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Institute of Economics
Scuola Superiore Sant'Anna

Piazza Martiri della Libertà, 33 - 56127 Pisa, Italy
ph. +39 050 88.33.43
institute.economics@sssup.it

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Digitalizing Firms: Skills, Work Organization and the Adoption of New Enabling Technologies

Valeria Cirillo [a]
Lucrezia Fanti [b]
Andrea Mina [c,d]
Andrea Ricci [b]

[a] Dipartimento di Scienze politiche, Università degli studi di Bari "Aldo Moro", Italy.
[B] Istituto Nazionale per l'Analisi delle Politiche Pubbliche (INAPP), Roma, Italy.
[c] Institute of Economics and EMbeDS, Scuola Superiore Sant'Anna, Pisa, Italy.
[d] Centre for Business Research, University of Cambridge, UK.

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DIGITIZING FIRMS: SKILLS, WORK ORGANIZATION AND THE ADOPTION OF NEW ENABLING TECHNOLOGIES

Valeria Cirillo
Dipartimento di Scienze politiche, Università degli studi di Bari "Aldo Moro", Bari
valeria.cirillo@uniba.it

Lucrezia Fanti
Istituto Nazionale per l'Analisi delle Politiche Pubbliche (INAPP), Roma
l.fanti.ext@inapp.org

Andrea Mina[1]
Institute of Economics and EMbeDS, Scuola Superiore Sant'Anna, Pisa
Centre for Business Research, University of Cambridge, Cambridge
andrea.mina@santannapisa.it

Andrea Ricci
Istituto Nazionale per l'Analisi delle Politiche Pubbliche (INAPP), Roma
an.ricci@inapp.org

ABSTRACT
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 behaviours. By using panel data on a large representative sample of Italian firms, we explore the patterns and determinants of new digital technology adoption. We build our theoretical framework on the nexus between technology, skills and the organisation of work. We then provide novel econometric evidence on the positive effects of human capital and training. Among the notable results of the paper, labour flexibility does not seem to favour new technology 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.

KEYWORDS: Digital technologies, Industry 4.0, skills, human capital, work organisation

JEL CODES: D20, L23, O33

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1. Introduction

Modern production technologies are characterised by increased digitization, automation and interconnectivity (Brynjolfsson and McAfee, 2014; Ford, 2015). These characteristics have been associated with disruptive process innovations that have been qualified as new 'enabling technologies' (Teece, 2018). Martinelli et al. (2021) argue that these digital technologies can be defined as emergent technologies displaying some of the characteristics of general purpose technologies (GPTs) (Bresnahan and Trajtenberg, 1995; Jovanovich and Rousseau, 2005; Bresnahan, 2010), but are not yet fully developed GPTs and are deeply dependent on the broader ICT paradigm where they function. In Europe these technologies are often subsumed in the policy debate under the umbrella term 'Industry 4.0'. This concept, which has roots in German industrial policy, captures the convergence of new operational technologies with Internet-driven IT, and marks a 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. These include a complex set of devices over a broad continuum of production possibilities, and production choices are arguably conditional on infrastructures and firm organization. While it remains to be seen whether particular configurations of 'enabling technologies' may or may not lead to a radically new 'techno-economic paradigm' (Dosi, 1982; Freeman and Perez, 1988), there can be no doubt that the high recombinatorial potential of digital technologies can foster new ways of performing economic activities. The ability of companies to select and exploit new sources of competitive advantage is, therefore, a likely determinant of growth because of the expected 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 a serious shortcoming for research and for evidence-based policy because it is diffusion, rather than invention or innovation, the broad manifestation of Schumpeterian structural change in the economy (Metcalfe, 1998; Stoneman and Battisti, 2010). Even though important work exists on the diffusion of robots, for which the International Federation of Robotics provides aggregate data (Acemoglu and Restrepo, 2017; Dauth et al., 2017), the analyses of individual firm choices has proved much more difficult, as clearly pointed out by Seamans and Raj (2018). To contribute to this important and under-researched aspect of the digital economy, we explore a large and unique firm-level survey of Italian businesses: the survey "Rilevazione Imprese e

Lavoro – RIL" (Longitudinal Survey of Businesses and Work), run by the Italian National Institute for the Analysis of Public Policies (INAPP). The survey contains specific questions on different digital technologies acquired by firms, thus offering a unique opportunity to study the determinants of adoption of new enabling technologies.

