

Technology adoption and upskilling in the wake of Industry 4.0

Mattia Pedota*, Luca Grilli, Lucia Piscitello

Politecnico di Milano, Department of Management, Economics, and Industrial Engineering
Via R. Lambruschini 4b, 20156, Milan, Italy

*corresponding author: mattia.pedota@polimi.it

Abstract

Understanding how Industry 4.0 (I4.0) technologies complement each other on one side, and human skills on the other, is an increasingly important concern for managers and policymakers alike: it is essential for the optimization of firm-level sociotechnical interactions as much as it is vital to smoothen the digital transition on a global scale. However, firm-level evidence on patterns of conjoint adoption of I4.0 technologies and their relationship with skills is still scant. The present work contributes to covering this gap by leveraging a large cross-sectional database of Italian firms. Distinguishing between digital and physical I4.0 technologies, we find that companies are primarily (though not exclusively) driven toward either the former or the latter category of technologies. Additionally, we find that both the adoption of digital I4.0 technologies and the adoption of physical ones lead to the upskilling of non-ICT employees alongside ICT-specialized personnel. However, small firms seem to be constrained in their ability to follow the same upskilling strategy as their larger counterparts. This may have key practical implications, especially in the context of recent industrial policies enacted at the European level.

Keywords: digitalization, fourth industrial revolution, industry 4.0, skills, technology, upskilling

1. Introduction

The Industry 4.0 (I4.0) phenomenon, often identified with the Fourth Industrial Revolution, is currently at the center of academic, managerial and institutional debates (EPO, 2017; OECD, 2017; Sung, 2018). Originally announced in 2013 as a German plan to modernize the industrial system (Xu, 2020), it now generally refers to the conjoint implementation of advanced digital and automation technologies like artificial intelligence, augmented reality, big data analytics, cloud computing, the internet of things, robots and 3D printing. Taken together, these technologies enable automation, flexibilization, human-machine interconnectivity and mass customization, leading to the emergence of innovative business models and smart factories (Kagermann, 2015; Osterrieder et al., 2020), with new skill requirements and far-reaching effects on the labor market (Ciarli et al., 2021; Felice et al., 2021; Frey and Osborne, 2017).

I4.0 technologies display remarkable dynamism and complementarity, but they have yet to become fully-fledged general purpose technologies, and their conjoint evolutionary pattern is still rather unpredictable (Martinelli et al., 2021). Although patent data indicate a general trend of convergence (EPO, 2017), it is still difficult to discern which I4.0 technological trajectories are truly interdependent and likely to form aggregate technological paradigms (Dosi, 1982; Pedota et al., 2021). In such a dynamic context, the ability by firms to benefit from the ongoing revolution requires skillful adaptation from a variety of perspectives. The mere adoption of I4.0 technologies may be a necessary but certainly not a sufficient condition to become competitive within the emerging paradigms. To this end, firms also need to anticipate the coevolution of I4.0 technological trajectories (Ciarli et al., 2021), reorganize factories and employees (Calabrese et al., 2020), improve coordination across organizational units (Horvath and Szabo, 2019), gather sufficient know-how (Cugno et al., 2021), overcome organizational resistance (Birkel et al., 2019) and endow themselves with complementary human skills (Kiel et al., 2017; Muller et al., 2018).

The latter factor has a remarkable practical relevance. I4.0 configurations may be framed as sociotechnical systems, where technologies and workers are complementary and interdependent (Neumann et al., 2020). Thus, the digital transition requires skills upgrading, as also testified by the “European Skills Agenda for sustainable competitiveness, fairness and resilience”, which proposes a series of measures aimed at supporting upskilling, reskilling, job-skill matching and lifelong learning (European Commission, 2020). However, despite the virtually unanimous consensus on the mutual complementarity of I4.0 technologies and the necessity of upskilling, several issues remain relatively unexplored. First, clearer boundaries should be set within the broad I4.0 cluster, based on technological characteristics, epistemological trends and adoption patterns. Second, it is still difficult to ascertain whether it is I4.0 as a whole that requires an upskilling of the workforce or, rather, a subcluster of technologies within it. Third, it is unclear whether I4.0 technologies require a selective upskilling only of part of the workforce, or a more holistic upskilling. Fourth, while some works suggest that small firms may be impaired in their ability to benefit from the I4.0 revolution (e.g. Horvath and Szabo, 2019; Zolas et al., 2021), we still lack an accurate understanding of the extent to which firm size plays a role in the adoption of different I4.0 technologies and the related upskilling of the workforce.

The present work contributes to covering these gaps by leveraging the “Survey on information and communication technology usage in enterprises - year 2018”, a cross-sectional database of 21,934 Italian firms taken from the Italian National Institute of Statistics (ISTAT). The database includes information about firm-level investments in six key I4.0 technologies, namely augmented reality, big data analytics, cloud computing, the internet of things, robots and 3D printing, and it also indicates whether firms have upgraded the ICT skills of ICT-specialized workers and/or non-ICT-specialized workers. Our analysis unfolds in two-steps. First, we perform an exploratory factor analysis on the firm-level adoption of the six technologies to identify possible patterns of conjoint adoption. The factor analysis yields a two-factor solution revealing two latent propensities to invest in digital or physical I4.0 technologies, respectively. Then, we run a bivariate probit model estimating a firm’s

likelihood of ICT upskilling, by distinguishing between ICT-specialized and/or non-ICT-specialized workers, as a function of such latent propensities and a set of control variables including firm size, industry, location and ICT intensity.

Our factor analysis confirms that I4.0 is a systemic phenomenon, with significant firm-level interrelations among all the six technologies considered. However, it also highlights firms' propensity toward either *digital* technologies, namely augmented reality, big data analytics and cloud computing, or toward *physical* technologies, namely robots and 3d printing, with the internet of things taking part in both categories coherently with its hybrid digital-physical status. Our analyses show that firms adopting I4.0 technologies (of any kind) have a greater relative tendency to upskill conjointly both ICT and non-ICT workers, rather than upskilling them selectively. Furthermore, our analyses align with the intuition that the tendency to adopt digital I4.0 technologies has a stronger association with the ICT upskilling of any part of the workforce than the tendency to adopt physical technologies. However, rather interestingly, we find that also the latter tendency is positively related to ICT upskilling, especially when it is directed toward the whole workforce. These results hold, with slight variations in magnitude, across medium and large enterprises. Interestingly, small firms constitute an exception, with digital and physical adoption propensities showing no stronger association with conjoint upskilling and no difference in the strength of their association with the upskilling of any part of the workforce (ICT vs non-ICT personnel).

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature on the topic. Specifically, Subsection 2.1 lays the theoretical background on technological complementarities and upskilling in general, while Subsection 2.2 focuses on the recent literature on the complementarities among I4.0 technologies and their relationship with human skills. Section 3 develops our empirical inquiry, presenting main results (Subsection 3.2) and supplementary analyses (Subsection 3.3) after a thorough description of the database and methodology (Subsection 3.1).

Section 4 concludes, discussing our findings in the light of extant literature and providing implications and future research directions.

2. Literature review

2.1. Technological complementarities and human skills

Technological change is one of the main engines of economic growth (Solow, 1956), but it is neither simple nor self-sufficient. Technologies often form complex systems where components are complementary (Brynjolfsson et al., 2018) and interdependent (Hughes, 1993; Rosenberg, 1979), and the architecture may matter more than its single building blocks. Such a complexity brings opportunities as well as challenges. On the one hand, the systemic nature of technology is reflected in the consolidation of concepts like combinatorial and architectural innovation, whereby mixing up technological components or subverting their overarching structure may reveal novel uses and properties (Arthur, 2009; Fleming, 2001; Henderson and Clark, 1990; Yoo et al., 2012). On the other hand, single components lagging behind in development may restrain the potential of the entire system they belong to (Bijker et al., 1987). Furthermore, functional complementarities, recombination potential and technical constraints extend beyond the level of technologies to the level of knowledge and heuristics, with know-how accumulation and learning effects playing a crucial role in the determination of adoption patterns (Martinelli, 2012). Technological interdependence may even translate into epistemological interdependence, with different technologies possibly giving rise to a new aggregate paradigm after a process of convergence (Pedota et al., 2021). These reasons, among others, underlie the frequent empirical observation of interdependencies in the adoption of technologies by firms (Battisti and Iona, 2009; Colombo and Mosconi, 1992; Wozniak, 1984).

Within systems of interdependent technologies, the human factor cannot be disregarded. Technological components do not only interact among themselves, but also with human skills. Dynamics of complementarity and substitution between technology and skills have been largely investigated both theoretically and empirically. According to the skill-biased technological change

hypothesis (Autor et al., 1998; Berman et al., 1994; Bresnahan et al., 2002), automation and computerization technologies complement high-skill workers and substitute for low-skill workers. A more recent hypothesis, routine-biased technological change (Goos et al., 2009, 2014), instead suggests that such technologies complement workers performing non-routine tasks, which tend to be at the opposite ends of the spectrum of skills (high and low). While informative at high levels of aggregation, the crude education-based distinction between high and low skills can be overcome with more fine-grained taxonomies of skills, recognizing cognitive and manual dimensions (Autor and Dorn, 2013); language, reasoning, vision and movement (Elliot, 2014); creative and social intelligence (Frey and Osborne, 2017). While the skill-biased and routine-biased hypotheses diverge on the focal determinant of complementarity, they both underline the necessity to couple technological advancement with adequate human resources.

2.2. The case of I4.0

These well-established facts seem to hold to an even greater extent in the case of I4.0 technologies. According to a recent categorization by the European Patent Office (2017), it is possible to distinguish between core technologies, enabling technologies and application domains in the realm of I4.0. Core technologies are basic functional constituents like advanced sensors, processors, adaptive databases and network protocols, and their combination forms the enabling technologies traditionally associated with I4.0, such as virtual reality, 3D printing, artificial intelligence and big data analytics. Such enabling technologies can be combined further to form new solutions into a variety of application domains, ranging from smart homes to autonomous driving and intelligent energy distribution networks. Examples are the combination of artificial intelligence with 3D printing to optimize production capacity and material selection (Valdivieso, 2020); the employment of internet of things-enabled cloud-based additive manufacturing platforms to support rapid product development (Wang et al., 2019); the conjoint use of augmented reality and robots to facilitate robot programming, thanks to the co-existence of a virtual robot model alongside the actual one (Karnik et al., 2021).

