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ABSTRACT

Digital technologies, labor market flows and investment in training: Evidence from Italian employer-employee data

New technologies can change the use of production factors, their quality and the way in which inputs are embedded in the organisation. By exploiting original firm-level data on digital technology adoption produced by the National Institute for the Analysis of Public Policies (Inapp), matched with employee-level information from the administrative archives of the Italian Ministry of Labor and Social Policies (COB-SISCO) and firm-level archival data (Asia-Imprese) provided by the Italian National Institute of Statistics, this paper explores the effects of new digital technologies on labour flows in the Italian economy. By means of a Diff-in-Diff empirical approach, we observe that digital technologies positively affect the hiring rate of young workers and reduce firm-level separation rates. We do not find strong evidence of higher demand for qualified workforce in association with the new technologies, but in our results there is evidence of positive associations with workplace training, proxied by the share of trained employees and training costs per employee among adopting firms.

KEYWORDS: Industry 4.0, digital technologies, hiring rate, separation rate, skills, training

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1. Introduction

New digital technologies promise dramatic improvements to production and service delivery processes and imply deep changes in the nature and organisation of employment. Much has been written about the possible economic advantages brought about by the adoption of advanced operational technologies that allow for increased automation, control, and interconnectivity (Brynjolfsson and McAfee 2014; Ford 2015). In Schumpeterian terms, these technologies are radical process innovations, and their disruptive potential qualifies them as important ‘enabling technologies’ or as ‘emergent general-purpose technologies’, if their diffusion becomes pervasive across industries and firms (Martinelli *et al.* 2021). New digital technologies include a diverse set of solutions and capabilities, encompassing robotics, artificial intelligence, industrial internet of things, big data, cloud computing, augmented reality, additive manufacturing and cybersecurity. Even though it can be often difficult to draw precise lines of demarcation between them, these are different technologies subject to convergence and recombinatory adoption among technology users. In the policy debate this cluster of technologies is often referred to as ‘Industry 4.0’ (I4.0) to capture the convergence of digital techniques and capabilities (Kagermann *et al.* 2013) under a new production paradigm (Dosi 1982) based on frontier internet-driven IT.

Economists have stressed how firms can exploit the new technologies to change the relative use of production factors, their quality and the way in which these inputs are embedded in the organisation. Compared to the enormous interest in the social and economic impact of new digital technologies, however, the lack of suitable microdata has been limiting empirical research in this field (Raj and Seamans 2019). In this paper, we are able to use original firm-level data on digital technology adoption produced by the National Institute for the Analysis of Public Policies (Inapp), matched with 1) complementary firm-level information drawn from the archive of the National Institute of Statistic (*Istituto Nazionale di Statistica* - Istat), and 2) employee-level information from the administrative archives of the Italian Ministry of Labor and Social Policies. The combined data give us a rare opportunity to study the effects of new digital technologies on labour flows in the Italian economy.

To foreshadow some of our main results, by means of extensive descriptive and econometric analyses we observe a positive and significant correlation between the adoption of digital technologies and new hirings. More precisely, digital technologies positively affect the hiring rate of young workers and reduce firm-level separation rates. We do not find strong evidence of higher demand for qualified workforce in association with the new technologies, but there is evidence of positive associations with workplace training, the share of trained employees and training costs per employee among adopting firms.

The paper is organised as follows: in the first section we set our research questions in the context of the literature that specifically addresses the problem of technology adoption and the labour choices of firms. In section 3 we present the data and provide some descriptive evidence of the phenomenon under investigation. Section 4 presents the empirical strategy. Section 5 contains the results of our econometric analyses, while section 6 explore technological heterogeneity on labour market flows and training. Finally, section 7 draws the contribution to a close.

2. Background literature and research questions

The co-evolution of organisational capabilities and the external economic environment where firms operate significantly influences firm competitive advantage (Nelson and Winter 1982; Dosi *et al.* 2000; Dosi and Marengo 2015). The firm's ability to absorb new knowledge and new technologies is an essential part of this complex picture. Both supply side and demand side factors drive adoption decisions (Hall and Khan 2003), but a number of contributions have placed particular emphasis on the complementarities between tangible and intangible capital (Rosenberg 1976; OECD 2011), conditional on firm demographic characteristics such as firm size and age, as well as on the implementation of different practices in the management of human resources (Bloom *et al.* 2012). Human capital theory (Becker 1994) posits that human capital is accumulated through investments in education and through training as the two main routes to improve the provision of labour services by employees. In many instances, there are clear trade-offs between the two forms of investments, and changing the composition of labour inputs, whose returns vary depending on their specific skills content (Acemoglu 2002; Link and Siegel 2003), might be preferable to investments in on-the-job training.

What do we know about the patterns of digital technology adoption and its effects on firm performance in the Italian context? In a previous contribution (Cirillo *et al.* 2021a), we have explored the effects of I4.0 investments on labour productivity, wages and firm revenues showing that the adoption of digital technologies exerts a positive effect on labour productivity and average wages. These results are aligned with the expectation that digital technologies enable firms to improve business processes, to automate routine tasks and to reduce costs of interactions with suppliers and customers (Bartel *et al.* 2007; Akerman *et al.* 2013). According to Bratta *et al.* (2020), who analyse the entire population of Italian companies that had access to fiscal incentives for I4.0 technologies, firms that invested in (subsidized) digital technologies in 2017 were ex-ante more productive, more likely to invest in R&D and in the acquisition of machinery and equipment and had higher returns on investments as well as lower levels of indebtedness. Firms that are able to adopt digital technologies are usually more suitable to interact with their specific technological requirements, already have an internal knowledge-base, and relevant organizational capabilities. In this respect, those firms that had already undertaken an innovation-oriented growth process may be more responsive to the adoption of new digital technologies vis-à-vis those companies characterized by absent or less dynamic, innovative patterns.

Evidence on the effects of digital technologies on employment is less clear, and a fundamental question remains how workers adjust to firm investments in technologies such as artificial intelligence, augmented reality, or 3D printing. Higher-quality microdata have appeared in very recent literature, even though they are mostly limited to the adoption of robotics. Koch *et al.* (2021), for example, use Spanish data from the ESEE Survey (*Encuesta Sobre Estregias Empresariales*) to study the effects of industrial robots in manufacturing. They find that robot adoption produces from 20 to 25% output gains, reduces labour costs and positively contributes to firm employment growth (at an average rate of approximately 10%). Acemoglu *et al.* (2020) and Domini *et al.* (2021) study the effects of investments in robots made by French firms. Acemoglu *et al.* (2020) show that adopting firms, while reducing the labour share and the share of production workers, increase their productivity and grow more than competitors. Domini *et al.* (2021) also find positive employment growth effects. In evaluating these results, it is extremely important to bear in mind that the ongoing transformation of productive processes is not limited to the adoption of robots, and robotics per se can be considered as a mature technology (robots they have been operating in manufacturing plants for decades now) unless the latest-generation robots converge with newer technologies such as big data analytics, artificial intelligence and industrial Internet of Things (IoT).

In a very recent paper Genz *et al.* (2021) consider richer data on adoption, combined with administrative social security data, for German firms. They compare individual outcomes for workers employed by technology adopters vs. non-adopters, and find evidence for improved employment stability, higher wage growth, and increased cumulative earnings in response to digital technology adoption. These findings are indeed dependent on the specific type of technology adopted, in line with Balsmeier and Woerter (2019). Moreover, positive adjustments to adoption seem to be driven by technologies used by service providers rather than manufacturers. These results are very interesting, even though the effects of digital technologies on workers are not homogenous across workers groups and adjustments might be skewed and uneven in outcomes. According to Genz *et al.* (2021), IT-related expert jobs with non-routine analytic tasks benefit most from technological upgrading, coinciding with highly complex job requirements. Overall, research suggests that the potential of automation is seriously overstated and that more attention should be to the adaptability of different jobs through the process of digital transformation (Arntz *et al.* 2017; Autor 2015).

One of the main constraints in empirical research has to do with the lack of direct measures of automation and digitalization. By adopting indirect measures of automation or robot adoption, several studies found that robot adoption generates substantial output and employment gains as well as reductions in the labor cost share, compared to non-adopting firms (Acemoglu *et al.* 2020; Koch *et al.* 2021). Further evidence suggests that robot adoption leads to higher wages. However, wage increases are limited to skilled workers such as computer analysts, engineers, and researchers while being negative for production workers (Humlum 2019). One of the few studies focusing on what happens to individual workers when their firm decides to automate is Bessen *et al.* (2019). The authors exploit information on firms' expenditures on third-party automation, and their findings indicate that firm-level automation increases incumbent workers' probability to separate from their employer, followed by wage income losses that are only partially offset by social benefits.

