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Original Article

Patenting in 4IR technologies and firm performance

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Abstract

We investigate whether firm performance is related to the accumulated stock of technological knowledge associated with the Fourth Industrial Revolution (4IR) and, if so, whether the firm's history in 4IR technology development affects such a relationship. We exploit a rich longitudinal matched patent-firm data set on the population of large firms that filed 4IR patents at the European Patent Office (EPO) between 2009 and 2014, while reconstructing their patent stocks from 1985 onward. To identify 4IR patents, we use a novel two-step procedure proposed by EPO (2020, *Patents and the Fourth Industrial Revolution: The Global Technology Trends Enabling the Data-Driven Economy*, European Patent Office), based on Cooperative Patent Classification codes and on a full-text patent search. Our results show a positive and significant relationship between firms' stocks of 4IR patents and labor and total factor productivity. We also find that firms with a long history in 4IR patent filings benefit more from the development of 4IR technological capabilities than later applicants. Conversely, we find that firm profitability is not significantly related to the stock of 4IR patents, which suggests that the returns from 4IR technological developments may be slow to be cashed in. Finally, we find that the positive relationship with productivity is stronger for 4IR-related wireless technology and for artificial intelligence, cognitive computing, and big data analytics.

JEL classification: O33, D24, J24

1. Introduction

The last decade has witnessed increasing attention to the Fourth Industrial Revolution—from now on, 4IR (Schwab, 2017). Academic scholars, practitioners (managers, entrepreneurs, and technologists), and policy makers have sparked a debate on the potential role of 4IR in the technological development and transformation of production processes (Brynjolfsson and McAfee, 2014; Santos *et al.*, 2017; Deloitte, 2018). The 4IR promises to revolutionize several aspects of social and economic life. Manufacturing is a case in point: digitalized information on customer needs, processed through analytics and social media, together with real-time, flexible manufacturing systems, allows mass customization to be achieved. Apart from production systems, 4IR technologies and applications open up unprecedented opportunities to drastically change already existing industries—for instance, transportation (through drones and driverless cars)

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and healthcare (personalized medication)—and create new ones (Rüßmann *et al.*, 2015; WEF, 2016a).

The current academic literature on 4IR has mainly focused on (i) the potential technological disruption of 4IR (Benassi *et al.*, 2020; EPO, 2020; Li *et al.*, 2021; Martinelli *et al.*, 2021) and the future consequences on employment (Frey and Osborne, 2017; Graetz and Michaels, 2018) and (ii) the analysis of specific 4IR technologies, such as artificial intelligence (AI) systems, robots, and the like (Cockburn *et al.*, 2018; Dernis *et al.*, 2019; Kromann *et al.*, 2020). However, despite this widespread interest, evidence on the implications of 4IR for companies is scant. We consider this lack of evidence particularly unfortunate, as a better understanding of the implications of the development of these technologies for firms' performance could significantly inform the current debate on firm-level competitiveness, performance, and strategy (Raj and Seamans, 2018).

In this paper, we analyze the extent to which the accumulation of knowledge in the development of 4IR technologies over time is associated with firm performance, as measured by labor productivity, total factor productivity, and accounting profitability. We further explore whether such a relationship is affected by the firm's history in the development of 4IR technologies, as measured by the firm's experience and continuity in 4IR technological development. Finally, we assess whether the relationship between 4IR technology development and firm performance is different for specific technological areas within the broader 4IR remit.

For our empirical analysis, we use a panel data set obtained from ORBIS-IP, including the population of large firms (i.e., with more than 250 employees) that have filed at least one patent in the 4IR domain at the European Patent Office (EPO) in the 2009–2014 period, and we reconstruct the firm-specific history of patent filings in the 4IR technological classes from 1985 onward. We identify 4IR patents by applying a novel two-step procedure proposed by the EPO, which is based on a combination of Cooperative Patent Classification (CPC) codes and a full-text patent search of multiple keywords identifying 4IR technologies (EPO, 2020). We analyzed six major technological groups comprising 4IR technologies: Cyber-Physical Systems (CPS); Industrial Internet of Things (IIoT); AI, cognitive computing, and big data analytics; cloud computing/manufacturing; Augmented Reality (AR); and wireless technology. We focused on large firms because they account for almost the totality of 4IR patent applications. From our computations on the ORBIS Intellectual Property (ORBIS-IP) data set, it emerges that large firms account for over 98% of all 4IR patent applications to the EPO since 1985. The possibility to go back in time by as much as 30 years in the construction of 4IR (and non-4IR) patent stocks allows us to capture the accumulated experience on 4IR technologies developed by companies since the 4IR inception. As is standard practice in the literature, we use patent filings as a proxy for a firm's innovation capabilities (e.g., see Artz *et al.*, 2010; Sears and Hoetker 2014; Grinza and Quatraro, 2019). Although they may be an imprecise proxy of technological and innovation activities at the firm level (e.g., because the propensity to patent differs across firms and industries; not all inventions are patented; and patents can be filed for strategic reasons), patents still represent the most commonly and widely accepted way of measuring a firm's technological capabilities and are generally considered valid and robust indicators of knowledge creation and innovation (Trajtenberg, 1987).

Our main results, obtained after controlling for a wide array of patent- and firm-level characteristics and firm fixed unobserved heterogeneity, show a positive and significant relationship between the stock of 4IR patents and productivity (both labor productivity and total factor productivity), but no correlation with profitability. The positive relationship with productivity is mainly driven by companies that are characterized by higher experience and continuity in 4IR technology development and that have started earlier to develop 4IR inventions (i.e., in the 1985–1994 decade). Furthermore, when we disentangle the specific subsets of 4IR technologies, we find that the positive relationship is stronger for 4IR-related wireless technology and for AI, cognitive computing, and big data analytics.

Our evidence thus suggests that the development of 4IR technologies has its major impact on the firm's production process, while the positive effects in terms of profitability remain still to be seen. Moreover, accumulated experience in the development of 4IR technological capabilities appears to be relevant for firm productivity, which suggests that learning in the 4IR domain heavily depends on the ability to take stock of the development of 4IR technologies.

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Our paper is but a preliminary exploration of the strategic, technological, and competitive implications of 4IR technology development and sheds light on these issues from a company perspective. The remainder of the article is structured as follows: Section 2 reviews the relevant works in the area of economics and management pertaining to 4IR technologies and outlines our conceptual framework and main research questions. Section 3 explains the empirical model. Section 4 reports on the sample construction, variables, and descriptive statistics. Section 5 describes the results. Finally, Section 6 concludes the article by highlighting the main limitations of our work and suggesting possible avenues for future research.

2. Background and conceptual framework

2.1 Background literature and context

The term "4IR" encompasses a broad set of convergent technologies and applications that have become prominent in the last few years and now interact across physical, digital, and biological domains (Gilchrist, 2016). Often connected to the term "Industry 4.0" (Xu *et al.*, 2018; Ustundag and Cevikcan, 2018), the term "4IR" was originally introduced at the Hannover Fair in 2011 and later supported by the German government in its strategic initiatives (Rojko, 2017). At first, it yielded a strong engineering connotation and mainly referred to automation technologies within manufacturing and the "smart factory" (Internet of Things—IoT, cloud computing, and CPS) (Morrar *et al.*, 2017). Subsequently, it was popularized thanks to the global agenda set forward at the World Economic Forum (WEF) Annual Meeting 2016 (WEF, 2016b), which was held under the theme "Mastering the Fourth Industrial Revolution" and the book by the WEF founder and chairman Klaus Schwab (Schwab, 2017). The term "4IR," despite still being technology-focused, is also referred to the interconnection between the different technologies and the impact on the organization of production and the changes in business processes.

The ability to use at the same time a set of convergent technological mega-trends is what sets apart 4IR from the Third Industrial Revolution (3IR or Digital Revolution), which has marked the transition from an industrial to an information era (Stankovic *et al.*, 2017). The 4IR heavily builds upon the digital technologies developed during the Digital Revolution, but brings important differences in terms of computational power, devices with human-like intelligence, and the importance placed upon integration and interconnectivity of material objects (Maynard, 2015).[1] In this respect, Philbeck and Davis (2018) define the 4IR as an "epi-digital" revolution where, as the new technologies become more integrated into the physical, social, and political worlds, they bring fundamental shifts to human behaviors, relationships, and way in which humans experience things (including products and services).

