Going Revolutionary: The Impact of 4IR Technology Development on Firm Performance

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Going Revolutionary: The Impact of 4IR Technology Development on Firm Performance

Mario Benassi[a], Elena Grinza[b,*], Francesco Rentocchini[a], Laura Rondi[b]

[a] Department of Economics, Management, and Quantitative Methods, University of Milan, Via Conservatorio 7, 20122 – Milan

[b] Department of Management and Production Engineering, Politecnico di Torino, Corso Duca degli Abruzzi 24, 10129 – Turin

* Corresponding author: elena.grinza@polito.it

Abstract

Drawing on the knowledge-based view of the firm, we investigate whether firm performance is related to the accumulated stock of technological knowledge associated with the Fourth Industrial Revolution (4IR), and what contextual factors affect this relationship. We test our research questions on a longitudinal matched patent-firm data set on large firms filing 4IR patents at the European Patent Office (EPO). Our results, which control for a large number of patent- and firm-level variables as well as firm fixed unobserved heterogeneity, show a significant and economically relevant positive association between the development of 4IR technologies and firm productivity. However, no significant relationship with firm profitability is detected, thereby suggesting that the returns from 4IR technological developments are slow to cash in. We also find that late innovators benefit more from the development of 4IR technological capabilities than early innovators and experience a substantial "boost effect". We provide empirical support to an explanation of these findings in terms of the ability of late innovators to (i) manage the inherent complexity of the bundle of technologies comprising the 4IR and (ii) exploit profitable downstream applications of the 4IR.

Keywords: Fourth Industrial Revolution (4IR); patenting; technology development; firm performance; longitudinal matched patent-firm data.

Jel codes: O33, D24, J24.

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1. Introduction

The last decade has witnessed increasing attention around the Fourth Industrial Revolution (from now on, 4IR). Academic scholars, practitioners (managers, entrepreneurs, and technologists), and policy makers have started a debate about the potential role of the 4IR for the technological development and transformation of production processes (Brynjolfsson and McAfee, 2014; Deloitte, 2018; Santos et al., 2017). The 4IR encompasses a broad set of convergent technologies and applications that have become prominent in the last years (Gilchrist, 2016) and now interact across the physical, digital, and biological domains (Schwab, 2017). These devices gather an incredible amount of information that gets distributed *via* cloud computing and analysed through sophisticated algorithms. Devices and machines with human-like cognitive capabilities can perform complex tasks, learn from experience, and autonomously perform simple and complicated tasks. The 4IR promises to revolutionise several aspects of social and economic life. Manufacturing is a case in point: digitalized information on customer needs, processed with analytics and social media, together with real-time, flexible manufacturing systems allow for mass customization. Besides production systems, 4IR technologies and applications open up unprecedented opportunities to drastically change existing industries – for instance, transportation (drones, driverless cars) and healthcare (personalized drugs) – and creating new ones (Rüßmann et al., 2015; World Economic Forum, 2016).

The current academic literature on the 4IR mainly focuses on: (i) the potential technological disruption of the 4IR (Benassi et al., 2020; EPO, 2017; Martinelli et al., 2019); (ii) the analysis of specific 4IR technologies such as artificial intelligence systems, robots, and the like (Cockburn et al., 2018; Dernis et al., 2019), and (iii) the consequences for the future of employment (Frey and Osborne, 2017; Graetz and Michaels, 2018). However, despite the widespread interest, the evidence on antecedents and implications of the 4IR for companies is scant. We see this as particularly unfortunate, as a better understanding of the core factors motivating firms to adopt (or not) 4IR technologies, as well as the implications of the development of these technologies, can contribute significantly to the current debate, particularly concerning firm-level competitiveness, performance, and strategy (Raj and Seamans, 2018).

In this paper, we adopt a knowledge-based view of the firm and analyse the extent to which the accumulation of knowledge in 4IR-related technologies is associated with firm performance as measured by labour and total factor productivity and accounting profitability. We further argue that the relationship between the development of 4IR technologies and firm performance is moderated by (i) the firm ability to manage the high complexity characterising 4IR technologies and (ii) the possibility of downstream applications of such technologies. Notably, the aim of this paper is not to make comparisons between the development of different technologies (i.e., 4IR *versus* other technologies) or to explore the differential performance of the firms that develop 4IR technologies *versus* the firms that do not. Our paper sets itself a different – possibly more limited, yet relevant – primary intent, that is, to explore what happens to a firm's performance when it starts patenting in 4IR technologies and what is the incremental effect of increasing the stock of 4IR-related knowledge.

For our empirical analysis, we use a panel of 1,386 large firms that have filed at least one patent in the 4IR domain at the European Patent Office (EPO) in the period 2009-2014, for which we reconstruct the firm-specific history of patent filings in 4IR fields since 1985. As it is standard in the literature, we use patent filings as a proxy for a firm's innovation capabilities (e.g., see Artz et al., 2010, Grinza and Quatraro, 2019, Sears and Hoetker 2014). While we are aware that this choice has some limitations (e.g., differential propensities to patenting across firms), patents correlate well with product and process innovations (Basberg, 1987). To date, patents represent the most common and widely accepted way to measure a firm's technological capabilities and are commonly considered valid and robust indicators of knowledge creation and innovation (Trajtenberg, 1987).

Our main result, obtained after removing firm fixed unobserved heterogeneity and controlling for a wide array of patent- and firm-level time-varying characteristics, is that there is a positive and significant association between the stock of 4IR patents from 1985 and both labour and total factor productivity, but no correlation with profitability. The positive relationship with productivity seems to be driven by companies that started developing 4IR technologies after the mid-2000s. We explain this finding in terms of the ability of these firms (i) to manage the inherent complexity of the bundle of technologies comprising the 4IR and (ii) to exploit profitable downstream applications of such technologies, and we provide empirical support in the data.

Our evidence suggests that the development of 4IR technologies mainly adds to internal process efficiency, while positive effects in terms of profitability are still to be seen. Moreover, the experience in the development of 4IR technological capabilities does not seem to be relevant for firm performance, which suggests that learning may be difficult to achieve and exploit when technologies and applications evolve rapidly, as in the 4IR context. With this respect, the nascent area of the 4IR still appears at an early stage of the technology lifecycle and characterised by a high degree of turbulence, making first-mover advantages still uncertain. Only more recent innovators appear to have been able to grasp some benefits from the development of 4IR technologies, and this seems to rely on their ability to manage the complexity in the combination of different flavours of 4IR sub-technologies and to exploit (profitable) downstream opportunities.

Our work is a first exploration of the strategic 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 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 data and methods. Section 4 reports on sample construction, variables, and descriptive statistics. Section 5 describes the main results. Finally, Section 6 concludes, also 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

There have recently been dramatic increases in the interest on the 4IR, which has spanned academic literature (Brynjolfsson and McAfee, 2014; Goldfarb et al., 2019), practitioners (Wee et al., 2015; World Economic Forum, 2016), and policy makers (EPO, 2017; Santos et al., 2017). This has come by tremendous advancements in a set of related technologies, including adaptive robotics, embedded systems, additive manufacturing, cloud systems, virtualisation technologies, simulation, data analytics, and communication and networking (Sarvari et al., 2018). These advancements have led to both excitement about the capability of 4IR technologies to contribute to economic and social well-being and concern about the future of human work (e.g., Frey and Osborne, 2017; Graetz and Michaels, 2018). 4IR technologies bring with them the promises to revolutionise several sectors of the economy and society (Martin, 1995). For example, in the manufacturing sector, digitalised information on customer needs, processed with analytics and social media, together with real-time, flexible manufacturing systems are expected to improve mass customisation.

Recent years have also witnessed a dramatic increase in the development of scientific and technological knowledge pertaining to 4IR-related technologies. Webb et al. (2008) offered several stylised facts about patenting in software and related areas at the United States Patent and Trademark Office (USPTO). The authors show a rampant increase in applications in many emerging technologies by a relatively small group of US, Japanese, and Korean inventors, which generally work for large firms with a robust patenting history. Similarly, Mann and Püttmann (2018) show that automation patents increased from 25% in 1976 to 67% in 2014. Cockburn et al. (2018) analyse the development of scientific publications and patents in the domain of artificial intelligence in the US and show an exponential increase in the fields of learning systems (both publications and patents) and robotics (patents only). More recently, several studies have provided evidence on the surge of 4IR-related technologies (Benassi et al., 2020; EPO, 2017; Martinelli et al., 2019; Venturini, 2019).

