INAPP
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WORKING PAPER

INAPP WP n. 53

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AGOSTO 2020

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AGOSTO 2020

This study has been developed within the research collaboration agreement "Tecnologia, processi lavorativi e dinamica delle imprese: analisi e valutazioni a fini di policy" between INAPP and the Institute of Economics-Scuola superiore Sant'Anna Pisa, 2017-2019.

* This paper is the outcome of research activities carried out in 2019 and 2020 when Valeria Cirillo was affiliated at INAPP.

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ABSTRACT

Digitizing firms: skills, work organization and the adoption of new enabling technologies

New enabling technologies are shaping the transformation of production activities. This process of change is characterised by growing digitization, inter-connectivity and automation. The diffusion of new technologies is, however, very uneven, and firms display different adoption patterns. By using the panel component of the RIL-Inapp survey wave of 2018, we explore the patterns and determinants of new technology adoption in a large representative sample of Italian firms. We build our theoretical framework on the nexus between technology and the quality and organisation of work. We then provide novel econometric evidence on the positive effects of human capital and training. Labour flexibility does not seem to help adoption, whereas second-level collective bargaining plays a positive role in the process. Results also show heterogeneous effects between large vs. small and medium-size firms, and between manufacturing and service sectors.

PAROLE CHIAVE: digital technologies, Industry 4.0, skills, work organization

JEL CODES: D20, L23, O33

1. Introduction

Modern production technologies are characterised by increased digitization, automation and interconnectivity (Brynjolfsson and McAfee 2014). These characteristics have been associated with new and disruptive process innovation technologies referred to as enabling technologies (Teece 2018). Following Martinelli *et al.* (2019), these can be defined as emergent technologies that display some of the characteristics of general purpose technologies (Bresnahan and Trajtenberg 1995) but are not yet fully developed GPTs independently from the broader ICT paradigm to which they contribute. These technologies are often subsumed in the policy debate under the notion of 'Industry 4.0', which captures the convergence of new operational technologies with Internet-driven IT, and has been linked to a fundamental shift of production systems towards the 'smart factory' of the future (Kagermann *et al.* 2013).

It is difficult to ascribe to a common matrix all the new digital technologies. Yet, they define a complex set of devices whose joint use identifies a broad continuum of production possibilities conditional on the infrastructural characteristics of production (or service provision), firms organizational choices, and the composition of value chains. It is important to stress that a cluster of 'enabling technologies' may or may not lead to a new and fundamentally different 'techno-economic paradigm' (Freeman and Perez 1988). Nevertheless, the high recombinatorial potential of digital technologies can foster new ways of organising economic activities on both the supply and the demand side. The ability of companies to select and exploit emergent sources of competitive advantage is, therefore, a likely determinant of growth because of the performance-enhancing attributes of these enabling technologies.

In this contribution we focus on the technology adoption choices made by individual firms. While information on the production of new technologies is usually available on a large scale from standard firm-level data, or could be derived from the examination of patent records, information on market diffusion is much rarer. This is unfortunate because diffusion, rather than invention, is the real manifestation of Schumpeterian structural change in the economy.

We explore a large and unique firm-level survey of Italian businesses: the Rilevazione Imprese e Lavoro (RIL) survey. The survey is run by the National Institute for the Analysis of Public Policies (Inapp) and contains specific questions on different digital technologies acquired by firms. This offers a unique opportunity to study the determinants of new enabling technology adoption. The theoretical framework focuses on the nexus between technology, human capital and the organisation of work. In the empirical section of the paper we describe the aggregate patterns of adoption, and then run econometric analyses of the role of skills, distinguishing between formal human capital endowments and on-the-job training, and the role of two important aspects of the organization of work within the firm: the use by the firm of temporary contracts and the role of second-level bargaining. Many empirical contributions have highlighted the patterns of complementarity between high-skilled workers and information technologies (see among others Bresnahan *et al.* 2002; Fabiani *et al.* 2005; Balsmeier and Woerter 2019). Very few studies have, however, been able to extend this line of research to new digital technologies, and none – to the best of our knowledge – has considered from a large-scale quantitative perspective the role of work organization in their adoption. This is clearly important in the context of the current debate on the role of automation and the risks of technological unemployment, but has not been investigated as much as it should have been given the lack of suitable microdata.

The paper is organised as follows: in the next section we review the relevant literature to frame our research questions and derive testable hypotheses (see section 2). In section 3 we illustrate the original data and provide some descriptive evidence on the diffusion of new digital technologies among Italian firms (section 2.2). Section 4 presents the empirical strategy; while section 5 presents the results of our econometric analyses. Section 6 concludes by drawing attention on the strategic and policy implications of the study, and by identifying new avenues for future research.

2. Digital Technologies and Skills

2.1 Literature Review and Research Hypotheses

In the study of technical change a broad set of drivers has been identified behind the individual technology adoption choices by firms, and how these choices translate into aggregate patterns of technology diffusion within and between sectors (Malerba and Orsenigo 1996; Malerba and Orsenigo 1997; Hall and Khan 2003). We can distinguish between: i) supply-side factors, including improvements of old and complementary technologies leading to incremental innovations or changes in the use of existent technologies (Gruber and Verboven 2001); ii) factors related to the demand of new technologies, such as the complementarity between new technologies, workers' skills and firms' specific stock of physical capital (Rosenberg 1976); iii) firms' specific (internal) characteristic ranging from firm size to the existence of credit-constraints, Human Resource Management practices (Bloom *et al.* 2012), and the firms' knowledge-base, shedding light on the interplay between idiosyncratic learning, the evolution of the workforce skills and knowledge, organizational capabilities and the economic environment in which firms operate (Nelson and Winter 1982; Dosi *et al.* 2000; Dosi and Marengo 2015); iv) external factors linked to market structure, production structure, market demand dynamics at the sector and country level (Mowery and Rosenberg 1993), and the institutional context in which firms operate (Dosi 1991). A growing stream of contributions have focused on the interplay between technology adoption choices (OECD 2011) and human capital, proxied by workers education levels as in the standard human capital theory (Becker 1994) or conceptualised as workers'standard human capital theory (Becker 1994) or conceptualised as workers' knowledge and routines (Nelson and Winter 1982; Winter 1997; Dosi and Marengo 2015).

Becker (1994)'s seminal contribution laid down the foundations of modern human capital theory by treating human capital in analogy with physical capital. Human capital can be accumulated through investments in education, training and any other means that improve the employees' ability to provide labour services. Becker (1994) distinguished between 'specific human capital', referring to skills or knowledge that is useful only to a single employer, and 'general human capital' that is useful to many employers. In the case of general skills, theory suggests the rewards for acquiring them accrue to the employee in the form of higher wages, as determined by the market (Prais 1995). This reflects both the higher value of a skilled employee's contribution to the production process, and the cost (in time or money terms) of training, which is shared by the employee. Specific skills, on the other hand, are only of value in a particular employment, and be the result of *ad hoc* training in a particular context of production.

Innovations may also require very specific skill sets that do not yet exist in the labour market. In this case workers have no direct incentive to develop these skills because they are not immediately tradable, so the cost of training falls on the employer. If, however, the employer is unable to fully appropriate the value of innovation, and imitators can enter the market, what started as 'specific skills' become more 'general skills': if they are only available in short supply they are likely to attract a high premium. Given the uncertainty surrounding the benefits of new technologies, and the heterogeneity of firm capabilities, calculations of rates of return to skills will vary greatly and will contain large error margins.

