Digital technology adoption: the dual role of firm leadership*

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Abstract

This work empirically examines the adoption of Fourth Industrial Revolution (4IR) technologies, using firm-level data from Italy for the period 2015-17. The analysis shows that technology adoption varies together with the scope of technological opportunities by industry, measured by the number of worldwide patents in a given 4IR domain and industry during the period 2000-2014, and that the extent to which firms are receptive to the technological progress depends on firms' absorptive capacity. The latter, in turn, varies across firms according to the characteristics of the firm's leaders, as these influence firms' exploratory capabilities and their internal organization. However, while the direct effects of leader characteristics on technology adoption are significant in all technological domains, their moderating effects vary significantly across technologies.

Keywords: Fourth Industrial Revolution, technology adoption, absorptive capacity, patents, leadership.
JEL Classification Codes: D22, O32, O33.

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1 Introduction

Digital transformation can be seen as one of the central new pathways through which firms are innovating entire systems of production, management and governance (Cefis et al., 2023; Nambisan et al., 2019). This transformation has been rapid due to the rapid advances in knowledge across different technology domains (Martinelli et al., 2021; Schwab, 2017) and is likely to lead society towards what has been called the Industry 4.0 paradigm or the 'Fourth Industrial Revolution' (4IR, hereafter) (Kagermann et al., 2013).

Recent evidence has shown that, within the 4IR group of technologies, there is considerable variation in adoption across technology domains and firms (Acemoglu et al., 2022). Some firms have adopted the available technologies faster than others (Benassi et al., 2020; Cirillo et al., 2023a;b; Kiel et al., 2017; Kinkel et al., 2022; Peerally et al., 2022; Raj et al., 2020; Teece, 2018b), despite the fact that these advances are well suited to most firms due to their enabling nature (Martinelli et al., 2021). Horvath and Szabo (2019) suggest that this heterogeneity depends on the firm's ability to recognise the opportunities offered by 4IR technologies and to face the organizational and management challenges associated with their adoption.

Using a recent large survey of Italian firms, this paper empirically examines the determinants of heterogeneity in the adoption of the main 4IR technologies, namely robotics, big data, virtual and augmented reality, the Internet of Things (hereafter IoT) and cybersecurity. In particular, it focuses on two factors that influence technology diffusion (Rogers, 1962): first, changes in the stock of global knowledge, that is, the scope of technological opportunities, available to firms in a given technology domain and industry, which is proxied by the number of new patents available at the global level in an industry-technology domain pair; second, the characteristics of firm leadership, which, by helping to determine the absorptive capacity of the firm, moderate the relationship between external opportunities and the actual adoption of technologies.

More specifically, in the spirit of opening the "black box" of technology adoption within firms, the empirical analysis in this paper aims to test a number of hypotheses about 4IR technology adoption that are related to two main conceptual pillars of technology diffusion. The first pillar is based on the observation that technology adoption begins with an initiation phase, when the firm becomes aware of the available technological advances (Frambach and Schillewaert, 2002; Kemp and Volpi, 2008). The likelihood that a firm adopts a technology in a given domain, thus, depends on the scope of opportunities that it can scan and consider: accordingly, the greater the number of technological innovations in a 4IR-related technology domain and industry, the higher the likelihood that a firm adopts (at least) one of them.[1] This knowledge-related pillar belongs to the supply side of the technology diffusion process. In particular, given that the characteristics of a technology affect its adoption (Kapoor et al., 2014; Rogers, 1962) and that each industry is characterized by different trajectories and technological regimes (Pavitt, 1984), one needs to distinguish the scope of opportunities for each 4IR technology domain in each industry, taking into account possible spillover effects.

The second conceptual pillar of our analysis relates to the microeconomic dimension of technology diffusion, that is, the firm-level characteristics that affect information transfer and technology adoption (Cho et al., 2023; Rogers, 1962). Adoption depends on the actual ability of the firm to scan the global set of technological opportunities and to identify those advances among those available in the technology domain that are both interesting and worth the risk. Indeed, as explained by Rogers (1962), the timing and intensity of adoption depend on the risk appetite of the decision makers as well as on other characteristics of the firm. This process refers to the demand side of the technology diffusion process and complements the supply side pillar. Thus, in this paper we postulate (and test) that absorptive capacity (ACAP, hereafter) exerts a moderating effect on the relationship between the set of technological opportunities available to the firm and its actual investment in the acquisition of new technological solutions. Borrowing the terminology from the literature on internal innovation (Cohen and Levinthal, 1989; 1990; Nieto and Quevedo, 2005; Zahra and George, 2002; Volberda et al., 2010), we empirically assess whether the firm's absorptive capacity (among other dynamic capabilities) affects its adoption of new digital technologies (Kinkel et al., 2022; Rey et al., 2021; Spanos and Voudouris, 2009; Stornelli et al., 2021).

Among the factors affecting firms' ACAP, we examine the characteristics of firm leadership. While the importance of firm leadership for the adoption of innovations developed within the firm is well established (more on this below), its role in the acquisition of new technological solutions from outside the firm has received little attention in the literature.[2] The characteristics of leaders may directly affect firms' propensity to invest, for example through varying degrees of risk aversion, but they may also affect it indirectly by influ-

[1] The evolution of the stock of knowledge in a technological domain is also positively correlated with the likelihood of adoption through network externalities because it affects the firm's entire operating environment, including its competitors: hence, the greater the growth in the stock of knowledge, the more likely it is that imitative behaviour emerges between firms.

[2] Technology adoption can occur both through the internal development of new technological advances (via R&D) and through investment in the purchase of hardware and software products produced outside the firm (Damanpour and Daniel Wischnevsky, 2006; Kemp and Volpi, 2008; Kurzhals et al., 2020; Stoneman and Battisti, 2010). This paper focuses only on the acquisition of technology produced outside the firm. While we use the terms 'adoption' and 'investment' interchangeably in the text for the sake of brevity, we acknowledge here that adoption may follow a different (internal) route that we do not explore empirically. A full discussion of this can be found in Section 5.

encing personal receptiveness to global technological progress and the ability of leaders to scan, identify and exploit external knowledge.[3] As technologies differ in complexity, rate of progress and historical failure rates, we expect (and test) that the moderating role of the leader characteristics is different across technologies: for instance, newer and more complex technologies may require leaders' awareness, whereas those associated with riskier development projects may interact with leaders' risk aversion.

To empirically investigate the moderating role of leader characteristics on the heterogeneous adoption of 4IR technologies via the ability of firms to access the available knowledge, the empirical analysis uses a large firm-level dataset from Italy for the period 2015-17, derived from the firm-level survey *Rilevazione Imprese Lavoro* (RIL), conducted by the National Institute for Public Policy Analysis (INAPP) and based on a representative and large sample of around 30,000 firms. The survey includes questions on the decision to invest in various 4IR technologies, in particular, robotics, big data, virtual and augmented reality, IoT and cybersecurity, in the period 2015-2017, as well as information on firms' leadership, in particular, gender, age, education, being a member of the family that owns the firm and the remuneration scheme, and other characteristics that are used as controls.

For changes in the available stock of knowledge at the global level, we use the lagged changes in the worldwide stock of patents in each technology domain at the 4-digit industry level over the period 2000-2014. Among the methods developed to identify patents (we refer to Bello et al., 2023, for an overview), we follow Caselli et al. (2024) and construct the number of patents by technology and industry in three steps. First, we use the classification codes assigned to each patent (Ménière et al., 2020) and select those related to different 4IR technologies. Then, we refine the selection through a textual analysis based on the presence of technology-specific keywords in the titles and abstracts of the patents (similar methods have been used by Benassi et al., 2021; Ménière et al., 2020; Martinelli et al., 2021). Finally, we use a probabilistic match between patent classification codes and their industry of use, as proposed by Goldschlag et al. (2020), to assign each patent to a given industry.

We empirically test our hypotheses by using regression models with interaction terms between changes in the global stocks of patents for each domain-industry pair and leadership characteristics, where leadership characteristics may act as moderating determinants of firm adoption, and a number of firm-specific controls and fixed effects. All estimates are based on seemingly unrelated regressions (SUR) to account for the fact that the

[3]We use the term leadership to include entrepreneurs, founders, executives and top managers. Although our empirical study focuses specifically on the individuals who make the key decisions in the firm, the theoretical motivation for our empirical analysis is more general and can be applied, *mutatis mutandis*, to any of the subgroups of leaders.

probability of investing in a particular technology is correlated with the probability of investing in the other technologies.

To preview the main results of this analysis, we find that firms in industries that have experienced stronger knowledge development in a 4IR technology domain, as measured by the number of related patents available at the global level in an industry-technology domain pair, are more likely to adopt a technological innovation in such a domain. This implies that the diffusion of a 4IR technology in the economy depends on the extent of the global progress in the technology domain relevant to the industry in which the firm operates (i.e., the supply side of the technology diffusion process). Thus, part of the observed heterogeneity in technology adoption is related to the different intensity of the knowledge creation process for different industries. However, the magnitude of the effect varies across technology domains. For example, a 10 percent increase in the change in the stock of patents related to robotics in an industry (at the 4-digit level) is associated with a 0.12 percentage point increase in the probability of adopting robots, while a 10 percent increase in the change in the stock of patents related to IoT and cybersecurity is associated with an approximately 0.2 percentage point increase in the probability of adopting these technologies. This effect drops to less than 0.1 percentage points for virtual reality.

Regarding the second pillar of our conceptual framework, we find that differences in firm leadership have both direct and indirect effects on the likelihood of technology adoption, and the indirect effects operate through a moderating effect on firms' ACAP. The estimated direct effects of leader characteristics on 4IR technology adoption are qualitatively consistent with previous evidence on firms' attitudes towards internal innovation, and the results are similar across 4IR technology domains. What is new in this paper is the evidence on the moderating role of leader characteristics, and we show that this effect varies considerably across characteristics and across technology domains. While most leader characteristics are important in the case of robotics, they do not always play a moderating role for other 4IR technologies. Thus, although this demand-side aspect of the technology diffusion process helps to explain the heterogeneous adoption of 4IR technologies across firms within the same industry and technology domain, our results do not allow us to draw unambiguous conclusions regarding the indirect effects of firm leadership for all 4IR technologies.

Taken together, our results suggest that developments in 4IR technologies are associated with a widespread process of technology adoption, which depends on both the evolution of the global stock of knowledge and the distribution of absorptive capacity among firms, in line with the tenets of the technology diffusion theory. Although our results confirm that knowledge growth remains an important supply-side driver of the transition to the 4IR industrial paradigm, such a transition cannot be considered as a foregone conclusion. As also argued by Peerally et al. (2022) and Raj et al. (2020), technology adoption is in fact moderated by several tangible and intangible factors within the firm, including the characters of firm leadership.

