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Digital Technologies, Labor market flows and Training: Evidence from Italian employer-employee data

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

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Abstract

New technologies can shape the production process by affecting the way in which inputs are embedded in the organization, their quality, and their use. Using an original employer-employee dataset that merges firm-level data on digital technology adoption and other characteristics of production with employee-level data on worker entry and exit rates from the administrative archive of the Italian Ministry of Labor, this paper explores the effects of new digital technologies on labor flows in the Italian economy. Using a Difference-in-Difference approach, we show that digital technologies lead to an increase in the firm-level hiring rate – particularly for young workers - and reduce the firm-level separation rate. We also find that digital technologies are positively associated with workplace training, proxied by the share of trained employees and the amount of training costs per employee. Furthermore, we explore the heterogeneity of effects related to different technologies (robots, cybersecurity and IoT). Our results are confirmed through several robustness checks.

Keywords: Industry 4.0; Digital technologies; Hiring rate; Separation rate; Skills; Training; Employer-Employee data
JEL Codes: D22, L23, J21

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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 organization 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 these inputs are embedded in the organization. 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 use novel employer-employee linked data merging: i) survey information on the adoption of digital technologies, training investments and other characteristics of production collected by the Italian National Institute for Public Policies Analysis (INAPP) for a large representative sample of Italian firms; ii) worker-level information on exit and entry rates provided by the administrative archive of the Italian Ministry of Labor and Social Policies (MLPS); iii) complementary firm-level information drawn from the archive of the Italian National Institute of Statistics (ISTAT) that allows us to compute the entire stock of employees within a firm.

Taking advantage of this matched data, we use a difference-in-difference approach combined with propensity score matching to investigate the effects of firm adoption of digital technologies on worker exit and entry rates in the Italian economy. To foreshadow some of our main results, we observe a positive and significant correlation between the adoption of digital technologies and new hiring. More precisely, digital technologies positively affect the hiring rate of young workers and reduce firm-level separation rates. We also find that digital technologies are positively associated with the share of trained employees and the amount of training costs per employee, confirming the expected complementarities between digital technologies and workplace training.

The paper is organized 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 labor demand. 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 explores technological heterogeneity and adoption intensity, proxied by the number of technologies introduced at the firm level, on labor market flows. Finally, Section 7 briefly draws the contribution to a close.

2. New technologies, worker flows and training

The co-evolution of organizational 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) and, consequently, the related employment dynamics. 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 several 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 labor services by employees. In many instances, there are clear trade-offs between the two forms of investments, and changing the composition of labor 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. Indeed, firms' organizational capabilities and the external economic environment such as market structures in which firms operate and the aggregate demand they face may contribute to shaping the impact that digital and automation technologies can have on labor demand for specific skills and training decisions. To which extent firms adopting new technologies rely on *external labor markets* to hire workers or, conversely, they prefer training workers to adapt workers' skills to new labor processes is our main research question.

Indeed, the complex and multidimensional nexus between innovation, employment, and skills has taken center stage in different streams of research from both a theoretical and an empirical viewpoint (Tether et al., 2005; Calvino and Virgillito, 2018; Mondolo, 2022; Montobbio et al., 2023b). On the one hand, from an equilibrium perspective, the introduction of innovations can lead to higher employment, via an increase in total output and wage reduction. On the other hand, as stressed especially by disequilibrium approaches, the effect of innovation on employment is much more difficult to predict, since technological progress is a complex and context-specific phenomenon. Fundamental disagreements also exist on the existence and speed of a self-adjusting labor market process, guaranteed by the functioning of compensation mechanisms (Freeman et al., 1982; Simonetti et al., 2000; Vivarelli, 1995; 2014).

From an empirical standpoint, the technology-employment nexus is hard to disentangle since there are at least three factors affecting the sign and magnitude of this relationship. First, the level at which the analysis can be performed is crucial: different results emerge from firm-level analyses relative to sector-level studies (i.e., regarding "business stealing" effects). The net job-creating effects of technology tend to appear very clearly when looking at highly innovative firms (Coad and Rao, 2011; Van Roy et al., 2018), and more clearly compared to sectoral analyses (Dosi and Mohnen, 2019) recently incorporating measures of vertical integration of R&D expenditures (Cresti et al., 2023). Similarly, it is crucial to consider the overall labor force effect but also disentangling the uneven impact on different categories of workers by skills, educational titles, job positions, gender and age. Far from being neutral, technological change can contribute to reshape the organizational ladder within firms according to the level of complementary of tasks with respect to new technologies and workers' ability to bargain on their introduction and use.

Second, the proxy chosen as an indicator for technological change matters: R&D expenditures usually capture disembodied technological change, whereas embodied technological change in capital inputs can be proxied by investments such as those in computers and ICT, robots and other automation technologies (Barbieri et al., 2019). Special attention has been devoted to Artificial Intelligence over the last few years (Frank et al., 2019; Lane and Saint-Martin, 2021; Dahlke et al., 2024), and indeed, results can be affected by the way in which the latter is measured (Mondolo, 2022; Montobbio et al., 2023b).

Third, the time span of the analysis is important since business cycle conditions can influence the link between technological change and employment: changing economic conditions such as credit constraints, opportunity costs of investing in innovation, appropriability and demand shape the innovation behavior of firms and, consequently, the creation or destruction of jobs (Peters et al., 2014). All these factors, including specific characteristics of firms, sectors and/or countries play a key role in determining the magnitude and the direction of the effect of technologies on employment.

Against this backdrop, one may wonder if the recent phase of technological change entailing digitalization, automation and interconnection implies deep changes in the organization of work and, through this channel, how this it has affected the demand for labor. Recent economic literature has begun to investigate what consequences the introduction of new technologies has on employees at the workplace level, looking at the extent to which computerization, robotization and automation may jointly affect the quantity and quality of employment (Frey and Osborne, 2013; Brynjolfsson and McAfee, 2014; Graetz and Michaels, 2018; Arntz et al., 2016; Montobbio et al., 2022). Although robots still play an important role, it is worth noting that the increasing adoption of a range of automation and new digital technologies has not been limited to robots since it encompasses a wide and diversified set of artefacts (Staccioli and Virgillito, 2021; Cirillo et al., 2023; Mondolo, 2022; Ciarli et al., 2021). The latter fall into the realm of new digital technologies or (new) enabling technologies (Martinelli et al., 2021). While robots tend to concentrate in specific manufacturing sectors (Aghion et al., 2020), new digital technologies are more widespread and provide a clearer picture of the ongoing digital transformation. However, firm-level data on the adoption of digital and automation technologies has only recently starting to be collected by national statistical offices (Balsmeier and Woerter, 2019). For this reason, several studies have relied on indirect proxies of technical change such as imports of intermediates embedding automation technologies (Domini et al., 2022) or, for instance, indicators of occupational task content widely employed in the task-based literature (Autor and Dorn, 2013). The latter have shown some criticalities since they implicitly assume that routinized tasks disappear due to the application of automation, and this is not always the case (Autor, 2022). Therefore, 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). Similarly, Koch et al. (2021) use Spanish data from the ESEE Survey (*Encuesta Sobre Estrategias Empresariales*) to study the effects of industrial robots in manufacturing. They find that robot adoption produces from 20 to 25% output gains, reduces labor costs and positively contributes to firm employment growth (at an average rate of approximately 10%). Acemoglu et al. (2020) and Domini et al. (2022) study the effects of investments in robots made by French firms. Acemoglu et al. (2020) show that adopting firms, while reducing the labor share and the share of production workers, increase their productivity and grow more than competitors. Domini et al. (2022) find positive employment growth effects.

Bessen et al. (2019) focus on what happens to individual workers when their firm decides to automate. They 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 partly offset by social benefits. In a more 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. Results highlight that the effects of digital technologies on workers are not homogenous across workers groups and adjustments might be skewed and uneven in outcomes. Indeed, 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. Dissecting heterogeneities among workers, Fossen and Sorgner (2022) model individual labor market transitions by using a sample of paid employees to investigate heterogeneous effects of new digital technologies, such as advances in AI and machine learning, on wage and employment dynamics in the US labor market. Their results shed lights on potential labor-displacing effects of new digital automation technologies on labor demand, more pronounced for individuals with higher levels of human capital.

All these findings are indeed dependent on the specific type of technology adopted, in line with Balsmeier and Woerter (2019). Overall, research suggests that the potential of automation is seriously overstated and that more attention should be given to the adaptability of different jobs throughout the process of digital transformation (Arntz et al., 2017; Autor, 2015; Autor, 2022).

