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Abstract

This study examines the causal influence of digital technologies, specifically operational (ODT) and information digital technologies (IDT), on firms’ employment structure using Italian firm-level data. It employs a unique empirical approach, constructing instrumental variables based on predetermined employment composition and global technological progress, proxied by patents. Findings indicate that IDT investment positively affects employment, favoring a skilled, IT-competent workforce, as supported by firms’ training and recruitment plans. Conversely, ODT investment does not significantly alter total employment but skews the workforce towards temporary contracts. The study contributes methodologically by distinguishing between ODT and IDT and highlighting nuanced employment dynamics within firms.

JEL-Codes: D220, J230, J240, M510, M530, O330.

Keywords: digital technologies, labour demand, training, firms.

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1 Introduction

Robotics and new digital technologies, such as artificial intelligence, big data, cloud computing and the Internet of Things, have fundamentally changed the industrial landscape and the world of work, by extending the impact of digitalisation beyond the narrow technological domain. The transformative impact of these innovations has led to the widespread adoption of the suggestive expressions 'Fourth Industrial Revolution' and Industry 4.0 (4IR, hereafter) to capture a more composite phenomenon associated with the greater connection of actors, objects, artefacts and systems in real time in the firm-level processes (Cefis et al., 2023; Horvath and Szabo, 2019; Schwab, 2017).

The economic literature has already provided convincing evidence of a growing demand for digital skills in the economy (OECD, 2022), most likely due to the diffusion of these innovations. However, there is more limited (and still conflicting) evidence on what happens to the level and composition of employment within firms that adopt digital technologies (Aghion et al., 2020; Acemoglu et al., 2023a; Bessen et al., 2023; Bonfiglioli et al., 2023; Domini et al., 2021; Koch et al., 2021). While studies looking at the variation in the net employment effects of technological progress across regions and countries have allowed policymakers to assess the macroeconomic relevance of the phenomenon,[1] microeconomic studies at the firm level are needed to disentangle more granular phenomena and to identify specific causal mechanisms linking technology adoption and employment outcomes.

In this paper, we use a comprehensive and representative survey of firms conducted by INAPP in Italy in 2015 and 2018, namely *Rilevazione Imprese e Lavoro* (RIL), and investigate the impact of firms' investments in 4IR digital technologies in the period 2015-2017 on their employment levels, the actual and prospective changes in the composition of labour in terms of types of contracts and broad categories of occupations, workers' training and other aspects of human resource management between 2014 and 2017. We

[1]See, for example, Acemoglu and Restrepo (2020); Adachi et al. (2024); Anton et al. (2022); Autor and Dorn (2013); Blanas et al. (2020); Caselli et al. (2021); Dauth et al. (2021); de Vries et al. (2020); Dottori (2021); Graetz and Michaels (2018); Klenert et al. (2020); Mann and Püttmann (2021); Prytkova et al. (2024).

distinguish but simultaneously analyse operational digital technologies (ODT), which relate to the physical production process, and information digital technologies (IDT), which relate to data production, collection, exploitation and protection (Bronzini et al., 2023). In particular, RIL includes information on investment in robotics, which is part of ODT, and investment in big data, Internet of Things, virtual reality, and cybersecurity, which are part of IDT. We include both ODT and IDT in our empirical analysis because their close interdependence risks confounding the analyses that treat them one at a time. In addition, given that the effects of new technologies are determined by workers' occupations and the characteristics of the innovations (Acemoglu and Restrepo, 2019), we distinguish between operational and information digital technologies as we expect them to affect workers differently.

We develop an empirical strategy to identify the causal effects of investment in both types of digital technology through a two-stage least squares (2SLS) estimation with exogenous instrumental variables (IVs) that affect firms' employment only through their impact on the probability of investing in ODT and IDT. Our instruments are based on the exogenous technological progress in ODT and IDT in each industry at the global level, proxied by the lagged change in the worldwide stock of patents in ODT and IDT at the 4-digit industry level. We construct the number of patents by technology and industry in three steps. First, we use the classification codes assigned to each patent (Ménière et al., 2020) and select those related to different digital technologies. Then, we refine the selection via a textual analysis based on the presence of technology-specific keywords in the titles and abstracts of the patents (similar procedures have been used by Benassi et al., 2021; Ménière et al., 2020; Martinelli et al., 2021). Finally, we exploit a probabilistic match between patent classification codes and their industry of use, as proposed by Goldschlag et al. (2020), to assign each patent to a given industry. The exogenous technological progress at the industry level represents the extent of technological opportunities available to firms. We also include in our set of IVs the interactions of the changes in patents in ODT and IDT and the predetermined composition of employment at the firm level, namely the shares of white- and blue-collar workers in the firm.

These interactions allow us to capture the differential ability of firms within industries to invest in new technological opportunities, a level of variation that industry-level instruments would not be able to capture on their own. This approach to predicting firms' investments in ODT and IDT in the first stage of estimation follows the intuition offered by Graetz and Michaels (2018), Dixon et al. (2021) and Bonfiglioli et al. (2023) about the link between the composition of firms' employment before investing in automation and the probability of automating. Equipped with valid exogenous instruments for each technology, this methodology allows us to identify the causal effects of ODT and IDT on firm employment separately.

Our empirical analysis provides evidence on how the introduction of ODT and IDT affects overall employment levels, the composition of firms' workforce in terms of the types of contracts, training practices and prospective recruitment plans. To preview our results, we find that the overall impact of robotics investment on firm employment is not statistically significant, but the composition of temporary (fixed-term) and permanent contracts changes in favour of the former after investment in ODT; ODT-investing firms also show a greater reliance on employment agencies. On the other hand, investment in IDT has a positive and significant effect on firm employment. It also leads to a relative increase in apprenticeships, a decrease in temporary contracts and a lower reliance on agency workers. The results are robust to several sensitivity checks, in particular different sets of covariates, including controls that capture other investments made by the firm and industry-level investment trends, a specification based on machine learning techniques (i.e., the least absolute shrinkage and selection operator, LASSO) to select the covariates from a large set, sample selection, further lagged shares of blue- and white-collar workers to construct our interacted instruments, different samples of firms and industries, and a falsification test based on lagged employment changes as the dependent variable.

We also analyse the effects of 4IR technologies on training as part of firms' management of human resources. Investment in IDT is found to have a positive effect on the likelihood of IT-related training. Firms investing in ODT, on the other hand, tend to promote training programmes for task-specific technical aspects of the jobs.

In addition, thanks to the richness of RIL, we examine the recruitment intentions of firms in the years following the investment in new technologies. These forward-looking questions allow us to study the impact of technology investment on the future worker profiles desired by firms. We find that firms investing in IDT look for qualified workers involved in the construction, repair or maintenance of artefacts, objects and machines, while they are less likely to look for workers involved in the management and control of industrial machines and automated or robotic systems, as well as unqualified workers. This is consistent with the idea that IDT allow firms to revise the way in which they control and manage the machines involved in the production process, and that these technologies require more human effort associated with construction, repair or maintenance. Firms that invest in ODT, on the other hand, are less likely to hire new workers to perform simple and repetitive activities that do not require a particular qualification: this is consistent with the idea that robots displace humans in routine activities. Thus, our results show the coexistence of both displacement and reinstatement effects (Acemoglu and Restrepo, 2019) within investing firms.

