Racing with (or without) the machine: Robot adoption and FDI driven transformation in the automotive industry

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1. Introduction

During the last decade, the interest towards the alleged "next industrial revolution" has increased substantially. A set of digital technologies is supposed to have a profound impact on the international organisation of work and production, leading to reshape global value chains (OECD, 2017; UNIDO, 2017). The observed rebound after the big crisis in terms of global output, cross-border investment and corporate profitability, while employment is still sluggish or increases at a much slower pace, has induced scholars to infer a generalised diffusion of such labour saving and highly transformative technologies. This has led the literature to focus on the effects, and especially on the expected labour disruption effects, of these new technologies, often disregarding the nature and characteristics of adoption processes.

Narrowing down on the industrial robots' technology in the automotive industry – i.e. a highly dynamic and transformative digital technology with a relatively long history of application to manufacturing in a specific industry – this paper contributes to highlight the mechanisms underlying the adoption of such devices within this industry across different countries. The idea is that the intensity of technology adoption and the mechanisms through which it occurs, affect the way global value chains are organised and ultimately impact on employment across countries. Specifically, we provide new evidence of how FDI (Foreign Direct Investments) have driven changes in robotization within the automotive sector. In doing that, we introduce new econometric evidence of the relationship linking FDI and robotization in the automotive industry.

In developing our analysis, we refer to the broader literature regarding the relationship between FDI and technological upgrade of recipient countries. Are FDI a key driver of technology transfer and adoption? Are FDI enough to trigger the introduction of advanced technologies such as industrial robots? Which is the role played by host country specific factors in the adoption of industrial robots? What are the specific features of the automotive sector we need to take into consideration and, thus, what is the relevant level of data disaggregation for the analysis of FDI-induced robotisation?

The paper innovatively combines two datasets, the International Federation of Robotics (IFR) dataset, and fDi Markets dataset, an online database provided by fDi Intelligence, a specialised division of FT Ltd. We focus on the middle part of the value chain, concerning manufacturing production processes, and analyse to which extent FDI are driving the adoption of industrial robots. Taking advantage of the high level of disaggregation and focusing on four segments of automotive, we construct an *ad hoc* panel dataset that incorporates the FDI and the application of industrial robots[1] of the automotive industry. We analysed 35 countries in a 10 years period (2005-2015) and at two levels: the first uses disaggregated descriptive statistics to describe the relationship between FDI and robots adoption within the four subsectors mentioned above. The second level is less disaggregated, we consider two segments, i.e., Automotive OEM and Automotive Components, and use OLS regressions to test the different role that FDI play in triggering the adoption of industrial robots in the two segments.

Adopting controls for different variables, related both to geographical areas and sectoral specificities, we found that FDI play a different role in triggering robotisation when referring to a different segment of the supply chain. Albeit FDI are an important driver when referring to OEM assembly, they are not a significant variable when referring to components' segments. Considering the heterogeneity between countries and the importance of domestic/regional value chains in developing industrial ecosystems, we formulate hypotheses around other factors driving robotisation more than FDI, i.e., the existence of local production systems and targeted technology policies.

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[1] The four subsectors are: motor vehicle manufacturing (OEM assembly), plastic and metal parts, electric/electronic parts and other parts, which includes car seats, airbags, safety belts.

2. Foreign Direct Investments and Technical Change

Since the 1980s, the role of FDI and MNCs in promoting growth, employment, and economic diversification in emerging developing countries has been widely debated. The questions around whether FDI and the role of MNCs are key elements to promote growth, employment, and economic diversification in emerging developing countries has been a matter of great interest in the literature and policy debates. The consensus is that FDI trigger development, but only to a certain extent and under certain conditions. The next paragraphs will review some of the literature on FDI's impact with a specific reference to economic growth and technological spillovers in receiving countries.

2.1 From FDI optimism to GVC literature: why FDI may not be enough

The global revolution in ICT that occurred starting from the 1980s and the consequent reorganization of international production in GVC (global value chains) deeply reshaped not only the way in which firms were organized but also how their activities were perceived. MNCs and their FDI were not observed in a positive way and a certain degree of hostility towards their activities was reflected in restrictive policies implemented until the 1980s (Lall, 2000; Safarian, 1999). Things started to change due to the emergence of two interrelated aspects.

First, positive experiences about capabilities development started to emerge in developing countries as a result of their strategic engagement with MNCs, such as the abilities to attract R&D, to master the absorption of leading technologies and develop local supply chains (Lall, 2000; Mpanju, 2012). This occurred in parallel to a shift in the international regulatory environment, with WTO rules that promoted free trade between countries.

Second, the accelerating pace of technological change, together with the rising cost of innovation, contributed in viewing MNCs as a strategic, and often the only, way to link up to new global waves of innovation and technologies. In a global landscape where the first unbundling, or the so-called "Great Divergence", made already possible to detach production from consumption, the second unbundling, or "Great Convergence", made possible to move ideas with a further decrease in the cost of moving people (Baldwin, 2016). As a result of these dynamics, FDI and manufacturing production grew incredibly, and developing countries started to attract FDI and to see an increase in the export of low, medium and high-value goods.

The promotion of liberalization that was also related to the failure of some Import Substitution Industrialisation (ISI) policies – those which were not coupled with Export Oriented Industrialisation (EOI) acted as a binding force of the new global actors, and MNCs saw exponential growth in their global activities (UNCTAD, 2001; Cimoli et al., 2009). The rise in MNCs activities led a great number of scholars to focus on this field and to use different measures to assess the impact of FDI effects on receiving countries. Despite the large effort, the results are not unanimous and the impact of MNCs' activities is considered mixed (Lall, 2000).

There is a mix of findings when we look at FDI both in their *direct effects*, mainly observed in terms of productivity, and in their *indirect effects*, related to technological externalities (Castellani et al., 2015).

Direct Effects

A substantial body of literature found a positive direct effect of inward FDIs on the host economies mainly in terms of : *(i)* productivity, where MNCs' productivity is found to be higher than local firms and trigger productivity of local companies (Dunning, 1993; Barba Navaretti and Venables, 2004; Criscuolo and Martin, 2009; Castellani et al., 2015; Denisia, 2010); and on *(ii)* employment creation (Ncunu, 2011; Chaudhuri and Banerjee, 2010 for FDI in agriculture).

For example, Vacaflores (2011) studied the relationship between FDI and employment in 12 Latin American countries finding a positive and significant effect. Nonetheless, a closer look at the different variables that contribute to economic growth, besides employment, reveals how the study adopted the case of Latin America, focusing on specific countries like Mexico and the Caribbean that implemented an attitude of "passive open-door policy with limited policy interventions and no industrial policy" (Lall, 1995). Latin American countries were among the highest recipients of FDI starting from the 1980s but, once compared to other regions like South East Asia or Eastern Europe, the impact was much weaker. For instance, Mexico is the country where the development of the auto cluster was impressive, but while export grew 18% a year over 1994-2002, GDP grew at 3% and the expected multiplier did not materialise (Mortimore and Vargara, 2004). The positive effect was very limited for local suppliers and there was not an overall increase in the manufacturing value added of the entire economy. In the case of some Latin American countries, the hype of positivism around FDI and liberal policies ignored free markets' deficiencies to a point where governments removed any tool even to attract, target or guide FDI (Lall, 2000; Mpanju, 2012).

Indirect Effects

Indirect effects on host economies occur through changes in the behaviour and performance of local firms. The standard assumption is that FDIs will determine some kind of technological externalities (determining shifts in the local firms' production function) or pecuniary externalities (determining shifts in the local firms' profit function). Empirical evidence on these impacts is more controversial. Some studies found a technological upgrade on a general level, where local firms learnt from MNCs by observing technologies employed by international actors and attracting employees trained by the same actors (Borensztein et al., 1998; Blomström and Sjöholm, 1999 for a study on Indonesia; Meyer, 2004). The availability of longitudinal firm level data has led to explore spillover effects of multinational presence across and within industries, leading to controversial results (Gorg and Greenaway 2004).

Overall, the most recent literature on this topic found that FDI are not beneficial *per se* and that capabilities improvements and learning depend on local firms' absorptive capacity (Kokko 1994), on technological gaps separating foreign and local firms as a source of technological opportunities (Findlay 1978, Blomstrom and Wolff 1997), and catching up potential (Meyer and Sinani, 2009). This implies a growing attention to the technological capabilities of local firms and institutions (Chang, 1994) as well as the nature of investment projects and the technological level of investors (Castellani and Zanfei 2003, 2006). Crowding out are also among the main concerns, which sometimes could even act in the opposite direction and thus hampering the development. Capabilities creation, absorptive capacity and production linkages are a key concern when considering spillovers to the rest of the economy (Jindra et al., 2009; Zanfei and Saliola, 2009; Meyer and Sinani, 2009).