Following its initial inception, there have been dramatic increases in the interest in 4IR, which has spanned academic literature (Brynjolfsson and McAfee, 2014; Goldfarb *et al.*, 2019; Fagerberg and Verspagen, 2020), practitioners (Wee *et al.*, 2015; WEF, 2016b), and policy makers (Santos *et al.*, 2017; EPO, 2020). The excitement about the capability of 4IR technologies to contribute to economic and social well-being has gone hand in hand with the concerns arising about the future of human work, inequality, and populism (e.g., Frey and Osborne, 2017; Graetz and Michaels, 2018; Koizumi, 2019). Despite this, the 4IR technologies bring with them promises of revolutionizing several sectors of the economy and society (Martin, 1995).

A rampant increase in the development of scientific and technological knowledge pertaining to 4IR-related technologies has also been witnessed in recent years. Webb *et al.* (2018) offered several stylized facts about patenting in software and related areas at the United States Patent and Trademark Office. The authors showed a significant increase in applications in many emerging technologies by a relatively small group of US, Japanese, and Korean inventors, who generally work for large firms with a robust patenting history. Similarly, Mann and Püttmann (2018) showed that the share of automation patents increased from 25% in 1976 to 67% in 2014. Cockburn *et al.* (2018) analyzed the development of scientific publications and patents in the AI domain in the USA and showed an exponential increase in the fields of learning systems (both

1 In a similar way, the development of digital technologies starting from the 1960s relied on the electricity and telecommunication systems, which were at the center of the Second Industrial Revolution.

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publications and patents) and robotics (patents only). Several studies have recently provided evidence on the surge of 4IR-related technologies (Venturini, 2019; Benassi *et al.*, 2020; EPO, 2020; Martinelli *et al.*, 2021).

The academic literature that deals with 4IR is quite scattered and has mainly concentrated on two broad areas: (i) the potential of 4IR technologies and their role on the future of work and (ii) the analysis of whether 4IR technologies share the same features as General Purpose Technologies (GPTs).

As far as the first stream of literature is concerned, most of the interest has revolved around the labor market consequences of the adoption of 4IR technologies. Most of this literature has focused on the role that automation, particularly the adoption of industrial robots, could have for employment and wage outcomes at the sectoral or occupational level (Dauth *et al.*, 2017; Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020). Recent works have instead dealt with the role of the recent advancements in AI and how these can affect the tasks performed by employees in the workplace (Frey and Osborne, 2017; Manyika *et al.*, 2017; Brynjolfsson *et al.*, 2018; Felten *et al.*, 2018).

The second stream of literature has instead attempted to understand whether 4IR technologies are characterized by the main features of GPTs, which have historically been drivers of long-term technological progress and economic growth (Bresnahan and Trajtenberg, 1995). By studying the technological and scientific development of AI, Cockburn *et al.* (2018) found that AI shares two central characteristics of a GPT: (i) AI is rapidly developing and (ii) it has been applied in several (economically) relevant sectors, but, at the current stage, (iii) it lacks a spill-over effect that is able to spawn innovation in application sectors. Other works have instead focused on either the relationship between 4IR technological development and productivity at the country level (Venturini, 2019) or on the technological bases and emergent patterns of 4IR technologies (Martinelli *et al.*, 2021).

Within this second stream of the literature investigating the potentially disruptive role of 4IR technologies, some studies criticize the radicalness and GPT nature of 4IR. In a recent contribution, Lee and Lee (2021) investigate whether the technological regimes of 4IR technologies differ from the technological regimes of 3IR technologies along with a number of relevant dimensions (e.g., cumulativeness, originality, generality, and appropriability). They conclude that, unlike the 3IR, which has seen radical technological changes, 4IR technologies are not providing a break as radical as 3IR technologies, but rather tend to follow a more evolutionary path of technological change. Similarly, recent studies claim that the framework of GPT is not the most appropriate to analyze one of the most representative technologies of 4IR (i.e., AI), but that the large technical system framework would be more informative (Vannuccini and Prytkova, 2020; Prytkova, 2021).

Although the above works have all contributed to our understanding of the economic implications of 4IR, they mostly focused on a subset of the technologies that comprise 4IR technologies (mainly industrial robots and, more recently, AI) from a predominantly technological/labor perspective. In our view, such approaches disregard relevant strategic and competitive implications from a firm-level perspective, and the implications of 4IR, in terms of competitive advantage for firms, remain poorly understood. Overall, there is a paucity of studies that aimed at answering relevant research questions from a firm-level perspective, such as how 4IR technologies affect firm-level performance and what types of firms are more (or less) likely to develop 4IR technological capabilities.

Although—as mentioned above—4IR comprises a wide set of convergent technologies, for conceptual and empirical clarity in our study, we refer to a well-defined set of technological advancements pertaining to 4IR. Given the broad remit of 4IR technologies, academic literature is not yet unanimous in providing a clear list of the technologies therein contained. To reach a consensus on the set of technologies that are likely to enter the list (and also for empirical purposes), we have conducted a review of the main contributions providing definitions of the technologies comprising 4IR or Industry 4.0 (the two terms are often used interchangeably in the literature). We referred to academic articles and reports by international organizations, mainly, European Commission, United Nations Industrial Development Organization, EPO, and Organisation for

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Economic Co-operation and Development (OECD).[2] The common denominator comprises the following technological domains, for each of which we provide a brief description.

2.1.1 Cyber-Physical Systems

These are natural- and human-made systems (physical space) integrated with computation, communication, and control systems (cyberspace). The interaction between the digital and physical parts provides an unprecedented combination of sensing, control, computation, and networking functions in real time (Bagheri *et al.*, 2015). CPS comprise technologies such as robotics (e.g., collaborative robots), smart grids, sensor networks, autonomous vehicles, and the like.

2.1.2 Industrial Internet of Things

This is a technological area where networked smart objects, information technologies, and computing platforms interact to enable real-time and autonomous collection and processing of information within an industrial environment. IIoT enables the integration of physical objects to the communication network in manufacturing and service processes. It can be seen as a dynamic global network infrastructure with self-configuring capabilities based on standard and interoperable communication protocols (Vermesan *et al.*, 2011).

2.1.3 Artificial Intelligence, cognitive computing, and big data analytics

This technological domain contains learning systems (i.e., machines that can become better at a task typically performed by humans with limited or no human intervention), cognitive systems (with the ability to learn and improve knowledge without reprogramming), and AI. AI itself covers a wide set of techniques—machine learning, probabilistic reasoning, logic programming, fuzzy logic, and ontology engineering—with several functional applications (e.g., speech processing) in many application fields (WIPO, 2019). The recent increase in the availability of huge volumes of data proved to be very important to further expand the efficiency and reach of these technologies.

2.1.4 Cloud computing/manufacturing

This technology enables ubiquitous, efficient, and real-time network access to a pool of resources (e.g., servers, storage, and applications) that can be provided with low management effort. Cloud computing is based on interconnected and virtualized computers that are employed by a service provider (Buyya *et al.*, 2008). Cloud computing capabilities can be enhanced for distant modeling and simulation, thus reducing the transportation, waiting, and processing of manufacturing systems.

2.1.5 Augmented Reality

This refers to technologies where virtual information can be encompassed to real-world presentation to enrich the human perception of reality with augmented objects and elements (Paelke, 2014). The application of AR to the industry domain has become increasingly relevant, with five major areas of application: human–robot interaction, maintenance–assembly–repair, training, products inspection, and building monitoring (De Pace *et al.*, 2018).

2.1.6 Wireless technology

This domain comprises wireless connectivity, particularly the fifth generation of mobile connectivity (i.e., 5G). 5G promises to offer unprecedented performance in connectivity by reducing

2 The academic articles and reports are the results of a search done following a strict review protocol. First, we searched for a number of simple keywords, namely "Fourth Industrial Revolution" and "Industry 4.0," together with a set of detailed technologies (e.g. AI, machine learning, IoT, AR, additive manufacturing, virtual reality, and collaborative robots) in three digital databases (Scopus, Web of Science, and Google Scholar). Second, within each of the 131 contributions identified, we searched for the definition or set of technologies included in the 4IR concept. Third, we compared the list of definitions/technologies and organized them in the broad technological areas briefly sketched in Section 1. A full list of the articles surveyed is not included for space reasons and is available from the authors upon request.