Overall, our paper confirms that the key to understanding the impact of technological progress on employment is its non-neutral nature (Zhang, 2019). In particular, our results suggest that the evolution of firm employment in innovative firms is skewed in favour of more skilled and IT-competent workers. This is consistent with (Feng and Graetz, 2020)'s findings that occupations with more engineering complexity and training requirements grow faster after the introduction of new digital technologies. This may also explain why firms investing in IDT are more likely to use apprenticeship contracts: in Italy, these contracts are associated with intensive training programmes leading to permanent jobs in the future.[2]

Italy is an interesting case study on the impact of new digital technologies on firms' employment for several reasons. First, in 2016/2017, the Italian government launched an ambitious "National Enterprise Plan 4.0" aimed at reducing financial constraints on investment and accelerating the diffusion of 4IR technologies. All companies

[2]The vast majority of the firms surveyed that use apprenticeship contracts say that they choose this contractual arrangement with a view to hiring the apprentices.

were eligible for the scheme and automatically received the incentive if they invested. As pointed out by Bratta et al. (2023) and Cirillo et al. (2023), this feature of the plan and the fact that the RIL 2018 survey followed its implementation reduce the risk of self-selection factors related to firms' financial conditions, and this facilitates the design of the study.[3] Second, Italy is the second European country after Germany for robot adoption (Caselli et al., 2021; Dottori, 2021), and this makes investment in robotics relatively more diffuse than elsewhere. Third, the duality of the Italian labour market is a well-known stylised fact, as it divides the labour force into different groups defined in terms of the duration of contracts (temporary versus permanent) and the likelihood of receiving on-the-job training (Garibaldi and Taddei, 2013).

We contribute to the literature along three main dimensions, covering both the empirical methods used to identify casual effects and the findings.

The first major contribution of this paper is methodological. We introduce a novel IV approach, based on changes in the worldwide stocks of patents in ODT and IDT at the industry level and their interactions with the predetermined composition of employment at the firm level, to study the causal impact of the endogenous adoption of digital technologies on firms' employment decisions. Previous works in the literature usually study the impact of investment in digital technologies on firms' employment using matching (see, for instance, Dixon et al., 2021; Domini et al., 2021) and difference-in-differences (DiD) event studies (such as Bisio et al., 2023) or a combination of the two methods (Bessen et al., 2023; Bratta et al., 2023; Cirillo et al., 2023; Koch et al., 2021; Nucci et al., 2023). In particular, matching methods address the possible selection bias due to the endogeneity of the investment decision by matching investing and non-investing firms on the basis of observable characteristics. The validity of this method depends on the quality of the matching process, which, in turn, depends on the observable covariates used to select the control group. Even assuming that the selection bias can be completely eliminated by matching on the observables, traditional omitted variable problems remain.

[3] On the other hand, the lack of eligibility criteria in the policy makes it difficult to exploit the policy as an instrumental variable to identify the causal impact of technological investment on firms' employment (Bratta et al., 2023).

DiD studies exploit changes in the outcome variable before and after the investment (treatment) and compare these changes between treated and control firms. This method relies on the so-called common trend assumption, whereby the outcome variable and the covariates evolve in parallel in the treated and control firms in the absence of treatment. However, if some time-varying unobservable firm characteristics affect or are correlated with the selection into treatment, these methods may fail to provide causal estimates of the impact of the treatment. The IV-2SLS strategy that we adopt instead allows us to address all of these problems at once, provided that the instrumental variables used in the first stage are valid and informative. In particular, the use of an IV approach requires the adoption of a local average treatment effects (LATE) interpretation of the estimates. This, in turn, requires that the assumption of monotonicity holds in the first stage. This is likely to be the case in our application as it is reasonable to think that no firm is encouraged to stop investing in a digital technology if it is exposed to more intense technological progress.

Aghion et al. (2020) and Dixon et al. (2021) use an IV approach with a firm-level instrument to identify the causal effects of automation on firm employment. Focusing on a sample of French firms that import automated industrial machinery, Aghion et al. (2020) use a shift-share IV design that exploits both changes in the market shares of international suppliers (as an exogenous industry-level shock) and the predetermined firm-level trade-related exposure shares. Focusing on the US, Dixon et al. (2021) instrument firms' robot investment by interacting the share of workers in occupations with high "manual dexterity" and low "verbal ability" and the inverse of the median price per robot in Canada; this instrument combines lagged firm characteristics and an aggregate but time-varying exogenous measure of technology. We propose a different firm-level instrument based on industry-level shocks due to changes in the worldwide stock of patents and the predetermined composition of firms' employment in terms of blue- and white-collar workers. Thus, our instrument exploits industry-level shocks (and not just country-level shocks) and can be applied to all firms, and not only to importing firms. This is particularly important given the LATE interpretation of our estimates.

Incidentally, our paper is also related to the literature that examines changes in global patents in digital technologies and how they relate to the adoption of such technologies and employment by firms. Among the various valid methods for identifying patents related to a given technology domain (Bello et al., 2023), we combine information from reference classifications with textual analysis of patent content (Benassi et al., 2021; Ménière et al., 2020; Martinelli et al., 2021). In addition, we match patents and industries based on their use (Goldschlag et al., 2020) rather than on semantic similarity between patent content and the description of occupations and industries (Montobbio et al., 2022; 2024; Prytkova et al., 2024). Our approach is consistent with Caselli et al. (2023), who empirically investigate the adoption of digital technologies using the same firm-level dataset. Their analysis shows that technology adoption varies together with the scope of technological opportunities across industries, measured by the number of worldwide patents in a given technological domain, and that the extent to which firms are receptive to the technological progress depends on their characteristics.

Our second major contribution is that this paper considers together the causal effects of both ODT and IDT on firms' employment. Existing studies either focus on one technology (typically, robotics) in isolation or group all digital technologies together without distinction. This is partly related to our first contribution. Indeed, previous works in the literature usually study the impact of investment in digital technologies on firms' employment using matching and DiD, and these methods are more suitable when dealing with one technology at a time. However, the high correlation of investment in different types of technological innovation observed in the data (Culot et al., 2020; Hwang and Kim, 2022) risks confounding the impact of each technology with that of the other. By using an IV approach, our paper succeeds in studying ODT and IDT simultaneously and in identifying the causal effects of each type of technological investment on firms' employment decisions. Few other studies look at the adoption of different digital technologies, but tend not to examine the causal effects of investing in 4IR technologies. A recent paper by Acemoglu et al. (2022) examines the heterogeneity of US firms in the adoption of specific types of digital technologies. Despite the detailed level of analysis, the study remains mainly descriptive and falls short of exploring any causal mechanisms between technology investment and firm-level performance. Jona-Lasinio and Venturini (2023) and Pedota et al. (2023) also point out the importance of distinguishing sub-clusters of 4IR technologies if the required upskilling of the workforce differs between them, and our results provide further evidence that this is the case.