The academic literature dealing with the 4IR is quite scattered, and studies have mainly concentrated on two broad areas: (i) the role of 4IR technologies on the future of work; (ii) the analysis of whether 4IR technologies share the same features of general-purpose technologies. As for the first stream of the literature, most of the interest has revolved around the labour market consequences of the adoption of 4IR technologies. Most of this literature has focussed on the role that automation, particularly the adoption of industrial robots, has on employment and wages at the sectoral or occupational level (Acemoglu and Restrepo, 2019; Dauth et al., 2017; Graetz and Michaels, 2018). Recent works have instead moved their attention to the role of recent advancements in artificial intelligence and how this can affect tasks performed by employees in the workplace (Brynjolfsson et al., 2018; Felten et al., 2018; Frey and Osborne, 2017; Manyika et al., 2017).

A second stream of the literature has instead tried to understand whether 4IR technologies are characterised by the main features of general-purpose technologies (GPTs), which have been historically drivers of long-term technological progress and economic growth (Bresnahan and Trajtenberg, 1995). Cockburn et al. (2018) study the technological and scientific development for artificial intelligence (AI) by tracing patent and publication data. The authors find 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, it lacks the spill-over effect able to spawn innovation in application sectors. Other works have instead focussed either on 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., 2019).

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

2.2 Conceptual framework and research questions

We focus our interest on the effect that the development of 4IR-related knowledge brings to the firm. To this purpose, we adopt a knowledge-based perspective. Notably, the knowledge-based view of the firm posits that the primary rationale for a firm's existence is its ability to create, transfer, and apply knowledge (Grant, 1996; Nonaka, 1994). One core argument is that heterogeneous knowledge bases and capabilities among firms are the main determinants of performance differences.

Previous literature has provided plenty of 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 investment (Kogut and Chang, 1991). This latter relationship is particularly strong and relevant in dynamic industries in terms of knowledge generation because they are dependent on the knowledge embedded in firms' research departments (DeCarolis and Deeds, 1999).

The development and adoption of GPTs are expected to contribute to a firm knowledge stock and thus continuously improve its technological capabilities (Thoma, 2009). Past GPTs (e.g., steam engine, railroad, electricity, computer, etc.) have been associated with significant gains at the firm level. For example, there is ample literature on the impact of information and communication technologies (ICTs) on firm performance. Brynjolfsson and Hitt (2000) provide a knowledgeable review of this body of works, and highlight how the value added of ICTs lies in their ability to (i) enable complementary organizational investments (e.g., new business processes and concerning work practices) and (ii) increase productivity by reducing costs and, more importantly, by enabling firms to increase output quality (e.g., radical and incremental product innovation).

As outlined in the previous section, there is new evidence on the assimilation of 4IR technologies to GPTs (Cockburn et al., 2018; Martinelli et al., 2019; Venturini, 2019). If this is the case, the three main features of GPTs are expected to bring performance benefits to firms developing 4IR technologies. First, the rapid development of 4IR technologies within its sector gives rise to improvements in the technologies that can be appropriated by the developing firms in terms of cost reduction due to improved efficiency or pre-emption of radical innovations. Second, the application of 4IR technologies to economically important sectors can be expected to increase firm diversification in activities related to these sectors and, thus, provide a "natural" growth strategy at the company level and benefit productivity and profitability. Finally, the ability to spawn innovations in applications 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 to integrate 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). Not only, some of the AI technologies seem to be an "invention of a method of invention", which brings further promises of improved efficiency and the creation of a new playbook for innovation (Cockburn et al., 2018). The above argument leads us to highlight our first research question relating to the relationship between the development of 4IR technological capabilities and firm productivity and profitability: (1) what is the association between the development of 4IR technological capabilities and firm performance (both productivity and profitability)?

We also expect idiosyncrasies in this relationship, due to the technical features of the technologies under consideration as well as firm strategic considerations. 4IR technologies are emergent and discontinuous technologies (Ehrnberg, 1995). By this definition, they are characterised by "discontinuous innovations derived from radical innovations [...] as well as more evolutionary technologies formed by the convergence of previously separate research streams" (Day and Schoemaker, 2000, p. 30). These technologies pose significant challenges for both incumbents and new innovators. As for established companies, 4IR technologies are likely to open up extraordinary market opportunities, but, at the same time, they foster competition from new innovators. Moreover, given the radical nature of 4IR technologies, they can bring competence-destroying discontinuities, which are often associated with increased environmental turbulence and uncertainty (Tushman and Anderson, 1986), particularly when a dominant design has not emerged yet (Anderson and Tushman, 1990). New innovators can leverage fresh and new knowledge but can lack long-term expertise and complementary assets needed to capture the value from the newly developed technology (Rothaermel and Hill, 2005; Teece, 2008). 4IR technologies are also complex to manage, as they entail several different core technologies to be combined, adapted, and exploited. As already mentioned, the 4IR comprises a set of different technologies such as sensors, cloud computing, AI algorithms, industrial robots, automated machines, three-dimensional (3D) systems of design, and additive manufacturing (Schwab, 2017). Given the co-existence of features and problems relating to different domains of knowledge (engineering, software, cognitive sciences, chemistry, etc.), companies may need time and a considerable amount of investments in cumulative knowledge stocks before operational and economic benefits of their investments emerge. Not only, the different technologies comprising the 4IR bundle are also characterised by heterogeneity in both their adherence to the main features of GPT and in their stage of technological development. For example, Martinelli et al. (2019) show sensible differences between 4IR technologies in terms of generality and originality of their technological development, their industrial knowledge base, the growth of patented technology, and rate of entrance in the technological area, thus pointing to different stages of development for the technologies comprising the 4IR. Following the argument above, the effect of the development of 4IR technologies can be different for different "vintages" of the technology because they refer to different periods in the technological evolution of the underpinning technologies. The argument above leads us to put forward a second research question, which mainly pertains to the starting period of 4IR technology development: (2) is the relationship between 4IR technological capabilities and firm performance contingent upon different stages of entrance into the development of 4IR technologies?

Given the uncertainty surrounding the technological development of 4IR technologies, strategic considerations at the firm-level become extremely important as companies need to decide when and how to enter the competitive race for the development of the related capabilities. There is extensive literature pointing to the mechanisms surrounding first- or early-mover advantages and disadvantages. In their seminal paper on the topic, Lieberman and Montgomery (1988) discuss both advantages (experience curve, technological leadership, pre-emption of scarce assets, and adopters' switching costs) and disadvantages (free-riding by competitors, resolution of technological uncertainty, change in demand, and incumbent inertia) of being a first mover in a market. Existing academic works have been inconclusive in the attempt to support or refute the existence of a direct first-mover advantage (see, for instance, the contradictory results in Robinson and Min, 2002 and Shepherd, 1999, or the survey provided by Kerin et al., 1992). This lack of conclusive results is also supported by a recent debate concerning a crucial advantage of being a first mover, namely the possibility to build experience by rapidly scaling the learning curve. While there is evidence on the positive association between an organisation gaining experience (in production and technological development) and firm performance (Hatch and Mowery, 1998), several contributions highlight a variety of factors that explain the variation observed in organisational learning (e.g., organisational inertia, employee turnover, rapid depreciation of acquired knowledge, etc.), and consequently point to the importance of learning from recent experience (Argote and Epple, 1990; Huckman and Pisano, 2006; Huesch and Sakakibara, 2009). Similarly, recent works highlight how it is the interplay between the components of a firm's environment (i.e., the pace of technological change and market evolution at the time of entry and their evolution over time) and the isolating mechanisms mentioned above that are associated with first- or late-mover advantages (Shamsie et al., 2004; Suarez and Lanzolla, 2007). Notably, first movers may face severe trade-offs between the provision of functionalities of the products descending from the technology they have already introduced, and additional functionalities requested by customers at later stages. On the contrary, late movers can enter the market when more functionalities are already known, and, by dealing with the richness of alternative configurations, can come up with superior complex designs (Querbes and

Frenken, 2017), which better meet untapped market demand *via* downstream applications. Following this, we foresee the presence of significant late-mover advantages in the development of 4IR technological capabilities. Late movers are expected to better exploit the greater variety and complexity of different 4IR technological configurations compared to early innovators and, at the same time, to devise more productive and profitable applications for the downstream market. In light of the above aspects, our study attempts to investigate also the following third original research question: (3) are firms entering later into the 4IR race able to benefit from the higher complexity of the technological configurations and the possibility to exploit downstream applications (late-mover advantages)?