It is difficult to disentangle the skills that drive innovation from those which are demanded as a result of change brought about by innovation (Tether *et al.* 2005). However, the question can be asked as to what skill sets are more suitable for the adoption of new technologies as part of broader firm-specific strategies. Moreover, firms often have to anticipate skills needs in preparation for particular technology choices. Firms that chose to digitize all or part of their activities may consider their position in the supply chain and identify an opportunity to achieve productivity gains. In making this strategic choice, they recognise that these gains may only be realised if skilled workers are able to use and extract value from the new technologies[1].

On this basis, we propose the following hypothesis:

- H1. *Firms with more skilled employees are more likely to invest in new digital technologies given the complementarity between workers' skills and technologies.*

Extensive theoretical and empirical literature indicates that the skills mix of firms is partly dependent on workers' formal education and partly generated through specific investments in training. Several contributions highlight the role of high-skilled and/or highly-trained human capital as a key driver of innovative activity and organizational change (see among others Leiponen 2005; Lundvall 2009; Toner 2011). High-quality human capital generates strong absorptive capacity (Cohen and Levinthal 1990a) and is also associated with the presence of new managerial practices (Böckerman *et al.* 2012) guiding the introduction of new capabilities and new organizational routines. As clearly stated in Cohen and Levinthal (1990b) p.132, a firm's absorptive capacity is not simply the sum of the absorptive capacities of its employees, but it still depends on the individuals who stand at the interfaces between the firm and the external environment, or between sub-units of the same firm. In case of rapid and uncertain technical change, a deep knowledge base and/or some predisposition for change might be required for effective communication with technology experts or to capture, assimilate and exploit new information for productive purposes[2].

[1] Investment in new enabling technologies can also be driven by a cost minimization approach and imply a fall in employment due to substitution effects between labour and technology. While it is plausible to assume that digital technologies enabling automation will decrease employment, either by substituting low skilled workers or working in routine occupations, in this paper we focus on the antecedents of technology adoption rather than the effects of technology on employment.

[2] Along a similar line of research McGuirk *et al.* (2015) have recently analysed the role of 'Innovative Human Capital' (IHC), measured it as a combination of education, training, but also willingness to change and job satisfaction, upon small firms' propensity to innovate.

While general human capital can be acquired through the market process, more specific skills, tailored to the exact requirement of the firm, can be developed through training. As we expect skills to have a positive effect on adoption, we also expect training to favour the acquisition of new enabling technologies. It is possible that the relative contribution of formal education levels and training varies across firms and sectors. Following Rubery and Grimshaw (2003) we could expect a prevailing role for the 'Occupational Labour Market (OLM)', based on nationally recognized occupational qualifications (such as apprenticeships or college-based training). Conversely, we could expect a more prominent role for the internal channel based on on-the-job training, which Rubery and Grimshaw (2003) identify as an Internal Labour Market (ILM) mechanism through which training is designed and organized by individual employers in accordance with their specific needs. We argue that firms planning changes in production are more likely to prepare their workers by updating or upgrading their skills sets to fully capture the benefits of new technologies[3].

Therefore, we posit that:

- H2. *The share of workers with 'on-the-job' training has a positive effect on the adoption of new digital technologies*.

A related aspect of the decision to adopt new technologies is the organisation of labour (Nelson and Winter 1982; Osterman 1994). Qualitative evidence on the processes of organisational adaptation indicates that this is as a necessary condition for the generation of productivity gains and competitive advantage stemming from the use of new enabling technologies (Cirillo *et al.* 2018; Fabbri *et al.* 2018). Process technologies, such as 'Industry 4.0' technologies, tend to be accompanied by organisational changes consistent with the principles of 'lean production' (Womack *et al.* 2007). This is an argument also made by Bresnahan *et al.* (2002) in the seminal paper on the combination of computerization, workplace organization and increased demand for skilled workers. Complementarity drives clusters of changes in modern firms. More specifically, the use of information and communication technologies is positively correlated with increases in the demand for various indicators of human capital and workforce skills; it also shows patterns of correlations with specific forms of work organization. One important feature of the implementation of ICT across many sectors is the concurrent use of short-term labour contracts and, therefore, higher levels of temporary work.

On the one hand, labour flexibility can help firms' to adjust quickly to new technological requirements by allowing rapid changes to their demand for labour. This is often seen as an agile way to optimize on labour endowments when production lines and whole firm sub-units are restructured to meet new market needs or increased market competition. On the other hand, many empirical contributions note that more flexible (internal) labour markets can hamper innovation at both firm and sector levels (see among others Cetrulo *et al.* 2019 and Kleinknecht *et al.* 2014). Increased reliance on temporary workers might lower the probability to invest in new enabling technologies because it is more compatible with cost competitiveness strategies rather than higher-value added models of technological advantages (see among others Michie and Sheehan 2003 and Castro Silva and Lima 2019). The accumulation of knowledge is hampered by frequent employees turnover, which prevents the attainment of productivity gains stemming from learning through the interplay between

[3] Naturally, the two mechanisms can also coexist in a more 'systemic integration model' combining higher-level science and engineering skills of a small elite of workers with highly trained employees.

technology and human labour. It is also possible that flexible work is applied by firms to non-core tasks. However, while this may be the case of large firms, it is a more unlikely behaviour among small firms, which are less diversified and less complex organisations.

All in all, we expect that continuous accumulation of tacit knowledge about production processes is important for the adoption of enabling technologies and therefore we hypothesise that:

- H3. *The use of flexible staff arrangements has a negative effect on the adoption of new digital technologies.*

The final aspect to which we draw our theoretical focus is the role of firm governance in shaping technology adoption decisions. Companies that plan to change or upgrade production technologies need to adapt capabilities and skills as quickly as possible, and this may entail changes in wages and the content of work. The structure of decision-making processes within firms can therefore have significant effects on the outcome of specific investment decisions. Company-level bargaining is supposed to be more flexible and versatile than centralized bargaining, thus offering some advantages in more dynamic environments (see Ponzellini 2017). This is especially relevant when investment decisions concern new technologies.

Lean production models associated with digital transformations require a relatively high level of work flexibility and adaptation that might be negotiated more easily at the company level rather than at the sectoral or national level. Company level bargaining may cover specific topics such as workers' involvement, changes in work organisation, working hours, work roles, workloads, vocational training, and productivity premia[4].

As noted by Freeman and Medoff (1984) and Metcalf (2003) economic theories have not been able to predict unambiguously the direction of the effect of bargaining (and more generally unionization) on firm performance. Thus, second-level bargaining could both increase or decrease productivity. According to the literature, one might expect negative effects when the conflictual behaviour of a trade union prevails; conversely, one might expect a positive impact if workplace unionism and collective bargaining are set in a collaborative and participatory environment. Several studies contain empirical investigations of the link between company-level agreements and firm performance (Frick and Möller 2003; Fairris and Askenazy 2010; Jirjahn and Mueller 2014; Devicienti *et al.* 2017; Antonietti *et al.* 2017; Damiani *et al.* 2018; Garnero *et al.* 2019). The evidence is overall inconclusive because results are sensitive to contexts (above all the countries included in the analyses), measures of productivity and econometric techniques.

Divergent results have also been found by several studies of the relation between collective bargaining and innovation (see Menezes-Filho and Van Reenen 2003; Addison and Wagner 1997; FitzRoy and Kraft 1990; Schnabel and Wagner 1994). Focusing on digital technologies, Genz *et al.* (2019) has recently found a robust negative relation between works councils and investments in Industry 4.0 technologies in Germany. The implementation of digital technologies broadens the responsibility of work councils to mediate the conflict between employees and management. Work councils can exert veto rights with respect to the implementation of digital technologies and can narrow the freedom of action of management. They tend to support the implementation of digital technologies in those

[4] Content and types of second-level agreements vary widely across countries, sectors and firms.

establishments with a high share of workers performing physical demanding jobs or in the presence of unavoidable competitive pressures.