This risk is confirmed by numerous studies, especially when referring to developed *vs*. developing countries. Although empirical research shows a positive correlation between FDI presence and productivity sectors in developed countries (Caves, 1974 on Australia; Globerman, 1979 on Canada; Pain and Hubert, 2000 on the United Kingdom), the picture becomes less clear when studies are referred to developing countries that do not have mature industrial systems, developed capabilities, and regulations. Xu (2000) carried out a study about more than 40 countries, and he found positive technology transfer in developed countries but not in developing countries. Similarly, positive effects are found on FDI in manufacturing firms in the United States but not in Mexico and Venezuela (Atiken, Harrison and Lipsey, 1996). Mixed results are found in a study on Uruguay where there are positive effects of FDI but only in firms with small technological gaps (Blomstrom and Sjoholm, 1999). Referring to emerging economies, Hanson (2001) claimed that positive effects are very few and Gorg and Greenaway (2004) that most effects would be negative.

Finally, Zanfei (2012) pointed out how the advantages that local firms can acquire are the result of costly efforts. Thus, it would be more appropriate to talk about the effects, and not the externalities induced by MNCs. The latter term recalls the idea of not-paid-for: this idea could be appropriate in the case of negative externalities intended as the disadvantages created by MNCs in terms of pollution, land grabbing and so on. Conversely, the positive externalities are well paid for: purchase, adoption, and development of technologies are difficult to acquire and imply complex learning processes and organizational changes, far away from an automatic process (Saliola and Zanfei, 2009).

FDI & Policy

The level of policy mitigation and intervention related to FDI depends on the policies adopted by different countries. The openness and benefits that developing countries supposedly obtained due to FDI inflows led some authors to advocate that governments should adopt friendly attitudes towards investors (Moeti, 2005). This approach underestimates that benefits possibly occurring because of FDI inflows are not automatic or free, and hence a complementary space for active policies is desirable. Without the right policy supports, countries could see unwanted outcomes like rising inequality between groups of people (Feenstra and Hanson, 1995; Tsai, 1995; Lall, 2000; Te Velde, 2001; Cimoli et al. 2009). Among the most famous examples of countries that successfully exploited FDI inflows, we found Singapore and Vietnam, two countries that adopted strong targeted industrial policies to attract not only FDI, but specific high-tech FDI. On the one hand, Singapore started from the 1960s to target firms providing strong incentives and grants to develop key sectors and key export platforms (Te Velde, 2001). On the other hand, Vietnam spent an important effort in order to attract IBM thanks to an educated, skilled labour force, and a proactive response from the government to provide the infrastructure required for the biggest foreign investment of IBM. Both countries had a so-called cluster approach as an instrument of industrial policy that attracts FDI, thereby leading at the same time to a promotion of linkages and spillovers (Te Velde, 2001).

Those scholars questioning the conditions required to have positive spillovers from FDI inflows stress the fact that FDI is not always good for the receiving country, especially in resource seeking type of FDI (for a review on different types of investments see: Dunning, 2008; Narula and Santangelo, 2012). Among the controversial aspects regarding the effect that FDI have on local economies when policy measures lack, there is the crowding out of domestic firms. This could take the form of product market crowding out, negatively affecting the learning trajectory of domestic firms, and factor market crowding out, reducing access of domestic firms (Lall, 2000). The dual role of local capabilities both in terms of attracting FDI and benefiting from FDI, increased the attention towards the *what* and the *how* does happen in receiving countries with a strong MNCs presence.

The recent emergence of the GVC literature is important because it raise some concern to the mainstream vision while, at the same time, proposing other tools for evaluating the role of FDI. Specifically, GVC literature shed some light on two critical elements, i.e., governance and upgrading (Gereffi 1994; Gereffi and Lee, 2016; Sturgeon, 2009). On the one hand, analysis of different types of governance define the way in which MNCs manage, organize and orchestrate their suppliers on a global scale. On the other hand, the focus on upgrading, intended as a shift to improve the competitive position within a GVC, led to a reconsideration of the role played by institutional and economic actors to improve local capabilities and economic conditions (Gereffi and Lee, 2016).

2.2 From vertical GVC linkages to horizontal clusters: the role of policy in building up domestic capabilities

The unevenness of globalisation imposed to look at how firms are linked to each other and specifically how functional integration between dispersed activities works (Gereffi and Kaplinsky, 2001). The GVC framework makes an important effort in going beyond the *sectoral* unit of analysis in order to include economic actors, organisations and institutions that operate across sectors, across functions within sectors and across countries. Despite the importance that this approach gives to understanding the interrelations at a global level, the sectoral characteristics are still important for many reasons. The ability of countries to link up through backward linkages, and then either adding value forward or remaining upstream, is strongly related to the types of FDI a country is able to attract and the types of linkages that develop from and around the FDI (Andreoni, 2019). Value creation and spaces for learning and development are distributed unevenly across value chains in different sectors (Andreoni and Chang, 2017), most often involving a fine-slicing of production and R&D activities also within sectors (Mudambi 2009, Zanfei et al. 2019).

From a developmental point of view, the linking up to GVCs through FDI is considered a channel to promote an industrialization-driven growth by accessing regional and global markets, while diversifying and upgrading in specific tasks and new products (Andreoni, 2019; Milberg and Winkler 2013). Nonetheless, relying on high-quality FDI does not guarantee the improvements of local capabilities (Te Velde, 2001), which are a crucial element to develop spillovers to the rest of the economy. Governance, intended as a non-market coordination of economic activities, is the key aspect of how big MNCs decide (or are forced to) to interact with suppliers. For instance, if we consider the automotive industry and its potential spillovers to the rest of the economy, a country like Mexico had a very different manufacturing development compared to Eastern Europe or the more recent Thai experience.

The two elements introduced by GVC (i.e., governance and upgrade) expand the level of the analysis in two important ways. The analysis of governance and hence of the power distribution along the value chain is an important element to observe both the sector and the policy space for domestic players. The two classical types of value producer-driven, and buyer-driven (Gereffi, 1994; Gereffi and Kaplinsky, 2001) have been recently expanded to take into account both vertical and horizontal relationships (Gereffi and Lee, 2016). These conceptualizations are important to analyse the elements influencing the relationships with local suppliers and how they affect the transfer of knowledge and technology (Humphrey, 2000).

The perspective that considers horizontal linkages cutting across different value chains is important because it brings back the upgrading concept under a different light. Upgrading recalls the strategies and policies that countries and/or regions put in place when they try to coordinate economic and private/public stakeholders to improve and promote development.

Specifically, from a technological point of view, local actors can take advantage of MNCs' operations only if they are *ready* to do so. The mechanism of purchase, adoption, and development of technologies requires many pre-activities that are fundamental to exploit MNCs' operations and upgrade towards value-adding activities. As mentioned already, absorptive capacities are necessary conditions for spill-overs (Cantwell, 1989). The purchase, adoption, and development of technologies are difficult to acquire and imply complex learning processes and organizational changes (Saliola and Zanfei, 2009). In this sense, the acquisition of tacit knowledge and technological capabilities cover an essential set of market failures. The learning by doing process is long and likely to be loss-making for a certain period (Khan, 2012). If these trajectories are financed by specific learning rents, local firms and suppliers are more likely to be *ready* when market-driven opportunities stemming from MNCs' activities arrive (Khan, 2012). These aspects are not pecuniary components linked to the market processes; they instead require profound structural changes with specific industrial and more generally socio-economic policies that force local actors to go through a "structural learning" process whereby set of interdependent changes trigger learning dynamics within and across firms (Andreoni, 2014).

When these capabilities are present, it is easier to access more formal channels of knowledge spill-overs. There are both incentives and political economy forces that are responsible for "a number of both inducement and constraining mechanisms" (Andreoni, 2019). The Local Production System framework is one innovative perspective to look at different types of linkages in a developing country's production system. While acknowledging the vertical links between different actors (economic and institutional), it provides new lenses to look at the role that horizontal relationships across different sectors have in the development of new capabilities. The idea is that the local production system is made of multiple types of production, technological, consumption and fiscal linkages. These linkages are hierarchically structured and each of them develop across firms both horizontally and vertically, depending on the nature of inter-firms relationships (including along GVCs) and the broader political economy and institutional setting which define the distribution of “rents chains” (Andreoni, 2019).

2.3 Automotive sector: how fragmentation of production and concentration of power shaped the industry

Different sectors experienced distinct trajectories in relation to FDI. Automotive production is highly fragmented across countries and its international organisation is often identified as a typical example of GVC. This characterisation stems from the degree of transnational dispersion of production, its capability to change and adapt to new geographic areas and reproduce such complex dynamics as the ones involved in the manufacture and assembly of motor vehicles. The automotive sector provides and effective illustration of the possibility that companies can create and well manage long-distance business relationships (Sturgeon and Lee, 2005). Also, the increased modularity has played a role in understanding how the global production has been changing. Nonetheless, while modularity is important to analyse the production features at a micro, meso, and macro level (Ponte and Sturgeon, 2014), the automotive industry seems to have specific features on its own, especially in relation to the micro and meso level. Indeed, more than a truly GVC, the automotive sector went through a fragmentation in specific geographic regions which tend to be places where there are both major components of OEM producers and an important share of the final demand. Strong regional patterns at the operational level emerged in a much stronger way than global ties (Lung et al., 2004).