3. Empirical model

In our econometric analysis (see Subsection 5.1), we estimate several versions of the following reduced-form equation:

$$Performance_{it} = \alpha + \vartheta 4IRtechnology\_development_{it-1} + \gamma X_{it-1} + \eta_i + \varepsilon_{it} \qquad (1)$$

Our dependent variable, $Performance_{it}$, is alternately defined as the productivity or profitability of the firm i at time t. Our variable of interest is $4IRtechnology\_development_{it-1}$, which measures the firm i's innovation capabilities in the development of 4IR technologies in period $t-1$. We use patent filings in the 4IR domain to proxy for firm i's innovation capabilities in the development of 4IR technologies. In Section 4, we discuss how we identified patent applications related to 4IR technologies and the rationale of using patent applications as a proxy for technology development. The vector X_{it-1} includes a variety of patent- and firm-level characteristics and several fixed effects included as controls, such as dummy variables for firm size, industry, and country, and interactions between size, industry, and country dummies with time dummies. Controlling for differential trends is crucial because there might be temporal trends in firms' performance outcomes and 4IR technology development that materialize along such dimensions. For instance, some countries might have started to implement plans or increased their efforts thereof to incentivize the firms' development of 4IR technologies in our period of interest.[1]

[1] The governments of many industrialized countries have recently launched programs to subsidize firms in developing 4IR technologies. For instance, South Korea's government is massively investing in 4IR technologies, especially concerning 5G networks, digital twins, and artificial intelligence (see https://www.4th-ir.go.kr/home/en).

The term η_i captures the firm-specific time-invariant heterogeneity. Unobserved factors such as the firm's culture, management quality, and degree of internationalization might substantially influence both firm performance and the development of 4IR technologies. For instance, forward-looking firms might invest more in 4IR technological capabilities and, at the same time, might perform better for reasons different from their involvement in 4IR technology development. If one does not take this into account, the estimated relationship between performance and 4IR technology development may be biased. Finally, ε_{it} is the error term of the regression.

Following from the previous section, we expect the development of technological capabilities in 4IR to influence firm performance: the estimation of Equation (1) above will provide an empirical test of this. To reduce the problem of reverse causality, whereby firm performance might influence its involvement in the development of 4IR technologies, we lag all the explanatory variables by one year.[2]

To investigate the relationship between developing 4IR technologies and firm performance (Equation (1)), we start by using ordinary least squares (OLS) estimations with a basic set of control variables. Then we progressively include additional controls and estimate more articulated specifications, which account for a wide array of time-varying patent- and firm-level characteristics. We finally turn to fixed effects (FE) regressions that account for unobserved time-invariant firm heterogeneity, which we also use when we investigate the role of experience, starting period of 4IR patenting activity, and technology domains of 4IR innovations.

4. Data

4.1 Sample construction

Our data source is ORBIS-IP, a very large and recently released matched patent-firm data set provided by the Bureau Van Dijk that combines rich firm- and patent-level information for around 110 million incorporated companies worldwide. The data set used in this analysis includes all the large private-sector (except for agricultural and financial) incorporated companies, which are headquartered in the United States, Germany, Japan, Italy, United Kingdom, South Korea, France,

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Similarly, the Italian government has recently launched the "Piano Nazionale Impresa 4.0" to finance firms' investments in developing 4IR technologies and sustain their competitiveness in an international perspective (see https://www.mise.gov.it/index.php/it/industria40).

[2] This is a standard practice in the innovation literature, which also allows capturing a (short-term) dynamic feature in the relationship of interest (Nesta and Saviotti, 2005). The impact of developing innovative 4IR technologies on productivity and profitability might indeed take time to materialize. Implementing 4IR innovations in the firm's production process or making them known to potential customers is not immediate.

Belgium, Sweden, Finland, Spain, Netherlands, China, or Austria and which have filed at least one 4IR patent at the EPO in the period 2009-2014. Following the OECD classification, large firms are defined as companies with more than 250 employees. It is crucial to clarify that we have data on a firm's patenting history since its first patent filing, which allows us to reconstruct the firm's efforts in the development of 4IR technologies over the past decades. However, we have to restrict attention to firms that have filed at least one 4IR patent over the more limited period 2009-2014, since financial-level information necessary to construct productivity and profitability indexes is available only from 2009.

The construction of our data set has required an intense work of data mining. In a nutshell, we have performed four steps.

First, we identified the firms involved in the development of 4IR technologies by selecting those which have 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 4IR and non-4IR technologies. This allowed us to also construct the stock of non-4IR patents, which we use as a control variable. Third, for each firm, we collected relevant balance-sheet data to construct measures of productivity, profitability, and other control variables (e.g., number of employees, the firm's location, and year of incorporation), from 2009 to 2014. Fourth, we reconstructed each firm's ownership structure and grouped the firms belonging to the same corporate group. To this end, we used 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. Controlling for group affiliation allows us to take into account the group dynamics – through synergic effects, strategic paths, and financial support – in the development of 4IR technologies.

The final database used in this paper comprises 1,386 firms and 5,464 firm-year observations. Appendix A discusses each step of the sample construction in more detail.[3]

4.2 The variables

Our dependent variable is firm performance. In the empirical analysis, we consider three performance measures, two of them related to firm productivity and one to firm profitability. In this

[3] Notably, as discussed in Appendix A, we are forced to consider companies with at least three consecutive observations in order to pursue our empirical estimations. Moreover, we focus on large firms for two reasons. First, the quality of balance-sheet and other firm-related information dramatically increases with firm size. Second, after applying the necessary restriction on the number of panel observations, smaller firms only represented a residual category of firms, thus introducing potential selection bias. Finally, we focused on the countries mentioned above in order to have a reasonable minimum number of observations (which we set to 10) for each country. This is an important precaution when one needs to accurately control for country-level specificities with country fixed effects.

paper, we use two different measures of firm productivity. The first is labour productivity, defined as (the natural logarithm of) revenues per employee. The second is the total factor productivity (TFP), which provides a measure of the firm's overall productive and organizational efficiency. As it is standard in the literature, we obtain the TFP estimates as the residuals from the estimation of a Cobb-Douglas production function (see, for instance, Devicienti et al., 2018).[4] In order to measure firm profitability, we follow many other studies (e.g., Arend et al., 2017) and use the accounting return on investments (ROI).

As a proxy for the 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 since 1985. We constructed the deflated stock of 4IR patents using the perpetual inventory method with a constant depreciation rate of 0.15, as typical in this literature (see, for instance, Grinza and Quatraro, 2019).[5] A large number of studies (e.g., Artz et al., 2010, Bloom and Van Reenen, 2002, Decarolis and Deeds, 1999, Grinza and Quatraro, 2019, Sears and Hoetker 2014) used patents as a proxy for firms' technological capabilities. While this choice has some limitations related to the fact that not all innovations are patented and that there might be differential propensities to patenting across industry and firm size (Schilling, 2015), patents have been shown to correlate well with product and process innovations (Basberg, 1987).[6] All in all, patents represent the most common and widely accepted way to measure firms' technological capabilities and are commonly considered valid and robust indicators of knowledge creation and innovation (Trajtenberg, 1987).

To identify 4IR patent applications, we use a recent study from the EPO (2017). This classification defines a list of technological areas, each related to cooperative patent classification (CPC) codes, which represent 4IR technologies. It is used in a number of recent studies on the 4IR (Benassi et al. 2020; Corrocher et al. 2018; Weresa, 2019). In the EPO classification method, 4IR patents are classified along three main technology domains: core technologies, enabling technologies, and application technologies. Core technologies are artifacts embodied in connected objects for data collection and transfer (e.g., 5G networks, networked sensors, and radio frequency

[4] In particular, we run a FE regression enriched with a large variety of other fixed effects (i.e., year fixed effects and interaction dummies between year and size, year and industry, and year and country) on a log-linearized Cobb-Douglas production function with revenues as the output variable and deflated tangible fixed assets and number of employees as capital and labour inputs, respectively. Unfortunately, our data do not allow us to estimate either a value-added production function (i.e., with value added as the output variable and labour and capital as inputs) or a revenues production function (i.e., with revenues as the output variable and labour, capital, and materials as inputs), but only a mix between the two. This is because the high number of missing values for both value added and materials in ORBIS-IP (and in ORBIS) would dramatically reduce the size of our data set (e.g., using value added to estimate value-added production function would entail a drop of more than 50% of observations in our sample).

[5] We compute the deflated stock of non-4IR patent applications – which we use as a control variable in our regressions – in the same way.

[6] Since we control for size and industry fixed effects as well as their differential evolution over time through interaction dummies, the differential propensity to patenting across firm size and economic sector is accounted for in our analyses.

ID). They allow transforming any object into a smart device connected through the Internet. Enabling technologies are technologies used in combination with connected objects and serve to collect, store, and analyse the data (e.g., artificial intelligence, cloud computing, and 3D systems). Application technologies relate to the area where connected objects can be applied (e.g., smart health, smart home, and smart manufacturing).[7] It is important to note that the EPO classification is non-exclusive. A 4IR patent can thus be classified as embedding a single-domain technology (i.e., only-core, only-enabling, or only-application technology) or a combination of two or more technology domains (i.e., core and enabling technologies, core and application technologies, enabling and application technologies, and core, enabling, and application technologies).