Our paper contributes to the strands of economic and business literature that focus on firm leadership and the antecedents of technology adoption. Despite the wealth of studies examining the impact of firm leadership on innovation efforts and the established link between firm and leader dynamic capabilities,[4] the relationship between leader characteristics and technology adoption, particularly in terms of moderating effects, remains unclear (Cortellazzo et al., 2019; Gerstner et al., 2013; Horvath and Szabo, 2019; Rey et al., 2021). Little is known about how leaders' characteristics moderate firms' ability to access and invest in knowledge available outside the firm. This is surprising given that leaders' personalities and attitudes shape the response to technological change and determine how firms recombine and reconfigure their assets and organizational structures to assimilate and exploit new opportunities (Duran et al., 2023; Teece, 2007; 2018a).[5] Previous work has examined a few specific channels. Kammerlander and Ganter (2015), for example, show that the goals of a family CEO influence whether the CEO judges an emerging technology to be relevant enough to warrant a firm response. Ricci et al. (2021) relate the search strategies of small and medium-sized enterprises within their ecosystem to their ability to identify digital opportunities. In this paper, we show that differences in firm leadership have both a direct and indirect effects on the likelihood of technology adoption: the direct effects on technology adoption are found to be homogeneous across 4IR domains and qualitatively similar to the previously found direct effects on internal innovation; the moderating role of leader characteristics on technology adoption, however, varies widely across characteristics and technology domains.

This paper also contributes to the recent literature that examines the adoption of digital technologies that fall within specific technology domains of the 4IR (Acemoglu et al., 2022; Martinelli et al., 2021; Prytkova et al., 2024). The literature has examined the direct role played by various attributes of the firm in the adoption of 4IR technologies (Cirillo

[4] See, among others, Arvanitis and Stucki (2012); Barker and Mueller (2002); Cohen (2010); Duran et al. (2023); Kurzhals et al. (2020); Protogerou et al. (2017); Scoresby et al. (2021); Thong and Yap (1995) and Yunlu and Murphy (2012).

[5] The idea that the observed heterogeneity in technology adoption is related to the characteristics of firm leadership is supported by several theories that are consistent with our conceptual framework. Upper echelons theory relates organizational outcomes to the characteristics of firm leaders that significantly influence decision making (Bromiley and Rau, 2016; Hambrick and Mason, 1984; Hiller et al., 2013). According to the resource-based approach, leader characteristics are complementary intangible resources that influence technology adoption (Gomez and Vargas, 2012; Kurzhals et al., 2020). The literature on firm leadership shows that leaders influence organizational capabilities and firm culture, thereby modifying its capacity for change (Bresnahan et al., 2002; Horvath and Szabo, 2019; Muller et al., 2018; Raj et al., 2020; Stornelli et al., 2021).

et al., 2023b; Kinkel et al., 2022; Oettmeier and Hofmann, 2017; Peerally et al., 2022; Rey et al., 2021; Stornelli et al., 2021). However, the evidence on firm-level characteristics acting as moderating factors remains limited. Previous contributions have focused on R&D expenditures, workers' human capital and capital investment, but the role of leadership has been neglected (Muller et al., 2021). Therefore, by examining the moderating role of leader characteristics on 4IR technology adoption, our paper falls within the micro-level literature that studies the moderating factors that affect technology diffusion through firm adoption.

The remainder of the paper is structured as follows. In Section 2 we review the rich theoretical background and the testable hypotheses of our empirical analysis. Section 3 introduces the data, describes the empirical specification used to test our hypotheses and presents the results of the estimations. Section 5 provides a discussion of the results and relates them back to the literature. Section 6 concludes.

2 Theoretical background and testable hypotheses

Notwithstanding the emphasis placed on the production of innovations within the firm, the adoption of external technology plays an important role in the process of technology diffusion (Kurzhals et al., 2020; Rogers, 1962; Stoneman and Battisti, 2010). In this paper we focus on firms' investment in the acquisition of new technological products. At the heart of this form of technology adoption is the process by which firms explore, appropriate and exploit external knowledge.[6]

The stock of knowledge available outside the firm is thus a crucial supply-side determinant of technology diffusion, because it determines the available scope of technological opportunities for the firm. Given that each technology domain is characterized by different trajectories and regimes across industries (Pavitt, 1984), we suggest that part of the observed heterogeneity in technology adoption may be due to the different evolution of knowledge across technology domains and industries. This is the core of the first pillar of our conceptual framework that we aim to test.

It is well known that, given the stock of knowledge in each technology domain-industry pair, technology adoption varies remarkably across firms. Such heterogeneity must be due to firm-level factors. The latter may affect the propensity of firms to adopt new technologies (direct effect) and may have a moderating effect on their ability to scope and identify the solutions of interest from the range of technological opportunities available (indirect effect on ACAP). This is the core of the second pillar of our conceptual frame-

[6] This is particularly relevant for firms that adopt an open innovation paradigm (Chesbrough, 2003; Dahlander and Gann, 2010; Lichtenthaler and Lichtenthaler, 2009; West and Bogers, 2014).

work that we aim to test. Direct and indirect effects need not work in the same way. A characteristic that makes a firm more inclined to adopt new technologies (i.e., direct effect) may make it less receptive to global technological progress (i.e., indirect effect).

Our conceptual framework borrows from the ideas developed by Cohen and Levinthal (1989) and Cohen and Levinthal (1990) to explain the role of absorptive capacity in the innovation process. The idea of identifying the direct and the indirect effects of leader characteristics on technology adoption recalls the dual role of R&D in firm innovation envisaged by Cohen and Levinthal (1989; 1990). Since our analysis focuses on firms' investments in acquiring technological products from outside, we adapt the theory of ACAP to this setting. Accordingly, ACAP is interpreted here as the firm's ability to scan the scope of external technological opportunities and identify those of interest with a view to investing in the purchase of externally produced advances. Given the differences between this interpretation of ACAP and that used in the innovation literature, we discuss this issue in more detail in Section 5.

Against this general two-pillar conceptual framework, we borrow from previous empirical studies of technology diffusion and technology adoption to derive a set of testable hypotheses for each of the two pillars in Section 2.1 and Section 2.2, respectively.[7]

2.1 Pillar 1: Technology adoption and the scope of technological opportunities

The first pillar of the conceptual framework is based on the observation that the probability that a firm adopts a particular technology is not independent of what happens outside the firm in the technology domain. Rather, the probability that a firm operating in an industry will be interested in a technological product in a given technology domain is expected to increase with the extent of technological advances available in that technology domain and industry. The more abundant the innovations in the technology domain and industry, the easier and less costly it is for the firm to identify promising technological paths and opportunities for its technological investments (Kaplan, 2008; Martinelli et al., 2021; Stoneman and Battisti, 2010). Various contributions (see, for example, Raj et al., 2020; Stornelli et al., 2021) have shown that the uncertainty about future technological paths and the risks associated with low technological maturity reduce the incentives for adoption, because scanning for opportunities and understanding their potential economic benefits can be difficult, expensive and risky. This suggests a positive relationship between the level of global technological progress and technology adoption by firms in a given technology domain-industry pair.

[7]This two-pillar approach allows us to capture an aspect of the technology-centric perspective of the digital transformation along with relevant actor-centric aspects (Nadkarni and Prugl, 2021).

However, this positive association is not forgone. Finding new valuable ideas may become more difficult for a firm as the technology matures and the technology domain becomes saturated. In addition, firms may suffer from information overload in the face of too much information. Both of these mechanisms would imply a negative relationship between the level of global technological progress and technology adoption.

Our first empirical exercise is therefore aimed at identifying the dominant mechanism in the case of 4IR technologies. Given that these technologies are far from mature and their enabling nature prevents a strong association with industry-specific life cycles, we expect to find a positive relationship between global technological progress and 4IR technology adoption. Thus, our first testable hypothesis regarding the supply side of technology diffusion can be formulated as follows:

H1: The greater the number of innovations available in a given 4IR technology domain and industry, the greater the likelihood that a firm will adopt such a technology.

Our account of the first pillar of technology adoption emphasizes the importance of the scope of technological opportunities to which a firm potentially has access. Given that adoption is influenced by the characteristics of the technology and the relationship between the latter and the characteristics of the industry (Kapoor et al., 2014; Rogers, 1962), each technology domain is characterized by different trajectories and regimes in different industries (Pavitt, 1984). Accordingly, for each of the five 4IR technologies, we use the number of new patents available at the 4-digit industry level over the period 2000-2014 as a measure of the scope of technological opportunities for a firm. Similar approaches have recently been used to address other relevant economic issues (Benassi et al., 2021; Caselli et al., 2024; Ménière et al., 2020; Martinelli et al., 2021).

2.2 Pillar 2: Technology adoption, absorptive capacity and firm leadership

Differences in the relative abundance of technological opportunities across technology domains cannot explain the observed heterogeneity in adoption across firms within a domain, even within an industry. The fact that new technologies are freely available on the market, but not all firms adopt them, suggests that firm-specific factors influence adoption.

The firm-level factors influencing technology adoption can play a dual role. They can have a direct impact on the firm's propensity to adopt technological innovations, and they can influence the firm's ability to identify the available opportunities. For example, leaders' risk aversion can have a direct impact on the likelihood of adopting new opportunities, and it can also influence the intensity of the efforts to browse (and select from) the scope of technological opportunities, thereby changing the extent to which the firm is receptive to global technological advances (Damanpour and Schneider, 2006; Kammerlander et al., 2015; Kurzhals et al., 2020; Ricci et al., 2021; Thong and Yap, 1995; Vaccaro et al., 2012; Volberda et al., 2013; Stornelli et al., 2021).

The ability of the firm to scan and identify the opportunities offered by new technological advances external to the firm is a fundamental component of the firm's absorptive capacity and it affects the likelihood that the firm will invest in externally generated technological advances. Absorptive capacity, defined as such, varies widely across firms and depends on several firm-level determinants: tangible factors (such as financial resources, past technological experiences, past R&D expenditures, and workers' human capital), and internal routines and organizational knowledge base (Agostini and Nosella, 2019; de Araujo Burcharth et al., 2015; Jansen et al., 2005; Lane et al., 2006; Volberda et al., 2010; 2013; Zahra and George, 2002).

