The Rush for Patents in the Fourth Industrial Revolution

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Abstract

Our paper provides a novel and in-depth analysis of the technological trends, geographic distribution, and business-level dynamics of the Fourth Industrial Revolution (4IR) in the European Union from patent- and firm-level perspectives. We do so *via* the analysis of patents filed at the European Patent Office between 1985 and 2014. We employ a new matched patent-firm data set provided by the Bureau Van Dijk: ORBIS-IP. We find evidence of a surge in the patenting activity related to the 4IR in the past three decades, particularly in networked devices. Our results also suggest that firms filing 4IR patents have become progressively younger on average. At the same time, we find a steady growth in the average number of 4IR patent applications filed yearly by each company. Further variance decompositions show that the surge in 4IR patent applications is mainly explained by incumbent firms filing more 4IR patent applications over time, rather than new entrants progressively populating the 4IR world. Finally, we uncover a general trend emerging at the firm level, whereby firms tend to specialise in a few technological areas and avoid differentiation.

Keywords: Fourth Industrial Revolution; Industry 4.0; matched patent-firm data; patent applications; EPO.
JEL codes: O30; O33; O34.

We would like to thank the Editor and two anonymous referees for helpful comments and suggestions. We would also like to thank the participants to the 18th Annual Workshop of the Italian Society of Industrial Economics and Policy (Venice, Italy) for insightful comments on an earlier version of the paper.

1. Introduction

In this paper, we explore the Fourth Industrial Revolution (4IR), also referred to as "Industry 4.0" (Kagermann, 2015; Muscio and Ciffolilli, 2019; Schwab, 2016). According to scholars and practitioners, 4IR brings about new, unparalleled opportunities to modify social and economic systems (Agrawal et al., 2019). In its essence, 4IR is at the basis of the so-called "Society 5.0", a new model of society based on a high degree of convergence between the cyberspace and the physical space, whereby a massive amount of information from sensors in the physical space is accumulated in the cyberspace (MEXT, 2019). In the cyberspace, these big data are analysed by artificial intelligence (AI), and the analysis results are fed back to humans in the physical space in various forms. In sum, 4IR promises to enhance the distributed knowledge of a system drastically, while decreasing the role of human decision-makers. Technology would be on the verge of creating an intelligence "external to humans", giving rise to a second economy (Arthur, 2017). Massive flows of sensible data gathered with the help of ubiquitous sensors and evolving machines would make intelligence an outcome of densely knitted artificial agents.

The 4IR term refers to a set of multi-layered, intertwined, and possibly convergent technologies, which emerged in the last decades (Gilchrist, 2016). These technologies leverage the potential of low-cost, "intelligent" devices. Equipped with sensors and processors and connected through the Internet, they gather, process, and exchange data collected from various sources. By interacting with sophisticated software, these devices understand how to perform several tasks independently and make decisions. They learn from experience and leverage multifaceted connections with similar units, forming a system of interdependent nodes. The label "Fourth Industrial Revolution" is being used to point out that "the fusion of these technologies and their interaction across the physical, digital and biological domains make the fourth industrial revolution fundamentally different from previous revolutions" (Schwab, 2016, p. 12). Examples of the effects of these technologies abound, ranging from manufacturing (as in the case of so-called "smart factories") to transport (ongoing experiments of driverless cars) to healthcare (sequencing machines to represent individual genetic maps). From a business perspective, it is foreseen that technologies associated with the 4IR will bring about highly significant changes at an unprecedented speed. There is the expectation that these changes will occur at various levels, inducing dramatic shifts among countries, reshaping entire industries, and bringing to the fore new firms (Gerbert et al., 2015; World Economic Forum, 2016).

Despite a surging interest related to the 4IR from different stakeholders (mainly practitioners and policy makers), less attention has come from academia, which has focused mainly on the single technologies comprising the 4IR such as AI (Aghion et al., 2017; Agrawal et al., 2019), additive manufacturing (Ben-Ner and Siemsen, 2017; Gibson, 2017; Despeisse and Ford, 2015), and the Internet of Things (Fleisch, 2010; Dijkman et al., 2015). Although there is a substantial body of scholarship in the area of engineering and information systems that has focused on the topic (see surveys from Lu, 2017, and Liao, 2017), comparatively fewer studies are available within the management and economics fields.

Our paper aims at filling this gap in the literature by identifying the peculiarities of the trends of the 4IR in the European Union (EU). In particular, it provides an in-depth description of the technological trends, geographic distribution, and business-level dynamics of the 4IR in the EU from patent- and firm-level perspectives. We do so by conducting an empirical assessment of the development of technologies related to the 4IR *via* the analysis of patents filed at the European Patent Office (EPO) between 1985 and 2014. We employ a new matched patent-firm data set provided by the Bureau Van Dijk: ORBIS-IP. In order to identify 4IR patents, we adopt the classification recently proposed by the EPO (2017), which maps 4IR technologies to Cooperative

Patent Classification (CPC) classes. We contribute to the literature by providing an in-depth overview of the patenting activity at the European level in the 4IR domain. Notably, we offer a complete analysis of patent protection at the firm level. Together, patent- and firm-level perspectives can offer a robust platform for further investigations in the protection of intellectual property.

The protection of intellectual property of 4IR technologies is expected to increase in future years. Patents are expected to play a critical role in making the 4IR possible. As repositories of long-term investments, patents represent an asset that can be deployed in several domains and complemented with other pieces of valuable knowledge. Ownership or right to use patents can be a necessary, though not sufficient, condition to operate effectively in the new competitive arena. Examining patents in the 4IR area is not an easy task. Notably, deciding what is 4IR-related, and what is not, is difficult. Schwab (2016, p. 12) points out that 4IR is much more than a set of smart and interconnected machines "in which virtual and physical systems of manufacturing cooperate with each other in a flexible way". Instead, the interaction between physical, digital, and biological domains would pave the way to highly significant breakthroughs in areas "ranging from gene sequencing to nanotechnology, from renewables to quantum computing" (*ibidem*, p. 12). While this description is suggestive, it is of limited help in setting the area of investigation rigorously. A possible alternative has been to rely on key informants and on illustrative case studies to list the most relevant technological trends that are paving the way to the 4IR. This is what the Boston Consulting Group has done recently (Gerbert et al., 2015). Unfortunately, the list of nine pillars of technological advancements – big data and analytics, autonomous robots, simulation, horizontal and vertical systems integration, Internet of Things, cybersecurity, the cloud, additive manufacturing, and augmented reality – that will radically transform production remains broad. A more convenient way of classifying 4IR technologies is provided by a recent study by the EPO (2017), which distinguishes 4IR-related technologies into three main sectors: core technologies, enabling technologies, and application technologies (see Section 3 for a detailed description of this classification, which we employ in this paper).

We offer stylized facts of the processed data along two main dimensions. First, we provide a broad picture of the 4IR at the patent level. We describe long-time trends in the development of technologies related to the 4IR, by also distinguishing between the different technological areas involved. Our second step refers instead to a characterization of the 4IR patenting activity from the firm-level point of view. We investigate the geographic patterns of firms 4IR patent applicants. Moreover, we analyse important characteristics of companies filing 4IR patent applications at the EPO: age, industry, and the number of 4IR patent applications, as well as the evolution of these dimensions over time. Finally, we conduct a cluster analysis aimed at identifying different groups of companies, which are strategically specialising in the diverse technological areas of the 4IR. We identified clusters across patent applicants that have similar features in terms of specialisation, size, and intensity of the 4IR-related innovation efforts. We observe an emerging pattern where most of the firms are specialised in a particular domain, and just a few of them focus on multiple technological fields.

Our results have broad implications. From an academic perspective, ours is one of the first studies attempting a comprehensive description and analysis of technologies surrounding the 4IR. Moreover, we take a further step and present the first stylized facts relating to the 4IR from a business perspective. Finally, since the data set we employ has not been used before, we provide the academic community with the opportunity to open new avenues for original research, particularly in the areas of intellectual property management and firm-level strategy and dynamics. From a business perspective, it informs managers to carefully evaluate the future perspective of the 4IR patent arena. Due to the steady increase in patent applications, protecting newly created knowledge might turn out to be complicated. Despite this crowded landscape, firms might leverage new opportunities in the market for patents.

The rest of the article is structured as follows. Section 2 introduces the relevant background literature and our main research questions. Section 3 describes the data set and discusses the identification of 4IR patents. Section 4 shows our results. Section 5 concludes discussing the main implications of our study for practitioners and policy makers.

2. Background and main research questions

Opinions about the 4IR differ. On the one side, there are scholars (mostly from applied science) and practitioners who expect a positive economic impact of the 4IR and list areas of improvement in almost any human affair (e.g., Kessler, 2017). According to this view, the combined capabilities of hardware, such as powerful sensors and low-cost computing capabilities, and software, including AI and machine learning, are already revolutionizing the economy. On the other side, a more sceptical view points out that the 4IR is not a new paradigm in itself, as it leverages a portfolio of information and communication technologies (ICTs) that have been around for quite a while. Besides, the 4IR might be offering promises that it will not be able to keep, at least in the short term. For example, several economists argue that its impact on factor productivity has been so far modest (Byrne et al., 2016). Notwithstanding the academic debate mentioned above, the interest in the 4IR has increased considerably in the last decade, and companies have started to invest heavily in technologies related to the 4IR. For example, Gerbert et al. (2015) estimate that German manufacturing companies will invest about 250 billion Euros during the next ten years in technologies related to the 4IR (about 1.5% of their revenues).