The third major contribution to the literature is that we provide evidence on how the introduction of ODT and IDT affects overall employment levels, different occupational groups within the firm's workforce, and training practices. The literature is inconclusive on the impact of new digital technologies on the evolution of employment in firms that adopt such technologies. On the one hand, Aghion et al. (2020); Acemoglu et al. (2023b); Balsmeier and Woerter (2019); Bisio et al. (2023); Bratta et al. (2023); Dixon et al. (2021); Domini et al. (2021); Hirvonen et al. (2022) and Koch et al. (2021) find a positive impact of automation-related investments on employment in the investing firms, often with differentiated effects for different types of workers in terms of skills and tasks.[4] On the other hand, Bessen et al. (2023) and Bonfiglioli et al. (2023) reach opposite conclusions, with investment in automation hurting employment levels within the firm.[5] Despite a persistent difference in the employment growth rates between investing and non-investing companies in the US, Acemoglu et al. (2023a) find no significant changes in growth rates following investment in new digital technologies: they conclude that self-selection into investment is the most important determinant of observed employment

[4]Focusing on French firms, Domini et al. (2021) and Bisio et al. (2023) find that investment spikes in the imports of automation-intensive goods are associated with positive net employment growth at the firm level. Also focusing on French companies, Aghion et al. (2020) find that firms' investment in automation (measured using either balance sheet data or imports) increases labour demand. Similarly, Dixon et al. (2021) show that the adoption of robots in Canada is associated with an increase in total firm employment and a decrease in total managerial employment, as well as a reduction in the employment of middle-skilled workers. According to Balsmeier and Woerter (2019), Swiss firms that adopt machine-based digital technologies tend to expand employment, especially among the most skilled workers. Koch et al. (2021) find that the adoption of robots leads to net job creation in Spanish firms. Similarly, Hirvonen et al. (2022) find that advanced technologies lead to increases in employment in Finland, with limited changes in skill composition within firms. Acemoglu et al. (2023b) study robot adoption in Dutch firms and show that it is associated with positive effects on hours worked for robot-adopting firms and negative effects for competitors.

[5]Using administrative data on automation expenditures in the Netherlands, Bessen et al. (2023) find that automation increases the likelihood of job separation for incumbent workers. Bonfiglioli et al. (2023) examine robot imports in French firms and find that, when firm-level product demand shocks are properly accounted for, firms' exposure to automation is associated with a decline in employment.

growth differentials across firms. Our results contribute to this debate along several dimensions. We show the coexistence of both displacement and reinstatement effects (Acemoglu and Restrepo, 2019) within investing firms, in particular with respect to IDT investment. Moreover, we show that ODT investment is conducive to changes in the composition of the workforce from those with permanent contracts to those employed on temporary contracts or through agencies. A holistic reading of our novel findings allows us to conclude that IDT-investing firms exhibit a relatively higher demand for highly skilled workers capable of interacting with the new technologies; more intensive IT-related training, a greater (lower) recourse to apprenticeship (temporary) contracts, and hiring prospects that are distinctively focused on scientific profiles and qualified workers (engaged in the construction, repair or maintenance of artefacts, objects and machines) confirm the important role that knowledge and skills play for firms investing in IDT. Our results thus provide evidence that the observed patterns of labour demand favouring skilled occupational groups at the aggregate level OECD (2022) also reflect granular employment changes within firms investing in IDT technologies, in addition to compositional effects between firms.

The rest of the paper is structured as follows. Section 2 describes the dataset and the variables, while Section 3 illustrates our empirical strategy. The results on the impact of ODT and IDT on firm employment growth are presented in Section 4, which also reports a series of robustness checks. Other results in Section 4 relate to changes in the composition of the workforce, training practices and prospective hiring procedures. Section 5 provides some concluding remarks.

2 Data and descriptive statistics

To test the impact of firms' investment in ODT and IDT on employment growth and composition, training and recruitment plans, we use data from the last two waves of the firm-level survey *Rilevazione Imprese Lavoro* (hereafter RIL), conducted by the *National Institute for Public Analysis* (INAPP) in 2015 and 2018 on a large and representative sample of Italian firms.[6]

The information provided by the survey covers various aspects of firm labour demand. In particular, the survey asks about employment, the composition of the workforce in terms of occupations (i.e., white- and blue-collar workers) and employment contracts, use of employment agencies, investment in on-the-job training, and occupational profiles sought by firms in 2018 or later. The survey also asks about firm and managerial characteristics. In particular, the survey provides information on firm size (both in terms of total employment and sales) and firm age, the number of plants, whether firms belong to groups and are owned by a family or a financial company, whether firms completed a capital operation in the period 2015-2017, gender, age, and level of education of the top manager, whether the top manager is a member of family owning the firm and her remuneration scheme, and investment decisions of different types of tangible and intangible fixed assets.

In addition, the 2018 wave of the survey includes a technology module that specifically examines the adoption of new digital technologies through a series of questions about investments made in 2015-2017. The questions cover robotics, big data analytics, the Internet of Things (IoT), virtual reality, and cybersecurity.

We distinguish two groups of investments, namely operational digital technologies and information digital technologies. This choice is due to the differences between these classes of technological investments in their potential impact on the organisation of production, workers' activities, and the level of employment. ODT represent forms of automation designed to perform specific tasks in the physical space (e.g., moving and modifying objects), whereas IDT refer more to the digital data-related domains.[7] According to the literature, ODT are potentially more likely to be associated with labour displacement effects, as they substitute humans in performing repetitive tasks that do not require cognitive skills. On the contrary, as explained by Martinelli et al. (2021); Sestino et al. (2020), IDT are mainly re-engineering factors for business processes, products and

[6] In one of our robustness checks, we will also consider a subsample of the firms surveyed in the last three waves (2010, 2015 and 2018), as in Cirillo et al. (2023).

[7] Following a similar logic, Pedota et al. (2023) study the adoption of 4IR technologies and distinguish between physical and digital technologies.

services: they are therefore associated with the collection and analysis of data coming from the production process and external sources. IDT can be used to improve workflow and efficiency in production, to increase knowledge of what consumers and buyers want, to stay ahead of the competition, to integrate remote work, and to protect their data and knowledge from external attacks. Access to more feedback data helps firms to develop appropriate business strategies. RIL includes information on firms' investment in robotics, big data, Internet of Things, virtual reality, and cybersecurity. Accordingly, we adopt a dichotomous measure of investment in ODT (by coding a variable that takes the value 1 if a firm has invested in robotics, and 0 otherwise) and a dichotomous measure of investment in IDT (by coding a variable that takes the value 1 if a firm has invested in at least one information digital technology, and 0 otherwise).[8]

Although the questions on firms' digital investments were only included in the 2018 wave of the survey, we restrict our sample to those firms that appear in both the 2015 and 2018 waves: this allows us to measure the changes in employment between 2014 and 2017 and to include several lagged controls (measured in 2014) in the estimations, thereby reducing endogeneity concerns related to omitted variables in our estimation strategy. [9] This approach is common practice and has been used in previous work using this database (see, for example, Dosi et al., 2021; Cirillo et al., 2023).