Finally, we constructed a series of other variables that we use as controls in our estimated productivity and profitability equations. First, we controlled for the (natural logarithm of the) number of employees in the company, in order to account for different propensities in the development of 4IR technologies based on firm size. In order to account for structural differences in the firms' production processes, we also controlled for the degree of capital intensity, expressed as the (natural logarithm of the) ratio between tangible fixed assets and employees. Finally, we inserted a control for the degree of intangibility of assets, expressed as the ratio between intangible fixed assets and total assets, in order to capture heterogeneities in firms' intangible investments, including R&D investments.[8]

4.3 Descriptive statistics

Before showing the results from our econometric analysis, we present some descriptive statistics of the estimation sample. Disentangling the data by firm characteristics (e.g., size, age, and patenting activity) and by patents' technological domain is of great help for the interpretation of the econometric results.

Table 1 provides an overview of the firms analysed in this study, together with summary statistics of the dependent variables and the main control variables used in the regressions. Our sample's firms are, on average, rather heterogeneous. The average size is around 14,000 employees, but the median size is considerably smaller, around 1,700 employees. Similarly, average revenues are around 5 billion Euros, but the median value is less than 600 million Euros. On average, labour

[7] EPO classification further subdivides each main technology domain into several categories. Core technologies are classified into three categories: hardware, software, and connectivity. Enabling technologies comprise seven categories: analytics, user interfaces, three-dimensional support systems, artificial intelligence, position determination, power supply, and security. Application technologies are classified into six classes: personal, home, vehicles, enterprise, manufacture, and infrastructure. Table A.1 in Appendix A provides a schematic representation of this classification.

[8] Although ORBIS-IP provides data on R&D investments (as of balance-sheet information), in practice, this information is unusable as R&D investments are provided with a huge amount of missing values (above 80%), which would dramatically reduce the sample size.

productivity (i.e., revenues per employee) is slightly less than 400 thousand Euros. The average ROI is around 10%, which suggests that our sample's firms are rather profitable. Most of the sample's firms belong to the manufacturing sector (about 77%), whereas the rest are services companies. Firms are not young on average (50 years), but at least 25% of them are less than 20 years old.

Insert Table 1 here

Table 2 focuses on 4IR technology development. On average, 4IR patents filed by our sample firms represent around 18% of their patent portfolios, which speaks for the importance of 4IR technologies for such companies. The second panel of the table reports summary statistics for the deflated stock of 4IR patents by different starting periods in 4IR patenting (i.e., based on when the firms filed their first 4IR patent). Starting from the last year of our data (i.e., 2014), we go back for three decades of 4IR patent filing history of the sample firms, and we define three periods, 2004-2014, 1995-2004, and 1985-1994. Starting from the earlier period, we define firms as "early innovators", then "middle-decade innovators", and finally "late innovators" for those that have filed their first 4IR patent in the last decade (2004-2014). Not surprisingly, the table shows that early innovators have the highest deflated stock of 4IR patents. However, the magnitude of the mean differences, as compared to both middle- and later-innovators, is considerable (though less so if one looks at the median values) and reflects the difference in firm size in the three decades of patent filings.[9]

Insert Table 2 here

Table 3 finally reports summary statistics for 4IR patent portfolios by technological domains, as well as their breakdown by starting period of 4IR patenting. For each of the possible seven combinations (e.g., only-core technologies, only-enabling technologies, etc. – see Subsection 4.2), we constructed the degree of intensity in that particular combination as the share of the deflated

[9] The average number of employees among early innovators is around 25,000, whereas among middle- and later-innovators is, respectively, around 6,300 and 10,200. Among early innovators, there are very large companies, such as Wallmart, IBM, and General Electric Company.

stock of 4IR patents referring to that particular combination over the total deflated stock of 4IR patents. So, for instance, the intensity of only-core technologies for a firm is the ratio between the firm's deflated stock of 4IR patents relating to only-core technologies over the total deflated stock of 4IR patents.[10] These indicators are useful to characterize the directions in terms of technological domains of the firms' efforts in developing 4IR technologies.

The upper panel in Table 3 shows that firms tend to develop mainly only-application 4IR technologies (27.5%). The second-largest patent category in the firms' portfolios (21.6%) combines elements of core, enabling, and application domains. Core-application technologies and only-core technologies represent 13.6% and 13.1% of the firms' patent portfolios, respectively. On average, as much as 49.8% of the firms' 4IR patent portfolios relate to 4IR technologies that combine two or more application domains (i.e., core-enabling, core-application, enabling-application, and core-enabling-application technologies). We refer to these technologies as "complex technologies". Instead, 44.1% of the firms' 4IR patent portfolios combine application technologies with other technology domains. We refer to these technologies as "application-oriented complex technologies".

Table 3 also reports the intensity in "complex", "only-application", and "complex application-oriented" technologies separately for early, middle-decade, and late innovators. The intensities in these three technology domains are rather stable across the three categories of firms. Notably, however, late innovators appear to invest relatively more in only-application technologies as compared to middle-decade and, especially, late innovators.

Insert Table 3 here

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5. Results

We now move to the results from the econometric analysis. Subsection 5.1 shows the main results from the estimation of Equation (1), where we examine the overall impact of the development of 4IR technologies on firms' productivity and profitability. Subsection 5.2 presents the analyses aimed at exploring the mechanisms behind the impact. In particular, we focus on the role of a firm's

[10] The seven combinations of 4IR technological domains are excludable, that is, either a patent is only-core, or only-enabling, or only-application, or core-enabling, or core-application, or enabling-application, or core-enabling-application. Therefore, the seven intensity indicators sum up to 1.

experience in and the starting period of 4IR technology development, as captured by 4IR patents, as well as on the role of the different 4IR technology domains.

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

Table 4 reports results for three different specifications of Equation (1) for each of the three performance outcomes considered: TFP, labour productivity, and ROI. For each dependent variable, the first two columns report OLS estimation of Equation (1), and the third one reports FE estimates. In particular, the basic specification in Columns (1a), (1b), and (1c) controls for the stock of non-4IR patents, the degree of capital intensity, the level of employment, the degree of intangibility of assets, and the year of incorporation. We also add time dummies, and controls for size, industry, and country fixed effects. Specifications in Columns (2a), (2b), and (2c) add interactions between time dummies and size, industry, and country fixed effects. Finally, Columns (3a), (3b), and (3c) report the FE coefficients, while including the full set of control variables, as already mentioned. These preferred estimates remove firm unobserved fixed heterogeneity, which instead is not controlled for in OLS specifications. Finally, the standard errors are robust to heteroskedasticity and clustered at the firm level.

Insert Table 4 here

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 labour productivity, but does not appear to be linked to firm profitability. Both OLS specifications point to significantly higher TFP and labour productivity due to higher 4IR deflated stock of patents, with estimated coefficients equal to 0.058. The FE specifications report significant positive impacts, too. However, the magnitude of the estimated effect is smaller (0.015 for TFP and 0.012 for labour productivity), which suggests that unobserved fixed firm specificities are relevant determinants of both firm performance and the degree of development of 4IR technological capabilities. At first glance, the magnitude of the effect seems modest: a 10% increase in the deflated stock of 4IR patents increases TFP by 0.15% and labour productivity by 0.12%.[11] However, one should note that a not negligible

[11] See, for example, Venturini (2019), who estimates, at the country level, the elasticity of productivity to the aggregate stock of knowledge related to intelligent technologies ranging from 0.02 and 0.06 for industrialized economies.

proportion of firms shift from not patenting at all to patenting in 4IR technologies, and another large proportion of firms increase their 4IR deflated stock of patents by much due to relatively small starting 4IR patent portfolio (e.g., passing from 3 to 6 4IR patents means a 100% increase). Indeed, the yearly average percentage increase of 4IR deflated patent stock (computed excluding firms that switch from zero to a positive number of 4IR patents – delta percentages cannot be computed in this case) is as high as 53.4%. Due to the average increase in firms' 4IR patent portfolios, TFP is estimated to raise by 0.80% and labour productivity by 0.64%.

When we turn to firm profitability, no significant impact is detected. Both OLS and FE estimations report virtually 0 coefficients. In the overall sample, the firms' development of 4IR technologies has thus no impact on their ROI, possibly due to significant sunk costs associated with the development of 4IR technologies (see the discussion in Section 6 below).[12]

5.2 The role of experience, starting periods, and different technology domains

So far, we found an affirmative answer to our first research question about the positive impact of developing 4IR technologies on productivity, while no significant effect emerges concerning firm profitability. We now proceed to address the second research question, by disentangling the main results in relation to the firms' different starting periods of 4IR technology development. It should be noted that, from now on, we report the (relevant coefficients of) our preferred FE estimates. We concentrate on either impact on TFP or ROI, depending on whether we are interested in firm productivity or profitability.[13]

First, we focus on the contingency role of firm-level experience and continuity in developing 4IR technologies. The first two panels of Table 5 present results for this.