Although the 4IR has attracted increasing interest from policymakers and practitioners, academic studies in the field of social sciences are rare and sporadic. On the one hand, given the technical roots of the 4IR in engineering, this discipline has mainly focused on the technical processes to advance the practical applications (Lu, 2017 and Liao, 2017). On the other hand, management and economics studies have examined specific topics relating to the 4IR, so far without analysing the overall phenomenon. For example, to date, most of the studies focus on specific technological areas of the 4IR, such as AI, additive manufacturing (Ben-Ner and Siemsen, 2017; Gibson, 2017; Despeisse and Ford, 2015) and the Internet of Things (Fleisch, 2010; Dijkman et al., 2015). Notably, scholars are debating the effect of AI on employment, whether new technologies can complement or substitute for labour (Bessen, 2017), which tasks will be the most affected (Brynjolfsson et al., 2018), and which new competencies will be required (Felten et al., 2018). Moreover, scholars are interested in the effect of AI on innovation, manufacturing productivity, and economic growth (Aghion et al., 2017; Cockburn et al., 2018; Raj and Seamans, 2018). Furman and Seamans (2018) provide a detailed review of works that focus on AI and its impact on the economy, thus a specific technology related to the 4IR. As a general trend in this field, they document considerable increases in corporate investments in AI-related projects, a wave of acquisitions on start-ups specialised in AI technologies, and a steep growth in venture capital investments in AI. Similarly, Webb et al. (2018) explore patents in software and related technologies (including cloud computing and AI) in the last twenty years. By using data containing the full text of all published US patent documents through February 2018 obtained from the United States Patent and Trademark Office (USPTO) bulk files, they document a 60.2% increase in successful filings (between 2000 and 2013) and a 168.6% increase in applications over the same period. They also find that the growth rate was far higher for new technologies such as machine learning and cloud computing. It is worth noting that all of the works covered above focus on the

US and that a systematic and comprehensive analysis of 4IR-related technologies in other areas seems not to be present.

The only exception to the paucity of studies about the EU cited above is a recent study from the EPO, which provides a preliminary description of 4IR-related patenting activity in the EU (EPO, 2017). This study is mainly a methodological one as it provides a novel method to identify and classify 4IR technologies *via* patent information. Although the work from the EPO provides a basic overview of 4IR applications filed at the EPO, the empirical work is limited to the description of basic trends and the geographic distribution of inventors of 4IR patents. Their results point to a surge in the 4IR patenting activity. According to their estimates, between 2000 and 2015, 4IR patent applications received by the EPO have increased fivefold, and such growth was driven mainly by application and core technologies. They also show that, when considering inventors' countries of origin, the US is the first country in terms of 4IR patent applications, followed by Japan and Germany.

Our paper takes stock of the limited evidence available on the 4IR described above and provides an in-depth description of the technological trends, geographic distribution, and business-level dynamics of the 4IR in the EU from patent- and firm-level perspectives. We do so by conducting an empirical assessment of the development of technologies related to the 4IR *via* the analysis of patents filed at the EPO over 30 years. In doing so, we exploit ORBIS-IP, a new and rich matched patent-firm data set. Our approach bears several advantages. First, to the best of our knowledge, we are the firsts to provide a thorough description of the 4IR patenting activity both at the patent *and* at the company level. Building upon our unique data source, we supply a description of the main actors in the 4IR, including whether they are established or new firms, the industries in which they specialise, their portfolios of 4IR patents and patent intensities in 4IR technologies. We also give a preliminary account of how the main actors in the 4IR operate, with particular emphasis on the way they cluster into different strategic groups with different specialisations in 4IR technological areas. Furthermore, our work contributes to the literature by providing an in-depth exploration of the 4IR, which is more European-centric compared to previous works. This is important as the bulk of the literature on the 4IR employs data from the USPTO, despite the importance of the EPO in worldwide patenting. According to our data extractions, which start from the collection of all 4IR patent applications in the world (i.e., filed at any patent office), the EPO was the second-largest patent office in terms of number of 4IR patent applications received in the 30 years of our analysis, second only to the USPTO. Finally, our paper represents a starting point for studies assessing the impact of 4IR technologies on firms, as it sets out a new, large matched patent-firm data set, which opens up to the possibility of investigating unexplored issues.

3. Data and methods

Our primary source of data is ORBIS-IP, a large data set provided by the Bureau Van Dijk. ORBIS-IP is a recently released data set combining rich firm-level and patent-level information for more than 300 million companies and more than 110 million patent records.

Here, we focus on patents applied for at the EPO.[1] This is because, as highlighted previously, no thorough description of the 4IR patenting activity in the EU exists, whereas, although limited,

[1] As patents granted under the European Patent Convention refer to a bundle of national patents in each of the contracting states designated by the applicants and EPO does not retain information on patent applications filed in national patent offices and not sent out for EPO examination, we acknowledge the non-complete coverage of patent applications within European countries of our work. We would like to thank one of the anonymous referees for this insight.

there is a growing literature studying technologies that are part of the 4IR (e.g., AI and cloud computing) by using data from the USPTO. We also restrict the period of interest to 1985-2014 to avoid truncation problems arising from patent publication lags.[2]

To pinpoint 4IR patent applications, we exploit a recent work from the EPO, which provides a novel classification of 4IR patents (EPO, 2017). This classification defines a list of technological areas, each related to CPC codes, which identify 4IR technologies. EPO (2017) carries out a second step aimed at minimizing type-I errors (i.e., false positives) *via* a patent full-text search for different keywords. Unfortunately, EPO (2017) does not provide details on the search strategy and the terms used to carry out the text search; therefore, we were not able to (also) pursue their more restrictive approach.[3]

Hence, differently from EPO (2017), we stopped at the first step of the procedure and defined as 4IR patent every patent belonging to a technological area included in the EPO classification. A potential drawback of our approach is that the classification of 4IR technologies alone (i.e., without the subsequent text search) may include classes of 4IR technologies that are too broad. Despite this potential limitation, our approach has instead the main advantage of reducing the risk of having false negatives (i.e., type-II errors) when identifying 4IR patents. At the early stage of development, new technologies are subject to substantial uncertainty, and different technological trajectories – even pertaining to different technological domains – can be investigated at the same time. For this reason, keeping a broad stance in the definition of 4IR technologies, even at the expense of including potential false positives, can help in the process of spotting new technological developments.

As far as we know, our study is the first that employs the new, rich ORBIS-IP data set and that provides not only patent- but also firm-level analyses relating to the 4IR so broadly defined.

The classification of 4IR technologies (and patents) by the EPO hinges on the concepts of "main sectors" and "technological fields", which we employ in this paper, too. In practice, 4IR patents are classified according to three main categories (i.e., the main sectors): core technologies, enabling technologies, and application domains. Core technologies refer to artifacts embodied in connected objects for the collection and transfer of data (e.g., networked sensors, 5G connectivity, radio frequency ID), which make it possible to transform any object into a smart device connected *via* the Internet. Enabling technologies are technologies that are used in combination with connected objects and serve the purpose of storing, collecting, and analysing the data (e.g., cloud computing, AI, three-dimensional systems). Finally, application domains refer to the area where connected objects can be exploited (e.g., smart health, smart home, smart manufacturing).

Each main sector is subdivided further into several categories (i.e., the technology fields). Core technologies are classified into three technology fields: hardware, software, and connectivity. Enabling technologies comprise seven technology fields: analytics, user interfaces, three-dimensional support systems, artificial intelligence, position determination, power supply, and security. Finally, application domains are classified into six technology fields: personal, home, vehicles, enterprise, manufacture, and infrastructure. Table A1 in Appendix A provides details on this classification, reporting short definitions for each technology field. It is crucial to underline that such classification is *non-exclusive*, neither as far as main sectors are concerned, nor as far as technology fields within main sectors are concerned. For instance, according to this classification, a 4IR patent can be classified as belonging to the category: "Personal, User interfaces, Hardware, Software, Connectivity", thus representing a core technology, an enabling technology, and with a

[2] As other patent offices, there is a patent publication lag. In particular, the EPO publishes patents as soon as possible after 18 months from the filing. Due to this publication lag, it is common in the literature to limit the attention to patents filed some years before (e.g., see Webb et al., 2018).

[3] EPO managers, personal communication to the authors.

specific application domain.

To construct our data set, we did an intense work of data mining from ORBIS-IP. It consisted of several steps, which we can summarize as follows. First, we collected the 4IR patent applications based on the CPC codes individuated by the EPO classification. Second, after selecting those patent applications that were filed at the EPO between 1985 and 2014 – our object of analysis – we gathered additional information on those patent applications, for example, referring to grant status and applicants. ORBIS-IP provides a firm identifier, called "bvdid", which uniquely identifies each company present in the data set (as previously mentioned, ORBIS-IP collects virtually all the incorporated firms in the world). Besides general information on applicants (e.g., names and countries of origin), ORBIS-IP also indicates, for each patent application, the bvdid of the applicant(s), whenever it exists (i.e., whenever the applicant is a company present in ORBIS-IP). Third, endowed with bvdid identifiers, we collected relevant firm-level information of the applicants, including, for instance, the year of incorporation and the sector of economic activity of the company. As only a small fraction (about 7%) of selected 4IR patent applications was not associated with a bvdid, we removed those 4IR patent applications given our focus on firm-level analyses. As a result, we obtained a matched patent-firm data set. Like every matched-type data set, we could exploit (and exploited) several dimensions: we either used it in its "original form", that is, using the patent level, or in its "collapsed form", that is, using the collapsed firm level.[4]

Finally, we applied an essential cleaning procedure that removed observations with missing necessary information (i.e., the year of incorporation and industry) and the very few firms operating in the primary sector (i.e., agriculture). Due to this cleaning procedure, a small fraction (less than 10%) of patent-observations was removed.