The industrial concentration of the sector is another key feature[2] that helps to understand the skewness of the power between OEM (and Tier 1) and the rest of the value chain. This is particularly relevant in the design part of vehicles that is where an important share of the value added lies; pre-production and engineers works, “where conceptual designs are translated into the parts and sub-systems that can be assembled into a drivable vehicle, remain centralized in or near

[2] The forecast of production engineered by the leading OEM (less than 10) is 83% of global output in light vehicles (IHS Markit, 2018)

the design clusters that have arisen near the headquarters of lead firms" (Sturgeon et al., 2008). The integral nature of vehicle design architecture (e.g., weight, noise, vibration, etc.) is so interrelated that changes in one component have, very often an impact on other components (Novak and Wernerfelt, 2006).

In the last decades, this concentration phenomenon has been accompanied by the rise of mega supplier that are the result of an important number of M&A (Wong, 2017). Hence, fewer larger first-tier suppliers have survived and consolidated while, at the same time, developing close relationship with big OEMs. However, it is less clear what has happened to the other parts of the supply chain. As pointed 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). Thus, the importance of attracting big MNCs runs parallel to the urgency of developing suppliers with the capabilities to deal with and respond to OEMs requirements. These aspects influence directly our analysis and the variables we are interested in; a description of the data used, and the model follow in the next section.

3. Data and Methods

We used two main sources of data, the International Federation of Robotics (IFR) and fDi Markets. The former collects data on industrial robots, provided by nearly all industrial robots suppliers world-wide (IFR, 2015). The robots included are based on the definition of the International Organisation for Standardization, according to which an industrial robot is: "an automatically controlled, reprogrammable, multi-purpose manipulator programmable in three or more axes, which may be either fixed in place or mobile for use in industrial automation applications" (IFR, 2015)[3]. Therefore, the IFR dataset provides many insights on the number of robots per industry, country and year. The two main information provided are: (i) the number of robots (both in operational stock and in market delivery value) by sector and segment up to three digits in ISIC rev. 4 classification; (ii) the type of application and sub-application (e.g., in the welding category there are laser welding, arc welding, spot welding, etc.). We will use the details offered by the first

[3] https://www.iso.org/obp/ui/#iso:std:iso: 8373:ed-2:v1:en

information regarding the automotive sector and its subsectors. We use 35 countries (96% of robots adoption), four subsectors in for descriptive statistics and two for the econometric analysis with a 10 years panel data, 2005-2015.

The fDi Markets database is an online dataset built and maintained by the Intelligent Unit of the Financial Times. It compiles data on cross-border investments covering all sectors, specified in NAICS 08 classification[4], and countries worldwide. The dataset is updated daily and relies on the announcement of the investments. Out of more than 142000 observations of investments, 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*, *industry_activity* and *sub_sector*. Out of all industry activities we considered just *Manufacturing*, in order to provide further consistency with the other data coming from IFR which are just related to industrial robots applied in the manufacturing sector.

[4] See Appendix A for more details on classification conversion

Country	Investment FDI_mil US$	% tot
China	151965.36	22%
Mexico	64562.4	9%
US	55213.67	8%
India	51921.74	8%
Brazil	45994.76	7%
Russia	41929.36	6%
Canada	24836.55	4%
Spain	21855.52	3%
Thailand	19355.78	3%
UK	17634.03	3%
Poland	16639.42	2%
Slovakia	13451.74	2%
Turkey	12394.78	2%
Hungary	10863.1	2%
Czech Rep.	10591.74	2%
Romania	9807.8	1%
Indonesia	9705.49	1%
South Korea	7352.61	1%
Germany	7135.77	1%
Argentina	6983.47	1%
South Africa	6145.99	1%
Belgium	5997.97	1%
Australia	4288.39	1%
Austria	3748.33	1%
Portugal	3576.99	1%
Vietnam	3305.62	less than 1%
France	3029.3	less than 1%
Malaysia	1826.01	less than 1%
Sweden	1759.2	less than 1%
Italy	1705.87	less than 1%
Netherlands	1151.74	less than 1%
Japan	602.43	less than 1%
Switzerland	373.1	less than 1%
Denmark	254.3	less than 1%
Finland	97.6	less than 1%
Total 2015	**690307.14**	**94% ca.**

Country	Number Robots_Auto	% tot
US (until 2010)	110842	18%
Japan	103844	17%
Germany	93082	15%
China	91726	15%
South Korea	71557	11%
Italy	15291	2%
Spain	15033	2%
France	14199	2%
Mexico (until 2010)	11228	2%
United Kingdom	9874	2%
Thailand	7740	1%
Canada (until 2010)	6789	1%
India	6547	1%
Czech Republic	6530	1%
Brazil	6136	1%
Sweden	4098	1%
Belgium	3969	1%
Slovakia	3393	1%
Poland	3344	1%
Turkey	3175	1%
Austria	2191	less than 1%
Hungary	1984	less than 1%
South Africa	1587	less than 1%
Netherlands	1476	less than 1%
Portugal	1410	less than 1%
Russia	1342	less than 1%
Indonesia	1153	less than 1%
Argentina	1101	less than 1%
Romania	851	less than 1%
Switzerland	747	less than 1%
Malaysia	440	less than 1%
Finland	423	less than 1%
Australia	240	less than 1%
Denmark	190	less than 1%
Vietnam	13	less than 1%
Total 2015	**623123**	**96%**

Table 1 and 2: Authors based on IFR and fDi data for the automotive sector

Table 1 and 2 below show our two main sources of data. We use 35 countries that constitute the 94% of the robots' adoptions and 96% of the FDI in the automotive sector. These countries almost correspond to countries that adopted more robotics in the whole manufacturing sector, but with different intensity[5]. From the countries with more robotics' applications we dropped Singapore, because of no investments in the automotive sector, and Taiwan, because of the difficulties to combine other data. Being the analysis centred in the automotive sector and not being Taiwan one of the main recipients of FDI, we believe that this choice as consistent with our methodology. To the major industrial robots' adopters, we added Vietnam and Argentina, being these countries among the major FDI recipient in the automotive sector.

Although the two datasets are extremely rich in detailed information, they present some limitations. Within the automotive classification there are two unspecified classes, which are Unspecified AutoParts (class 2999) and Automotive Unspecified (class 299). For the descriptive statistics at four levels disaggregation, we were not able to use none of the two unspecified classes, while for the regression at two level disaggregation we use Unspecified AutoParts in the Component segment[6]. Another limitation is due to the fact that up until 2010 the United States, Mexico and Canada were classified together by one of the two databases, therefore in order to have 10-year panel we kept NAFTA for the entire period (IFR, 2015).

Taking advantage of the high level of disaggregation of the data mentioned, we construct an *ad hoc* panel dataset that incorporates the application of industrial robots in four subsectors of the automotive industry and FDIs in the same segment. These subsectors are: *2910* motor vehicle manufacturing (OEM assembly), *2931* metal and plastic parts, *2933* electric/electronic parts and *2939* other parts, which includes car seats, airbags and safety belts. We use descriptive statistics to provide some insights at the more disaggregated level at four segments, thus looking at the extent (if any) of the relationship between robotic application and FDI presence in these four subsectors. We then use the econometric analysis on the two-level disaggregation dataset, where the two classes are 2910 (OEM assembly) and 2930 (OEM Components). The econometric

[5] Ibidem

[6] See Appendix A for more detailed information on how the dataset was built

analysis consists in a simple OLS regression with fixed effects where the dependent variable is the number of robotic applications per country, value chain segment and year. Data on stock of robots are expressed in absolute values. Normalisation effects are coming from other control variables in the model.

The main independent variables are:

- FDI inflow stock per country, year and segment. We use FDI variable interacted with the segments (named IFRclass) and with two of the three geographical dummies. Being the countries in our sample extremely heterogenous, not only in their stages of development but also in how the automotive sector developed, this interaction variable gives further consistency to our model.
- Patents. We use it as a proxy of the innovation level of the destination country. The method used to link IPC classes and industry classification is based on an 'Algorithmic Links with Probabilities' approach developed by Lybbert and Zolas (2014). This approach obtained new concordances between IPC and industry classification mining patent data with specific keywords extracted from industry descriptions and processes and with the use of a probabilistic framework.
- We use a series of control variables: (i) employment share in manufacturing (World Bank Data) so to take into account the different sectoral composition of each country; (ii) the domestic value added (share) of export in the automotive sector[7] so to consider both the size of the market, and the competitiveness of the country in the industry (TiVa data); (iii) export data in the two sub-classes of Automotive OEM and Automotive Components from UNCOMTRADE; (iv) data the domestic value added (millions dollars) of all exports (TiVa data), which controls for both countries that are in a different stages of industrial diversification and for the dimension of the country; (v) GDP per capita (World Bank Data).