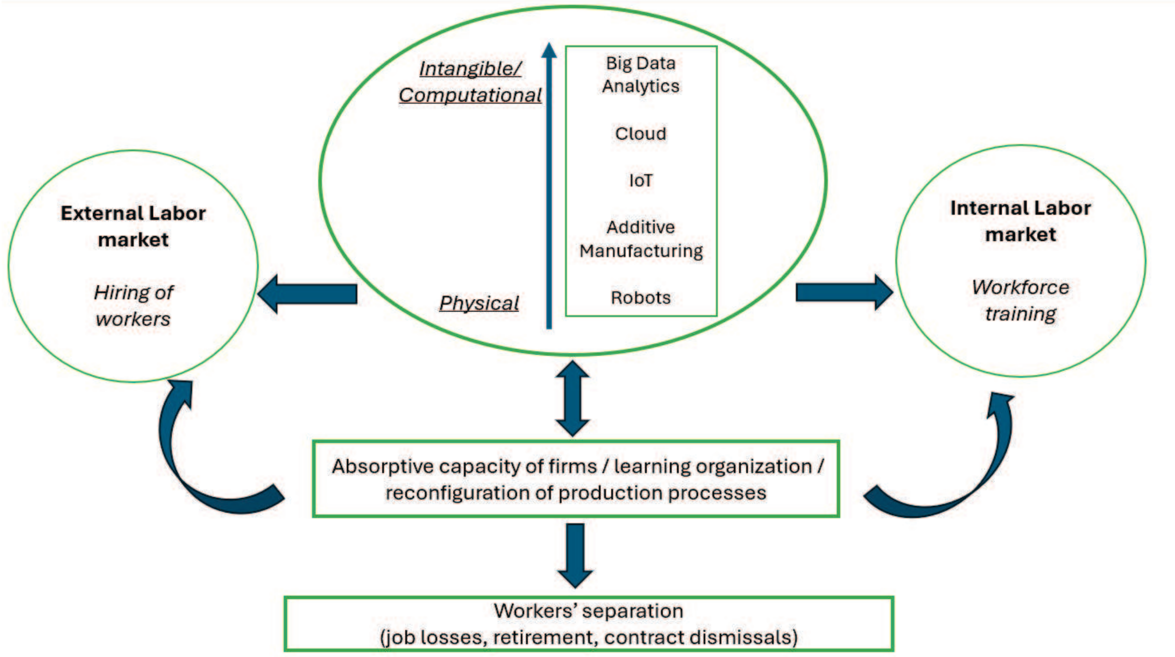
Firm-level analyses building on the conceptual framework presented in Acemoglu and Restrepo (2018a, 2018b, 2019) predicts that labor-displacing effects of automation technology can be countervailed by labor-reinstating effects depending on the type of technology and ability to spur productive effects and to generate new tasks for labor. Most of existing empirical literature focuses on the labor impacts of industrial robotics by emphasizing displacement effects rather than labor reinstatement or productivity effects that new digital technologies can generate.

Therefore, 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 labor relations to overcome the limited interpretation that can be made of aggregate employment outcomes. Furthermore, as said, 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).

This paper goes in this direction aiming to disentangle the effects of new digital technologies – and not only robots - on labor flows by exploring (i) the relationship between the adoption of digital technologies and new hirings; (ii) the relationship between adoption and job separations; (iii) the heterogeneous effects across age and skills groups; and finally, (iv) the role of on-the-job training in the process of adoption. Companies may rely on *external labor markets* hiring specific profiles or/and on *internal labor markets* by creating the occupational figures they need.

Figure 1 presents a visual representation of the anticipated connections between the adoption of new digital technologies in the workplace — ranging from physical technologies like robots to more computational ones such as Big Data analytics — and their impact on both internal and external labor markets.

Figure 1. Digital technologies, internal and external labor markets



While factors such as a firm's absorptive capacity and the reconfiguration of production processes, which are integral to the adoption of these technologies, are not directly observed, we argue that they significantly influence the labor market outcomes associated with the implementation of new machinery. Access to high-quality microdata is required to test these relationships, as it provides detailed information on the specific types of new technologies implemented at the firm level, as well as insights into job turnover, training investments, and unique organizational and structural characteristics that influence the innovation process and the development of organizational capabilities over time.

3. Data and descriptive statistics

Our empirical analysis focuses on Italy, one of the largest European economies. This represents a very interesting context of study since the adoption of new technologies has accelerated significantly over the last years, although with a very uneven distribution across sectors and regions, and with strong heterogeneity across firms. The existing evidence indicates that in the Italian context the adoption of digital technologies has been the source of competitive advantage for firms, positively contributing to productivity and firm growth (Bratta et al., 2022; Cirillo et al., 2023). This is aligned with the expectation that digital technologies help firms to improve business processes, increase operational efficiency and reduce costs of interactions with suppliers and customers (Bartel, et al., 2007; Akerman et al., 2013). In this paper we dig deeper into the ways in which the adoption of new digital technologies impacts upon their specific labor market dynamics.

We use 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 para-subordinate collaborations[1]; (ii) *Archivio Statistico delle Imprese Attive* (ASIA-Imprese), the archive of Italian firms provided by the Italian National Institute of Statistics (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 representative 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 behavior, the asset of industrial relations at workplace as well as workforce composition in terms of gender, age, education, contractual type, 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 technologies (Cirillo et al., 2023). 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 allowed, we adopt a dichotomous measure of new technologies' investment and create a new variable – "New tech" - that is equal to 1 if firms have invested in at least one of the above-mentioned technologies, 0 otherwise. We also build a countable variable "Number of New Tech" taking value from 0 to 5 according to the number of investments realized.

Although RIL-INAPP survey provides a rich set of information – including number of employees at the firm level - for the purpose of this analysis we rely on *ASIA-Imprese* for the exact number of employees by firm for each year. Linking the three different sources of information through firms' fiscal codes allows us to create a unique longitudinal employer-employee linked database - hereafter also 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

[1] Information in the COB-SISCO archives is provided at the contractual level; therefore, it has been linked to each individual by considering their longest contractual arrangement 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: <http://www.inapp.org/it/ril>.

and separations for each firm by age group, educational titles and type of contract stemming from administrative archives.

Overall, the complex matching procedure of the various sources 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 new technologies as well as several productive, managerial and workplace characteristics.

Our analysis focuses 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 year to get hiring and separation rates and, therefore, to grasp evidence 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) – for example lower employment may be due to lower creation or higher destruction of jobs, which is crucial information when designing policies to tackle (eventual) employment effects of new technologies.

The second set has to do with workplace training practices that is proxied in this analysis by three different variables: (i) activation of training activities 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 RIL-INAPP in 2010, 2015 and 2018. These variables have been put in relation with investments in new technologies, as defined in the RIL-INAPP survey. Further, 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 type of management of the firm), ii) workforce characteristics (occupation, gender, age, education) and iii) other firm characteristics (size, product and process innovation, propensity to export, etc.).

3.1 Descriptive statistics

Table 1 shows the incidence of the new technologies' adopters in 2010, 2014 and 2018 on the longitudinal component of the RIL-COB-ASIA merged sample. Table 1 also provides information on the share of firms declaring to adopt three specific types of technologies over the period: the Internet of Things (IoT), robotics, and cybersecurity. It is worth recalling that the question on investments in new technologies is addressed to Italian firms exclusively in the RIL-INAPP 2018 questionnaire (V wave). Firms have been asked if during 2015-2017 have invested in at least one of the following technologies: cybersecurity, IoT, augmented reality, robotics, big data analytics. If firms declare to have invested in at least one of the new technologies, they have been 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 have been classified as adopting new technologies even in the previous waves of the survey. This allow us to identify a so-called "treated group" composed by I4.0 adopters – about 25% - versus 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 show that about 29% of Italian firms have declared to invest in at least one of the technologies related to the *Industry 4.0 plan* over 2015-2017[6] - hereafter we refer to I4.0 technologies

[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 (Pardi, 2019), in this

or new technologies. Such investments have been unevenly distributed in the Italian economy, polarized in Northern regions and high-tech and knowledge intensive sectors. Bratta et al. (2022) focusing on administrative fiscal data of Italian companies highlight that most recipient firms of the hyper-depreciation measure incentivizing the introduction of I4.0 technologies were small- and medium-sized companies, located in Northern regions. However, a crucial distinction to analyse 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 portion. It came as no surprise since 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].

Table 1. Share of firms investing in new technologies, Robotics, IoT, Cybersecurity

	New Technologies	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

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

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 (left axis) and by specific educational and age groups (right axis). 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%.

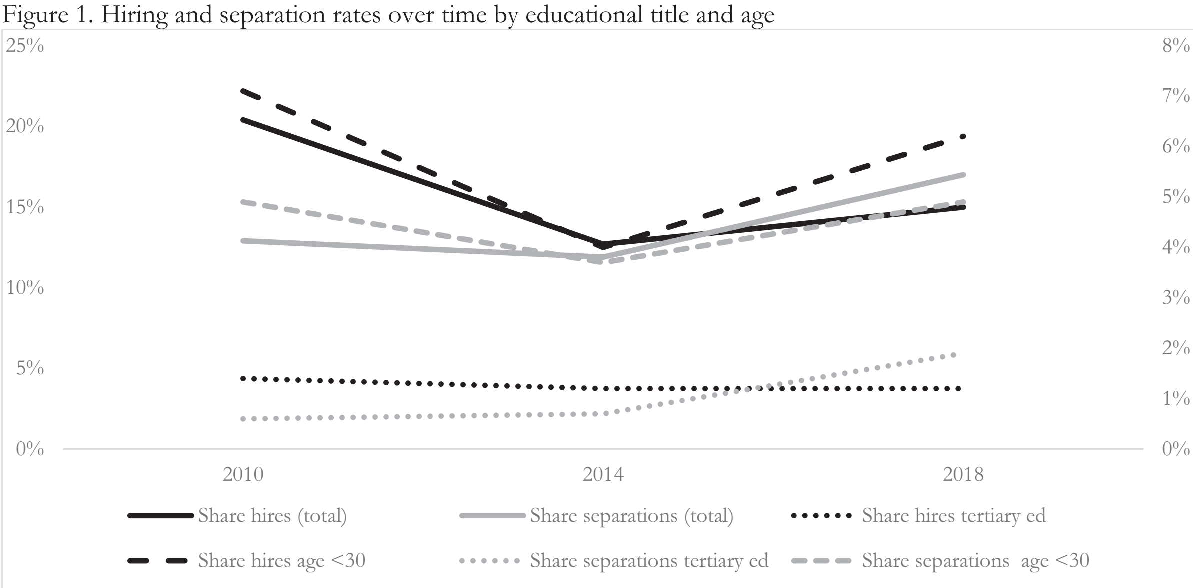
context for simplicity we use "Industry 4.0" to identify a set of multiple technologies that have been usually linked to the Industry 4.0 National Plan implemented by the Italian Ministry of Economic Development.