Several theories in the business literature have shown the centrality of firm leadership for ACAP (Kurzhals et al., 2020).[8] Indeed, the specific channels through which leader characteristics may act as moderating factors of ACAP are numerous. Imprinting and reflexivity may affect leaders' perceptual apparatus and influence the firm's ability to explore and appropriate external knowledge (Suddaby et al., 2015). According to (Ocasio, 1997), they can also determine what leaders focus their attention on. Kammerlander et al. (2015) claim that the CEO's regulatory focus orientation can influence the firm's exploration activities, and Kammerlander and Ganter (2015) find that the non-economic goals of family firm CEOs alter the perceived relevance of emerging technologies. Stornelli et al. (2021) and Horvath and Szabo (2019) show that the reluctance of managers and their lack of appropriate skills are significant barriers to the adoption of digital technologies. Leaders also shape the organizational culture of the firm (Gillani et al., 2020) and influence many organizational factors that affect ACAP.

This is not to say that leader characteristics play only a moderating role in technology adoption. In fact, leader characteristics can directly influence the propensity of firms to adopt new technologies. For example, leaders' cognitive and emotional framing and their

[8] Upper echelons theory suggests that all organizational outcomes depend on the characteristics (e.g., demographics, beliefs, values, work experience and educational background) of top managers (Bromiley and Rau, 2016; Hambrick and Mason, 1984; Hiller et al., 2013). According to the resource-based approach, the characteristics of firm leadership are intangible resources that influence technology adoption (Becker, 1992; Damanpour and Schneider, 2006; Marcati et al., 2008). The Technology-Organization-Environment framework, based on the seminal work of Tornatzky et al. (1990), allows leadership support to be interpreted as a moderating organizational factor affecting the adoption of new technologies (Arnold and Voigt, 2019; Chatterjee et al., 2021; Chen et al., 2015; Cruz-Jesus et al., 2019; Gillani et al., 2020; Lin, 2014; Oliveira et al., 2019). As shown by Pijpers et al. (2001); Damanpour and Schneider (2006), similar conclusions can be reached on the basis of the technology acceptance models (Davis, 1989). Leaders' characteristics can also influence the co-evolution of organizational forms and combinative capabilities that affect knowledge absorption in a changing environment (Van den Bosch et al., 1999).

risk aversion alter the general attitude towards investing in new technologies, regardless of the scope of opportunities (Raffaelli et al., 2019; Scoresby et al., 2021). There is a recent growing literature studying the direct firm-level determinants of technology adoption, such as R&D expenditures, firm organization, managers' risk aversion, and workers' cultural background and skills. With respect to 4IR technological advances, Peerally et al. (2022) emphasize the importance of hardware, human capital and managerial systems for firms' ability to adopt technological changes. Similar conclusions are reached by Oettmeier and Hofmann (2017) and Stornelli et al. (2021) on additive manufacturing technologies, Rey et al. (2021) on the Internet of Things, and Kinkel et al. (2022) on artificial intelligence (AI).[9] Little attention has been paid to the indirect influence on technology adoption through the firm's ACAP. Accordingly, in this paper we consider the existence of both channels of influence and empirically assess the dual role of leader characteristics in technology adoption.

Against this general conceptual background, we derive a set of more specific hypotheses about the role of leader characteristics in technology adoption. The literature on firm innovation has identified a wide range of potential aspects to investigate: demographic factors, education, prior work experience, skills, self-perception, values, personality, and the like. In this study, we focus on those characteristics that we can operationalize using the questions in the RIL survey (described in Section 3).

Education is the first leader characteristic to consider, as ACAP is linked to individuals' cognitive foundations (Cohen and Levinthal, 1990; Schweisfurth and Raasch, 2018). More educated individuals are more likely to have the knowledge required to reduce the information-related uncertainty associated with a wide scope of technological opportunities. The lower this ability, the higher is the perceived risk of choosing the wrong technological advances in which to invest. However, the evidence that leaders' education and prior experience have a direct effect on technology adoption is mixed. Ciarli et al. (2021) show that leaders' prior experience and educational background affect the firm's propensity to innovate and the early adoption of new external technologies. Damanpour and Schneider (2006), on the other hand, find no evidence that leaders' education favours adoption. To explore this issue further and to address the moderating effect of education, we formulate the following testable hypothesis:

[9] Oettmeier and Hofmann (2017) find that advanced manufacturing technologies are rarely adopted in industrial manufacturing due to the existence of multiple (technological, firm, market structure, and supply chain) barriers. Stornelli et al. (2021) provide a comprehensive review of the literature on the main barriers and enablers to the adoption of advanced manufacturing technologies. Kinkel et al. (2022) discuss how various technological, organizational and environmental factors (in particular, digital skills, firm size, and R&D intensity) influence the adoption of AI technologies in manufacturing. Rey et al. (2021) find that the adoption of IoT technologies is positively influenced by the firm's absorptive capacity and entrepreneurs' perceptions of the benefits of related technologies.

H2a: Firms with less educated leaders tend to be less receptive to changes in the technological knowledge stock in the 4IR domains, thereby indirectly reducing the likelihood of technology adoption.

Age is a leader characteristic that can directly and indirectly influence technology adoption. Young managers may adopt relatively more innovations because of their better cognitive resources (as suggested by the Upper Echelons Theory), their greater openness to risk, and their lower psychological commitment to the existing practices (Damanpour and Schneider, 2006); however, young leaders may be less interested in making long-term commitments to a firm, which may counterbalance their advantages in terms of stamina, awareness and cognitive abilities. Age can also be correlated with risk-taking attitudes and time preferences which can, in turn, affect ACAP by influencing decisions characterized by highly uncertain outcomes, such as identifying the technology to adopt among alternatives (Faccio et al., 2016; Farag and Mallin, 2018; Scoresby et al., 2021; Strohmeyer et al., 2017). In addition, age can change how leaders interpret the difficulties associated with technology adoption: if they tend to see difficulties as insurmountable barriers, they reduce the firm's ability to scan, identify and adopt a new technological opportunity (D'Este et al., 2012). This would lead to a negative association between age and ACAP. However, it is possible that older managers are more experienced, especially if they have been in the same industry throughout their careers, and know better how to scan the scope of technological opportunities. Given this uncertainty, and assuming that old leaders are less receptive to innovation, the hypothesis we test regarding the moderating effect of age can be specified as follows:

H2b: Firms with older leaders tend to be less receptive to changes in the technological knowledge stock in the 4IR domains, thereby indirectly reducing the likelihood of technology adoption.

Gender-related hypotheses are highly controversial because it is difficult to distinguish the impact of social norms from those of intrinsic gender differences. Nevertheless, some researchers have noted the existence of gender differences in communication style, risk aversion and socialization that may affect innovation and technology adoption. For example, Strohmeyer et al. (2017) conclude that firms led by women have less innovation breadth and depth due to differences in the extent to which male and female entrepreneurs resemble jacks-(or jills-)of-all trades (in turn associated with gender-segregated educational choices and work experiences). Instead, DeTienne and Chandler (2007) find that women and men use different methods to identify opportunities, although this does not lead to differences in their innovativeness. On this basis, we formulate our next hypothesis on the moderating role of gender as follows:

H2c: Firms with female leaders tend to be less receptive to changes in the technological knowledge stock in the 4IR domains, thereby indirectly reducing the likelihood of technology adoption.

The nature of the relationship linking leaders to the ownership status of firms deserves attention. As discussed in the rich literature on innovation in family-owned and family-run firms (De Massis et al., 2013; Duran et al., 2016; Heider et al., 2022; Kammerlander and Ganter, 2015; Konig et al., 2013), family involvement in the top management may affect innovation inputs, activities, and outputs. For example, according to Duran et al. (2016), family members tend to be more risk averse and the involvement of external managers in the top management team has positive effects on exploratory innovation, which is an important component of ACAP. This finding is consistent with Konig et al. (2013)'s conclusion that family firms recognize discontinuous technologies with a delay, thereby slowing down the early stages of technology adoption.[10] Assuming that similar mechanisms are at work in technological adoption, the following hypothesis is tested:

H2d: Firms with leaders belonging to the family owning the firm tend to be less receptive to changes in the technological knowledge stock in the 4IR domains, thereby indirectly reducing the likelihood of technology adoption.

Finally, we adapt the theoretical framework to non-demographic characteristics and consider the pay-related incentives of the firm's leaders. The literature has shown that the alignment of incentives between the firm and executives can affect innovation and technology adoption (Atkin et al., 2017; Fong, 2010; Heyden et al., 2017; Zona, 2016). Atkin et al. (2017) show that misalignment of incentives due to the ownership structure of the firm and leaders' remuneration schemes can reduce technology adoption.[11] Scoresby et al. (2021) claim that variable compensation schemes can reduce the incentives to invest in activities that only produce effects in the medium/long term, which can have a negative impact on the firm's ACAP. On this basis, we express the last hypothesis to be

[10] This is particularly relevant for Italy, which has a remarkably high incidence of family firms.

[11] With respect to innovation, Fong (2010) finds that relative CEO underpayment is associated with reductions in R&D spending in low R&D-intensive industries. Zona (2016) shows that CEO incentives affect R&D spending in ways that vary with CEO tenure. This, in turn, is influenced by their relationship with the entire top management team (Heyden et al., 2017).

tested as follows:

H2e: Firms whose leaders have a variable compensation scheme tend to be less receptive to changes in the technological knowledge stock in the 4IR domains, thereby indirectly reducing the likelihood of technology adoption.

As anticipated in the Introduction, the moderating role of each leader characteristic may differ across technologies. For example, newer and more complex technologies (e.g., big data) may require greater awareness as an ability to scan for new business opportunities, while those associated with more well-known characteristics but riskier development projects may interact with leaders' risk aversion.

It is worth recalling that all these hypotheses concern the moderating effects of leader characteristics on technology adoption. This does not mean that their direct effects are not discussed. However, given that existing empirical studies have only examined their direct effects on technology adoption, our paper contributes in particular by testing their indirect effects on a large sample of Italian firms. More precisely, we test whether certain leader characteristics (i.e., gender, age, education, being member of the family that owns the firm and the remuneration scheme) are statistically associated with significant differences in the extent to which firms are receptive to the available global technological advances in five 4IR technology domains, i.e., robotics, big data, virtual and augmented reality, IoT and cybersecurity.

3 Data and empirical models

3.1 Data and variables

The dependent variables of interest in our empirical analysis are the decisions to invest in various new 4IR technologies, namely robotics, big data analytics, IoT, virtual reality, and cybersecurity.[12] Information on the adoption of this set of 4IR technologies comes from the firm-level survey Rilevazione Imprese Lavoro (RIL, hereafter), conducted by the National Institute for Public Policy Analysis (INAPP) on a representative sample of about 30,000 Italian firms operating in the non-agricultural private sector.[13] The RIL survey collects a rich set of information about firms, including management and corporate governance characteristics, the composition of the workforce, and other workplace characteristics. In particular, the 2018 wave of the RIL questionnaire includes direct

[12]Given the sensitivity of data protection and exploitation, cybersecurity can be considered an integral part of data-related 4IR technologies (Gomes et al., 2023; Lattanzio and Ma, 2023).