To this end, we constructed a firm-specific indicator of experience in 4IR technology development and classified firms based on their degree of experience (low, medium, high). 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 4IR patent applications; the year in which the firm files its first 4IR patent, the experience is set to 1, the subsequent year, it is set to 2, and so on. We then took the panel-average experience to make it time-invariant and divided firms into three categories (i.e., firms with low, medium, or high experience) based on whether their panel-average experience was below the 25th percentile, within

[12] We have also experimented with alternative measures of accounting firm profitability, including the return on assets (ROA) and the return on sales (ROS). The results are coherent with what emerges for ROI, that is, that no significant relationship between the development of 4IR technologies and firm profitability is detected.
[13] Note that estimates with labor productivity as the dependent variable are similar to those obtained with TFP. We did not report them in the paper for conciseness, but they are available upon request.

the 25th and 75th percentiles, and above the 75th percentile, respectively. Finally, we estimated a version of Equation (1) that adds interaction terms multiplying a firm's deflated stock of 4IR patents and the relative degree of experience. These terms allow us to assess the impact of 4IR technology development in the different categories of firms.

The first panel of Table 5 shows that firms with low experience obtain the highest productivity gains from developing 4IR technologies. The estimated coefficient is 0.022 and significant at the 1% level. Firms with medium levels of experience also obtain a significant productivity gain from investing in 4IR technologies, though lower in magnitude (0.016). In firms with high experience, higher stocks of 4IR patents are instead associated with lower productivity.

With a methodology similar to the one used for experience, we constructed an indicator of continuity in 4IR technology technologies, and classified firms according to their degree of continuity. Continuity is an indicator constructed as the number of years in which the firm has filed at least one 4IR patent application over the number of years since it is 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 is active in 4IR patenting, whereas it approaches 0 as 4IR patenting activity is more sporadic. It is set to 0 when the firm has never patented. We then took the panel-average continuity and divided the firms into three categories (firms with low, medium, and high continuity) following the same classification we adopted for experience (below 25th percentile, within 25th and 75th percentiles, and above 75th percentile). Finally, we interacted a firm's deflated stock of 4IR patents with its degree of continuity to obtain the differential effect of 4IR technology development for firms with high, medium, and low degree of continuity in filing patents in the 4IR domain.

The second panel of Table 5 shows the results for this test. Firms with low and medium levels of continuity in 4IR patenting obtain positive and significant productivity increases from developing 4IR technologies. On the contrary, the significant positive relationship between productivity and 4IR patent filings does not surface within firms that have continuously filed these patents over time. Although these findings may appear counterintuitive, recall that high continuity in filing 4IR patents might be associated with marginal improvements of technologies. In short, in the uncertain and fast-changing world of 4IR, a high continuity in the development of 4IR technologies does not appear effective in terms of actual productivity enhancements.

Conversely, substantial and significant positive productivity effects for firms with low experience (and continuity) are consistent with the presence of an evident productivity jump experienced by firms developing 4IR technologies for the first time.[14] The third panel of Table 5

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[14] In the category of low-experienced firms are encompassed those firms that started developing 4IR technologies during our observation period. The same holds for the category of low-continuity firms, where, by construction, firms

shows this effect. Here, the deflated stock of 4IR patents is interacted with two binary variables. The first one takes the value 1 when the firm passes from not having any 4IR patent applications to having at least one (i.e., when it starts patenting in 4IR technologies) and then again turns 0 afterwards. This variable can thus switch from 0 to 1 only once for each firm, in the year of a firm's first 4IR patent application. Moreover, it should be noted that if a firm files its first 4IR patent before the first year of observation in our data, this variable never takes the value 1. The second dummy variable takes the value 1 when the firm has already patented in 4IR technologies (or has never patented in 4IR technologies) and 0 otherwise. This regression shows that a "boost effect" on productivity is associated with 4IR patenting, whereby the effect of 4IR technology development on productivity is substantially higher when the firm develops 4IR technologies for the first time compared to when it is not its first time (0.022 versus 0.013), case in which the impact is nonetheless positive and significant. For robustness, we have also performed an additional test (last panel of Table 5) to check that the "boost effect" is not entirely attributable to the extensive margin (i.e., if the firm invests in 4IR technology development), but that also the intensive margin is relevant (i.e., how much the firm invests in 4IR technology development). The effect of the extensive margin, while positive, is not significant, whereas the effect attributable to the intensive margin is positive, significant, and in line with the overall effects previously found.[15]

Insert Table 5 here

The results so far, that is, the impossibility to climb the learning curve, the fact that continuity in the development of 4IR technologies does not pay, and the presence of a boost effect, suggest that it is important to further investigate the starting period of 4IR technology development.

In Table 6, we run productivity and profitability estimations of Equation (1) separately for early, middle-decade, and late innovators. For early and middle-decade innovators, our FE estimates indicate no significant productivity and profitability effect stemming from the development of 4IR technologies, as captured by the stock of 4IR patents accumulated since 1985. The effect on productivity for late innovators (third panel of the table) is instead positive, large in magnitude, and strongly significant. Interestingly, a positive and significant impact also emerges on firm profitability for those firms, suggesting that they are able to profit from the development of

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without experience in the development of 4IR technologies have 0 levels of the continuity index (which most likely entails low values of the panel-average continuity index).

[15] For a similar "boost" effect on firm growth, see also Helmers and Rogers (2011) in relation to start-ups which patent for the first time.

4IR technologies in the short-term. Notably, the same results hold when we consider the effect of the more recent patent stock. These results are shown in Table C.1 of Appendix C, where we re-run the estimations of Table 6, but with the stock of 4IR patents from 2005 (instead of 1985) as the regressor of interest. This allows us to obtain a neater comparison among the different categories of firms, since all the firms have patents filed in the last decade, and to better assess the marginal benefits of 4IR technology developments for such firms.

Insert Table 6 here

How do late innovators get such productivity and profitability gains? To answer our third research question, we investigate how/whether late innovators get their returns from combining different technological domains associated with the 4IR. Differently from the dimensions of experience and continuity, the analysis by 4IR technological domains – core, enabling, application, and their mix – is an uncharted territory. If late innovators can build on earlier innovators' accumulated knowledge and at the same time develop technologies that better respond to new needs of the market and production process, they might be more effective in combining different technological domains (i.e., in exploiting complex technologies). At the same time, they might be advantaged in the exploitation of technologies with evident applicative characteristics. They might be advantaged in the development of more effective application-oriented technologies, as they have more flexibility in responding to changing environments (i.e., they do not have enormous sunk costs stemming from the accumulation of long-standing investments).

To answer these questions, we use three methods and present the results in Table 7. In the first panel, we test whether late innovators have differential performance effects stemming from the development of complex 4IR technologies (i.e., those that combine two or more technological domains), and we find that late innovators have a significantly higher capability of extracting productivity advantages from such technologies. We find a similar, but more pronounced, pattern deriving from the development of application-oriented complex 4IR technologies (i.e., those that focalize in application technologies in conjunction with other technology domains). Late innovators show a significantly higher capability to exploit productivity benefits stemming from the development of application-oriented 4IR technologies. Interestingly, the late comers show a marginally significant (p-value equal to 0.120) but quantitatively substantial impact of 4IR patent filings also on profitability, a finding consistent with the fact that application-oriented technologies are more easily converted into revenue streams compared to other technologies because they are more directly linked to downstream markets. Finally, we see that late innovators have no increased differential effect when it comes to the exploitation of simple only-application technologies (second panel of the table), which suggests that they are more able to obtain beneficial effects from more complex technologies that entail the combination of different knowledge domains.

Insert Table 7 here

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6. Discussion and conclusions

Our study focused on the impact of 4IR technology development, an area of investigation so far largely unexplored, in favour of the adoption of these technologies and consequent effects (Venturini, 2019). We investigated (i) the association between the development of 4IR technological capabilities and firm performance, (ii) the moderating role of experience, continuity, and starting period in 4IR technology development, and (iii) whether late innovators benefit from the higher complexity of the technological configurations and the possibility to exploit applications downstream.

The empirical investigation offers three main conclusions.