Our final sample comprises patent- and firm-level longitudinal information for 41,767 companies that filed 758,218 4IR patents over the period 1985-2014.[5] The patent information that we used in this paper, either to construct the data set or to conduct our empirical analysis, includes the application number and date, the patent office, CPC codes, the grant status, information on the applicant(s), and information on the technological area (i.e., main sectors and technology fields) that we constructed starting from the CPC codes based on the EPO classification. As for companies, we retained basic information concerning the year of incorporation (from which we computed firm age) and the sector of economic activity. We also extracted information on the firms' overall patent applications to the EPO over the period 1985-2014, whereby we calculated the size of overall patent portfolios and the ratio of 4IR to overall patent portfolios, which we used as a proxy for the degree of intensity of effort in 4IR-related areas.

4. Results

We now present our results at two different levels of analysis. In the first subsection, we show a series of figures displaying information at the patent level.[6] In the second subsection, we report several descriptive results when aggregating information at the firm level. There, we also report the results from the cluster analysis carried out to uncover groups of companies that behave similarly

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[4] Note that we followed a similar procedure to construct information on the firms' overall patent portfolios (i.e., also including non-4IR patent applications). In particular, for each firm in our sample, we collected the complete list of patents filed at the EPO between 1985 and 2014.

[5] In this paper, we account for patents with multiple applicants. About 3% of the 758,218 4IR patent applications collected in our sample have multiple applicants.

[6] Different methods are available to count patents by applicants, inventors, and technological classes (e.g., whole counting, fractional counting, straight counting). In our work, we adopt a whole counting approach, also based on recent evidence showing a lack of dependence of country rankings to the different counting methods (Zheng et al., 2013).

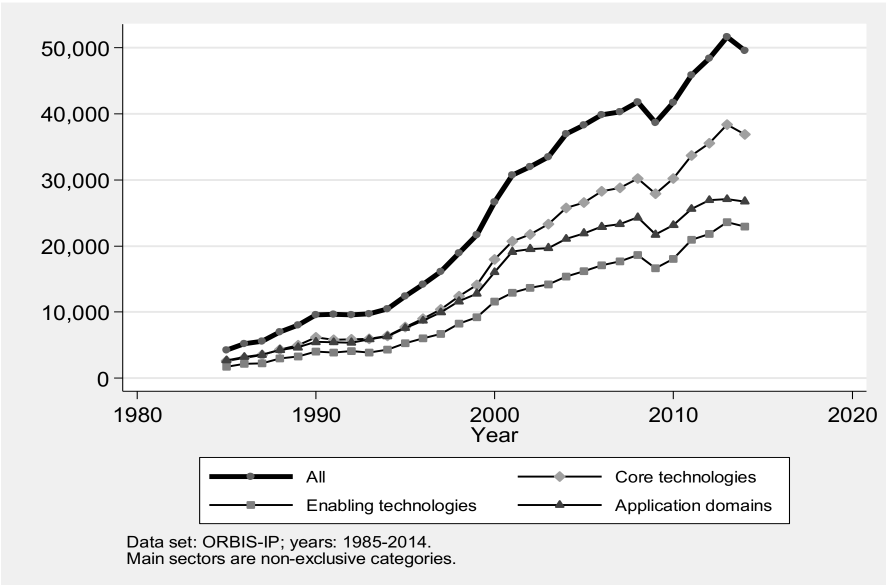
along several dimensions, including the specialisation in particular 4IR technological areas and intensities of efforts in 4IR technologies.

4.1 Results at the patent level

Figure 1 shows the evolution of 4IR patent applications over our reference period. Between 1985 and 2014, the number of 4IR patent applications filed at the EPO in each year increased rampantly. Growth rates of 4IR patent applications have been far higher than growth rates of overall patent applications, although they were sizeable, too.[7] Within three decades, from 1985 to 2014, 4IR patent applications passed from about 5,000 to roughly 50,000 per year, thus increasing tenfold, a much higher growth compared to overall patent applications, which have "only" quadrupled. Therefore, 4IR applications as a share of total applications have increased significantly. While 4IR patent applications represented about 13% of total patent applications in 1985, in 2014, this percentage increased to around 33%.[8]

Figure 1 also reports the number of 4IR applications by main sector. Recall that main sectors (and the technology fields thereof) are non-exclusive, meaning that a 4IR patent can embed at the same time a core technology and an enabling technology, for instance. This feature is reflected in the figure, as the (vertical) sum of 4IR patent applications classified as core technologies, enabling technologies, or application domains is higher than the overall number of 4IR applications. While patents belonging to core, enabling, and application sectors were approximately in the same amount in earlier periods, significant differences across main sectors emerged starting from 2000. Nowadays, patents that represent a core technology are by far the firsts filed at the EPO, followed by application-type patents, and, somewhat behind, by those embedding an enabling technology.

Fig. 1: Number of 4IR patent applications, overall and by main sector, by filing year



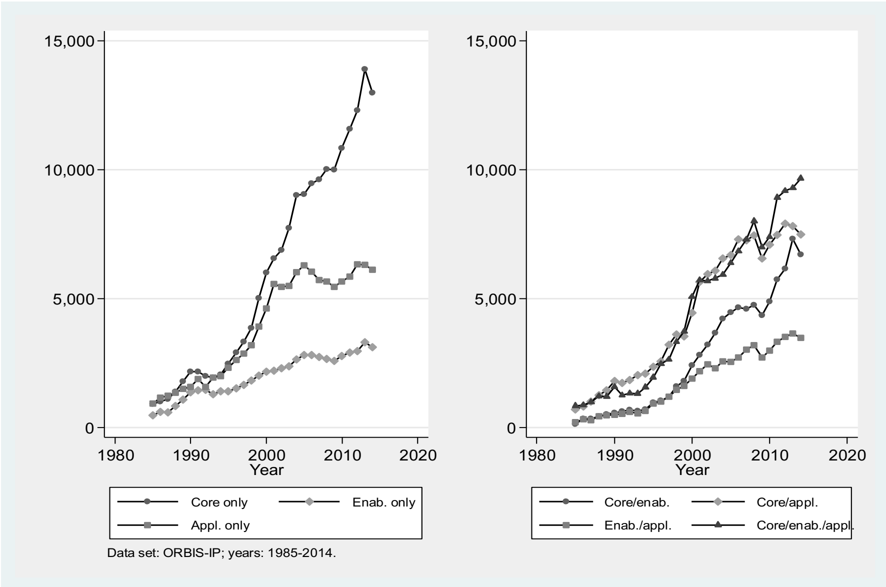
Source: authors' elaborations on ORBIS-IP data

[7] This is coherent with the surge in overall patent applications in the last twenty years documented elsewhere (see, for instance, Kim and Marschke, 2004 and Fink et al., 2016).

[8] We have also checked for the increasing complexity of 4IR technologies by computing the technological scope (i.e., the number of distinct CPC codes by filing year), which has been shown to be associated with the propensity of the invention to find potential applications in multiple domains (Lerner, 1994). Interestingly, the figure reported in Appendix B shows an increasing technological complexity through time.

Figure 2 shows the evolution of the seven possible combinations of main sectors (i.e., core technology only, enabling technology only, core and enabling technologies, and so forth). While 4IR patents in the various combinations of main sectors were approximately equally represented in earlier years, in recent years, significant differences emerged. Since 2000, many 4IR patent applications embed only a core technology (first occurrence). A significant number of applications refer to more articulated technologies: core and enabling technologies with an application domain (second occurrence), core technologies with an application domain (third occurrence), and core and enabling technologies (fourth occurrence). Conversely, a few 4IR applications are classified as only enabling technologies, only application domains, and enabling technologies joint with an application domain.