[7] TiVa data, class D29.

- Finally, in order to limit endogeneity, we made our FDI-interacted variables, patents, employment share in manufacturing, GDP per capita, domestic value added (both in the automotive sector and total) with one-year lag.

4. Results

Descriptive evidence

We conducted our first analysis at four levels of disaggregation and used descriptive statistics to show the relationships between FDI inflow, robots' adoption, sub sector and country.

Bubble graphs, shown in Figure 1 and 2, correlate three variables, using the value of FDI inflow (vertical axis), the number of robots (the size of the bubble), and how this relation changes over a five-year time (horizontal axis)[8]. Furthermore, in the graph each bubble represents a country. To have a better representation of the three segments related to automotive components, we excluded the 2910 class, i.e., the most numerous one, from Table 2. Both Figures 1 and 2 do not show a high and significant correlation between the stock of FDI inflow and robots' application. Indeed, the biggest bubbles (i.e., those representing larger number of robot's adoption) spread across the graph and they are not concentrated at the top, as we would expect with a high correlation between FDI and robots. Looking at the time dimension, we can see that a drop in Automotive Components (Figure 2) in 2012 and 2013 -probably related to the global crisis-, does not correspond to a similar drop for Automotive OEM (Figure 1).

[8] See Appendix for dataset specifications and major limitation of descriptive statistics.

Relation between FDI and robot's adoption, four-subsectors (time:2010-2015)

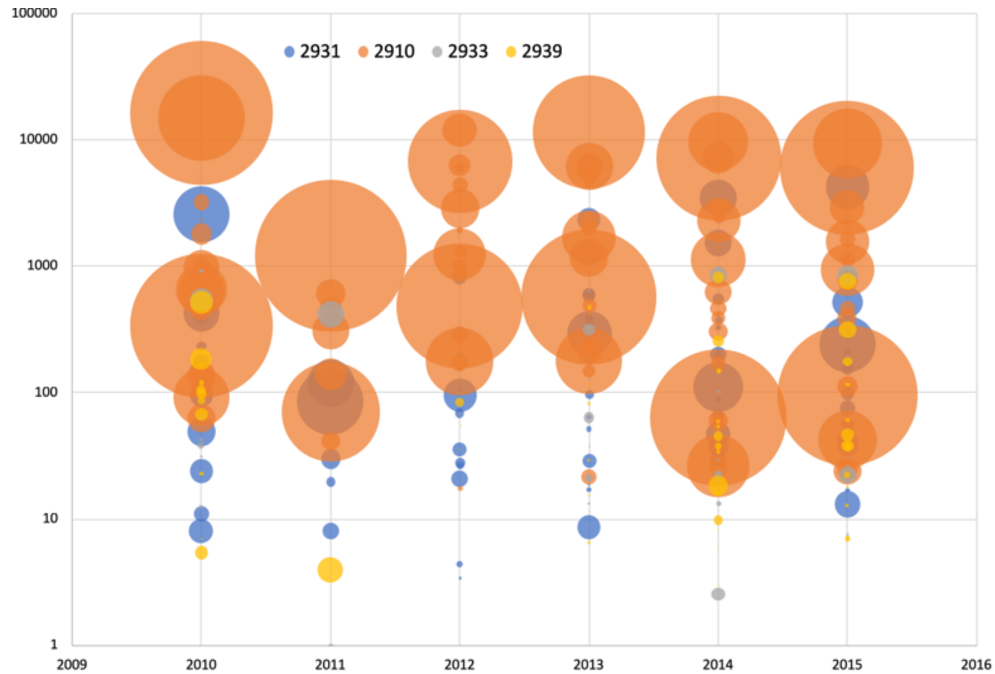

Figure 1: Authors based on IFR and fDi Markets data. *Vertical axis: FDI intensity; Horizontal axis: year; Size of the bubble: N. of robots; Colour of the bubble: different subsectors. Each bubble represents a different country*

Relation between FDI and robot's adoption, three-subsectors (time:2010-2015)

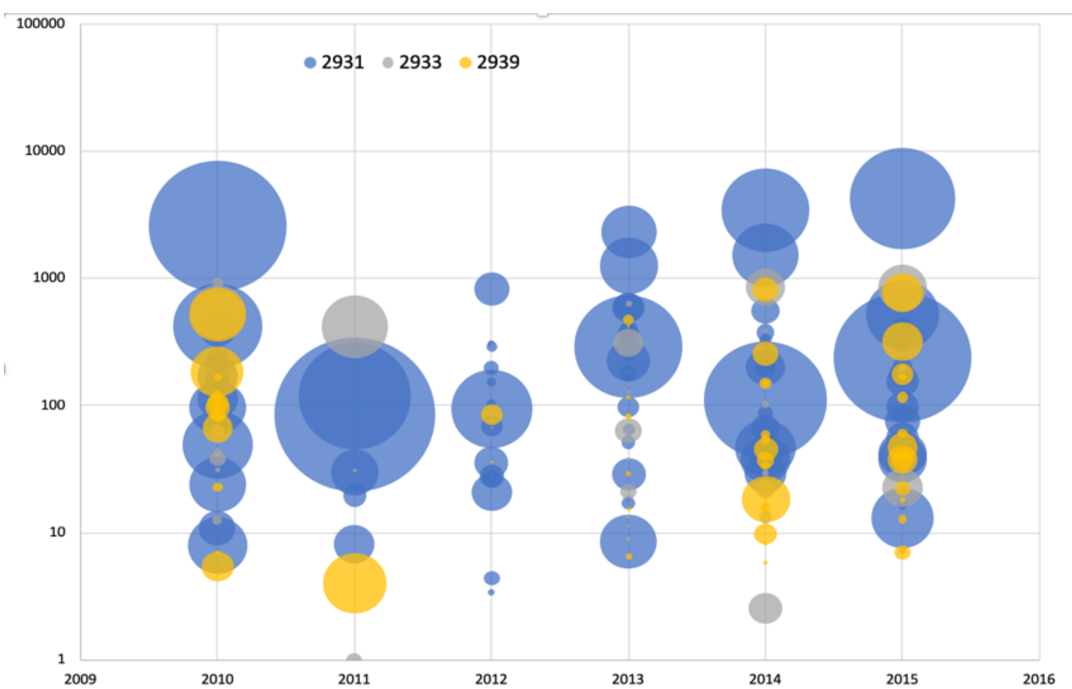

Figure 2: Authors based on IFR and fDi Markets data. *Vertical axis: FDI intensity; Horizontal axis: year; Size of the bubble: N. of robots; Colour of the bubble: different subsectors. Each bubble represents a different country*

Bubble graphs in Tables 3 and 4 use country specificity as an additional dimension. We selected some significant countries from our sample, and demonstrated that there is no strong correlation between the number of robots adopted and the inflow of FDI. This is described by the presence of big sized bubbles even in relation to a relatively small amount of FDI received (e.g., see Germany in both tables). The disaggregation we use for these graphs suffer of some limitations, e.g., the panel is limited to five years, due to the fact that IFR data are aggregated in the components segment until 2010 in most of the countries. Moreover, we could not retrieve a considerable amount of data because of the unspecified classes mentioned above[9].

Relation between FDI and robot's adoption, four-subsectors (country focus)

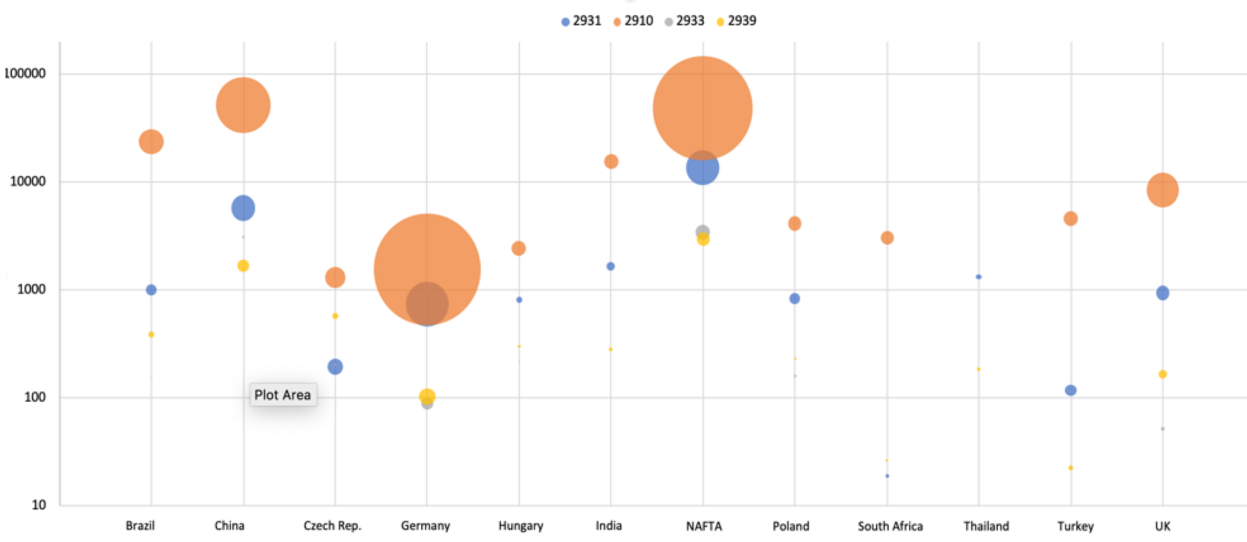

Figure 3. Authors based on IFR and fDi market data. *Vertical axis: FDI intensity; Horizontal axis: selection of countries; Size of the bubble: N. of robots; Colour of the bubble: different subsectors.*

[9] See Appendix A for more specifications on the data.

