibergen-Paap rk Wald F statistic and the value is above the 10 per cent critical value.*

TABLE A6. Robustness check - countries' level of industrialization at sectoral level

	Y =N_Rob	Y =N_Rob	Y =N_Rob
	OLS	OLS	IV
	(1)	(2)	(3)
FDI_t-1 2910	-0.300 *(0.382)*	-0.0400121 *(0.115)*	0.463 *(0.341)*
FDI_t-1 2930	-0.187 *(0.230)*	-0.181 *(0.14)*	0.338 *(0.452)*
Pat_t-1 2910		18.080 *(14.735)*	41.721** *(17.790)*
Pat_t-1 2930		135.6542 *(83.943)*	150.142*** *(37.442)*
FDI*Pat 2910		.0126*** *(0.003)*	
FDI*Pat 2930		-0.004 *(0.013)*	
Exp_MillUS 2910		0.323*** *(0.018)*	0.332*** *(0.171)*
Exp_MillUS 2930		0.391*** *(0.071)*	0.519*** *(0.070)*
Gross Fixed Cap_Form		.0001 *(0.0012)*	0.0005 *(0.001)*
Employm_share_manuf		265.383*** *(55.080)*	336.60*** *(62.374)*
Volume_lead		0.0002** *(0.0001)*	0.0003*** *(0.0001)*
Emerging	8.735758 *(204.6036)*	3668.114*** *(789.120)*	4506.494*** *(789.082)*
Industrialised	8658.485*** *(804.6494)*	4532.883*** *(699.184)*	5011.644*** *(788.577)*
Dummy_China	7564.867*** *(1849.799)*	4483.073 *(3379.577)*	2742.778 (3147.508)
Dummy_sector 2	-884.363 *(1016.92)*	-373.944 (446.806)	-641.017 (629.512)
Time fixed effects	Yes	Yes	Yes
Country fixed effects	No	No	No
R squared	0.11	0.79	0.76
F value			5.23

*Standard errors in parentheses *** p < 0.01, ** p < 0.05, * p < 0.1. The F value for the validity of the instrument is the Kleibergen-Paap rk Wald F statistic and the value is above the 5 per cent critical value.*

We performed another robustness check to control for those countries that have a significant indigenous production of motor vehicle units. We use OICA data from 2005 to 2016 and used countries whose indigenous firms have been producing more than one million units per year for the entire period. Our variable is named *natfirmbig*. The countries and the firms are reported below. Robustness checks are presented in Table A8.

TABLE A7. Countries with indigenous production.

Firm	Country
General Motors Ford	United States
VW Daimler BMW	Germany
Honda Hyundai Kia	South Korea
Renault PSA	France
Fiat	Italy
Mazda Daihatsu Mitsubishi Toyota Nissan Suzuki	Japan
TATA	India
Changhan BAIC Dongfeng Motor SAIC	China

TABLE A8. Robustness check – countries' production of motor vehicle units.

	Y =N_Rob	***Y =N_Rob***	***Y =N_Rob***
	OLS	*OLS*	*IV*
	(1)	*(2)*	*(3)*
FDI_t-1	*-0.22*	*-0.107*	*0.147*
	(0.133)	*(0.102)*	*(0.224)*
Pat_t-1	39.85	36.502	42.52**
	(27.14)	*(28.118)*	*(20.81)*
FDI*Pat	0.021** (0.006)	0.015** (0.005)	
Natfirmbig	17795.12*** (1313.5)	11401.36*** (1209.394)	11498.16*** (1937.12)
Exp_MillUS		0.19***	0.137*
		(0.037)	*(0.073)*
Gross Fixed Cap_Form		0.005** *(0.0021)*	0.007** *(0.002)*
Employm_ share_manuf		-102.22 *(162.749)*	-148.33 *(164.42)*
Volume_lead		0.0003 *(0.0001)*	0.0002 *(0.0001)*
Time fixed effects	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes
R squared	0.80	0.86	0.88
F value			18.86

Standard errors in parentheses *** p < 0.01, ** p < 0.05, * p < 0.1. *The F value for the validity of the instrument is the Kleibergen-Paap rk Wald F statistic and the value is above the 10 per cent critical value.*

We performed a final robustness check in order to control for the robot manufacturing industry of different countries. We used the value of exported industrial robots – using class 847950: *industrial robots, not elsewhere specified or included.* The latter is a residual class including machines that are either industrial robots or very similar to the standard industrial robots definition. Our variable is named *Exp_ind_rob*. Robustness checks are presented in Table A9.

TABLE A9. Robustness check – Countries' performance of robot manufacturing industry.

	Y =N_Rob *OLS*	***Y =N_Rob*** *OLS*	***Y =N_Rob*** *IV*
	(1)	*(2)*	*(3)*
FDI_t-1	*-0.12*	*-0.12*	*0.110*
	(0.111)	*(0.110)*	*(0.238)*
Pat_t-1	34.24	35.69	41.86**
	(29.69)	*(28.17)*	*(22.44)*
FDI*Pat	0.018**	0.015**	
	(0.005)	(0.005)	
Natfirmbig		12173.96***	12326.24***
		(1995.823)	(2308.015)
Exp_MillUS	0.19***	0.18***	0.135*
	(0.036)	*(0.037)*	*(0.072)*
Gross Fixed Cap_Form		0.005**	0.007**
		(0.002)	*(0.002)*
Employm_ share_manuf		-81.52	-131.89
		(164.93)	*(168.08)*
Volume_lead		0.0003	0.0002
		(0.0001)	*(0.00007)*
EXP_ind_rob	9.70	4.64	1.14
	(0.0001)	(0.00001)	(6.42)
Time fixed effects	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes
R squared	0.84	0.86	0.88
F value			17.68

Standard errors in parentheses *** p < 0.01, ** p < 0.05, * p < 0.1. *The F value for the validity of the instrument is the Kleibergen-Paap rk Wald F statistic and the value is above the 10 per cent critical value.*