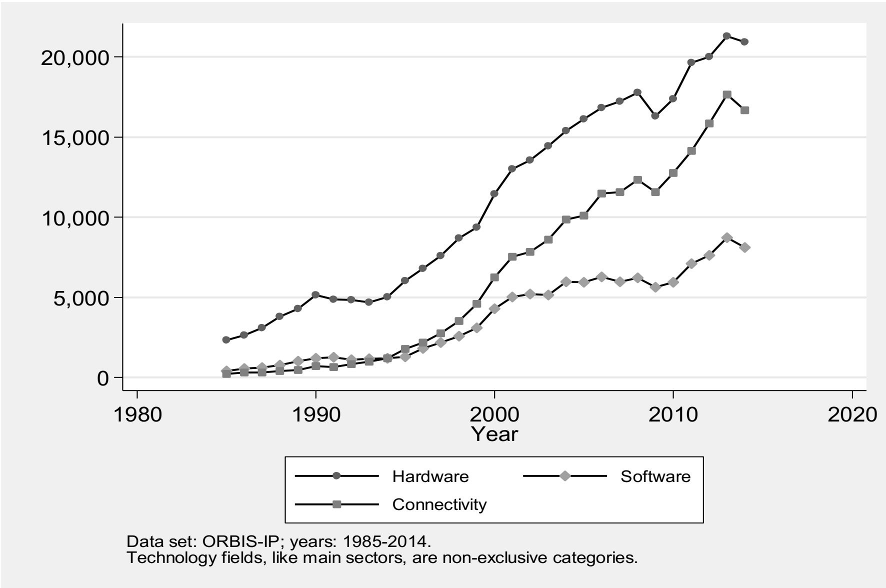
Fig. 2: Number of 4IR patent applications by exclusive combination of main sectors, by filing year



Source: authors' elaborations on ORBIS-IP data

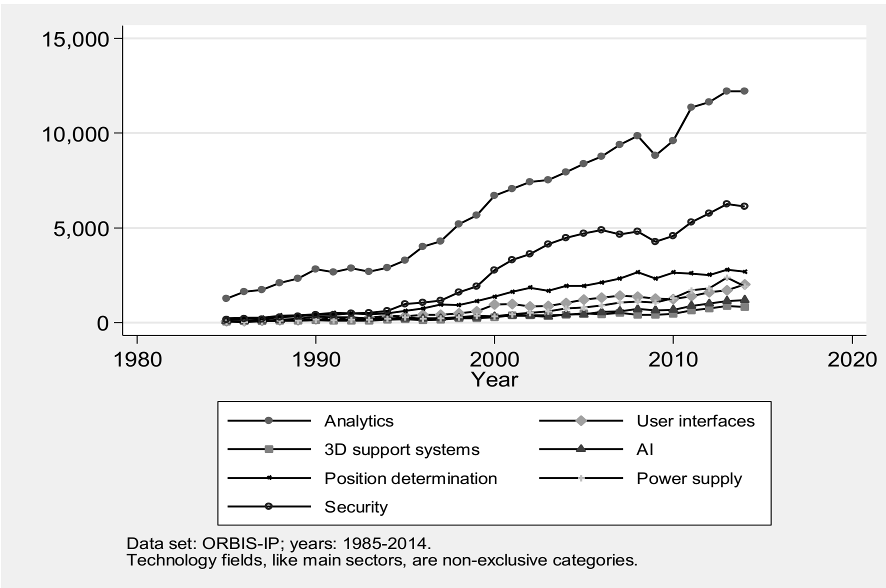
Figure 3, Figure 4, and Figure 5 show the evolution of 4IR applications over time for the different technology fields in the core technology, enabling technology, and application domain sectors, respectively. As the different combinations (both within sectors and overall) are too many, we only report the non-exclusive categories of technology fields separately for the three main sectors. As far as core technologies are concerned, hardware is the most represented technology field, with around 20,000 4IR patent applications per year in the most recent period. Hardware is followed closely by connectivity, which underwent a rapid surge in recent years. Software, instead, lagged far behind connectivity since 2000. As for enabling technologies, the most important technology field is analytics, with around 12,000 4IR applications per year in the last few years. Somewhat behind, there is security, with slightly more than 5,000 4IR applications per year in the most recent period. The other technology fields are far behind, with position determination in the third place, followed by power supply, user interfaces, artificial intelligence, and, lastly, three-dimensional support systems. Artificial intelligence, while remaining relatively poorly represented, has started a slow but constant growth in the most recent years, approximately since 2010. As for the application domain sector, while its six technology fields were roughly equally represented in the earliest period, marked differences emerged in the subsequent years. The most common application domains in the last years are the personal and enterprise technology fields. Far behind, there are vehicles, manufacture, and home. Infrastructure is the less represented technology field within the application domain sector.

Fig. 3: Number of 4IR patent applications referring to core technologies by technology field, by filing year



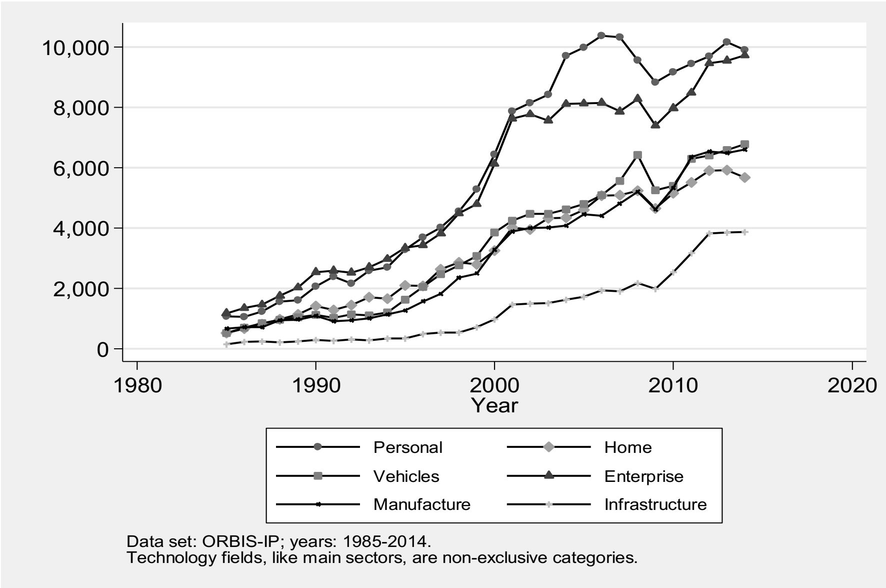
Source: authors' elaborations on ORBIS-IP data

Fig. 4: Number of 4IR patent applications referring to enabling technologies by technology field, by filing year



Source: authors' elaborations on ORBIS-IP data

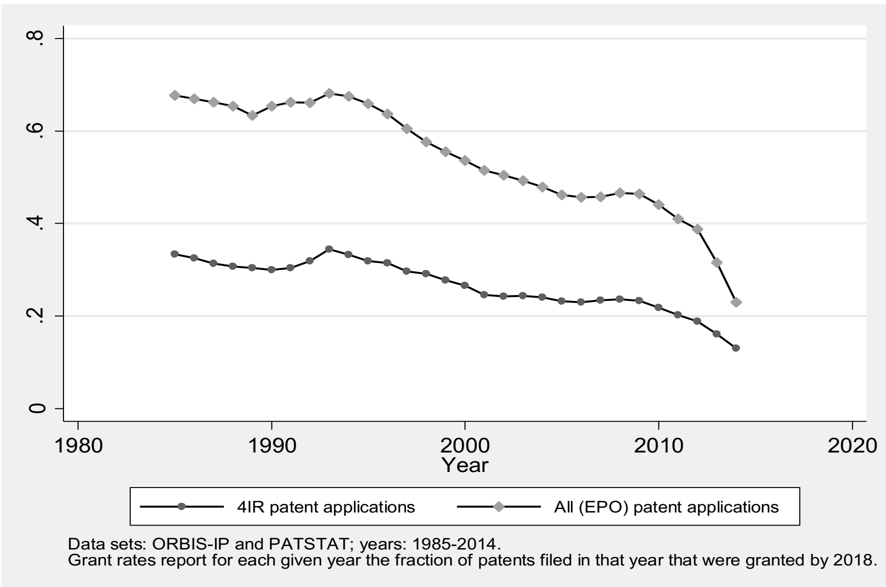
Fig. 5: Number of 4IR patent applications referring to application domains by technology field, by filing year



Source: authors' elaborations on ORBIS-IP data

Figure 6 plots the grant rates for all the EPO patent applications (retrieved from PATSTAT) and for the 4IR patent applications by filing year. The grant rates for both patent types are decreasing over time, with an acceleration starting from 2008. Overall, the grant rate for the 4IR patents is always lower than that for all the EPO patents, but there is a trend towards closing the gap between the two, which became particularly nuanced since 2008.[9]

Fig. 6: Grant rates by filing year



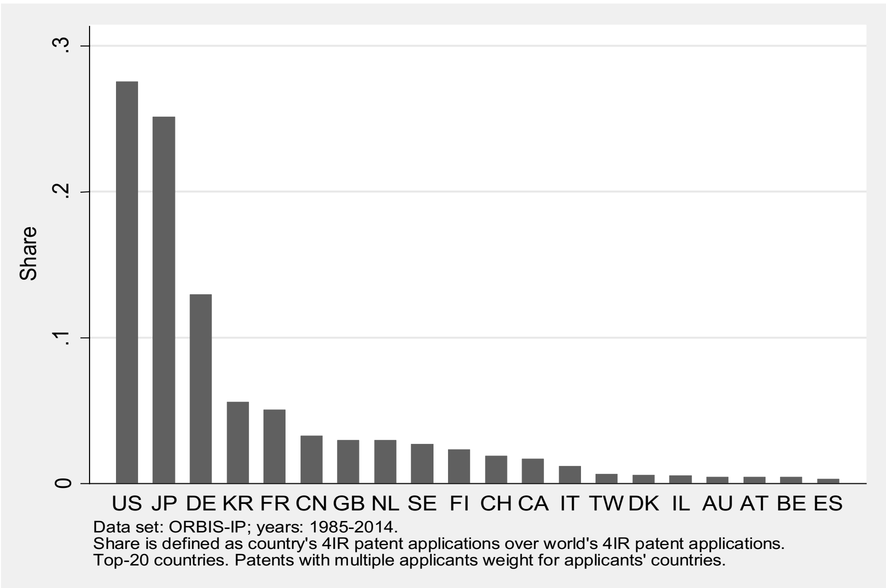
Source: authors' elaborations on ORBIS-IP data

[9] The decreasing trend in the grant patent rates is likely due to the increasing examination lags. Notably, differently from the USPTO, where the increasing backlog is mainly explained by low fees and lower quality of examination, the long pendency at the EPO has been shown to be more due to the strategic filing of applicants (Meyer and De La Potterie, 2011). We would like to thank one of the reviewers for pointing this out.