Building on a qualitative research approach and in-depth interviews with trade unions' delegates and managers of Italian companies, Cirillo *et al.* (2020) detect a lack of trade unions' involvement in the design phase of Industry 4.0 artefacts, regardless of the degree of digitalisation and robotisation in action. However, trade unions play a crucial role in the implementation of new technologies, encouraging acceptance and adaptation among workers.

Second-level bargaining could allow firms to better appropriate the gains of technological and organisational improvements. Through the implementation of second-level bargaining trade unions might also be able to foster a collaborative environment and create preconditions for work practices that could improve improve motivation, job quality and productivity (see Huselid 1995). On these bases, our fourth and final hypothesis is that:

- H4. *Second-level agreements have a positive effect on the adoption of new digital technologies*.

2.2 The diffusion of digital technologies among Italian firms

The secondary data available on the diffusion of digital technologies among Italian firms show a scattered adoption of new enabling technologies. According to the Digital Economy and Society Index (DESI), which summarizes a set of indicators on Europe's digital performance, Italy is placed at the bottom of the ranking in terms of use of digital technologies (European Commission 2018).

This pattern is rooted in structural features of the Italian production structure. First, the specialization of the Italian firms in producing and exporting low-value added production - the share of value added of traditional sectors on the manufacturing industries is about 15%, almost double with respect to the rest of the EU, and almost three times compared to Germany, France and the U.K. (Giovannetti and Quintieri 2008). Second, the presence of a production structure populated by a large share of small and micro firms. According to Bugamelli *et al.* (2012) firms' size is a more important barrier to innovation than sectoral specializations. A recent report by Istat (2018) highlights the difficulty experienced by Italian companies in positioning themselves at the technological frontier and fully exploiting the potential of the ongoing digital transformation through investments in ICT and new technologies capable of reviving productivity dynamics (Brynjolfsson and Hitt 1996; Biagi 2013). Among those factors hampering the adoption of new production technologies by Italian firms, there are structural factors linked to the productive fabric of the country, stagnant growth dynamics, strong territorial dualism, the preeminent weight of small and medium-sized enterprises on national production and a lower average propensity to innovate, with negative outcomes for both productivity and employment (Codogno 2009; Calligaris *et al.* 2016; Istat 2017).

The data provided by the survey on the use of ICTs run by the Italian Statistical Office (Istat) contain interesting contextual information on the state-of-the-art of digitization in the country. Istat reports a significant increase in the number of production units that have introduced the use of enabling technologies to support business data sharing (ERP) in various sectors (approximately 36.5% in 2017, compared to 21.5% in 2012), with particular emphasis on the automotive and telecommunications sectors. As regards the investment in other types of enabling technologies related to I4.0, Istat (2018) shows that between 2014 and 2016 about 44.9% of Italian companies invested in enabling technologies related to IT security, 27.9% in web-related goods and services, 18.4% in social media and 16.1% in cloud computing. The diffusion of these technologies and their impact on the competitiveness and development of Italian companies are heterogeneous: the most widespread are those related to cybersecurity and web applications, while, IoT and Big Data Analytics are adopted mainly by large companies. Similar patterns emerge from a separate study conducted by the Italian Ministry of Economic Development (MISE 2018) on the diffusion of I4.0 techs through the analysis of specific data collected on a sample of about 23,700 enterprises. This survey shows a more rapid diffusion of I4.0 technologies among large enterprises located in the Central and Northern regions. The survey also shows a significantly higher incidence of investments towards 'data technologies', i.e. representative of intensive information exploitation (horizontal or vertical information integration, cloud, big data analytics, etc.) than those more closely related to production (interconnected robots, additive manufacturing, simulations, augmented reality and intelligent materials).

3. Empirical investigation

3.1 Data

The empirical analysis is based on an original database drawn from the 'Rilevazione Imprese e Lavoro' (RIL) survey conducted by Inapp during 2015 and 2018 on a representative sample of partnerships and limited liability firms. Each wave of the survey covers over 30000 firms operating in non-agricultural private sectors. A sub-sample of the firms included in the survey (around 45%) are followed over time, making the RIL dataset a partial panel over the period under investigation[5].

The RIL-Inapp survey collects a rich set of information about the composition of the workforce, including the amount of investments in training, hiring and separations, the use of flexible contractual arrangements, the asset of the industrial relations and other workplace characteristics. Moreover, the data contains an extensive set of firm level controls, including management and corporate governance characteristics, productive specialization and other variables proxying firms' strategies (such as propensity to introduce product and process innovations and share of export on value added).

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The V wave of the RIL-Inapp survey included a new set of questions specifically designed to collect information on the introduction of new digital technologies – hereafter I4.0 techs. In the section "Innovation, Internationalization, Extension of markets", a specific question was added on investments in new technologies over the period 2015-2017: "In the period 2015-2017 did the firm

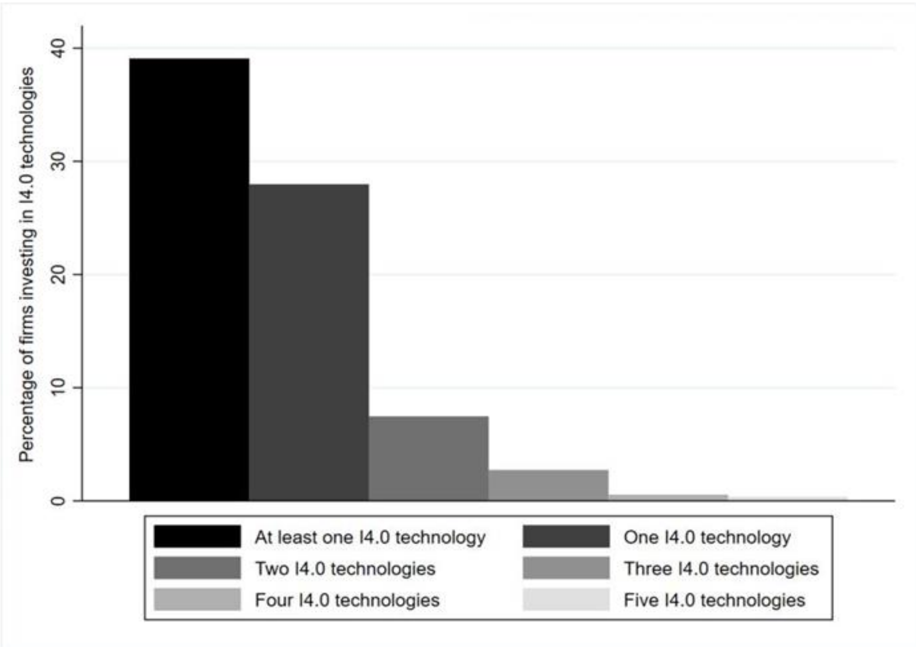
[5] The RIL Survey sample is stratified by size, sector, geographical area and the legal form of firms. Inclusion depends on firm size, measured by the total number of employees. For more details on RIL questionnaire, sample design and methodological issues see: http://www.inapp.org/it/ril.

invest in new technologies?”. The respondent was presented with the following options: Internet of things (IoT), Robotics, Big data analytic, Augmented reality and Cybersecurity.
It was possible to give multiple answers. In order to obtain productivity gains, firms pursue different strategies and decide to invest in one specific I4.0 tech or in more than one I4.0 techs. The data were collected after the implementation of the ‘National Enterprise Plan 4.0’, an incentives scheme that was specifically designed by the Italian Government to lower financial constraints to investment and accelerate the diffusion of I4.0 technologies. All firms were eligible to the scheme and all received the incentive if they invested[6]. In what follows we present descriptive evidence on the diffusion of I4.0 among Italian firms, disaggregating the data by sector, firm size and geographical location.
Our empirical analysis is performed on firms with at least 5 employees in order to examine only productive units with a minimum level of organizational structure. After imposing this selection criterion and deleting observations with missing values for the key variables used in the analysis, the final sample is given by a panel of around 8000 firms observed in each year considered.