While there is no doubt on the dynamism and combinability of I4.0 technologies in general, more evidence is needed on which I4.0 technologies exactly complement each other and why. A related problem is understanding technical and epistemological similarities and differences within the I4.0 cluster. In an effort to evaluate whether the enabling technologies of I4.0 can be considered general purpose technologies (Bresnahan and Trajtenberg, 1995), Martinelli and colleagues (2021) provide some evidence in this direction, by estimating indicators of generality, originality and longevity for six I4.0 technologies based on patent data. They find that artificial intelligence, 3D printing, robots and the internet of things are more pervasive and original than cloud computing and big data analytics. They also find that cloud computing, big data analytics and artificial intelligence have similar industrial knowledge bases and are part of a stable pattern of joint development, diverging from 3D printing (which instead converges with robots). However, these results are not definite in highlighting technological complementarities in use at the firm level. Some micro-level evidence in this sense comes instead from a recent survey by the U.S. census bureau, finding that firms adopting advanced business technologies like robots and artificial intelligence often also implement cloud services and widespread digitization (Zolas et al., 2021). While most mechanisms of firm-level complementarity in adoption are theoretically clear, notably data-gathering technologies (e.g. the internet of things) fueling data-hungry technologies (e.g. artificial intelligence and big data analytics) (Javaid et al., 2021), their relevance in practice is still uncertain, calling for more empirical investigations at all levels of analysis.

Besides technological complementarities, the human factor is of paramount importance in the I4.0 context (Lorenz et al., 2015). Views concerning the labor markets are rather mixed (Ciarli et al., 2021): some are more pessimistic, forecasting the elimination of some jobs as a consequence of I4.0 (Acemoglu and Restrepo, 2019; Frey and Osborne, 2017; Korinek and Stiglitz, 2017); others are more optimistic, predicting the emergence of new jobs and the improvement of extant ones (Arntz et al., 2017; Autor and Salomons, 2018; Felten et al., 2019); others take a neutral perspective (Das et al., 2020; Nedelkoska and Quintini, 2018).

Conversely, there is a strong consensus on the need to bridge the skill gap and prepare the workforce for I4.0 (Galaske et al., 2017; Motyl et al., 2017; Ras et al., 2017; Schallock et al., 2018). While previous industrial revolutions prioritized physical resources like coal and oil, the fourth one prioritizes human and intellectual resources, to the point of spurring the emergence of new prospective educational paradigms such as the “open loop university” (Li, 2020). I4.0 entails the emergence of complex engineering problems, requiring the coupling of multidisciplinary teams and advanced computational software (Xu et al., 2018). One of the greatest obstacles to the effective implementation of I4.0 lies indeed in the complexity of the theoretical and practical expertise required, which is usually scattered among different employees (Xu, 2020). Given their digital constituents and their data-driven nature, I4.0 technologies need to be complemented by STEM skills like statistical knowledge, programming, coding, and the ability to cope with large amounts of data and innovative interfaces. In this respect, Pinzone et al. (2020) provide a comprehensive overview of the technical skills required by I4.0 in the subfields of operations management, supply chain management, product-service information management, data science management and IT-OT (i.e. information technology-operational technology) integration management. Other works convey a more boundary-spanning perspective, pointing to the necessity for cross-functional roles, broader skillsets and lifelong learning (Fisk, 2017; Onar et al., 2018). Furthermore, an increasing body of research is underlining the relevance of soft skills in the I4.0 era, including emotional intelligence, critical thinking, communication, leadership, and creativity (Ciarli et al., 2021; Deming, 2017; Maisiri et al., 2019; Pedota and Piscitello, 2022).

While this picture suggests the necessity for firms to endow themselves with adequate bundles of I4.0 technologies and human skills to remain competitive, much is still to be learnt on the characterization of such bundles. For example, while it would be tempting to lean toward a selective upskilling of the workforce based on the precise technical requirements of I4.0, the boundary-spanning nature and soft skill orientation of I4.0 point to the necessity of a more holistic upskilling (Hecklau et al., 2016). Firms are social contexts permeated by continuous multilevel interactions, facilitated and magnified

by the massive machine-machine, human-machine and human-human interconnectivity provided by advanced technologies. Thus, upskilling isolated portions of the workforce (notably ICT employees) may no more be sufficient in the I4.0 context. A concurrent upskilling of ICT and non-ICT employees may be necessary, constituting the embodiment of the systemic character of I4.0 technologies at the level of human resources.

To inquire into these issues, we perform an empirical investigation accounting for both the technological and the human side of I4.0, which are usually considered separately. First, we aim to understand the extent to which augmented reality, big data analytics, cloud computing, the internet of things, robots and 3D printing are conjointly adopted. Most importantly, we do not only look at pairwise correlations in adoption, but also capture patterns of conjoint adoption of multiple technologies, thus enhancing our understanding of I4.0 technological complementarities. Then, we investigate which patterns are most strongly associated with the ICT upskilling of different parts of the workforce: a selective ICT upskilling of ICT workers, a selective ICT upskilling of non-ICT workers, or the ICT upskilling of the whole workforce. This analysis informs us on the interaction between I4.0 and human skills. In both steps, we replicate the analysis on subsamples according to firm size, in order to test for possible differences in I4.0 technologies adoption and upskilling patterns across small, medium and large enterprises.

3. Empirical analysis

3.1. Description of the sample and methodology

The database¹ underlying our empirical investigation comes from a cross-sectional survey on information and communication technologies (ICT) developed in 2018 conjointly by Eurostat and ISTAT, the Italian National Institute of Statistics, in collaboration with the European Commission.

¹ Information on the database and the sampling procedure comes from the methodological note provided by ISTAT along with the questionnaire. The entire questionnaire can be found at the following link: <https://listarilevazioni.istat.it/>, under “società dell’informazione”.

The survey aims at providing a variegated ensemble of data about the adoption of ICT technologies in Italian firms with at least 10 employees. Such data include information about the presence and training of ICT workers, the use of e-commerce and social media, the use of electronic invoicing, the strategic determinants of digital transformation, and, most notably, the presence of investments in augmented reality, big data analytics, cloud computing, the internet of things, robots and 3D printing, both in 2016 and 2017. The reference population for the survey consists of Italian firms with at least 10 employees operating in any of the following sectors, according to the Italian ATECO classification: manufacturing (C); supply of electricity, gas, steam and air conditioning (D); water supply, sewerage and waste management (E); construction (F); wholesale and retail trade and repair of motor vehicles and motorcycles (G); transport and storage (H); accommodation and catering services (I); information and communication services (J); real estate activities (L); professional, scientific and technical activities (M, except division 75: veterinary services); rental, travel agencies and business support services (N); repair of computers and communications equipment (group 95.1 of section S: other service activities).

The whole sub-population of firms with at least 250 employees is included in the database, whereas firms with a number of employees between 10 and 249 have been sampled. The sampling method follows a stratified random logic whereby each observation belonging to a given stratum has the same probability of being selected. Strata are defined according to industry (at a predefined level of aggregation), number of employees (10-49, 50-99, 100-249) and geographical location. The total dimension of the sample is 21,934 firms. As a first step, we divided the sample into three categories based on firm size, distinguishing between 13,761 small firms, 4,716 medium firms and 3,457 large firms. To this end, we relied on the revenue criterion, using as reference thresholds those indicated

by the European Commission to recognize small and medium enterprises². Subsequently, we identified the following variables of interest:

- A binary variable taking the value of 1 if the firm engaged in the ICT upskilling of ICT workers in 2017, and 0 otherwise. The variable was generated from the following section of the questionnaire: “Indicate whether, in 2017, the company provided (directly or through external companies) any type of training aimed at developing or updating the ICT skills of its ICT-specialized employees (yes or no)”.
- A binary variable taking the value of 1 if the firm engaged in the ICT upskilling of non-ICT workers in 2017, and 0 otherwise. The variable was generated from the following section of the questionnaire: “Indicate whether, in 2017, the company provided (directly or through external companies) any type of training aimed at developing or updating the ICT skills of its employees without ICT skills (yes or no)”.
- A vector of six binary variables, each of which takes the value of 1 if the firm invested in the corresponding I4.0 technology in both years 2016 and 2017³, the six technologies being augmented reality, big data analytics, cloud computing, the internet of things, advanced robots and 3D printing.

Tables I and II provide a description of the sample with respect to these focal dimensions.

INSERT TABLE I ABOUT HERE

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INSERT TABLE III ABOUT HERE

² Referring to the EU recommendation 2003/361, we identified firms with revenues lower than or equal to 10 million as small firms, firms with revenues between 10 and 50 million as medium-sized firms, and the remaining firms as large ones.

³ We opted to consider investment in both years 2016 and 2017 as a proxy for adoption of each of the six I4.0 technologies in order to capture a more solid commitment to the technology. Given that the database lacks the extent of the investments, considering only 2017 or only 2016 would have entailed the risk of defining as adopters firms with minimal and/or sporadic investments.

Not surprisingly, firm size seems to play a definite role in the frequency of adoption of I4.0 technologies (see Table I). While most large firms and about one third of medium firms adopted at least one technology, the overwhelming majority of small firms did not adopt any of the six technologies in the dataset (12,161 out of 13,761 firms). Conversely, there is a high degree of uniformity in the patterns of adoption by adopting firms (see Table II). The most frequently adopted technology is cloud computing, constituting 60%, 49% and 41% of the total instances of adoption in small, medium and large firms, respectively. The internet of things follows, constituting 23% of total instances of adoption across all firm size categories. Big data analytics scores 10%, 13% and 16% in small, medium and large firms respectively, whereas augmented reality and 3D printing show a relatively low rate of adoption across all size categories (2% to 4%). Advanced robots are the only case where a significantly different pattern can be observed across size categories, as they constitute only 2% of total instances of adoption in small firms, as opposed to 9% and 13% in medium and large firms respectively. This may be due to medium and large firms being more skewed toward large-scale manufacturing and construction segments, where robots are more frequently used. It is also worth noting that, while cloud computing is the most frequently adopted technology across all size categories, it has a much higher relative frequency of adoption in small firms. This may be due to the technical characterization of cloud computing, which allows adopting firms to tap into external storage and computing capacity, a feature that is most valuable for small firms due to their relatively limited resources.