As far as the geographic distribution of patent applications is concerned, Figure 7 reports the share of 4IR patent applications by country of applicants. We observe that the top-20 countries account for about 99% of the 4IR patent applications at the EPO, with United States, Japan, and Germany accounting for the highest proportions (27.5%, 25.1%, and 13.0%, respectively). As this pattern resembles the one for all patent applications at the EPO in the period considered here, it seems that the usual suspects are leading the 4IR race.[10] Interestingly, despite China's unprecedented growth in worldwide patent applications (Wei et al., 2017), it seems to lag compared to other countries as it covered only 3.3% of the 4IR patent applications at the EPO. However, when it comes to patent application intensity in the 4IR (defined as the share of 4IR patent applications over all the patent applications), the picture changes considerably. China is the country with the highest intensity of 4IR patent applications, as about 40% of its patent applications at the EPO belong to 4IR technologies.

Figure 8 plots the intensity of specialisation in 4IR patents by country. Apart from the above-mentioned leading role of China, several countries that have recently focused their attention on the 4IR are among the highly ranked (e.g., Canada and Taiwan).[11] This suggests that, beyond being the result of the pre-existing technological structures of a country, the 4IR patenting activity in a country might also be the result of national-level deliberate strategic decisions.

Fig. 7: Share of 4IR patent applications by country

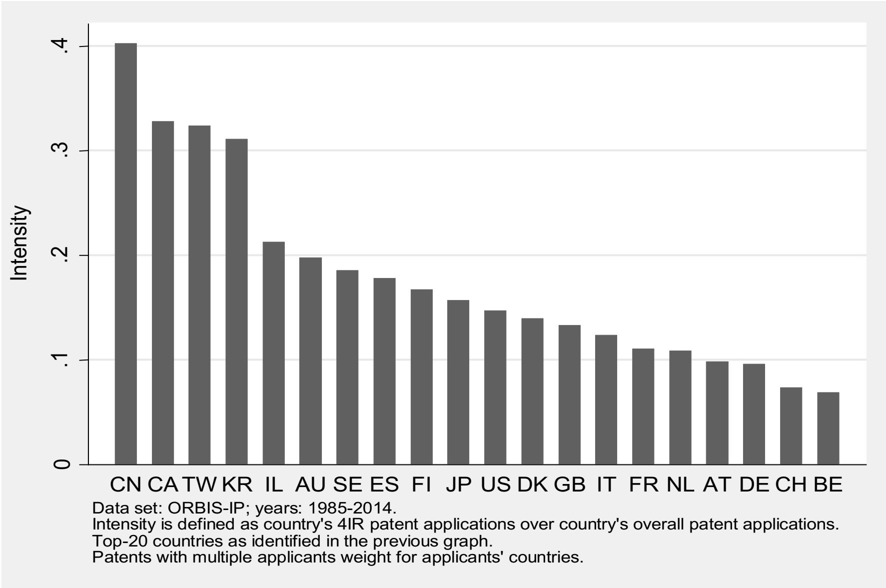


Source: authors' elaborations on ORBIS-IP data

[10] Statistics provided by the EPO, available at https://www.epo.org/about-us/annual-reports-statistics/statistics.html, show that, up to 2014, the top-3 countries in terms of number of applications to EPO were the US, Japan, and Germany (since 2015, China ranked third, overthrowing Germany of its usual third place).

[11] For instance, Canada recently launched the strategy to become the first in the area of data science (see https://open.canada.ca/en/content/canadas-new-plan-open-government-2016-2018 on this). Similarly, Taiwan is massively investing in 4IR technologies to become an innovator leader in high-tech technologies (see, for instance, https://thediplomat.com/2016/11/can-taiwan-build-an-asian-silicon-valley/).

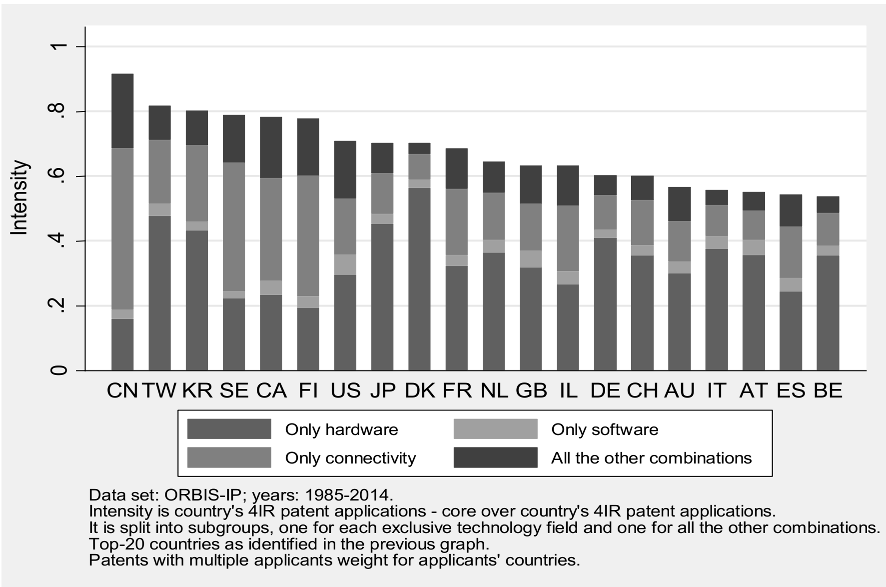
Fig. 8: Intensity of 4IR patent applications by country



Source: authors' elaborations on ORBIS-IP data

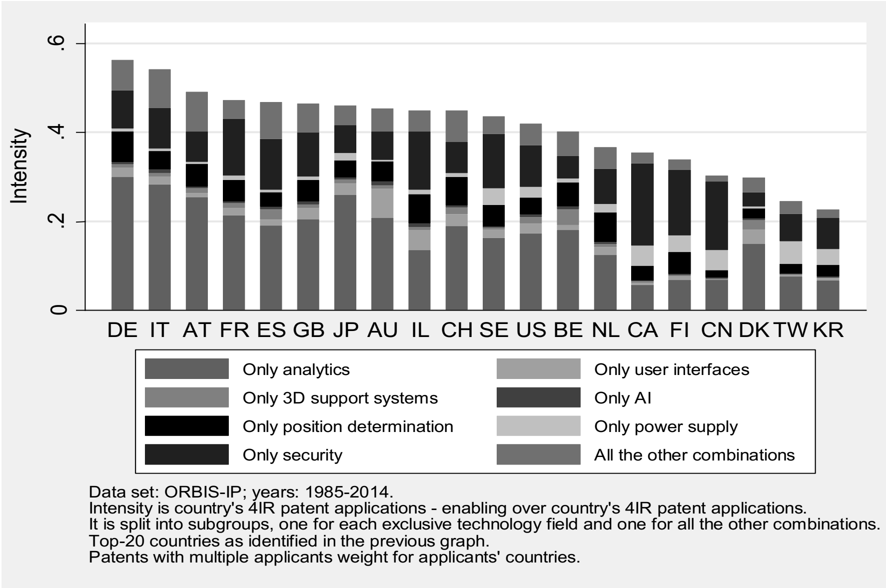
When we check the intensity at the country level by technology field, an interesting specialisation pattern seems to emerge (Figure 9, Figure 10, and Figure 11). We observe that China, Taiwan, and Korea have the highest patent application intensities in core technologies. Germany is the country with the highest intensity in enabling technologies, as slightly less than 60% of 4IR patent applications refer to enabling technologies. Finally, economies whose industrial structure is mainly manufacturing-oriented (i.e., Germany and Italy) tend to specialise in enabling and application technologies.

Fig. 9: Intensity of 4IR patent applications referring to core technologies by country



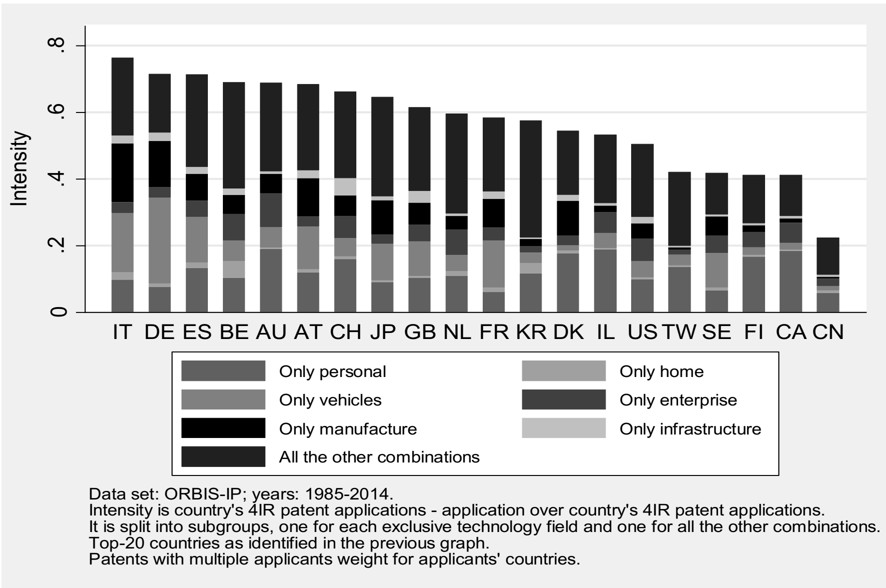
Source: authors' elaborations on ORBIS-IP data

Fig. 10: Intensity of 4IR patent applications referring to enabling technologies by country



Source: authors' elaborations on ORBIS-IP data

Fig. 11: Intensity of 4IR patent applications referring to application domains by country



Source: authors' elaborations on ORBIS-IP data

4.2 Results at the firm level

When aggregating the information at the corporate level, we found more than 40,000 companies associated with the patent applications identified as pertaining to the 4IR.