First, the development of 4IR technologies significantly increases firms’ productivity but does not appear to be linked to profitability. Productivity may rise due to increased efficiency in the production process thanks to the development and implementation of 4IR technologies, or it might be related to increased revenues generated from the output that incorporates 4IR technologies. Although at first glance it may appear surprising that such positive impacts on firm productivity do not lead to higher profitability, it should be noted that the development of 4IR technologies entails enormous investments that have the characteristics of fixed (and sunk) costs. While these costs do not enter productivity indexes, they impact firms’ profitability. Therefore, it may take several years for initial investments to become profitable. Moreover, despite high expectations about new market segments, demand has not taken off yet. For example, the driverless car market, despite promises, is still struggling with technological and regulatory issues (among others) and still in its infancy.

Second, firms capitalize more on productivity when they develop 4IR technologies for the first time compared to when it is not the first time (i.e., there is a “boost effect”). This might be due to different reasons. It can be the case that first patents collect more advanced knowledge that the firm has accumulated in the past periods. Moreover, subsequent patents might be due to strategic needs, such as protecting the core knowledge, building up a more robust patent portfolio, or accumulating patents for competitive reasons. Experience appears to have counter-intuitive effects. Low-experienced firms get the highest productivity gains. On the other hand, in firms with higher experience, higher stocks of 4IR patents are associated with lower productivity. Our results suggest that learning curves are difficult or even impossible to climb in the 4IR domain. Such an impossibility to effectively climb learning curves is consistent with the result that too much continuity in developing 4IR technologies does not pay (see also Guarascio and Tamagni, 2019). More in general, our research contributes to the literature on first movers' advantages. In the case of 4IR technologies, being first, experienced, and continuous is not a sufficient condition for improved economic performances.

Third, we found that the effect on productivity for late comers is positive, large in magnitude, and strongly significant. In contrast with Teece (1986) and Rothaermel and Hill (2005), a positive and significant impact also emerges on firm profitability for those actors, suggesting that they can profit from the development of 4IR technologies in the short-term. Late comers in the development of 4IR technologies might have significant advantages over first movers, as suggested by several scholars (Querbes and Frenken, 2017). Late comers are not anchored to previous and sometimes outdated technological paradigms. Paradoxically, high levels of experience in rapidly changing environments, such as the 4IR context, might be a double-edged sword (Tushman and Anderson, 2016). A "wait and see" strategy can be highly beneficial when technological trajectories are subject to rapid changes and when emerging technologies need time to consolidate. "Wait and see" strategies also allow firms to carefully choose when entering the technological race and avoid possible organizational inertia, which is likely when firms make huge commitments for a long time.

Our study has several implications from a firm's perspective. The first implication is that the timing of entry is highly relevant when new technologies emerge. Being the first movers offers clear advantages over competitors. This is the case of patents that we have considered here. First-patenting firms can block competitors, enjoy a temporary monopoly, and get extra profits. However, when the technological domain is broad, undefined, and evolving, what matters is capitalizing on discernible and valuable knowledge. The second implication has to do with the complexity and interconnectedness of technological domains. Although core technologies can have several downstream implications and allow firms to achieve technological leadership in several segments, firms focusing on application technologies together with other technology domains experience significant performance results. Third, the combination of different technologies seems to be relevant, 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.

Future research can shed light on these mechanisms and find invariants in the firms' behaviour, possibly overcoming the limitations of our research. The first limitation has to do with the measurement of 4IR technology development. Data on patents that we used have the usual drawbacks. The quality of patents differs, and patents can be filed for specific competitive and strategic reasons. Moreover, patents are just one component of the firms' knowledge stock (e.g., quality of human capital). Second, the classification of 4IR used in the paper following EPO (2017) can be improved to make specific investigations possible in distinctive subdomains and pave the way to cumulative analysis in longer periods. Data availability for longer periods is also critical in analysing technological domains that are emergent. Third, quantitative analyses are a robust way for investigating complex phenomena, but triangulation through quantitative and qualitative methodologies can shed light on some aspects that this research has touched on the surface.

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Table 1: Sample summary statistics: general information

Variable	Mean/ %	Std. dev.	25th Pct.	Median	75th Pct.	Min.	Max.
Dependent variables							
TFP (log)	6.577	0.615	6.125	6.511	6.937	4.928	9.061
Labour productivity (log)	5.777	0.608	5.354	5.713	6.141	4.192	7.977
ROI	0.096	0.120	0.026	0.082	0.152	-0.480	0.874
Independent variables							
Deflated stock of 4IR patents (log)	2.224	1.736	0.993	1.877	3.221	0	9.268
Deflated stock of non-4IR patents (log)	4.016	2.077	2.542	3.952	5.464	0	10.013
Capital to labor ratio (log)	4.260	1.129	3.561	4.262	4.948	-4.414	8.489
Employment (log)	7.772	1.629	6.468	7.415	8.809	5.521	14.604
Inangible fixed assets over total assets	0.097	0.150	0.006	0.024	0.120	0.000	0.837
Year of incorporation	1964.610	37.869	1946	1977	1994	1689	2012
Other variables							
Employment	14,309	75,328	660.000	1,714	6,895	250	2,200,000
Revenues (1,000 Euros)	5,009,832	17,486,702	188,148	584,893	2,512,789	50,577	429,589,408
Labour productivity (1,000 Euros)	397.418	318.194	211..405	302.634	464.663	66.171	2,912
Manufacturing	76.90%						
Services	23.10%						

Number of firm-year observations: 5,464

Number of firms: 1,386

Source: ORBIS-IP (years: 2009-2014)

For consistency with the regressions, all the variables listed in the “independent variables” section are lagged by one year. Note that here, as well as in the regressions, we have shifted the distribution of the deflated stock of both 4IR patents and non-4IR patents by 1 unit in order not to miss observations with 0 values in the logarithmic transformations.

Table 2: Sample summary statistics: 4IR technology development; overall view and by starting period

Variable	Mean	Std. dev.	25th Pct.	Median	75th Pct.	Min.	Max.
Overall view							
Deflated stock of 4IR patents	94.525	518.958	1.700	5.537	24.060	0	10,592
Deflated stock of non-4IR patents	419.974	1,433	11.710	51.050	235.070	0	22,309
Deflated stock of overall patents	514.499	1,852	17.543	63.530	273.105	0.040	27,231
							Number of firm-year observations: 5,464
							Number of firms: 1,386
Deflated stock of 4IR patents by firms with different starting period of 4IR technology development							
Deflated stock of 4IR patents by early innovators (firms active in 4IR technology development since the period 1985-1994)	255.060	871.712	7.425	26.759	97.662	0.017	10,592
							Number of firm-year observations: 1,833
							Number of firms: 460
Deflated stock of 4IR patents by middle-decade innovators (firms active in 4IR technology development since the period 1995-2004)	25.592	67.120	2.879	8.105	21.413	0.054	897.571
							Number of firm-year observations: 1,549
							Number of firms: 384
Deflated stock of 4IR patents by late innovators (firms active in 4IR technology development since the period 2005-2014)	4.474	18.628	0	1.700	3.499	0	533.491
							Number of firm-year observations: 2,082
							Number of firms: 542

Source: ORBIS-IP (years: 2009-2014)
For consistency with the regressions, all the variables listed here are lagged by one year.

Table 3: Sample summary statistics: 4IR technology development; 4IR technology domain and starting period

Variable	Mean	Std. dev.	25th Pct.	Median	75th Pct.	Min.	Max.
Intensity of only-core 4IR technologies	0.131	0.249	0	0	0.133	0	1
Intensity of only-enabling 4IR technologies	0.096	0.214	0	0	0.068	0	1
Intensity of only-application 4IR technologies	0.275	0.357	0	0.084	0.458	0	1
Intensity of core-enabling 4IR technologies	0.057	0.144	0	0	0.022	0	1
Intensity of core-application 4IR technologies	0.136	0.245	0	0.008	0.147	0	1
Intensity of enabling-application 4IR technologies	0.089	0.201	0	0	0.072	0	1
Intensity of core-enabling-application 4IR technologies	0.216	0.324	0	0.032	0.318	0	1
Intensity of complex 4IR technologies	0.498	0.378	0.120	0.492	0.895	0	1
Intensity of application-oriented complex 4IR technologies	0.441	0.386	0.044	0.362	0.861	0	1
Number of firm-year observations: 4,872 Number of firms: 1,386							
Intensity of complex 4IR technologies among early innovators	0.525	0.321	0.242	0.503	0.845	0	1
Intensity of only-application 4IR technologies among early innovators	0.228	0.292	0.017	0.093	0.342	0	1
Intensity of application-oriented complex 4IR technologies among early innovators	0.458	0.340	0.162	0.421	0.802	0	1
Number of firm-year observations: 1,833 Number of firms: 460							
Intensity of complex 4IR technologies among middle-decade innovators	0.485	0.369	0.124	0.465	0.872	0	1
Intensity of only-application 4IR technologies among middle-decade innovators	0.286	0.351	0	0.109	0.495	0	1
Intensity of application-oriented complex 4IR technologies among middle-decade innovators	0.426	0.380	0.059	0.328	0.835	0	1
Number of firm-year observations: 1,549 Number of firms: 384							
Intensity of complex 4IR technologies among late innovators	0.480	0.443	0	0.458	1	0	1
Intensity of only-application 4IR technologies among late innovators	0.321	0.422	0	0	0.793	0	1
Intensity of application-oriented complex 4IR technologies among late innovators	0.436	0.441	0	0.298	1	0	1
Number of firm-year observations: 1,490 Number of firms: 542							

Source: ORBIS-IP (years: 2009-2014)

For consistency with the regressions, all the variables listed here are lagged by one year. As "intensity" of a particular 4IR technology domain is computed as the deflated stock of 4IR patents in that particular 4IR technology domain over the total stock of 4IR patents, it is only defined when the latter is positive (i.e., when the firm has at least one 4IR patent application).