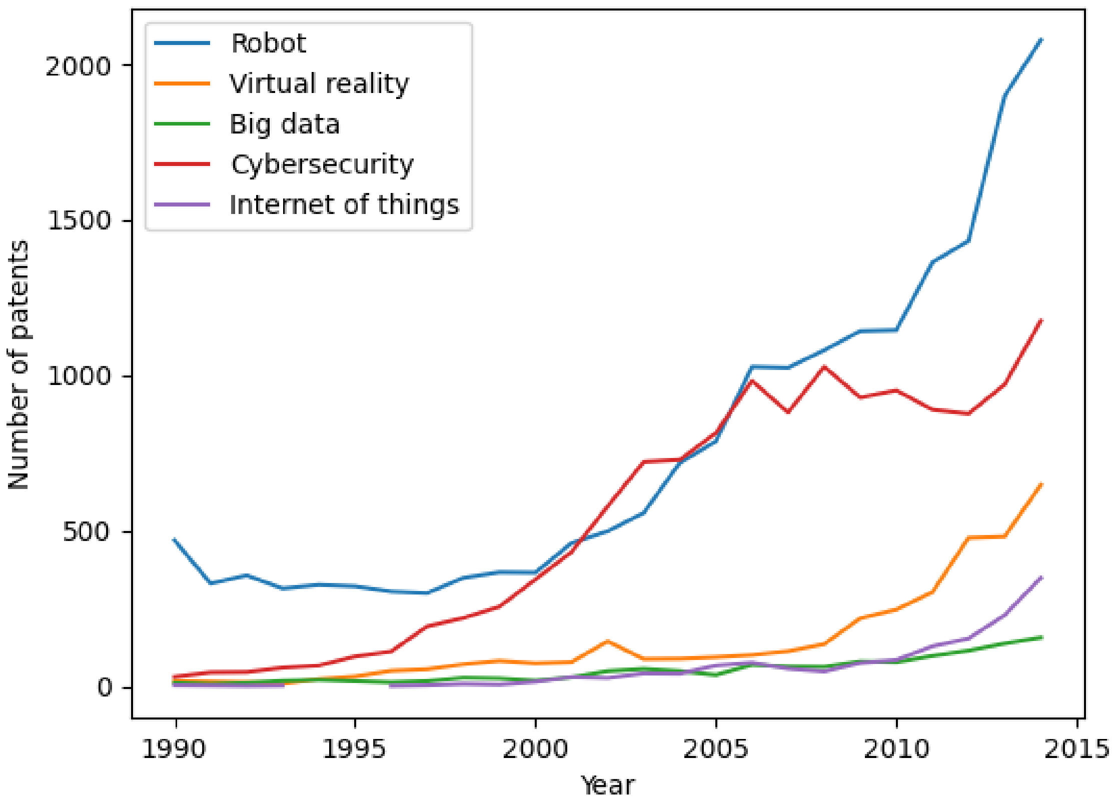
[13]The survey sample is stratified by size, sector, geographical area and the legal status of firms.

questions on the firms' decision to adopt each of the 4IR technologies mentioned above over the period 2015-2017. Accordingly, we construct five dichotomous variables that take the value of one if the firm invested in a specific technology domain over the period 2015-2017.

To measure technological progress in 4IR technologies at the global frontier, we use changes in the global stock of patents in the technologies of interest by industry. Starting from the Google Patent database, which contains over 140 million patents worldwide, we identify patents in 4IR technologies based on their Cooperative Patent Classification (hereafter CPC) codes. In particular, we use the classification provided by Ménière et al. (2020) to identify the CPC codes for big data, virtual and augmented reality and cybersecurity technologies, while we use the former U.S. patent classification (USPC) class *901* and the junction CPC group *Y10S901* to identify patents related to robotics. To identify CPC codes for IoT, we use the classification provided by IPO (2014) as well as other relevant groups sampled from the literature. We further refine the analysis through textual analysis, following the approach of Ménière et al. (2020); Martinelli et al. (2021). Among the patents found in the relevant CPC groups for each 4IR technology, we select only those that contain at least one of a set of predetermined keywords in either their title or abstract. All CPC codes and keywords used are reported in Table A1 in the Appendix. Then, duplicate patents are removed by keeping only patents with the earliest publication date among patents belonging to the same patent family and having the same (translated if necessary) title. Finally, in order to have a precise measure of the exposure of each industry to the new 4IR technologies, we count the number of new patents published between 2000 and 2014 for each ATECO industry at the 4-digit level using the concordance between the CPC and the International Standard Industrial Classification (ISIC) (itself matched with the NACE/ATECO classification) provided by Goldschlag et al. (2020). In total, we end up with 19,007 new patents on robotics, 1,245 new patents on big data, 3,638 new patents on virtual reality, 1,433 new patents on IoT, and 13,409 new patents on cybersecurity. The number of new patents by year of publication and by technology is shown in Figure 1. The number of new patents related to virtual reality, big data, IoT and cybersecurity has been increasing since the mid-90s, while the number of new patents related to robotics started to explode after 2000, after reaching a plateau in the 90s. As some patents could be classified in several technologies and this would make our classification less informative, we show in Table A2 in the Appendix that the proportion of common patents is negligible (i.e., always less than 1%).

To explore the extent to which firms' exposure to 4IR technologies at the global level affects their adoption and is moderated by leadership characteristics, we use specific information on firm leadership from the RIL. In particular, as anticipated in Section 2,

Figure 1: Evolution of new worldwide 4IR patents, 1990-2014



Notes: The figure shows the number of new patents, i.e., the flow of patents, over the period 1990-2014 for 4IR technologies.

we focus on gender, age, and education of the firm's leader, as well as whether he or she belongs to the family that owns the firm and his or her remuneration scheme (with or without a variable component).

To reduce simultaneity issues, we exploit the panel component of RIL by using the previous wave (2015) to construct the above variables as well as other firm-related controls. Although this leads to a significant reduction in the number of firms observed in both 2015 and 2018, this is common practice in previous work exploiting this representative database (see, for example, Cirillo et al., 2023a; Dosi et al., 2021).

We exclude from the sample firms that reported no activity in 2015, firms with less than 1 employee and firms with ATECO codes that are not included in the patent correspondence table. Furthermore, due to the nature of 4IR technologies, we restrict our sample to the following sectors: mining and quarrying; manufacturing; electricity, gas, steam and air conditioning supply; water supply, sewerage, waste management and remediation activities; construction; transport and storage; information and communication. After cleaning the dataset, the resulting (longitudinal) sample consists of 7,675 firms over

Table 1: Descriptive statistics

	Average	SD	Min	Max
Adoption of robotics	0.03	0.16	0.00	1.00
Adoption of virtual reality	0.04	0.21	0.00	1.00
Adoption of IoT	0.11	0.31	0.00	1.00
Adoption of big data	0.11	0.32	0.00	1.00
Adoption of cybersecurity	0.38	0.49	0.00	1.00
No. patents in robotics, log (2000-2014)	0.17	0.35	0.00	5.44
No. patents in virtual reality, log (2000-2014)	0.26	0.59	0.00	7.13
No. patents in IoT, log (2000-2014)	0.14	0.37	0.00	6.84
No. patents in big data, log (2000-2014)	0.19	0.40	0.00	4.46
No. patents in cybersecurity, log (2000-2014)	0.51	1.04	0.00	8.12
Leader's gender - female	0.14	0.35	0.00	1.00
Leader's relationship - family	0.82	0.39	0.00	1.00
Leader's age - 50+	0.70	0.46	0.00	1.00
Leader's education - lower	0.12	0.33	0.00	1.00
Leader's remuneration - variable	0.46	0.50	0.00	1.00

Notes: Technology adoption variables cover the period 2015-2017, patent variables cover the period 2000-2014 and leader characteristics are based on 2015. The number of observation is 7675.

two years: 2015 and 2018. Descriptive statistics on the main variables used in the analysis are presented in Table 1.

3.2 Empirical models

To test our first hypothesis (H1), that is whether the probability of investing in a new digital technology increases with exposure to 4IR technological progress at the global frontier, we estimate the following baseline specification:

$$Tech_i^j = \alpha^j Pat_s^j + \beta^j X_i + \phi_n^j + \psi_r^j + \epsilon_i^j, \tag{1}$$

where $Tech_i^j$ is a dummy variable that takes the value one if firm i has adopted technology j in the period 2015-2017; Pat_s^j is the logarithm of the changes in the global stock of patents associated with technology j in industry s at the 4-digit level; X_i is a vector of firm-specific variables capturing leadership characteristics of firm i; ϕ_n^j and ψ_r^j are sectoral (at the 1-digit level following the ATECO classification) and regional (NUTS 2) fixed effects, respectively, to capture unobserved common factors. ϵ_i^j is the error associated with firm i and technology j. Sectoral and regional fixed effects are introduced to account for unobservable differences that may exist in technology adoption and global technological advances.[14]

To control for potential complementarities between 4IR technologies (Culot et al., 2020), we estimate a system of seemingly unrelated regressions (SUR). This estimation

[14] It is well known that the drivers of adoption depend on the characteristics of the sector and product market (such as the degree of competition, the availability of skilled workers and the cost of labour) in which the firm operates. For this reason, our empirical analysis includes both sectoral and regional fixed effects to explore the determinants of cross-firm variation in technology adoption within each sector and region.

takes into account that the decisions to adopt different 4IR technologies are not independent of each other at the firm level, i.e., $cov(\epsilon_i^j, \epsilon_i^{j'}) \neq 0$ for all pairs of technologies j and j'. To account for possible correlation across firms operating in the same industry and for the fact that changes in the global stock of patents for each technology are only available at the 4-digit industry level, we cluster the standard errors at the 4-digit industry level. This approach improves the efficiency of parameter estimation and leads to more robust inference.

This specification has several advantages. First, changes in the global stock of patents for each technology can be treated as exogenous, given the relatively modest contribution of Italian firms to the rapid increase of patents at the global level. The scope of technological opportunities in 4IR technologies at the global level has been hardly influenced by the production of technological innovations and patents in Italy. Second, although the system of equations allows us to take technological complementarities into account, the probability of adopting a given technology j depends mainly on changes in the stock of knowledge in that particular domain j: the main explanatory variable therefore varies between equations. As for the firm-specific variables, the controls and the interaction terms, we note that they are all calculated on the basis of lagged values, thus avoiding simultaneity problems at the firm level.