As for the ICT upskilling patterns, Table I provides some descriptive insights. There are relevant differences both between upskilling patterns of adopters vs non-adopters, and across firm size categories within adopters and non-adopters. Small firms tend to upskill the least, with 85% of non-adopters and 56% of adopters performing no ICT upskilling. Conversely, large firms upskill the most, especially the whole workforce as opposed to a part of it (27% of non-adopters and 49% of adopters upskill conjointly). Intuitively, there is a significantly lower proportion of non-upskilling firms in the adopters rather than in the non-adopter category, which holds across all firms sizes (56%, 47% and

25% as opposed to 85%, 70% and 47% in small, medium and large firms, respectively). The other tendency that varies significantly and uniformly between adopters and non-adopters is conjoint upskilling, with adopters performing it much more frequently than non-adopters, again across all firm size categories (18%, 25% and 49% as opposed to 3%, 10% and 27% in small, medium and large firms, respectively). On the contrary, patterns of selective upskilling are less uniform. Small adopting firms tend to selectively upskill ICT workers much more frequently (13% as opposed to 3%), and non-ICT workers slightly more frequently (12% as opposed to 9%), with respect to non-adopters of the same size. Medium adopting firms have a slightly higher selective upskilling frequency relative to non-adopters in both the ICT (11% vs 6%) and the non-ICT case (17% vs 14%). Large adopting firms have a slightly higher selective ICT upskilling frequency (15% as opposed to 11%) and, most interestingly, a lower selective non-ICT upskilling frequency (12% as opposed to 15%) with respect to non-adopters of the same size. This may suggest that the great tendency toward conjoint upskilling by large adopting firms (49% of large adopting firms have performed conjoint upskilling) eats away the propensity to upskill selectively non-ICT employees.

These insights are corroborated by the tetrachoric correlation matrix (Table III). Both the ICT upskilling of ICT workers and the ICT upskilling of non-ICT workers are negatively correlated with the small size category (-0.51 and -0.45, respectively) and positively correlated with the large size category (0.59 and 0.49, respectively), while being neutral with respect to the medium size category (0.08 and 0.13). Furthermore, each of the six technologies has at least a moderate positive correlation with both kinds of upskilling, with coefficients ranging from 0.34 to 0.51. This complements from a different angle the indication given by Table I: adopting firms have a stronger tendency toward ICT upskilling, and this holds for each of the six I4.0 technologies considered. A further insight emerging specifically from the tetrachoric correlation matrix (Table III) concerns the interdependencies in technology adoption by firms. All the six technologies are indeed interrelated at least moderately, with pairwise correlation coefficients ranging from 0.32 to 0.64. However, a subtlety that can already be appreciated from the matrix concerns the different magnitudes of the correlation. For example, big

data analytics has a much stronger correlation with cloud computing and augmented reality (0.64 and 0.61, respectively), rather than advanced robots and 3D printing (0.37 and 0.41, respectively). The latter two are instead strongly correlated among themselves (0.64). This evidence seems to resonate with the realization that big data and cloud computing have similar industrial knowledge bases, which diverge from robots and 3D printing (Martinelli et al., 2021). Overall, the correlation matrix indicates that patterns of conjoint adoption may be present. However, pairwise correlation coefficients on their own are not enough to spot them.

To this end, we conducted a factor analysis based on the correlation matrix among the six technologies in the dataset (leaving all the other variables aside). The Bartlett test of sphericity is significant at less than 1% and the Kaiser-Meyer-Olkin measure of sampling adequacy is 0.76, indicating the suitability of a factor analysis. We extracted two factors and applied the Varimax rotation technique to facilitate interpretation, identifying a latent propensity toward *digital* I4.0 technologies (i.e. augmented reality, big data analytics and cloud computing) and a latent propensity toward *physical* I4.0 technologies (i.e. robots and 3D printing) (more details on the interpretation of factor loadings are offered in the next Subsection). Then, we replicated the whole process on each subsample based on firm size (small, medium and large firms), identifying the same two propensities in all cases, with little variation in factor loadings. Factor loadings of the whole sample as well as each subsample are reported in Table IV.

INSERT TABLE IV ABOUT HERE

Subsequently, we calculated the scores on the two extracted factors⁴ for each observation and used them as the focal independent variables in a bivariate probit regression concurrently estimating the probability of upskilling ICT and non-ICT employees as a function of a set of regressors. Besides the

⁴ We rescaled the factor scores in the interval from 0 to 100 to facilitate interpretation of the marginal effects without affecting statistical significance.

two factor scores (i.e. digital and physical adoption propensities), we included the following controls as independent variables, at the highest level of detail provided by the database:

- A proxy for size. Besides segmenting the sample in three subsamples based on revenues, we used classes of revenues at a finer level of granularity as control variables within each subsample. While our three classes of size are widely (if not universally) adopted to segment firms according to their size, a higher level of granularity could offer better opportunities to control for potential confounding effects within each category.
- The geographic location. We used 4 binary variables to capture the location of the firm within Italy: Northeast, Northwest, Center, South and Islands. Location plays indeed an important role due to the stronger presence of key industrial clusters in the North of Italy as opposed to the South and the Islands. The absence of any control for that could possibly confound the relationship between upskilling and technology adoption propensity.
- The share of ICT workers employed by the firm. We used the percentage of ICT workers as a proxy for the degree of importance that ICT activities have within the firm. This is the most important confounder to control for, as it greatly affects both the probability of ICT upskilling and the propensity toward digital I4.0 technologies.
- Industry dummies. We used a vector of 11 binary variables to account for the sector each firm belongs to, according to the first level of aggregation of the ATECO classification: manufacturing (C); supply of electricity, gas, steam and air conditioning (D); water supply, sewerage and waste management (E); construction (F); wholesale and retail trade and repair of motor vehicles and motorcycles (G); transport and storage (H); accommodation and catering services (I); information and communication services (J); real estate activities (L); professional, scientific and technical activities (M, except division 75: veterinary services); rental, travel agencies and business support services (N); repair of computers and communications equipment (group 95.1 of section S: other service activities). Given the

presence of the share of ICT workers as a very effective control for ICT intensity, we regard this level of aggregation as sufficient.

We performed four different bivariate probit regression with the ICT upskilling of ICT workers and the ICT upskilling of non-ICT workers as the two dependent variables. One was performed on the whole sample, while the remaining three were performed on each subsample based on firm size. The four regressions do not differ in any aspect except for the factor scores, which are calculated separately according to the four different factor analyses based on the specific correlation matrix of each subsample⁵. After running each bivariate probit model, we computed the marginal effects of an increase in the factor scores capturing the *digital* and *physical* adoption propensities on each possible combination of outcomes: no ICT upskilling, selective ICT upskilling of ICT workers, selective ICT upskilling of non-ICT workers, and conjoint ICT upskilling. Finally, we ran two robustness checks and a supplementary analysis. First, we ran a multinomial logit model adopting the three aforementioned combinations of ICT upskilling as the dependent variables (i.e. selective ICT upskilling of ICT workers, selective ICT upskilling of non-ICT workers, and conjoint ICT upskilling) and the absence of upskilling as the baseline, keeping the same controls and focal independent variables (i.e. the two latent propensities). Second, we replicated the bivariate probit analysis by distinguishing between ICT and non-ICT firms, to check whether key results hold or differ across these categories. Finally, we employed an indirect strategy to deepen the “ICT upskilling” construct, by checking whether firms that had difficulty hiring ICT specialists from the outside were more or less likely to engage in the ICT upskilling of their ICT and/or non-ICT employees.

3.2. Main results

The first main result emerges from the factor analysis. As Table IV shows, augmented reality, big data analytics and cloud computing load heavily on the first factor, whereas 3D printing and robots

⁵ However, even using the same factor scores would not have produced significantly different results, as the factor loadings are similar across the four separate factor analyses (see Table IV).

load heavily on the second one. The remaining technology, the internet of things, has an average loading on both factors. This outcome offers a clear interpretation: the first and the second factor represent latent propensities to adopt *digital* and *physical* I4.0 technologies, respectively. Augmented reality, big data analytics and cloud computing are all characterized by a digital nature and high degree of immateriality: they are concerned with data elaboration and visualization, rather than object creation and manipulation. The opposite holds for 3D printing and robots, which are primarily used for manufacturing and moving physical objects. This interpretation is also coherent with the undetermined status of the remaining technology, the internet of things. Referring to the equipment of objects with intelligent sensors creating a bridge between the physical and the digital world, the internet of things is well-suited to represent a digital-physical hybrid having a comparable loading on both factors.

Another aspect worth underlining is the absence of low or negative loadings on either factor. This suggests that the existence of two well-defined propensities does not induce a polarization in adoption. In other terms, the propensity to adopt digital (physical) technologies does not limit the adoption of physical (digital) technologies. On the contrary, it can be argued that each propensity implies the other, though to a significantly lower extent. This reflects the positive bivariate correlations among all technologies (Table III), and it is coherent with the view of I4.0 as a systemic phenomenon, characterized by multidirectional complementarities (EPO, 2017). Such complementarities seem to be correctly pursued by firms through conjoint adoption, and some technologies tend to be adopted conjointly with a higher relative frequency, according to the two patterns we identified (i.e. digital and physical adoption propensities).

The associations between the two identified propensities and ICT upskilling are reported in the following tables. Table V reports the marginal effects of an increase in each factor's score on the probability of each outcome resulting from the bivariate probit analyses (for completeness, Table A1 in the Appendix also reports bivariate probit coefficients), while Table VI reports the Wald tests for

the difference in the coefficients of the two factors in the bivariate probit analyses. All results refer to the whole sample as well as each subsample based on firm size.

INSERT TABLE V ABOUT HERE

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First, both propensities have a negative, sizable and statistically significant relationship with the absence of upskilling (see Table V). This is true for all firm size categories. According to the marginal effect estimates, a 10-point increase⁶ in digital adoption propensity reduces by roughly 2.7%, 3.7% and 4.1% the probability of no ICT upskilling in small, medium and large firms, respectively. A 10-point increase in physical adoption propensity reduces by roughly 2.8%, 1.5% and 2.3% the probability of no ICT upskilling in small, medium and large firms, respectively. Delving into the specificities of the three combinations of upskilling, it is worth comparing the marginal effects of both propensities on the probability of conjoint upskilling as opposed to selective upskilling (see Table V). The propensity to adopt I4.0 technologies, whether physical or digital, correlates more strongly with conjoint ICT upskilling rather than selective ICT upskilling, at least in medium and large firms. A 10-point increase in digital adoption propensity augments by roughly 2.1% and 4.1% the probability of conjoint ICT upskilling in medium and large firms respectively, while it only augments by roughly 0.8% the probability of both kinds of selective ICT upskilling in medium firms, and it has an even smaller and less statistically significant effect on selective ICT upskilling in large firms (-0.4% to 0.4%). A marginal increase in physical adoption propensity augments by roughly 0.8% and 2.3% the probability of conjoint ICT upskilling in medium and large firms respectively, while it has a statistically insignificant effect on both kinds of selective ICT upskilling both in medium and large firms. Small firms constitute an exception, with the marginal effects of both propensities being highest on non-ICT upskilling rather than conjoint ICT upskilling (roughly 1.3% vs 0.8% and

⁶ 10-point increases are relative to a 0-100 scale (see footnote number 4). They are always calculated at the means of independent variables.