Table 4: Results: the impact of 4IR technology development on firm productivity and firm profitability

	Dep. var.: TFP (log)			Dep. var.: labor productivity (log)			Dep. var.: ROI		
	(1a)	(2a)	(3a)	(1b)	(2b)	(3b)	(1c)	(2c)	(3c)
	OLS1	OLS2	FE	OLS1	OLS2	FE	OLS1	OLS2	FE
Deflated stock of 4IR patents (log) at t-1	0.058***	0.058***	0.015**	0.058***	0.058***	0.012*	-0.001	-0.001	-0.000
	(0.010)	(0.010)	(0.006)	(0.010)	(0.010)	(0.007)	(0.002)	(0.002)	(0.004)
Deflated stock of non-4IR patents (log) at t-1	0.028***	0.030***	0.005	0.029***	0.031***	0.009	-0.008***	-0.009***	-0.007
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)	(0.002)	(0.002)	(0.005)
Capital to labor ratio (log) at t-1	0.118***	0.121***	-0.008	0.266***	0.268***	0.056***	-0.011***	-0.011***	-0.007**
	(0.025)	(0.026)	(0.013)	(0.024)	(0.025)	(0.014)	(0.004)	(0.004)	(0.008)
Employment (log) at t-1	0.116***	0.124***	-0.005	-0.055**	-0.049**	-0.068***	0.006	0.005	-0.021**
	(0.022)	(0.023)	(0.022)	(0.022)	(0.023)	(0.025)	(0.005)	(0.005)	(0.014)
Intangible fixed assets over total assets at t-1	-0.913***	-0.935***	-0.049	-0.934***	-0.954***	-0.033	0.005	0.007	-0.070
	(0.116)	(0.120)	(0.080)	(0.114)	(0.118)	(0.082)	(0.023)	(0.024)	(0.045)
Year of incorporation	0.001**	0.001**	-	0.001**	0.001**	-	0.000***	0.000***	-
	(0.000)	(0.000)		(0.000)	(0.000)		(0.000)	(0.000)	
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Size dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	-	Yes	Yes	-	Yes	Yes	-
Country dummies	Yes	Yes	-	Yes	Yes	-	Yes	Yes	-
Time*size dummies	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Time*industry dummies	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Time*country dummies	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Firm fixed effects	No	No	Yes	No	No	Yes	No	No	Yes

Number of firm-year observations: 5,464
Number of firms: 1,386

Source: ORBIS-IP data set (years: 2009-2014)

Standard errors, reported in parentheses, are robust and clustered at the firm level. ***, **, and * denote, respectively, the 1%, 5%, and 10% significance level. Note that we have shifted the distribution of the deflated stock of both 4IR patents and non-4IR patents by 1 unit in order not to miss observations with 0 values in the logarithmic transformations. Size dummies divide the firms into 5 size categories based on the size distribution of firms in the sample. Industry dummies are at the 2-digit level of the NACE Rev. 2 classification of economic activities. Country dummies identify the 15 countries represented by the firms in our sample as of Table 1.

Table 5: Results: the impact of 4IR technology development on firm productivity by experience, continuity, and boost effect

Experience		
Deflated stock of 4IR patents (log) at t-1*firm with low experience	0.022***	(0.008)
Deflated stock of 4IR patents (log) at t-1*firm with medium experience	0.015*	(0.009)
Deflated stock of 4IR patents (log) at t-1*firm with high experience	-0.026*	(0.014)
Continuity		
Deflated stock of 4IR patents (log) at t-1*firm with low continuity	0.020**	(0.008)
Deflated stock of 4IR patents (log) at t-1*firm with medium continuity	0.017*	(0.009)
Deflated stock of 4IR patents (log) at t-1*firm with high continuity	-0.004	(0.013)
Boost effect I		
Deflated stock of 4IR patents (log) at t-1*first time at t-1	0.022***	(0.008)
Deflated stock of 4IR patents (log) at t-1*not first time at t-1	0.012*	(0.007)
Boost effect II		
Deflated stock of 4IR patents (log) at t-1	0.012*	(0.007)
First time at t-1	0.013	(0.010)
Number of firm-year observations: 5,464		
Number of firms: 1,386		

Source: ORBIS-IP data set (years: 2009-2014)

In all these estimations, the dependent variable is TFP (log). Estimation method: FE. Standard errors, reported in parentheses, are robust and clustered at the firm level. ***, **, and * denote, respectively, the 1%, 5%, and 10% significance level. These estimates include the same set of controls of Specification (3a) of Table 4. Experience is defined as the number of years since the first 4IR patent application. A 0-year experience means that the firm has never filed 4IR patent applications; the year in which the firm files its first 4IR patent, experience is set to 1, the subsequent year, it is set to 2, and so on. We then take the panel-average experience and divide firms into the three categories, firms with low, 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. Continuity is an indicator constructed as the number of years in which the firm has filed at least one 4IR patent application over the number of years since it is 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 is active in 4IR patenting, whereas it approaches 0 as 4IR patenting activity is more sporadic. It is set to 0 when the firm has never patented. As for the case of experience, we then take the panel-average continuity and divide the firms into the three categories (firms with low, medium, and high continuity) following the same classification we adopt for experience (below 25th percentile, within 25th and 75th percentile, and above 75th percentile). The variable "first time" is a dummy variable which takes the value 1 when the firm passes from not having any 4IR patent applications to having at least one (i.e., when it starts patenting in 4IR technologies) and then again turns 0 afterwards. For all the rest, see the footnote of Table 4.

Table 6: Results: the impact of 4IR technology development on firm productivity and firm profitability by starting period

Early innovators (firms active in 4IR technology development since the period 1985-1994)		
Dep. var.: TFP (log)		
Deflated stock of 4IR patents (log) at t-1	-0.016	(0.017)
Dep. var.: ROI		
Deflated stock of 4IR patents (log) at t-1	-0.008	(0.009)
Number of firm-year observations: 1,833		
Number of firms: 460		

Middle-decade innovators (firms active in 4IR technology development since the period 1995-2004)		
Dep. var.: TFP (log)		
Deflated stock of 4IR patents (log) at t-1	0.002	(0.014)
Dep. var.: ROI		
Deflated stock of 4IR patents (log) at t-1	-0.009	(0.009)
Number of firm-year observations: 1,549		
Number of firms: 384		

Late innovators (firms active in 4IR technology development since the period 2005-2014)		
Dep. var.: TFP (log)		
Deflated stock of 4IR patents (log) at t-1	0.030***	(0.010)
Dep. var.: ROI		
Deflated stock of 4IR patents (log) at t-1	0.010*	(0.006)
Number of firm-year observations: 2,082		
Number of firms: 542		

Source: ORBIS-IP data set (years: 2009-2014)

Estimation method: FE. Standard errors, reported in parentheses, are robust and clustered at the firm level. ***, **, and * denote, respectively, the 1%, 5%, and 10% significance level. These estimates include the same set of controls of Specification (3a) (for the case of TFP) and Specification (3c) (for the case of ROI) of Table 4. The distribution of the deflated stock of 4IR patents for late innovators has been shifted by 1 unit in order not to lose observations with 0 values. For consistency, we have applied the same transformation to early innovators and middle-decade innovators. For all the rest, see the footnote of Table 4.