The research frontier on this topic is shifting to the use of more granular data about heterogeneous technology adoption, and to data that bring together firm-level information with detailed records on individual labour relations to overcome the limited interpretation that can be made of aggregate employment outcomes. The objective of this paper is to disentangle the effects of new digital technologies on labour flows. More specifically we want to explore 1) the relationship between the adoption of digital technologies and new hirings; 2) the relationship between adoption and separations; 3) the heterogeneous effects across age and skills groups; and finally, 4) the role of on-the-job training in the process of adoption. These are our main research questions.

3. Data and descriptive statistics

The empirical analysis is based on an original and unique database merging three different sources of information: (i) *Comunicazioni Obbligatorie* (COB-SISCO), an administrative archive provided by the

Italian Ministry of Labor and Social Policies recording from 2009 each job relationship that started or ended (for firing, dismissal, retirement, or transformation of the contractual arrangement within the same firm) for all individuals working in Italy as an employee or through apprenticeship, temporary agency work arrangements, and parasubordinate collaborations[1]; (ii) *Archivio Statistico delle Imprese Attive* (ASIA-Imprese), the archives of Italian firms provided by National Institute of Statistic (*Istituto Nazionale di Statistica* - Istat) containing information on Italian firms, and (iii) the sample survey *Rilevazione Imprese e Lavoro* (RIL) conducted by the National Institute for Public Policy Analysis (Inapp).

For each job relationship, the COB-SISCO archive provides the fiscal code of the firm, allowing to merge firms' features – drawn from ASIA-Imprese and RIL-Inapp survey – with the characteristics of each worker who had a job relationship with a specific firm over the year[2]. Furthermore, the COB-SISCO dataset records, in addition to several individual characteristics, the contractual arrangement (i.e., open-ended employment, fixed-term employment, apprenticeship, temporary agency work, para-subordinate collaboration), the working time regime of employment relationship (part-time/full-time) and the date of activation and termination of the job relationship. This two last information allows to compute the total number of workers hired and fired/separated for each firm by year, distinguishing for age, gender, educational attainment, and citizenship.

On the other hand, the ASIA-Imprese archive complements the information stemming from COB-SISCO providing details on industry (coded at 3-digit NACE Rev. 2), region where the firm is located and number of employees of each firm over the year[3].

Lastly, the *Rilevazione Imprese e Lavoro* (RIL) is a survey conducted periodically by Inapp on a large representative sample of partnerships and limited liability firms operating in the non-agricultural private sector. A subsample of the included firms is followed over time, making the RIL dataset partially panel over the period under study[4]. The RIL dataset collects a rich set of information on management and corporate governance, firms' productive characteristics and competitive behaviour, the asset of industrial relations at workplace as well as workforce composition in terms of gender, age, education, contractual type, the amount of hirings and separations, and other aspects of personnel policies.

The V wave of the RIL-Inapp survey includes a specific set of questions designed to collect information on the introduction of new digital technologies (see Cirillo *et al.* 2020, 2021a). The key question concerns investments over the period 2015-2017 ("In the period 2015-2017 did the firm invest in new technologies?"); firms choose among the following answers: (i) Internet of things (IoT); (ii) Robotics; (iii) Big data analytics; (iv) Augmented reality; (v) Cybersecurity. Although multiple answers are

[1] Information in COB-SISCO archives is provided at the contractual level, therefore it has been linked to each individual by considering the longest contractual arrangement she has over the year.

[2] In detail, the fiscal code of RIL-Inapp firms has been used to merge COB-SISCO and ASIA-Imprese archives. This allows to select a representative sample of firms and to integrate information stemming from COB-SISCO and ASIA-Imprese archives with administrative files.

[3] While COB-SISCO provides information on job flows, ASIA-Imprese contains detailed information on occupational stocks (for more info see Bloise *et al.* 2021).

[4] For more details on RIL questionnaire, sample design and methodological issues see <https://inapp.org/it/dati/ril>.

allowed, we adopt a dichotomous measure of Industry 4.0 investment and create a new variable – "I4.0" – that is equal to 1 if firms have invested in at least one I4.0 technology, 0 otherwise.

The RIL-Inapp surveys provide a very rich of set of information at few years intervals, and for the purposes of this analysis we also rely on ASIA-Imprese to integrate annual firm-level observations on the number of employees.

Linking the three different sources of information through firms' fiscal codes allows us to create a unique longitudinal matched employer-employee database – hereafter referred to as RIL-COB-ASIA – where information at the individual level stemming from COB-SISCO has been collapsed at the firm level for each year. Therefore, we have high-quality information on the total number of hirings and separations for each firm by age group, educational titles and type of contract extracted from administrative archives.

Overall, the complex matching procedure of the various sources described above allowed us to create an employer-employee longitudinal dataset that, once collapsed at the firm level, records information of hirings and separations (from administrative archives), training investment, adoption of digital technologies as well as several productive, managerial and workplace characteristics (from the RIL-Inapp survey).

For the purpose of this analysis, we focus on two main sets of variables. The first set concerns job flows at the firm level the share of hirings, and separations (over total employment) recorded by each firm over time year, which gives us interesting indications of on employment dynamics related to investments in digital technologies. This allows us to have a clear picture not only of aggregate changes in employment, but also of the gross flows providing a much richer picture of the dynamics underlying net job creation figures (Criscuolo *et al.* 2014): lower employment may be due to either lower creation or higher destruction of jobs, which is crucial information when designing policies to tackle (eventual) employment effects of digital technologies.

The second set has to do with workplace training practices that is proxied by three different variables: (i) activation of training at the firm level; (ii) share of trained workers over total employment; (iii) amount of training costs per employee declared by each firm sampled in the 2010, 2015 and 2018 RIL-Inapp surveys. These variables have been put in relation with investments in I4.0, as defined in the RIL-Inapp survey. Furthermore, given the richness of the RIL-Inapp survey, we add in the empirical specification information about i) management and corporate governance characteristics of companies (managers' education, information on family or non-family ownership and management of the firm), ii) workforce characteristics (occupation, gender, age, education) and iii) other firm characteristics (size, product and process innovation, propensity to export).

3.1 Descriptive statistics

Table 1 shows the incidence of I4.0 adopters in 2010, 2014 and 2018 on the longitudinal component of the RIL-COB-ASIA merged sample. Furthermore, table 1 also provides information on the share of firms declaring to adopt three specific types of technologies over the period: internet of thing (IoT), robotics, and cybersecurity. It is worth recalling that the question on investments in I4.0 and specific types of technologies is addressed to Italian firms exclusively in the RIL-Inapp 2018 questionnaire (V wave) (Inapp 2018). Firms were asked if during 2015-2017 they had invested in at least one of the following technologies: cybersecurity, IoT, augmented reality, robotics, big data analytics. If firms declared to have invested in at least one I4.0 technologies, they were classified as "adopters" also in the previous waves of the survey – 2010 and 2014. Therefore, table 1 shows the incidence of adopters over time, where firms were classified as adopting I4.0 technologies even in the previous waves of the survey. This will allow us to identify a so-called treated group composed by I4.0 adopters – about 25% – against a control group of non-adopting companies (see section 4 for an in-depth discussion on the empirical strategy)[5].

Focusing on 2018, table 1 shows that about 29% of Italian firms declared to invest in at least one of the technologies related to the Industry 4.0 plan over 2015-2017[6]. As previously discussed in Cirillo *et al.* (2020), such investments were unevenly distributed in the Italian economy, being concentrated in Northern regions and high-tech and knowledge intensive sectors. A similar picture has been highlighted by Bratta *et al.* (2020) focusing on administrative fiscal data of Italian companies highlighting that most recipient firms of the hyper-depreciation measure that incentivize the introduction of I4.0 technologies were small- and medium-sized companies, located in Northern regions. However, a crucial distinction to analyze diffusion of I4.0 should be made in relation to the specific type of technologies. To this purpose, table 1 distinguishes I4.0 investments in specific types of technologies, showing that the majority of I4.0 investments are concentrated in cybersecurity, whereas robotics and IoT cover only a marginal share of adopters. This came as no surprise since the last available data on Italian business census display that most companies use a limited number of technologies, giving priority to infrastructure investments (cloud solutions, optical fiber or mobile connectivity, management software and cyber-security) while leaving the adoption of application technologies such as IoT, automation, robotics, and big data analysis to a later stage (Istat 2020). Workplace digitalization can occur as a multistage process, while in a first phase it is necessary to set technical conditions to initiate the digital transformation; in a second phase, workplace organizational levers are crucial and interact with application technologies aiming to affect efficiency and productivity[7]. In this sense, the multistage adoption of digital technologies can shape work organization, business processes and even lead to restructuring or staff reductions. This is what we intend to explore in the remaining part of this contribution.

[5] Of course, this percentage sharply decreases when considering adopters of IoT (about 4%) and robotics (about 2,5%) – a smaller group of treated firms. It should be noticed that multiple adoption is possible, therefore when considering IoT, robotics or cybersecurity, we are identifying companies that have invested in at least one of these techs, although also multiple investments are allowed.