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latency, dramatically increasing speed, and exponentially raising the number of connected objects. 5G also offers network slicing, a virtualization of the network allowing several logical service networks (called "slices") to be provided over the same underlying physical network. This, in turn, will allow specific operators to offer customized services with features tailored to different groups of users (OECD, 2019). From an industrial perspective, sensor-based technologies in association with wireless communication are playing a prominent role to make the factory "smart." All technologies contributing to increasing network speed, quality, and reliability within the factory are included within this technological area.[3]

2.2 Conceptual framework and research questions

Previous literature has provided much evidence on the relationship between the development of technological capabilities and firm-level outcomes. Technological capabilities are positively associated with customer value and competitive advantage (Afuah, 2002), product innovation (Zhou and Wu, 2010), profitability (Hao and Song, 2016), market valuation (DeCarolis and Deeds, 1999), and foreign direct investments (Kogut and Chang, 1991). These relationships are particularly strong and relevant in dynamic industries (DeCarolis and Deeds, 1999).

The development and adoption of technologies are expected to contribute to a firm's knowledge stock (Thoma, 2009) and its performance. For example, past GPTs (e.g., steam engines, railroads, electricity, and computers) were associated with significant gains at the firm level. There is, in fact, ample literature on the impact of Information and Communication Technologies (ICTs) on firm performance. Brynjolfsson and Hitt (2000) provided a knowledgeable review of this body of work. The authors highlighted how the value added of ICTs lies in their ability (i) to enable complementary organizational investments (e.g., new business processes and investments concerning work practices) and (ii) to increase productivity by reducing costs and by enabling firms to increase output quality (e.g., radical and incremental product innovation).

There are some features of 4IR that one can expect to bring performance benefits for firms. First, 4IR is at an initial stage of development and still has a wide scope for improvement. Once it becomes widely used, improvements in 4IR technologies can take place at a much faster pace. These rapid technological improvements can bring important economic benefits, such as cost reduction or the pre-emption of radical innovations, which can be appropriated by the developing firms. Second, the application of 4IR technologies to economically important sectors can be expected to increase firm diversification in the activities related to these sectors and, thus, provide a "natural" growth strategy at the company level, thereby benefiting productivity and profitability. Finally, the ability to spawn innovations in application sectors implies that 4IR technologies can be employed by different potential downstream clients and can accommodate their different strategies. This can lead firms to develop relevant 4IR technologies that are then integrated downstream or to rely on the market for technology. Both decisions can be expected to improve their ability to capture a larger share of the value that their technology creates (Gambardella and McGahan, 2010). The above argument leads to our first research question on the relationship between the development of 4IR technological capabilities and a firm's productivity and profitability.

Research question #1: What is the association between the development of 4IR technological capabilities and a firm's performance (both productivity and profitability)?

Idiosyncrasies can be expected in this relationship, due to the technical features of the technologies under consideration and to firm strategic considerations. The 4IR technologies can be seen as contributing to technological change given their radical nature (Ehrnberg, 1995; Day and Schoemaker, 2000). These technologies pose significant challenges for both incumbents and newcomers. The 4IR technologies are likely to open up extraordinary market opportunities for established companies, but at the same time, they foster competition by newcomers. Moreover,

3 We thank an anonymous reviewer for helpful comments in the construction of this section.

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given the radical nature of 4IR technologies, they can lead to competence-destroying discontinuities, which are often associated with increased environmental turbulence and uncertainty (Tushman and Anderson, 1986).

Newcomers can leverage fresh and new knowledge, but can lack long-term expertise and the complementary assets needed to capture the value from the newly developed technology (Rothaermel and Hill, 2005; Teece, 2008). On the other hand, established companies might be reluctant to focus on technologies that are emerging due to organizational inertia or, if they decide to, they might discover new territories to be unexpectedly hazardous (Barnett and Pontikes, 2008). The 4IR technologies can also prove to be complex to manage, as they entail several different technologies being combined, adapted, and exploited. Given the coexistence of the features and problems related to different domains of knowledge (e.g., engineering, software, cognitive sciences, and chemistry), companies may need time and a considerable amount of investments in cumulative knowledge stocks before the operational and economic benefits of their investments emerge. Early entrants into the 4IR technological domain can thus exploit first-mover advantages and enter into a virtuous path-dependent process, thus pre-empting future competition by newcomers (Antonelli, 1997; Ruttan, 1997).

Moreover, the different technologies that make up the 4IR bundle are also characterized by heterogeneity. Martinelli *et al.* (2021) showed remarkable differences between 4IR technologies, in terms of generality and originality of their technological development, their industrial knowledge base, the growth of patented technology, and the rate of entrance into the technological area, thus pointing to different stages of development for the technologies comprising 4IR. According to the above-mentioned arguments, the effect of the development of 4IR technologies may be different for different types of 4IR technologies (e.g., AI, IIoT, and wireless technology) as well as for the different levels of experience accumulated by the firm in the development of 4IR technologies. The arguments presented in this subsection lead us to forward a second research question, which pertains to experience in 4IR technology development and the specific technological area of 4IR development.

Research question #2: Is the relationship between 4IR technological capabilities and firm performance contingent upon (i) the experience in the development of 4IR technologies by the firm and (ii) the specific technological domains comprising the 4IR?

3. Empirical model

Our empirical analysis aims at connecting a firm's development of 4IR technologies to its performance. We do so by first testing the overall relationship for the full sample. We then investigate the role of experience in 4IR technology development and the effect on firm performance of the different technologies in the 4IR domain. We focus on the productivity and profitability outcomes over a 6-year period (i.e., long enough to capture "average" firm performance and to purge away short-term disequilibrium shocks), and we test their relationship with the accumulated knowledge in 4IR technology development as captured by the stock of 4IR patents filed starting from 1985.

We estimate several versions of the following baseline reduced-form equation:

$$Performance_{it} = \alpha + \vartheta_1 4IR_{it-1} + \vartheta_2 4IR_{it-2} + \gamma_1 X_{it-1} + \gamma_2 X_{it-2} + \eta_i + \varepsilon_{it} \quad (1)$$

The dependent variable, $Performance_{it}$, is alternately defined as the productivity or profitability of firm i at time t. Our variable of interest is $4IR$, which measures a firm's development of 4IR technologies through its deflated stock of patent filings in the 4IR domain. In Section 4, we discuss how we identified the patent applications related to 4IR technologies and the rationale of using patent filings as a proxy for technology development.

The vector X collects a variety of relevant patent- and firm-level characteristics and several fixed effects (FE) control variables, including sector–year and country–year interactions. Controlling for these interaction effects is important because there may be country- and sector-specific trends in the performance outcomes and 4IR technology development of firms. For instance,

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some countries have recently implemented innovation and industrial policies to promote the development of 4IR technologies by domestic firms.[4]

The term η_i captures firm-specific time-invariant heterogeneity. Unobserved variables, such as a firm's culture, quality of management, and degree of internationalization, might influence its performance and, at the same time, its efforts in 4IR technology development to a great extent. If these factors are not controlled for, the estimated relationship of interest may be biased. We thus rely on FE estimation, which accounts for unobserved time-invariant firm heterogeneity by exploiting only within-firm variation. Finally, ε_{it} is the error term of the regression.

All the explanatory variables, including our regressor of interest, are lagged by 1 and 2 years. First, excluding contemporaneous variables helps reduce the problem of reverse causality, whereby firm performance may influence the involvement of a firm in the development of 4IR technologies. Second, this standard practice in the innovation literature (e.g., Nesta and Saviotti, 2005; Grinza and Quatraro, 2019) allows a (short-term) dynamics in the relationship of interest to be captured. The impact on productivity and profitability of developing 4IR technologies might take time to materialize, as implementing 4IR innovations in a firm's production process or making them known to potential customers is not immediate. Therefore, the effects on performance might start manifesting with some delay.[5]

The FE estimation of Equation (1) tests the overall relationship between a firm's 4IR technology development and its performance (see Subsection 5.1). We then estimate different versions of this baseline equation, which include interactions with the firms' levels of experience and persistence in the development of 4IR technologies and with the period in which they started to patent 4IR technologies. We finally estimate a version of Equation (1) where we evaluate the performance effects of different technological domains of 4IR innovations (see Subsection 5.2). Before showing the econometric results, we describe the data and present-relevant descriptive statistics.

4. Data

4.1 Sample construction

Our data source is ORBIS-IP. It is a large and recently released matched patent-firm data set provided by the Bureau van Dijk, which combines rich firm- and patent-level information on around 110 million companies throughout the world. The data set used in this analysis includes all the large[6] private-sector incorporated companies (except for agricultural and financial companies) with headquarters in the United States, Germany, Japan, Italy, the United Kingdom, South Korea, France, Belgium, Sweden, Finland, Spain, the Netherlands, China, and Austria,[7] which have filed at least one 4IR patent at the EPO in the 2009–2014 period.