Table 7: Results: the role of 4IR technology domain and staring period

Complex 4IR technologies		
Dep. var.: TFP (log)		
Intensity of complex 4IR technologies	0.003	(0.022)
Intensity of complex 4IR technologies*late innovator	0.087***	(0.033)
Dep. var.: ROI		
Intensity of complex 4IR technologies	-0.011	(0.013)
Intensity of complex 4IR technologies*late innovator	0.013	(0.026)
Only-application 4IR technologies		
Dep. var.: TFP (log)		
Intensity of only-application 4IR technologies	-0.016	(0.025)
Intensity of only-application 4IR technologies*late innovator	-0.032	(0.040)
Dep. var.: ROI		
Intensity of only-application 4IR technologies	0.027*	(0.015)
Intensity of only-application 4IR technologies*late innovator	-0.025	(0.028)
Application-oriented complex 4IR technologies		
Dep. var.: TFP (log)		
Intensity of application-oriented complex 4IR technologies	-0.005	(0.023)
Intensity of application-oriented complex 4IR technologies*late innovator	0.095***	(0.035)
Dep. var.: ROI		
Intensity of application-oriented complex 4IR technologies	-0.016	(0.013)
Intensity of application-oriented complex 4IR technologies*late innovator	0.038	(0.028)
Number of firm-year observations: 4,872		
Number of firms: 1,386		

Source: ORBIS-IP data set (years: 2009-2014)

Estimation method: FE. Standard errors, reported in parentheses, are robust and clustered at the firm level. ***, **, and * denote, respectively, the 1%, 5%, and 10% significance level. In addition to the variables shown in the table, these estimates include the same set of independent variables of Specification (3a) (for the case of TFP) and Specification (3c) (for the case of ROI) of Table 4. As "intensity" of a particular 4IR technology domain 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 only when the latter is positive (i.e., when the firm has at least one 4IR patent application). For all the rest, see the footnote of Table 4.

Appendices

A. The construction of the data set

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

To empirically identify the firms involved in 4IR technology development and measure their activity thereof, we used patent applications filed at the European Patent Office (EPO). Based on the identified 4IR patent applications, we then individuated the firms that file these 4IR patent applications. This was possible thanks to the matched patent-firm nature of the ORBIS-IP data set, whereby each firm in the data set is linked to the patents it applied for through a unique firm identifier, called "bvd id number". To select the firms which constitute our sample, we considered 4IR patents filed between 2009 and 2014. This means that each firm in our final sample has at least one 4IR patent application filed between 2009 and 2014. We restricted the attention to the years between 2009 and 2014 for two reasons. On the one hand, we could not obtain firm-level data (e.g., those necessary to construct performance outcomes) before 2009.[16] On the other hand, we selected 2014 as the last year of observation (and identification of firms developing 4IR technologies) to avoid truncation (and selection) problems arising from the publication lag associated with patent filings.[17]

After having identified the firms that filed 4IR patent applications at the EPO in the period 2009-2014 (i.e., our sample's firms), we reconstructed their histories in 4IR technology development by going back to as much as 30 years. In practice, we reconstructed the stock of 4IR patents since 1985. This allows us to have a more precise measure of the degree of development of technological capabilities related to 4IR innovations. It also allows constructing detailed long-run indexes of experience and continuity in 4IR technology development and differentiating firms by the starting period of 4IR technology development (see Subsection 5.2).

We then gathered the necessary firm-level information, including balance-sheet variables used to construct performance indexes and firm-level controls (e.g., number of employees, the firm's

[16] ORBIS-IP provides a 10-year history of firm-level information, including balance-sheet variables.
[17] The EPO publishes patents as soon as possible after the expiry of a period of 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).

location, and year of incorporation). For consistency with patent-level information related to 4IR technologies, we have also reconstructed the firms' technological capabilities in non-4IR innovation since 1985, by computing the stock of non-4IR patents, which we use as a control variable.

Finally, by resorting to rich information on ownership and corporate structure provided by ORBIS-IP, we reconstructed the ownership structure of our sample's firms and grouped those belonging to the same corporate group. In particular, we have 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. These possible criteria to identify a firm's ultimate owner are mainly related to the percentage of stock ownership and the type of entity, including, for instance, whether it is a business firm, a financial holding company, a physical person, a government. Relating to the type of entity, we set business firms as admissible ultimate owners. Concerning the percentage of stock ownership, we set the thresholds typically used in the literature (see, for instance, Belenzon and Berkovitz, 2010). For non-publicly listed firms, we have set a minimum threshold of 50% of stock ownership, whereas we set a less restrictive threshold of 25% if the firm is publicly owned. In publicly listed firms, the ownership is more dispersed, and a less strict threshold is more suitable (Belenzon and Berkovitz, 2010). The ultimate owners so defined were then used to group our sample's firms. In particular, we aggregated firms by ultimate owners by summing up relevant variables.[18] Grouping firms belonging to the same corporate group is crucial because it allows us to take into account any effects stemming from group dynamics explicitly. Belonging to a group in which other firms develop 4IR technologies might indeed have an impact on the firm's development of 4IR technologies (and performance), for instance, through sharing knowledge among the parent company and affiliate firms, receiving external financial supports, and other forms of synergic effects. If one does not take this into account, results might be biased. We chose business firms as admissible ultimate owners because we wanted to capture more precisely the situations in which those synergic effects most likely materialize, that is, when the linkage among the parent company and the other firms in the group expresses in ways that are not only related to a mere financial control, without any exchange of knowledge and common strategic goals.

Since we run within-firm estimation (i.e., fixed effects regressions) with one-year lagged variables, we are forced to focus on companies with at least three consecutive years of observations. This

[18] Concerning balance-sheet information, we summed up variables from unconsolidated balance sheets. Concerning non-numeric variables (e.g., year of incorporation and country or industry), we have attached the value of the company with the highest revenues in the group. From now on, when we refer to a "firm", we mean the group of firms aggregated based on the common ultimate owner as previously defined.

unavoidable restriction led us not to consider a relatively small fraction of observations, amounting to less than 10%. As mentioned in the main text, here we focus on large firms. We follow the OECD classification and define large firms as those that employ more than 250 workers. Two main reasons motivate this choice. First, the quality of balance-sheet and other firm-level information drastically increases with firm size. Differently from large companies, smaller firms in ORBIS-IP are associated with large amounts of missing information, which may render usable observations largely selected in unknown directions, thereby introducing potential bias in the results. Second, after applying the necessary restriction on the number of panel observations (see above), smaller firms represented a residual category, thereby exacerbating potential selection bias. Finally, we focus on firms headquartered in the United States, Germany, Japan, Italy, United Kingdom, South Korea, France, Belgium, Sweden, Finland, Spain, Netherlands, China, or Austria. This is done in order to have a reasonable minimum number of observations for each country, which we have set to 10 observations. While this entails a very tiny drop of observations, it is important when one needs to accurately control for country-level unobserved heterogeneity through country fixed effects.

B. Classification of 4IR patents

Table A.1: 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.

C. Robustness: results by start of 4IR patenting activity

Table C.1: Results: the impact of 4IR technology development on firm productivity and firm profitability by starting period of 4IR patenting activity (stock of 4IR patents restricted to years from 2005 onwards)

Early innovators (firms active in 4IR technology development since the period 1985-1994)		
Dep. var.: TFP (log)		
Deflated stock of 4IR patents filed between 2005 and t-1 (log)	-0.019	(0.015)
Dep. var.: ROI		
Deflated stock of 4IR patents filed between 2005 and t-1 (log)	-0.010	(0.009)
Number of firm-year observations: 1,833		
Number of firms: 460		
Middle-decade innovators (firms active in 4IR technology development since the period 1995-2004)		
Dep. var.: TFP (log)		
Deflated stock of 4IR patents filed between 2005 and t-1 (log)	0.007	(0.013)
Dep. var.: ROI		
Deflated stock of 4IR patents filed between 2005 and t-1 (log)	-0.007	(0.008)
Number of firm-year observations: 1,549		
Number of firms: 384		
Late innovators (firms active in 4IR technology development since the period 2005-2014)		
Dep. var.: TFP (log)		
Deflated stock of 4IR patents filed between 2005 and t-1 (log)	0.030***	(0.010)
Dep. var.: ROI		
Deflated stock of 4IR patents filed between 2005 and t-1 (log)	0.010*	(0.006)
Number of firm-year observations: 2,082		
Number of firms: 542		

Source: ORBIS-IP data set (years: 2009-2014)

Estimation method: FE. Standard errors, reported in parentheses, are robust and clustered at the firm level. ***, **, and * denote, respectively, the 1%, 5%, and 10% significance level. These estimates include the same set of controls of Specification (3a) (for the case of TFP) and Specification (3c) (for the case of ROI) of Table 4. The distribution of the deflated stock of 4IR patents for late innovators has been shifted by 1 unit in order not to lose observations with 0 values. For consistency, we have applied the same transformation to early innovators and middle-decade innovators. For all the rest, see the footnote of Table 4.

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Science Policy Research Unit
University of Sussex, Falmer
Brighton BN1 9SL
United Kingdom

SPRU website: **www.sussex.ac.uk/business-school/spru**
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