This functional form has a limitation in that it imposes the same coefficient α_j on technology j for all firms in the same industry. This amounts to assuming that the ability of firms to scan and identify opportunities from the global stock of knowledge is homogeneous across firms, while it varies across 4IR technologies. This would contradict the second pillar of our conceptual framework, where heterogeneity in adoption across firms is associated with different levels of ACAP. To test whether firm heterogeneity in receptivity to the evolution of global knowledge is related to leader characteristics (hypotheses H2a-H2e), we extend the baseline specification in equation 1 with various interaction terms and estimate the following model:

$$Tech_i^j = \gamma^j Pat_s^j + \delta^j X_i + \zeta^j Pat_s^j * X_i^L + \eta_n^j + \mu_r^j + \varepsilon_i^j, \tag{2}$$

where η_n^j and μ_r^j are, respectively, sectoral (at the 1-digit level according to the ATECO classification) and regional (NUTS 2) fixed effects to capture unobserved common factors. The matrix X_i^L contains the five leader characteristics introduced in the previous section and is a subset of the controls in X_i.

We recall that leader characteristics may have a direct effect on technology adoption, in addition to their moderating effect on absorptive capacity. To capture this dual role in technology adoption, leader characteristics enter the equation both linearly (as part of X_i) and interacted with the changes in the global patent stocks. The estimated parameter ζ^j allows us to capture how ACAP varies across firms (within each sector and each technology domain) due to differences in their leadership characteristics. ε_i^j is the error associated with firm i and technology domain j and, as above, we assume that $cov(\varepsilon_i^j, \varepsilon_i^{j'}) \neq 0$. As before, we cluster the standard errors at the 4-digit industry level.

Of course, leadership characteristics are only some of the direct determinants of technology adoption. Therefore, following the empirical literature, we include regional and sectoral fixed effects and other firm-level variables, such as firm size and firm age, that previous studies have shown to be significant determinants of technology adoption. These additional factors, which are likely to have a direct effect on the probability of adopting a 4IR technology, are included as controls in the robustness checks. Given our focus on the moderating effects of leader characteristics on ACAP, we do not discuss them in detail.

Indeed, in our main estimations we will not include all types of firm-level variables. As these variables may be influenced by the covariates of interest (e.g., firm size may be correlated with leaders' education), they could be considered as 'bad controls'.[15] Accordingly, the estimates including the full list of additional firm-level controls are only presented in the Appendix. It is reassuring to note that their inclusion does not significantly alter our main findings.

4 Results

4.1 The scope of opportunities across technology domains and industries

We begin by presenting and discussing the results for the first hypothesis we test, i.e., H1. We refer to our baseline specification, equation (1), which includes our measure of the changes in the global stock of technological knowledge and leadership characteristics among the covariates (together with regional and sectoral fixed effects), without any interaction terms. The estimates are reported in Table 2.

The estimates suggest that firms are more likely to adopt a 4IR technology in those industries where the global stock of technology-specific patents increases. These results confirm the intuition in the first pillar of our conceptual background: technology adoption at the firm level depends on the scope of industry-specific technological opportunities at the global level. To provide a quantitative assessment, the estimates show that a 10

[15] In recent empirical work, firm size and firm age emerge as significant direct determinants of technology adoption (see, for example, Cho et al., 2023; Cirillo et al., 2023b; Kinkel et al., 2022; Muller et al., 2018) because they subsume various unobserved size- and age-related factors associated with organizational policies and project management capabilities that act as either barriers or enablers of technology adoption (Ariss et al., 2000; Dosi, 1988; Horvath and Szabo, 2019; Miller and Roth, 1994). This suggests that these variables may also reflect leader characteristics.

Table 2: Determinants of 4IR technology adoption

	Robotics	Virtual reality	IoT	Big data	Cybersecurity
No. patents, log (2000-2014)	0.012***	0.008***	0.023***	0.017***	0.020***
	(0.004)	(0.003)	(0.006)	(0.007)	(0.006)
Leader's gender - female	-0.029***	-0.014**	-0.020*	-0.028***	-0.051***
	(0.009)	(0.006)	(0.011)	(0.010)	(0.018)
Leader's relationship - family	-0.042***	-0.028***	-0.051***	-0.071***	-0.150***
	(0.013)	(0.008)	(0.012)	(0.015)	(0.018)
Leader's age - 50+	0.003	-0.005	-0.017**	-0.004	0.019
	(0.008)	(0.004)	(0.007)	(0.007)	(0.016)
Leader's education - lower	-0.024***	-0.008**	-0.037***	-0.034***	-0.092***
	(0.008)	(0.004)	(0.008)	(0.007)	(0.016)
Leader's remuneration - variable	-0.023***	-0.007	-0.010	0.001	-0.026**
	(0.007)	(0.004)	(0.007)	(0.006)	(0.011)
Observations	7675	7675	7675	7675	7675
Region FE	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes

Notes: The estimates are based on Seemingly Unrelated Regressions. The dependent variable in each column is the adoption of the corresponding technology. The variable *"No. patents, log (2000-2014)"* is equation-specific and corresponds to the logarithm of the change in the worldwide stock of patents between 2000 and 2014 in each technology at the 4-digit industry level. Leader characteristics include gender, whether the leader is a member of the family owning the firm, age, education and remuneration scheme. The estimated covariance terms are: cov(robotics, virtual reality) = 0.007, cov(robotics, IoT) = 0.021, cov(robotics, big data) = 0.016, cov(robotics, cybersecurity) = 0.024, cov(virtual reality, IoT) = 0.008, cov(virtual reality, big data) = 0.008, cov(virtual reality, cybersecurity) = 0.013, cov(IoT, big data) = 0.022, cov(IoT, cybersecurity) = 0.032, cov(big data, cybersecurity) = 0.026. Standard errors clustered at the 4-digit industry level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

percent increase in the change in the stock of patents related to robotics leads to a 0.12 percentage point increase in the probability of adopting robots. The increase is equal to 0.17 percentage points for big data, 0.2 percentage points for cybersecurity and 0.23 percentage points for IoT. A smaller impact is found for virtual reality (0.08 percentage points). Thus, these results suggest that it remains important to consider the evolution of the global stock of technological knowledge in order to assess the degree of diffusion of a given technology in the economy. This finding supports the relevance of supply-side factors in the technology diffusion process: the greater the increase in the stock of knowledge, the greater the scope of opportunities to scan, the greater the probability that some investments will be made in the acquisition of externally produced new technology.

These results are robust to two alternative specifications that we explore. First, we show that excluding leadership characteristics from the covariates does not affect the results (Table A3 in the Appendix). Given that the explanatory variable of interest varies across industries, this suggests that there is no correlation between the average characteristics of leaders in a given industry and the global development of 4IR patents in that industry. Second, although changes in the global stock of patents in a given technology domain and industry can be treated as exogenous to the individual firm, we estimate an additional specification that includes additional controls that influence technology adoption at the firm level to limit issues of omitted variable bias (Table A4 in the Appendix). We include the logarithm of firm size (in terms of employees and plants) and the logarithm of firm age because the literature has shown that these firm-level characteristics capture a number of unobserved factors that affect innovation and, presumably, technology adoption. In addition, we include a set of variables related to firm ownership, on-the-job training and employment composition. However, as these covariates may be influenced by our variables of interest, there is a risk that they are bad controls. For this reason, we do not treat the most extended specification as our baseline, as we have anticipated earlier. Nevertheless, our estimates of interest are robust to the inclusion of all these controls.

In addition, we examine the robustness of our results with respect to a change in the period over which patents were published. It could be argued that, especially in new technology domains, the depreciation of knowledge over time reduces the importance of older patents (de Rassenfosse and Jaffe, 2018). In such a case, only the most recent set of innovations would be worth considering. Instead of an interval of 10 years (i.e., 2000-2014), we consider a shorter interval of 5 years (i.e., 2010-2014). This robustness check leads to similar results with generally stronger estimated effects (Table A5 in the Appendix).

4.2 Direct and moderating effects of leader characteristics

Before illustrating the moderating effect of leader characteristics on technology adoption, we illustrate the direct role of these characteristics on the likelihood of adopting 4IR technologies. As previous studies have mainly focused on the direct, rather than indirect, effects of these characteristics, this will help us to compare our findings with others.

Regarding the education of the leaders, estimates show that firms with leaders who have not completed upper secondary (including vocational) education or tertiary education are less likely to adopt new digital technologies, especially in cybersecurity and big data. Higher education is often associated with greater ability to process complex information and deal with uncertainty, which are two important antecedents of innovation and technology adoption (Koellinger, 2008).

A consistent result across all the technologies we consider is that firms with leaders who are members of the family that owns the firm are less likely to adopt technological innovations. This is consistent with the literature showing that family firms face greater difficulties in responding to innovation (De Massis et al., 2013; Heider et al., 2022; Konig et al., 2013). For example, firms owned by a controlling family may have distinctive authority structures and internal norms that reduce the propensity to invest in new technologies. Moreover, leaders in these firms may seek to avoid perceived threats to their socio-emotional wealth, such as those associated with the adoption of new technologies.

The gender dimension plays a role in most technology domains, although it is only marginally significant for IoT: firms with female leaders are less likely to adopt 4IR technologies, ceteris paribus. As anticipated, it is difficult to identify the ultimate causes (e.g., self-selection, nurture, nature) of gender differences in leader attributes that affect innovation, such as risk tolerance and self-confidence. However, several (though not all) analyses in the literature have reported significant differences between female- and male-led firms in terms of their propensity to innovate. Exposito et al. (2023) find that this is particularly true when it comes to process innovation.

On the other hand, the age of the leader is not a relevant direct antecedent of technology adoption: firms led by older leaders do not show a systematically different propensity to adopt new digital technologies, except for IoT, where a negative effect is found. This could be explained by the reluctance of older leaders to take on IoT projects, which historically have a relatively high failure rate (75% according to CISCO).[16]

Having a leader with variable remuneration does not affect the likelihood of adopting 4IR technologies, with the exception of robotics and cybersecurity. This finding is consistent with the results of Scoresby et al. (2021), who find that CEO variable compensation schemes may reduce the incentives to invest in medium/long-term impact activities, thereby negatively moderating the relationship between CEO promotion focus and R&D spending.

The previous discussion relates to the direct relationship between leader characteristics and technology adoption. Next, we turn to the moderating effects of leaders, which is one of the main contributions of our paper to the literature. This is explored by estimating equation (2), which allows us to identify how leader characteristics affect how firms explore and are receptive to the scope of technological opportunities at the global level, and thereby adopt new technologies. This is the core of the second pillar of our conceptual framework. The results are reported in Table 3.