Table 1 provides descriptive statistics on 4IR patents at the firm level, overall and by main sector. The firms in our sample produce, on average, 8.2 4IR patent applications per year, with substantial heterogeneity (standard deviation is 48.3). The median number of 4IR applications is much lower compared to the average number. This points to a skewed distribution in the number of 4IR patent applications per firm in the sample, with a large proportion of firms contributing little to the overall 4IR patent pool (e.g., 32.2% of firms in the sample filed only one patent in the overall period) and a small number of companies contributing disproportionately more (e.g., 0.2% of firms in the sample filed more than 1,000 patents each in the period of reference). The decomposition of the standard deviation in the "between" and "within" components shows that the "within" component is much larger than the "between" component (31.0 *versus* 11.5). This denotes the crucial role of changes in the patent strategies at the firm level in explaining the variations through time. These two descriptive results point to a picture where the recent surge in 4IR patent applications can be explained by a restricted number of companies, which disproportionately increased their patenting activity in 4IR technological fields. Notably, the first four companies in terms of number of 4IR patent applications accounted for 8.82%, the first eight for 15.44%, and the first twenty for 31.35% of all the 4IR patent applications (see Table C1 in Appendix C).[12]

Table 1 also reports the decomposition by main sector. In line with the results obtained at the patent level, the sector of core technologies is the one in which firms have the highest number of patent applications per year and the highest "within" variation. This is also confirmed in Figure 12, which shows an increase in the average number of 4IR patent applications per firm through sub-periods, with a surge of core technologies compared to the other main sectors.

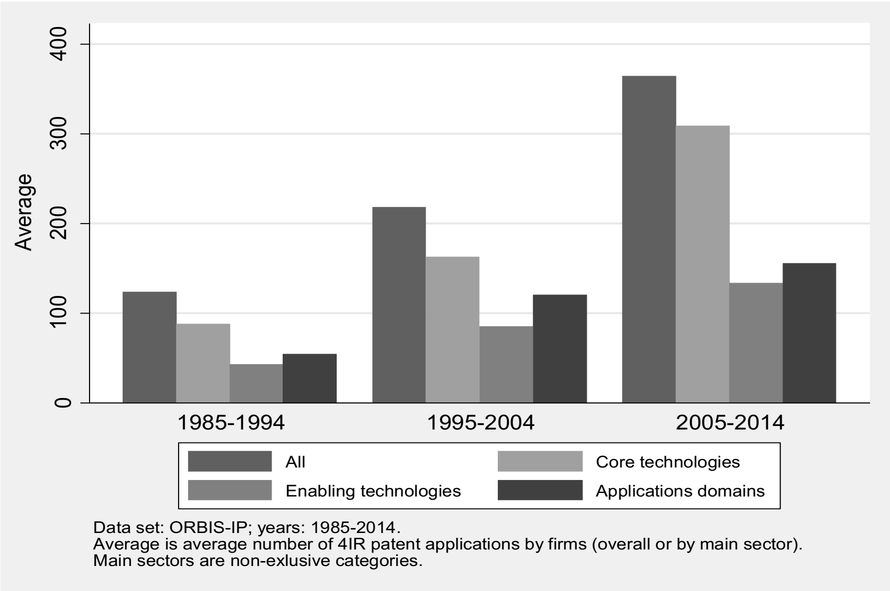
Tab. 1: Summary statistics on the number of 4IR patent applications at the firm level, overall and by main sector

Statistic/Variable	Mean	Median	Std. Dev.	Between std. Dev.	Within std. Dev.	Min	Max
4IR patent applications	8.2	2	48.3	11.5	31.0	1	2,584
4IR patent applications referring to core technologies	5.7	1	40.1	9.5	26.8	0	2,447
4IR patent applications referring to enabling technologies	3.6	1	20.2	4.7	13.2	0	1,101
4IR patent applications referring to application domains	4.8	1	25.0	6.0	15.5	0	1,215
							Number of firm-year observations: 95,124
							Number of firms: 41,767

Data set: ORBIS-IP; years: 1985-2014.
Source: authors' elaborations on ORBIS-IP data

[12] Table C1 in Appendix C provides some general information on the top-20 companies in terms of number of 4IR patent applications.

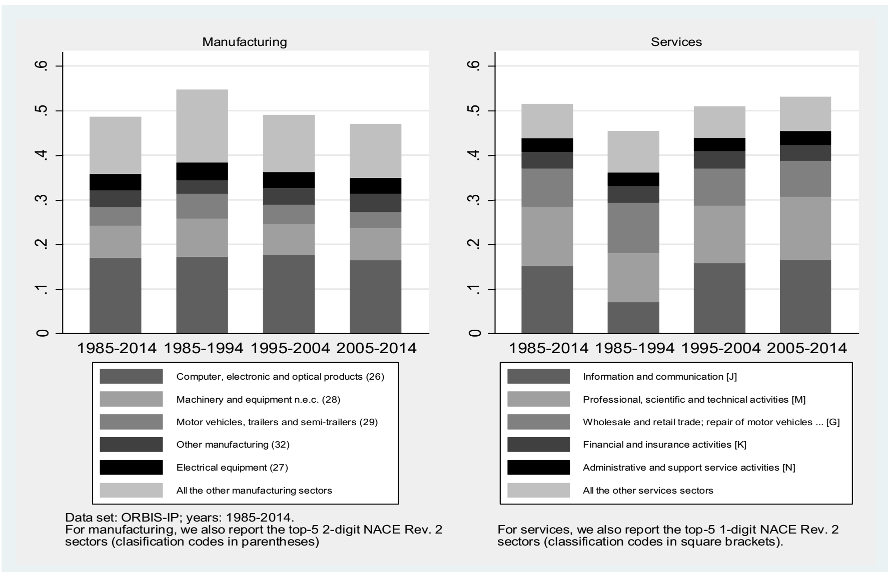
Fig. 12: Average number of 4IR patent applications filed at the firm level, overall and by main sector, by sub-period



Source: authors' elaborations on ORBIS-IP data

Figure 13 plots the distribution of firm-year observations by industry (NACE Rev. 2 classification) for the whole period and the three decades. The distribution of firms by macro-industry (i.e., manufacturing *versus* services) through time supports the general trend towards firm servitisation (Neely, 2008). Before 2000, the majority of firms with at least one 4IR patent application per year were manufacturers, while, after 2000, the trend reversed. The figure also reports the primary industries where companies filing 4IR patents operate. Manufacturing companies mainly operate in the computer, equipment, and automotive industries. Companies belonging to services tend to operate in ICT, professional/scientific activities, retail, and financial activities.

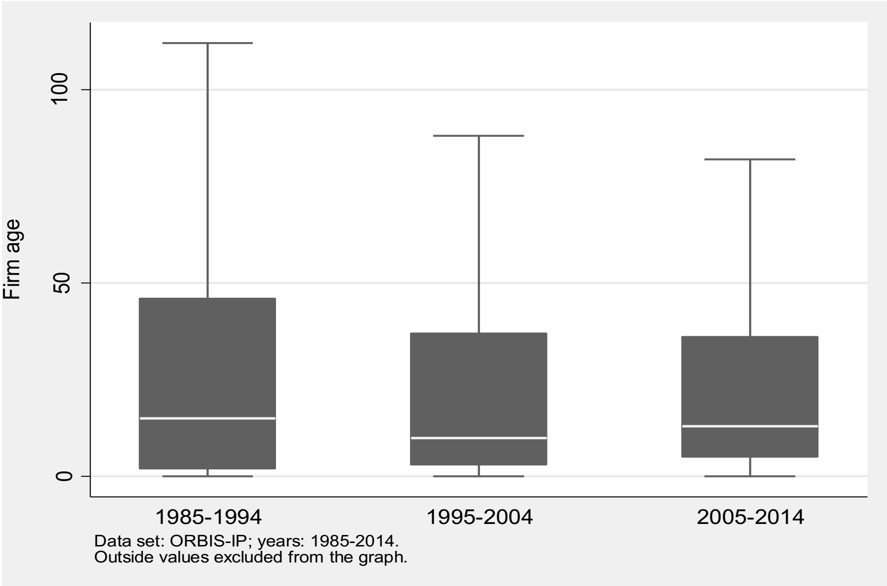
Fig. 13: Distribution of firms (based on firm-year observations) by macro-industry and main sub-industries, overall and by sub-period



Source: authors' elaborations on ORBIS-IP data

Figure 14 shows the boxplot of firm age for the three decades comprising our period of analysis. While firm age tends to have an ample range of variation in the first period (1985-1994) – with some companies more than 100 years old – and a wide inter-quartile range, the following two periods show a decrease in the average firm age and its variation in the sample. This points to the presence of a younger cohort of companies (either stemming from young entrants progressively populating the market or old incumbents exiting the market).