The specific focus of the paper is the nexus between technology, human capital and the organisation of work. This is a fundamental aspect of the debate about the disruptive potential of new digital technologies because the skills profile of firms filters the penetration of technical change in the economy and lay the foundations for the productivity gains that could be generated in the process (Acemoglu, 2002; Link and Siegel, 2003). After describing the aggregate patterns of adoption, we perform an econometric analysis of the role of skills, distinguishing between formal human capital endowments and on-the-job training, and the role of two essential aspects of the organisation of work within the firm: the use of temporary contracts and the role of second-level bargaining in the governance of the firm. Many empirical contributions have highlighted the patterns of complementarity between high-skilled workers and information technologies (among others, Autor et al., 2000; Bresnahan et al., 2002; and Fabiani et al., 2005; Piva et al., 2005, for Italy). This body of empirical evidence seems to lend broad support to the skill-bias technical hypothesis (Acemoglu, 2002). So far very few studies have, however, been able to extend this line of enquiry to new digital technologies, and none – to the best of our knowledge – has considered from a large-scale quantitative perspective the joint role of skills and work organisation in firm adoption. This study contributes to filling this gap in the literature.

The paper is organised as follows: in the first section we review the literature on technology adoption and skills to frame our research questions and derive testable hypotheses (section 2). In section 3 we present the data and provide some descriptive evidence on diffusion among Italian firms (section 2.2). Section 4 presents the empirical strategy; while section 5 contains 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. Background literature and hypotheses

In the study of technical change, several factors have been identified as drivers of technology adoption choices, and much has been written on how these choices translate into aggregate patterns of technology diffusion (for comprehensive reviews of this literature, see Karshenas and Stoneman, 1993; Geroski, 2000, Hall and Khan, 2003; Stoneman and Battisti, 2010).[2] Among the drivers of adoption, we can distinguish between: i) supply-side factors, including improvements of older technologies leading to incremental innovations or changes in the use of existing technologies (Gruber and Verboven, 2001); ii) factors related to the demand for new technologies, such as technological complementarities between producers and users, and the adopters' stock of tangible and intangible capital (Rosenberg, 1976); iii) specific (internal) characteristics of the firm, such as size, age, and human resource management practices (Bloom et al., 2012); and finally iv) the external organisation of the firm and the institutional context in which businesses operate (Dosi, 1991; Mowery and Rosenberg, 1993). More broadly, the co-evolution of organizational capabilities and economic environment shapes the sources of competitive advantage (Nelson and Winter, 1982; Dosi et al., 2000; Dosi and Marengo, 2015).

An important stream of contributions has specifically focused on the interplay between technology and human capital (OECD 2011), proxied by workers' education levels as in standard human capital theory (Becker 1994) or conceptualised as workers' knowledge and routines from an evolutionary perspective (Nelson and Winter, 1982; Dosi and Marengo, 2015). 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 that 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 instance of employment, and are the result of *ad-hoc* training in a specific production context.

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, skills that started as 'specific' can become more 'general', and if these are only available in short supply, they will attract a high

[2] The literature on this topic is very rich, starting at least from the pioneering contributions of Rogers (1962), Mansfield (1968), David (1969), Davies (1979), Metcalfe (1981) and Stoneman (1981), but its coverage is well beyond the scope of this paper.

market 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; Leiponen, 2005). It is nevertheless possible to ask which skill sets are more suitable for the adoption of new digital technologies as part of firm-specific strategies. Firms have to anticipate skills needs in preparation for particular technology choices, and are bound in their technology choices by path-dependent human capital endowments. 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. We argue that in making this strategic choice, firms recognise that these gains may only be realised if skilled workers are able to use and extract value from the new technologies. Therefore, we propose the following baseline hypothesis:

HP1. *Firms with more skilled employees are more likely to invest in new digital technologies.*

As we have already suggested, 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 studies point to the role of high-skilled and highly-trained human capital as key drivers 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 1990) 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. While a firm's absorptive capacity is more than the sum of the absorptive capacities of its employees (Cohen and Levinthal, 1990), it is related to the skills of employees, including those who stand at the interface between the firm and its external environment. 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.[3]

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

Whereas general human capital can be acquired through the market process, more specific skills, tailored to the exact requirements of the firm, can only 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. The contribution of formal education levels and training varies across firms and sectors, depending on the relative importance of ‘Occupational Labour Markets’ vs. ‘Internal Labour Market’ mechanisms of human capital upgrading (Rubery and Grimshaw, 2003). The former depends on nationally recognized qualifications; the latter is designed and organised as on-the-job training by individual employers in accordance with their specific needs.