1.6% vs 0.7%, in front of a 10-point increase in digital adoption and physical adoption propensities respectively, as Table V shows). This may be due to the higher industrial specialization and more limited resources of small firms, which makes conjoint ICT upskilling a priori less likely (as also reflected in Table I) and the upskilling of non-ICT workers more urgent. Another potential reason may lie in the peculiarities of small firms' business models (we further elaborate on these hypotheses in the concluding section).

Taken together, these pieces of evidence imply that adoption of I4.0 technologies goes in tandem with ICT upskilling. Depending on industrial specificities, resource availability and firm-level idiosyncrasies, ICT upskilling may be directed toward either the whole workforce or a part of it, but it is in any case likelier than its absence. Furthermore, conjoint ICT upskilling appears to be the likeliest outcome for medium and large adopting firms, suggesting that I4.0 and human skills form indeed a complex sociotechnical system, where I4.0 technology adoption (whether digitally or physically oriented) should be ideally complemented by a holistic upskilling of the workforce.

Unsurprisingly, there is a difference in the magnitude and, in some cases, even the statistical significance of the digital adoption propensity marginal effects as opposed to the physical adoption propensity ones (see Table V). Digital adoption propensity almost always has a higher marginal effect on the probability of all kinds of ICT upskilling (for both ICT-specialized and non-ICT specialized personnel)⁷, the only exception being selective ICT upskilling of non-ICT employees in small firms⁸. In the case of medium and large firms, the physical adoption propensity marginal effects on selective ICT upskilling are not even statistically significant, besides being lower than their digital counterparts. A series of Wald tests for the difference in factor coefficients confirm that digital and

⁷ Please note that, in the case of “no upskilling”, the marginal effect of the digital adoption propensity is lower. However, being a negative marginal effect on the negative of upskilling, the direction is the same as in the other cases, from a conceptual viewpoint.

⁸ Strictly speaking, the magnitude is (slightly) lower also in the case of selective ICT upskilling by large firms. However, it should not be considered, as the physical adoption propensity coefficient is not statistically significant in that case.

physical adoption propensities are differently associated with the probability of ICT upskilling in all cases, except for small firms (see Table VI).

The stronger association between digital adoption propensity and ICT upskilling is not surprising, as digital technologies are by definition closer to the domain of ICT. However, intuition would suggest that, precisely for this reason, the consequent ICT upskilling would be directed mainly toward ICT employees, who are supposed to be the direct operators of digital technologies. Intuition would also suggest that, being farther from the ICT domain, physical technologies have no significant relationship with ICT upskilling, whether it be directed toward ICT or non-ICT employees. Instead, our results seem to suggest that both physical and digital I4.0 technologies require ICT skills and, most importantly, they require upskilling on the part of both ICT-specialized and non-ICT specialized personnel. In particular, for what concerns medium and large firms, physical adoption propensity relates positively and significantly only to the conjoint ICT upskilling of both ICT and non-ICT employees, and not to the selective ICT upskilling of either of the two. Leaving on the background small firms, which could simply be incapable of following the same strategy⁹, this result would not only imply that physical I4.0 technologies also require ICT skills, but it would even suggest that, taken together, they definitely require those skills on the part of both ICT and non-ICT employees. Overall, these findings seem to indicate that both digital and physical I4.0 technologies form a new language that requires ICT skills to be interpreted and transmitted. Besides strengthening the ICT skills of ICT employees, this language also requires endowing non-ICT employees with the necessary ICT skills to make sense of the new organizational reality together with their ICT-specialized colleagues.

⁹ Possible explanations may be the well-documented presence of greater financial constraints suffered by this typology of firm compared to larger counterparts (see e.g. Becchetti and Trovato, 2002; Beck and Demircuc-Kunt, 2006) or the higher specialization of a non-negligible number of start-ups and small firms (in terms of market and/or technology) (see e.g. the literature on Italian industrial districts, e.g. Becattini, 2004). We elaborate more on these possibilities in the concluding section, leaving the disentanglement between these (not necessarily alternative) or other motives to future research endeavors.

3.3. Robustness checks and supplementary analyses

To further test the results above through a different estimation method, we ran a multinomial logit model adopting “no upskilling” as the baseline outcome. As with the bivariate probit, we performed the analysis on the whole sample as well as each subsample based on firm size. Table A2 in the Appendix reports the marginal effects for each subsample (for completeness, Table A3 in the Appendix reports the multinomial logit coefficients as well). Although marginal effects slightly differ from those of the bivariate probit model (which is expected, given the different estimation method), their relative magnitude is the same. The only relevant difference between the two models concerns the levels of statistical significance, which are generally weaker in the multinomial logit. However, the two pictures are overall coherent and lead to the same conclusions. Specifically, the multinomial logit analyses confirm that both digital and physical adoption propensities are positively related to the probability of ICT upskilling, and that conjoint upskilling is the outcome most strongly associated with the propensity to adopt physical and digital technologies (except for small firms).

While this work features firm size as the main attribute for sample segmentation, and uses sectors as control variables, we also performed a supplementary analysis by segmenting the sample according to an industrial criterion rather than a dimensional one. The analysis exploits a key dichotomous variable distinguishing between ICT and non-ICT firms, where ICT firms are defined as belonging to industry 261, 262, 263, 264, 268, 465, 582, 61, 62, 631 or 951 according to the Italian Ateco classification (e.g. manufacturing of computers and electronic products, telecommunication, video production).¹⁰

We replicated the bivariate probit analysis described in the previous subsection on the two subsamples based on the ICT/non-ICT distinction, looking again at the marginal effects of digital and physical adoption propensities on the probability of each combination of ICT upskilling. Results are reported in Table A4 in the Appendix. In both ICT and non-ICT firms, both digital and physical adoption

¹⁰ Please check <https://www.codiceateco.it> for a detailed account of all the industries included.

propensities are negatively associated with the probability of not engaging in ICT upskilling (of any kind), although the absolute value of marginal effects in the ICT case is higher. Specifically, a 10-point increase in the propensity to adopt digital (physical) I4.0 technologies reduces by 5.2% (2.9%) the probability of not upskilling for ICT firms, while the same increase reduces that probability by 3.2% (2.3%) for non-ICT firms. As for selective upskilling, results align with intuition. As expected, the ICT subsample features a higher marginal effect on the probability of upskilling selectively ICT workers rather than non-ICT workers (1.6% vs -0.7% for the digital adoption propensity, and 1.6% vs -0.6% for the physical one (not statistically significant), as a result of a 10-point increase), while the non-ICT subsample features a higher marginal effect on the probability of upskilling selectively non-ICT workers rather than ICT workers (1.2% vs 0.6% for the digital adoption propensity, and 0.8% vs 0.4% for the physical one, as a result of a 10-point increase). However, for both ICT and non-ICT firms, it is conjoint upskilling that shows the strongest association with both digital and physical adoption propensities. For ICT firms, the marginal effect of the digital adoption propensity on conjoint upskilling is almost three times larger than the one on selective upskilling of ICT workers (4.3% vs 1.6%, as a result of a 10-point increase), while the marginal effect of the physical adoption propensity, besides being larger in magnitude (1.9% vs 1.6%), is statistically significant only in the case of conjoint upskilling. For non-ICT firms, the marginal effects of both digital and physical adoption propensities on conjoint upskilling are just slightly higher than the ones on selective upskilling of non-ICT workers (1.5% vs 1.2% for the digital and 1.1% vs 0.8% for the physical, as a result of a 10-point increase).

This analysis confirms and extends the main result of the previous section. Regardless of whether firms belong to ICT or not, the adoption of I4.0 technologies is significantly associated with the probability of upgrading the ICT skills of at least a portion of the workforce. Conditioning on the decision to upskill selectively, as expected, ICT (non-ICT) firms tend to focus on ICT (non-ICT) workers. However, both ICT and non-ICT firms feature a stronger tendency to upskill their whole workforce in tandem with I4.0 technology adoption. Interestingly, ICT firms show a much stronger

tendency to upskill conjointly rather than selectively (considering magnitude for the digital adoption propensity, and statistical significance for the physical one), while the discrepancy between conjoint and selective upskilling is less pronounced for non-ICT firms. Thus, while the main result of the previous section is robust to this key sectoral distinction, it is worth noting that ICT firms seem to be the ones keenest on upgrading the ICT skills of their whole workforce in tandem with I4.0 technology adoption. Interestingly, this holds for both digital and physical I4.0 technologies.

Finally, in an effort to deepen the (admittedly coarse-grained) ICT upskilling construct offered by the database, we performed a further supplementary analysis exploiting two additional dichotomous variables. The first (denoted as “hire ICT”) takes the value of 1 for firms that tried to hire ICT specialists in 2017 (regardless of whether they had success or not), and 0 otherwise. The second (denoted as “difficulty ICT”) takes the value of 1 for firms that tried to hire ICT specialists in 2017 and found difficulties in this process (regardless of whether such difficulties were eventually overcome). We took the complement of the latter to construct an additional variable (denoted as “no difficulty ICT”) that takes the value of 1 for firms that tried to hire ICT specialists in 2017 and did not find difficulties in the process. Then, we replicated the bivariate probit analysis described in the previous Subsection (on the whole sample) by employing “difficulty ICT” and “no difficulty ICT” as additional regressors. Our focus here is on the difference between the “difficulty ICT” and the “no difficulty ICT” coefficients with respect to the upskilling of ICT employees, as its direction and statistical significance might reveal something more about the nature of upskilling. Based on the characteristics of I4.0 technologies, we hypothesize that ICT upskilling is not merely a refresh of generic ICT competences, but the acquiring of new, non-standard competences. If firms that experienced difficulties in hiring external ICT specialists were more likely to engage in the upskilling of their own ICT specialists, it would be plausible to conclude that ICT upskilling is meant (at least partly) as an internal remedy for a deficiency in the labor market, thereby entailing that the ICT training is directed at new, non-standard competences that can hardly be found outside.