[7] Several works have highlighted the interconnection between adoption of I4.0 technologies and lean production systems (Moro and Virgillito, 2022).

[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. See Table 1A in the Appendix for a comparison of hiring and separation rates between cross-sectional and panel components of the survey.

Hiring rates have been linked to share of separations to provide a more complete picture of labor flows within firms[9]. Separations increased during 2014-2018 by 6 percentage points, whereas they have been 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 slightly recovery over 2014-2018; (ii) flat trend of hirings for tertiary educated workers for the entire period till 2018 when separations of tertiary educated workers overcome the average firms' hiring rate. Overall, Figure 1 highlights that firm-level labor flows have been shrinking over 2010-2014 for all type of workers. In the recovery phase 2014-2018 job flows in entrance (hirings) have been mainly detected for young workers under 30 years old, whereas separation rate outperforms hirings for tertiary educated workers.

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



Source: our calculations on longitudinal component of RIL-COB-ASIA merged sample. Note: sampling weights applied. Share of total hirings and separations (left axis); share of hirings and separations by education, age group (right axis)

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 labor markets* by recruiting new workers and, therefore, hiring employees but also on *internal labor 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

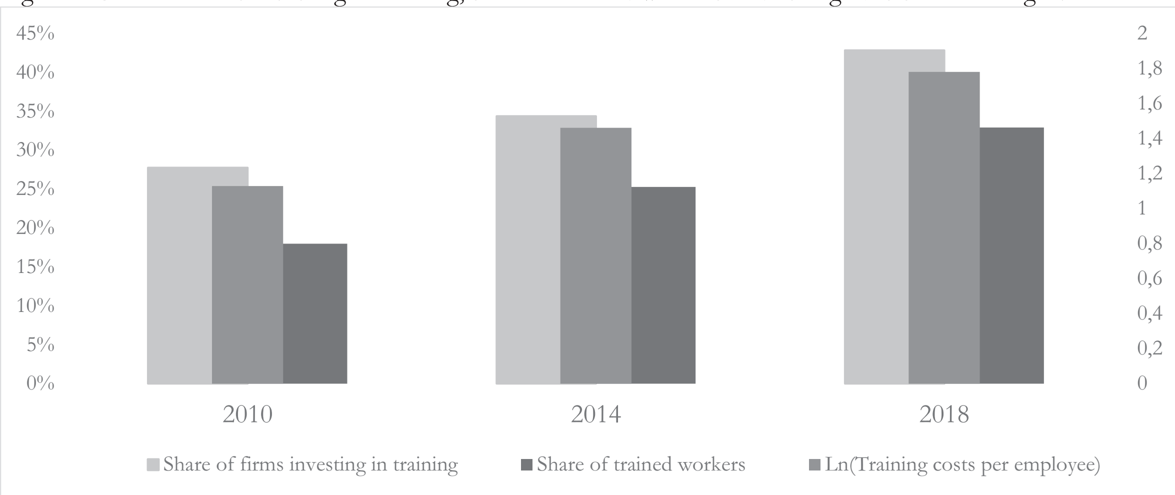
[9] It is worth recalling that in the RIL-COB-ASIA merged sample, each worker is linked exclusively to the firm in which the longest working relationship has been activated over the year. Similarly, the share of hirings is computed by considering the longest contractual relationship that each worker has activated with one specific firm.

digital transformation of enterprises, particular attention should be paid to the need to adequately train workforce for the effective use of new technologies (ISTAT, 2020)[10].

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?"[11], 0 otherwise; (ii) share of employees participating to training initiatives[12]; (iii) average costs for training divided by the number of employees[13].

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 quality of training provided. Regarding the explanatory and control variables, Table 6A in the Appendix contains their exact definition, and Table 7A reports their means and standard deviations for the 2010, 2014 and 2018 waves of the RIL-INAPP survey (note that these values are calculated on the longitudinal component of the merged RIL-COB-ASIA sample[14].

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



Source: our calculations on longitudinal component of RIL-COB-ASIA merged sample. 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 (in logarithms).

10 According to the 2019 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.

11 An identical question has been addressed to firms in relation to 2010 and 2014.

12 Firms have been asked the following question: "How many employees in the company participated in training initiatives?".

13 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.

14 Expenditure in training has been deflated by Value Added deflators in 2018, source OECD STAN. See Table 2A in the Appendix for a comparison of training variables between cross-sectional and panel components of the survey.

4. Estimation strategy

To assess the impact of new technologies on labor markets flows and workplace training we estimate the following equation:

$$Y_{i,t} = \beta_1 NT_i + \beta_2(NT_i \cdot 2018) + \beta_3(NT_i \cdot 2014) + \gamma M_{i,t} + \delta W_{i,t} + \vartheta F_{i,t} + \alpha_i + \lambda_t + \varepsilon_{i,t} \quad [1]$$

where Y_i, indicates alternatively i) the total share of newly hired and of separated workers over firms' employment, ii) the share of hired and separated with tertiary education, iii) the share of hired and separated with ≤30 years old, iv) different measures of workplace training formalized by a dichotomous indicator of financing training, the share of trained employees, the (log of) training costs per employees for each firm *i* in year t=2010, 2014, 2018.

Our key explanatory variables, NT_i is a dummy taking value of 1 whether the firm invested in at least one *new technology* - Internet of things, robotics, big data analytics, augmented reality and cybersecurity - over the period 2015-2017, and 0 otherwise (control group). The year 2018 is a time indicator for the "post-treatment" period and the year 2014 (and 2010) is the pre-treatment one; then the interaction term $NT_i \cdot 2018$ identifies the *diff-in-diff effect* of digital tech, while the $NT_i \cdot 2014$ allows us to inspect the common trends assumption (CTA) with respect to the initial period 2010.

Among the other controls, the vector $M_{i,}$ includes managerial and corporate governance characteristics, $W_{i.t}$ represents the workforce composition while $F_{i,}$ captures a rich set of firms' characteristics, geographical location and sectoral specialization. All these covariates have been discussed in the descriptive section (for further details see Appendix). Finally, the parameter α_i captures firms' time-invariant unobserved heterogeneity, λ_t are year dummies and $\varepsilon_{i,}$ is the idiosyncratic error term.

To begin with, we run the pooled OLS regressions of the equation [1] by imposing α_i=β_2= β_3=0. The OLS model is used as benchmark and permits to verify the direction of the impact of digital technologies on the outcome variables - see Angrist and Pischke (2009) and Wooldridge (2010). Note that we include a broad set of controls for managerial, organizational and corporate features, as well as firm productive strategies in order to minimize the potential biases due to omitted variables. The pooled OLS estimates associated with β_1 would be unbiased if time-invariant unobserved heterogeneity and endogeneity issues do not influence the impact of new technology investments on hiring, separations, and training. However, this might not be the case for several reasons. For example, the existence of complementarities between technology, labor and work organization may induce reverse causality – firms willing to invest in I4.0 technologies decide in advance to hire/fire workers or to implement training investment to fully exploit productivity gains stemming from implementation of I4.0 technologies. In addition, there may be at play common factors influencing job flows and training decisions as well as technology adoption. 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. According to Bratta et al. (2022), 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. More innovative firms are those registering more dynamic employment trends[15].

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-COB sample and a rich set of firm level observational information 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 new technologies over 2015-2017 (*NT=1*) while the control group consists of those firms that did not invest in the same time span (*NT=0*). Therefore, the *Diff-in-Diff fixed effect* model is run to estimate the parameter β_3, i.e. the effect of the investment in new technologies on the outcome variables (Cirillo et al., 2023)[16] .

As mentioned before, we need to verify 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, the *Diff-in-Diff* estimator has the advantage of removing any common period effects influencing both the treatment and control groups (see Gebel and Voßemer, 2014)[17].

Moreover, as additional robustness check we perform the *Diff-in-diff* regression model with propensity score matching (PSM). PSM matching aims to take into account the selection into the treatment based on observables while the *Diff-in-diff fixed effects* allow to control for time-invariant unobservable factors influencing outcome differences between treated and control firms. In detail, we apply a two-step procedure, performing the *Diff-in-Diff fixed effects* model of equation [1] after having restricted the RIL-COB-ASIA sample to the subgroups of firms with common support on the pre-treatment period (2010), i.e. to those firms with similar observables characteristics in the pre-treatment period except for the treatment, that is in our approach the investment in new technologies (Heckman et al.,1998; Abadie and Imbens, 2006).

Finally, it is worth noticing that the *Diff-in-Diff* method is increasingly applied in management and human resource studies as well as to evaluate the impact of investment and industrial relations on firm-level labor market outcomes and competitive performance. For example, scholars use the *Diff-in-Diff* methods in areas such as employee monitoring (Pierce et al., 2015), organizational goals management (Holm, 2018) and lean production (Distelhorst et al., 2016). Recent research has also relied on this empirical strategy to estimate the effect of performance-related pay schemes on labor productivity and average wages, and the mediating effects of corporate governance (Damiani et al., 2023).

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 refers 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

[15] Recent literature (Bessen et al., 2019; Domini et al., 2022) has pointed out that investments in advanced manufacturing technologies tend to be lumpy, and their effect may be difficult to observe unless this aspect is taken into account.