The estimates suggest that the relevance of leader-related moderating factors varies across technology domains. While firms' ACAP is significantly affected by most leader characteristics in the case of robot adoption, few significant interactions are found for the other 4IR technologies. It follows that the available evidence neither clearly rejects nor

[16]Several works, such as Yim and Kang (2024), find that younger CEOs are, in general, more likely to participate in firm innovation. Yet, innovation is a concept broader than technology adoption. As explained, age can be correlated with lower risk-taking attitudes (hindering adoption) and with greater experience in scanning the scope of technological opportunities (favoring adoption).

Table 3: Determinants of 4IR technology adoption. The moderating effect of leaders

	Robotics	Virtual reality	IoT	Big data	Cybersecurity
No. patents, log (2000-2014)	0.013***	0.008**	0.022***	0.018**	0.019***
	(0.004)	(0.003)	(0.006)	(0.007)	(0.006)
Leader's gender - female	-0.013	-0.014*	-0.021*	-0.024**	-0.056***
	(0.009)	(0.007)	(0.012)	(0.011)	(0.020)
Leader's gender × No. patents, log	-0.011**	0.001	0.003	-0.009	0.008
	(0.005)	(0.008)	(0.014)	(0.013)	(0.014)
No. patents, log (2000-2014)	0.025***	0.013*	0.020*	0.043**	0.030***
	(0.008)	(0.008)	(0.011)	(0.018)	(0.011)
Leader's relationship - family	-0.013	-0.024**	-0.053***	-0.054***	-0.141***
	(0.014)	(0.009)	(0.014)	(0.015)	(0.022)
Leader's relationship × No. patents, log	-0.015**	-0.006	0.003	-0.031*	-0.011
	(0.007)	(0.008)	(0.011)	(0.017)	(0.013)
No. patents, log (2000-2014)	0.013***	0.012**	0.016**	0.025**	0.019**
	(0.005)	(0.006)	(0.008)	(0.012)	(0.008)
Leader's age - 50+	0.005	-0.002	-0.021***	0.001	0.019
	(0.008)	(0.005)	(0.008)	(0.007)	(0.018)
Leader's age × No. patents, log	-0.001	-0.006	0.009	-0.011	0.001
	(0.004)	(0.007)	(0.009)	(0.011)	(0.008)
No. patents, log (2000-2014)	0.012***	0.009***	0.025***	0.020***	0.022***
	(0.004)	(0.003)	(0.007)	(0.007)	(0.007)
Leader's education - lower	-0.019**	-0.004	-0.031***	-0.026***	-0.083***
	(0.008)	(0.005)	(0.008)	(0.008)	(0.018)
Leader's education × No. patents, log	-0.003	-0.008	-0.015	-0.024**	-0.014
	(0.004)	(0.006)	(0.012)	(0.010)	(0.011)
No. patents, log (2000-2014)	0.015***	0.004	0.016***	0.013**	0.020***
	(0.004)	(0.003)	(0.006)	(0.007)	(0.005)
Leader's remuneration - variable	-0.012*	-0.011**	-0.018***	-0.003	-0.026**
	(0.007)	(0.005)	(0.007)	(0.007)	(0.012)
Leader's remuneration × No. patents, log	-0.006*	0.008	0.017**	0.009	-0.000
	(0.004)	(0.007)	(0.008)	(0.010)	(0.010)

Notes: The estimates are based on separated Seemingly Unrelated Regressions. The dependent variable in each column is the adoption of the corresponding technology. The variable *"No. patents, log (2000-2014)"* is equation-specific and corresponds to the logarithm of the change in the worldwide stock of patents between 2000 and 2014 in each technology at the 4-digit industry level. Leader characteristics include gender, whether the leader is a member of the family owning the firm, age, education and remuneration scheme. Standard errors clustered at the 4-digit industry level are reported in parentheses. The number of observation is 7675. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

fails to reject our hypotheses. Therefore, a domain-specific discussion is preferable.

The relatively more important role of leader characteristics as moderating factors of ACAP in the case of robotics can be explained by the transformative nature of this technology. Previous contributions on the impact of robotics on firms' activities have generally shown that firms adopt robots to improve the quality and variety of their products. The adoption of robots is, thus, linked to medium- to long-term objectives that go beyond achieving greater efficiency in production. Thus, the adoption of robots may be influenced by the incentives of leaders, which are related to the exploitation (i.e., realized ACAP), rather than the mere recognition, of the scope of opportunities offered by new technologies. This helps to explain why, in the case of robotics, we cannot reject hypotheses H2c, H2d, H2e, which better reflect the exploitative side of absorptive capacity (Zahra and George, 2002; Muller et al., 2021). Less important are those characteristics of leaders that are associated with the purely explorative side of absorptive capacity. Indeed, we reject hypotheses H2a and H2b, as leaders' education and age do not appear as significant moderating factors of ACAP in the case of robotics.

As for the other 4IR technologies, we find significant moderating effects only in a few cases. Having a leader who is a member of the family that runs the firm significantly reduces ACAP in the case of big data, while the evidence rejects the hypothesis in the other technology domains. The importance of firm ownership in the case of big data can be explained by the fact that the adoption of big data analytics requires a high level of awareness (Lycett, 2013), which is largely absent in family firms. Moreover, as big data helps to transform the business model and the management strategies of firms (Fosso Wamba et al., 2015), the ability and incentives to explore and exploit its possible applications may be lower in conservative family firms. As pointed out by Arzubiaga et al. (2021), the tendency of family firms to protect their socio-economic wealth may reduce their willingness to explore and implement opportunities related to big data.[17]

The negative coefficient associated with lower education suggests that the explorative side of ACAP is also affected in the case of big data, as firms with less educated leaders may be less able to scan available technological opportunities. These results suggest that both the explorative and exploitative sides of absorptive capacity (Zahra and George, 2002) are affected by leader characteristics in the case of big data, as suggested by (Muller et al., 2021).

The last significant moderating factor is the leader's remuneration scheme in the IoT technology domain. The estimated coefficient of the parameter for the interaction term is positive and statistically significant. This implies that firms with leaders who receive a variable remuneration scheme are more likely to invest in IoT than the other firms. This result is in contrast with our hypothesis, but can be explained by the fact that variable compensation schemes are expected to be positively associated with innovative strategies aimed at achieving positive results in the short term and negatively associated in the medium/long term. While the adoption of robotics is a transformative investment that ultimately allows a company to expand its activities and the quality of its products (and a negative correlation with a variable remuneration scheme is expected and found),

[17] An alternative explanation is that firms whose leaders are members of the family that owns the firm are less likely to reach a scale of operation that requires the adoption of big data technologies. Admittedly, it could be argued that the characteristics of the leader in this interpretation would mainly proxy for a characteristic of the firm. The effect of family ownership can also be explained through the lens of poor management quality (Bloom and Van Reenen, 2010).

the adoption of IoT is more likely to be associated with attempts to improve efficiency through real-time tracking, which is consistent with leaders having remuneration schemes that favour short-term objectives.

5 Discussion

Our analysis aims to capture leadership-related antecedents of technology adoption that have a dual (direct and indirect) impact on technology adoption. Our reference to the concept of ACAP is based on the idea that technology adoption requires firms to be able to scan the stock of external technological knowledge and to identify the opportunities to invest in externally produced technological products. In their seminal works, Cohen and Levinthal (1989) and Cohen and Levinthal (1990) refer to as ACAP as the ability of the firm to scan the scope of technological opportunities outside the firm (i.e., potential ACAP, according to Zahra and George, 2002) as well as the capacity to exploit them in the firm's innovative efforts (i.e., realized ACAP, according to Zahra and George, 2002). The exploitative component refers to the ultimate goal of the firm, i.e., the introduction profitable innovations. In our work, we do not limit the analysis to the adoption of technologies that affect firm innovation. Rather, our study focuses on the technology diffusion, which is determined by the adoption of technologies acquired outside the firm. Thus, in line with the literature on technology adoption, we interpret ACAP as the firm's ability to scan the scope of technological opportunities and identify those of interest with a view to investing in the acquisition of externally produced advances, regardless of whether these are ultimately intended to produce innovations.

It could be argued that technology adoption itself is a means of strengthening the firm's capacity to absorb external knowledge in order to innovate (Kastelli et al., 2022). This interpretation of investment in digital technologies would turn our analysis into a study of the relationship between two sources of potential and realized absorptive capacity: leader characteristics and firms' technological investment. Since investment in the purchase of hardware and software products is different from investment in internal R&D and workers' training, we do not consider investment in 4IR technologies as a mere means of strengthening the realized ACAP that facilitates firm innovation. Rather, as Rey et al. (2021) and others, we argue that technology adoption through investment in externally purchased products represents a distinct channel in the diffusion of a global technology: information transfers occur before, and even in the absence of, firm innovations produced within the firm.

The introduction explained that we use the terms adoption and investment in technology almost interchangeably. We acknowledge that this juxtaposition is imperfect because technology adoption involves many activities (even internal R&D) in addition to the purchase of external technological products.[18] On the other hand, investment in technologically advanced products in the 4IR domains differ significantly from the usual acquisition of physical and working capital. It is no coincidence that the technological products for which the Italian authorities have increased the ordinary depreciation deduction since 2017 belong to selected equipment with a 4IR character. Therefore, we believe that, by focusing on investment in the acquisition of technological products, our analysis allows us to address a very important type of 4IR technology adoption.

Despite the use of fixed effects and lagged values of firm-level covariates, our estimates may still suffer from endogeneity problems. The main problem that could affect our results is related to the sorting of leaders across firms (Zhou et al., 2023), for example if firms that are more prone to adopt new technologies are led by certain types of leaders. Although possible, we believe that this risk is not too relevant. First, by controlling for industry fixed effects, we capture systematic differences in firm leadership and technology adoption at the industry level. Second, we estimate distinct moderating effects of firm leadership on adoption in each technology domain and find different results across domains; if within-industry sorting effects were particularly strong, we would have found more homogeneous estimates of the moderating role of firm leadership. Nevertheless, we interpret the results cautiously and avoid language that implies causality.

Finally, we note that our empirical analysis is based on a large representative survey of Italian firms. This prevents us from using qualitative research methods (such as semi-structured interviews with firm leaders and workers) and also from testing more detailed mechanisms through which leader characteristics may affect the adoption of 4IR technologies. While this is a limitation, the use of a large representative sample of firms allows us to provide quantitative results on an important, but understudied, aspect of firm heterogeneity, while differentiating across technology domains, industries and firms. Accordingly, our findings are novel and complement more qualitative studies, especially in the business literature.