We consider large firms for our study because they cover almost the totality of 4IR patent applications. From our computations on the ORBIS-IP data set, the firms with more than 250 employees account for 98.5% of all the 4IR patent applications at the EPO since 1985. While this might reflect the fact that small firms are less involved in the development of 4IR technologies, it might also be due to the different propensity to patent across firm size (Schilling, 2015). It is well known that small firms are less inclined to apply for patents than large firms and this tendency might exacerbate in the complex and fast-changing 4IR technological environment, thus reducing

4 For instance, South Korea's government is massively investing in 4IR technologies, especially those concerning 5G networks, digital twins, and AI (https://www.4th-ir.go.kr/home/en). Similarly, the Italian government has recently launched the "Piano Nazionale Impresa 4.0" to finance firms' investments aimed at developing 4IR technologies and to sustain their international competitiveness (https://www.mise.gov.it/index.php/it/industria40).

5 Due to our relatively short panel and the use of within-firm estimates, we cannot reliably include further lags in our regressions.

6 To define firm size, we refer to the criteria in the OECD (2017) classification, according to which firms are defined as "large" when they have more than 250 employees.

7 Other countries had to be excluded because they did not have a reasonable minimum number of firm-year observations (which we set to 10).

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the ability of patents to reliably estimate the investments in 4IR technology development in the case of small firms.[8]

It is important to point out that data on the patenting history of each firm are available from its first patent filing onward, which allows us to reconstruct a firm's efforts in the development of 4IR technologies over the past decades. However, ORBIS balance-sheet data—which we need to construct the firms' productivity and profitability indicators—are only available starting from 2009 (i.e., in a 10-year window from data extraction). Because of this, we focus on the period 2009–2014 (and estimate the performance effects in this 6-year span).

We devoted an intense data mining effort to build our data set. In a nutshell, we performed four steps. First, we selected firms that filed at least one 4IR patent at the EPO between 2009 and 2014. Second, we reconstructed their patenting history by going back, year by year, to 1985, singling out patents related to both 4IR and non-4IR technologies. This allowed us to construct the stock of 4IR patents, our regressor of interest, and non-4IR patents, which we use as a control variable. Third, we collected balance-sheet information on each firm to construct measures of productivity, profitability, and other control variables (e.g., number of employees, location, and sector of economic activity). Fourth, we reconstructed each firm's ownership structure and grouped the firms belonging to the same corporate group. To this end, we employed information from ORBIS-IP on the "global ultimate owner," whereby a given entity is reported as being—under different possible configurations—the ultimate owner of a firm. Controlling for group affiliation allows us to take into account the group dynamics (e.g., through synergic effects, strategic paths, and financial support) in the development of 4IR technologies.

The final data set used in the estimations comprises 491 firms and 1,492 firm-year observations. Appendix A provides a detailed description of the construction of our data set.

4.2 The variables

4.2.1 Firm performance

Our dependent variable is firm performance. In the empirical analysis, we consider three performance measures, two of which are related to firm productivity and one to firm profitability. The first productivity indicator is the total factor productivity (TFP), which provides a measure of a firm's overall productive and organizational efficiency. We obtain the TFP estimates as the residuals from the estimation of a Cobb–Douglas production function (see, for instance, Devicienti *et al.*, 2018).[9] The second productivity variable is labor productivity, defined as (the natural logarithm of) revenues per employee. To measure firm profitability, we follow several studies (e.g., Arend *et al.*, 2017) and use the accounting return on investment (ROI).

4.2.2 Firm technological capabilities

As a proxy of a firm's technological capabilities in developing 4IR technologies, we use the (natural logarithm of the) deflated stock of patent applications related to 4IR technologies filed at the EPO from 1985 onward. We constructed the deflated stock of 4IR patents using the perpetual inventory method with a constant depreciation rate of 0.15, as is typical in this literature (see, for instance, Grinza and Quatraro, 2019).[10] Many studies (e.g., DeCarolis and Deeds, 1999; Bloom and Van Reenen, 2002; Artz *et al.*, 2010; Sears and Hoetker 2014; Marin and Lotti, 2017; Grinza and Quatraro, 2019) have used patents as a proxy of the technological capabilities of a firm. Although this choice suffers from some limitations (e.g., not all innovations are patented;

8 Moreover, accounting data to construct performance variables for small firms are often missing or not consistently available over the time frame required for panel estimation (i.e. at least four observations).

9 We ran an FE regression augmented with a large set of other FE (i.e. year FE and interaction dummies between year and size, year and industry, and year and country) on a log-linear Cobb–Douglas production function with revenues as the output variable and deflated tangible fixed assets and the number of employees as capital and labor inputs, respectively. Unfortunately, the data did not allow us to estimate either a value-added production function (i.e., with value added as the output variable and labor and capital as inputs) or a revenue production function (i.e., with revenues as the output variable and labor, capital, and materials as inputs), but only a mix of the two. This is because the high number of missing values for both value added and materials in ORBIS would have dramatically reduced the size of our data set (e.g., using value added to estimate a value-added production function would entail dropping more than 50% of the observations).

10 Similarly, we computed the deflated stock of non-4IR patent applications.

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see Schilling, 2015), patents have been shown to correlate well with product and process innovations (Basberg, 1987).[11] On the whole, patents represent the most common and widely accepted way of measuring the technological capabilities of a firm and are generally considered valid and robust indicators of knowledge creation and innovation (Trajtenberg, 1987).

4.2.3 Identification of 4IR-related patents

To identify 4IR patents, we used a novel two-step procedure recently proposed by the EPO (EPO, 2020). The first step of the procedure collects a list of CPC codes that circumscribe the pool of patents potentially related to 4IR technologies. The second step, which identifies 4IR patents, provides a detailed list of keywords to apply through patent text search to the patents retrieved from the first step.[12] We applied the first-step search on CPC codes to primary and secondary CPC codes. We conducted the second-step text search on the full texts of patents, which we retrieved from the EP full-text database.[13] In this way, we are able to search for the relevant combinations of keywords in the patent full texts (i.e., title, abstract, claims, and description) and not only title and abstract as is common practice in the economics of innovation literature. Starting from the EPO (2020) report and our analysis of the technological/innovation literature (see Subsection 2.1), we finally classified the identified 4IR patents into the six technological classes described earlier: wireless technology; IIoT; CPS; AR; cloud computing/manufacturing; and AI, cognitive computing, and big data analytics. Notably, the EPO only recently disclosed (in December 2020, through the EPO, 2020 report) the list of keywords for the text search in the second step of the classification procedure. This second step is critical to obtain a more precise and narrow identification of patents embedding 4IR technologies and has the advantage of being based on an official source.[14] At least to our knowledge, we are the first to use this complete two-step procedure to identify 4IR patents.[15]

4.2.4 Controls

We then include several other variables as controls in the productivity and profitability equations. The natural logarithm of the number of employees in the company accounts for different propensities in 4IR technology development based on firm size. Capital intensity, measured by the (natural logarithm of the) ratio between tangible fixed assets and employees, controls for structural differences in the firms' production processes. We finally add a control for the degree of intangibility of assets (computed as the ratio between intangible fixed assets and total assets), to capture heterogeneities in firms' intangible investments, including research and development (R&D) investments.[16]

4.3 Descriptive statistics

We now present some descriptive statistics of the sample. Disentangling the data according to the firms' characteristics (e.g., size, age, and 4IR patenting activity) and according to the patents' technological domain is of great help for the interpretation of the econometric results.

Table 1 provides an overview of the firms analyzed in this study, together with summary statistics of the dependent variables and the main control variables used in the regressions. Our sample of firms is rather heterogeneous. The average number of employees of a firm is around 23,750, but the median is considerably smaller, around 4,000 employees. Similarly, the average revenues are around 9.2 billion Euros, whereas the median value is less than 1.5 billion Euros.

11 We controlled for the differential propensity to patent across firm size and economic sector by including size and industry FE and industry–year interactions.

12 The list of keywords is reported in Subsection 3.1 of the EPO (2020) report annex, which can be downloaded at http://documents.epo.org/projects/babylon/eponet.nsf/0/06E4D8F7A2D6C2E1C125863900517B88/$File/patents_and_the_fourth_industrial_revolution_study_2020_annex_en.pdf.

13 This data set can be retrieved at https://www.epo.org/searching-for-patents/data/bulk-data-sets/data.html.

14 We would like to thank an anonymous reviewer for helpful comments on the identification of 4IR patents.

15 Different versions of the EPO classification based on the EPO (2017) release—which only disclosed the CPC codes related to the first step—have been used in recent studies on 4IR (e.g., Weresa, 2019; Benassi *et al.*, 2020; Corrocher *et al.*, 2020).