3.2 The digitization of Italian businesses

Figure 1 shows uneven patterns of adoption, with less than 40% of the Italian companies with at least 5 employees stating that they had made at least one investment in I4.0 technologies over the period 2015-2017[7].

Figure 1. Percentage of firms investing in I4.0 technologies



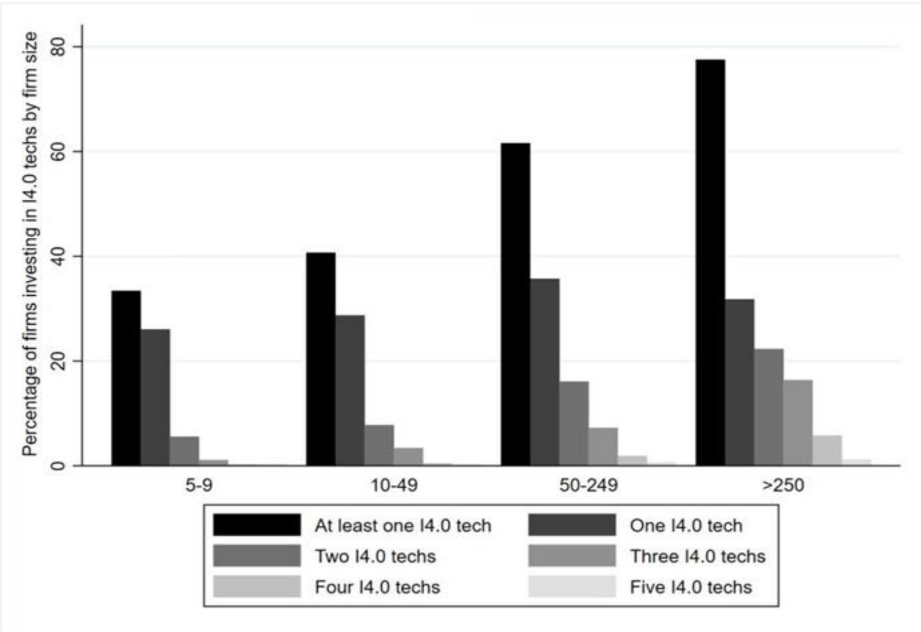
Note: sampling weights applied.
Source: Authors’ elaborations on RIL 2015-2018 panel data

[6] This means that there was no self-selection into the scheme.
[7] This percentage falls to 26% if we consider all the 30.000 firms interviewed in 2018 (with at least one employee). For a descriptive analysis on the cross-sectional wave of the RIL-Inapp survey, see Cirillo *et al.* (2020).

A relatively small group of firms shows combined adoption of several, possibly complementary, I4.0 technologies. Almost 30% of firms invest only in one type of technology - showing a 'single-technology' approach to digitization[8]. These percentages fall sharply when we consider a simultaneous investment in more than one I4.0 technology: only 7.4% invest in two types of technologies, 2.7% invest in three technologies, 0.5% in four techs and a minute share – 0.3% of the subsample of the RIL-Inapp panel (with at least 5 employees) – declared to invest in all I4.0 techs (IoT, Robotics, Big Data Analytics, Augmented reality and cybersecurity). The diffusion of the new Industry 4.0 paradigm among Italian companies is generally limited to a 'single technology' adoption approach rather than a 'multi-technology' strategy based on simultaneous investments in complementary technologies. Unsurprisingly, the adoption of I4.0 techs is associated with firm size, highlighting the existence of well-known differences in cost barriers between small and large and varying absorptive capacities (Cohen and Levinthal 1990a).

The percentage of firms adopting at least one I4.0 technology increases with firm size (see figure 2) – from 33% in small firms (5-9 employees) to 77% in large enterprises (more than 250 employees). Similarly, the 'multi-technology' approach to the adoption of I4.0 is strongly associated to firm size. The percentage of firms introducing contemporaneously five I4.0 techs increases from 0.3% of micro firms (5-9 employees) to 1.2% among large business (i.e. firms with more than 250 employees).

Figure 2. Percentage of firms investing in I4.0 technologies



Note: sampling weights applied.
Source: Authors' elaborations on RIL 2015-2018 panel data

Tables 1 and 2 show the distribution of I4.0 adopters by type of technology, firm size and firm location – see table 1 – and by sector – see table 2. Technology diffusion is strongly conditioned by the

[8] This percentage falls to 20% including firms with less than 5 employees and more than 1 and to 15% including companies without employees.

heterogeneity of the Italian productive structure. In particular, a distinction can be made between companies that have invested in 'at least one' enabling technology and companies that have introduced a specific typology among those indicated, i.e., 'IoT', 'Robotics', 'Big Data', 'Augmented Reality' and 'Information Security'. Table 1 shows how the diffusion of enabling technologies connected to I4.0 is strongly influenced by the size of the enterprises. Cybersecurity is the most adopted technology: on average 33.9% of Italian firms have invested in some forms of information security; while augmented reality and robotics only concern a small portion of Italian companies - respectively 2.5% and 5.1%. Again, firm size plays a prominent role. Companies located in the North East and North West regions, which are well-connected with international value chains, invest more in I4.0 techs then their counterparts located in Central and Southern regions.

Table 1. Percentage of firms investing in I4.0 tech by firm size and geographical area

Firm size	**IoT**	**Robotica**	**Big Data Analytics**	**Augmented reality**	**Cybersecurity**
5 -9	6.4	2.6	3.4	1.9	29.3
10-49	7.6	5.9	6.7	2.7	34.9
50-249	14.0	14.1	14.3	4.7	53.4
> 250	28.1	21.8	27.4	9.4	68.2
Total	**7.7**	**5.1**	**5.9**	**2.5**	**33.9**
Geographical area					
North West	8.3	5.8	5.6	3.4	38.9
North East	8.8	6.1	6.1	2.1	34.2
Center	7.0	3.9	6.8	2.2	29.1
South	5.8	3.4	5.0	2.0	29.7
Total	**7.7**	**5.1**	**5.9**	**2.5**	**33.9**

Note: sampling weights applied.
Source: Authors' elaborations on RIL 2015-2018 panel data