As usually done, we exclude from the sample agricultural and financial firms, public administrations, households and extra-territorial organisations, as well as firms with coding errors. We also remove firms that reported no activity in 2015, with less than 1 employee, and with zero sales in 2015 and 2018. We remove the firms in the bottom and top 5% of the variation rate of the total number of employees in order to eliminate

[8] Given the sensitivity of data to business optimisation, firms that invest in data-related technologies tend to also invest in cybersecurity (Gomes et al., 2023; Lattanzio and Ma, 2023). In view of this technological and functional interdependence, investments in cybersecurity are included in the IDT domain.

[9] Although this approach substantially reduces the sample size, we observe similar rates of investment in our longitudinal sample (8% for ODT and 42% for IDT) as in the 2018 representative RIL sample (7% for ODT and 38% for IDT). Our statistics are also comparable with a different survey run by the Italian National Istitute of Statistics (ISTAT) on the use of information and communications technologies in firms, which reports that around 4% of firms have purchased goods or services in robotics, 5% in big data (compared to 8%), 10% in IoT (compared to 9% in our sample), 1% in virtual reality (compared to 3%), 45% in cybersecurity (compared to 36%).

the effects of mergers and acquisitions and possible errors in data imputation. Finally, we remove the firms with non-matching ATECO codes in the table of correspondence of patents (more on this below). After cleaning the dataset, the resulting sample consists of approximately 9,380 firms that responded to the survey in both 2015 and 2018.

To overcome the potential endogeneity of technological investment as described in more detail in Section 3, our empirical strategy adopts instrumental variables based on a measure of firms' exposure to the progress made in that technology at the industry level. Then, to exploit within-industry variation for identification, we also consider the interaction of these instruments with firm-level measures of the ability and interest to invest in the technology.

As a measure of exogenous technological progress in ODT and IDT in each industry at the global level, we use the lagged change in the worldwide stock of patent grants in ODT and IDT at the 4-digit industry level. There are different valid methods for identifying patents related to a given technology domain, and a single reference classification is still lacking.[10] Following the approach of Martinelli et al. (2021), we combine the information from reference classifications with the textual analysis of patent content. This combined approach allows us to take a more conservative approach that minimizes the likelihood of selecting false positives, i.e., patents that are not actually related to one of our specific digital technologies of interest. Therefore, in order to construct our measure of new patents at the 4-digit industry level and specific to ODT and IDT, we proceed in three steps. First, we use the Google Patent database, which contains over 140 million patents worldwide, and identify patents in all digital technologies based on their Cooperative Patent Classification (CPC, hereafter) codes. In particular, we use the classification provided by Ménière et al. (2020) for identifying the CPC codes for big data, virtual reality and cybersecurity technologies, whereas we use the former U.S. patent classification (USPC) class *901* and the junction CPC group *Y10S901* to identify robotics-related patents. Finally, to identify CPC codes for the Internet of Things, we use the classification provided by IPO (2014) as well as other relevant CPC

[10] For a discussion of the alternative approaches, see Bello et al. (2023).

groups sampled from the literature. Then, we refine the research through textual analysis: among the previously selected patents, we choose only those that contain at least one of a set of predetermined keywords in either their title or their abstract. The lists of CPC codes and keywords are reproduced in Table A1 in the Appendix.[11] As third and last step, we count the number of patents published between 2005 and 2014 for each ATECO sector at the 4-digit level using the concordance between CPC and the International Standard Industrial Classification (ISIC) (itself matched to the NACE/ATECO classification) provided by Goldschlag et al. (2020). Notably, this concordance takes into account the sector of use, not production, of patents. In our empirical framework, we focus on the association of patents with industries based on their use, because patent use helps to explain technology adoption. There are other methods to match patents and technologies that are based on semantic similarity between patent content and the description of occupations and industries: these alternative approaches do not fit our research objectives and are better suited to estimating measures of the potential exposure of occupations and industries to technology-related displacement effects (Montobbio et al., 2022; 2024; Prytkova et al., 2024).

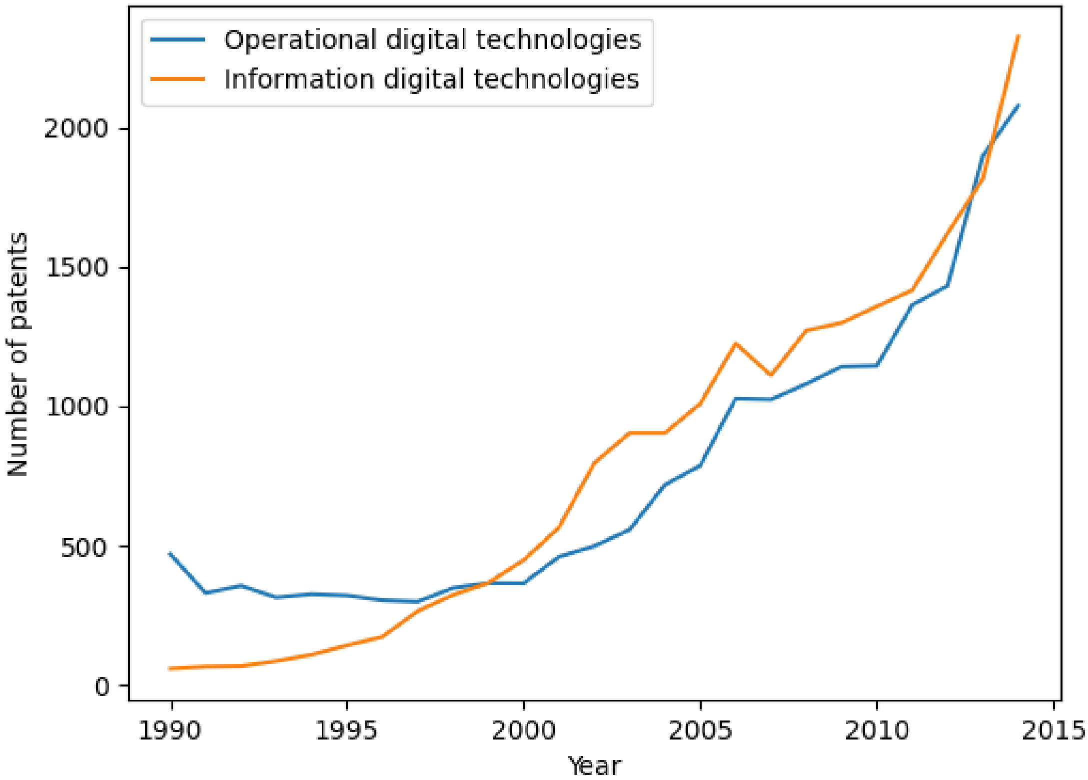
We end up with a total of 19,007 patents for ODT and 19,725 patents for IDT. The number of patents by year of publication and technology group (aggregated over all industries) is shown in Figure 1. The number of IDT patents has been increasing since the mid-1990s, whereas the number of ODT patents only started to grow rapidly after the 2000s, after reaching a plateau in the 1990s. It is worth noting that the evolution of the two groups of patents is highly, but not perfectly, correlated, even if industry-specific differences are ignored.[12]

Our instrumental variables also exploit the variation across firms in the share of workers engaged in specific activities to obtain a firm-level technology-specific determinant of digital investment. Specifically, we construct interaction terms between the

[11] We drop the duplicated patents by keeping only those with the earliest publication date within the same patent family and having the same (translated, if necessary) title.