16 Although ORBIS-IP provides data on R&D investments (from balance-sheet information), this information is unusable because of the high number of missing values (more than 80%).

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Table 1. Summary statistics: general information

Variable	Mean %	Std. dev.	25th Pct.	Median	75th Pct.	Min.	Max.
Dependent variables							
TFP (log)	6.764	0.628	6.305	6.717	7.159	5.334	8.923
Labor productivity (log)	5.839	0.597	5.411	5.776	6.201	4.260	7.977
ROI	0.091	0.114	0.026	0.084	0.145	–0.410	0.696
Independent variables							
Deflated stock of 4IR patents (log)	1.132	1.034	0.381	0.894	1.546	0.000	6.070
Deflated stock of non-4IR patents (log)	5.552	1.847	4.202	5.602	6.845	0.187	10.190
Capital-to-labor ratio (log)	4.284	0.961	3.666	4.262	4.876	0.196	7.858
Employment (log)	8.498	1.779	7.089	8.293	9.690	5.549	12.981
Intangible fixed assets over total assets	0.102	0.146	0.009	0.031	0.137	0.000	0.781
Other variables							
Employment	23,748	53,931	1,199	3,997	16,153	257	434,246
Revenues (1,000 Euros)	9,183,407	21,156,902	376,287	1,479,154	6,261,546	51,589	164,682,400
Labor productivity (1,000 Euros)	418.654	321.966	223.842	322.499	493.253	70.801	2,912
Year of incorporation	1957.656	40.599	1930	1969	1991	1805	2012
Manufacturing	81.23%						
Services	18.77%						
						Firm-year observations: 1,492	
						Firms: 491	

Source: ORBIS-IP (years: 2009–2014).
We have shifted the distribution of the deflated stocks of both 4IR patents and non-4IR patents by 1 unit in order not to miss observations with 0 values in the logarithmic transformations.

On average, labor productivity (i.e., revenues per employee) is around 419 thousand Euros per year. The average ROI is 9.1%, which suggests that the firms in our sample are rather profitable. Most of the firms belong to the manufacturing sector (about 81%), whereas the rest are services companies. The firms are not young on average (53 years), but at least 25% of them are less than 20 years old.

Table 2 focuses on 4IR technology development. The average stock of 4IR patents of each firm in the sample is around 7.6 patents, against a total patent stock of 1,215 patents. 4IR patents thus represent a small fraction (around 0.6%) of the overall patent portfolios of firms, which is consistent with the restrictive definition of 4IR adopted in this study and coherent with the figures reported in EPO (2020). Among the top 4IR patent applicants in our sample, there are Nintendo, Intel, Sony, IBM, Microsoft, Bosch, Ericsson, Qualcomm, Nokia, and Volkswagen (stocks of 4IR patents above 50, on average).

The second and third panels in the table report the summary statistics of the stocks of 4IR patents according to different levels of experience and, relatedly, different starting periods in 4IR technology development. Experience in the development of 4IR technologies was defined as the number of years since the first 4IR patent application. A 0-year experience means that the firm has never filed a 4IR patent application; experience is set to 1 for the year in which the firm files its first 4IR patent, it is set to 2 for the subsequent year, and so on. We then took the panel-average

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Table 2. Summary statistics: 4IR patents; overall view, by experience in 4IR patenting activity and by starting period of 4IR patenting activity

Variable	Mean	Std. dev.	25th Pct.	Median	75th Pct.	Min.	Max.
Overall view							
Deflated stock of 4IR patents	7.580	31.425	0.463	1.445	3.692	0	431.615
Deflated stock of non-4IR patents	1,208	2,997	65.796	270.020	938.568	0.206	26,642
Deflated stock of overall patents	1,215	3,012	66.931	270.877	940.923	0.272	26,662
					Firm-year observations: 1,492		
						Firms: 491	
By experience in 4IR patenting activity							
Deflated stock of 4IR patents of firms with limited experience	1.830	2.530	0.522	1.228	2.434	0	24.250
					Firm-year observations: 332		
Deflated stock of 4IR patents of firms with medium experience	5.984	24.933	0.522	1.518	3.667	0.087	431.615
					Firm-year observations: 781		
Deflated stock of 4IR patents of firms with high experience	15.908	50.031	0.270	1.748	6.538	0.012	360.030
					Firm-year observations: 379		
By starting period of 4IR patenting activity							
Deflated stock of 4IR patents of early 4IR applicants (1985–1994)	17.765	49.559	0.410	2.409	8.149	0.012	360.030
					Firm-year observations: 279		
Deflated stock of 4IR patents of intermediate 4IR applicants (1995–2004)	8.736	35.981	0.455	1.739	4.500	0.054	431.615
					Firm-year observations: 568		
Deflated stock of 4IR patents of late 4IR applicants (2005–2014)	2.158	3.279	0.522	1.044	2.573	0	43.682
					Firm-year observations: 645		

Source: ORBIS-IP (years: 2009–2014).
Experience is defined as the number of years since the first 4IR patent application. Experience is set to 1 for the year in which the firm files its first 4IR patent, it is set to 2 for the subsequent year, and so on. We take the panel-average experience and divide firms into three categories, firms with limited, medium, or high experience, if their panel-average experience is below the 25th percentile, within the 25th and 75th percentiles, and above the 75th percentile, respectively. "Early 4IR applicants" are firms that started their 4IR patenting activity between 1985 and 1994. "Intermediate" refers to the 1995–2004 decade and "late 4IR applicants" identify firms whose first 4IR patent was filed between 2005 and 2014.

experience to make it time-invariant and divided the firms into three categories (i.e., firms with limited, medium, or high experience) according to whether their panel-average experience was

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below the 25th percentile, between the 25th and 75th percentiles, or above the 75th percentile, respectively. We then classified the firms based on different starting periods of 4IR technology development. Starting from the last year in our data (i.e., 2014), we went back for three decades on the 4IR patent filing history of the sampled firms and defined firms as "early 4IR applicants" if they filed their first 4IR patent in the period 1985–1994. We classified firms as "intermediate 4IR applicants" if their first 4IR patent application lies in the 1995–2004 period. Finally, we defined a firm as a "late 4IR applicant" if its first 4IR patent was filed between 2005 and 2014.

Not surprisingly, highly experienced firms and—consistently—early 4IR applicants have the highest stocks of 4IR patents (15.9 and 17.8 patents, respectively). The magnitude of the mean differences, when compared to firms with low and medium levels of experience, on the one hand, and intermediate and late 4IR applicants, on the other hand, is considerable (although less so if looking at the median values) and reflects the difference in firm size among such companies.[17]

Table 3 reports summary statistics of the firms' 4IR patent portfolios according to the different 4IR technologies. In the first panel, we report the stocks of the patents related to the six 4IR technologies identified in this study. The second panel reports indicators of the intensity of these 4IR technologies, which we constructed as the share of the deflated stock of 4IR patents belonging to a particular 4IR technology over the total deflated stock of 4IR patents. For instance, the intensity of wireless technology of a firm is defined as the ratio of wireless technology 4IR patents to total 4IR patents.[18] These indicators are useful to characterize the directions, in terms of technological domains, of a firm's efforts in developing 4IR technologies.

Wireless technology is, on average, the most widespread. Around 44.3% of a firm's 4IR patents are related to wireless technology. The second-largest patent category relates to IIoT, with 23.8% of 4IR patents. CPS and AR technologies represent 21.2% and 11.7% of the firms' 4IR patent portfolios, respectively. Around 2.5% of 4IR patents are attributable to cloud computing/manufacturing, and the same fraction refers to AI, cognitive computing, and big data analytics. In line with the EPO (2020) report, connectivity-related technologies represent a relevant share of 4IR patents, whereas—however in the spotlight—AI-related patents are a minority fraction.

5. Results

We now present the results of the econometric analysis. Subsection 5.1 shows the results of the estimation of Equation (1), where we examine the overall relationship between a firm's development of 4IR technologies and its productivity and profitability. Subsection 5.2 focuses on the firms' history in 4IR technology development and tests the relationships for different 4IR technologies.

5.1 Main results: the relationship between the development of 4IR technologies and firm performance

Table 4 reports the FE estimates of Equation (1) for each of the three outcomes of performance: TFP, labor productivity, and ROI. We include, as control variables, the deflated stock of non-4IR patents, the degree of capital intensity, the level of employment, and the degree of intangibility of assets. We also add time dummies and year-industry and year-country FE. Our within-firm estimates remove the remaining time-invariant unobserved firm-specific heterogeneity of the firms. Standard errors are robust to heteroskedasticity and clustered at the firm and sectoral levels.