To verify the hypothesis, we performed a Wald test on the difference between the “difficulty ICT” and the “no difficulty ICT” coefficients. Results are reported in Table A5 in the Appendix (for completeness, we tested the difference also with respect to the upskilling of non-ICT employees). As expected, the difference is sizable and statistically significant at less than 1% for the ICT upskilling of ICT employees, while it is very small and not statistically significant for the ICT upskilling of non-ICT employees. Despite its obvious limitations, this supplementary analysis gives some (albeit indirect) evidence on the nature of the ICT upskilling measured by the questionnaire, suggesting that it probably relates to new competences that can hardly be found in the labor market.

4. Discussion

In the present work, we provide a first attempt to investigate the technological and human sides of I4.0 conjointly, leveraging a large cross-sectional database of Italian firms to highlight a series of important findings. First, while confirming that I4.0 is a systemic phenomenon (EPO, 2017), we also identify two distinct latent propensities to invest primarily (though not exclusively) in either digital or physical I4.0 technologies at the firm level. Since a considerable part of the impulse toward technological development comes from R&D, this may have implications both at the level of the firm and at the level of technological change. Regarding the former, the present work indicates that firms may want to channel their resources (Barney, 1991), routines (Nelson and Winter, 1982) and absorptive capacity (Cohen and Levinthal, 1990) toward the exploitation of precise subclusters of I4.0 technologies, depending on their needs. For instance, managers of digitally oriented firms may want to hire employees well-versed not only in big data analytics, but also in cloud computing and augmented reality, and encourage the development of heuristics supporting the use and recombination of these particular technologies. These and other analogous strategic implications are likely to stem from the identification of subclusters of technologies that are complementary in use. Regarding general dynamics of technological change, our results combine well with the work of Martinelli and colleagues (2021), giving an indication on the fact that big data analytics, cloud computing and

augmented reality, as well as robots and 3D printing, may eventually become part of two unique, aggregate technological paradigms (Pedota et al., 2021). However, technological trajectories are currently too unpredictable to draw definite conclusions in this regard.

Most importantly, the present work sheds new light on the intertwinement between I4.0 technologies and skills. First, it provides evidence that the adoption of I4.0 technologies, whether digital or physical, is likelier to be coupled with a conjoint ICT upskilling of both ICT and non-ICT employees, rather than a selective upskilling of either of the two. Second, it suggests that even the propensity to adopt physical I4.0 technologies like robots and 3D printing is directly and positively related to the conjoint ICT upskilling of ICT and non-ICT specialized personnel (although with a weaker magnitude than the propensity to adopt digital I4.0 technologies). Beyond their inherent degree of digitalization, all I4.0 technologies seem to constitute the foundation of a new language that all employees (both ICT and non-ICT) need to get familiar with, through the acquisition of appropriate ICT skills. This interpretation resonates well with the realization that I4.0 requires lifelong learning and multidisciplinary (Li, 2020; Xu et al., 2018; Xu, 2020), as well as sociability and creativity (Ciarli et al., 2021; Pedota and Piscitello, 2022), which favor employee interconnection and technological recombination.

A further important implication concerns the labor market. The tendency for conjoint upskilling seems to indicate that, in the new I4.0 scenario, the classical clear-cut separation between the ICT skills needed by ICT employees and non-ICT employees is going to fade away or, at least, become more blurred. Although some of the ICT skills required of ICT employees may differ from those required of their non-ICT colleagues, a corpus of core ICT skills is likely to benefit every worker. While ICT employees are inherently drawn toward that corpus of skills, non-ICT employees may be tempted to believe that they can disregard the digital side of technology. In the light of our findings, familiarity with digital I4.0 technologies and innovative interfaces (e.g. augmented reality) may constitute an increasingly important competitive advantage in the labor market, having the two-fold

effect of making workers possessing it more appealing ex-ante, and facilitating ex-post the process of upskilling enacted by medium and large firms, thanks to the self-sustaining properties of learning and knowledge accumulation.

Such findings have great relevance from a policymaking perspective, given the centrality of skill upgrading in the commitment by the European Commission to support the so-called twin transitions (green and digital). The European Commission has recently released a Skills Agenda aimed at enabling workers to leverage advanced technologies, with a view to strengthening sustainable competitiveness, building social fairness and ensuring resilience to unexpected shocks like the COVID-19 pandemic. The Skills Agenda is grounded in five building blocks: a) the establishment of a “Pact for Skills”, which gathers multiple stakeholders to define key principles for upskilling and reskilling, encouraging private-public collaborations and resource pooling; b) the alignment of skills to job requirements, through the dissemination of skill needs at regional and sectoral levels, the support of national strategies for upskilling, the collaboration with universities and the promotion of an entrepreneurial mindset; c) the empowerment of lifelong learning, through ad hoc devices like the recognition of micro-credentials; d) the setting of ambitious skill objectives, measured and monitored through quantitative indicators such as the share of adults with basic digital skills; e) the mobilization of public and private investment, through direct budgetary initiatives and active engagement with national authorities (European Commission, 2020).

Besides confirming the general importance of ICT skills, our findings yield specific insights with regard to the Skills Agenda. Within the “Pact for Skills”, special attention should be devoted to the experience matured by I4.0 technology adopters. These latter should play a definite role in establishing principles for upskilling and reskilling, by sharing the reasons underlying their patterns of conjoint I4.0 technology adoption and the related skill upgrading pathways. The emergence of a physical and a digital I4.0 technology adoption propensity is significant, as is their relationship with conjoint ICT upskilling: a qualitative identification of the commonalities and differences between the

digital and the physical side of I4.0 in terms of upskilling needs may lead to more accurate upskilling programs, perhaps offered even outside firms. Once the requirements are clear, explicit and implicit signals should be given to ICT and especially non-ICT workers to endow themselves with the necessary ICT skillset. The latter should probably be the object of dedicated campaigns, as a mindset of “ICT/non-ICT” separation is still well entrenched in the collective consciousness. Relatedly, along with lifelong learning, a paradigm of transversal learning should be promoted by means of financial supports, ad hoc events and active dialogues with national authorities.

As it is often the case, our analysis opens new, we believe interesting, questions. As a future research direction, we recommend developing additional empirical and theoretical insights into the reasons why, in some respects, the relationship between I4.0 technology adoption and upskilling in small firms seems to diverge from the one characterizing medium and large enterprises. Unlike the other cases, in small firms the digital adoption propensity does not relate more strongly to ICT upskilling than the physical one. Furthermore, selective non-ICT upskilling is the outcome most strongly associated with both propensities, rather than conjoint upskilling. We conjecture that this may be due to a combination of resource constraints and higher industrial specialization. The former limits the ability of small firms to engage in conjoint ICT upskilling, while the latter implies a lower indirect exposure of non-ICT employees to digital technologies. Taken together, these facts would make it necessary to selectively upgrade the ICT skills of non-ICT employees, to help them take part in the new I4.0-driven interconnected organizational reality together with their ICT colleagues. Another possible explanation lies in the peculiarities of small firms’ business models¹¹, which tend to be more flexible and customer-centric. Having fewer customers, small firms are typically in a better position to tailor their services to them. In this respect, particularly for small firms, I4.0 technologies may open new possibilities in terms of collaborative product development (customer-producer), due to the numerous improvements in the flow of data exchange (e.g. thanks to cloud computing and the internet

¹¹ We thank an anonymous reviewer for suggesting this additional possible explanation.

of things) and the customization potential of technologies like 3D printing. This may entail an urgent, selective ICT upskilling of customer specialists (usually non-ICT employees), which need to act as a bridge between customer insights and I4.0 technologies.

A mix of these and other reasons (to varying extents) may underlie our findings on small firms. If the hypothesis on resource constraints were true, it would have, once again, important policy implications. Parallel to the Skills Agenda, the European Commission has recently launched “An SME strategy for a sustainable and digital Europe”, which builds on the extant policy framework (e.g. the 2016 Start-up and Scale-up initiative) to empower small and medium enterprises to fully capitalize on the digital transition. Recognizing that SMEs encounter more difficulties in upskilling their personnel relative to their larger counterparts, the program already offers valuable initiatives like digital crash courses for SME employees in areas like cybersecurity, blockchain and artificial intelligence (European Commission, 2020). In this regard, our findings offer two key insights. First, contrary to small firms, the upskilling tendency of medium-sized adopting firms does not appear to deviate significantly from that of large ones. This indicates that financial and non-financial supports should be skewed more heavily toward small firms, rather than spread equally among SMEs. Second, the holistic character of our investigation suggests that sociotechnical interactions are likely to be more important than upskilling on its own. This should be reflected also in the industrial policies enacted at European and national levels. Policies incentivizing the adoption of key I4.0 technologies in concomitance with the conjoint upskilling of ICT and non-ICT workers may be more effective than generic policies supporting upskilling, especially when directed toward small firms.

Still, the evidence in this regard not conclusive. The database underlying this work collects numerous different pieces of information, but does not measure them deeply. Key variables related to ICT upskilling and technology adoption are binary, and the database does not offer detailed information on the nature of ICT upskilling, nor does it provide a fine-grained specification of the targets of ICT upskilling, apart from the ICT/non-ICT employee distinction. Thus, our empirical findings would

benefit from ad hoc qualitative inquiries into the nature of ICT upskilling and the reasons for implementing it conjointly. Most importantly, such qualitative inquiries may also help test the alternative hypotheses we put forward on why small firms seem to display a peculiar upskilling pattern. It is also worth underlining that the database refers to year 2017, while I4.0 technologies are evolving rapidly. As most I4.0 technologies are still far from maturing and the European Skills Agenda is still *in fieri*, we believe upskilling needs are still there (and probably even stronger). However, the dynamicity of the I4.0 context requires frequent updating. Hence, we encourage further empirical and theoretical efforts aimed at making sense of the intertwinement between technological and skill complementarities in the context of I4.0. There is still much to be learnt on how skills and I4.0 technologies interact as the Fourth Industrial Revolution unfolds.

References

- Acemoglu, D., & Restrepo, P. (2019). *The wrong kind of AI? Artificial intelligence and the future of labor demand*. Cambridge, MA: National Bureau of Economic Research, <https://doi.org/10.3386/w25682>.
- Arntz, M., Gregory, T., & Zierahn, U. (2017). Revisiting the risk of automation. *Economics Letters*, 159, 157-160.
- Arthur, W. B. (2009). *The nature of technology: What it is and how it evolves*. New York, NY: Simon and Schuster.
- Autor, D. H., Katz, L. F., & Krueger, A. B. (1998). Computing inequality: have computers changed the labour market? *The Quarterly Journal of Economics*, 113(4), 1169-1213.
- Autor, D., & Dorn, D. (2013). The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market. *American Economic Review*, 103(5), 1553-1597.
- Autor, D., & Salomons, A. (2018). Is automation labor-displacing? Productivity growth, employment, and the labor share. *Brookings Papers on Economic Activity Conference Drafts* (pp. 1-72).

- Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, 17(1), 99–120.
- Battisti, G., & Iona, A. (2009). The intra-firm diffusion of complementary innovations: Evidence from the adoption of management practices by British establishments. *Research Policy*, 38(8), 1326-1339.
- Becattini, G. (2004). *Industrial districts: A new approach to industrial change*. Cheltenham, UK: Edward Elgar Publishing.
- Becchetti, L., & Trovato, G. (2002). The determinants of growth for small and medium sized firms. The role of the availability of external finance. *Small Business Economics*, 19(4), 291-306.
- Beck, T., & Demirguc-Kunt, A. (2006). Small and medium-size enterprises: Access to finance as a growth constraint. *Journal of Banking & Finance*, 30(11), 2931-2943.
- Berman, E., Bound, J., & Griliches, Z. (1994). Changes in the demand for skilled labour within US manufacturing: evidence from the annual survey of manufactures. *The Quarterly Journal of Economics*, 109(2), 367-397.
- Bijker, W. E., Hughes, T. P., & Pinch, T. J. (1987). *The social construction of technological systems: New directions in the sociology and history of technology*. Cambridge, MA: MIT press.
- Birkel, H. S., Veile, J. W., Müller, J. M., Hartmann, E., & Voigt, K. I. (2019). Development of a risk framework for Industry 4.0 in the context of sustainability for established manufacturers. *Sustainability*, 11(2), 384.
- Bresnahan, T. F., Brynjolfsson, E., & Hitt, L. M. (2002). Information technology, workplace organisation, and the demand for skilled labour: Firm-level evidence. *The Quarterly Journal of Economics*, 117(1), 339-376.
- Brynjolfsson, E., Rock, D. & Syverson, C. (2018). *The productivity J-curve: How intangibles complement general purpose technologies*. Cambridge, MA: National Bureau of Economic Research, Working Paper n. 25148.
- Calabrese, A., Levialdi Ghiron, N., & Tiburzi, L. (2020). ‘Evolutions’ and ‘revolutions’ in manufacturers’ implementation of industry 4.0: a literature review, a multiple case study, and a conceptual framework. *Production Planning & Control*, 32(3) 1-15.

- Ciarli, T., Kenney, M., Massini, S., & Piscitello, L. (2021). Digital Technologies, Innovation, and Skills: Emerging Trajectories and Challenges. *Research Policy*, 50(7), DOI: <https://doi.org/10.1016/j.respol.2021.104289>.
- Cohen, W. M., & Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly*, 35(1) 128-152.
- Colombo, M. G., & Mosconi, R. (1995). Complementarity and cumulative learning effects in the early diffusion of multiple technologies. *The Journal of Industrial Economics*, 43(1), 13-48.
- Cugno, M., Castagnoli, R., & Büchi, G. (2021). Openness to Industry 4.0 and performance: The impact of barriers and incentives. *Technological Forecasting and Social Change*, 168, n. 120756.
- Das, S., Steffen, S., Clarke, W., Reddy, P., Brynjolfsson, E., & Fleming, M. (2020). Learning occupational task-shares dynamics for the future of work. *Proceedings of the AAAI/ACM Conference on AI, Ethics, and Society* (pp. 36–42).
- Deming, D., 2017. The growing importance of social skills in the labor market. *The Quarterly Journal of Economics*, 132(4), 1593-1640.
- Dosi, G. (1982). Technological paradigms and technological trajectories: a suggested interpretation of the determinants and directions of technical change. *Research Policy*, 11(3), 147-162.
- Elliott, S. (2014). Anticipating a Luddite Revival. *Issues in Science and Technology* (pp. 27- 36).
- European Commission (2020). *An SME Strategy for a sustainable and digital Europe*. Retrieved April 27th, 2022 from: https://ec.europa.eu/info/sites/default/files/communication-sme-strategy-march-2020_en.pdf.
- European Commission (2020). *European Skills Agenda for sustainable competitiveness, social fairness and resilience*. Retrieved April 27th, 2022 from: <https://eur-lex.europa.eu/legal-content/EN/ALL/?uri=COM:2020:274:FIN>.
- European Patent Office (2017). *Patents and the Fourth Industrial Revolution*. Retrieved May 1, 2020 from: <http://www.lemoci.com/wp-content/uploads/2017/12/Patents-and-the-Fourth-industrial-Revolution-2017.pdf>

- Felice G., Lamperti F., & Piscitello L. (2021). The employment implications of Additive Manufacturing. *Industry & Innovation*, forthcoming. DOI: [10.1080/13662716.2021.1967730](https://doi.org/10.1080/13662716.2021.1967730)
- Felten, E., Raj, M., & Seamans, R. (2019). The effect of artificial intelligence on human labor: An ability-based approach. *Academy of Management Proceedings* (p. 15784).
- Fisk, P. (2017). *Education 4.0*. Retrieved May 05, 2021 from: <http://www.thegeniusworks.com/2017/01/future-education-youngeveryone-taught-together/>
- Fleming, L. (2001). Recombinant uncertainty in technological search. *Management Science*, 47(1), 117-132.
- Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change*, 114, 254-280.
- Galaske, N., Arndt, A., Friedrich, H., Bettenhausen, K. D., & Anderl, R. (2017). Workforce management 4.0-assessment of human factors readiness toward digital manufacturing. *International Conference on Applied Human Factors and Ergonomics* (pp. 106-115).
- Goos, M., Manning, A., & Salomons, A. (2009). Job polarisation in Europe. *American Economic Review*, 99(2), 58-63.
- Goos, M., Manning, A., & Salomons, A. (2014). Explaining job polarisation: Routine-biased technological change and offshoring. *American Economic Review*, 104(8), 2509-2526.
- Hecklau, F., Galeitzke, M., Flachs, S., & Kohl, H. (2016). Holistic approach for human resource management in Industry 4.0. *Procedia Cirp*, 54, 1-6.
- Henderson, R. M., & Clark, K. B. (1990). Architectural innovation: The reconfiguration of existing product technologies and the failure of established firms. *Administrative Science Quarterly*, 35(1), 9-30.
- Horváth, D., & Szabó, R. Z. (2019). Driving forces and barriers of Industry 4.0: Do multinational and small and medium-sized companies have equal opportunities? *Technological Forecasting and Social Change*, 146, 119-132.
- Hughes, T. P. (1993). *Networks of power: electrification in Western society, 1880-1930*. Baltimore, MD: JHU Press.

- Javaid, M., Haleem, A., Singh, R. P., & Suman, R. (2021). Artificial Intelligence Applications for Industry 4.0: A Literature-Based Study. *Journal of Industrial Integration and Management*, 1-29.
- Kagermann, H. (2015). Change through digitalization: Value creation in the age of Industry 4.0. In Albach, H., Meffert, H., Pinkwart, A., Reichwald, R (Eds.), *Management of Permanent Change* (pp. 23-45). Wiesbaden: Springer.
- Karnik, N., Bora, U., Bhadri, K., Kadambi, P., & Dhatrak, P. (2021). A comprehensive study on current and future trends towards the characteristics and enablers of industry 4.0. *Journal of Industrial Information Integration*, n.100294.
- Karre, H., Hammer, M., Kleindienst, M., & Ramsauer, C. (2017). Transition towards an Industry 4.0 state of the LeanLab at Graz University of Technology. *Procedia Manufacturing*, 9, 206-213.
- Kiel, D., Müller, J. M., Arnold, C., & Voigt, K. I. (2020). Sustainable industrial value creation: Benefits and challenges of industry 4.0. *International Journal of Innovation Management*, 21(8), n.1740015.
- Korinek, A., & Stiglitz, J. (2017). *Artificial intelligence and its implications for income distribution and unemployment*. Cambridge, MA: National Bureau of Economic Research, Working Paper n. 24174.
- Li, L. (2020). Education supply chain in the era of Industry 4.0. *Systems Research and Behavioral Science*, 37(4), 579-592.
- Lorenz, M., Rüßmann, M., Strack, R., Lueth, K. L., & Bolle, M. (2015). *Man and machine in industry 4.0: How will technology transform the industrial workforce through 2025*. Retrieved June 09, 2021 from: http://englishbulletin.adapt.it/wp-content/uploads/2015/10/BCG_Man_and_Machine_in_Industry_4_0_Sep_2015_tcm80-197250.pdf.
- Maisiri, W., Darwish, H., & Van Dyk, L. (2019). An investigation of Industry 4.0 skills requirements. *South African Journal of Industrial Engineering*, 30(3), 90-105.
- Martinelli, A. (2012). An emerging paradigm or just another trajectory? Understanding the nature of technological changes using engineering heuristics in the telecommunications switching industry. *Research Policy*, 41(2), 414-429.

- Martinelli, A., Mina, A., & Moggi, M. (2021). The enabling technologies of industry 4.0: Examining the seeds of the fourth industrial revolution. *Industrial and Corporate Change*, forthcoming.
- Motyl, B., Baronio, G., Uberti, S., Speranza, D., & Filippi, S. (2017). How will change the future engineers' skills in the Industry 4.0 framework? A questionnaire survey. *Procedia Manufacturing*, 11, 1501-1509.
- Müller, J. M., Buliga, O., & Voigt, K. I. (2018). Fortune favors the prepared: How SMEs approach business model innovations in Industry 4.0. *Technological Forecasting and Social Change*, 132, 2-17.
- Nedelkoska, L., & Quintini, G. (2018). *Automation, Skills Use and Training*. Paris: OECD, Working Paper n. 202.
- Nelson, R. R., & Winter, S. G. (1982). *An evolutionary theory of economic behavior and capabilities*. Cambridge, MA: Harvard University Press.
- Neumann, W. P., Winkelhaus, S., Grosse, E. H., & Glock, C. H. (2021). Industry 4.0 and the human factor—A systems framework and analysis methodology for successful development. *International Journal of Production Economics*, 233, n. 107992.
- OECD. (2017). *Enabling the Next Production Revolution*. Retrieved February 08, 2021 from: <https://www.oecd.org/sti/ind/next-production-revolution.htm>.
- Onar, S. C., Ustundag, A., Kadaifci, Ç., & Oztaysi, B. (2018). The changing role of engineering education in industry 4.0 Era. *Industry 4.0: Managing the digital transformation* (pp. 137-151).
- Osterrieder, P., Budde, L., & Friedli, T. (2020). The smart factory as a key construct of industry 4.0: A systematic literature review. *International Journal of Production Economics*, 221, n. 107476.
- Pedota, M., Grilli, L., & Piscitello, L. (2021). Technological paradigms and the power of convergence. *Industrial and Corporate Change*, 30(6), 1633-1654
- Pedota, M., & Piscitello, L. (2022). A new perspective on technology-driven creativity enhancement in the Fourth Industrial Revolution. *Creativity and Innovation Management*, 31(1), 109-122.