[6] Although Industry 4.0 refers to a specific political project to boost high-tech manufacturing and support the uptake of advanced digital technologies in analogy with specific programs in Germany, the United States and China (see in this regard Pardi 2019), in this context for simplicity we use "Industry 4.0" to identify a set of multiple technologies that have been usually linked to the Industry 4.0 National Plan implemented by the Italian Ministry of Economic Development.

[7] Several works have highlighted the existence of a continuity between adoption of I4.0 technologies and lean production systems (see Moro and Virgillito 2021; Cirillo *et al.* 2021, for case studies on selected Italian companies).

Table 1. Share of firms investing in I4.0, Robotics, IoT, Cybersecurity

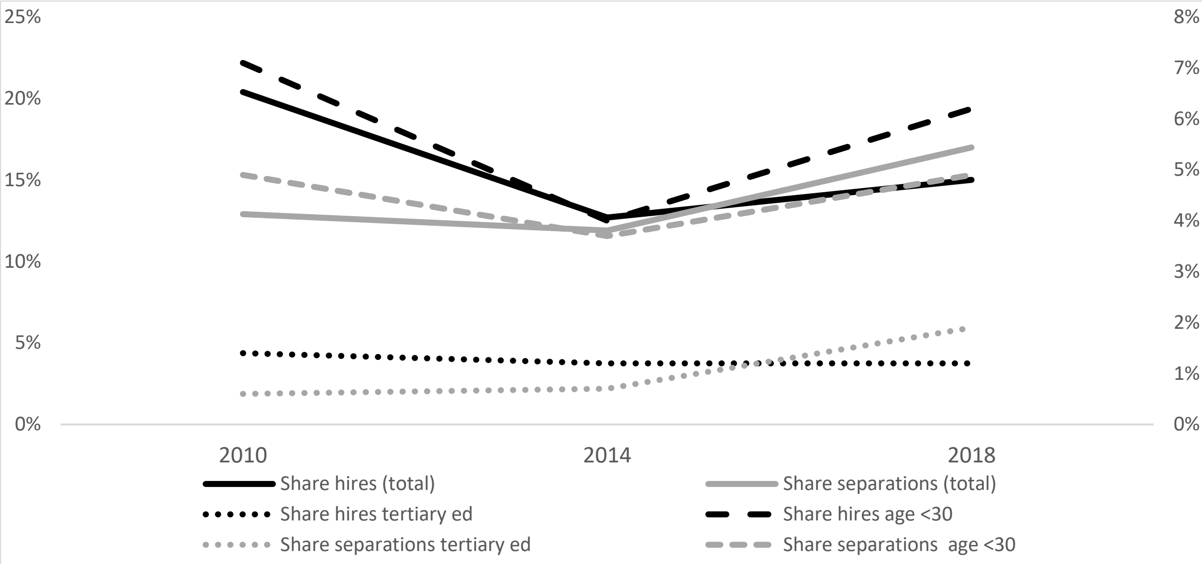
	Investment I4.0	Internet of things	Robotics	Cyber security
		2010		
Mean	0.255	0.042	0.025	0.223
Sd	0.436	0.201	0.156	0.416
N	3975	3975	3975	3975
		2014		
Mean	0.276	0.044	0.028	0.239
Sd	0.447	0.205	0.164	0.426
N	3277	3277	3277	3277
		2018		
Mean	0.292	0.047	0.026	0.257
Sd	0.455	0.212	0.159	0.437
N	4005	4005	4005	4005

Note: sampling weights applied.
Source: our calculations on longitudinal component of RIL-COB-ASIA merged sample

Going further in the descriptive analysis, figure 1 displays the evolution over time (in the three periods of the analysis) of hiring and separation rates computed as share of employees hired/separated over total firm employment and by specific educational and age groups. This is one of our main outcome variables[8]. Overall, the share of workers hired by firms has decreased over time by about 5 percentage points, recording the lowest value in 2014, when the share of new hires on total employment was about 12%. A modest recovery has occurred over 2014-2018 when average firm hiring rate increased by 3 percentage points reaching 15%. Indeed, information on hirings needs to be linked to share of separations to gain a complete picture of labour flows within firms[9]. Separations increased during 2014-2018 by 6 percentage points, whereas they were almost stable over the previous five years. This picture is consistent with job losses experienced by the Italian economy in 2011-2013; in fact the distance between hiring and separation rate thins out till 2014 when the average separation rate is almost equal to the hiring rate. In the last available period (2018) average firm level separation rate is higher than average hiring rate, meaning that firms lose employment more than creating new jobs. However, by dissecting job flows by characteristics of employees, two dynamics characterize job flows of Italian companies: (i) contraction of hirings over 2010-2014 of young employees and then a slight recovery over 2014-2018; (ii) a flat trend in the hirings of tertiary educated workers for the entire period until 2018 when separations of tertiary educated workers overcome the average firm's hiring rate. Overall, figure 1 highlights that firm-level labour flows shrank the over the 2010-2014 period for all types of workers. In the recovery phase 2014-2018 incoming job flows (hirings) have been mainly detected for young workers under 30 years old, whereas separation rate outperforms hirings for tertiary educated workers.

[8] This share has been computed for each firm relying on administrative archives of SISCO-COB and for specific groups of workers (employees): those with a tertiary education and those less than 30 years old.
[9] It is worth recalling that in the RIL-COB-ASIA merged sample, each worker is linked exclusively to the firm in which the longest working relationship is activated over the year. Similarly, the share of hirings is computed by considering the longest contractual relationship that each worker has activated with one specific firm.

Figure 1. Hiring and separation rates over time by educational title and age



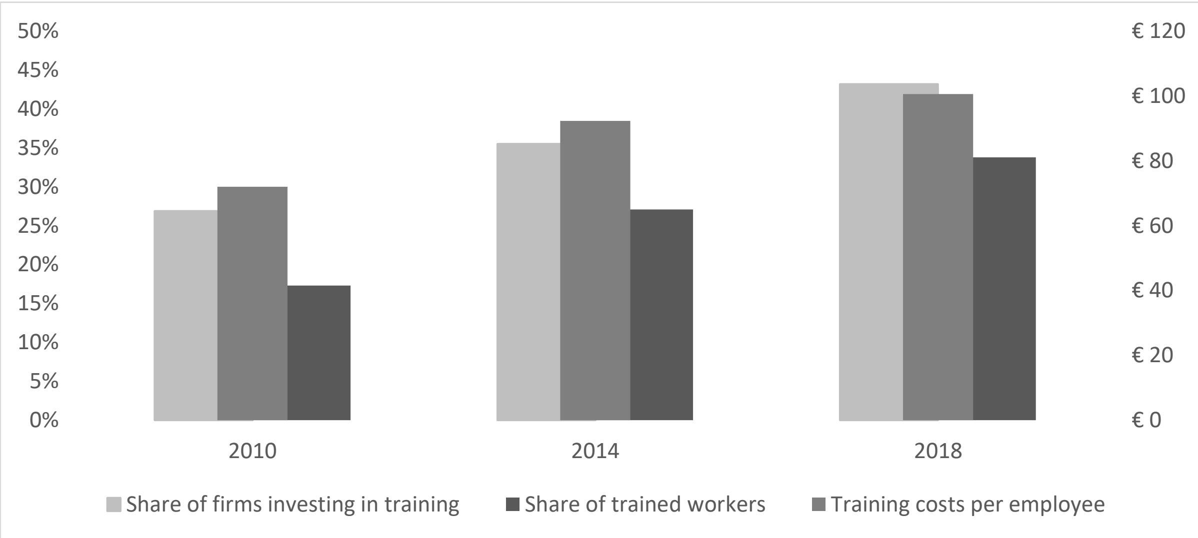
Note: sampling weights applied. Share of (total) hires and separations on the left axis; other shares on the right axis. See table 1A in appendix.
Source: our calculations on longitudinal component of RIL-COB-ASIA merged sample

Our final research question concerns firms' propensity toward training practices. We aim to investigate if there is a robust correlation between investments in I4.0 technologies and work organizational practices, such as activation of specific training for employees. Indeed, firms approaching to I4.0 technologies may rely on *external labour markets* by recruiting new workers and, therefore, hiring employees but also on *internal labour markets* – internal to the firm – by creating and activating specific competencies among workers to deal with digital technologies. Among the various challenges hindering the process of digital transformation of enterprises, particular attention should be paid to the need to adequately prepare staff for the effective use of new technologies (Istat 2020). In fact, according to the last Business Census provided by the Italian National Statistical Office, large enterprises reported the need of adequate training specifically in relation to the introduction of cyber-security, which is, on average, the third digital technology requiring training support. Conversely, small and medium-sized enterprises - which have low levels of adoption of digital technologies - did not consider training on big data, 3D printing, Internet of Things (IoT) to be relevant. This may be explained by the fact that more advanced digital technologies requiring high levels of integration among different tools are usually provided with support services by high-tech companies selling packages that also include assistance and training for staff.
Therefore, our third dependent variable concerns firms' effort in workforce training practices proxied by three different variables, that are: (i) activation of training practices within firms, a dichotomous variable stemming from RIL-Inapp survey, taking value equal to 1 if firms positively answer to the following question: "Were any training initiatives organized for company employees during 2017?"[10],

[10] An identical question has been addressed to firms in relation to 2010 and 2014.