Table 4 shows a consistent pattern of results, whereby the development of 4IR technologies is positively and significantly related to firm productivity, both TFP and labor productivity, but not to profitability.

17 For instance, the average number of employees among early 4IR applicants is around 48,200, whereas it is 26,000 and 11,020, respectively, for intermediate and late 4IR applicants. There are some very large companies, leaders in 4IR technology development, among early 4IR applicants (e.g., Volkswagen, Bosch, and IBM).

18 Around 5% of the 4IR patents are attributable to more than one 4IR technology class so that the intensity indicators sum up to slightly more than 1.

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Table 3. Summary statistics: 4IR patents; by technology

Variable	Mean	Std. dev.	25th Pct.	Median	75th Pct.	Min.	Max.
Deflated stock of wireless technology 4IR patents	2.002	9.964	0	0.321	1.700	0	190.100
Deflated stock of IIoT 4IR patents	3.380	22.310	0	0	0.781	0	369.777
Deflated stock of CPS 4IR patents	0.817	2.623	0	0	0.614	0	34.496
Deflated stock of AR 4IR patents	1.435	8.042	0	0	0	0	168.372
Deflated stock of cloud computing/manufacturing 4IR patents	0.105	0.526	0	0	0	0	9.058
Deflated stock of AI, cognitive computing, and big data analytics 4IR patents	0.097	0.408	0	0	0	0	3.667
						Firm-year observations: 1,492	
						Firms: 491	
Intensity of wireless technology 4IR patents	0.443	0.437	0	0.335	1	0	1
Intensity of IIoT 4IR patents	0.238	0.351	0	0	0.387	0	1
Intensity of CPS 4IR patents	0.212	0.350	0	0	0.286	0	1
Intensity of AR 4IR patents	0.117	0.270	0	0	0	0	1
Intensity of cloud computing/manufacturing 4IR patents	0.025	0.118	0	0	0	0	1
Intensity of AI, cognitive computing, and big data analytics 4IR patents	0.025	0.129	0	0	0	0	1
						Firm-year observations: 1,402	
						Firms: 491	

Source: ORBIS-IP (years: 2009–2014).
The "intensity" of a particular 4IR technology is computed as the deflated stock of 4IR patents in that particular 4IR technology domain over the total stock of 4IR patents. It is defined when the latter stock is positive (i.e., when the firm has at least one 4IR patent application).

The positive and significant effects on productivity emerge with a 2-year lag. The estimated impacts on productivity are 0.023 and 0.022, for TFP and labor productivity, respectively. At a first glance, the magnitude of the effect seems modest: a 10% increase in the deflated stock of 4IR patents is estimated to increase TFP by 0.23% and labor productivity by 0.22%.[19] However, it should be noted that a non-negligible share of firms starts applying for 4IR patents from scratch

19 See Venturini (2019), who estimated, at the country level, that the elasticity of productivity to the aggregate stock of knowledge related to intelligent technologies ranges from 0.02 and 0.06 for industrialized economies.

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Table 4. The impact of 4IR technology development on productivity and profitability

	Dep. var.: TFP (log)	Dep. var.: labor productivity (log)	Dep. var.: ROI
Deflated stock of 4IR patents (log) at t-1	−0.009	−0.011	−0.015
	(0.010)	(0.013)	(0.010)
Deflated stock of 4IR patents (log) at t-2	0.023**	0.022*	0.002
	(0.009)	(0.012)	(0.010)
Deflated stock of non-4IR patents (log) at t-1	0.011	0.019	−0.003
	(0.013)	(0.011)	(0.012)
Deflated stock of non-4IR patents (log) at t-2	−0.007	−0.003	0.013
	(0.014)	(0.016)	(0.008)
Firm-level controls	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes
Time × industry dummies	Yes	Yes	Yes
Time × country dummies	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
			Firm-year observations: 1,492
			Firms: 491

Source: ORBIS-IP data set (years: 2009–2014).
Standard errors, reported in parentheses, are robust and clustered at the sector and firm levels. ***, **, and * denote, respectively, the 1%, 5%, and 10% significance levels. We have shifted the distribution of the deflated stocks of both 4IR patents and non-4IR patents by 1 unit in order not to miss observations with 0 values in the logarithmic transformations. Firm-level controls include employment (number of employees; log), capital-to-labor ratio (log), and intangible assets over total assets; all at t-1 and t-2. Industry dummies are at the 2-digit level of the NACE Rev. 2 classification of economic activities. Country dummies identify the 14 countries represented by the firms in our sample.

during the 2009–2014 period, and another significant share of firms starts from very small 4IR patent portfolios (e.g., passing from 2 to 4 patents implies a 100% increase). Indeed, the yearly average percentage increase of 4IR deflated patent stocks (excluding firms that switched from zero to a positive number of 4IR patents) is as high as 67.3%. As a result of the average increase in the firms' 4IR patent portfolios, TFP is estimated to rise by 1.54% (0.673×0.023×100) and labor productivity by 1.48% (0.673×0.022×100).

When we turn to the effect of the deflated stock of 4IR patents on firm profitability, we find no significant impact. As discussed in Section 6, this is possibly due to significant sunk costs associated with the development of 4IR technologies.[20]

5.2 Role of the firm's history in 4IR technology development and different 4IR technologies

Based on the evidence so far, our answer to the first research question is that developing 4IR technologies has a positive effect on total factor and labor productivity and no significant effect on accounting profitability. We now address the second research question, by disentangling this positive effect in relation to the firm's history in 4IR technology development. We use three different—but complementary—indicators to measure the firm's history in 4IR technology development: the number of years since the first 4IR patent (experience), the persistence in 4IR patenting (continuity), and the starting period of 4IR patenting. It should be noted that, from now on, we report only the coefficients of the variables of interest in the tables, focusing on the impacts on TFP and labor productivity.[21]

To begin with, we test whether the effect on productivity changes with the level of experience and continuity in developing 4IR technologies. The results are presented in Table 5.

To account for experience, we classified firms in three classes, that is, with low, medium, or high experience in 4IR patenting, as described in Subsection 4.3. We then estimated a specification that adds to Equation (1) interaction terms multiplying the firm's deflated stock of 4IR

20 We also experimented with alternative measures to account for firm profitability, that is, the return on assets and the return on sales, but the results do not change.

21 The estimates with ROI as the dependent variable are consistent with the general result that 4IR technological development has no (short-term) effects on profitability, as they typically produce small and not significant coefficients.

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Table 5. The impact of 4IR technology development on productivity by experience and continuity in 4IR patenting activity

Experience; dep. var.: TFP (log)		
Deflated stock of 4IR patents (log) at t-2 × firm with limited experience	0.013	(0.017)
Deflated stock of 4IR patents (log) at t-2 × firm with medium experience	0.021	(0.017)
Deflated stock of 4IR patents (log) at t-2 × firm with high experience	0.038***	(0.011)
Experience; dep. var.: labor productivity (log)		
Deflated stock of 4IR patents (log) at t-2 × firm with limited experience	0.010	(0.018)
Deflated stock of 4IR patents (log) at t-2 × firm with medium experience	0.021	(0.018)
Deflated stock of 4IR patents (log) at t-2 × firm with high experience	0.041***	(0.014)
Continuity; dep. var.: TFP (log)		
Deflated stock of 4IR patents (log) at t-2 × firm with limited continuity	0.037	(0.032)
Deflated stock of 4IR patents (log) at t-2 × firm with medium continuity	0.008	(0.024)
Deflated stock of 4IR patents (log) at t-2 × firm with high continuity	0.023**	(0.009)
Continuity; dep. var.: labor productivity (log)		
Deflated stock of 4IR patents (log) at t-2 × firm with limited continuity	0.046	(0.048)
Deflated stock of 4IR patents (log) at t-2 × firm with medium continuity	0.007	(0.022)
Deflated stock of 4IR patents (log) at t-2 × firm with high continuity	0.021*	(0.012)
	Firm-year observations: 1,492	
	Firms: 491	

Source: ORBIS-IP data set (years: 2009–2014).
Standard errors, reported in parentheses, are robust and clustered at the sector and firm levels. ***, **, and * denote, respectively, the 1%, 5%, and 10% significance levels. These estimates include the same set of controls as the estimations in Table 4. Interactions between the deflated stock of 4IR patents at t-1 and the three categories for experience/continuity are also included. Experience is defined as in Table 2. Continuity is defined as the number of years in which the firm has filed at least one 4IR patent application over the number of years since it became active in 4IR patenting (i.e., experience). It ranges between 0 and 1. It equals 1 when the firm has filed at least one 4IR patent application in each year since it became active in 4IR patenting, whereas it approaches 0 when 4IR patenting activity is more sporadic. We take the panel-average continuity and divide firms into three categories (firms with low, medium, and high continuity) according to the same classification we adopted for experience (below the 25th percentile, within the 25th and 75th percentiles, and above the 75th percentile). For other information, see the footnote of Table 4.

patents by its relative degree of experience.[22] The first panel in Table 5 shows that firms with higher experience obtain greater productivity gains from developing 4IR technologies. The estimated coefficients for such firms are 0.038, for TFP, and 0.041, for labor productivity, both significant at the 1% level. On the contrary, for firms with low and medium levels of experience, the coefficients—despite being positive—are never statistically significant, thus suggesting that they do not attain significant productivity gains from 4IR technology development.