Relation between FDI and robot's adoption, three-subsectors (country focus)

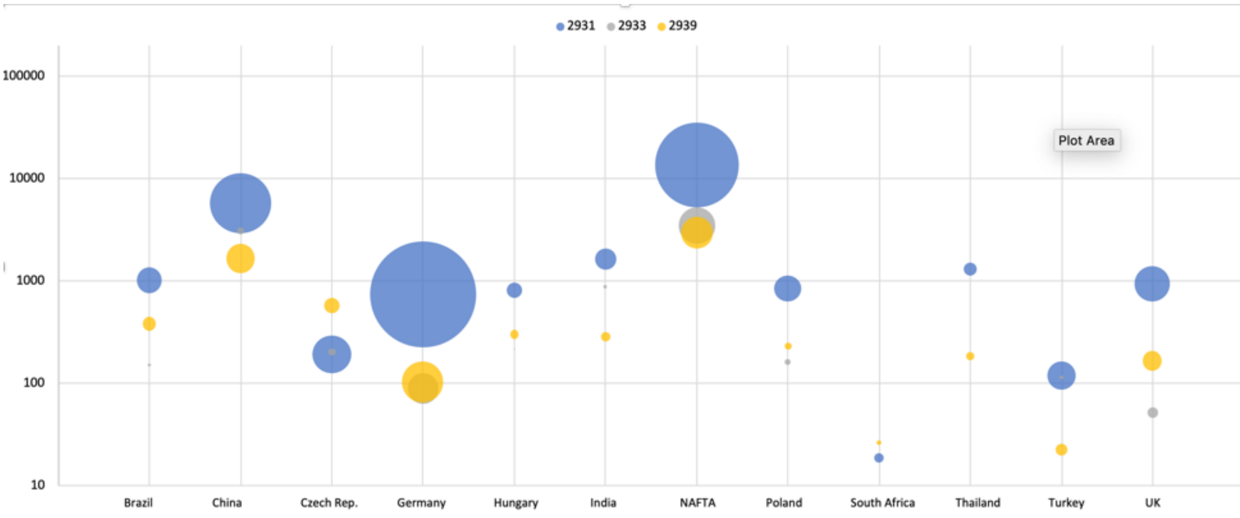

Figure 4: Authors based on IFR and fDi market data. *Vertical axis: FDI intensity; Horizontal axis: selection of countries; Size of the bubble: N. of robots; Colour of the bubble: different subsectors*.

The evidence coming out from the bubble graphs are partially reflected in the way different commodities are produced. Robotisation is more common across the final assembly and metal parts' operations were production tasks tend to be particularly demanding – heavy handling operations, dangerous and physical exhausting for workers (e.g., pressing, welding, handling of heavy materials). This might explain part of the robotization phenomenon, in our view. However, there are also countries that are at the technological frontier where robots are used in more labour intensive sectors. For example, looking at NAFTA and Germany (Figure 4), even tasks associated to production of electric/electronic parts (grey bubble) and leather seats, airbags (yellow bubble) present a high number of robots.

Drivers of robots' adoption: econometric evidence

In order to capture potential heterogeneity effects within the automotive sector, we conducted our second analysis at two levels of disaggregation. We run a regression first considering the automotive sector as a whole, and then using the two market segments of Automotive OEM (assembly, 2910) and Automotive Components (the sum of the 2931, 2933 and 2939 mentioned above). By these means, we aimed at delving deeper into the extent to which FDI inflow in automotive triggers the adoption of industrial robots in different segments of the automotive sectoral value chain. Table 2, 3 and 4 present the econometric analysis in three stages.

Robots and FDI, aggregated results						
Y= lrob	**Coef.**	**Std. Err.**	**t**	**P>t**	**[95% Conf.**	**Interval]**
lfdi	0.1591641	0.0573444	2.78	0.006	0.0464342	0.271894
laglpat	0.6670467	0.1304211	5.11	.0.000	0.41066	0.9234335
laglexp	0.6475953	0.1094343	5.92	.0.000	0.4324651	0.8627255
lagDVA_million_dollars	0.0026977	0.0007547	3.57	.0.000	0.0012141	0.0041813
lag_gdp_capita	0.0000251	8.00E-06	3.13	0.002	9.33E-06	0.0000408
_cons	-16.01196	2.421731	-6.61	.0.000	-20.77269	-11.25123
Year FE						**R-squared = 0.71**

Table 2 Robots adoption and FDI, aggregated results

- As for the first level of the analysis, in Table 2, we present FDI aggregated (Automotive OEM and Automotive Components) for the automotive sector with some standard control variables. This is a baseline estimate on the impact that FDI have on the application of industrial robots. FDI show a statistically significant positive correlation with the number of adopted robots. Hence, for one million more FDI in the automotive sector, robots' adoption is estimated to yield an increase of 0.15 robots. Also, patents, which we used as a proxy for describing innovation, and exports in the two segments are positive and statistically significant. Furthermore, we used the domestic value added in all export and GDP per capita as controls for country specific variables, which also show a positive and statistically significant correlation. These control variables suggest that the impact of FDI on robotisation is mediated by a number of other sector and country factors. Specifically, the number of robots tend to be higher when a number of other country and sector factors – innovation, export and domestic value addition capacity – are positive. Hence, this baseline model is broadly consistent with the idea that FDIs do play a role as a driver of robot adoption, for any given level of innovation capacity, size and richness of examined countries. However, at this level of aggregation, there is no way to identify the underlying mechanism leading to such a positive impact of FDIs. In fact, one could envisage either a direct effect of multinational presence in the automotive sector of a given country, with MNEs exerting a higher demand for robots to carry out their own manufacturing activity; or an indirect effect reflecting the stimuli generated by MNEs on local firms, which might be induced to adopt more advanced technologies to compete with foreign firms in the same market (horizontal spillovers) or to better satisfy the demands for inputs by MNEs (vertical spillovers). To move in the direction of disentangling these effects we shall undertake a second, more disaggregated level of analysis with reference to each of the two subsectors of automotive industry, wherein the demand for robots may well be affected differently by FDIs.

Robots and FDI, disaggregated results (i)

Y= lrob	**Coef.**	**Std. Err.**	**t**	**P>t**	**[95% Conf.**	**Interval]**
lfdi2910	0.143748	0.0596432	2.41	0.016	0.0264973	0.2609988
lfdi2930	0.0770761	0.0768439	1	0.316	-0.0739888	0.2281411
laglpat2910	0.7356692	0.1634977	4.5	.0.000	0.4142542	1.057084
laglpat2930	0.6441637	0.1346103	4.79	.0.000	0.3795377	0.9087897
laglexp	0.6605027	0.1167216	5.66	.0.000	0.4310434	0.8899619
lagDVA_million_dollars	0.0025506	0.0007629	3.34	0.001	0.0010509	0.0040502
lag_gdp_capita	0.0000234	8.26E-06	2.83	0.005	7.14E-06	0.0000396
_cons	-16.0145	2.547	-6.29	.0.000	-21.02175	-11.00732
Year FE						**R-squared = 0.72**

Table 3 Robots adoption and FDI, disaggregated results

- At the second level of analysis, in Table 3, we show the results of the same regression as in Table 2 but with disaggregated data for both FDI and patents. Class 2910 refers to OEM Assembly and class 2930 refers to Components. Given the fact that: (i) FDI in Assembly may be different from the ones in components; and that (ii) our sample includes 35 countries that present a high degree of heterogeneity on these segment innovation level, we interacted our two segments both with FDI and with patents. The disaggregation of the data allows us to have patents at four digits and, thus, to match them with our automotive segments. FDI in the OEM Assembly class (2910) remains statistically significant and positive, confirming the role of FDI in inducing adoption of robots in production; instead, FDI in the Components segment (2930) completely lose its significance in determining robots' adoption. While the selected country and export factors – innovativeness (proxied by patents), export competitiveness (export capacity) and domestic value addition – remain statistically significant and positive for the two segments, the fact that FDI does not drive robotisation in the Components segment – typically at the level of first and second tier suppliers – is a particularly important results in our view which would require further firm-level investigations. Indeed, as suggested by the FDI literature reviewed above, the impact of FDI might not trigger technology absorption and diffusion in the local production system, which may depend also on the relationships between OEM and local suppliers and the way in which country specific industrial policies shape them.