0 otherwise; (ii) share of employees participating in training initiatives[11]; (iii) average costs for training divided by the number of employees[12].
Histograms in figure 2 below clearly show an increasing trend of training practices over time. The share of firms declaring to organize training initiatives for employees has risen by more than 10 percentage points and, similarly, the pool of workers who have benefited from training investments from 17% to 33%. Moreover, the average firm cost per training has increased suggesting an improvement in the quality of training provided[13].

Figure 2. Share of firms investing in training, share of trained workers and average costs for training over time



Note: sampling weights applied. Share of firms investing in training and share of trained workers on the left axis; training costs on the right axis. See table 2A in appendix.
Source: our calculations on longitudinal component of RIL-COB-ASIA merged sample

Lastly, to complete the aggregate picture, we present in table 2 average values of main explanatory variables included in the analysis and calculated on the longitudinal component of the RIL-COB-ASIA merged sample. These variables stem from RIL-Inapp survey and are time variant since they refer to specific questions of the RIL questionnaire available in 2010, 2014 and 2018. At first glance, one can notice an increasing share of tertiary educated and female managers/owners, that mirrors a slightly higher percentage of tertiary educated workers. Surprisingly between 2014 and 2018 the percentage of workers over 50 years old increased by about 2 percentage points, probably as a consequence of monetary incentives disposed by the Italian Budgetary Law 2015 for firms hiring workers with the new

[11] Firms have been asked the following question: "How many employees in the company participated in training initiatives?".
[12] Firms have been addressed the following question: "Overall (taking into account both out-of-pocket costs and external contributions), what is the amount of expenditure on staff training during 2017?". An identical question has been addressed to firms in RIL survey waves 2010 and 2014.
[13] Expenditure in training has been deflated by Value Added deflators in 2018, source OECD STAN.

contract type introduced by the Jobs Act[14]. Between 2014 and 2018, the share of firms registering vacancies has slightly increased, whereas all other features concerning corporate governance, workforce composition and firms' features remains almost stable over the period.

Table 2. Descriptive statistics for control variables: corporate governance, workforce and firms' characteristics

	2010		2014		2018	
	Mean	SD	Mean	SD	Mean	SD
	Corporate governance					
Managements with tertiary education	0.194	0.396	0.186	0.389	0.240	0.427
Management with upper secondary edu	0.562	0.496	0.594	0.491	0.535	0.499
Management with lower secondary edu	0.244	0.429	0.221	0.415	0.224	0.417
Female management	0.179	0.383	0.171	0.376	0.216	0.412
Family owner	0.948	0.223	0.938	0.241	0.932	0.251
External management	0.016	0.125	0.017	0.130	0.034	0.182
	Workforce characteristics					
Share of tertiary educated workers	0.063	0.167	0.089	0.204	0.120	0.244
Share of upper secondary workers	0.513	0.377	0.548	0.368	0.559	0.367
Share of lower educated workers	0.424	0.389	0.363	0.376	0.321	0.363
Share of Fixed-term contracts	0.109	0.218	0.087	0.210	0.129	0.242
Share female workers	0.434	0.367	0.451	0.369	0.444	0.360
Share workers more than 50 years old	0.189	0.281	0.246	0.296	0.356	0.337
Share workers 35-49 years old	0.470	0.357	0.460	0.344	0.417	0.318
Share executives	0.035	0.137	0.033	0.104	0.041	0.123
Share white collar workers	0.400	0.392	0.487	0.392	0.452	0.392
Share blue collar workers	0.565	0.403	0.480	0.402	0.507	0.402
	Firms' characteristics					
Firms registering vacancies	0.064	0.245	0.056	0.230	0.106	0.308
Average firm wage (in logarithm)	9.758	0.595	9.883	0.616	9.859	0.709
Firm operating on foreign markets	0.164	0.370	0.221	0.415	0.193	0.395
Multinational company	0.005	0.073	0.009	0.092	0.010	0.098
Firm signing II level bargaining	0.039	0.193	0.039	0.193	0.047	0.212
N of Observations	3,975		3,277		4,005	

Note: sampling weights applied.

Source: our calculations on longitudinal component of RIL-COB-ASIA merged sample

[14] Between the 1st of January and the end of 2015, each firm hiring under an open-ended contract (including all changes from a temporary to permanent contract), has been exempt from paying contributions to social security up to 8,060 euros per year for three years. As discussed by Cirillo *et al.* (2017), differently to previous cases, monetary incentives accompanying the new contract (*Contratto a Tutele Crescenti*) were not targeted at specific groups or industries and were mainly used by firms to employ or transform temporary contracts of older workers.

4. Estimation strategy

The empirical strategy we use to assess the impact of digital technologies on labour markets flows and workplace training begins with the estimation of the following equation:

$$Y_{i,t} = \alpha + \beta_1 I4.0_i + \beta_2 year2018 + \beta_3 I4.0_i * year2018 + \gamma M_{i,t} + \delta W_{i.t} + \partial F_{i,t} + \mu_i + \varepsilon_{i,t} \quad [1]$$

where $Y_{i,t}$ indicates alternatively the share of new hired, the share of separated over firm total employment and workplace training proxied by adoption of training, share of trained employees, the (log of) training costs per employees for each firm (*i*) at the sample year $t = [2010, 2014, 2018]$.

Our key explanatory variable $I4.0_i$ is a dummy taking value of 1 whether the firm has invested in Industry 4.0 type of technologies, therefore at least one digital tech has been introduced over the period 2015-2017 among Internet of things (IoT), robotics, big data analytics, augmented reality and cybersecurity, and 0 otherwise.

The year 2018 is a time indicator for the "post-treatment" period while the coefficient β_3 of the interaction term $I4.0_i * year\ 2018$ identifies the Diff-in-Diff effect of digital investments over the period 2015-2017 on firms' outcomes. Among the other controls, vector $M_{i,t}$ includes managerial and corporate governance characteristics, $W_{i.t}$ represents the workforce composition while $F_{i,t}$ captures a rich set of firms' characteristics, geographical location and sectoral specialization (for further details see table 2). Furthermore, the parameter μ_i represents firm fixed-effects capturing time-invariant unobserved heterogeneity, while $\varepsilon_{i,t}$ is the idiosyncratic error term.

As first step we perform a Pooled OLS estimation of the equation [1] by imposing the parameter β_3=0. In this case the coefficient estimates associated with β_1 are expected to be unbiased if time invariant unobserved heterogeneity and endogeneity issues play no significant role in shaping the impact of digital investment on hirings, separations and workforce training. However, this might not be the case for several reasons. First, there is a complex interaction between technology and productivity, and strong complementarities between technology, labour and work organization. Therefore, there is a risk of endogeneity resulting from both reverse causality – firms willing to invest in I4.0 technologies decide in advance to hire/fire workers or to implement training courses for employees to fully exploit productivity gains stemming from implementation of I4.0 technologies – and common factors influencing job flows and training decisions at the firm level and adoption of digital techs. Among these factors an important role is played by productivity: more productive firms are those more likely to invest in I4.0 technologies and those registering positive job flows and training expenses with respect to less productive companies. As stated in Gal *et al.* (2019), potential drivers of digital adoption such as workforce and managerial skills, institutional or industrial relations, or favourable business environments can impact productivity directly, and indirectly through digital adoption[15]. Also Bratta *et al.* (2020) working on the Italian population of firms highlight that once controlling for initial size, sector and geographical location, firms that invested in digital technologies are found to be ex-ante

[15] Kock *et al.* (2021) on a representative sample of Spanish manufacturing firms have recently highlighted that firms adopting robots in their production process perform better (in terms of total output and labour productivity) than non-adopters already before adopting robots. Since the adoption decision is not random, but according to authors' analysis governed by, among other things, firm size and skill intensity, econometric analyses face a fundamental endogeneity problem.

more productive, more likely to invest in R&D and in the acquisition of machinery and equipment, and to have higher returns on investments as well as lower levels of indebtedness. More productive firms are those registering more dynamic employment trends.

In order to tackle these issues, we apply a Diff-in-Diff approach to equation [1] by exploiting the three-period structure of the RIL-Orbis sample and a very rich set of firm level observational data on both treatment and control groups in the pre- and post-investment periods. In this framework the treatment group is composed by those firms declaring to have invested in I4.0 over 2015-2017 (I4.0=1) while the control group consists of those firms that did not invest in I4.0 in the same time span (I4.0=0). Therefore, the Diff-in-Diff fixed effect estimate of the parameter β_3 is expected to identify the causal impact of Industry 4.0 investments on share of hirings, separations and workplace training. Indeed, there are several limitations. For instance, we are not able to track companies before 2015-2017 on I4.0 decisions. Ideally, we would like to have repeated observations for the technology adoptions.