- Pinzone, M., Fantini, P., Perini, S., Garavaglia, S., Taisch, M., & Miragliotta, G. (2017). Jobs and skills in Industry 4.0: an exploratory research. *IFIP International Conference on Advances in Production Management Systems* (pp. 282-288).
- Ras, E., Wild, F., Stahl, C., & Baudet, A. (2017). Bridging the skills gap of workers in Industry 4.0 by human performance augmentation tools: Challenges and roadmap. *Proceedings of the 10th International Conference on Pervasive Technologies Related to Assistive Environments* (pp. 428-432).
- Rosenberg, N. (1979). Technological interdependence in the American economy. *Technology and Culture*, 20(1), 25-50.
- Schallock, B., Rybski, C., Jochem, R., & Kohl, H. (2018). Learning Factory for Industry 4.0 to provide future skills beyond technical training. *Procedia Manufacturing*, 23, 27-32.
- Solow, R. M. (1956). A contribution to the theory of economic growth. *The Quarterly Journal of Economics*, 70(1), 65-94.
- Sung, T. K. (2018). Industry 4.0: a Korea perspective. *Technological Forecasting and Social Change*, 132, 40-45.
- Valdivieso, C. (2020). *Why combine artificial intelligence and 3D printing?* Retrieved July 30, 2020 from: <https://www.3dnatives.com/en/artificial-intelligence-and-3d-printing-060120204/>
- Wang, Y., Lin, Y., Zhong, R. Y., & Xu, X. (2019). IoT-enabled cloud-based additive manufacturing platform to support rapid product development. *International Journal of Production Research*, 57(12), 3975-3991.
- Wozniak, G. D. (1984). The adoption of interrelated innovations: A human capital approach. *The Review of Economics and Statistics*, 66(1), 70-79.
- Xu, L. D. (2020). Industry 4.0—Frontiers of fourth industrial revolution. *Systems Research and Behavioral Science*, 37(4), 531-534.
- Xu, L. D. (2020). The contribution of systems science to Industry 4.0. *Systems Research and Behavioral Science*, 37(4), 618-631.

Xu, L. D., Xu, E. L., & Li, L. (2018). Industry 4.0: state of the art and future trends. *International Journal of Production Research*, 56(8), 2941-2962.

Yoo, Y., Boland Jr, R. J., Lyytinen, K., & Majchrzak, A. (2012). Organizing for innovation in the digitized world. *Organization Science*, 23(5), 1398-1408.

Zolas, N., Kroff, Z., Brynjolfsson, E., McElheran, K., Beede, D. N., Buffington, C., ... & Dinlersoz, E. (2021). *Advanced Technologies Adoption and Use by US Firms: Evidence from the Annual Business Survey*. National Bureau of Economic Research, Working Paper n.28290.

Appendix

INSERT TABLE A1 ABOUT HERE

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Table I. Type of upskilling by firm size and adoption

Status	Type of upskilling	Small	Medium	Large	Total
Adopter	No upskilling	901 (50%) (56%)	542 (30%) (47%)	371 (20%) (25%)	1814 (100%) (43%)
	Only ICT upskilling	208 (38%) (13%)	124 (23%) (11%)	215 (39%) (15%)	547 (100%) (13%)
	Only NON-ICT upskilling	198 (35%) (12%)	192 (34%) (17%)	174 (31%) (12%)	564 (100%) (13%)
	Conjoint upskilling	293 (23%) (18%)	288 (22%) (25%)	717 (55%) (49%)	1298 (100%) (31%)
	Total	1600 (38%) (100%)	1146 (27%) (100%)	1477 (35%) (100%)	4223 (100%) (100%)
Non-adopter	No upskilling	10338 (75%) (85%)	2505 (18%) (70%)	926 (7%) (47%)	13769 (100%) (78%)
	Only ICT upskilling	383 (47%) (3%)	209 (26%) (6%)	221 (27%) (11%)	813 (100%) (5%)
	Only NON-ICT upskilling	1079 (58%) (9%)	490 (26%) (14%)	291 (16%) (15%)	1860 (100%) (11%)
	Conjoint upskilling	361 (28%) (3%)	366 (29%) (10%)	542 (43%) (27%)	1269 (100%) (7%)
	Total	12161 (69%) (100%)	3570 (20%) (100%)	1980 (11%) (100%)	17711 (100%) (100%)

The Table shows the number of firms that do not upskill, upskill selectively ICT employees, upskill selectively non-ICT employees and upskill conjointly, categorizing them according to their size and their status in terms of technological adoption. The status of adopter means that the firm has adopted at least one of the six technologies in the dataset, while the status of non-adopter means that the firm has adopted none of the six technologies in the dataset. Percentages to the side of absolute numbers indicate the relative frequency with respect to the horizontal dimension (i.e. type of upskilling), whereas percentages below indicate the relative frequency with respect to the vertical dimension (i.e. firm size). Percentages are rounded to the nearest integer. Total number of observations: 21,934.

Table II. Technologies adopted by firm size

Technology	Small	Medium	Large	Total
Augmented reality	52 (32%) (3%)	38 (23%) (2%)	73 (45%) (3%)	163 (100%) (3%)
Big data analytics	201 (26%) (10%)	194 (25%) (13%)	388 (50%) (16%)	783 (100%) (13%)
Cloud computing	1200 (40%) (60%)	765 (26%) (49%)	1003 (34%) (41%)	2968 (100%) (50%)
Internet of things	461 (33%) (23%)	362 (26%) (23%)	558 (40%) (23%)	1381 (100%) (23%)
3D printing	34 (18%) (2%)	49 (26%) (3%)	103 (55%) (4%)	186 (100%) (3%)
Advanced robots	45 (9%) (2%)	139 (28%) (9%)	318 (63%) (13%)	502 (100%) (8%)
Total	1993 (33%) (100%)	1547 (26%) (100%)	2443 (41%) (100%)	5983 (100%) (100%)

The Table shows the number of firms that adopt each of the six I4.0 technologies in the dataset, categorizing them according to their size. Percentages to the side of absolute numbers indicate the relative frequency with respect to the horizontal dimension (i.e. the technology), whereas percentages below indicate the relative frequency with respect to the vertical dimension (i.e. firm size). Percentages are rounded to the nearest integer. Total number of observations: 4,223.

Table III. Tetrachoric correlation matrix among focal variables

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) <i>ICT upskilling</i>	1.00										
(2) <i>NON-ICT upskilling</i>	0.72	1.00									
(3) <i>Firm size: small</i>	-0.51	-0.45	1.00								
(4) <i>Firm size: medium</i>	0.08	0.13	-1.00	1.00							
(5) <i>Firm size: large</i>	0.59	0.49	-1.00	-1.00	1.00						
(6) <i>Big data analytics</i>	0.51	0.43	-0.42	0.05	0.45	1.00					
(7) <i>Augmented reality</i>	0.46	0.36	-0.28	0.02	0.32	0.61	1.00				
(8) <i>Cloud computing</i>	0.52	0.39	-0.35	0.09	0.38	0.64	0.48	1.00			
(9) <i>Internet of things</i>	0.44	0.35	-0.37	0.08	0.40	0.55	0.49	0.50	1.00		
(10) <i>3D printing</i>	0.44	0.36	-0.42	0.06	0.41	0.41	0.53	0.41	0.48	1.00	
(11) <i>Advanced robots</i>	0.39	0.34	-0.60	0.08	0.55	0.37	0.36	0.32	0.51	0.64	1.00

The Table shows the tetrachoric correlation coefficients for every couple of focal variables. Variables are arbitrarily listed from 1 to 11. The leftmost column reports the full name of the variable besides its reference number, whereas the uppermost row reports only the reference number, for graphical convenience. Total number of observations: 21,934.

Table IV. Factor loadings by firm size

Factor	Technology	Small	Medium	Large	Whole sample
Digital adoption propensity	Augmented reality	0.6271	0.6321	0.5589	0.6080
	Big data analytics	0.7603	0.6902	0.7861	0.7591
	Cloud computing	0.7745	0.5862	0.6456	0.6768
	Internet of things	0.5054	0.5184	0.4912	0.5269
	3D printing	0.2289	0.2420	0.2974	0.3274
	Advanced robots	0.1116	0.1782	0.1226	0.2340
Physical adoption propensity	Augmented reality	0.3381	0.2814	0.3956	0.3740
	Big data analytics	0.1892	0.1358	0.1979	0.2696
	Cloud computing	0.1086	0.2541	0.1602	0.2491
	Internet of things	0.4893	0.4361	0.4072	0.4774
	3D printing	0.7191	0.6455	0.6847	0.7033
	Advanced robots	0.6591	0.6021	0.7112	0.7012

The Table summarizes the output of the factor analyses on the whole sample and on each subsample based on firm size. Each column from “small” to “whole sample” constitutes the output of a separate factor analysis based on the polychoric correlation matrix of the corresponding subsample, and it reports the rotated factor loadings for each technology on the factor indicated in the leftmost column (digital adoption propensity and physical adoption propensity). Total number of observations: 21,934 (whole sample); 13,761 (small); 4,716 (medium); 3,457 (large).