Skills upgrading through training is beneficial to the adoption of new technologies because embodied technical change can only generate productivity gains it is successfully integrated in contextual production processes (Boothby et al., 2010). Whenever skills requirements are firm-specific, or in a context with stronger labour market frictions, training is the relative more efficient solution (Ramachandran, 1993; Hamermesh and Pfann, 1996). Moreover, in the complex cognitive process of adaptation to radical new technologies (Raffaelli et al., 2019), training can shape workers' perception of a new technology and influence their attitude to change (Ouadahi, 2008). It is interesting to notice that there are contrasting results in the literature on ICT adoption and training: for example, Arvanitis (2005) found evidence of complementary between investment in information technology and training, whereas Giuri et al. (2008) did not. We would argue that the most plausible hypothesis that can be made for the new digital technologies follows the expectation that firms planning changes in production are more likely to prepare their workers by updating or upgrading their skill sets to fully capture the benefits of new technologies[4]. Even though technical change always entails an element of uncertainty also in diffusion processes, it can argue that firms expect technologies to require contextual adjustments and may benefit from having training programmes in place. For this reason, we posit that:

> HP2. *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

[4] Naturally, the two mechanisms can also coexist in a more ‘systemic integration model’, for example combining higher-level science and engineering skills of a small group of workers with highly trained employees.

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 (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., 1990). This is an argument clearly made by Bresnahan et al. (2002) in their seminal paper on the combination of computerization, workplace organization and increased demand for skilled workers. Complementarity drove clusters of structural adjustments 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. Moreover, it can show patterns of correlations with specific forms of work organization that include higher levels of labour flexibility and the use of short-term labour contracts.

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 (Bartelsman et al., 2016). 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 in the presence of increased market competition. On the other hand, evidence exists that more flexible (internal) labour markets can hamper innovation at both firm and sector levels (see for example Kleinknecht et al., 2014, Cetrulo et al., 2019, Hoxha and Kleinknecht, 2020). More 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 (Michie and Sheehan, 2003; Castro Silva and Lima, 2019). The accumulation of knowledge would thus be hampered by frequent employees turnover, preventing the attainment of productivity gains derived from idiosyncratic activities of learning by doing.[5]

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:

> HP3. *The use of flexible staff arrangements has a negative effect on the adoption of new digital technologies.*

[5] 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. We are going to subject this conjecture to empirical tests in the analysis of heterogeneous effects in Section 4.

The final aspect to which we draw our attention 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 can be more flexible and versatile than centralized bargaining, thus offering some advantages in more dynamic environments (Appelbaum and Berg, 1999). This is especially relevant when investment decisions concern new technologies.

Lean production models associated with digital transformations require a relatively high level of 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[6]. As already noted by Freeman and Medoff (1984) and Metcalf (2003), economic theories have not been able to predict unambiguously the impact of bargaining (and more generally unionisation) on firms. Second-level bargaining could both increase or decrease productivity. 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), but the evidence is contradictory and overall inconclusive. 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).

Kleinknecht (2020) argues that decentralised bargaining would hamper innovation because it can induce firms to use downward wage flexibility rather that innovation or technology adoption to remain competitive. In a rare contribution specifically focused on digital technologies and based on establishment survey data and employee data, Genz et al. (2019) have recently found a strong negative relation between work councils and investments in Industry 4.0 technologies in Germany. The implementation of digital technologies broadens the responsibility of work councils to mediate

[6] Content and types of second-level agreements vary widely across countries, sectors and firms (see Kleinknecht, 2020, for a discussion of this issue).

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 only in those establishments characterised by a high share of workers performing physically demanding jobs or subject to competitive pressures (Genz et al., 2019).