[12] A potential problem that needs to be addressed is that some patents could be classified in more than one technology, which would make our classification less informative. Therefore, for each pair of technologies, we report in Table A2 in the Appendix the proportion of patents that are common. For each technology, this proportion is negligible (i.e., always less than 1%).

Figure 1: Evolution of worldwide patent grants in digital technologies, 1990-2014



Notes: The figure shows the number of new patents, i.e., the flow of patents, over the period 1990-2014 for operational digital technologies and information digital technologies.

changes in the global stock of patents by technology and 4-digit industry over the period 2000-2014 and the firm-level share of white-collar workers in 2014 for ODT on the one hand and the firm-level share of blue-collar workers in 2014 for IDT on the other.

Finally, we also construct a measure of the change in the industry-specific stock of patents that fall neither in ODT nor in IDT. This covariate captures possible industry-specific investment trends that are not captured by sector fixed effects. To construct this measure, we randomly draw 500 000 patents from which we drop patents that contain at least one CPC code or one keyword associated with robotics and IDT, as shown in Table A1 in the Appendix. To be consistent with our instrumental variable strategy, we also interact the number of global patents related to other technologies with the shares of blue-collar and white-collar workers in the firm.

Descriptive statistics for the main variables described above are presented in

Table 1.[13] Among the firms in both waves, the total number of employees has increased over time. Blue-collar workers represent the largest share of employees, as expected for a sample of firms mainly active in manufacturing. It is worth noting that the share of firms investing in IDT is much higher (42%) than those investing in robotics (8%). This is largely due to investments in cybersecurity, which are widespread (though limited in size) in Italy during the period of interest (Biancotti, 2017).

Table 1: Descriptive statistics

	Mean	SD
No. employees (2014)	65.91	222.52
No. employees (2017)	70.26	236.58
Growth no. employees (2014-2017)	0.04	0.21
Investment in ODT (2015-2017)	0.08	0.27
Investment in IDT (2015-2017)	0.42	0.49
No. patents in ODT (2000-2014) ×1000	0.06	0.34
No. patents in IDT (2000-2014) ×1000	0.03	0.38
Share of white-collar workers (2014)	0.37	0.32
Share of blue-collar workers (2014)	0.60	0.34

Notes: Growth no. employees (2014-2017) is calculated as the difference of the log of the number of employees between 2017 and 2014. Investment in ODT (2015-2017) equals one if the firm has invested in robotics between 2015 and 2017. Investment in IDT (2015-2017) equals one if the firm has invested either in big data, Internet of Things, virtual reality or cybersecurity between 2015 and 2017. No. patents in ODT (2000-2014) is the change in the worldwide stock of patents related to robotics (2000-2014, ×1000). No. patents in IDT (2000-2014) is the change in the worldwide stock of patents related to big data, Internet of Things, virtual reality or cybersecurity (2000-2014, ×1000).

3 Empirical model

To analyse the impact of firms' investments in digital technologies on employment, we estimate the following equation:

$$Y_{isr} = \alpha T_{isr}^{ODT} + \beta T_{isr}^{IDT} + X_{isr}'\delta + \gamma_s + \gamma_r + \epsilon_{isr}, \tag{1}$$

where Y_{isr} is an employment outcome, i.e., the growth in the number of employees and the change in the shares of different groups of employees between 2014 and 2017, investment in on-the-job training, and occupational profiles sought by firms in 2018 or later, for firm i in sector s and region r. T_{isr}^{ODT} and T_{isr}^{IDT} are binary variables indicating if firm

[13] Additional descriptive statistics are reported in Table A3 and Table A4 in the Appendix.

i has respectively invested in ODT and IDT between 2015 and 2017, X_{isr} is a vector of firm- and management-related controls, γ_s and γ_r are sector (ATECO 1 digit) and region (NUTS 2) fixed effects, and ϵ_{isr} is the error term.[14]

Estimating equation (1), i.e., the impact of digital investment on employment, by OLS may suffer from endogeneity problems. Endogeneity may arise from firms' self-selection into digital technology investment due to (time-invariant or time-varying) observed or unobserved factors that also affect employment. For example, a positive demand shock may induce firms to invest in digital technologies and increase their employment. Alternatively, a particular type of management may see digital technologies as a way to automate production and reduce labour costs. Thus, a priori, it may be difficult to understand the direction of the bias of the OLS estimation.

To overcome the potential endogeneity of technological investment, we adopt an IV-2SLS strategy and we include various lagged (i.e., measured in 2014) firm- and management-related controls in the vector X_{isr}. Although our IV strategy can deal with endogeneity due to omitted variable bias, the inclusion of meaningful controls can improve the precision of the estimates and the quality of the first stage.

We propose an original IV strategy based on the lagged change in the worldwide stock of patent grants at the 4-digit industry level related to ODT and IDT. The idea behind these instruments is that firms' adoption of artefacts related to digital technologies follows the development of new ideas outside the firm: the scope of technological opportunities depends on the evolution of knowledge at the world level. However, given the available stock of knowledge in the world, not all firms within an industry invest in new digital technologies. Indeed, firms' decisions to invest in digital technologies may depend on firms' capabilities as well as on the characteristics of the production process. Since the composition of the workforce reflects both factors, we construct interaction terms between the changes in the global stock of patents by technology and 4-digit industry over the period 2000-2014 and the firm-level share of white-collar workers in 2014 for

[14]The results are robust to the inclusion of 2-digit sector fixed effects, although the first stage becomes less informative due to the reduction in variation, particularly for the instrumental variables. These additional results are available upon request.

ODT on the one hand and the firm-level share of blue-collar workers in 2014 for IDT on the other.

The composition of the firm's workforce helps to predict the probability that the firm will invest in digital technologies for two main reasons. First, the composition of the workforce and the adoption of new technologies are correlated with the absorptive capacity of the firm according to the theoretical channels explained by Cohen and Levinthal (1990); Zahra and George (2002). Second, the predetermined composition of the workforce captures the production processes that the firm may be willing to re-engineer. Thus, we argue that firms with a larger share of blue-collar (white-collar) workers are more (less) likely to invest in digital technologies because blue-collar workers are more likely (due to functional complementarities) and more capable (due to better knowledge and skills) to interact with them.[15] Our choice to focus on the composition of the workforce to capture the likelihood of investing in digital technologies is related to the works of Graetz and Michaels (2018), Dixon et al. (2021) and Bonfiglioli et al. (2023). Graetz and Michaels (2018) adopt a measure of replaceability for each occupation, and calculate the industry-level share of replaceable workers to instrument for the intensity of robot adoption in different industries. Dixon et al. (2021) interact the lagged share of workers in occupations with high "manual dexterity" and low "verbal ability" with the inverse of the median price per robot in Canada. Bonfiglioli et al. (2023) reproduce Graetz and Michaels (2018)'s variable at the firm level and use this regressor directly in an OLS estimation as a proxy for technology adoption. We also construct firm-level measures, but we use them as instruments in our IV strategy.