The same empirical strategy has been applied in Cirillo *et al.* (2021a). In that paper, we already noticed that the crucial assumption to obtain unbiased estimates of β_3 is the Common Trend Assumption (CTA) which implies that parallel trends in the outcome of treated and control firms should be observed in absence of treatment. If CTA holds, compared to the fixed effects estimator, the Diff-in-Diff estimator has the advantage of removing any common period effects influencing the treatment and control groups in identical ways (see Gebel and Voßemer 2014). Further, in order to avoid potential biases due to omitted variables, we include a broad set of controls for managerial, organisational and corporate features, as well as firm internationalization and innovation.

It is also worth pointing out that in the design of our study we are helped by the timing of the 2018 survey, which followed the implementation of the Italian 'National Enterprise Plan 4.0', an incentives scheme introduced by the Italian Government to lower financial constraints to investment and accelerate the diffusion of digital technologies. All firms were eligible to the scheme and all of them automatically received the incentive if they invested, from this point of view the policy was 'neutral' with respect to firm characteristics and did not involve any external selection into the scheme.

5. Results

In this section we illustrate the main results stemming from the estimation of equation [1] for each set of dependent variables, both including and excluding the interaction term β_3. The first set of variables refer to newly hired workers, that is the firm average share of new hirings over total employment, even dissected by age – hiring rate of young employees under 30 years old – and by education – share of newly hired workers with tertiary education (see subsection 5.1). Dynamics of hirings need to be related to separation rates that measure the percentage of employees who left the firm during the year. It reflects both voluntary and involuntary separation reasons (firings, resignation, termination of contract etc.). Also, in this case we dissect firm separation rate computed as total number of separations over total employment by age and education to grasp a more complete picture of job flows in relation to the introduction of digital technologies (subsection 5.2). Finally, the last subparagraph 5.3 is devoted to analyse the relation between investment in I4.0 technologies and workforce training, our third set of dependent variables. The latter has been specified to include: (i) realization of training practices (a dichotomous variable taking value of 1 if training has been activated, 0 otherwise); (ii) share of trained employees; (iii) average cost of training per employee.

5.1 Hiring rate

Table 3 shows the pooled OLS estimates of the equation [1] for the whole sample, when the dependent variable is the share of newly hired workers. Newly hired employees are employees who have not previously been employed by the employer, or who were previously employed by the same employer but have been separated from such prior employment for more than a year. The first column shows the estimation of equation [1] having as dependent variable the firm hiring rate, which includes all types of new contract activations at the firm level (linking each employee to one firm for each year according to the longest work contract), i.e. fixed-term employment, open-ended employment, apprenticeships, seasonal employment, temporary employment, intermittent employment[16]. We observe a positive and significant correlation between the adoption of digital technologies and the share of newly hired workers. Having realized an investment in at least one of the technologies among IoT, big data, cloud computing, cybersecurity, robotics in 2015-2017 seems to be positively associated to one percentage point change in the hiring rate. Splitting these correlations by age and education, it emerges that investment in I4.0 technologies is also associated with an increase in the number of newly hired workers with tertiary education by about 0,3 percentage points, whereas it does not appear to lead to new hirings for young workers.

Table 3. Pooled OLS estimates. Dep var: Hiring rate

	Workers over total employment	**Workers <30 years old over total employment**	**Graduated workers over total employment**
I4.0	0.010*	0.005	0.003*
	[0.006]	[0.003]	[0.002]
Year 2018	-0.026***	-0.003	0.001
	[0.006]	[0.003]	[0.001]
Year 2014	-0.039***	-0.011***	-0.001
	[0.004]	[0.003]	[0.001]
Firms registering vacancies	0.025***	0.009***	0.004***
	[0.005]	[0.003]	[0.001]
Log wage per employee	-0.017***	-0.005*	-0.003**
	[0.004]	[0.003]	[0.001]
Other controls	Yes	Yes	Yes
Constant	0.308***	0.121***	0.036***
	[0.041]	[0.027]	[0.012]
Observations	11255	11255	11256
R2	0.223	0.188	0.103

Note: other controls include: managerial characteristics (education, age and gender), family ownership and the presence of external managers; workforce composition (education, professions, age, female, contractual arrangements); firms productive characteristics such as NACE e sectors, NUTS 2 regions, international markets, second level bargaining, multinationals, vacancy. Clustered robust standard errors in parentheses.
Source: our calculations on RIL-COB-ASIA merged sample

[16] On average the share of new activations of open-ended contracts over total activations ranges between 30% (2015) and 16% (2018).

With the aim to tackle endogeneity and unobserved heterogeneity issues, table 4 reports the Diff-in-Diff fixed effects estimates of the equation [1]. Again, we observe that investment in I4.0 technologies leads to an increase of the share of newly hired workers by 2 percentage points and more specifically of those who are less than 30 years old. Once controlling for endogeneity and unobserved heterogeneity, the effect of I4.0 investments on new hirings for graduated workers disappears compared to OLS estimates, whereas what emerges as slightly significant is the impact of I4.0 technologies, by 8 percentage points, on the share on newly hired young workers, in line with the expectations that young workers are more inclined and able to use digital technologies. The CTA is verified only for the hiring rate of young workers (less than 30 years old), while it does not hold for total employment. The positive and significant coefficient of the interaction between I4.0 and 2014 (0.013) clearly suggests a positive hiring trend before 2018 and therefore excludes the possibility to interpret β_3 in terms of causality.

Table 4. Diff-in-Diff fixed effects estimates. Dep var: Hiring rate

	Workers over total employment	**Workers <30 years old over total employment**	**Graduated workers over total employment**
I4.0* year 2018	0.019**	0.008*	0.004
	[0.008]	[0.005]	[0.002]
I4.0*year 2014	0.013*	0.008	0.001
	[0.008]	[0.005]	[0.003]
Year 2018	-0.026***	-0.008*	-0.002
	[0.007]	[0.004]	[0.002]
Year 2014	-0.045***	-0.016***	-0.003*
	[0.006]	[0.004]	[0.002]
Firms registering vacancies	0.028***	0.014***	0.001
	[0.006]	[0.004]	[0.002]
Log wage per employee	-0.021***	-0.007***	-0.003***
	[0.004]	[0.002]	[0.001]
Other controls	Yes	Yes	Yes
Constant	0.468***	0.157***	0.004
	[0.088]	[0.061]	[0.044]
N of Obs	11257	11257	11257
R2	0.064	0.045	0.03

Note: other controls include: managerial characteristics (education, age and gender), family ownership and the presence of external managers; workforce composition (education, professions, age, female, contractual arrangements); firms productive characteristics such as NACE e sectors, NUTS 2 regions, international markets, second level bargaining, multinationals, vacancy. Clustered robust standard errors in parentheses.
Source: our calculations on RIL-COB-ASIA merged sample

5.2 Separation rate

Table 5 completes the picture emerging from previous tables by showing results of the association between investment in I4.0 at the firm level and separation rate calculated as number of separations by firms over total employment. Separations can be due to several reasons such as dismissal for economic or disciplinary reasons, voluntary resignation, termination of contract, or other reasons[17]. The separation rate provides useful information on firm turnover and can be helpful in understanding the overall rate at which employees are leaving the organization. In this case we see from table 5 that adopting firms – i.e. those firms that invest in I4.0 type of technologies – register on average lower separation rates with respect to non-adopting firms, meaning that outgoing turnover in digitizing firms is lower. Not significant results emerge when dissecting estimates by age and education, suggesting that most separations maybe linked to retirement. This picture is broadly confirmed by table 6 once controlling for unobserved heterogeneity and endogeneity by applying a Diff-in-Diff approach: I4.0 technologies reduced the share of separations by 1,6 percentage points. The non-significant coefficient of I4.0* year 2014 term highlights that the CTA holds, and we can consider β_3 as a causal relation.