Building on a qualitative research approach and in-depth interviews with trade unions' delegates and managers of Italian companies, Cirillo et al. (2020) detect instead 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, the authors also suggest that trade unions play a key role in the implementation of new technologies by encouraging workers' acceptance and adaptation. Second-level bargaining could therefore 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 motivation, job quality and productivity (Huselid, 1995). In light of this qualitative evidence, our fourth and final hypothesis is that:

HP4. *Second-level agreements have a positive effect on the adoption of new digital technologies*.

3. Data and methodology

3.1 Context: Digitalization in the Italian economy

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 digital technologies use (European Commission, 2018). This pattern is generally ascribed to well-known structural features of the Italian production system, above all the large share of small and micro firms, and the share of value added coming from traditional sectors (Bugamelli et al., 2012). A recent report by the Italian Institute of Statistics (2018) highlighted the difficulty experienced by Italian companies in positioning themselves at the technological frontier and in exploiting the ongoing digital transformation through investments in technologies capable of reviving productivity dynamics. Among the factors hampering diffusion, there are stagnant macroeconomic growth dynamics, strong territorial dualism, the preeminent weight of small and medium-sized enterprises on national production and a low 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 also run by the Italian Statistical Office (ISTAT) contain interesting contextual information on the state-of-the-art of digitization in the country. ISTAT (2018) reports a significant increase in the number of production units that have introduced the use of ITC 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. Against this backdrop, more detailed microeconomic analyses are much needed to acquire deeper understanding of the dynamics at play.

3.2 Data

Our empirical analysis is based on an original database drawn from the 'Rilevazione Imprese e Lavoro' (RIL) survey conducted by INAPP in 2015 and 2018 on a representative sample of partnerships and limited liability firms. Each wave of the survey covers over 30,000 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[7].

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).

The fifth wave of the RIL-INAPP survey collected information on the introduction of Industry 4.0 technologies – hereafter I4.0 technologies. A specific question was added on investments in new technologies over the period 2015-2017: "In the period 2015-2017 did the firm invest in these new technologies?". The respondent was presented with the following options: Internet of things (IoT), Robotics, Big data analytics, Augmented reality and Cybersecurity. It was possible to give multiple answers. The timing of this survey is important: the data were collected right after the

[7] 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.

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 of them automatically received the incentive if they invested[8]. In what follows we present descriptive evidence on the diffusion of technologies, 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 organisational structure. After imposing this selection criterion and excluding observations with missing values for the key variables used in the analysis, the final sample is given by a panel of around 8,000 firms observed in each year considered.

3.3 Descriptive evidence.

Figure 1 shows uneven patterns of adoption, with less than 40% of companies with at least 5 employees stating that they had made at least one investment in I4.0 technologies over the period 2015-2017[9].

INSERT FIGURE 1 ABOUT HERE

A relatively small group of firms shows combined adoption of several I4.0 technologies. Almost 30% of firms invest only in one type of technology – showing a ‘single-technology’ approach to digitalization[10]. These percentages fall when we consider simultaneous investments in more than one I4.0 technology: only 7.4% of the RIL-INAPP panel invested in two types of technologies, 2.7% invested in three technologies, 0.5% in four technologies, 0.3% in all I4.0 technologies (IoT, Robotics, Big Data Analytics, Augmented reality and Cybersecurity). All in all, the diffusion of the new Industry 4.0 paradigm 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, 1990).

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[8] This means that there was no selection or self-selection into the scheme.

[9] This percentage falls to 26% if we consider all the 30.000 firms (i.e. all firms with at least one employee) interviewed in 2018.

[10] This percentage falls to 20% including firms with less than 5 and more than 1 employees, and to 15% if we include companies without employees.

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). A ‘multi-technology’ approach to I4.0 adoption is also strongly associated with firm size: the percentage of firms introducing contemporaneously five I4.0 technologies increases from 0.3% of micro firms (5-9 employees) to 1.2% among large business (i.e. firms with more than 250 employees).

INSERT FIGURE 2 ABOUT HERE

Tables 1 and 2 show the distribution of I4.0 adopters by type of technology, firm size and firm location (Table 1) and by sector (Table 2). A first distinction can be made between companies that invested in ‘at least one’ enabling technology and companies that introduced a specific typology among those indicated, i.e., ‘IoT’, ‘Robotics’, ‘Big Data’, ‘Augmented Reality’ and ‘Cybersecurity’. Table 1 shows how the diffusion of new enabling technologies is strongly influenced by the size of the enterprises. Cybersecurity is the most frequent choice: on average 33.9% of Italian firms invested in some forms of information security, while augmented reality and robotics concern a smaller share 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 new technologies than their counterparts located in Central and Southern regions.