Robots and FDI, disaggregated results (ii)		
Y= lrob	***1***	***2***
lfdi2910	***0.1649927***	***0.0966277***
	(0.0606)***	(0.0556)*
lfdi2930	***0.044605***	***-0.0428344***
	(0.0740)	(0.0694)
laglfdiindustrialised	***0.1873236***	***0.2099261***
	(0.0575)***	(0.0432)***
laglfdiemerging	***0.2483777***	***0.222225***
	(0.0476)***	(0.0431)***
laglpat2910	***0.7831484***	***0.3159331***
	(0.1876)***	(0.1400)**
laglpat2930	***0.6081418***	***0.1140577***
	(0.1767)***	(0.1492)
lemployment_share_ manufacturing	***0.1898731***	***0.1680468***
	(0.0185)***	(0.0192)***
laglexp		***0.6298042***
		(0.0842)***
lag_dva_share	***0.0315714***	***0.0380579***
	(0.00856)***	(0.0083)***
lagDVA_million_dolla rs	***0.0011885***	***0.0014257***
	(0.0007)***	(0.0007)*
lag_gdp_capita	***0.0000951***	***0.0000726***
	(0.00001)***	(0.00001)***
_cons	***-8.881441***	***-23.07915***
	(1.1865)***	(2.2633)***
R-squared	*0.71*	*0.76*
	Year FE	*Year FE*

Table 4: Robots adoption, FDI and *local* variables

- Building on the results of Table 3, in Table 4, we further investigate other possible factors driving the adoption of robots in the segment 2930. First of all, due to the high heterogeneity of our sample and due to the fact that FDI tend to be different according to where they are directed – FDI directionality, we construct three geographical dummy variables: industrialised, emerging and Eastern-Europe countries. The dummies were built according to the level of countries' industrialisation using a modified classification from UNIDO 2013, which classifies countries based on manufacturing value added per capita (Teng, 2019). We added Eastern-Europe because of the specific dynamics of the region in the automotive sector[10]. We assigned China in the emerging group, and observed that the results are slightly different according to which group of countries China is supposed to belong to[11]. Nonetheless, the two variables (emerging and industrialised) interacted with FDI are both statistically significant and positive, although the coefficient is higher when FDIs in Emerging countries are considered. Employment share in manufacturing which controls for the level of industrialisation of a country is positive and statistically significant. The two columns in Table 4 differ in one variable. In column *2*, we added export as a control variable and the only significant change is that patents in the 2930 subsector become non-significant.

  Finally, we included fixed effects to control for unobserved heterogeneity across time. To check the robustness of our analysis, we repeated the regressions using the number of FDI, instead of their stock in million dollars. Notably, results remain consistent with previously reported observations (Appendix A). In order to test some of our hypothesis we performed other regressions interacting FDI with patents as one of the main variables of the local ecosystem. We found interesting results that need further exploration, see Appendix A.

  The econometric strategy and data present a number of limitations: first of all, the lack of other data at the sub sectoral level (such as employment, skills, wages) prevent us to add other significant variables that could partly explain why industrial robots are adopted. In spite of these limitations, our study is important because it is the first in attempting an

[10] See Appendix A for more specifications.
[11] Explain how they change please

analysis about results do shed some novel light on the relationship between FDI and robotics, one of the latest and most sophisticated technologies in the automotive sector. In the next paragraph we discuss the main implications from our analysis introducing some hypothesis on the determinants of industrial robots.

5. Discussion

FDI have been an important driver of economic growth. Especially in the most recent times of GVCs, when the fragmentation of production increased the possibilities for developing countries to receive FDI and link up to global dynamics of production.

Nonetheless, as Lall (2000) pointed out, if there is one stylised fact about countries that benefited from FDI is that these countries engaged with FDI in a strategic way, including restricting their scope and modalities of operation and engagement with suppliers in the hosting countries. Lall was referring to countries that managed to link up to GVCs upstream but that were then able to move downstream and acquire capabilities in sophisticated sectors. Archetypical examples are countries like South Korea, Taiwan, China (Lee, 2016; Amsden, 1989 and 2001).

Prima facie this could mean that to move up to the developmental and technological ladder FDI should be strategically managed through appropriate industrial policy. The reasons behind this approach are numerous and well explored in the literature (Amsden, 1989; Chang, 2004; Andreoni and Chang, 2019). High technologies require time to be absorbed and mastered and they build up on production systems that are complex and need to be adapted to local conditions.

The automotive sector is characterised by specific dynamics that influence the distribution of its international activities. More than truly global, the sector increasingly became clustered in specific areas, the most important are NAFTA, Germany and Eastern Europe, East Asia, Argentina/Brazil to a certain extent and, more recently, China. Historically, the automotive sector has been a major driver of industrialisation in several successful country experiences. The length and complexity of its value chain, alongside the development of production and technological complementarities, allowed countries involved in the automotive sector to achieve several goals. The automotive sector has also been a fertile field for many improvements in production technologies, being the sector characterised by intensive economies of scale and by the use of automated machines since the 1980s. Industrial robots were not an exception and the first introduction of spot welding and arc welding robots took place in the automotive sector (APO, 1987). The introduction of industrial robots, despite not being recent, experienced a growth because of the improvement in the technologies, the consequent increase in productivity and, to a certain extent, flexibility.

The differences that we found in our analysis when referring to the role of FDI in robots' adoption in the Automotive OEM and Automotive Components can have two major explanations:

(i) Automotive OEM are the main drivers of robotisation. No matter which other variables we control for, the impact on robot adoption of FDI in assembly remain statistically significant and positive. This is consistent with what we expected because of the capacity that big OEM have to invest in new technologies and because of the ultimate system integration tasks they perform. The final assembly of a motor vehicle requires an increasing number of robots in the pressing shop, the white body shop, the paint shop. Thus, we glimpse two main dynamics that develop as effect of FDI from big OEM. On the one hand they are the first adopters of industrial robots in their new facilities; on the other hand, they also activate an important trigger for components suppliers, especially big international Tier 1 suppliers which are closely linked to OEM operations.

(ii) Nonetheless, induced mechanisms related to OEMs are not sufficient to fully explain our results. Before analysing which are the different variables that may drive robotics adoption in the automotive components sectors it is important to understand why FDI are not one of the main drivers for this segment of the value chain. We cluster our hypothesis in this sense around three main elements:

- The heterogeneity of our data is particularly strong in the automotive components. The major adopters of robotics in the automotive segments (Korea, Japan) are not at all important recipients of FDI (Appendix A). While assembly FDI, also because of the role of the few global OEM assemblers, can pull the results despite the presence of countries such as Japan and South Korea, this is not what happens in components where the situation is much more fragmented for the reasons explained below.

- There is an indirect effect. MNCs -mainly Tier 1- which are responsible for the FDI in the components' segments, are tied to big OEMs. Thus, they also are constrained by their way of producing (especially) in developing countries. For instance, an important MNC Tier 1 in SA, produces commodities for both BMW and Ford; while for the former they use laser welding robots, for the latter they use manual welding. Suppliers may be influenced by the type of vehicles OEMs produce in specific countries (e.g. picks up *vs*. light vehicles)

- Most of the OEMs have international standards they have to comply with. Thus, their production processes across countries tend to be very similar. Differently, suppliers (especially Tier 2 and 3) are more influenced by local dimensions especially because of policy push and capabilities pull.

The fact that we do not find econometric evidence that FDI has driven robotisation at the first and second tier suppliers' level is telling of the challenges that suppliers face in emerging countries. A plausible pattern in the case of FDIs in the automotive component subsector might be the substitution of local suppliers with foreign ones. Hence, while foreign investors in this subsector may increase the demand for robots, the overall effect on robotisation may well be null to the extent that local competitors are crowded out. Furthermore, the non significant impact of FDIs in automotive components might reflect challenges in linking up technologically with OEMs in a highly concentrated and standardized sector, where spaces for different technological and operational models are limited, and in a technological field where the capital expenditure threshold is particularly high. By the same token, our analysis also suggests the importance of looking at the factors complementing FDI in driving robotisation in these countries, including different OEMs-suppliers relationships and policies.