Fig. 14: Distribution of firm age (based on firm-year observations) by sub-period



Source: authors' elaborations on ORBIS-IP data

As a final analysis, we group firms together based on some relevant characteristics. In particular, we identify a restricted number of relevant inputs, and we feed them to a chosen clustering algorithm. The variables used as inputs for our cluster analysis can be grouped into three classes. The first group encompasses a set of three variables that give an index of the firm's specialisation into a particular main sector and of its complexity (i.e., its coverage of multiple technology fields within that main sector). First, for each patent, we construct one index for each main sector (i.e., three indexes in total) reporting the number of technological fields covered within that main sector by that patent. Then, we take the average of these three indexes for each firm. In conclusion, we obtain (i) one index related to core technologies, which ranges from 0 to 3 (recall that technology fields within core technologies are, in fact, three); (ii) one index related to enabling technology, which ranges from 0 to 7 (the number of technology fields within enabling technologies); (iii) one index related to application domains, which ranges from 0 to 6 (the number of technology fields within application domains). The second variable used to individuate the clusters is the number of all patent applications filed by the firm to the EPO in the relevant period. Such a variable, measuring the size of the firm's patent portfolio, indicates its effort in innovative activities. The third variable that we used as an input for the cluster analysis is the ratio of 4IR patent applications to all patent applications filed by the firm at the EPO over the relevant period. Such a variable gives a proxy for the intensity of the firm's efforts into 4IR technologies compared to non-4IR technologies. All these variables are standardized, both to pursue the cluster analysis and in the tables. Finally, note that, due to the computational burden imposed by the large size of our sample, we rely on a partition-clustering method (k-means clustering) based on the Calinski/Harabasz pseudo-F stopping rule index for selecting the optimal number of clusters.

This exercise yields five clusters. Table 2 contains information on several dimensions for the five clusters, including averages of the variables used as inputs for the cluster analysis, the average year of incorporation, and the proportions of firms operating in the manufacturing *versus* services industries. The first cluster, which we labelled "giants", includes a restricted group of companies (24). These companies tend to have an extensive patent portfolio (more than 35,000 patent applications on average), and to be established (more than 80 years old on average), manufacturing (more than 87% of them) companies. Such firms seem to use 4IR patent applications as a complement to their core technological activities (the share of 4IR patent filings to total patent filings is around 33%) and tend to specialise in the development of 4IR core technologies (with a value of the index of core technologies well above the mean). The second cluster is labelled "next-to-the-giants" and contains a large number of companies (11,669), mainly operating in services sectors (66.46%). These firms specialise in core 4IR technologies, too, and even more than "giants", and make massive investments in 4IR: on average, the 62.5% of their patent portfolio comprises 4IR patent applications. Furthermore, they are medium-sized companies, mainly founded in the Nineties. The third cluster is labelled "enablers" and contains mostly services companies (nearly 57%) and specialises in 4IR enabling technologies, with a large share of 4IR applications within their portfolio (about 55% on average). This cluster mainly comprises medium/large companies founded in the Eighties. The fourth cluster, "application-oriented", includes the largest group of companies, which again belong for the most part to services sectors (about 60%). These firms specialise in 4IR application domains, make substantial investments in 4IR technologies, and are mostly medium/large companies founded in the Eighties. Finally, the last cluster (labelled "combinators") contains a comparatively smaller group of companies (5,791), mainly from services industries (roughly 60%). Interestingly, this cluster of companies combines (and hence the name "combinators") both 4IR enabling technologies and application domains. In this last sector, they bear the highest degree of specialisation. Their patent portfolio comprises a high share of 4IR patent applications (nearly 60%). These companies are mostly SMEs founded in the Eighties.

Tab. 2: Cluster analysis, full period (1985-2014)

Variables	Cluster 1 "Giants"	Cluster 2 "Next-to-the-giants"	Cluster 3 "Enablers"	Cluster 4 "Application-oriented"	Cluster 5 "Combinators"
Number of firms	24	11,669	12,285	11,998	5,791
Index core technologies*	0.485 (0.365)	0.962 (0.781)	-0.043 (0.856)	-0.899 (0.255)	0.012 (0.864)
Index enabling technologies*	-0.107 (0.354)	-0.518 (0.505)	1.133 (0.760)	-0.711 (0.231)	0.114 (1.019)
Index application domains*	-0.377 (0.392)	-0.661 (0.589)	-0.496 (0.570)	0.302 (0.520)	1.760 (0.759)
Number of patent applications	36,991.080 (16,740.430)	99.911 (653.546)	132.377 (856.476)	122.745 (879.703)	42.385 (237.390)
Share of 4IR patent applications	0.330 (0.163)	0.625 (0.378)	0.547 (0.392)	0.575 (0.403)	0.604 (0.391)
Year of incorporation	1931.125 (46.362)	1990.816 (27.498)	1986.190 (30.254)	1983.881 (32.646)	1988.170 (28.513)
Manufacturing	87.50%	33.54%	42.92%	40.42%	39.08%
Services	12.50%	66.46%	57.08%	59.58%	60.92%
					Number of firms: 41,767

Data set: ORBIS-IP; years: 1985-2014.
* Standardized.
Averages, standard deviations in parentheses.
Source: authors' elaborations on ORBIS-IP data

To gain a more robust characterization of the clusters described above, we check for statistical correspondences between our indexes of 4IR specialisation and clusters. This is done by regressing the likelihood of belonging to a particular cluster against the indexes of 4IR specialisation constructs and a set of other characteristics, such as the size of the patent portfolio, the share of 4IR patent applications, the year of incorporation, and industry and country fixed effects. The results (Table D1 in Appendix D) corroborate the insights obtained from the description of results in Table 2 above.

5. Discussion and conclusions

In this paper, we have explored the recent patent rush in the 4IR technological areas at the EU level. The general aim was providing a “thick” description of what is currently happening at the patent application level and firm level. Due to the mainly descriptive nature of our investigation, we did not explore the causes and consequences of developing 4IR patents. Nevertheless, we believe our paper offers three main contributions.

The first contribution of our work is to offer a controlled set of data and statistics about EU 4IR patent applications, based on an existing classification of technologies pertaining to the 4IR field. So far, evidence on patenting in the 4IR is mainly limited to the US and still mostly exploratory. By adopting the EPO classification and by combining different sources of information, we provide a comprehensive, up-to-date picture of the patent rush in the 4IR at the European level. We document the overall trend since 1985, as well as the evolution of the three main technological categories (core technologies, enabling technologies, and application technologies). Overall, we show that 4IR patent applications have increased significantly in the last years. Out of the three main categories, core technologies – particularly those related to hardware and connectivity – still retain a leading role.

The second most relevant contribution of our work is at the firm level. By connecting each 4IR patent application to a company, we were able to analyse applicant firms from different perspectives. We investigated the geographic patterns of the firms patent applicants and found that US-based companies account for slightly less than 30% of the total 4IR applications. However, when it comes to 4IR patent intensity (i.e., the share of 4IR patents over the total) China plays a leading role. New countries are emerging. This is, for instance, the case of Taiwan and other “emerging” countries that are going to play a crucial role in specific technological areas. Second, we document that the majority of applicant firms operate in services sectors, not in manufacturing industries. Third, we show that the average number of patents per company has increased significantly, suggesting that the surge in the 4IR patenting activity took place mostly within firms. However, considering the age of applicant firms, other relevant features emerge. Namely, the lower average age of patent applicants between 1985 and 2014 might suggest that young companies have successfully entered the market.

The third most relevant contribution is the identification of several specific groups of firms with similar patent applications’ features. Overall, a clear pattern emerges: most firms tend to specialise in a specific technological domain, be it core technology, enabling technology, or application technology. Only a small minority of firms focus on several technology domains. This is particularly true for application and enabling technologies.

Our exploration also offers some managerial implications, although mainly speculative. At the macro level, it documents the emergence and rapid growth of 4IR technologies. It also suggests that patent applications in this domain are likely to grow steadily in the future. Therefore, the patent arena might become crowded, so that finding a specific niche to patent newly created knowledge might become complicated. Overall, the 4IR patent domain might become a forest. Companies should carefully balance the advantages of being granted a patent with a longer and more complicated patenting process. On the same ground, our analysis shows that the geographic picture is changing. Namely, new emerging countries seem to become key players in specific technologies. Managers and companies should, therefore, pay attention to a broader set of regions and reinforce their antennas to detect new sources of innovation. Finally, the analysis of strategic groups shows that, as far as patent applications in the 4IR domain are concerned, as the degree of specialisation remains significant, managers should carefully evaluate possible sources of knowledge differentiation.

Our analysis has several potential limitations. First, the identification of 4IR patent applications is not without possible mistakes. Unfortunately, this is because EPO (2017) does not provide details on a refinement step consisting of a full-text search for different keywords to circumscribe 4IR patents further. However, while this further step could alleviate the problem of false positives, on the other hand, retaining a broader classification helps avoid false negatives. This seems particularly relevant in this case as new technologies (like 4IR technologies) are subject to a large degree of uncertainty, and different technological trajectories can be investigated at the same time so that a broader definition might even be more pertinent.

Second, we analyse 4IR patent applications, not granted patents. Despite the apparent correlation between the two, several reasons suggest that three discrepancies might emerge in the future. The first discrepancy has to do with the time lag between the application and grant, due to an unexpected increase in patent applications. The second discrepancy has to do with a possible negative outcome of the technical due diligence done by the EPO, resulting in a number of granted patents significantly different from the applications. The third discrepancy has to do with strategies deliberately pursued by companies. Quite often, only for the sake of collecting valuable information, and not for really getting a patent, companies might submit patent application *pro-forma*. Overall, the analysis of 4IR patent applications ought to be complemented by a scrutiny on granted patents.