Table V. Bivariate probit marginal effects by firm size

Firm size category	Outcome	Digital adoption propensity marginal effect	Physical adoption propensity marginal effect
Whole sample	No upskilling	-0.0036*** (0.0002)	-0.0024*** (0.0003)
	Only ICT upskilling	0.0008*** (0.0001)	0.0005*** (0.0001)
	Only NON-ICT upskilling	0.0012*** (0.0001)	0.0008*** (0.0002)
	Conjoint upskilling	0.0016*** (0.0001)	0.0010*** (0.0001)
Small	No upskilling	-0.0027*** (0.0002)	-0.0028*** (0.0005)
	Only ICT upskilling	0.0006*** (0.0001)	0.0005*** (0.0001)
	Only NON-ICT upskilling	0.0013*** (0.0002)	0.0016*** (0.0004)
	Conjoint upskilling	0.0008*** (0.0001)	0.0007*** (0.0001)
Medium	No upskilling	-0.0037*** (0.0004)	-0.0015** (0.0007)
	Only ICT upskilling	0.0008*** (0.0002)	0.0002 (0.0003)
	Only NON-ICT upskilling	0.0008** (0.0003)	0.0005 (0.0005)
	Conjoint upskilling	0.0021*** (0.0002)	0.0008** (0.0004)
Large	No upskilling	-0.0041*** (0.0003)	-0.0023*** (0.0005)
	Only ICT upskilling	0.0004* (0.0002)	0.0005 (0.0003)
	Only NON-ICT upskilling	-0.0004 (0.0002)	-0.0005 (0.0003)
	Conjoint upskilling	0.0041*** (0.0003)	0.0023*** (0.0005)
Industry controls: included Size controls: included Geographical controls: included ICT intensity controls: included			

The Table summarizes the output of the bivariate probit analyses on the whole sample and on each subsample based on firm size. It reports the effect of a marginal increase in each of the two factor scores indicated in the last two columns on every possible outcome in terms of upskilling, for the whole sample as well as each subsample based on firm size (as indicated by the leftmost column). Standard errors are reported in parentheses. Three stars indicate a p-value of 1% or lower; two stars indicate a p-value between 1% and 5%; one star indicates a p-value between 5% and 10%. The absence of stars indicates that the coefficient is not statistically significant. Total number of observations: 21,934 (whole sample); 13,761 (small); 4,716 (medium); 3,457 (large).

Table VI. Wald tests for the difference in factor coefficients

Outcome	Small	Medium	Large	Whole dataset
ICT upskilling	0.0018 (0.4304)	0.0075 (0.0061)	0.0042 (0.0142)	0.0044 (0.0001)
Non-ICT upskilling	-0.00010 (0.6105)	0.0046 (0.0759)	0.0046 (0.0053)	0.0033 (0.0029)

The Table reports the outcome of a series of Wald tests following the bivariate probit estimations on the whole sample as well as each subsample based on firm size (see Table V). For each combination of dependent variable (indicated in the leftmost column) and size (indicated in the top row), the Table reports the difference between the coefficients for the digital adoption propensity and the physical adoption propensity. The null hypothesis is that this difference is zero. Levels of significance (reported in parentheses) suggest that the null hypothesis can be safely rejected for the whole database as well as large firms with respect to both ICT and non-ICT upskilling. It can also be rejected in the case of medium firms, although with a weaker level of significance in the case of non-ICT upskilling. Definitely it cannot be rejected in the case of small firms.

Table A1. Bivariate probit coefficients by firm size

Firm size category	Dependent Variable	Digital adoption propensity coefficient	Physical adoption propensity coefficient
Whole sample	ICT upskilling	0.0131*** (0.0007)	0.0087*** (0.0011)
	NON-ICT upskilling	0.0100*** (0.0006)	0.0067*** (0.0010)
Small	ICT upskilling	0.0143*** (0.0010)	0.0126*** (0.0025)
	NON-ICT upskilling	0.0102*** (0.0009)	0.0112*** (0.0022)
Medium	ICT upskilling	0.0114*** (0.0014)	0.0039* (0.0021)
	NON-ICT upskilling	0.0086*** (0.0013)	0.0040* (0.0020)
Large	ICT upskilling	0.0111*** (0.0010)	0.0069*** (0.0016)
	NON-ICT upskilling	0.0092*** (0.0010)	0.0046*** (0.0015)
Industry controls: included Size controls: included Geographical controls: included ICT intensity controls: included			

For each subsample indicated in the leftmost column, the Table reports the bivariate probit coefficients for the two factors on each dependent variable (i.e. the ICT upskilling of ICT employees and the ICT upskilling of non-ICT employees). Standard errors are reported in parentheses. Three stars indicate a p-value of 1% or lower; two stars indicate a p-value between 1% and 5%; one star indicates a p-value between 5% and 10%. The absence of stars indicates that the coefficient is not statistically significant. Total number of observations: 21,934 (whole sample); 13,761 (small); 4,716 (medium); 3,457 (large).

Table A2. Multinomial logit marginal effects by firm size

Firm size category	Outcome	Digital adoption propensity marginal effect	Digital adoption propensity marginal effect
Whole sample	No upskilling	-0.0029*** (0.0002)	-0.0019*** (0.0003)
	Only ICT upskilling	0.0006*** (0.0001)	0.0004*** (0.0001)
	Only NON-ICT upskilling	0.0010*** (0.0002)	0.0007** (0.0003)
	Conjoint upskilling	0.0013*** (0.0001)	0.0008*** (0.0001)
Small	No upskilling	-0.0021*** (0.0002)	-0.0028*** (0.0005)
	Only ICT upskilling	0.0004*** (0.0001)	0.0005*** (0.0001)
	Only NON-ICT upskilling	0.0011*** (0.0002)	0.0018*** (0.0004)
	Conjoint upskilling	0.0006*** (0.0001)	0.0005*** (0.0001)
Medium	No upskilling	-0.0035 (0.0024)	-0.0015 (0.0015)
	Only ICT upskilling	0.0007 (0.0051)	0.0003 (0.0020)
	Only NON-ICT upskilling	0.0009 (0.0041)	0.0006 (0.0026)
	Conjoint upskilling	0.0020 (0.0028)	0.0007 (0.0012)
Large	No upskilling	-0.0041*** (0.0012)	-0.0016* (0.0009)
	Only ICT upskilling	0.0002 (0.0005)	-0.0001 (0.0005)
	Only NON-ICT upskilling	-0.0005* (0.0003)	-0.0012* (0.0006)
	Conjoint upskilling	0.0044*** (0.0016)	0.0029*** (0.0010)
Industry controls: included Size controls: included Geographical controls: included ICT intensity controls: included			

The Table summarizes the output of the multivariate logit analyses on the whole sample and on each subsample based on firm size. It reports the effect of a marginal increase in each of the two factor scores indicated in the last two columns on every possible outcome in terms of upskilling, for the whole sample as well as each subsample based on firm size (as indicated by the leftmost column). Standard errors are reported in parentheses. Three stars indicate a p-value of 1% or lower; two stars indicate a p-value between 1% and 5%; one star indicates a p-value between 5% and 10%. The absence of stars indicates that the coefficient is not statistically significant. Total number of observations: 21,934 (whole sample); 13,761 (small); 4,716 (medium); 3,457 (large).

Table A3. Multinomial logit coefficients by firm size

Firm size category	Outcome	Digital propensity multinomial logit coefficient	Physical propensity multinomial logit coefficient
Whole sample	No upskilling	baseline	baseline
	Only ICT upskilling	0.0195*** (0.0017)	0.0132*** (0.0028)
	Only NON-ICT upskilling	0.0119*** (0.0016)	0.0079*** (0.0026)
	Conjoint upskilling	0.0280*** (0.0013)	0.0175*** (0.0022)
Small	No upskilling	baseline	baseline
	Only ICT upskilling	0.0237*** (0.0026)	0.0268*** (0.0061)
	Only NON-ICT upskilling	0.0136*** (0.0023)	0.0222*** (0.0049)
	Conjoint upskilling	0.0327*** (0.0023)	0.0292*** (0.0055)
Medium	No upskilling	baseline	baseline
	Only ICT upskilling	0.0181*** (0.0036)	0.0072 (0.0057)
	Only NON-ICT upskilling	0.0111*** (0.0031)	0.0060 (0.0046)
	Conjoint upskilling	0.0235*** (0.0028)	0.0090** (0.0043)
Large	No upskilling	baseline	baseline
	Only ICT upskilling	0.0129*** (0.0027)	0.0033 (0.0040)
	Only NON-ICT upskilling	0.0074*** (0.0028)	-0.0040 (0.0045)
	Conjoint upskilling	0.0234*** (0.0021)	0.0123*** (0.0030)
Industry controls: included Size controls: included Geographical controls: included ICT intensity controls: included			

For each subsample indicated in the leftmost column, the Table reports the multinomial logit coefficients for the two factors on each combination of upskilling, using “no upskilling” as the baseline. Standard errors are reported in parentheses. Three stars indicate a p-value of 1% or lower; two stars indicate a p-value between 1% and 5%; one star indicates a p-value between 5% and 10%. The absence of stars indicates that the coefficient is not statistically significant. Total number of observations: 21,934 (whole sample); 13,761 (small); 4,716 (medium); 3,457 (large).

Table A4. Bivariate probit marginal effects by firm typology (ICT vs NON-ICT)

Firm typology	Dependent Variable	Digital adoption propensity marginal effect	Physical adoption propensity marginal effect
ICT	No upskilling	-0.0052*** (0.0005)	-0.0029** (0.0011)
	Only ICT upskilling	0.0016*** (0.0005)	0.0016 (0.001)
	Only NON-ICT upskilling	-0.0007*** (0.0002)	-0.0006 (0.0004)
	Conjoint Upskilling	0.0043*** (0.0005)	0.0019* (0.0011)
NON-ICT	No upskilling	-0.0032*** (0.0002)	- 0.0023*** (0.0003)
	Only ICT upskilling	0.0006*** (0.0001)	0.0004*** (0.0001)
	Only NON-ICT upskilling	0.0012*** (0.0001)	0.0008*** (0.0001)
	Conjoint Upskilling	0.0015*** (0.0001)	0.0011*** (0.0002)
Industry controls: included Size controls: included Geographical controls: included ICT intensity controls: included			

For each firm typology indicated in the leftmost column, the Table reports the effect of a marginal increase in each of the two factor scores indicated in the last two columns on every possible outcome in terms of upskilling. Standard errors are reported in parentheses. Three stars indicate a p-value of 1% or lower; two stars indicate a p-value between 1% and 5%; one star indicates a p-value between 5% and 10%. The absence of stars indicates that the coefficient is not statistically significant. Total number of observations: 1933 (ICT), 20001 (NON-ICT).

Table A5. Wald tests on the difference in the coefficients of dummy variables on ICT hiring

Outcome	Difference
ICT upskilling	0.2263 (0.0000)
Non-ICT upskilling	0.0248 (0.5989)

For each firm typology indicated in the leftmost column, the Table reports the effect of a marginal increase in each of the two factor scores indicated in the last two columns on every possible outcome in terms of upskilling, for the whole sample as well as each subsample based on firm size (as indicated by the leftmost column). Standard errors are reported in parentheses. Three stars indicate a p-value of 1% or lower; two stars indicate a p-value between 1% and 5%; one star indicates a p-value between 5% and 10%. The absence of stars indicates that the coefficient is not statistically significant. Total number of observations: 21,934 (whole sample); 13,761 (small); 4,716 (medium); 3,457 (large).