[16] It is worth to notice that all results are confirmed if we select the subsample of first adopters, that is those companies that did not finance any investment before the adoption of new technologies over the period 2015-2017.

[17] 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 new technologies.

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 new 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 defined as follows: (i) implementation of training practices (a dichotomous variable taking a value of 1 if training has been activated, 0 otherwise); (ii) percentage of trained employees; and (iii) average training cost per employee.

5.1 Hiring rate

Table 2 shows the pooled OLS estimates of the equation [1] for the whole sample when the dependent variable is the share of newly hired workers. The latter 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.

Table 2. Pooled OLS estimates. Dep var: Hiring rate

	Workers over total employment	Workers <30 years old over total employment	Graduate workers over total employment
New Techs	0.0101*	0.0024*	0.0049*
	[0.005]	[0.002]	[0.003
year 2018	-0.0255***	-0.0022	-0.0033
	[0.007]	[0.001]	[0.003]
year 2014	-0.0392***	-0.0022	-0.0107***
	[0.005]	[0.002]	[0.003]
Firms registering vacancies	0.0254***	0.0028	0.0095***
	[0.005]	[0.002]	[0.003]
Log wage per employee	-0.0168***	-0.0031	-0.0046
	[0.005]	[0.002]	[0.003]
Management characteristics	Yes	Yes	Yes
Workforce characteristics	Yes	Yes	Yes
Firms characteristics	Yes	Yes	Yes
Constant	0.3435***	0.0377**	0.1429***
	[0.057]	[0.019]	[0.031]
Obs	11251	11251	11251
R2	0.222	0.127	0.188

Source: our calculations on RIL-COB-ASIA merged sample. 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 sectors, NUTS 2 regions, international markets, second level bargaining, multinationals, vacancy. Clustered robust standard errors (at firm level) in parentheses. Statistical significance: *** at 1%, ** at 5% and * at 10%

The first column shows the estimation of equation [1] having as dependent variable the firm hiring rate that includes all types of activation of new contracts at the firm level - fixed-term employment, open-ended employment, apprenticeships, seasonal employment, temporary employment, intermittent employment[18]. We observe a positive and significant correlation between the adoption of new 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 over 2015-2017 seems to be positively associated to one percentage point change in the hiring rate. Dissecting by age and education these correlations, it emerges that investment in I4.0 technologies is also associated with an increase of

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

the newly hired workers with tertiary education by about 0.2 percentage points and to new hirings for young workers by almost 0.5 percentage points.

In order to tackle endogeneity and unobserved heterogeneity issues, Table 3 reports the diff-in-diff fixed effects estimates of the equation [1]. Again, we observe that investment in new technologies leads to an increase of the share of newly hired workers by 2 percentage points and more specifically of those who are ≤30 years old. Once controlling for endogeneity and unobserved heterogeneity, the effect of I4.0 investments on new hirings for graduate workers disappears compared to OLS table, whereas it emerges as slightly significant on the share of newly hired young workers by 0.4 percentage points – in line with the expectation that young workers are more prone and able to use new technologies. The CTA is verified for the hiring rate of young workers (≤30 years old) and for total employment since the interaction term between *New Techs*year 2014* is not significant for 2010.

Table 3. Diff-in-diff fixed effects estimates. Dep var: Hiring rate

	Workers over total employment	Workers <30 years old over total employment	Graduate workers over total employment
New Techs * year 2018	0.0179***	0.0041*	0.0084**
	[0.006]	[0.002]	[0.004]
New Techs *year 2014	0.0125	0.0016	0.0076*
	[0.008]	[0.003]	[0.004]
year 2018	-0.0268***	-0.0024	-0.0080**
	[0.007	[0.002	[0.004]
year 2014	-0.0459***	-0.003	-0.0164***
	[0.006]	[0.002]	[0.003]
Firms registering vacancies	0.0280***	0.0006	0.0139***
	[0.006]	[0.002]	[0.003]
Log wage per employee	-0.0213***	-0.0035**	-0.0070***
	[0.005]	[0.001]	[0.003]
Management characteristics	Yes	Yes	Yes
Workforce characteristics	Yes	Yes	Yes
Firms characteristics	Yes	Yes	Yes
Costant	0.3777***	0.0491***	0.1344***
	[0.058]	[0.016]	[0.030]
N of Obs	10703	10703	10703
R^2	0.394	0.259	0.331

Source: our calculations on RIL-COB-ASIA merged sample. 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 sectors, NUTS 2 regions, international markets, second level bargaining, multinationals, vacancy. Clustered robust standard errors (at firm level) in parentheses.

5.2 Separation rate

Table 4 enriches the picture emerging from previous tables by showing the 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[19]. The separation rate provides useful information on firm turnover.

In this case we see from Table 4 that adopting firms – those investing 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

[19] 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.

education, suggesting that most separations maybe linked to retirement. This picture is broadly confirmed by Table 5 once controlling for unobserved heterogeneity and endogeneity by applying a diff-in-diff approach: new technologies reduced the share of separations by 1.6 percentage points. The non-significant coefficient of *New Tech*year 2014* term highlights that the CTA holds, and we can consider β_3 as a causal relation.

Combining results from Tables 4 and 5, we can affirm that the adoption of I4.0 technologies positively affects the firm-level hiring rate – in particular for young workers - and reduces the firm-level separation rate. This picture is consistent with the one defined in Bratta et al. (2022) identifying a positive employment effect in Italian companies induced by corporate investments in subsidized 4.0 technologies. Their findings pointed to an increase in hirings for firms having benefitted from hyper-depreciation, not 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 headquarters is in the South.

Our results seem to complete this evidence suggesting that "I4.0 companies" are more likely to hire young workers and favour longer and stable work relationships since the separation rate is lower.

Furthermore, our results point to a non-significant effect of new 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 in Bratta et al. (2022) working on the entire population of Italian firms benefitting from a hyper-depreciation plan. In fact, the authors detect a very modest impact of new technologies on high-skilled hiring (corresponding largely to tertiary educated workers) explained by the behavior of small- and medium-sized enterprises, which are predominant in the Italian economy. Overall, our results suggest that the digital transformation had, so far, a positive effect on hiring – especially for young workers, however, the change in the demand for qualified workforce due to I4.0 technologies is not significant.

Table 4. Pooled OLS estimates. Dep var: Separation rate

	Workers over total employment	Workers <30 years old over total employment	Graduate workers over total employment
New Techs	-0.0154**	0.0007	-0.0009
	[0.007]	[0.002]	[0.004]
year 2018	0.0320***	0.0035*	0.0017
	[0.006]	[0.002]	[0.003]
year 2014	-0.0073*	0.0008	-0.0072***
	[0.004]	[0.001]	[0.002]
Firms registering vacancies	0.0222***	0.0017	0.0081***
	[0.005]	[0.002]	[0.003]
Log wage per employee	0.0161***	-0.0004	0.0024
	[0.005]	[0.002]	[0.003]
Management characteristics	Yes	Yes	Yes
Workforce chacacteristics	Yes	Yes	Yes
Firms characteristics	Yes	Yes	Yes
Constant	-0.0344	0.0078	0.0477*
	[0.061]	[0.020]	[0.028]
Obs			
R2	11251	11251	11251

Source: our calculations on RIL-COB-ASIA merged sample. 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 sectors, NUTS 2 regions, international markets, second level bargaining, multinationals, vacancy. Clustered robust standard errors (at firm level) in parentheses. Statistical significance: *** at 1%, ** at 5% and * at 10%.

Table 5. Diff-in-diff fixed effects estimates. Dep var: Separation rate

	Workers over total employment	Workers <30 years old over total employment	Graduate workers over total employment
New Techs* year 2018	-0.0152**	0.002	-0.0005
	[0.007]	[0.003]	[0.005]
New Techs*year 2014	-0.0104	-0.0021	-0.0026
	[0.008]	[0.003]	[0.004]
year 2018	0.0299***	0.0046**	0.0004
	[0.006]	[0.002]	[0.005]
year 2014	-0.0042	0.0021	-0.0072**
	[0.006]	[0.002]	[0.003
Firms registering vacancies	0.0215***	0.0006	0.0087**
	[0.005]	[0.002]	[0.004]
Log wage per employee	0.0192***	0.0023	0.0031
	[0.005]	[0.002]	[0.002]
Management characteristics	Yes	Yes	Yes
Workforce chacacteristics	Yes	Yes	Yes
Firms characteristics	Yes	Yes	Yes
Constant	-0.0397	-0.0029	0.036
	[0.058]	[0.017]	[0.028]
Obs	10703	10703	10703
R2	0.347	0.251	0.313

Source: our calculations on RIL-COB-ASIA merged sample. 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 sectors, NUTS 2 regions, international markets, second level bargaining, multinationals, vacancy. Clustered robust standard errors in parentheses.

5.3 Workplace training

In previous sections we have analyzed how and to which extent investments in new technologies can be related to job flows within firms, meaning that firms can acquire specific profiles on the labor market by activating new labor contracts or facilitating job turnover. However, firms can also create internally specific skills through workplace training designed in accordance with the firms' specific needs. 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 the introduction of digital technologies more profitable. Results in Table 6 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 7), the relationship between investment in new technologies and training is confirmed. The introduction of new technologies increases the percentage of trained workers by 3.3 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 new technologies.