INSERT TABLE 1 AND 2 ABOUT HERE

Table 2 illustrates the distribution of I4.0 adopters across sectors. The sectors featuring a greater incidence of companies investing in the new enabling technologies are chemistry (45.2%), financial services (54.9%), information and communication (48.6%) and mechanics (57.2%). ICT displayed a higher incidence of I4.0 adopters in IoT (11.8%), Big Data (15.7%) and Cybersecurity (43.2%). The mechanical and chemical sectors are instead characterised by the most pronounced adoption of robotics.

Linking the investment in new digital technologies to the skill mix of firms, Figure 3 shows that on average firms that report investments in the new technologies 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 for training, or even fear of not reaping the returns on investment in training because of the risk of poaching. The latter might be especially relevant to highly-innovative and high-tech industries.

INSERT FIGURE 3 ABOUT HERE

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 new technology adoption with respect to those relying on other levels of bargaining. Leading multiple-technology adopters – those reporting simultaneous investments in all types of digital technologies – tend to be large businesses and record a relatively low incidence of second-level bargaining.[11]

INSERT FIGURE 4 ABOUT HERE

Having sketched the broad patterns of diffusion, we now move on to investigate the determinants of firm technology choices in a multivariate setting.

3.4 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:

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

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 indicate, 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,

[11] This is in line with the suggestion that larger firms could face more resistance by unions due to concerns that the new technologies may exacerbate the risk of control over workers (Moro et al., 2019).

vector X_i includes a 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 for full descriptive statistics of the control variables), while the parameter $u_{i,t}$ indicates an idiosyncratic error term.

Non-linear regression models are used to estimate different specifications of equation 1. We run a Probit and a Zero Inflated Poisson model to estimate, respectively, the average marginal effects associated to the probability of introducing at least one technology and the total number of new digital technologies (Wooldridge, 2010; Trivedi, 2013). Potential issues concerning unobserved heterogeneity and sample selection (endogeneity) may arise in this set-up. 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[12]. The inclusion of a broad set of controls allows us to minimize the endogeneity bias arising from the presence of omitted variables. Moreover, including these variables as pre-determined controls helps to address reverse causality concerns[13].

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:

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

$$Y_{i,t}^{*} = \alpha + \beta_1 E_{i,t-1} + \beta_2 T_{i,t-1} + \beta_3 FT_{i,t-1} + \beta_4 SB_{i,t-1} + \beta_5 X_{i,t-1} + \mathrm{l}_i + \varepsilon_{i,t} \tag{3}$$

The dependent variable $Pr(I_{i,t-1})$ in the selection equation (2), is a probability index assuming value 1 if firm i made investments in 2015 and 0 otherwise. As for the explanatory variables, vector X

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[12] 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.

[13] In particular, we refer to variables related to corporate governance, demographic profile of managers, recruitment policies and industrial relations.

includes the entire set of controls already considered in equation (1). We use as exclusion restriction a variable indicating the firm's demand for bank loans due to cash or liquidity problems[11]. The dependent variable $Y^{*}_{i,t}$ in equation (3), represents either the dummy indicator for any *I4.0* technology, or the number of I4.0 technologies (*Number I4.0*). This is observed mainly if *Pr* (I_{t-1}) is equal to 1, i.e. if firm *i* realised an investment in 2015. Accordingly, the right-hand side variables are the same set of controls for managers, firms and workforce characteristics use in equation (1), while λ_i is the Inverse Mills Ratio (IMR) accounting for self-selection into the investment decision[12]. The Probit equation for the probability of firm investment in 2015 is therefore completely observed on data, while the selected sample is available for analysing the impact of human capital mix on I4.0 technology adoption. Equations (2) and (3) are estimated simultaneously by Maximum Likelihood. This procedure allows us to correct for sample selection bias and to obtain consistent estimates of 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 4, while results from estimation of equation (2) are reported in Table A2 of Appendix.