This experience variable has the advantage of being a simple and clear indicator of a firm's history in 4IR patent filings. However, it does not account for the degree of continuity in 4IR patenting between the first year of filing and later years, which may be a critical dimension of differentiation.[23] For instance, the experience variable does not distinguish between a firm that patents 4IR technologies every year (i.e., with much continuity) from a firm that files 4IR patents every 10 years (i.e., much more sporadically) and consequently misses to capture an important aspect of 4IR technology development. To shed some light also on this issue, we constructed an indicator of persistence in 4IR technology development and classified firms according to their different degrees of continuity in 4IR patenting. Continuity is an indicator constructed as the number of years in which a firm has filed at least one 4IR patent application over the number of years since it became active in 4IR patenting (i.e., our experience variable). It ranges between 0 and 1. It is 1 when the firm has filed at least one 4IR patent application every year since its first 4IR patent; it approaches 0 when the 4IR patenting activity is more sporadic. We then took the panel-average continuity and divided the firms into three categories (i.e., firms with low, medium, or high continuity) according to the same classification we adopted for experience (i.e., below the

22 In the estimating model, we included interactions with both 1- and 2-year lags. As the impact stems from the 2-year lag, we only report the results for the second-year lag. The full set of results is available upon request.

23 For a study that highlights the importance of controlling for the persistence in innovation activity when estimating the impact of innovation on firm productivity, see Huergo and Moreno (2011).

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Table 6. The impact of 4IR technology development on productivity by starting period of 4IR patenting activity

Starting period; dep. var.: TFP (log)		
Deflated stock of 4IR patents (log) at t-2 × early 4IR applicant	0.040***	(0.010)
Deflated stock of 4IR patents (log) at t-2 × intermediate 4IR applicant	0.021	(0.022)
Deflated stock of 4IR patents (log) at t-2 × late 4IR applicant	0.015	(0.015)
Starting period; dep. var.: labor productivity (log)		
Deflated stock of 4IR patents (log) at t-2 × early 4IR applicant	0.040***	(0.012)
Deflated stock of 4IR patents (log) at t-2 × intermediate 4IR applicant	0.023	(0.026)
Deflated stock of 4IR patents (log) at t-2 × late 4IR applicant	0.012	(0.016)
	Firm-year observations: 1,492	
	Firms: 491	

Source: ORBIS-IP data set (years: 2009–2014).
Standard errors, reported in parentheses, are robust and clustered at the sector and firm levels. ***, **, and * denote, respectively, the 1%, 5%, and 10% significance levels. These estimates include the same set of controls as the estimations in Table 4. Interactions between the deflated stock of 4IR patents at t-1 and the three categories for starting period are also included. "Early 4IR applicant," "intermediate 4IR applicant," and "late 4IR applicant" are defined as in Table 2. For other information, see the footnote to Table 4.

25th percentile, between the 25th and 75th percentiles, and above the 75th percentile). We thus interact the firm's deflated stock of 4IR patents with its degree of continuity in 4IR patenting in order to estimate whether the effects of 4IR technology development change with the firm's high, medium, or low continuity in filing 4IR patents. The lower panel in Table 5 shows the results of this test. Firms with high levels of continuity in 4IR patenting show a positive and significant productivity increase from developing 4IR technologies, which emerges for both TFP and labor productivity. On the contrary, firms that are less continuous in filing 4IR patents do not show significant positive relationships between productivity—either TFP or labor productivity—and 4IR technology development.[24]

The results so far suggest that the accumulated experience is critical to enable the firm to extract productivity gains from the development of 4IR technologies, with apparent benefits from being in the upper portion of the learning curve. Furthermore, high continuity in the development of 4IR technologies turns out to be another important factor to grab the productivity advantages of 4IR technology development, thereby suggesting that benefits might be accrued through incremental and cumulative steps.

In Table 6, we further investigate the moderating role of a firm's history in 4IR technology development by testing whether the impact on productivity depends on the firm's starting period of 4IR patenting activity.

We interact the firm's deflated stock of 4IR patents with a binary variable denoting the decade in which it started to file 4IR patents, that is, whether the firm filed its first 4IR patent in the period 1985–1994, 1995–2004, or 2005–2014. Table 6 thus estimates the productivity effects of 4IR technology development separately for early, intermediate, and late 4IR patent applicants. In line with the results on experience, we find no significant positive productivity effects stemming from the development of 4IR technologies for both late and intermediate 4IR applicants. The effect on TFP and labor productivity for early 4IR applicants is instead positive, large in magnitude (0.040 for both productivity measures), and significant at the 1% level.[25]

These results consistently indicate that having a long history in 4IR patenting is fundamental to take advantage from 4IR technology development. As discussed in the next section, being a first mover has several advantages, including the possibility of setting standards, pre-empting the market, and exploiting higher accumulated knowledge, all factors that turn out to be relevant in the 4IR context. However, what types of 4IR technologies are more important for productivity

24 In the estimation with our experience variable, we performed different tests to directly control for the firm's persistence in 4IR patenting. In practice, we included (time-varying) controls for the degree of continuity, either as a continuous variable or as a categorical variable, and we observed no changes in the results.

25 Positive, but small and only weakly significant, impacts emerge also on firm profitability for highly experienced firms (coefficient significant at the 10% level) and early 4IR applicants (*P*-value around 0.15), thus suggesting that, for such firms, the high observed productivity gains might translate into profitability increases already in the short run.

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Table 7. The impact of 4IR technology development on productivity by technology

	Dep. var.: TFP (log)	Dep. var.: labor productivity (log)
Deflated stock of wireless technology 4IR patents (log) at t-2	0.041**	0.031*
	(0.018)	(0.017)
Deflated stock of IIoT 4IR patents (log) at t-2	−0.002	−0.003
	(0.010)	(0.014)
Deflated stock of CPS 4IR patents (log) at t-2	−0.004	0.002
	(0.017)	(0.017)
Deflated stock of AR 4IR patents (log) at t-2	−0.014	−0.002
	(0.017)	(0.017)
Deflated stock of cloud computing/manufacturing 4IR patents (log) at t-2	0.016	0.020
	(0.040)	(0.042)
Deflated stock of AI, cognitive computing, and big data analytics 4IR patents (log) at t-2	0.067*	0.062
	(0.040)	(0.055)
		Firm-year observations: 1,492
		Firms: 491

Source: ORBIS-IP data set (years: 2009–2014).
Standard errors, reported in parentheses, are robust and clustered at the sector and firm levels. ***, **, and * denote, respectively, the 1%, 5%, and 10% significance levels. These estimates include the same set of controls as the estimations in Table 4. Controls for the deflated stocks of 4IR patents by technology at t-1 are included. For other information, see the footnote of Table 4.

gains? The final step of our study explores this issue in Table 7, where we split a firm's deflated stock of 4IR patents into the six 4IR technology classes defined earlier.

The table clearly shows that the positive productivity effects stem from two important 4IR technology classes: wireless technology and AI, cognitive computing, and big data analytics. As shown earlier, wireless-related technologies are the most widespread, representing over 40% of the firms' 4IR patent portfolios, on average. The productivity impact associated with such technologies is somewhat large in magnitude (0.041 for TFP and 0.031 for labor productivity) and significant at conventional levels. On the contrary, AI, cognitive computing, and big data analytics is a restricted technology class, with only 2.5% of the firms' 4IR patents. However, it is undoubtedly one of the 4IR technologies that generates the highest expectations, in terms of capability to revolutionize our lives and societies. From our estimations, it appears that such expectations are not disappointed as far as the productivity of AI-developing firms is concerned. We detect positive and very large productivity effects stemming from AI, cognitive computing, and big data analytics: 0.067 on TFP and 0.062 on labor productivity (although the latter coefficient is not significant at conventional levels).[26]

6. Discussion and conclusions

Our study has focused on the impact of 4IR technology development, an investigation area that so far has largely been unexplored, in favor of the adoption of these technologies and consequent effects (Venturini, 2019; Bassetti *et al.*, 2020). We investigated (i) the relationship between the development of 4IR technological capabilities and firm performance, (ii) the moderating role of the firm's history in 4IR technology development, and (iii) which technological domains of the 4IR explain the contribution of 4IR to productivity at the firm level.