It is worth noting that our IVs exploit two important dimensions of technological adoption, which strengthens their validity and informativeness, as suggested by Kline and Walters (2016). First, their exogeneity is ensured by the use of global technological trends at the 4-digit industry level proxied by patents, which do not directly affect firm-level employment outcomes. Second, the inclusion of interaction terms with firm-level lagged

[15] It is worth noticing that the share of blue-collar workers and the share of white-collar workers sum almost to one for each firm. Therefore, in the empirical identification we use two different interaction terms (one for each of the two technology domains), but investment in both ODT and IDT is positively associated with the share of blue-collar workers in the firm for a given number of patents.

occupational shares allows us to examine variation within industries at the 4-digit level. This is a step forward from those papers that use industry-level instruments in firm-level studies, as it reduces the risk of projecting industry-specific employment patterns onto firm-level employment variation.

Thus, the IV strategy that we adopt allows us to deal effectively with various endogeneity problems, including selection on unobservables, since the instrumental variables are valid and informative. The validity of the instruments is given by their exogeneity, i.e., all the potential outcomes are independent of the instruments, with no direct effect of the latter on the former (Imbens and Wooldridge, 2009). The informativeness of the instruments refers to their ability to predict the investment decisions in the first stage of the estimation, as will be shown in Section 4. In addition, we argue that our estimated coefficients can be interpreted as local average treatment effects (LATE). This interpretation requires that an increasing level of the instrument does not decrease the level of the treatment for any units (Imbens and Wooldridge, 2009), which implies excluding the presence of defiers that would only invest in a technology when the change in the global stock of patents is relatively low. This monotonicity assumption in our setup is equivalent to assuming that the probability of technology adoption cannot decrease with the growth of the global stock of knowledge in the firm's industry. As shown by Imbens and Angrist (1994), such an assumption allows us to interpret the estimated coefficients as local average treatment effects of digital investment on the employment of firms that adopt a new technology in response to an exogenous increase in the global stock of patents in their industry (Blundell and Dias, 2009). We believe that the monotonicity condition holds in our application because it is reasonable to assume that no firm would be encouraged to stop undertaking an investment if it were exposed to more intense technological progress. As shown in the literature (see, for instance, Raj et al., 2020; Stornelli et al., 2021), the uncertainty about future technological trajectories, the risks associated with low technological maturity, and the lack of clarity about the potential economic benefits of recent innovations are important barriers to firms' adoption of digital technologies: we maintain that the larger the increase in knowledge codified in patents, the lower these barriers to adoption are. Moreover, our assumption of monotonicity is consistent with the processes of innovation diffusion whereby the scope of technological opportunities available to firms is determined by the stock of knowledge in their surrounding environment.[16]

Regarding the lagged controls, the first set that we include concerns firm characteristics. As in empirical studies of firm growth, we include variables for firm size (both in terms of total employment and sales) and firm age, all in logarithms. In addition, we control for the log of the number of plants of the firm, as this captures an important organisational dimension of the firm that may affect the composition of the workforce. Three dummy variables capture whether the firm belongs to a group and whether it is owned by either a family or a financial company. We also control for whether the firm completed a capital operation in the period 2015-2017, as this can create artificial discontinuities in employment and investment.

The second set of lagged controls includes the characteristics of the workforce. We control for its initial composition, namely the shares of white-collar and blue-collar workers, as these also form the interaction terms that we use as instruments in the first stage. We also introduce lagged variables for whether the firm provides on-the-job training and whether the firm employs agency workers.

Another set of controls relates to the firm's management, as the latter could potentially be correlated with both investment decisions and employment dynamics. Thus, we include the gender, age, and educational level of the top manager, as well as dummies for whether she is a member of the firm's owning family or she was recruited from outside the firm, and the type of remuneration scheme, i.e., fixed, variable according to the firm's performance or some another kind of arrangement.

In order to distinguish the effects of ODT and IDT investment from any general investment, we include additional variables capturing other types of investment in 2014

[16] It could be argued that the monotonicity assumption is less likely to hold when the scope of opportunities is reduced as an effect of the sectoral lifecycle, with a larger number of patents actually indicating fewer technological opportunities. This is not a concern in our setting for two reasons: first, IDT and ODT are very recent and far from mature, as shown by the unabated growth in the number of patents; second, the new digital technologies have horizontal and pervasive applications that are not associated with the industry lifecycle of investing firms.

and 2017.[17] This is a conservative approach, as these controls are likely to capture some of the effects of interest and they also increase the degree of collinearity between the explanatory variables, potentially making inference worse.

In order to distinguish the specific effect of our instrumental variables from any general technological progress in the industry, we also include a measure of the change in the industry-specific stocks of patents that fall neither in ODT nor in IDT during the period 2000-2014. The idea is to take into account progress in other technological fields, thereby reducing the likelihood that we are capturing other investment-related industry-specific trends related to both demand and supply of new technologies. Again, this is a conservative approach as it is likely to weaken the effect of our instrumental variables. To be consistent with our IV strategy, we interact the number of global patents related to other technologies with the shares of blue-collar and white-collar workers in the firm.

4 Empirical results

4.1 Main results

Our baseline estimates for the impact of investment in ODT and IDT on the growth of total employment over the period 2014-2017 are presented in Table 2. The specification in column (1) includes all controls for firm, workforce and manager characteristics. In column (2), we add controls that capture other investments made by the firm. Then we also include the number of patents in technologies other than ODT and IDT (column 3). All three specifications yield similar results. As explained earlier, the most complete specification is the most conservative, as these controls may capture some of the effects of interest and weaken the effect of our instrumental variables. While the firm's investment in ODT does not seem to be associated with significant changes in total employment, firms investing in IDT show a positive and significant increase in total employment over

[17] This additional investment includes marketing, advertising, land, buildings, and other types of investment except for R&D, certifications, patents, licenses, trademarks, software, industrial plant and equipment, machinery and IT equipment. The latter are in fact highly correlated with investment in digital technologies.

the period 2014-2017. According to the coefficient in column (3), investment in IDT is associated with an increase in total employment growth of 23% over the three-year period, roughly equivalent to one standard deviation. This estimated causal effect of IDT investment on firm total employment can be explained by the fact that investment in IDT leads firms to change their business processes, products and services in order to improve efficiency and product quality, not to shed workers. Conversely, ODT investment does not appear to have a significant impact on total employment, in line with the mixed empirical findings on the impact of robotics and automation-related technologies in the literature. As explained above, the parameters estimated using our IV-2SLS approach capture the local average treatment effect for the firms investing in IDT in response to an exogenous increase in the global stock of patents in their industry, not the average treatment effect on the treated. Accordingly, the size of the effects is not directly comparable with studies using matching and DiD approaches.

We can compare the estimates in Table 2 with those obtained from OLS regressions to examine the direction of the bias. The OLS estimates are shown in Table A5 in the Appendix. The parameters for investment in ODT and investment in IDT are positive and significant and have a similar magnitude, around 0.03. Accordingly, the direction of the bias of the OLS estimation is different for investment in the two technology domains: positive for ODT and negative for IDT. This suggests that investment in ODT is positively related to other factors that lead to the expansion of firms' economic activities, while investment in IDT is undertaken by firms whose employment tends to grow less for reasons unrelated to IDT. Moreover, since the bias is in the opposite direction for ODT and IDT, it is reasonable to conclude that unobserved factors at the industry and firm levels linked to the general adoption of new technologies are not driving our results, and thus our IV strategy effectively mitigates endogeneity issues.