4. Results

Table 3 contains the main results of our econometric analysis. First of all, these concern the relationship between skills and 1) the probability of adoption (first column) and 2) the intensity of adoption measured by the number of technologies (second column). We find that firms characterized by a higher share of educated workforce invest more in new technologies and are more likely to display a multi-technology adoption strategy. A higher proportion of trained workers also appears to favour both 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 result is statistically weaker, but is not correlated with the adoption of multiple technologies. Second-level agreements seem to favour adoption and exert a positive effect on the number of technologies adopted.

When we control for selection bias (columns 3 and 4), the share of fixed-term workers and second-level agreements are no longer significant, but both skills and training maintain a positive and significant effect on the probability to invest in digital technologies. This means that controlling for the firm propensity to invest, these particular enabling technologies remain strongly associated with skills and training, but not with work organisation variables. As we mentioned in the discussion of the descriptive results (section 2.2), the probability of introducing nw 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 complementary (firm) characteristics that may 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 a higher probability to introduce digital technologies as well as to follow an adoption pattern characterized by investment in multiple I4.0 technologies. Conversely, a higher share of older workers and family-ownership are strongly and negatively correlated with the adoption of I4.0 technologies and also with 'multi-technology' strategies.

INSERT TABLES 3 AND 4 ABOUT HERE

As for hypothesis 2, investment in training seem to favour technology adoption, validating the argument about the importance of tacit knowledge and the development of firm-specific capabilities that will enable the extraction of productivity gains from the new investments. Interestingly, 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 provide useful insights on the relation between firm-level work organization and the propensity to invest in new technologies. As discussed in section 2, adoption goes hand in hand with organizational change. The use of ICTs has already shown patterns of complementarity with specific forms of work organisation involving decentralised decision-making and team working (Bresnahan et al., 2002). We find this effect also here, where our second hypothesis on the role of flexible staff arrangements is confirmed.

Our results also indicate that the introduction of I4.0 technologies benefit is facilitated by the accumulation of knowledge through longer-term work relationships rather than by the expectation of efficiency gains derived from the use of short-term contracts (in line with Kleinknecht, 2020). Results presented in column 1 of Table 3 show that firms with a higher share of temporary jobs are on average less digitized than those characterised by a higher share of permanent jobs. Finally, with respect to our final hypothesis, the role of second-level bargaining is also confirmed and follows 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. Note as well that 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 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 less 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-graduates and trained workers have a positive and statistically significant effect on the adoption of I4.0 technologies for both SMEs and large firms, and for firms operating in manufacturing and service sectors. Interestingly, the share of trained workers does not affect the probability of adoption for large firms, and the effect of second-level agreements is positive for SMEs but negative for larger firms. Decentralised bargaining seems to favour technology adoption in leaner organisations, and not in larger firms typically more reliant on sector-level bargaining. This may indicate that in large businesses, second-level bargaining might hamper the diffusion of I4.0 technology possibly because of concerns among the labour force of increased control by managers through technological surveillance. A more corporative attitude may prevail in small and medium-size firms, either fostering better information exchanges about the technology within the company or favouring a generally more cooperative context for shared technology adoption decisions.

All in all, these findings suggest that there is significant heterogeneity in the population of adopters, but results are very similar between the manufacturing and service sectors, indicating that the new 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 bargaining. 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. This could be a fruitful avenue for further research.

5. 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 if the new wave of digital technologies is the backbone of 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 – and least in the Italian context – the process of diffusion of new enabling technologies is on its way and it is already possible to identify some defining characteristics of adopters, even in a context that is lagging behind in terms of digitalisation relative to comparable economies.

In this contribution we have exploited a large and unique dataset that includes fine-grained information about the technology adoption choices made by firms. 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, arguably 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.

New microeconomic evidence on adoption behaviours is essential to shape strategy and policy decisions. This paper contributes to filling an important gap in the literature on the emergent Fourth Industrial Revolution, but of course many important questions remain unanswered. First of all, further work must investigate the effects of digitization on firm productivity and growth. Secondly, it will be fundamental to identify the consequences of digitization on employment and wages, as the literature has begun to do with a sharp, but perhaps too limited, focus on robots (Domini et al., 2021; Acemoglu et al., 2020). Given that the ongoing process of digitization includes a broad group of technologies and a multiplicity of devices and techniques (as stressed by Balsmeier and Woerter, 2019; and Martinelli et al., 2021), it is possible that different technological combinations will generate different effects on productivity and employment, and these should be investigated in a variety of contexts of application. Finally, it would be extremely important 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 related local vs. global development of value chains.