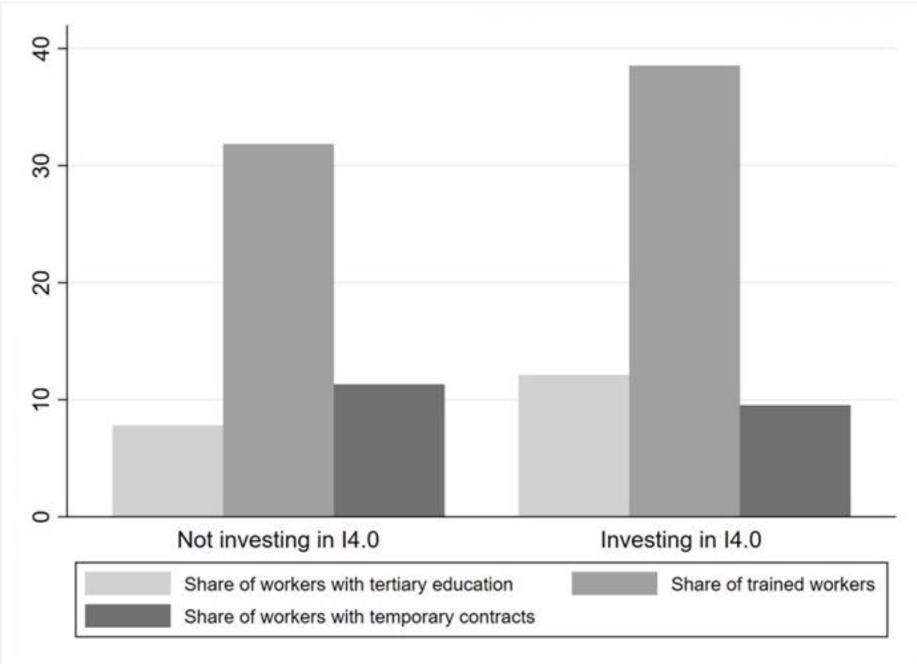
Table 2. Percentage of firms investing in I4.0 techs by sectors

	At least one	**IoT**	**Robotica**	**Big Data Analytics**	**Augmented reality**	**Cybersecurit y**
Mechanical industry	57.2	12.5	14.7	7.0	3.9	46.9
Financial services	54.9	7.4	0.7	11.0	2.1	51.9
ICT Activities	48.6	11.8	2.1	15.7	7.5	43.2
Chemical industry	45.2	9.7	17.3	7.2	4.0	36.8
Education, Healthy	43.1	11.1	3.3	7.9	1.1	37.6
Other manufacturing	42.4	7.8	7.8	4.1	1.7	36.1
Other services	41.8	9.3	2.1	6.2	4.7	37.5
Mining	40.2	7.7	2.6	3.5	1.2	36.2
Food industry	38.7	6.7	8.6	5.3	1.7	33.1
Trade	38.1	7.5	1.8	6.8	2.1	35.0
Textile industry	38.1	7.2	6.2	2.4	1.9	32.1
Transport	34.3	5.4	5.3	8.8	0.9	26.6
Constructions	33.8	2.9	0.8	2.0	1.2	31.3
Hotel and restaurants	21.0	5.5	0.7	2.5	1.6	16.2
Total	**39.1**	**7.7**	**5.1**	**5.9**	**2.5**	**33.9**

Note: sampling weights applied.
Source: Authors' elaborations on RIL 2015-2018 panel data

Table 2 illustrates the distribution of I4.0 adopters among sectors. As expected, sectors featuring a greater incidence of companies investing in enabling technologies are chemistry (45.2%), financial services (54.9%), information and communication (48.6%) and mechanics (57.2%). Among service activities, ICT services displayed a higher incidence of I4.0 adopters in IoT (11.8%), Big Data (15.7%) and information security (43.2%). The mechanical and chemical sector are instead characterised by the most pronounced adoption of robotics.
Linking the investment in new digital technologies (I4.0 techs) to the skills mix of firms, figure 3 shows that on average firms declaring to invest in new digital techs have a higher share of tertiary educated workers and register a more intense use of training activities. Conversely, I4.0 adopters register on average a lower share of employees on short-term contracts. There may be several reasons for this, including lack of information on the returns to education and training, lack of access to finance to fund training or even fear of not reaping the return on their investment in training because of the risk of poaching. The latter might be especially relevant to highly-innovative and high-technology industries.

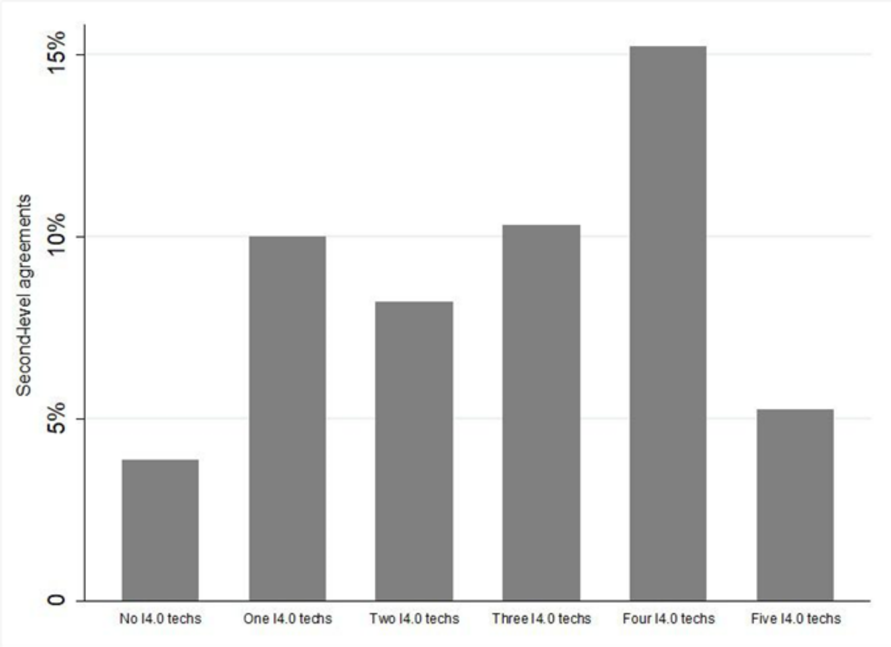
Figure 3. Education, Training, Temporary Work by I4.0 investors



Note: sampling weights applied.
Source: Authors' elaborations on RIL 2015-2018 panel data

When it comes to industrial relations, we detect a positive association between second-level agreements and the number of new digital technologies introduced (see figure 4). On average, firms recurring to decentralized bargaining show a higher incidence of I4.0 techs with respect to those relying on other levels of bargaining. Surprisingly, among leading adopters – those declaring to invest simultaneously in five types of new digital technologies – the incidence of second-level bargaining is low. These firms – on average large businesses – more often resort to sectoral bargaining or experience forms of resistance by unions with respect to the introduction of enabling techs that might exacerbate controls of workers (Moro *et al.* 2019; Cirillo and Zayas 2019). Qualitative researches suggest that it may depend on firm union culture and organizational practices – ranging in large Italian firms from Japanese Toyotism to co-determination *à-la-German* 'Mitbestimmung' (see for further details Cirillo *et al.* 2020).

Figure 4. Share of firms signing second-level bargaining by number of I4.0 techs



Note: sampling weights applied.
Source: Authors' elaborations on RIL 2015-2018 panel data

After sketching the broader patterns of adoption, we investigate the determinants of firm technology choices in a multivariate setting. In the next section, we present our empirical strategy and econometric tests.