Third, our exploration is a first step towards a better comprehension of the 4IR patent arena. As it is mainly a "thick" description, we did not analyse the antecedents and effects of 4IR patent applications. As we pointed out, many 4IR technologies did not emerge all of a sudden. Several 4IR technologies, such as AI, have a long history. It is reasonable to assume that patent applications should be associated with significant R&D investments both at the national and firm levels. The conditions that make a country or a firm more productive as far as the patent generation in the 4IR domain is concerned is an unexplored issue. For the same token, we know little about the effects of patent applications, our unit of observation. A comparative and longitudinal analysis of patent applications and patents granted would be a first step in this direction. As a second step, quantitative and qualitative studies on how 4IR patents contribute to firms' exploration and exploitation capabilities would be highly beneficial.

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APPENDIX A – 4IR main sectors and technology fields

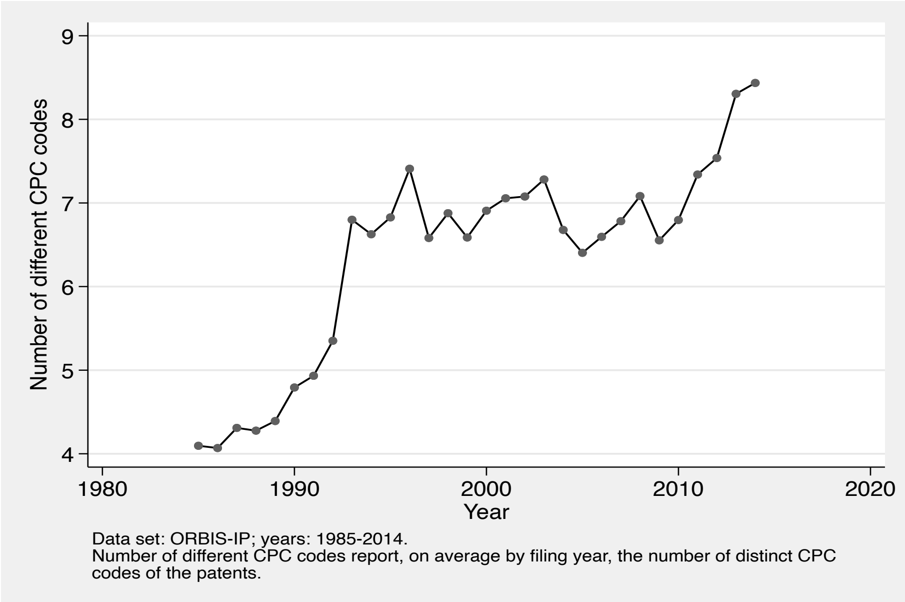
Tab. A1: Classification of 4IR patent applications by main sector and associated technology fields

Sector	Technology field	Definition	CPC example
Core	Hardware	Basic hardware technologies	Accessing, addressing, or allocating within memory systems or architectures (G06F12/00)
Core	Software	Basic software technologies	Arrangements for software engineering (G06F8/00)
Core	Connectivity	Basic connectivity systems	Telephonic communication systems adapted for combination with other electrical systems (H04M11/00)
Enabling	Analytics	Enabling the interpretation of information	Methods or arrangements for marking the record carrier in digital fashion (G06K1/00)
Enabling	User interfaces	Enabling the display and input of information	Head-up displays (G02B27/01)
Enabling	Three-dimensional (3D) support systems	Enabling the realization of physical or simulated 3D systems	Computer-aided design (G06F17/50)
Enabling	Artificial intelligence (AI)	Enabling machine understanding	Computer systems based on biological models (G06N3/00)
Enabling	Position determination	Enabling the determination of the position of objects	Systems for determining distance or velocity not using reflection or reradiation (G01S11/00)
Enabling	Power supply	Enabling intelligent power handling	Means for saving power (G06F1/32)
Enabling	Security	Enabling the security of data or physical objects	Security arrangements for protecting computers, components thereof, programs, or data against unauthorized activity (G06F21/00)
Application	Personal	Applications pertaining to the individual	Details of electrophonic musical instruments (G10H1/00)
Application	Home	Applications for the home environment	Controlling a series of operations in washing machines, e.g., program-control arrangements for washing and drying cycles electrically (D06F33/02)
Application	Vehicles	Applications for moving vehicles	Vehicle cleaning apparatus not integral with vehicles (B60S3/00)
Application	Enterprise	Applications for business enterprise	Payment architectures, schemes, or protocols (G06Q20/00)
Application	Manufacture	Applications for industrial manufacture	Automatic control systems specially adapted for drilling operations, i.e., self-operating systems which function to carry out or modify a drilling operation without intervention of a human operator, e.g., computer-controlled drilling systems (E21B44/00)
Application	Infrastructure	Applications for infrastructure	Systems or methods specially adapted for specific business sectors, e.g., utilities or tourism: electricity, gas or water supply (G06Q50/06)

Source: EPO (2017). The fourth column is an addition from the authors.

APPENDIX B – technological scope

Fig. B1: Average number of distinct CPC codes by filing year



Source: authors' elaborations on ORBIS-IP data

APPENDIX C – top-20 companies involved in 4IR patenting

Tab. C1: Top-20 companies involved in 4IR patenting, general information

Company	Country	Number of 4IR patents – 1985-2014	Share of 4IR patents filed in the first period (1985-1994)	Share of 4IR patents filed in the second period (1995-2004)	Share of 4IR patents filed in the third period (2005-2014)	Share of 4IR patent applications over all patent applications
Samsung Electronics Co., Ltd.	KR	20,457	0.005	0.163	0.832	0.391
Sony Corporation	JP	16,161	0.115	0.387	0.498	0.351
Panasonic Corporation	JP	16,132	0.112	0.491	0.397	0.253
Siemens AG	DE	14,197	0.155	0.459	0.386	0.189
Microsoft Corporation	US	13,536	0.015	0.247	0.738	0.753
LG Electronics Inc.	KR	12,746	0.002	0.131	0.867	0.447
Huawei Technologies Co., Ltd.	CN	11,906	0.000	0.020	0.980	0.465
Koninklijke Philips N.V.	NL	11,904	0.084	0.513	0.403	0.211
Robert Bosch GmbH	DE	11,803	0.120	0.402	0.478	0.192
Canon Inc.	JP	11,409	0.310	0.380	0.310	0.244
Toyota Motor Corporation	JP	11,310	0.029	0.292	0.679	0.401
Telefonaktiebolaget LM Ericsson	SE	10,916	0.022	0.251	0.727	0.365
International Business Machines Corporation	US	10,868	0.508	0.313	0.179	0.404
Qualcomm Incorporated	US	10,586	0.007	0.189	0.804	0.411
Nokia Oyj	FI	10,367	0.024	0.533	0.443	0.187
Fujitsu Limited	JP	9,714	0.180	0.286	0.534	0.316
NEC Corporation	JP	9,297	0.199	0.309	0.492	0.310
Hitachi, Ltd.	JP	8,310	0.232	0.426	0.342	0.231
BlackBerry Limited	CA	8,224	0.001	0.141	0.858	0.644
Intel Corporation	US	7,866	0.005	0.199	0.796	0.476

Data set: ORBIS-IP; years: 1985-2014.
Source: authors' elaborations on ORBIS-IP data

APPENDIX D – multivariate regression results

Tab. D1: Multivariate regression results, full period (1985-2014)

Variables	Cluster 1 "Giants"	Cluster 2 "Next-to-the-giants"	Cluster 3 "Enablers"	Cluster 4 "Application-oriented"	Cluster 5 "Combinators"
Index core technologies*	-1.88e-05 (4.38e-05)	0.272*** (0.00361)	-0.103*** (0.00172)	-0.217*** (0.00635)	0.0479*** (0.00273)
Index enabling technologies*	-9.44e-05** (4.17e-05)	-0.198*** (0.00334)	0.343*** (0.00334)	-0.163*** (0.00568)	0.0186*** (0.00259)
Index application domains*	7.39e-05 (4.87e-05)	-0.132*** (0.00535)	-0.160*** (0.00802)	0.0292*** (0.00317)	0.262*** (0.00277)
Number of patent applications	1.44e-05*** (1.96e-06)	-7.07e-06*** (1.07e-06)	-2.32e-06*** (5.07e-07)	-7.87e-07 (1.05e-06)	-4.25e-06*** (7.50e-07)
Share of 4IR patent applications	0.00308*** (0.000587)	-0.0164*** (0.00455)	-0.0191*** (0.00502)	0.0356*** (0.00741)	-0.00323 (0.00691)
Year of incorporation	2.65e-05*** (8.06e-06)	2.66e-05 (4.43e-05)	0.000104*** (3.61e-05)	-0.000300*** (7.43e-05)	0.000143** (5.68e-05)
Industry dummies	Yes	Yes	Yes	Yes	Yes
Country dummies	Yes	Yes	Yes	Yes	Yes
Number of firms	41,767	41,767	41,767	41,767	41,767

Data set: ORBIS-IP; years: 1985-2014.
* Standardized.
*,**,*** denote, respectively 10%, 5%, and 1% significance levels. Robust standard errors, clustered at the country level, are shown in parentheses. Industry is defined according to the 2-digit NACE Rev. 2 classification.
Source: authors' elaborations on ORBIS-IP data

Declaration of interest and funding statement

The authors of this paper declare that they do not have any conflict of interest. They also declare that this research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.