Table 6. Pooled OLS estimates. Dep var: Workplace training

	Training investment	Share of trained employees	Training costs per employee
New Techs	0.0744***	0.0489***	0.4762***
	[0.015]	[0.013]	[0.085]
year 2018	0.1332***	0.1610***	0.5919***
	[0.012]	[0.010]	[0.065]
year 2014	0.1070***	0.1161***	0.5837***
	[0.010]	[0.008]	[0.053]
Firms registering vacancies	0.1075***	0.0627***	0.6817***
	[0.013]	[0.011]	[0.075]
Log wage per employee	0.0184***	0.0218***	0.1648***
	[0.007]	[0.006]	[0.042]
Management characteristics	Yes	Yes	Yes
Workforce chacacteristics	Yes	Yes	Yes
Firms characteristics	Yes	Yes	Yes
Constant	0.2459***	0.0395	0.1397
	[0.073]	[0.064]	[0.434]
Obs	11251	11251	10214
R2	0.203	0.148	0.193

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

Table 7. Diff-in-diff fixed effects estimates. Dep var: Workplace training

	Training investment	Share of trained employees	Training costs per employee
New Techs* year 2018	0.0517***	0.0333**	0.2918***
	[0.019]	[0.016]	[0.109]
New Techs*year 2014	0.0371*	0.0255	0.0999
	[0.02]	[0.017]	[0.11]
year 2018	0.1574***	0.1749***	0.7508***
	[0.014]	[0.012]	[0.076]
year 2014	0.0951***	0.1059***	0.5381***
	[0.014]	[0.011]	[0.072]
Firms registering vacancies	0.0468***	0.0281**	0.3223***
	[0.016]	[0.014	[0.093]
Log wage per employee	0.0117	0.0169*	0.1101*
	[0.009]	[0.009]	[0.06]
Other controls	Yes	Yes	Yes
Managment characteristics	Yes	Yes	Yes
Workforce chacacteristics	Yes	Yes	Yes
Firms characteristics	Yes	Yes	Yes
Constant	0.3927***	0.1151	0.9167
	[0.1]	[0.095]	[0.644]
Obs	10699	10699	9361
R2	0.396	0.359	0.408

Source: our calculations on RIL-COB-ASIA merged sample. 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 sectors, nuts 2 regions, international markets, second level bargaining, multinationals, vacancy. Clustered robust standard errors (at firm level) in parentheses. Statistical significance: *** at 1%, ** at 5% and * at 10%.

5.4 Robustness

The robustness of previous evidence is tested by running *diff-in-diff fixed effects models* of equation [1] combined with propensity score matching[20]. More in detail, we perform a logit model to estimate the observable factors – measured in 2010 – that affect the probability of adopting at least one new technology over the period 2015-2017; the propensity score matching is implemented with a nearest-neighbor method (one-to-one matching) and replacement[21]. To assess the quality of the matching, tables 3A, 4A, 5A in the Appendix report the distribution of propensity score and balance property test. They show the differences between the mean values of a large subset of the variables we used to match the treatment and control groups. Overall, the figures in these tables confirm that the two groups, although initially different, appear to be rather similar after matching.

Coefficients in Table 8A confirm results shown in Table 3, indicating that the adoption of new technologies leads to an increase in the hiring rate of about 2 percentage points. The positive effect of new technologies on hiring rates is largely confirmed, also for graduate workers. Table 9A also confirms results reported in Table 5 since a negative effect is detected on the separation rate when companies adopt digital technologies. On average and *ceteris paribus*, companies investing in Industry 4.0 technologies are more likely to experience a lower separation rate by about 1.6 percentage point. No significant effects are detected for graduate workers and young workers, probably due to the activation/expiration of temporary job contracts. Lastly, Table 10A shows the estimates on the relation between the introduction of new technologies and firm-level training. Coefficients obtained after the propensity score matching procedure are in line with the main results. Investing in new technologies positively affects both the share of trained workers and the average training cost per employee.

Overall, these results suggest that two kinds of firm level practices coexist at the workplace when new technologies are introduced. On the one hand, the recruitment of the labor force on *external labor markets* leads to higher hiring rate for young workers. On the other hand, training of employees reshapes *internal labor markets* and improves the skill set of the workforce. In both cases – hiring or training of the workforce - the adoption of new technologies does not lead to employees' separations from employer. The latter can be due to fewer firings, but also to lower recruitment rates through temporary contracts.

6. Exploring technological heterogeneity

In this section we dig deeper into the main relationship tested in paragraph 5 by focusing on specific types of new technologies. It is important to bear in mind that new digital technologies are a cluster of heterogeneous artefacts, including a multiplicity of devices and techniques (Martinelli et al., 2021). It is therefore plausible to expect that they may not have exactly the same impact on job flows and the extent to which companies engage in workplace training. In what follows we focus on three types of Industry 4.0 artefacts: cybersecurity, IoT and robotics. Instead of grouping technologies by their features as in Balsmeier and Woerter (2019), we consider each of them separately to obtain a clearer and more

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[20] To adjust for observable differences between the treated and untreated firms, the matching procedure is run on the longitudinal component of the RIL-COB-ASIA sample referred to the 2010 year, in such a way to compute the common support on the observables in the pre-treatment period.

[21] We use the command psmatch2 in Stata 15. The results obtained with other PSM procedures (i.e., *nearest neighbor matching without replacement*) do not differ significantly; they are available upon request. We also impose a common support condition where the rule is dropping treatment observations whose propensity score is higher than the maximum or less than the minimum propensity score of the controls. In our case, no treated observation is dropped according to the common support condition.

disaggregated picture of their relative role[22]. Finally, we consider the number of investments realized – a proxy for the intensity of technological upgrades - and code a continuous treatment taking discrete values from 0 to 5 according to the number of technological artefacts introduced.

6.1. Cybersecurity

Most Italian companies have invested in cybersecurity (MISE, 2018), defined as "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 investment that is crucial for operating in a more interconnected and automated environment. This technology is quite widespread across firms, including: (i) companies facing constraints in their digital transition, such as those related to their size, even if they recognize the potential of digital technology; and (ii) digitally mature companies with a clear digital strategy that frames the conditions for the integrated use of other technologies. For this second group, investment in cybersecurity is essential. Generally, as the level of digital maturity increases, so does the need for companies to protect their equipment (ISTAT, 2020). How does this group of companies behave in terms of occupational choices?

According to estimates in Table 8, the investment in cybersecurity is positively associated with the hiring rate (first column), specifically of graduate workers (third column), and negatively with the firm-level separation rate (Table 9).

Table 8. Diff-in-diff fixed effects estimates. Dep var: Hiring rate

	Workers over total employment	Workers <30 years old over total employment	Graduate 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]
Management characteristics	Yes	Yes	Yes
Workforce characteristics	Yes	Yes	Yes
Firms characteristics	Yes	Yes	Yes
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

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

[22] 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), p. 4.

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

	Workers over total employment	Workers <30 years old over total employment	Graduate 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]
Management characteristics	Yes	Yes	Yes
Workforce chacacteristics	Yes	Yes	Yes
Firms characteristics	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

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

Combining results from Tables 8 and 9, one can observe that firms investing in cybersecurity have registered a positive (net) effect on employment, as hiring rates exceed separation rates. Furthermore, compared to the baseline scenario – Tables 3 and 5 – the focus on cybersecurity sheds light on the positive impact of cybersecurity on graduate workers in the region of 0.4 percentage points. Connecting this evidence with results from previous Tables, we can argue that cybersecurity has been introduced in large companies and is more transversal across manufacturing and services.

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 use of sensors, monitoring and remote-control systems via the Internet and, of course, an adequate digital infrastructure given by investments in optical fiber, mobile connectivity, management software, and cybersecurity. From this point of view, firms adopting IoT solutions depict higher digital maturity, since they foresee an integrated use of I4.0 technologies.

These companies investing in IoT have registered a significant positive increase of newly hired graduate workers by about 0.8 percentage points (0.4 percentage points more than cybersecurity), while separations do not change. Overall, IoT seems to increase net employment of highly qualified workers probably due to the specific competencies required to manage these systems.

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

	Workers over total employment	Workers <30 years old over total employment	Graduate 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]
Management characteristics	Yes	Yes	Yes
Workforce chacacteristics	Yes	Yes	Yes
Firms characteristics	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

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

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

	Workers over total employment	Workers <30 years old over total employment	Graduate 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]
Management characteristics	Yes	Yes	Yes
Workforce chacacteristics	Yes	Yes	Yes
Firms characteristics	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

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

6.3. Robotics

Finally, we focus on robotics. The RIL survey covers both industrial robots – i.e. new-generation and service robots designed to work alongside humans by specializing in particular tasks[23] - and collaborative robots – i.e. robots that have a certain degree of autonomy and are able to operate in a complex and dynamic environment requiring interaction with humans, objects, or other intelligent devices. Investments in robots are usually associated with 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 reported in Table 12 - have registered a significant increase in the hiring rate of tertiary graduate workers of about 0.4 percentage points, whereas non-significant effects characterize the separation rate (Table 13).

Combining results from Tables 12 and 13 it can be said that investments in robotics are significantly associated with positive job flows, in particular for graduate workers. This is not surprising and is in line with findings in other firm-level studies building employer-employees linked databases and 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 manufacturing establishments. Similarly, Domini et al. (2022) 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. Adachi et al. (2023) exploit unique information on the unit cost of robots to estimate the effects of robotization on Japanese firms, finding that a fall in the price of technology leads to increases in both productivity and employment[24]. Overall, our novel evidence on the Italian context discards a strong *labor-displacing* effect of robots on jobs, and shows that robots are associated with job creation for qualified workers.

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[23] 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.).