Table 5. Pooled OLS estimates. Dep var: Separation rate

	Workers over total employment	**Workers <30 years old over total employment**	**Graduated workers over total employment**
I4.0	-0.015**	-0.001	0.001
	[0.006]	[0.003]	[0.002]
Year 2018	0.032***	0.002	0.004**
	[0.006]	[0.003]	[0.002]
Year 2014	-0.007*	-0.007***	0.001
	[0.004]	[0.002]	[0.001]
Firms registering vacancies	0.022***	0.008***	0.002
	[0.005]	[0.003]	[0.001]
Log wage per employee	0.016***	0.002	0.000
	[0.004]	[0.002]	[0.001]
Other controls	Yes	Yes	Yes
Constant	-0.031	0.029	0.008
	[0.045]	[0.023]	[0.014]
Obs	11255	11255	11255
R2	0.164	0.149	0.093

Note: other controls include: managerial characteristics (education, age and gender), family ownership and the presence of external managers; workforce composition (education, professions, age, female, contractual arrangements); firms productive characteristics such as NACE e sectors, NUTS 2 regions, international markets, second level bargaining, multinationals, vacancy. Clustered robust standard errors in parentheses.
Source: our calculations on RIL-COB-ASIA merged sample

Combining results from table 5 and 6, we can affirm that the adoption of I4.0 technologies positively affects the hiring rate of young workers and reduces firm-level separation rate. This picture is consistent with the one defined in Bratta *et al.* (2020) identifying a positive employment effect in Italian companies induced by corporate investments in subsidized 4.0 technologies. The findings of this study pointed to an increase in hirings for firms having benefitted from hyper-depreciation, not

[17] According to aggregated figures from INPS data, about 18% of total separations are due to contractual dismissals for disciplinary or economic reasons, while 22% can be linked to voluntary resignations and more than 50% of separations depend on termination of contracts.

coupled with a contemporary increase in separations. The net positive employment effect is greater for large companies (over 250 employees) and for firms whose geographical location of Italian headquarter is in the South.

Our results complete this evidence by suggesting that “I4.0 companies” are more likely to hire young workers and favour longer and stable work relationships since separations are lower[18].

Furthermore, our results point to a non-significant effect of I4.0 technologies on tertiary educated workers. This can be explained by the composition of the RIL-Inapp sample made by a large group of small and micro enterprises and is coherent again with findings reported in Bratta *et al.* (2020) on the entire population of Italian firms benefitting from the hyper-depreciation plan. In fact, the authors detect a very modest impact of 4.0 technology investments on high-skilled hirings (corresponding largely to tertiary educated workers) explained by the behavior of small- and medium-sized enterprises, which are predominant in the Italian economy. Conversely, when estimates are split by firm size, demand for high skilled occupations has increased substantially in large companies.

Overall, our results suggest that the digital transformation had, so far, a positive effect on hirings – especially for young workers (and probably medium-skilled workers), whereas the demand for qualified workforce has been very modest, almost insignificant.

Table 6. Diff-in-Diff fixed effects estimates. Dep var: Separation rate

	Workers over total employment	**Workers <30 years old over total employment**	**Graduated workers over total employment**
I4.0* year 2018	-0.016**	0.000	0.002
	[0.008]	[0.005]	[0.002]
I4.0*year 2014	-0.011	-0.003	-0.002
	[0.008]	[0.004]	[0.002]
Year 2018	0.030***	0.000	0.005***
	[0.007]	[0.004]	[0.002]
Year 2014	-0.004	-0.007*	0.002
	[0.006]	[0.004]	[0.002]
Firms registering vacancies	0.021***	0.009***	0.001
	[0.006]	[0.003]	[0.002]
Log wage per employee	0.019***	0.003	0.002
	[0.004]	[0.002]	[0.002]
Other controls	Yes	Yes	Yes
Constant	-0.009	0.109**	0.013
	[0.083]	[0.045]	[0.02]
N of Obs	11257	11257	11257
R2	0.028	0.015	0.013

Note: other controls include: managerial characteristics (education, age and gender), family ownership and the presence of external managers; workforce composition (education, professions, age, female, contractual arrangements); firms productive characteristics such as NACE e sectors, NUTS 2 regions, international markets, second level bargaining, multinationals, vacancy. Clustered robust standard errors in parentheses.

Source: our calculations on RIL-COB-ASIA merged sample

[18] This is also consistent with Bratta *et al.* (2020)’s findings highlighting that the acceleration of job creation associated with investments in 4.0 technologies benefitted individuals under 35 more than older ones.

5.3 *Workplace training*

In previous sections we have analyzed how and to which extent investments in I4.0 technologies can be related to job flows within firms, meaning that firms can acquire specific profiles on the labour market by activating new labour contracts or facilitating job turnover. However, firms can also create internally specific skills through workplace training. Investments in both formal education and on-the-job training may increase complementarity between digital technologies and skills – as it was largely verified for ICTs – making for companies more profitable the introduction of I4.0 techs. As we highlighted in Cirillo *et al.* (2020), investments in training are positively associated to the adoption of enabling technologies in Italian companies. In fact, training can be designed internally by individual employers in accordance with firms' specific needs. Results in table 7 confirm this synergy between on-the-job training and digital technologies, showing a positive association between the realization of training at the workplace level (first column), the share of trained employees over total employment (column 2) and the (log of) training costs per employee (column 3). When controlling for unobserved heterogeneity and endogeneity through the application of a fixed-effects estimator (table 8), the relationship between investment in I4.0 technologies and training is confirmed. The introduction of I4.0 technologies increases the percentage of trained workers by 3,5 percentage points, whereas the average cost of training rises by 30 euros per employee compared to non-adopting firms. This picture is coherent with previous results highlighting that firms are more likely to hire young workers but also, presumably, middle and low skilled workers. Therefore, they should create internally a trained workforce able to interact with digital technologies.

Table 7. Pooled OLS estimates. Dep var: Workplace training

	Training investment	**Share of trained employees**	**Training costs per employee**
I4.0	0.074*** [0.015]	0.050*** [0.013]	0.484*** [0.084]
Year 2018	0.136*** [0.012]	0.163*** [0.010]	0.607*** [-0.065]
Year 2014	0.110*** [-0.01]	0.118*** [-0.008]	0.600*** [-0.053]
Firms registering vacancies	0.108*** [-0.013]	0.064*** [-0.011]	0.689*** [-0.075]
Log wage per employee	0.018*** [-0.007]	0.022*** [-0.006]	0.164*** [-0.042]
Other controls	Yes	Yes	Yes
Constant	0.213*** [-0.078]	0.067 [-0.069]	0.237 [-0.46]
N of Obs	11257	11251	10214
R2	0.202	0.148	0.193

Note: other controls include: managerial characteristics (education, age and gender), family ownership and the presence of external managers; workforce composition (education, professions, age, female, contractual arrangements); firms productive characteristics such as NACE e sectors, NUTS 2 regions, international markets, second level bargaining, multinationals, vacancy. Clustered robust standard errors in parentheses.
Source: our calculations on RIL-COB-ASIA merged sample

Table 8. Diff-in-Diff fixed effects estimates. Dep var: Workplace training

	Training investment	Share of trained employees	Training costs per employee
I4.0* year 2018	0.050***	0.035**	0.303***
	[0.019]	[0.016]	[0.108]
I4.0*year 2014	0.036*	0.026	0.106
	[0.02]	[0.017]	[0.11]
Year 2018	0.158***	0.177***	0.761***
	[0.014]	[0.012]	[0.076]
Year 2014	0.096***	0.107***	0.549***
	[0.014]	[0.011]	[0.072]
Firms registering vacancies	0.047***	0.029**	0.329***
	[0.016]	[0.014]	[0.093]
Log wage per employee	0.012	0.017*	0.108*
	[0.009]	[0.009]	[0.06]
Other controls	Yes	Yes	Yes
Constant	0.175	-0.256	-2.205*
	[0.176]	[0.162]	[1.301]
N of Obs	11257	11251	10214
R2	0.061	0.087	0.062

Note: other controls include: managerial characteristics (education, age and gender), family ownership and the presence of external managers; workforce composition (education, professions, age, female, contractual arrangements); firms productive characteristics such as NACE e sectors, NUTS 2 regions, international markets, second level bargaining, multinationals, vacancy. Clustered robust standard errors in parentheses.
Source: our calculations on RIL-COB-ASIA merged sample

6. Technological heterogeneity: typologies of I4.0 Investment

In this section we investigate the main relationship tested in paragraph 5 by focusing on specific types of I4.0 technologies. Why shall we expect that I4.0 technologies differently affect job flows and the extent to which companies are involved in workplace training? Since I4.0 technologies are a cluster of heterogeneous technologies, a multiplicity of devices and techniques, it is likely that different technological combinations will generate diverse effects on job flows and training investment. To get a better grasp of the heterogeneous influence of different technologies on job flows and internal labour markets, in what follows we focus on three types of I4.0 technologies: cybersecurity, IoT and robotics. Instead of grouping technologies by peculiar features as in Balsmeier and Woerter (2019), we consider separately each of them[19].

[19] Following Balsmeier and Woerter (2019) while IoT and robotics can be framed as machine-based digital technologies due to the complexity of their adoption and disruptive potential, cybersecurity can be considered as non-machine-based digital technologies. As the authors highlight, the crucial difference between the two groups can be found in their powerful combination of data access, computation and communication technologies with acting hardware Balsmeier and Woerter (2019, 4).