We believe that a great emphasis should be placed on the role that other factors, related to the conditions of the local production system and broader industrial ecosystem, play. With industrial ecosystem we intend "co-evolving systems involving a broad range of interdependent organisations and institutions, co-existing and complementing each other in co-value creation processes" (Andreoni, 2018). Three of our independent variables are our main proxy for the local ecosystem: patents that we use as a proxy of the innovativeness of the country in the specific segments of automotive; domestic value added in export of goods belonging to D29 (motor vehicles in TiVa classification), which we use as a proxy of the manufacturing sophistication level within automotive; export of goods related to the two automotive segments that we use as a proxy of the competitiveness of the country. The other variables such as domestic value added in all export and employment share in manufacturing, despite referring to the whole manufacturing sector and not just the automotive, are punctual controls for the industrial levels of the countries and the overall capacity of the local production system to add value in trade. The ecosystem is based on the development of a series of complementarities based on the existence of linkages between close but dissimilar types of firms. Within a dynamic local system, firms and organisation that are linked to each other along sectoral value chains (vertical linkages), and across different sectors (horizontal linkages) trigger the development of complementary capabilities (Andreoni, 2019). The development of automotive component parts and its technological level require a mix of internal forces and coordination mechanisms that are rarely left just to the market. Moreover, being industrial robots one of the latest technologies that require high expertise and important infrastructure, the role played by each country's policy is extremely important. Thailand is one example in this sense. It is the developing country (China excluded) with the highest number of industrial robots, and one of the highest in the automotive sector (IFR, 2015). The 'robotisation' of the country is based on a series of policies that aim at building up the local ecosystem. Demand and supply policies have been combined in a way where technological skill push met demand pull in a country where firms have been 'accompanied' by fiscal incentives to adopt industrial robots. Lastly, a wide range of enabling institutions and infrastructures permitted the Thai government to provide the right set up for firms both local and international. Components production suppliers are more fragmented than big OEM assemblers, they rely on a series of close complementarities that can be fully developed and explored in geographical proximity with OEMs and with the right incentives provided from government, from FDI and from other local intermediate actors.

6. Conclusion

This paper examines the determinants of industrial robots' adoption in the automotive sector. In particular it investigates the role that FDI *vis a vis* "local" variables have in the adoption of robots, using two rich sources of highly disaggregated and detailed data.

On the one hand, descriptive statistics show a first correlation between FDI and robots adoption also drawing on specific countries' experiences. On the other hand, the econometric analysis shows how results change, once that FDI heterogeneity is accounted for.

While investments in the OEM assembly are relevant at all levels of disaggregation and using different control variables, the picture changes when FDI related to the automotive components are considered. We put forward some plausible explanations, including the important role played by other factors that matter in the adoption of industrial robots in the automotive sector. Specifically, the readiness of the sector and of the country, its competitiveness and its innovativeness are all considered in our regression and they are positive and statistically significant. Following Andreoni (2019) framework we claim that a well-developed local production system is what makes the difference in the auto components dynamics.

The empirical literature on the new technologies remains at the macro level and mainly focusses on the impact of robotics. This study contributes to a new field that looks at the determinants of industrial robots in a strategic, high-manufacturing sector such as the automotive.

Our study has important limitations. Particularly, the lack of data at more than three digits prevents from a more complete analysis. Nonetheless our results open for a new stream of research and specifically under two aspects. The importance of sector specific studies has great possibilities to disclosure dynamics and insights that are difficult to grasp at an aggregated level. Moreover, the analysis of a single technology (data permitting) gives some elements to study its diffusion throughout the economy.

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Appendix A

Our dataset builds on data from two main sources: IFR data and fDi market data. We undertook two types of analysis: more disaggregated descriptive statistics and a less disaggregated regression analysis.

1) Data description

Our data are classified in two different classification: IFR responds to ISIC rev. 4 classification and fDi market dataset responds to NAICS 07 classification. Nonetheless, IFR in the automotive sub-sector, presents a further disaggregation inserting auto metal parts (2931), plastic parts (2932), glass parts (2934), electronic parts (2933) (2939, and others. Although this enriches the dataset, it also creates some issues in the matching operation.

- From IFR data we use the sub-sectors of Automotive (class 29). From fDi market we use Automotive OEM and Automotive Components sub-sectors and we extracted just manufacturing activities. Since IFR data are only related to industrial robots used in the production process we used just manufacturing activities for a matter of consistency.

- We use 35 countries that constitute i) 94% of total FDI recipients in the automotive sector and ii) 96% of total industrial robots in automotive

- We use conversion table (available online at: http://www.census.gov/eos/www/naics/concordances/concordances.html) from NAICS to ISIC rev. 4.

- Below a series of tables illustrate specificities of our data. All data are intended as cumulative for the period 2005-2015

Table I

Country	FDI_Component	FDI_OEM	TOTAL
Argentina	31	32	63
Australia	20	17	37
Austria	18	12	30
Belgium	14	31	45
Brazil	99	115	214
China	660	241	901
Czech Republic	181	22	203
Finland	3	0	3
France	88	25	113
Germany	76	18	94
Hungary	150	19	169
India	274	166	440
Indonesia	60	51	111
Italy	15	4	19
Japan	9	3	12
Malaysia	19	26	45
Poland	192	38	230
Portugal	10	14	24
Romania	150	14	164
Russia	119	142	261
Slovakia	98	21	119
South Africa	18	51	69
South Korea	49	11	60
Spain	66	58	124
Sweden	7	4	11
Switzerland	2	1	3
Thailand	160	72	232
Turkey	41	47	88
United Kingdom	97	67	164
Vietnam	47	29	76
North America	1100	301	1401
TOTAL	3873	1652	5525

Table II

Country	Number of Robots_Auto Parts	Number of Robots_Assembly	TOTAL robots
Argentina	1087	4263	5350
Australia	1137	389	1526
Austria	10991	3173	14164
Belgium	7094	15930	23024
Brazil	8027	20990	29017
China	31853	87641	119494
Czech Republic	14196	14384	28580
Denmark	1219	65	1284
Finland	2545	765	3310
France	72972	130975	203947
Germany	297511	502120	799631
Hungary	2283	6160	8443
India	2977	8636	11613
Indonesia	371	130	501
Italy	91645	119461	211106
Japan	728788	491620	1220408
Malaysia	751	328	1079
Netherlands	4844	946	5790
North America	6703	489388	496091
Poland	6042	8386	14428
Portugal	5114	1521	6635
Romania	946	2584	3530
Russia Total	1700	3649	5349
Slovakia	4446	10667	15113
South Africa	1781	6048	7829
South Korea	148253	188987	337240
Spain	92161	86181	178342
Sweden Total	13630	19289	32919
Switzerland	4148	183	4331
Thailand	1240	59	1299
Turkey	6079	7475	13554
United Kingdom	40455	56318	96773
Vietnam	46	22	68
TOTAL	1613035	2288733	3901768

2) Four level disaggregation

The disaggregation at four levels which we presented in bubble graphs in the text was based on the following matching.
We use four subsectors in the automotive: Motor vehicle (OEM), metal and plastic parts (aggregated), electric/electronic parts, others (airbag, car seats, safety belts.

Table III presents sub-sectors from fDi dataset, which belong to the two sub-sectors Automotive OEM and Automotive Components.

Table III

Sub_sector fDi market	***Number of Fdi per sub_sector***
Automobiles	894
Heavy duty trucks	280
Light trucks & utility vehicles	176
Motor vehicle body & trailers	389
Motor vehicle brake systems	200
Motor vehicle electrical & electronic equipment	427
Motor vehicle gasoline engines & engine parts	845
Motor vehicle seating & interior trim	461
Motor vehicle stamping	33
Motor vehicle steering & suspension components	448
Motor vehicle transmission & power train parts	125
Other motor vehicle parts	937
Total	**5215**
DROP	
Motor vehicle & parts dealers	2
Communication & energy wires & cables	4
All other transportation (Automotive)	15

We match the sub-sector in Table III with IFR data through word mining[12] and matching between the two classification in the NAICS 07-ISIC rev. 4 table; both IFR data and fDi dataset provide detailed description about their specifications. We drop three sub-sectors (indicated at the end of Table III) because of the lack of a correspondent in IFR classification. After word mining, we were able to match 4513 investments. A brief description of each class is provided.

[12] fDi market also provides description in the dataset

- ***2910*** (IFR, *Motor vehicle manufacturing*): According to NAICS conversion: Automobiles, Heavy Duty Track, Light trucks & utility vehicles, Motor vehicle body and trailers.
  TOT: **2080 observations**

- ***2931+ 2932*** (IFR: plastic and metal, components for engines). NAICS: Motor vehicle brake system, Motor vehicle stamping, Motor vehicle steering and suspension component, Motor vehicle transmission and power train parts, Motor vehicle gasoline engines and engine parts
  TOT: **1386 observations**

- ***2933*** (IFR, *Electric/electronic parts)* → Motor vehicle electrical and electronic equipment (word mining on motor vehicle gasoline engines and engines parts).
  TOT: **475 observations**

- ***2939*** (IFR, Other auto parts (car seats, safety belts, airbags): Other Components parts, with word mining
  TOT: **572 observations**

3) **Econometric Analysis**
The econometric analysis performed with OLS regression used a two-level disaggregation. The complexity of the data diminished, and we were able to match the two sub-sectors from fDi markets (Automotive OEM and Automotive Components) with IFR classes (Motor vehicles body and AutoParts). Two more specifications have to be made about the multiple regressions:

i) We used three geographical dummies based on the UNIDO revised version (see Teng, 2017). The classification responds directly to the level of industrialization of each country. We have three dummies: industrialised, emerging and Eastern Europe. Because of the specific characteristics of Eastern European countries, due to their rapid integration in German automotive value chains, we built this third group.