We also report various tests of the informativeness and validity of our instruments. According to the Kleibergen-Paap LM statistic, we can reject the null hypothesis that the system is underidentified. In addition, the Kleibergen-Paap Wald F statistic is large enough to be confident that the instruments are not weak. Despite these tests, one might still be concerned about the presence of weak instruments affecting inference. However, according to the Anderson-Rubin Wald Chi-sq statistic, we can reject the null hypothesis of joint non-significance of the endogenous regressors. Since we have more instruments than endogenous variables, we can also compute the Hansen J statistic, which shows that we cannot reject the null hypothesis that the instruments are valid, i.e., uncorrelated with the error term. Furthermore, based on the first stage results in Table A6 in the Appendix, the estimated coefficients of all our instruments are significant for at least one of the technologies and the instruments contribute positively to identification and are not weak (see also Sanderson-Windmeijer statistics for underidentification and weak identification).[18] The estimates show that the larger the share of blue-collar workers (and the smaller the share of white-collar workers), the more likely firms are to invest in IDT and ODT.

These results confirm our decision to distinguish between investment in ODT and IDT, while including both in the estimation. Despite the correlation in the adoption of the two groups of technologies, their relative impact on firm employment is significantly different.

Previous firm-level studies on the impact of automation on firm employment in Italy have found contrasting effects, ranging from the positive effects in Domini et al. (2021) to the negative effects in Bonfiglioli et al. (2023). Our estimates provide evidence that investment in robotics has no effect on firm employment once endogeneity concerns and the presence of other, partially overlapping, technologies, are properly controlled for. As we shall see, this does not mean that firm investment in ODT is completely unimportant. On the contrary, it has an impact on the composition of firm employment, in line with the theoretical results predicted by Acemoglu and Restrepo (2019)'s task-based models.

[18] While ODT-related patents are positively associated with the probability of investing in IDT, IDT-related patents are not positively associated with the probability of investing in ODT. This ensures that the identification strategy works effectively while allowing for possible technological complementarities in the two domains.

Table 2: Effect of investment in digital technologies on total employment growth

	(1)	(2)	(3)
Investment in ODT	-0.064	-0.057	-0.065
	(0.071)	(0.072)	(0.071)
Investment in IDT	0.199***	0.198***	0.232***
	(0.064)	(0.065)	(0.072)
Firm controls	yes	yes	yes
Workforce controls	yes	yes	yes
Manager controls	yes	yes	yes
Other investments	no	yes	yes
No. patents in other technologies	no	no	yes
Region FE	yes	yes	yes
Sector FE	yes	yes	yes
Observations	9332	9332	9332
Kleibergen-Paap LM stat	8.237**	7.957**	7.029*
Kleibergen-Paap Wald F stat	58.083	84.927	80.148
Anderson-Rubin Wald Chi-sq stat	21.97***	18.58***	19.47***
Hansen J stat	0.909	1.152	0.807

Notes: The dependent variable is the difference in the log of the total number of workers between 2014 and 2017. Firm controls include the log of the total number of employees in 2014, total sales in 2014, the log of firm age in 2014, the log of the number of plants in 2014, a dummy equal to one if the firm belongs to a group in 2014, a dummy equal to one if the firm is owned by a family in 2014, a dummy equal to one if the firm is owned by a financial company in 2014, and a dummy equal to one if the firm completed a capital operation in the period 2015-2017. Workforce controls include the share of white-collar workers in 2014, the share of blue-collar workers in 2014, a dummy equal to one if the firm provides on-the-job training in 2014, and a dummy equal to one if the firm employs agency workers. Manager controls include gender, age, and dummies for the level of education of the top manager in 2014, a dummy equal to one if the top manager is a member of family owning the firm, and dummies for the top manager's remuneration scheme. Other investments includes two dummies equal to one if the firm makes investment in marketing, advertising, land, buildings, and other types of investment in 2014 and 2017. No. patents in other technologies includes the change in the worldwide stock of patents that fall neither in ODT nor in IDT at the 4-digit industry level (2000-2014) and its interactions with the shares of blue-collar and white-collar workers. All regressions are estimated with the 2SLS estimator. The instruments are the change in the worldwide stock of patents in ODT (2000-2014) and its interaction with the share of white-collar workers, and the change in the worldwide stock of patents in IDT (2000-2014) and its interaction with the share of blue-collar workers. Standard errors clustered at the 4-digit industry level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.2 Robustness checks

Before examining the impact of digital investment on additional firm employment outcomes, we provide some auxiliary estimations to show the robustness of our empirical strategy and our main results.

The first concern we address is sample selection, which is related to the reduction in the sample size due to merging the 2015 and 2018 waves of the survey. If the firms that appear in the sample in both 2015 and 2018 are systematically different from those that participate only once, a sample selection issue may affect the results. We perform a Heckman correction to account for the possible bias due to a non-randomly selected sample. In the first step, we run a probit regression on a selection equation that includes all the exogenous variables and an additional variable that explains selection; in the second step, we add the inverse Mills ratio from the first step to our 2SLS estimation.[19] The selection variable in the first step needs to be correlated with the probability of the firm being sampled in 2015 and 2018, but not with its employment changes between 2014 and 2017. Since we can merge the 2010 wave with the following two waves, we obtain a binary variable that takes the value 1 if the firm is present in all three surveys and use it as the selection variable. The results in Table A7 in the Appendix show that our selection equation works well and the estimated impact of investment in ODT and IDT does not change significantly. Moreover, the inverse Mills ratio is not statistically significant in the main equation of interest, but it is significant in one of the two first stage regressions. Overall, this suggests that there might be some sample selection issues, but they are not strong enough to significantly bias the results.

To show that the results are not driven by limited groups of firms, we look at different subsamples of firms and industries. First, we exclude the firms in the machinery and equipment sector to see whether the results are driven exclusively by those firms that are at the centre of the 4.0 industrial revolution. As column (1) of Table A8 in the Appendix shows, this is not the case. Second, we exclude large firms (with more than 250 employees) from the sample, as they tend to be less affected by financial constraints and more likely to adopt new technologies. The estimates in column (2) of Table A8 in the Appendix show that this is not the case. Despite the removal of almost 500 firms, the results are not statistically different from those in the full sample.