6 Closing remarks

This paper empirically examines the factors influencing firms' adoption of 4IR technologies using firm-level data from Italy for the period 2015-17. Despite a rich literature focusing on innovation, the available evidence on the antecedents and moderating effects of technology adoption is much less developed. By exploring the firm-level heterogeneity

[18]For example, Agostini and Nosella (2019) distinguish between firms' investment in advanced manufacturing activities and the adoption of digital technologies, and study the relationship between the two.

in the relationship between 4IR technology adoption and the scope of technological opportunities within industries and technology domains, this paper aims to fill this gap in the literature.

Our empirical models allow us to distinguish two important dimensions of technology diffusion: the supply side, which is external to the firm and specific to the industry and technology domain, and the demand side, which is associated with firm-specific characteristics and their interaction. Thus, we explore multiple dimensions of the highly heterogeneous rates of technology adoption observed across technology domains, industries and firms (Acemoglu et al., 2022).

The empirical analysis is based on testing two sets of hypotheses for the two theoretical pillars developed in our conceptual framework.

The first pillar concerns the relationship between the probability of technology adoption and the scope of technological opportunities external to the firm, i.e., the extent of global advances in new 4IR technologies. Our evidence shows that technology adoption varies together with changes in the stock of patents related to a specific technology domain in the industry in which the firm operates. This finding confirms the importance of what happens outside the firm's boundaries in each technology domain, consistent with the idea that firms scan and choose the new technologies to adopt from the available scope of technological opportunities. Our analysis allows us to differentiate the technological opportunities at the 4-digit industry level for each technology domain, and our results suggest that part of the cross-industry differences in technology adoption can be explained by variation in global supply, that is, the industry-specific development path observed in global knowledge of each technology domain.

The second pillar of our analysis focuses on whether the characteristics of firm leadership moderate the relationship between the technological opportunities available to the firm and its innovative efforts. Our estimates show that the extent to which firms are receptive to global technological advances in their industry is highly heterogeneous, in part due to the differences in firm leadership. The analysis shows that, for any given level of global technological progress, the characteristics of firm leaders matter in shaping the likelihood that a firm will adopt a particular 4IR technology. First, for all technological domains, our estimates confirm previous findings that leader characteristics (i.e., gender, education, age, being a member of the family that owns the firm, and remuneration scheme) have a direct impact on the likelihood of adopting 4IR technologies. Second, in the case of robotics, IoT, and big data, we show that some leader characteristics (i.e., gender, education, being a member of the family that owns the firm, and remuneration scheme) moderate the absorptive capacity of new digital technologies. If the global technological advances in a technology domain and industry help to capture the observed cross-industry differences in adoption, the differences in leadership characteristics help to explain the heterogeneity observed across firms within each industry for each technology domain.

Interestingly, our estimates do not provide clear evidence on the moderating effects of leader characteristics on the capacity to absorb 4IR technologies. In fact, the estimated moderating effects vary considerably across technology domains. More specifically, we find that leader characteristics associated with the exploitative side of absorptive capacity (Zahra and George, 2002; Muller et al., 2021) appear as relevant moderating factors in the case of robotics. The other two technology domains where leader characteristics have a significant moderating effect are IoT (in the case of the remuneration scheme) and big data (in the case of education and family firms).

This variation in the relevance of individual moderating factors across technology domains suggests that it is important to differentiate between 4IR technologies when discussing their adoption. On the one hand, different characteristics of firm leaders affect the explorative side of absorptive capacity, while others affect the exploitative side Zahra and George (2002); Muller et al. (2021). On the other hand, firms may adopt technological novelties in certain technology domains (e.g., robotics) to improve the quality and variety of their products, whereas they may adopt innovations in other domains (e.g., IoT) to increase firm efficiency. If technological change is associated with different purposes in different domains, it is normal that the moderating effect of the different characteristics of firm leaders will have different relevance across domains.

Our findings are relevant to the lively debate on digital transition. The adoption of new technologies through the purchase of external products has been supported by a number of fiscal incentives in several countries. In Italy, for example, the authorities increased the ordinary depreciation deduction for investment in new selected industrial equipment with a 4IR character. As organizations transform to take advantage of the ever-expanding range of digital solutions available, this has a profound impact on firm performance. The heterogeneous timing and extent of technology adoption across firms can help determine long-term competitive advantage. To be successful, these publicly funded programs to stimulate technology investment need to be matched by motivated and aware leaders who are able to scan the scope of opportunities and identify those that are most appropriate for their firms.

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A Appendix

Table A1: Identification of patents

Technology	CPC classes	Keywords
Robotics	B25J19/0016, B25J7/00, B25J19/0079, B25J9/0093, B25J15/0253, B25J19/0012, G01B5/25, B25J9/1612, B65G47/90, B25J19/06, B25J18/025, B25J9/109, B23P19/102, B25J9/1065, H05K13/0408, B21D43/105, B25J9/107, B25J9/161, G05B19/4083, B25J19/0029, B25J19/002, G05B2219/45213, A61B2019/464, A47L2201/00, H01L21/6838, B23P19/105, B05B13/0431, A63H11/00, B62D57/032, A61B2019/2296, H01L21/681, B25J19/023, H01L21/67742, B25J15/0616, B25J17/0275, B25J9/042, G01L5/228, A61B19/2203, G05B19/427, A61B2019/223, B25J19/021, B25J9/026, G05D1/0255, G05B2219/45083, A61B2019/2292, A61F2002/701, B25J15/0491, G01N29/265, A61B19/5212, B25J9/14, B25J9/00, B25J9/1692, B05B13/0452, B25J17/0266, B25J9/04, B23K9/0956, B05B12/14, B23Q7/04, B25J15/0009, B25J9/101, A61B2019/2242, F22B37/003, B25J13/082, B25J15/04, B25J18/02, B25J9/1697, B25J15/0019, B25J9/08, B25J9/046, B25J17/0208, B25J13/084, B25J17/0258, G05B19/41825, B25J9/1671, H05K13/0413, G05B19/4207, B25J17/0241, G05D1/0272, B25J9/1682, A61B2019/5259, B25J9/102, B23Q3/002, B23Q1/38, B23K9/287, B25J15/02, G06N3/008, B25J9/1689, B25J19/0008, H01L21/68707, B25J9/06, B25J9/104, B25J15/00, B05B13/0292, B23K9/1274, B25J15/0206, B25J17/0283, B25J9/10, G05B19/425, B65G61/00, B23Q1/5462, B25J19/0025, B25J13/085, B25J19/063, G05B19/4182, G21C17/01, B23P19/12, A61B19/22, G05B2219/37572, B25J9/041, G05D1/0225, B25J9/0084, G01N27/902, G01B7/008, G05B19/416, B25J9/1045, B65G47/91, B25J9/045, A61B2019/2223, G05B19/42, G05B2219/45104, B25J9/023, B25J9/0081, B25J15/103, G05D1/0274, Y10S901	robot, cobot, [self driving, self-driving, driveless, autonomous, automated, automated guided, automated-guided, unmanned]*[cell, car, vehicle, automobile, aircraft, airplane, aeroplane, marine]

(continued)

Table A1 – continued

Technology	CPC classes	Keywords
Big data	A61B5/72-A61B5/7296, A61B6/581, A61B8/4472, A61B8/56-A61B8/565, A61B8/582, A63B24/00-A63B2024/0096, B05C11/10-B05C11/105, B60S5/02, B60S5/06, B60W10/00-B60W10/30, B60W30/00-B60W2030/206, B60W50/00-B60W50/16, B60W60/00-B60W60/007, B61L15/00-B61L15/02, B61L23/00-B61L23/34, B61L27/00-B61L27/04, B61L3/00-B61L3/246, B64C2201/12-B64C2201/128, B64C39/024, B64F1/228, B64F5/40-B64F5/45, B64F5/60, D06F33/00, E05C17/58, E21B44/00-E21B44/10, E21B47/00-E21B47/24, F01K13/02-F01K13/025, F01N11/00-F01N11/007, F01N2900/04-F01N2900/0422, F01N9/00-F01N9/007, F02C9/00-F02C9/58, F02D1/00-F02D41/408, F02K9/00-F02K9/978, F02N11/08-F02N2011/0896, F02N2200/00-F02N2200/14, F02P5/00-F02P5/1558, F03B15/00-F03B15/22, F03D17/00, F03D7/042-F03D7/048, F04B49/06-F04B49/065, F04B51/00, F04C14/00-F04C14/28, F04C28/00-F04C28/28, F04D27/00-F04D27/0292, F05D2270/00-F05D2270/71, F16D66/00-F16D66/028, F22B35/00-F22B35/16, F22B35/18, F22D5/00-F22D5/36, F23N5/00-F23N5/265, F24D19/10-F24D19/1096, F24F11/00-F24F11/89, F24S50/00-F24S50/80, F25B49/00-F25B49/046, F25D21/006, F25D29/00-F25D29/008, F25J1/0244-F25J1/0256, F28F27/00-F28F27/02, G03G15/00-G03G15/5095, G05B15/00-G05B15/02, G05B19/00-G05B19/427, G05B23/02-G05B23/0297, G05D23/00-G05D23/32, G06F11/22-G06F11/277, G06F11/30-G06F11/3495, G06F11/36-G06F11/3696, G16B5/00-G16B45/00, G16C20/00-G16C20/90, G16C60/00, G06K9/00-G06K9/82, G06Q10/04-G06Q10/047, G06Q10/06-G06Q10/067, G06Q50/10-G06Q50/265, G07C5/00-G07C5/12, G08G1/00-G08G1/22, H02J13/00-H02J13/0089, H04N17/00-H04N17/06, G06F17/18	online analytical process, multi-dimensional analytic, tensor, dimensionality reduction, reduce dimension, reducing dimension, multilinear subspace learn, massively parallel, clustered file system, big data, [cloud, parallel]*[comput, process], [data]*[capture, storage, mining, integration, lake, warehouse], [distributed]*[parallel architecture, file system, cache, data]
Virtual reality	A61B2017/00115-A61B2017/00128, A61B34/25-A61B2034/258, A63B71/06-A63B71/0697, A63F2300/00-A63F2300/8094, B60K35/00, B60K37/06, B64D45/00-B64D45/08, D06F34/28, G02B27/01-G02B2027/0198, G10L13/00-G10L2013/105, G10L15/00-G10L15/34, G10L17/00-G10L17/26, G10L19/00-G10L19/265, G10L21/00-G10L21/18, G10L25/00-G10L2025/937, G06F40/20-G06F40/58, G06T19/00-G06T19/20	data eyeglass, google glass, data spectacle, data display, display helmet, [head, wearable]*[mount, display], [augment, augmented, virtual, mixed, enhanced, mediated]*[reality, environment, world]