[24] The only country for which evidence is somewhat divergent is the Netherlands. In their analysis of the adoption of robotic technologies, Acemoglu et al. (2023) report negative wage and employment effects for workers directly affected by the new technology (i.e. low-skilled workers in routine occupations), but positive effects for the other groups (i.e. highly-skilled workers). Bessen et al. (2023) also use Dutch microdata, and by proxying the degree of automation with firms' automation expenditures, find that technology adopters see an increase in the probability of incumbent workers' separation, and falls in both wages and days worked.

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

	Workers over total employment	Workers <30 years old over total employment	Graduate 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]
Management characteristics	Yes	Yes	Yes
Workforce chacacteristics	Yes	Yes	Yes
Firms characteristics	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

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

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

	Workers over total employment	Workers <30 years old over total employment	Graduate 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]
Management characteristics	Yes	Yes	Yes
Workforce chacacteristics	Yes	Yes	Yes
Firms characteristics	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

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

6.4 Number of new technologies

Lastly, we inspect how and to which extent the intensity of technological upgrades proxied by the number of technologies introduced in the 2015-2017 period affects employment decisions. Tables 14 and 15 clearly highlight that an increasing number of investments in new technologies positively affects the company hiring rate mostly for young workers, whereas it is not significant for graduate workers. Furthermore, multiple adoption decisions are not significantly linked to separation rates.

Table 14. Diff in Diff FE estimates. Dep var: share of hired.

	Workers over total employment	Workers <30 years old over total employment	Graduate workers over total employment
N of New Techs* year 2018	0.0079**	0.0020*	0.0029
	[0.004]	[0.001]	[0.002]
N of New Techs*year 2014	0.0042	0.0008	0.0019
	[0.004]	[0.001]	[0.002]
year 2018	-0.0241***	-0.002	-0.0063
	[0.006]	[0.002]	[0.004]
year 2014	-0.0433***	-0.0029*	-0.0144***
	[0.006]	[0.002]	[0.004]
vacancy	0.0280***	0.0006	0.0139***
	[0.006]	[0.002]	[0.004]
lwage pc	-0.0215***	-0.0035***	-0.0070***
	[0.004]	[0.001]	[0.002]
Management characteristics	Yes	Yes	Yes
Workforce chacacteristics	Yes	Yes	Yes
Firms characteristics	Yes	Yes	Yes
Constant	0.3803***	0.0492***	0.1348***
	[0.048]	[0.015]	[0.026]
Obs	10707	10707	10707
R2	0.393	0.259	0.33

Source: our calculations on RIL-COB-ASIA merged sample. 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 sectors, NUTS 2 regions, international markets, second level bargaining, multinationals, vacancy. Clustered robust standard errors (at firm level) in parentheses. Statistical significance: *** at 1%, ** at 5% and * at 10%

Table 15. Diff in Diff FE estimates. Dep var: share of separated.

	Workers over total employment	Workers <30 years old over total employment	Graduate workers over total employment
N of New Techs* year 2018	-0.0064*	0.0016	-0.0001
	[0.004]	[0.001]	[0.002]
N of New Techs*year 2014	-0.0067*	-0.0003	-0.0017
	[0.004]	[0.001]	[0.002]
year 2018	0.0272***	0.0048***	-0.0002
	[0.007]	[0.002]	[0.004]
year 2014	-0.0047	0.0017	-0.0076**
	[0.006]	[0.002]	[0.003]
vacancy	0.0215***	0.0007	0.0086***
	[0.006]	[0.002]	[0.003]
lwage pc	0.0192***	0.0023	0.0032
	[0.004]	[0.002]	[0.002]
Management characteristics	Yes	Yes	Yes
Workforce chacacteristics	Yes	Yes	Yes
Firms characteristics	Yes	Yes	Yes
Constant	-0.0396	-0.0028	0.0359
	[0.049]	[0.015]	[0.024]
Obs	10707	10707	10707
R2	0.347	0.251	0.313

Source: our calculations on RIL-COB-ASIA merged sample. 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 sectors, nuts 2 regions, international markets, second level bargaining, multinationals, vacancy. Clustered robust standard errors (at firm level) in parentheses. Statistical significance: *** at 1%, ** at 5% and * at 10%

7. Conclusions

In recent years the academic debate has focused on the transformative potential of new technologies, i.e. those technologies that enable the digitization, automation and interconnection of production processes and service provision, blurring the boundaries between manufacturing and services, and reconfiguring firm activities internally (through a redesign of in-house operations) and externally (through a redesign of the value chain). 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 difficult to draw precise lines of demarcation between them. Even though previous studies have produced invaluable insights on the disruptive and potentially general-purpose nature of the current technological transformation, much more work is required to understand ongoing shifts in the organization of work. Studying this transformation entails the adoption of multiple levels of analysis, from the fine-grained micro level of the workplace up to the entire – sometimes global – value chain. Transformations that change the boundaries of the firm and involve modularization and new reconfigurations of skills and tasks across the manufacturing-service divide. There are extremely important issues at stake, and companies, workers and policy makers have an interest in the social and economic impact of new digital technologies. The generation of empirical evidence that can inform stakeholders' behaviors has often been hampered by the lack of suitable microdata. One important source of information are qualitative case studies that can shed new light on stakeholders' decisions and organizational dynamics. Recent qualitative evidence on Italy based on semi-structured interviews with managers, HR personnel, and trade union representatives, indicates that technology-adopting companies (including metalworking firms located in Northern Italy) have increased production and productivity without the need for new hires (Cirillo et al., 2021). In many cases, automation involved moving workers who previously handled the automated tasks on to other departments or to other duties. This has implied a transition from operating a single machine to managing several, thus increasing workers' versatility and role-flexibility. Important impacts on employment are emerging in the internal logistics of manufacturing firms: for example, supply lines are now automatically managed by electronic Kanban systems. In this respect, interviews with managers and HR representatives supported the view that the adoption of digital technologies has led to a significant reorganization of labor processes, revealing a strong correlation between the introduction of new digital technologies and certain forms of lean production. Moreover, the expectation – at least for the moment – gathered from the workplace is that it will not be possible to fully replace human labor due to the need for some degree of creativity and flexibility in the production process, which is even more critical in the case of services (Cirillo et al., 2022).

This complementary evidence is very useful to qualify and contextualize the quantitative and systematic empirical analyses of the Italian economy we have performed in this study. We have focused on the labor market effects of the adoption of new digital technologies by leveraging unique and original dataset produced through the matching of different sources of official statistics. We have used firm-level data on digital technology adoption from the National Institute for the Analysis of Public Policies (INAPP), complementary firm-level information drawn from the archive of the National Institute of Statistics (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 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.

The combined data have given us the opportunity to study the effects of new technologies on labor flows in the Italian economy. More specifically, we examined firm internal and external labor markets, and explored how adopters of new digital technologies behave in terms of hirings, separations and workplace training. This allows us to have a clear picture not only of aggregate changes in employment, but also – and this is our contribution relative to the prior art – of the gross flows, with a detailed analysis of the dynamics underlying net job creation figures.

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

We further explored technological 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, *labor-displacing* effects of new technologies on jobs. Conversely, they appear to be associated to job creation, at least for young workers. More research is needed to explore which kind of workers are more likely to be affected by the digital transformation of companies, since workers can be unevenly affected by these complex processes.

While we cannot over-generalize the evidence produced from the analysis of one single economy, it is unlikely that these patterns are specific only to Italian firms because the nature of new digital technologies does not vary so much across regions. However, it will be important to extend this research programme to other contexts in order to verify empirically the external validity of our study. It may be interesting, for example, to explore the moderating role of different institutional set-ups, including cross-country heterogeneity of labor market regulation.

We believe that there are multiple avenues for further research building on the findings of our work. First of all, there is no doubt that more qualitative studies – and in particular firm and workers' case studies – could shed light on aspects of firm organization and decision-making processes that cannot be captured by official statistics, even though qualitative evidence may not have the advantages of statistical representativeness and may suffer from reporting biases. Second, it will be extremely important to investigate long-term effects of technology adoption strategies, because it is possible that some decisions may have delayed consequences, or that the effects of new technologies will be heavily mediated through learning by-doing, which can only emerge more slowly over time relative to other forms of knowledge acquisition. Third, it will be crucial to acquire a more complete picture of earnings, and identify how different groups of workers interact with different technologies, as well as with specific bundles of new digital technologies, and to assess how productivity gains will be redistributed at the firm level. This is crucial not only to assess the dynamics of firm competitiveness, but also to monitor the possible deepening of income inequalities between groups of workers, by skills and by tasks.

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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

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

Table 2A. Workplace training: Longitudinal sample

	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

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

Table 3A. Quality of the matching procedure. Balance property test. Dep var: share of hired.