   Industrialised: Argentina, Australia, Austria, Belgium, China, Denmark, Finland, France, Germany, Italy, Japan, South Korea, Netherlands, North America, Portugal, Russia, Spain, Sweden, Switzerland, UK

   Emerging: Brazil, India, Indonesia, Malaysia, South Africa, Thailand, Turkey,

   Eastern Europe: Czech Republic, Hungary, Poland, Slovakia, Romania,

ii) In our independent variable export, we use trade data from UNCOMTRADE.
   At two sub-sectors disaggregation our match was as follow:

- ***For 2910 (Automotive OEM):*** 8703 (motor cars and other motor vehicle, principally designed for the transport of persons) e 870710 (vehicle, bodies for the 8703 vehicle)
- ***For 2930 (Automotive Components):*** 8706 (chassis; fitted with engines, for motor vehicle 8703) 8708 (motor vehicle parts and accessories) 940120 (seats, used for motor vehicles)

4) Limitations

Disaggregated data are an important source because they permit to study a specific phenomenon closer and more in depth. Nonetheless they present also important limitations, among the most important we see

1. There are two big unclassified sections in the IFR data: Unspecified AutoParts (2999) and Automotive Unspecified (299). While we were able to insert Unspecified AutoParts in the regression analysis under the Automotive Components sub-sector, this was not possible in the statistical evidence. Therefore, in our graph bubbles there are two important classes that are not included in the data we presented. See Table IV for specific data on this 'missing' classes. We contacted the administrators of IFR dataset in Germany and after a careful analysis we claimed that these data could not be inserted in any other classes.

2. As specified in the paper, we had to use North America as a whole including Mexico, Canada and United States. This is due to the fact that IFR presents aggregated data for North America up until 2010.

Table IV[13]

Country	Automotive Unspecified 299	Unspecified Autoparts 2999
ZA-South Africa	6.36%	9.07%
US-United States	0.05%	33.63%
CA-Canada	0%	45.78%
MX-Mexico	0%	36.47%
BR-Brazil	4.56%	7.74%
AR-Argentina	16.44%	4.63%
CN-China	54.62%	5.85%
IN-India	63.30%	0.64%
ID-Indonesia	87.51%	0.43%
KR-Rep. of Korea	54.95%	0.23%
TH-Thailand	56.23%	46.15%
VN-Vietnam	0%	9.75%
CZ-Czech Republic	0%	5.54%
HU-Hungary	0%	16.48%
PL-Poland	1.53%	1.65%
RO-Romania	0%	5.59%
RU-Russian Federation	0.29%	3.27%
SK-Slovakia	0%	14.29%
DE-Germany	3.96%	20.96%
ES-Spain	0%	22.02%
FR-France	0%	15.70%
TR-Turkey	0.60%	6.49%
PT-Portugal	0.10%	0.20%
MY-Malaysia	0.16%	0.04%
NL- Netherlands	0.01%	0.21%
JP-Japan	0%	47.90%
IT-Italy	0.01%	2.54%
KR_Rep. Korea	3.02%	12.66%
SE-Sweden	0%	0.43%
AT-Austria	0%	0.38%
AU-Australia	0.01%	0.06%
BE- Belgium	0%	0.27%
FI-Finland	0.09%	0.12%
CH- Switzlerland	0%	0.16%

[13] *Percentages have to be intended as the share belonging to these unknown categories on the total amount of robots*.

5) **Robustness Check**

As a robustness check we undertook the same regressions that are presented in the paper with the number of FDI, instead that with the value of FDI in million dollars as performed in the text. We obtained very similar results as it is showed by the following tables:

Table V

Robots and FDI, aggregated results. Number FDI						
lrob	**Coef.**	**Std. Err.**	**t**	**P>t**	**[95% Conf.**	**Interval]**
lFDI_number1	0.7600113	0.1447815	5.25	.0.000	0.4751468	1.044876
laglpat	1.053583	0.1417969	7.43	.0.000	0.7745909	1.332575
lemployment_share_manufa	0.1432137	0.0228059	6.28	.0.000	0.098342	0.1880854
lag_dva_share	0.0218752	0.009486	2.31	0.022	0.003211	0.0405395
lagDVA_million_dollars	0.002603	0.0010292	2.53	0.012	0.000578	0.004628
lag_gdp_capita	0.0000621	0.0000112	5.55	.0.000	0.0000401	0.0000841
Year FE						*R-squared = 0.68*

Table VI

Robots and FDI, disaggregated results. Number FDI						
lrob	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
lFDI_number12910	0.6517314	0.1554582	4.19	.0.000	0.3457066	0.9577561
lFDI_number12930	0.360587	0.1722182	2.09	0.037	0.0215696	0.6996043
laglFDI_number1emerging	0.5077549	0.1758314	2.89	0.004	0.1616248	0.8538849
laglFDI_number1industrialise	0.1961121	0.157392	1.25	0.214	-0.1137194	0.5059436
laglpat2910	0.993373	0.1622622	6.12	.0.000	0.6739543	1.312792
laglpat2930	0.6390008	0.1603385	3.99	.0.000	0.323369	0.9546325
lemployment_share_manufa	0.1480211	0.0249265	5.94	.0.000	0.0989524	0.1970897
lag_dva_share	0.0184038	0.0096021	1.92	0.056	-0.0004981	0.0373058
lagDVA_million_dollars	0.003035	0.0009543	3.18	0.002	0.0011563	0.0049137
lag_gdp_capita	0.0001015	0.000014	7.25	.0.000	0.000074	0.0001291
Year FE						*R-squared = 0.74*

Table VII

Robots and FDI, disaggregated results. Number FDI						
lrob	**Coef.**	**Std. Err.**	**t**	**P>t**	**[95% Conf.**	**Interval]**
lFDI_number12910	0.5925257	0.1558845	3.8	0	0.2856568	0.8993945
lFDI_number12930	0.2458573	0.168254	1.46	0.145	-0.0853617	0.5770764
laglFDI_number1emerging	0.3624424	0.1732631	2.09	0.037	0.0213628	0.703522
laglFDI_number1industrialise	0.2965357	0.1600541	1.85	0.065	-0.0185411	0.6116125
laglpat2910	0.4439033	0.1421268	3.12	0.002	0.1641174	0.7236893
laglpat2930	0.1085049	0.1446326	0.75	0.454	-0.1762137	0.3932235
lemployment_share_manufa	0.1269583	0.0213439	5.95	0	0.0849415	0.1689752
laglexp	0.6287468	0.0924155	6.8	0	0.4468209	0.8106727
lag_dva_share	0.0261978	0.009418	2.78	0.006	0.0076578	0.0447378
lagDVA_million_dollars	0.0030804	0.00092	3.35	0.001	0.0012694	0.0048914
lag_gdp_capita	0.0000777	0.0000106	7.3	0	0.0000568	0.0000987
Year FE						*R-squared = 0.78*

Table VIII

Robots and FDI, aggregated results. Number FDI						
Y= lrob	**Coef.**	**Std. Err.**	**t**	**P>t**	**[95% Conf.**	**Interval]**
lfdi2910	0.21304	0.0608988	3.5	0.001	0.0932113	0.3328688
lfdi2930	0.1259589	0.0727454	1.73	0.084	-0.0171802	0.2690979
laglfdiindustrialised	0.2495392	0.0435019	5.74	.0.000	0.1639419	0.3351366
laglfdiemerging	0.2127129	0.042046	5.06	.0.000	0.1299802	0.2954457
laglpat2910	0.5737352	0.3678504	1.56	0.12	-0.1500733	1.297544
laglpat2930	1.727554	0.2918529	5.92	.0.000	1.153284	2.301825
laglpatlfdi2910	-0.0453861	0.061439	-0.74	0.461	-0.1662779	0.0755056
laglpatlfdi2930	-0.3278427	0.056187	-5.83	.0.000	-0.4384003	-0.2172851
laglexp	0.6798557	0.0838174	8.11	.0.000	0.5149307	0.8447807
lemployment_share_manufacturing	0.1562818	0.0192275	8.13	.0.000	0.1184485	0.1941151
lag_dva_share	0.030714	0.0088012	3.49	0.001	0.0133962	0.0480319
lagDVA_million_dollars	0.0012788	0.0007359	1.74	0.083	-0.0001691	0.0027267
lag_gdp_capita	0.000064	0.0000136	4.72	.0.000	0.0000373	0.0000907
Year FE						***R-squared = 0.78***