6.1 Cybersecurity

Most Italian companies declaring to have introduced at least one of I4.0 technologies has invested in cybersecurity (MiSE 2018; Istat 2018; Cirillo *et al.* 2020) referring to the set of technologies, processes and practices designed to protect computer networks, devices, programmes and data from attack, damage, or unauthorized access (Istat 2020). The investment in cybersecurity is usually considered as an infrastructural type of technology crucial to set an adequate environment for interconnected, digital and automation applications that can be introduced in a subsequent phase. Therefore, this investment is one of the more widespread across firms including: (i) companies that although perceiving the potential of digital technology, because of their size or sectoral location, faces several constraints in envisaging a systematic transition to an intensively digitalised organisational set-up; (ii) digital mature companies having a clear digital strategy creating the conditions for the integrated use of other technologies, such as the Internet of Things. For this latter group, the investment in security is essential and, in general, as the level of digital maturity increases, so does the need for companies to secure their equipment (Istat 2020). How does this group of companies behave in terms of occupational choices?
According to the estimates in table 9, the investment in cybersecurity is positively associated to hiring rate (first column), specifically of graduated workers (third column), and negatively to firm-level separation rates (table 10).

Table 9. Diff-in-Diff fixed effects estimates. Dep var: Hiring rate

	Workers over total employment	**Workers <30 years old over total employment**	**Graduated workers over total employment**
Cybersecurity* year 2018	0.016**	0.006	0.004*
	[0.008]	[0.005]	[0.003]
Cybersecurity *year 2014	0.005	0.004	0.001
	[0.008]	[0.005]	[0.003]
Year 2018	-0.025***	-0.007	-0.002
	[0.007]	[0.004]	[0.002]
Year 2014	-0.043***	-0.015***	-0.003
	[0.006]	[0.004]	[0.002]
Firms registering vacancies	0.028***	0.014***	0.001
	[0.006]	[0.004]	[0.002]
Log wage per employee	-0.021***	-0.007***	-0.004***
	[0.004]	[0.002]	[0.001]
Other controls	Yes	Yes	Yes
Constant	0.468***	0.158***	0.005
	[0.088]	[0.061]	[0.044]
N of Obs	11257	11257	11257
R2	0.064	0.044	0.031

Note: other controls include: managerial characteristics (education, age and gender), family ownership and the presence of external managers; workforce composition (education, professions, age, female, contractual arrangements); firms productive characteristics such as NACE e sectors, NUTS 2 regions, international markets, second level bargaining, multinationals, vacancy. Clustered robust standard errors in parentheses.
Source: our calculations on RIL-COB-ASIA merged sample

Combining results from tables 9 and 10, one can observe that firms investing in cybersecurity have registered a positive (net) effect on employment, whereby the hiring rate exceeds the separation rate.

Furthermore, compared to the baseline scenario – the one on I4.0 technologies – the focus on cybersecurity sheds lights on a positive impact of cybersecurity on graduated workers by about 0,4 percentage points. Linking this evidence with previous tables, we can argue that cybersecurity has been introduced in large companies and is more transversal across manufacturing and services.

Table 10. Diff-in-Diff fixed effects estimates. Dep var: Separation rate

	Workers over total employment	Workers <30 years old over total employment	Graduated workers over total employment
Cybersecurity* year 2018	-0.017**	0.000	0.001
	[0.008]	[0.005]	[0.003]
Cybersecurity *year 2014	-0.011	-0.003	-0.003
	[0.008]	[0.004]	[0.002]
Year 2018	0.030***	0.000	0.005***
	[0.007]	[0.004]	[0.002]
Year 2014	-0.004	-0.007**	0.002
	[0.006]	[0.004]	[0.002]
Firms registering vacancies	0.021***	0.009***	0.001
	[0.006]	[0.003]	[0.002]
Log wage per employee	0.019***	0.003	0.002
	[0.004]	[0.002]	[0.002]
Other controls	Yes	Yes	Yes
Constant	-0.009	0.109**	0.013
	[0.083]	[0.045]	[0.02]
N of Obs	11257	11257	11257
R2	0.028	0.015	0.013

Note: other controls include: managerial characteristics (education, age and gender), family ownership and the presence of external managers; workforce composition (education, professions, age, female, contractual arrangements); firms productive characteristics such as NACE e sectors, NUTS 2 regions, international markets, second level bargaining, multinationals, vacancy. Clustered robust standard errors in parentheses.
Source: our calculations on RIL-COB-ASIA merged sample

6.2 Internet of Things

A more complex level of interactions among digital equipment is required by Internet of Things having a greater impact on the business process and only marginally adopted by Italian factories. IoT implies application and usage of sensors, monitoring and remote-control systems via the Internet and, of course, an adequate digital infrastructure given by prior investments in optical fiber, mobile connectivity, management software, cybersecurity. From this point of view, firms adopting IoT solutions depict higher digital maturity, since they foresee an integrated use of I4.0 technologies.
Table 11 shows that companies investing in IoT have registered a significant positive increase of newly hired graduated workers by about 0,8 percentage points (0,4 percentage points more than cybersecurity); table 12 indicates instead that IoT does not affect separations. Overall, IoT seems to increase net employment of highly qualified workers probably due to the specific competencies required to manage these systems.

Table 11. Diff-in-Diff fixed effects estimates. Dep var: Hiring rate

	Workers over total employment	Workers <30 years old over total employment	Graduated workers over total employment
IoT* year 2018	0.005	0.009	0.008*
	[0.014]	[0.008]	[0.004]
IoT*year 2014	-0.003	0.003	0.005
	[0.013]	[0.007]	[0.005]
Year 2018	-0.020***	-0.005	-0.001
	[0.006]	[0.004]	[0.002]
Year 2014	-0.041***	-0.014***	-0.003**
	[0.005]	[0.003]	[0.001]
Firms registering vacancies	0.028***	0.014***	0.001
	[0.006]	[0.004]	[0.002]
Log wage per employee	-0.021***	-0.007***	-0.003***
	[0.004]	[0.002]	[0.001]
Other controls	Yes	Yes	Yes
Constant	0.469***	0.159***	0.006
	[0.088]	[0.061]	[0.044]
N of Obs	11257	11257	11257
R2	0.064	0.044	0.031

Note: other controls include: managerial characteristics (education, age and gender), family ownership and the presence of external managers; workforce composition (education, professions, age, female, contractual arrangements); firms productive characteristics such as NACE e sectors, NUTS 2 regions, international markets, second level bargaining, multinationals, vacancy. Clustered robust standard errors in parentheses.
Source: our calculations on RIL-COB-ASIA merged sample

Table 12. Diff-in-Diff fixed effects estimates. Dep var: Separation rate

	Workers over total employment	Workers <30 years old over total employment	Graduated workers over total employment
IoT* year 2018	-0.003	0.007	0.012**
	[0.013]	[0.007]	[0.005]
IoT*year 2014	-0.006	-0.001	0.008*
	[0.013]	[0.006]	[0.005]
Year 2018	0.024***	0.000	0.004***
	[0.006]	[0.003]	[0.001]
Year 2014	-0.008	-0.008***	0.001
	[0.005]	[0.003]	[0.001]
Firms registering vacancies	0.021***	0.009***	0.000
	[0.006]	[0.003]	[0.002]
Log wage per employee	0.019***	0.003	0.002
	[0.004]	[0.002]	[0.002]
Other controls	Yes	Yes	Yes
Constant	-0.012	0.108**	0.014
	[0.083]	[0.045]	[0.02]
N of Obs	11257	11257	11257
R2	0.028	0.015	0.014

Note: other controls include: managerial characteristics (education, age and gender), family ownership and the presence of external managers; workforce composition (education, professions, age, female, contractual arrangements); firms productive characteristics such as NACE e sectors, NUTS 2 regions, international markets, second level bargaining, multinationals, vacancy. Clustered robust standard errors in parentheses.
Source: our calculations on RIL-COB-ASIA merged sample

6.3 Robotics

Finally, we focus on robotics which includes in the RIL survey both industrial robots – that are new generation and service robots designed to work alongside humans and specialised in carrying out specific tasks[20] – and collaborative robots – having a certain degree of autonomy and able to operate in a complex and dynamic environment that requires interaction with people, objects, or other devices. Investments in robots are usually associated to large companies that have almost reached the threshold of digital maturity and are experimenting with different IT solutions (Istat 2020). These companies are likely to face significant investments in the exploitation of information flows (big data), in simulation and robotics; indeed, they have financial capacity and technical capabilities to achieve the greatest benefits in terms of efficiency and productivity.

These companies – according to results in table 13 – have registered a significant increase in the hiring rate of tertiary graduated workers of about 0,4 percentage points, whereas table 14 shows that robotics has not significant effect on separation rate.