	Mean		%bias	%|reduction| bias	t-test	
	Treated	Control			t	p>t
	Management					
Tertiary education	0.35	0.36	-2.3	91.6	-0.60	0.548
Upper secondary ed.	0.48	0.48	1.4	80.7	0.40	0.693
Females	0.11	0.12	-4.8	65.3	-1.41	0.159
Family ownership	0.79	0.78	3.8	87.2	0.92	0.357
External management	0.07	0.07	0.9	95.4	0.21	0.836
	Workforce composition (in shares)					
Tertiary education	0.12	0.12	-1.8	91.7	-0.48	0.635
Upper secondary	0.47	0.47	-0.7	94.0	-0.21	0.833
Females	0.37	0.38	-2.6	-735.8	-0.76	0.450
Age>50	0.17	0.17	1.4	64.8	0.45	0.654
34< Age<49	0.51	0.51	0.3	96.7	0.08	0.935
Executives	0.05	0.05	1.9	87.3	0.54	0.591
White collars	0.42	0.43	-5.2	78.4	-1.46	0.144
Temporary contracts	0.10	0.09	5.0	-20.4	1.56	0.118
immigrants	0.04	0.04	1.9	79.0	0.63	0.529
	Firms caracteristics					
Firms registering vacancies	0.17	0.16	2.8	90.0	0.68	0.494
Log wage per employee	10.02	10.03	-2.1	92.5	-0.62	0.538
foreign markets	0.41	0.38	5.3	87.4	1.36	0.174
Multinational	0.04	0.04	-0.8	94.3	-0.19	0.847
II level bargaining	0.21	0.22	-2.9	91.5	-0.70	0.484
9<n of employee<50	0.42	0.42	-0.8	92.5	-0.22	0.827
49<n of employee<250	0.20	0.21	-2.6	92.6	-0.62	0.536
n of employee>249	0.08	0.07	5.6	81.0	1.27	0.203

Source: longitudinal sample RIL-COB, reference years 2010. Note: calculations performed with the *psmatch2* module in Stata17. Full results including covariates for industries-, 110 provinces, and the remainder of controls are available upon request. These omitted covariates also present a significant bias reduction.

Table 4A. Quality of the matching procedure. Balance property test. Dep var: share of separated.

	Mean		%bias	%|reduction| bias	t-test	
	Treated	Control			t	p>t
	Management					
Tertiary education	0.35	0.36	-2.3	91.6	-0.60	0.548
Upper secondary ed.	0.48	0.48	1.4	80.7	0.40	0.693
Females	0.11	0.12	-4.8	65.3	-1.41	0.159
Family ownership	0.79	0.78	3.8	87.2	0.92	0.357
External management	0.07	0.07	0.9	95.4	0.21	0.836
	Workforce composition (in shares)					
Tertiary education	0.12	0.12	-1.8	91.7	-0.48	0.635
Upper secondary	0.47	0.47	-0.7	94.0	-0.21	0.833
Females	0.37	0.38	-2.6	-735.8	-0.76	0.45
Age>50	0.17	0.17	1.4	64.8	0.45	0.654
34< Age<49	0.51	0.51	0.3	96.7	0.08	0.935
Executives	0.05	0.05	1.9	87.3	0.54	0.591
White collars	0.42	0.43	-5.2	78.4	-1.46	0.144
Temporary contracts	0.10	0.09	5.0	-20.4	1.56	0.118
immigrants	0.04	0.04	1.9	79.0	0.63	0.529
	Firms caracteristics					
Firms registering vacancies	0.17	0.16	2.8	90.0	0.68	0.494
Log wage per employee	10.02	10.03	-2.1	92.5	-0.62	0.538
foreign markets	0.41	0.38	5.3	87.4	1.36	0.174
Multinational	0.04	0.04	-0.8	94.3	-0.19	0.847
II level bargaining	0.21	0.22	-2.9	91.5	-0.70	0.484
9<n of employee<50	0.42	0.42	-0.8	92.5	-0.22	0.827
49<n of employee<250	0.20	0.21	-2.6	92.6	-0.62	0.536
n of employee>249	0.08	0.07	5.6	81.0	1.27	0.203

Source: longitudinal sample RIL-COB, reference years 2010. Note: calculations performed with the psmatch2 module in Stata17. Full results including covariates for industries-, 110 provinces, and the remainder of controls are available upon request. These omitted covariates also present a significant bias reduction

Table 5A. Quality of the matching procedure. Balance property test. Dep var: training costs

	Mean		%bias	%|reduction| bias	t-test	
	Treated	Control			t	p>t
	Management					
Tertiary education	0.34	0.37	-6.8	74.2	-1.71	0.088
Upper secondary ed.	0.49	0.48	3.0	47.6	0.82	0.413
Females	0.10	0.10	0.6	95.5	0.18	0.855
Family ownership	0.80	0.81	-3.7	87.3	-0.89	0.372
External management	0.07	0.07	2.5	86.7	0.59	0.558
	Workforce composition (in shares)					
Tertiary education	0.11	0.11	-0.6	97.0	-0.16	0.870
Upper secondary	0.47	0.49	-7.4	41.4	-2.1	0.035
Females	0.37	0.37	2.8	-232.5	0.79	0.430
Age>50	0.17	0.18	-2.3	50.6	-0.7	0.483
34< Age<49	0.51	0.51	-0.8	89.1	-0.24	0.81
Executives	0.05	0.05	-4.4	68.9	-1.18	0.236
White collars	0.41	0.43	-4.4	81.8	-1.18	0.238
Temporary contracts	0.10	0.09	3.9	-35.9	1.18	0.238
immigrants	0.04	0.04	0.4	95.4	0.12	0.903
	Firms caracteristics					
Firms registering vacancies	0.16	0.15	2.4	91.5	0.56	0.574
Log wage per employee	10.01	10.03	-3	89.3	-0.82	0.412
foreign markets	0.40	0.42	-3.5	91.5	-0.87	0.385
Multinational	0.04	0.04	-4.4	71.1	-0.95	0.343
II level bargaining	0.20	0.19	3.2	90.7	0.75	0.456
9<n of employee<50	0.42	0.40	4.5	58.2	1.21	0.227
49<n of employee<250	0.20	0.21	-2.8	92.0	-0.64	0.521
n of employee>249	0.08	0.07	4.8	83.3	1.06	0.288

Source: longitudinal sample RIL-COB, reference years 2010. Note: calculations performed with the psmatch2 module in Stata17. Full results including covariates for industries-, 110 provinces, and the remainder of controls are available upon request. These omitted covariates also present a significant bias reduction.

Table 6A. Variables definition and description.

	Outcome variabiles
share of hired (by subgroups)	Share of hirings over total employment.
share of separated (by subgroups)	Share of separations over total employment
training investment	Dummy variable that equals to 1 if firms invest in workplace training, 0 otherwise
share of trained	Share of employees that received workplace training over firms' total employemnt
training costs per empl	(log of) the amount in euros of training costs per employees (+1) The amount of training costs is deflated relying on sectoral (2-digit NACE) deflators of production prices. The total number of employees is calculated on RIL data.
	Management and corporate governance
education	Three dummy variables that equals to 1 whether the educational level of the employers/managers who run the firm is, respectively: i) tertiary; ii) upper secondary iii) lower secondary or no education (0 otherwise)
female	Dummy variable that equals to 1 if the manager/employer who run the firm is female, 0 otherwise
family owner	Dummy variable that equals to 1 if the ownership of the firm is held by a family, 0 otherwise
external management	Dummy variable that equals to 1 if firm is run by an external manager which has been recruited on the labor market, i.e outside dynastic ties of firms ownership, 0 otherwise
	Workforce characteristics
educational composition	Three variables indicating the share of employees (on the firms' total number of employees) with: i- tertiary education; ii- upper secondary education; iii- lower secondary, primary or no education
age composition	Three variables indicating the share of employees (on the firms' total number of employees) with: i- less than 35 years old; ii- between 34 and 50 years old; iii- more than 49 years old
professional composition	Three variables indicating the share of employees (on the firms' total number of employees) who are : i- executives; ii- white collars; iii- blue collars
sh temporary	share of employees with fixed term contract (on the firms total number of employees)
share immigrants	share of extra EU employees (on the firms total number of employees)
sh female	share of female employees (on the firms' total number of employees)
	Firms' characteristics
size	4 dummy variables for different size classes of the total number of employees: i) n of employee<10; ii) 9< n. empl.<50; iii) 49< n. empl<250; iv) n. empl>249
Firms registering vacancies	dummy variable that equals to 1 if firms open a job vacancy (i.e is searching for workers) in the current years, 0 otherwise
foreign trade	dummy variable that equals to 1 if firm operates (selling or buying products/services) on international trade markets, 0 otherwise
multinational	dummy variable that equals to 1 if firm is a mutinational , 0 otherwise
average wages	(log of) the average wages per employee. The amount of labor cost is derived from RIL survey and it is deflated relying on sectoral (2-digit NACE) deflators of production prices.
II level bargaining	dummy variable that equals to 1 if the firm signs a II level agreement (over the CCNL), 0 otherwise
pension reform	dummy variable that equals to 1 if the firm was forced to give up previously planned hirings because of the Law 201/2011 (the so-called 'Fornero pension reform'), 0 otherwise. The "pension reform" variable is always zero before the Law 214/2011 was introduced, i.e in the sampled year 2010.
geographical localization	110 dummies variables for province localization of firms

sectors of activities	14 dummies variables derived from NACE_2 digit classification: 1) Electricity, Gas water distribution; 2) Food, beverage and tobacco; 3) textile and wearing apparel; 4)chemistry, 5) metallurgy and machinery; 6) other manufacturing; 7) Construction; 8) retail and wholesale; 9) tourism, hotels and restaurants; 10) transportation; 11) insurance and financial intermediation, 12) information and communication services; 13) other business services; 14) healthcare, educational and other social and personal services. The level of aggregation is consistent with that used in the RIL sample stratification.

Source: RIL-COB-ASIA data.