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TABLES

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

Firm size	**IoT**	**Robotics**	**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
Centre	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 technologies by sector

	At least one	**IoT**	**Robotics**	**Big Data Analytics**	**Augmented reality**	**Cybersecurity**
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	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 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 *R*2	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

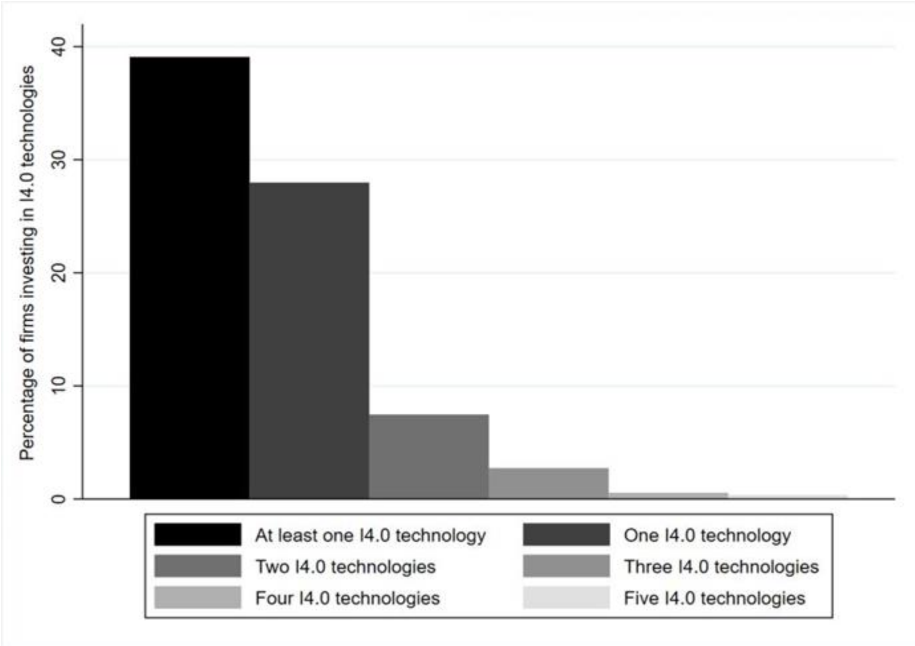
Table 4. Estimates of the average marginal effects by firms' size and sector of activity. Dep var: Probability to invest in I4.0 and number of I4.0 technologies

	(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 *R*2	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