Table 13. Diff-in-Diff fixed effects estimates. Dep var: Hiring rate

	Workers over total employment	**Workers <30 years old over total employment**	**Graduated workers over total employment**
Robot* year 2018	0.024**	0.009	0.004*
	[0.012]	[0.007]	[0.002]
Robot *year 2014	0.026***	0.014**	0.003
	[0.010]	[0.006]	[0.002]
Year 2018	-0.021***	-0.005	-0.001
	[0.006]	[0.004]	[0.002]
Year 2014	-0.043***	-0.014***	-0.003*
	[0.005]	[0.003]	[0.001]
Firms registering vacancies	0.028***	0.014***	0.001
	[0.006]	[0.004]	[0.002]
Log wage per employee	-0.021***	-0.007***	-0.003***
	[0.004]	[0.002]	[0.001]
Other controls	Yes	Yes	Yes
Constant	0.469***	0.158***	0.006
	[0.088]	[0.061]	[0.044]
N of Obs	11257	11257	11257
R2	0.064	0.044	0.031

Note: other controls include: managerial characteristics (education, age and gender), family ownership and the presence of external managers; workforce composition (education, professions, age, female, contractual arrangements); firms productive characteristics such as NACE e sectors, NUTS 2 regions, international markets, second level bargaining, multinationals, vacancy. Clustered robust standard errors in parentheses.

Source: our calculations on RIL-COB-ASIA merged sample

Combining results from tables 13 and 14 it can be said that investments in robotics are significantly associated to positive job flows specifically for graduated workers. This evidence is not surprising and is in line with findings in other firm-level studies building employer-employees linked databases and

[20] They can be automatically controlled and reprogrammable, either stationary or mobile, and are used in industrial automation applications (e.g., robotic welding, laser cutting, spray painting etc.).

controlling for endogenous selection of firms. Among them, Kock *et al.* (2021) on an employer-employee database of Spanish companies, find a strictly non-negative employment effects for all types of workers, including low-skilled workers as well as workers employed in the firm's manufacturing establishments. Similarly, Domini *et al.* (2021) on French manufacturing companies show that the decision to automate positively affect firms' employment in terms of both a reduction in the separation rate and an increase in the hiring rate. Overall, our evidence discards, so far, a *labour-displacing* effects of robots on jobs, conversely, they appear to be associated to job creation of qualified workers.

Table 14. Diff-in-Diff fixed effects estimates. Dep var: Separation rate

	Workers over total employment	**Workers <30 years old over total employment**	**Graduated workers over total employment**
Robot* year 2018	-0.011	0.002	-0.001
	[0.011]	[0.007]	[0.002]
Robot*year 2014	-0.012	0.004	0.001
	[0.009]	[0.005]	[0.002]
Year 2018	0.025***	0.000	0.006***
	[0.006]	[0.003]	[0.001]
Year 2014	-0.007	-0.009***	0.001
	[0.005]	[0.003]	[0.001]
Firms registering vacancies	0.021***	0.009***	0.001
	[0.006]	[0.003]	[0.002]
Log wage per employee	0.019***	0.003	0.002
	[0.004]	[0.002]	[0.002]
Other controls	Yes	Yes	Yes
Constant	-0.011	0.108**	0.013
	[0.083]	[0.045]	[0.02]
N of Obs	11257	11257	11257
R2	0.028	0.015	0.012

Note: other controls include: managerial characteristics (education, age and gender), family ownership and the presence of external managers; workforce composition (education, professions, age, female, contractual arrangements); firms productive characteristics such as NACE e sectors, NUTS 2 regions, international markets, second level bargaining, multinationals, vacancy. Clustered robust standard errors in parentheses.
Source: our calculations on RIL-COB-ASIA merged sample

7. Conclusions

In recent years the academic debate has focused on the transformative potential of new technologies, those enabling the digitization, automation and interconnection of production processes, which, on the one hand, define the overcoming of the demarcation between manufacturing and services, and, on the other, lead to a reconfiguration of production processes at a global level. Since new digital technologies include a diverse set of solutions and capabilities, encompassing robotics, artificial intelligence, industrial internet of things, big data, cloud computing, augmented reality, additive manufacturing, and cybersecurity, it can be often difficult to draw precise lines of demarcation between them. Even though previous studies have shed lights on the disruptive and potential general-purpose nature of the current technological transformation radically reshaping organization of work and productions. These transformations overcome the boundaries of the firm and involve the entire value chains which are often themselves more and more dependent on digital technologies able to connect in a modular but integrated way different phases of production and service delivery (Cirillo *et al.* 2021b). The stakes are high and it is not surprising that these technologies have attracted great interest among scholars and policy-makers alike. Against this backdrop, the empirical evidence specific to the new digital technologies is limited due to data constraints. Whereas patents can be used to track the invention and supply of new technologies, they are not informative on those adoption and diffusion patterns through which structural change takes place by altering the relative productivity of firms.

In this paper we aim to fill this gap providing evidence on the labour market effects of the adoption of I4.0 technologies in the Italian economy. To do that, we took advantage of a unique and original firm-level database on digital technology adoption produced by the National Institute for the Analysis of Public Policies (Inapp), matched with complementary firm-level information drawn from the archive of the National Institute of Statistic (*Istituto Nazionale di Statistica* - Istat), and employee-level information from the administrative archives of the Italian Ministry of Labor and Social Policies. Linking the three different sources of information through firms' fiscal codes allowed us to create a unique longitudinal employer-employee linked database (RIL-COB-ASIA) containing high-quality information on the total number of hirings and separations for each firm by age group, educational titles and type of contract stemming from administrative archives.

Therefore, the combined data give us a rare opportunity to study the effects of new digital technologies on labour flows in the Italian economy. We focused specifically firm internal and external labour markets and explore how and to which extent I4.0 adopters behave in terms of hirings, separations and workplace training. This made it possible to build a clear picture not only of aggregate changes in employment, but also of the gross flows, thus providing a much richer picture of the dynamics behind net job creation proc figures (see Criscuolo *et al.* 2014 for a similar analysis).

The application of a Diff-in-Diff empirical strategy generated interesting results. First, the digital transformation had, so far, a positive effect on hirings – especially for young workers, even though the demand for qualified workforce has been so modest as to appear almost insignificant. Second, firms investing in I4.0 experienced a decreasing separation rate compared to non-adopters, suggesting that digital companies rely more on stable working arrangements. Third, Italian companies that have invested in I4.0 technologies increased workplace training by enlarging the pool of workers receiving training and by augmenting the average amount spent in training for each worker.

Moreover, we explored technologies heterogeneities by dissecting the effect that three specific technologies – cybersecurity, IoT and robotics – may have on job flows and training initiatives. Compared to general results, we detect that cybersecurity, IoT and robotics are associated with higher hiring rate for graduates, whereas no significant effects emerge for separations, except for cybersecurity which is negatively associated to firm level separation rate.

Overall, our evidence discards, so far, *labour-displacing* effects of I4.0 technologies on jobs; conversely, they appear to be associated with job creation at least for young workers. Our evidence seems to support the thesis that new technologies could have a positive impact on employment, requiring 3D printing, IoT, augmented reality, and big data analytics new skills to be properly managed (Freddi 2017). This is in line with the vision in Zysman and Kenney (2018) highlighting that innovation processes can never be totally ‘automated’ and remains a domain of human creativity and initiative (Fareri and Solinas 2021).

Further research is certainly needed to explore which kind of workers are more likely to be affected by the digital transformation of companies in the longer term, since workers can be unevenly involved in these processes, given the specific and evolving tasks they perform, and their ability to take part in the digital transformation of the economy.

Researchers and policy makers should pay attention to potential winners and losers of the ongoing digitalization. In this regard, focusing on skills and tasks associated with professional profiles might help to shed lights on the complex relationship between recent technological changes and employment.

Appendix

Table 1A. Hiring and separation rates. Longitudinal sample vs cross sectional samples

	Share of hirings	Share of hired <30	Share of hired with tertiary edu	Share of separated	Share of separated <30	Share of separated with tertiary edu
			Longitudinal sample			
2010	0.204	0.071	0.014	0.129	0.049	0.006
2014	0.127	0.040	0.012	0.119	0.039	0.009
2018	0.150	0.062	0.012	0.170	0.049	0.019
			Cross sectional sample			
2010	0.246	0.089	0.012	0.182	0.076	0.010
2014	0.187	0.062	0.014	0.165	0.052	0.011
2018	0.195	0.077	0.015	0.219	0.072	0.013
Total	0.209	0.076	0.014	0.190	0.067	0.011

Note: * in euros. Sampling weights applied.
Source: our calculations on RIL-COB-ASIA sample

Table 2A. Workplace training: Longitudinal sample vs cross sectional samples

	Training investment (%)	Share of trained workers (%)	Training costs per employee*
		Longitudinal sample	
2010	0.269	0.173	72.01
2014	0.355	0.271	92.37
2018	0.432	0.338	100.62
Total	0.347	0.256	86.93
		Cross sectional sample	
2010	0.269	0.173	72.01
2014	0.355	0.271	92.37
2018	0.432	0.338	100.62
Total	0.347	0.256	86.9

Note: * in euros. Sampling weights applied.
Source: our calculations on RIL-COB-ASIA sample

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