4. Empirical strategy

The central research questions of this paper focus on the role of skills, training and the organisation of work as determinants of technology adoption. We estimate the following equation:

$$Y_{i,t} = \alpha + \beta_1 E_{i,t-1} + \beta_2 T_{i,t-1} + \beta_3 FT_{i,t-1} + \beta_4 SB_{i,t-1} + \beta_5 X_{i,t-1} + u_{i,t} \qquad t = [2015{,}2018] \qquad (1)$$

where the dependent variable of equation 1 ($Y_{i,t}$) represents, alternatively: (i) a dichotomous indicator (*I4.0*) taking value 1 if the firm *i* has invested in at least one I4.0 technology over the period 2015-2017, and 0 otherwise; (ii) a categorical indicator (*Number I4.0*) assuming discrete values from 0 to 5 according to the total number of I4.0 technologies introduced. As for our key explanatory variables, E_i , T_i , FT_i and SB_i formalise, respectively, the share of workers with college education, the share of trained workers, the share of fixed-term workers, that is a proxy for flexible within-firm work arrangements, measured in 2015, and the adoption of second-level bargaining. Analogously, the

vector X_i includes a wide set of lagged controls for management and corporate governance, workforce composition, firms' productive and competitive characteristics as well as industrial relations (see table A1 in appendix), while the parameter $u_{i,t}$ indicates an idiosyncratic error term.
Non-linear regression models are then used to estimate different specifications of equation 1. We run a Probit and Zero Inflated Poisson model to estimate, respectively, the average marginal effects associated to the probability of introducing at least one I4.0 technology and the total number of new digital technologies (Wooldridge 2010; Trivedi 2013). In this econometric framework, however, potential issues concerning unobserved heterogeneity and sample selection (endogeneity) may arise. Namely, if there are both observable and unobservable factors simultaneously affecting workforce human capital endowment and the propensity to invest in new technologies, the Probit and Zero Inflated Poisson estimates might suffer from potential omitted variable bias and reverse causality[9].
The inclusion of a wide set of controls allows us to minimize the endogeneity bias arising from the presence of omitted variables; while the inclusion of these controls as pre-determined controls helps to address issues related to reverse causality[10].
We also implement a two stage Heckman procedure (Amemiya 1985; Heckman 1979) conditioning the adoption choice on the likelihood that firms were investment-active. In our framework this is equivalent to performing a binary or count response model with sample selection (Wooldridge 2010), as follows:

$$\Pr(I_{i,t-1}) = \alpha + \beta_1 E_{i,t-1} + \beta_2 T_{i,t-1} + \beta_3 FT_{i,t-1} + \beta_4 SB_{i,t-1} + \beta_5 X_{i,t-1} + \gamma Z_{i,t-1} + u_{i,t} \tag{2}$$

$$Y^*_{i,t} = \alpha + \beta_1 E_{i,t-1} + \beta_2 T_{i,t-1} + \beta_3 FT_{i,t-1} + \beta_4 SB_{i,t-1} + \beta_5 X_{i,t-1} + \lambda_i + \varepsilon_{i,t} \tag{3}$$

where the dependent variable $Pr(I_{i,t-1})$ in the selection equation 2, is a probability index assuming value 1 if firm *i* has invested in 2015 and 0 otherwise. As for the explanatory variables, the vector *X* includes the entire set of controls already considered in equation 1. As exclusion restriction, we use a variable that accounts for firms' bank loans demand due to cash or liquidity problems[11]. The dependent variable $Y^*_{i,t}$ in equation (3), represents the dummy indicator *I4.0* or the number of I4.0 technologies (*Number I4.0*), which is observed mainly if $Pr\ (I_{t-1})$ is equal to 1, that is if firm *i* realised an investment in 2015. Accordingly, the righ-hand side variables are the same set of controls for managers, firms and workforce characteristics discussed in equation 1, while λ_i is the Inverse Mills Ratio (IMR) accounting for the self-selection in the investment decision[12]. Therefore, the Probit equation for the probability of firm investment in 2015 is completely observed on data while the selected sample is available for analysing the impact of human capital mix on the adoption of I4.0 technologies.

[9] This happens, for example, when implicit social norms at workplace and managers' personal traits, typically not observed by the researcher, affect both the quality of human resource practices (low workers turnover, high share of skilled and trained workers, and so on) as well as firms' innovative and productive behaviour. In this case, a positive non-linear estimates in equation 1 may reflect firms and managers' unobserved characteristics rather than the impact of human capital on the adoption of I4.0 technologies.
[10] In particular, we refer to variables related to corporate governance, demographic profile of managers, recruitment policies and industrial relations.

Finally, equations 2 and 3 are simultaneously estimated by using a Maximum Likelihood method. This procedure allows us to correct for the sample selection bias so to obtain consistent estimates of the average marginal effects.
Auxiliary information and the main statistical tests for the sample selection hypothesis are reported in the last rows of table 3 and table 4, while results from equation 2 are shown in the appendix (table A2).

5. Results

In table 3 we show the main results of our econometric analysis, concerning, first of all, the correlation between skills and 1) the probability of adoption (first column) and 2) the intensity of adoption measured by the number of technologies (second column). What we find is that firms characterized by a higher share of educated workforce – i.e. the share of workers with college degree – invest more in new technologies and show a multi-technology adoption strategy. A higher proportion of trained workers also appears to favour the probability of investment and the number of digital technologies adopted. Conversely, the share of fixed-term workers is negatively associated to the adoption choice, even though this results is statistically weaker, and it is not correlated with the adoption of multiple technologies. Moreover, second-level agreements play a positive role in the probability adoption and the number of technologies adopted. Controlling for potential 'selection bias', (columns 3 and 4), the share of fixed-term workers and second-level agreements are no longer significant, while both tertiary educated and trained workers still positively affect the propensity to invest in I4.0. This means that controlling for the firm propensity to invest, these particular enabling technologies remain strongly associated with skills and training, but not with the the work organisation variables. As we mentioned in the discussion of the descriptive results (section 2.2), the probability of introducing new digital technologies and the adoption of a multi-technology strategy are strongly and positively correlated with a wide set of control variables. These provide very useful insights into which firms' complementary characteristics may successfully trigger investment in new enabling technologies. The results suggest that larger firms, led by higher quality management in terms of educational level, higher productivity levels, more innovative both in terms of process and product innovation, and more internationalised present higher probability to introduce digital technologies as well as to follow an adoption pattern characterized by investment in multiple types of I4.0 technologies. Conversely, a higher share of older workforce and family-ownership are strongly and negatively correlated with the the adoption of I4.0 technologies and also with a 'multi-technology' profile. Thus, the results presented in table 3 confirm H1. Moreover, investment in training also favours the adoption of enabling technologies, we argue, because of the importance of tacit knowledge and the generation of firm-specific skills that will be use to extract productivity gains from the new technologies. However, the complementarity effect between skills and digital technologies is stronger for skills generated through the education system than through on-the-job training. Results from table 3 also provide some insights on the relation between firm-level work organization and the propensity to invest in I4.0 techs. As stated in section 2, the adoption of new technologies at the plant level goes along with organizational changes. The use of ICTs has already shown proven patterns of complementarity with specific forms of work organization involving decentralized decision-making and team working