Table 7A. 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 edu	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
Share of non-EU workers	0.016	0.125	0.017	0.130	0.034	0.182
			Firms' characteristics			
Firms registering vacancies	0.064	0.245	0.056	0.230	0.106	0.308
Log average wage	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
Benefitting from IRAP discount	0	0	0.023	0.151	0.023	0.150
Firm size: less than 10 employees	0.797	0.403	0.794	0.404	0.762	0.426
Firm size: 9<employees<50	0.176	0.381	0.185	0.389	0.214	0.410
Firm size: 49<employees<250	0.024	0.152	0.017	0.131	0.020	0.140
Firm size: more than 249 employees	0.004	0.061	0.003	0.057	0.004	0.064
North West	0.307	0.461	0.385	0.487	0.378	0.485
North East	0.305	0.460	0.288	0.453	0.271	0.445
Centre	0.215	0.411	0.184	0.387	0.181	0.385
South	0.173	0.378	0.143	0.350	0.170	0.375
N of Observations		3.973		3.276		4.002

Source: our calculations on longitudinal component of RIL-COB-ASIA merged sample. Note: sampling weights applied. *Average share over total employees. In the table one can notice an increasing share of tertiary educated and female managers/owners, mirroring a slightly higher percentage of tertiary educated workers. Between 2014 and 2018 the percentage of workers over 50 years old increased by about 2 percentage points, probably as a consequence of the monetary incentives provided by the Italian Budgetary Law 2015 for firms hiring workers under a new contract type introduced by the 2016 Labor Reform ("Jobs Act"). Between 2014 and 2018, the share of firms registering vacancies slightly increased, whereas all other firm variables remained fairly stable.

Table 8A. Diff-in-diff Fixed effects estimates with propensity score matching. Dep. var: Hiring rate

	Workers over total employment	Share of graduate workers	Share workers aged<30
New Techs* year 2018	0.018**	0.004*	0.008*
	[0.008]	[0.002]	[0.005]
New Techs*year 2014	0.013	0.002	0.008
	[0.008]	[0.003]	[0.005]
year 2018	-0.027***	-0.002	-0.008*
	[0.007]	[0.002]	[0.005]
year 2014	-0.046***	-0.003*	-0.016***
	[0.006]	[0.002]	[0.004]
Managment characteristics	Yes	Yes	Yes
Workforce chacacteristics	Yes	Yes	Yes
Firms' characteristics	Yes	Yes	Yes
Constant	0.379***	0.049***	0.134***
	[0.048]	[0.015]	[0.026]
Obs	10707	10707	10707
R2	0.394	0.259	0.331

Source: our calculations on RIL-COB-ASIA merged sample. 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 sectors, NUTS 2 regions, international markets, second level bargaining, multinationals, vacancy. Clustered robust standard errors (at firm level) in parentheses. Statistical significance: *** at 1%, ** at 5% and * at 10%

Table 9A. Diff-in-diff Fixed effects estimates with propensity score matching. Dep. Var: Separation rate.

	Workers over total employment	Share of graduateworkers	Share workers aged<30
New Techs* year 2018	-0.016*	0.002	-0.001
	[0.008]	[0.002]	[0.005]
New Techs *year 2014	-0.011	-0.002	-0.003
	[0.008]	[0.002]	[0.004]
year 2018	0.030***	0.005***	0.000
	[0.007]	[0.002]	[0.004]
year 2014	-0.004	0.002	-0.007**
	[0.006]	[0.002]	[0.004]
Managment characteristics	Yes	Yes	Yes
Workforce chacacteristics	Yes	Yes	Yes
Firms' characteristics	Yes	Yes	Yes
constant	-0.04	-0.003	0.036
	[0.049]	[0.015]	[0.024]
Obs	10707	10707	10707
R2	0.347	0.251	0.313

Source: our calculations on RIL-COB-ASIA merged sample. 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 sectors, NUTS 2 regions, international markets, second level bargaining, multinationals, vacancy. Clustered robust standard errors (at firm level) in parentheses. Statistical significance: *** at 1%, ** at 5% and * at 10%.

Table 10A. Diff-in-diff Fixed effects estimates with propensity score matching. Dep. Var.: workplace training

	Training investment	Share of trained workers	Training costs per employee
New Techs* year 2018	0.052***	0.033**	0.289***
	[0.019]	[0.016]	[0.109]
New Techs*year 2014	0.037*	0.026	0.096
	[0.020]	[0.017]	[0.110]
year 2018	0.157***	0.175***	0.752***
	[0.014]	[0.012]	[0.076]
year 2014	0.095***	0.106***	0.540***
	[0.014]	[0.011]	[0.073]
Managment characteristics	Yes	Yes	Yes
Workforce chacacteristics	Yes	Yes	Yes
Firms' characteristics	Yes	Yes	Yes
Constant	0.393***	0.115	0.915
	[0.100]	[0.095]	[0.644]
Obs	10699	10699	9359
R2	0.396	0.359	0.408

Source: our calculations on RIL-COB-ASIA merged sample. 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 sectors, nuts 2 regions, international markets, second level bargaining, multinationals, vacancy. Clustered robust standard errors (at firm level) in parentheses. Statistical significance: *** at 1%, ** at 5% and * at 10%

Figure 1A. Common trend hiring rate.

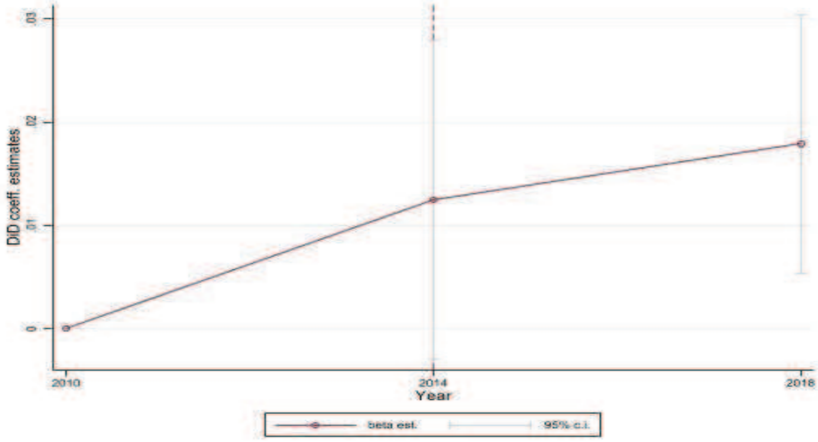

Figure 2A. Common trend separation rate.

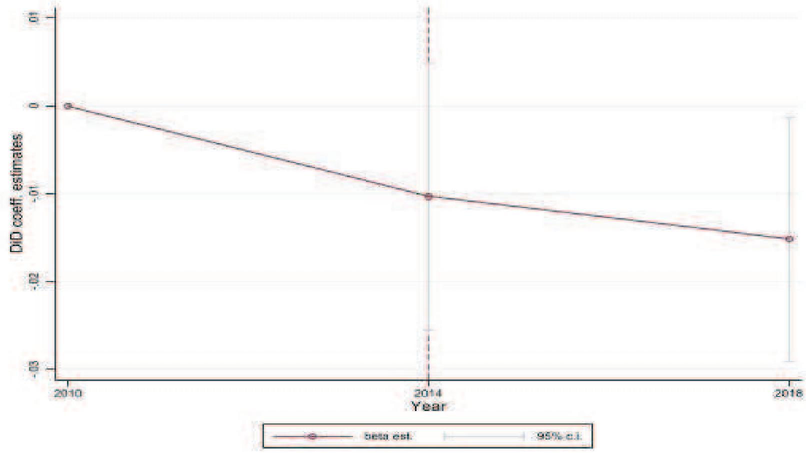

Figure 3A. Common trend for share workers trained.

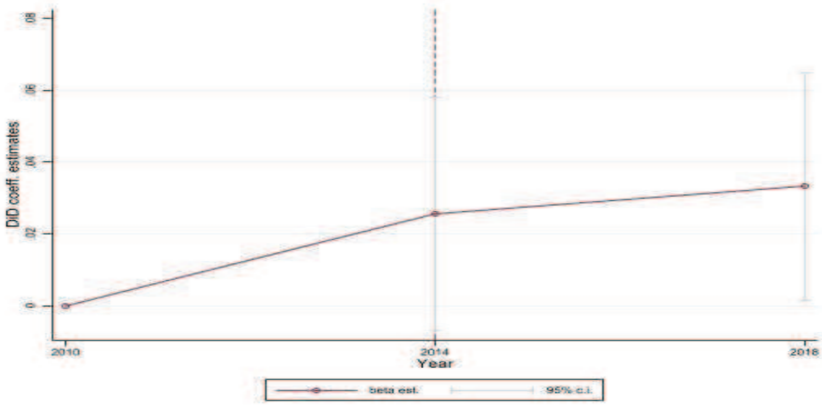

Figure 4A. Common trend for amount of training investments.

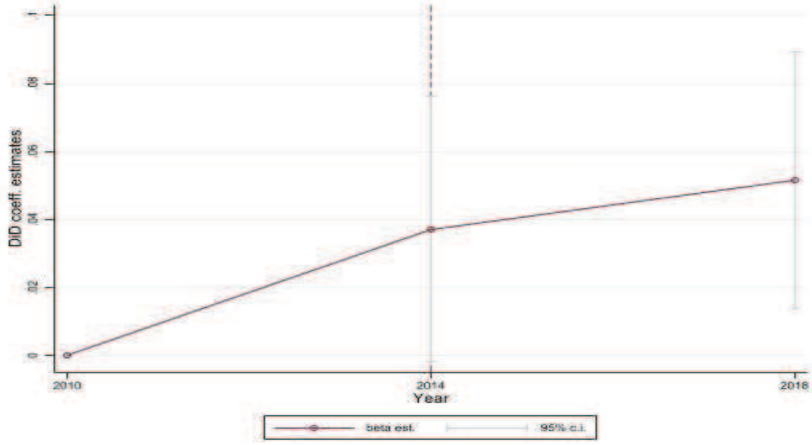

Figure 5A. Common trend for cost of training per employee.