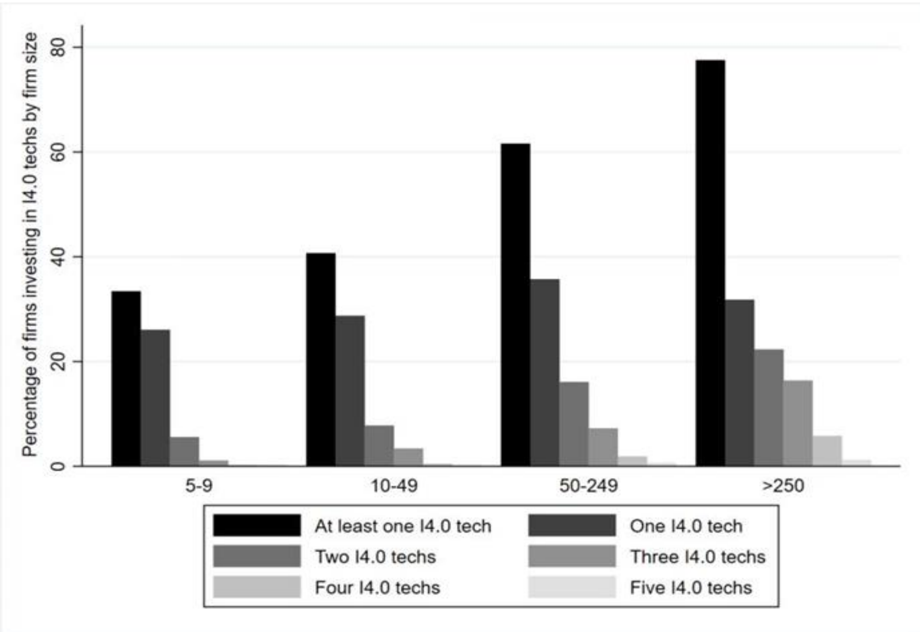
FIGURES

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



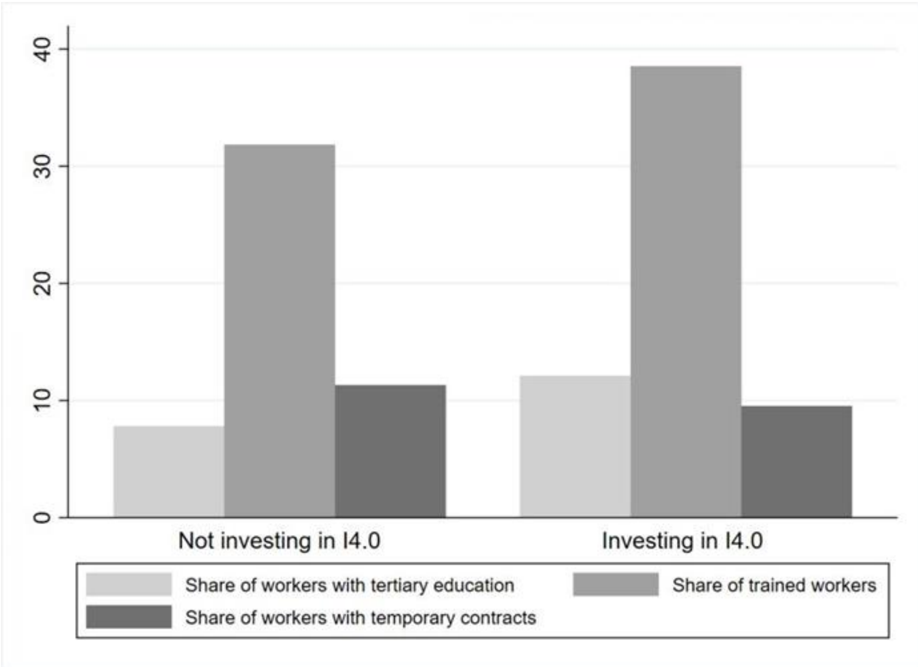
Note: sampling weights applied. Source: Authors' elaborations on RIL 2015-2018 panel data

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



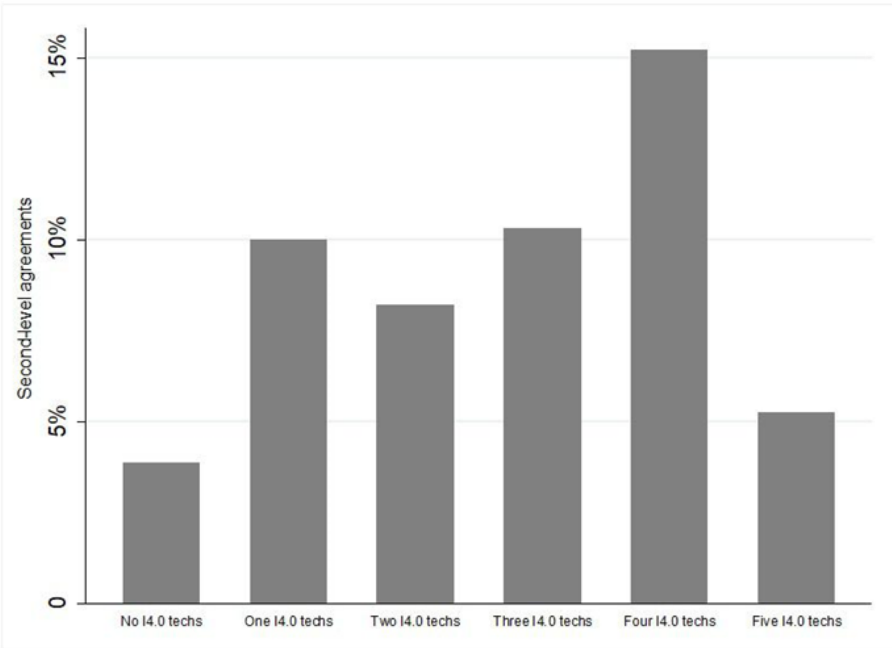
Note: sampling weights applied. Source: Authors' elaborations on RIL 2015-2018 panel data

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



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

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



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

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
Robotics	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
Management 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 *R*2	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.