(Bresnahan *et al.* 2002). Focusing on flexible staff arrangements, our second hypothesis is confirmed, indicating that the introduction of I4.0 technologies benefit from the accumulation of knowledge through longer-term work relationships than from efficiency gains possibly derived from the use of short-term contracts (see Kleinknecht (2020) for a detailed discussion on this). Results presented in column 1 of table 3 show that firms with higher share of temporary employment are on average less digitized with respect to those characterised by a higher share of permanent employment. The role of second-level bargaining (H4) is also confirmed according to our expectations. The underlying mechanism is likely to be that more collective decision-making process, shared across the firm's hierarchical structure, favour riskier investment in new technology. Conditioning on the probability of prior investment, that is to say underplaying the role of first technology adopters relative to persistent investors, the statistical significance of flexibility and second-level bargaining disappears.
In table 4 we also show the results of our econometric estimation on the probability of adopting at least one I4.0 technology, by disaggregating firms into size classes, i.e. firms with size lower than 250 employees vs. firms with more than 250 employees, and the broad economic sector in which they operate, i.e. manufacturing and services. Consistently with the results presented table 3, college and trained workers have a positive and statistically significant effect on the adoption of I4.0 technologies for both small/medium and large firms and for firms operating in both manufacturing and service sectors, even though the share of trained workers does not affect the probability of adoption for large firms. Interestingly, the effect of second-level agreements is positive for SMEs but negative for larger firms, indicating that decentralised bargaining favours technology adoption in a leaner organisation (among small and medium sized firms) but is not associated with new enabling technologies in larger firms, which are arguably more likely to rely on sector-level bargaining. In large businesses second-level bargaining might hamper investments in I4.0 because of a possible conflictual attitude of unions endorsing concerns of increased control and surveillance behind the management's adoption of digital technologies. Conversely, a more corporative attitude could prevail in small and medium-size firms, either fostering better information exchanges about the technology within the company or favoring a generally more cooperative context for technology adoption decisions.
Among the control variables, the positive effect of a wide set of firms' characteristics previously discussed, such as firm performance in terms of labour productivity, educational level of the management, both product and process innovations and the degree of internationalization, seem to be confirmed only for small and medium enterprises. These findings suggest that there is significant heterogeneity in the population of adopters, but it is very interesting to notice that results are very similar between the manufacturing and services sector, indicating that the new enabling technologies affect very different economic activities and have the potential to permeate not only manufacturing (the production model more closely associated with the 'smart factory') but also services. Between the two macro-areas, the variable that is significant for manufacturing but not for services is the role second-level barganing. This might signal different patterns of governance for technology adoption decisions between manufacturing and services, which may also be associated with different performance and employment effects post-adoption.

Table 3. Estimates of the average marginal effects. Dep var: Probability to invest in I4.0 and number of I4.0 technologies

	(1) At least one b/se	(2) Number of I4.0 b/se	(3) At least one b/se	(4) Number of I4.0 b/se
College workers	0.177028***	0.396379**	0.115041***	0.266226**
	(0.037)	(0.155)	(0.035)	(0.111)
Trained workers	0.043859***	0.087007***	0.060826***	0.003022
	(0.013)	(0.026)	(0.012)	(0.040)
Fixed-term workers	-0.063911*	0.020456	-0.004203	-0.022740
	(0.036)	(0.100)	(0.035)	(0.104)
Second lev. agreem.	0.036378**	0.117391***	0.037491***	0.066634
	(0.017)	(0.041)	(0.014)	(0.043)
Firm size1	0.070322***	0.002281***	0.074574***	0.000298***
	(0.005)	(0.001)	(0.005)	(0.000)
Log (VA per worker)	0.009902**	0.034536***	0.012234***	0.028623**
	(0.005)	(0.009)	0.004	(0.013)
Old-age (>55)	-0.050792	-0.301616***	-0.063056**	-0.333603***
	(0.033)	(0.068)	(0.030)	(0.095)
Middle-age (35-55)	0.029385	-0.036414	-0.000807	-0.005286
	(0.029)	(0.057)	(0.028)	(0.088)
Family firm	-0.000216	-0.083669***	-0.022762*	-0.126162***
	(0.015)	(0.028)	(0.013)	(0.041)
High school	0.096306***	0.079446*	0.051784***	0.062981
	(0.021)	(0.047)	(0.019)	(0.063)
In a trade group	0.032560***	0.076495***	0.044883***	0.035137
	(0.012)	(0.025)	(0.011)	(0.036)
Graduate manag.	0.029777*	0.108422***	0.012871	0.059479
	(0.018)	(0.039)	(0.016)	(0.048)
High-school manag.	0.009442	0.059701*	-0.004793	0.051265
	(0.015)	(0.035)	(0.014)	(0.041)
Female manag.	0.012188	-0.014869	0.023233	0.002512
	(0.017)	(0.033)	(0.015)	(0.045)
Product innovators	0.065874***	0.159434***	0.088955***	0.106009***
	(0.013)	(0.025)	(0.011)	(0.036)
Process innovators	0.081530***	0.186082***	0.123046***	0.060461*
	(0.013)	(0.025)	(0.012)	(0.036)
Firm age	0.000136	0.000540**	0.000233*	0.000924*
	(0.000)	(0.000)	(0.000)	(0.000)
FDI inv.	0.090194***	0.207316***	0.104813***	0.287045***
	(0.028)	(0.060)	(0.023)	(0.074)
Share of export	0.000168	0.000536	0.000246	0.001423*
	(0.000)	(0.000)	(0.000)	(0.001)
Sec. and reg. dummies	Yes	Yes	Yes	Yes
Observations	7746	7746	7675	7675
Non zero obs.		3719		
Censored obs			3413	3.413
Uncensored obs			4262	4262
Wald Chi2	996.03	714.49	1479.55	375.60
Prob > Chi2	0.0000	0.0000	0.0004	0.0000
Pseudo $R2$	0.1051			
Sample sel. stat.:				
athrho			1,7084***	-0.4169
			0.4801	0.0535
LR test (rho = 0):				
chi2(1) =			12.66	60.66
Prob > Chi2	0.0000	0.0000	0.0004	0.0000

1 number of employees in columns (2) and (4), log of number of employees in (1) and (2).

Note: marginal effects (1); Zero-Inflated Poisson (2); Heckprobit selection model (3); Heckman selection model (4). Omitted variables: managers with lower secondary and primary education, workers with lower secondary and primary education; workers less than 35 years old. First stage exclusion restrictions "financially weak" (3, 4): “During 2014 did the company apply for a bank credit for cash or liquidity reasons?”.

*** p<0.01, ** p<0.05, * p<0.1.

Source: Authors’ elaborations on RIL 2015-2018 panel data

Table 4. Estimates of the average marginal effects by firms' size and sector of activity. Dep var: Probability to invest in I4.0 and number of I4.0 technologies

	(1) At least one < 250 b/se	(2) At least one > 250 b/se	(3) At least one Manuf. b/se	(4) At least one Serv. b/se
College workers	0.156862***	0.254780**	0.271261***	0.157283***
	(0.030)	(0.120)	(0.082)	(0.046)
Trained workers	0.050749***	0.024989	0.037894*	0.038673*
	(0.012)	(0.050)	(0.020)	(0.021)
Fixed-term workers	-0.023647	-0.180278*	-0.013164	-0.036111
	(0.029)	(0.108)	(0.064)	(0.049)
Second lev. agreem.	0.029340*	-0.091568**	0.048062**	-0.008001
	(0.017)	(0.042)	(0.024)	(0.029)
Firm size (log)	0.080092***	0.112861***	0.087764***	0.061900***
	(0.005)	(0.022)	(0.009)	(0.008)
Log (VA per worker)	0.010587**	0.016044	0.009562	0.008513
	(0.004)	(0.011)	(0.007)	(0.007)
Old-age (>55)	-0.041770*	0.036595	0.011375	-0.078847
	(0.025)	(0.128)	(0.049)	(0.051)
Middle-age (35-55)	0.000515	-0.042711	0.043077	0.018206
	(0.021)	(0.118)	(0.045)	(0.043)
Family firm	0.005604	-0.012948	0.044743**	-0.053089**
	(0.015)	(0.034)	(0.022)	(0.022)
High school	0.107682***	0.042262	0.059836*	0.120764***
	(0.017)	(0.086)	(0.032)	(0.033)
In a trade group	0.039165***	0.058112	0.041175**	0.031277*
	(0.010)	(0.045)	(0.018)	(0.018)
Graduate manag.	0.039798**	-0.024698	0.034329	0.024055
	(0.016)	(0.075)	(0.025)	(0.030)
High-school manag.	0.014181	0.005985	0.031547	-0.007562
	(0.013)	(0.073)	(0.021)	(0.027)
Female manag.	0.006637	0.037783	-0.005873	0.030459
	(0.014)	(0.067)	(0.026)	(0.025)
Product innovators	0.068400***	-0.003449	0.038097**	0.100257***
	(0.011)	(0.044)	(0.019)	(0.020)
Process innovators	0.078312***	0.038322	0.101617***	0.034341
	(0.012)	(0.047)	(0.018)	(0.022)
Firm age	0.000139	0.000315	-0.000016	0.000364
	(0.000)	(0.000)	(0.000)	(0.000)
FDI inv.	0.059672**	0.066113	0.051836	0.103243*
	(0.030)	(0.044)	(0.036)	(0.053)
Share of export	0.000246	-0.001320*	-0.000137	0.000603
	(0.000)	(0.001)	(0.000)	(0.001)
Sec. and reg. dummies	Yes	Yes	Yes	Yes
Observations	9428	536	3533	2233
Wald Chi2	1212.91	105.02	519.69	345.66
Prob > Chi2	0.0000	0.0000	0.0000	0.0000
Pseudo $R2$	0.1086	0.1836	0.1219	0.0852