The empirical investigation offers three main conclusions first, firm productivity is positively and significantly related to the development of 4IR technologies, whereas firm profitability does not appear to be affected. Increases in productivity may be due to higher efficiency in the production process (thanks to the development and implementation of 4IR technologies) as well as to larger revenues from the sale of products that incorporate 4IR technologies. Although, at a first glance, it may be surprising that such positive productivity effects do not translate into

26 In general, more imprecise estimates on the analysis by technology classes are to be expected since the regressor of interest is split into six categories, some of which with a relatively low number of patents.

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higher profitability, it should be noted that the development of 4IR technologies requires huge, sunk investments (Schwab, 2017; Venturini, 2019). While these costs do not enter our productivity indexes directly, they significantly impact the profitability of firms Therefore, it may take several years for initial investments to become profitable. Moreover, new market segments with high expectations have not yet taken off. For example, despite being promising, the driverless car market is struggling with technological and regulatory issues (among others) and still in its infancy (Cummings and Ryan, 2014).

Second, firms that started developing 4IR technologies earlier seem to capitalize more on productivity than those that started later. This effect may emerge for various reasons. Experience in 4IR patenting seems to indicate a first-mover advantage, as more experienced firms achieve higher productivity gains. Our results suggest that climbing the 4IR learning curve can bring important benefits, at least in terms of TFP and labor productivity. This is also confirmed by our other result, which shows the positive contribution of persistence in 4IR technology development on productivity (Demirel and Mazzucato, 2012; Deschryvere, 2014). More in general, our research contributes to the literature on the advantages and disadvantages of being a first mover. In the case of 4IR technologies, building a history of 4IR technology development from the outset seems to pay off in terms of economic performance. This conclusion is in line also with the emerging state of 4IR technologies, where further technical developments and new market applications can potentially trigger future innovations (Adner and Levinthal, 2002) and even more robust economic performance (e.g., concerning profitability).

Third, productivity gains originating from the development of 4IR technologies seem to be mainly due to the domains of wireless technology and of AI, cognitive computing, and big data analytics. This evidence confirms the importance of developing the technological infrastructure for other 4IR technologies in order to obtain efficiency gains (i.e., 5G) and the potential GPT role of prediction algorithms for the technological change. Overall, this resonates well with the great expectations put in these technologies by policy makers, managers, and the popular press in the recent period.

Our study has several implications for firm strategy. First, our results confirm that the timing of entry is highly relevant when new technologies emerge. Being a first mover generally offers clear advantages over competitors, as first-patenting firms can thwart competitors, enjoy a (temporary) monopoly, and reap performance benefits. Our study shows that even when the technological domain is broad and highly dynamic (such as the 4IR domain), capitalizing on early technological development and valuable knowledge still matters. Second, the combination of different technologies seems to be relevant, thus urging firms to orchestrate and coordinate distinctive know-how that emerges at different times. This requires an in-depth analysis of past accumulated experience and a fine-grained scrutiny of existing know-how. Third, some technologies in the 4IR remit seem to matter more than others (at least, to date) in reaping efficiency benefits. Nevertheless, as profitability gains have not materialized (yet), firms need to be alert and carefully pick future investment decisions in new 4IR technological developments.

Future research may shed light on these mechanisms and find invariants in firms' behavior, thereby possibly overcoming the limitations of our research. The first limitation has to do with the measurement of 4IR technology development. The patent data that we used suffer from the usual drawbacks. The quality of patents differs, and patents can be filed for competitive and strategic reasons. Moreover, patents are just one component of a firm's knowledge stock (e.g., quality of human capital). Second, the availability of data for longer periods is also critical for the analysis of emerging technological domains. Third, quantitative analyses are a robust way of investigating complex phenomena, but triangulation through quantitative and qualitative methodologies can shed light on some aspects that this research has just touched on the surface.

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Appendix A
The construction of the data set

The patent-level information contained in ORBIS-IP includes the application number and date of a patent, CPC codes, and information on the applicants. As for firm-level information, ORBIS-IP includes balance-sheet data, the number of employees, as well as the firm's year of incorporation, sector of economic activity and location.

To identify the firms involved in 4IR technology development, we used the 4IR patent applications filed at the EPO. This was possible thanks to the matched patent-firm nature of the ORBIS-IP data set, whereby each firm in the data is linked to its patent applications through a unique firm identifier, called "bvdid." We considered 4IR patents filed between 2009 and 2014 to select the firms that constitute our sample. This means that each firm in the sample filed at least one 4IR patent application between 2009 and 2014. We restricted the attention to this period for two reasons. First, we were not able to obtain firm-level data (i.e. those necessary to construct performance outcomes) before 2009.[27] Second, we selected 2014 as the last year of observation to avoid truncation (and selection) problems arising from the publication lag associated with patent filings.[28]

After having identified the firms in our sample, we reconstructed their histories in 4IR technology development by going back as far as 30 years. We thus computed their stocks of 4IR patents filed since 1985. This allowed us to have a more precise measure of the firms' technological capabilities related to 4IR innovations. It also allowed us to construct detailed long-run indexes of experience and continuity in 4IR technology development and to differentiate the firms according to their starting period of 4IR patenting activity.

We then gathered the necessary firm-level information, including balance-sheet variables used to construct the performance indexes and firm-level controls. For consistency with patent-level information related to 4IR technologies, we also reconstructed the firms' technological capabilities in non-4IR innovations, by computing their stocks of non-4IR patents from 1985 onward.

Finally, by exploiting rich information on ownership and corporate structure provided by ORBIS-IP, we reconstructed the ownership structure of the firms and grouped those belonging to the same corporate group. We used the information on the so-called "global ultimate owner," whereby—under different possible configurations—a given entity is reported as being the ultimate owner of a firm. The possible criteria to identify a firm's ultimate owner are mainly related to the percentage of stock ownership and the type of entity, and include, for instance, whether the entity is a business firm, a financial holding company, a physical person, or a government. Concerning the type of entity, we set business firms as admissible ultimate owners. As far as the percentage of stock ownership is concerned, we set the thresholds according to those typically used in the literature (see, for instance, Belenzon and Berkovitz, 2010). We set a minimum threshold of 50% of stock ownership for non-publicly listed firms, whereas we set a less restrictive threshold of 25% if the firm was publicly owned. Ownership is more dispersed in publicly listed firms, and a less rigid threshold is more suitable in this case (Belenzon and Berkovitz, 2010).

The thus defined ultimate owners were then used to group our sample firms. In particular, we aggregated firms according to their ultimate owners by summing the relevant variables.[29] Grouping firms that belong to the same corporate group was crucial because it allowed us to explicitly take into account any effects stemming from group dynamics. Belonging to a group in which other firms develop 4IR technologies might have had an impact on a firm's development of 4IR technologies (and performance), for instance, through sharing knowledge between the parent company and affiliate firms, receiving external financial support, and other forms of

27 ORBIS-IP provides a 10-year history of firm-level information from the time of data extractions.

28 The EPO publishes patents as soon as possible after the expiry of a period of 18 months from the filing. As a result of 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).

29 As far as balance-sheet information is concerned, we summed the variables from the unconsolidated balance sheets. As for the non-numeric variables (e.g., year of incorporation and country or industry), we attached the value of the company with the highest revenues in the group. When we refer to a "firm," we mean the group of firms aggregated on the basis of the previously defined common ultimate owner.

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synergic effects. We chose business firms as the admissible ultimate owners because we wanted to precisely capture the situations in which those synergic effects most likely materialized, that is, when the linkage between the parent company and the other firms in the group is expressed in ways that are not only related to a mere financial control, without any exchange of knowledge and common strategic goals.

As discussed in the main text, we here focused on large firms. We followed the OECD classification and defined large firms as those that employ more than 250 workers. We focused on firms with their headquarters in the United States, Germany, Japan, Italy, the United Kingdom, South Korea, France, Belgium, Sweden, Finland, Spain, the Netherlands, China, and Austria. This choice was made to obtain a reasonable minimum number of observations for each country, which we set to 10 observations. Finally, since we ran within-firm estimations with 1- and 2-year lagged variables, we had to focus on companies with at least 4 years of observations.

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