(continued)

Table A1 – continued

Technology	CPC classes	Keywords
IoT	G16Y, H04L29/08, H04L12/28, H04L29/06, G06F15/16, G05B19/418, H04W84/18, H04W4/00, G08C17/02, H04W72/04, H04B7/26, H04W4/70, Y02B70/3, Y02B90/20	iot, internet of thing, web of thing, internet of everything, ambient intelligence, ubiquitous comput, [car, vehicle, device, machine, peer]*[-, 2, to]*[car, vehicle, infrastructure, server, device, machine, peer, anything, something], [inter, connected, networked, smart]*[car, vehicle, device, machine, grid, home]
Cyber security	G06F21/00-G06F21/88, H04L63/00-H04L63/308, H04L9/00-H04L9/38, H04W12/00-H04W12/128	cybersecurity, access control, cryptography, encryption, firewall, mobile secure gateway, secure sockets layer, [it, information technology, information-technology, application, app, computer, data, information, endpoint, end-point, cyber, transport layer, transport-layer, cloud]*security, anti*[virus, malware, spyware]

Table A2: Overlapping patents

	Robotics	Virtual reality	IoT	Big data	Cybersecurity
Robotics	-	0.0001	0	0.0001	0.0002
Virtual reality	0.0005	-	0	0	0.0008
IoT	0	0	-	0.0007	0.0042
Big data	0.0016	0	0.0008	-	0.0024
Cybersecurity	0.0002	0.0002	0.0004	0.0002	-

Notes: The table indicates the proportion of patents included in the 4IR technologies in each row that are also included in the 4IR technologies in each column.

Table A3: Determinants of 4IR technology adoption, no controls

	Robotics	Virtual reality	IoT	Big data	Cybersecurity
No. patents, log	0.013***	0.008***	0.024***	0.020***	0.024***
	(0.004)	(0.003)	(0.006)	(0.007)	(0.007)
Observations	7675	7675	7675	7675	7675
Region FE	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes

Notes: The estimates are based on Seemingly Unrelated Regressions. The dependent variable in each column is the adoption of the corresponding technology. The variable *"No. patents, log (2000-2014)"* is equation-specific and corresponds to the logarithm of the change in the worldwide stock of patents between 2000 and 2014 in each technology at the 4-digit industry level. The estimated covariance terms are: cov(robotics, virtual reality) = 0.007, cov(robotics, IoT) = 0.021, cov(robotics, big data) = 0.016, cov(robotics, cybersecurity) = 0.026, cov(virtual reality, IoT) = 0.008, cov(virtual reality, big data) = 0.008, cov(virtual reality, cybersecurity) = 0.014, cov(IoT, big data) = 0.022, cov(IoT, cybersecurity) = 0.034, cov(big data, cybersecurity) = 0.028. Standard errors clustered at the 4-digit industry level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A4: Determinants of 4IR technology adoption, additional controls

	Robotics	Virtual reality	IoT	Big data	Cybersecurity
No. patents, log	0.009**	0.006**	0.017***	0.010*	0.012**
	(0.004)	(0.003)	(0.005)	(0.006)	(0.005)
Leader's gender - female	-0.011	-0.008	-0.004	-0.011	-0.024
	(0.009)	(0.006)	(0.010)	(0.009)	(0.016)
Leader's relationship - family	0.022*	-0.008	0.023	0.002	-0.034
	(0.014)	(0.010)	(0.015)	(0.014)	(0.022)
Leader's age - 50+	-0.012*	-0.008*	-0.024***	-0.010	-0.003
	(0.007)	(0.004)	(0.007)	(0.007)	(0.016)
Leader's education - lower	0.007	0.001	-0.006	-0.008	-0.033**
	(0.007)	(0.004)	(0.007)	(0.006)	(0.015)
Leader's remuneration - variable	0.002	-0.001	0.009	0.017***	0.015
	(0.007)	(0.004)	(0.007)	(0.006)	(0.011)
Firm - no. employees, log	0.044***	0.009***	0.038***	0.029***	0.070***
	(0.005)	(0.003)	(0.004)	(0.004)	(0.005)
Firm - age, log	0.006	-0.003	-0.015**	-0.007	-0.004
	(0.006)	(0.004)	(0.007)	(0.006)	(0.010)
Firm - no. plants, log	-0.005	-0.004	0.012	0.004	0.016
	(0.007)	(0.005)	(0.008)	(0.007)	(0.010)
Firm - belongs to a group	0.024*	0.008	0.042***	0.045***	0.050***
	(0.014)	(0.009)	(0.013)	(0.014)	(0.019)
Firm - owned by a family	0.028	0.000	0.001	-0.015	0.037
	(0.017)	(0.011)	(0.019)	(0.018)	(0.029)
Firm - owned by a financial comp.	0.047**	0.001	-0.003	0.002	-0.000
	(0.021)	(0.013)	(0.021)	(0.019)	(0.029)
Firm - performed capital op.	-0.009	0.029**	0.023	0.021	0.014
	(0.018)	(0.014)	(0.018)	(0.020)	(0.028)
Firm - provided training	0.018**	0.018***	0.031***	0.025***	0.082***
	(0.009)	(0.006)	(0.011)	(0.008)	(0.015)
Firm - financed training	-0.007	-0.010	-0.024**	-0.023***	-0.019
	(0.009)	(0.006)	(0.010)	(0.009)	(0.016)
Prop. of employees with low. sec. education	-0.041***	-0.009	-0.032***	-0.005	-0.074***
	(0.010)	(0.007)	(0.011)	(0.011)	(0.023)
Prop. of employees with tert. education	-0.010	0.030*	0.065**	0.127***	0.112***
	(0.025)	(0.018)	(0.028)	(0.026)	(0.038)
Prop. of employees with age < 25	0.037	0.018	0.064**	-0.005	0.033
	(0.025)	(0.014)	(0.027)	(0.023)	(0.054)
Prop. of employees with age [25,34]	-0.022*	0.000	0.018	0.004	0.009
	(0.013)	(0.013)	(0.014)	(0.013)	(0.029)
Prop. of employees with age > 50	-0.019	-0.008	-0.013	-0.040***	-0.018
	(0.012)	(0.010)	(0.013)	(0.014)	(0.028)
Prop. of employees with temporary contract	-0.020	-0.017*	0.002	-0.007	-0.032
	(0.022)	(0.010)	(0.023)	(0.019)	(0.042)
Prop. of employees in apprenticeship	0.022	-0.020	0.039	0.083**	-0.048
	(0.036)	(0.026)	(0.050)	(0.042)	(0.073)
Prop. of employees in freelance	-0.052*	0.021	-0.077***	0.021	-0.013
	(0.028)	(0.037)	(0.027)	(0.043)	(0.133)
Prop. of employees in part-time	0.012	-0.018**	0.033**	-0.002	-0.021
	(0.012)	(0.008)	(0.014)	(0.011)	(0.026)
Ratio of interim workers / total no. employees	0.236***	-0.022	-0.033	0.055	0.136*
	(0.071)	(0.021)	(0.047)	(0.047)	(0.075)
Prop. of female employees	-0.016	0.004	-0.015	-0.007	0.031
	(0.018)	(0.011)	(0.015)	(0.013)	(0.024)
Observations	7675	7675	7675	7675	7675
Region FE	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes

Notes: The estimates are based on Seemingly Unrelated Regressions. The dependent variable in each column is the adoption of the corresponding technology. The variable *"No. patents, log (2000-2014)"* is equation-specific and corresponds to the logarithm of the change in the worldwide stock of patents between 2000 and 2014 in each technology at the 4-digit industry level. Leader characteristics include gender, whether the leader is a member of the family owning the firm, age, education and remuneration scheme. The estimated covariance terms are: cov(robotics, virtual reality) = 0.006, cov(robotics, IoT) = 0.017, cov(robotics, big data) = 0.012, cov(robotics, cybersecurity) = 0.016, cov(virtual reality, IoT) = 0.007, cov(virtual reality, big data) = 0.007, cov(virtual reality, cybersecurity) = 0.011, cov(IoT, big data) = 0.018, cov(IoT, cybersecurity) = 0.024, cov(big data, cybersecurity) = 0.019. Standard errors clustered at the 4-digit industry level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A5: Determinants of 4IR technologies' adoption (patents 2010-2014)

	Robotics	Virtual reality	IoT	Big data	Cybersecurity
No. patents, log (2010-2014)	0.012***	0.008**	0.027***	0.021**	0.025***
	(0.004)	(0.003)	(0.007)	(0.009)	(0.008)
Leader's gender - female	-0.029***	-0.014**	-0.020*	-0.028***	-0.052***
	(0.009)	(0.006)	(0.011)	(0.010)	(0.018)
Leader's relationship - family	-0.042***	-0.028***	-0.051***	-0.071***	-0.151***
	(0.013)	(0.008)	(0.012)	(0.015)	(0.018)
Leader's age - 50+	0.003	-0.005	-0.017**	-0.003	0.020
	(0.008)	(0.004)	(0.007)	(0.007)	(0.016)
Leader's education - lower	-0.024***	-0.008**	-0.036***	-0.034***	-0.092***
	(0.008)	(0.004)	(0.008)	(0.007)	(0.016)
Leader's remuneration - variable	-0.023***	-0.007	-0.010	0.001	-0.026**
	(0.007)	(0.004)	(0.007)	(0.006)	(0.011)
Observations	7675	7675	7675	7675	7675
Region FE	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes

Notes: The estimates are based on Seemingly Unrelated Regressions. The dependent variable in each column is the adoption of the corresponding technology. The variable *"No. patents, log (2010-2014)"* is equation-specific and corresponds to the logarithm of the change in the worldwide stock of patents between 2010 and 2014 in each technology at the 4-digit industry level. Leader characteristics include gender, whether the leader is a member of the family owning the firm, age, education and remuneration scheme. The estimated covariance terms are: cov(robotics, virtual reality) = 0.007, cov(robotics, IoT) = 0.021, cov(robotics, big data) = 0.016, cov(robotics, cybersecurity) = 0.024, cov(virtual reality, IoT) = 0.008, cov(virtual reality, big data) = 0.008, cov(virtual reality, cybersecurity) = 0.013, cov(IoT, big data) = 0.022, cov(IoT, cybersecurity) = 0.032, cov(big data, cybersecurity) = 0.026. Standard errors clustered at the 4-digit industry level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.