Note: omitted variables: managers with lower secondary and primary education, workers with lower secondary and primary education; workers less than 35 years old.
*** p<0.01, ** p<0.05, * p<0.1.
Source: Authors' elaborations on RIL 2015-2018 panel data

6. Conclusions

What firm characteristics favour the adoption of new production technologies? This is a fundamental question if we are on the eve of a Fourth Industrial Revolution and the new wave of digital technologies is a key part of the ongoing transition towards the so-called ‘smart factory’, i.e. the hyper-connected company of the future, characterized by strong interaction between new production technologies (smart production) and information and network infrastructures (smart services). While the average firm is still very far from this archetypal model of production, the process of diffusion of new enabling technologies has begun and it is already possible to identify some defining characteristics of early adopters, even in a context, such as the Italian one, which is still lagging behind in the penetration of the incumbent ICT paradigm.

In this contribution we have exploited a large and unique dataset that includes fine-grained information about the technology adoption choices made by firms. Analyses of the broad patterns of adoption show significant variations by firm size, sector and location. The vast majority of adopters opt for a single-technology, rather than an integrated (multiple technology) approach. The econometric evidence confirms a line of continuity with previous studies of ICTs, with strong complementarities between skills and new technology. Both human capital measured by education attainment levels and on-the-job training are positively associated with the adoption of digital technologies. Comparatively weaker evidence points to the role of flexible work. Regarding this variable, some of the estimations indicate a negative, rather than positive, effect, pointing to the importance of knowledge accumulation embodied in firm employees rather than the efficiency gains of labour market flexibility. Decentralised bargaining instead appears to favour new technology adoption, albeit with strongly heterogeneous effects. The key implication for firm strategy is that workers skills are primary determinants of the adoption of digital enabling technologies, because they are necessary conditions for the extraction of productivity gains from the new assets. The corresponding policy lesson is that industrial policies that incentivise digitization cannot only focus on the acquisition of assets but must include strong components of upskilling and training, as well as appropriate policies for the supply of new skills through the institutional formation of digital competences.

In this paper we have provided rare microeconomic evidence of adoption behaviours, but of course many important questions remain unanswered. First of all, further work should investigate the effects of digitization on firm productivity and growth. Second, it will be fundamental to identify the consequences of digitization on employment and wages. Moreover, given that this cluster of technologies includes a multiplicity of devices and techniques, it is possible that different technological combinations will generate different effects on productivity and employment. Finally, it would be extremely interesting to evaluate whether and how the implementation of new models of production changes not only the internal but also the external organisation of the firm, and the local vs. the global development of the value chain.

Appendix

Table A1. Descriptive statistics

	Mean	Sd	Min	Max
At least one	0.39	0.49	0	1
Number of I4.0 tech	0.55	0.84	0	5
IoT	0.08	0.27	0	1
Robotica	0.05	0.22	0	1
Big Data Analytics	0.06	0.24	0	1
Augmented Reality	0.03	0.16	0	1
Cybersecurity	0.34	0.47	0	1
Share of trained	0.34	0.42	0	1
Share of fixed-term	0.11	0.20	0	1
Share of workers with tertiary education	0.10	0.19	0	1
Number of employees	25.67	155.38	0	9775
Value Added per employee	11.71	1.19	0.09	16.11
Share of workers over 50	0.22	0.22	0	1
Share of workers 35-50	0.46	0.26	0	1
Family firm	0.91	0.29	0	1
Share of workers with high school degree	0.50	0.32	0	1
Taking part of a trade group	0.57	0.49	0	1
Management with tertiary education	0.23	0.42	0	1
Managemnt with high school degree	0.56	0.50	0	1
Female management	0.16	0.37	0	1
Product Innovation	0.36	0.48	0	1
Process Innovation	0.29	0.45	0	1
Firm age	25.77	21.10	0	1009
FDI	0.02	0.13	0	1
Share of export on value added	7.19	19.23	0	100
International agreements	0.10	0.31	0	1
Second level agreement	0.06	0.24	0	1

Note: sampling weights applied.
Source: Authors' elaborations on RIL 2015-2018 panel data

Table A2. Test of exclusion restriction

	(1) Investment I4.0 b/se	(2) Number of I4.0 b/se
College workers	0.182506***	0.297719***
	(0.037)	(0.074)
Trained workers	0.042909***	0.089882***
	(0.013)	(0.025)
Fixed-term workers	-0.063130*	-0.010188
	(0.037)	(0.062)
Second lev. agreem.	0.037520**	0.162264***
	(0.017)	(0.034)
Firm size	0.070131***	0.000369***
	(0.005)	(0.000)
Log(VA per worker)	0.009296**	0.031605***
	(0.005)	(0.009)
Old-age	-0.050115	-0.257149***
	(0.033)	(0.057)
Middle-age	0.031327	-0.028903
	(0.029)	(0.052)
Family firm	0.000794	-0.128519***
	(0.015)	(0.031)
High school	0.096769***	0.088260**
	(0.021)	(0.038)
In a trade group	0.033435***	0.069015***
	(0.012)	(0.022)
Graduate manag.	0.030788*	0.103339***
	(0.018)	(0.032)
High-school manag.	0.009667	0.051493**
	(0.015)	(0.026)
Female manag.	0.012318	-0.018181
	(0.017)	(0.030)
Product innovators	0.066726***	0.162801***
	(0.013)	(0.025)
Process innovators	0.081139***	0.207712***
	(0.013)	(0.026)
Firm age	0.000135	0.000732**
	(0.000)	(0.000)
FDI inv.	0.089610***	0.407903***
	(0.028)	(0.067)
Share of export	0.000173	0.001701***
	(0.000)	(0.001)
Financially weak	-0.005122	0.003832
	(0.012)	(0.022)
Constant		-0.182672
		(0.159)
Observations	7,707	7,707
Wald Chi2	991.71	
F(52, 7654)		24.05
Prob > Chi2	0.0000	0.0000
Prob > F		0.0000
Pseudo *R2*	0.1052	
R^2		0.1737
Root MSE		0.88051

Note: marginal effects (1); Zero-Inflated Poisson (2). Omitted variables: managers with lower secondary and primary education, workers with lower secondary and primary education; workers less than 35 years old.
*** p<0.01, ** p<0.05, * p<0.1.
Source: Authors’ elaborations on RIL 2015-2018 panel data

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