As discussed in the previous sections, the precision of the estimates depends on the quality of the controls used in the estimation. Next, we show that the results are robust to the choice of different sets of covariates by estimating a specification based on machine learning techniques to select the covariates from a large set. In particular, we use the least absolute shrinkage and selection operator, LASSO, and we include all variables

[19] As the inverse Mills ratio is a generated control variable, we bootstrap the standard errors.

included in the 2015 wave of RIL among the potential covariates that LASSO can select. These include, among others, measures of exports, offshoring, employment turnover, use of public incentives, investment in R&D, and unionisation, all measured in 2014. We also combine LASSO with our IV strategy (IV-LASSO). In a second specification of IV-LASSO, we interact our instruments with all variables included in the 2015 wave of RIL and we let LASSO select the additional interactions to be included among the instruments. In both specifications, our original instruments are not penalised by LASSO, so that they are always included in the estimation. Table A9 in the Appendix shows that our results are robust to the IV-LASSO estimations, so omitted variable bias does not seem to be a problem in our main specification. It should be noted that, as discussed by Angrist and Frandsen (2022), machine learning procedures, such as LASSO, place too much emphasis on fit, potentially at the expense of causality, the primary focus in empirical labour applications. Despite these issues, LASSO can still be helpful in applications with many covariates and many instruments as it can mitigate overfitting and data mining.

The causal interpretation of our estimates with multiple treatments as LATE may suffer if the estimates of the effect of each treatment are contaminated by the effects of other treatments. While the actual relevance of this potential problem is an empirical question, we can show that our identification strategy does not suffer from contamination effects. As Table A10 in the Appendix shows, our estimates do not vary much in the case of separate treatments. In particular, this estimation should not be interpreted as suggesting that it is preferable to estimate one technology at a time: by definition, if both types of investment were relevant, any separate estimation would suffer from an omitted variable problem by construction. We simply show that investment in each technology is captured precisely by the instrumental variable and the interaction term that we specifically identify.

Next, we propose a robustness check related to the shares of blue-collar and white-collar workers used to construct our interacted IVs. The exogeneity of the stock of patents by technology group and industry stems from the global nature of this measure of knowledge, and patent-related shocks are the exogenous factors driving the identification. The blue-collar and white-collar shares used in the interaction terms are also predetermined as they are calculated in 2014. Notwithstanding the good results of the test statistics in the first stage of our estimation, it could be argued that the shares of blue-collar and white-collar workers could be correlated with the future evolution of employment in the firm. To make sure that we condition on this, we include the shares of blue-collar and white-collar workers among the controls in all regressions. As suggested by Kline and Walters (2016), the introduction of such interaction terms allows us to better explore the variation in the data across firms within each sector, thus improving the estimates. We propose a robustness check based on the use of the shares of blue-collar and white-collar workers taken from the 2010 wave of RIL, which reports data for 2009. The results are presented in Table A11 in the Appendix. The results are not qualitatively different, although investment in robotics has a positive and significant impact on employment growth at the 10% level. However, the test statistics tend to indicate some problems of weak identification, which undermine this alternative approach. Indeed, the Kleibergen-Paap LM statistic does not reject the hypothesis that the system is under-identified and the Kleibergen-Paap Wald F statistic is below the standard critical values. The problems of weak identification could be due to the longer lag in the shares of blue-collar and white-collar workers, which leads to a weaker first stage. In addition, when we merge the three waves of RIL, we observe a sharp reduction in the sample (in line with Cirillo et al., 2023).

Finally, we perform a falsification test using lagged changes in employment as the dependent variable. As before, this estimation can only be carried out on a smaller sample of firms present in all three waves. The results are presented in Table A12 in the Appendix. As we do not find a significant effect, the results of this falsification test confirm that our main estimates do not capture pre-existing employment trends within firms.

4.3 Composition of workforce, training and recruitment

4.3.1 Composition of workforce

In this section we examine the impact of investment in ODT and IDT on additional employment outcomes. It is plausible to expect that investment in ODT and IDT leads to a change in the composition of the workforce. Indeed, as shown by Dauth et al. (2021), changes at the occupation level are an important component of the overall impact of technological innovation. In order to explore this possibility, we identify different dimensions of the composition of the workforce to be studied.

The estimates of the impact of technological investment on the composition of contracts used by the firm are shown in Table 3. Regarding ODT, the results suggest that investment in robotics favours the substitution of permanent workers by temporary workers. These results can be explained by the fact that, after investing in ODT, firms need some flexibility along the significant reorganisation process that most often accompanies the introduction of this type of technology (Battisti et al., 2023; Ciarli et al., 2021); temporary contracts allow firms to access specific skills temporarily, while robots can perform some routine tasks permanently. It is also possible that innovative firms adopting ODT gradually replace older workers on permanent contracts with younger workers on temporary contracts.

On the contrary, firms investing in IDT show a decrease in the share of temporary jobs and an increase in apprenticeship contracts. This composite effect suggests that these firms need their workforce to evolve to keep up with the new advanced tasks that the technological upgrading brings. As IDT allow firms to reorganize the production process with a view to increasing efficiency and security (Martinelli et al., 2021), permanent contracts are better suited to accompany this transformation. As noted by Consoli et al. (2023), task reorientation within occupations is one channel through which labour markets adapt to technological change: this may be achieved through the training of incumbent workers with permanent contracts (more on this below), but also through greater recourse to apprenticeship contracts, which by their very nature involve general and specific training. Indeed, additional questions in the survey show that more than 85% of firms using apprenticeship contracts look for young workers to train and take on permanently, independently of whether they invest in IDT or not.[20] In line with our results, but in a different institutional context, Genz et al. (2022) find that employees with vocational training in German firms are among those who benefit most from the adoption of new technologies in their firms.

4.3.2 On-the-job training

The results on the composition of workers suggest that it is necessary to examine how investment in ODT and IDT affects general and specific forms of on-the-job training.

The estimates reported in Table 4 show that firms investing in IDT are more likely to develop IT-specific training activities, while those investing in ODT are more likely to undertake task-specific technical training not related to IT. These findings on the impact of investment in ODT on firms' training activities can be interpreted in conjunction with the previous findings on the share of temporary and permanent contracts and, as we will see next, the findings on the relatively greater importance of agency workers for firms investing in ODT.

Firms investing in ODT do not reduce employment, but they appear to reorganise production by using more flexibility and focusing more on task-specific training. On the contrary, firms adopting IDT tend to invest more in IT-specific training and to rely more on training-intensive apprenticeship programmes. In particular, our results for IDT investment are in line with Battisti et al. (2023), who show that workers in firms introducing technological innovations gradually move to more abstract activities and that training becomes an essential element in this process, as it helps to upskill both incumbent workers and workers with apprenticeship contracts. This is consistent with their finding that firms with experience in training young workers are also more likely to retrain adult workers after the introduction of technological and organisational innovations. Our findings are also in line with Nedelkoska and Quintini (2018), who observe

[20] This implies that only a small fraction of firms say they are motivated by lower labour costs, lower redundancy costs or public incentives.

Table 3: Effect of investment in digital technologies on the composition of workforce

	Permanent (1)	Temporary (2)	Apprenticeship (3)	On demand (4)
Investment in ODT	-0.090**	0.096**	-0.002	-0.003
	(0.044)	(0.046)	(0.051)	(0.009)
Investment in IDT	-0.008	-0.149***	0.153**	0.004
	(0.067)	(0.033)	(0.076)	(0.006)
Firm controls	yes	yes	yes	yes
Workforce controls	yes	yes	yes	yes
Manager controls	yes	yes	yes	yes
Other investments	yes	yes	yes	yes
No. patents in other technologies	yes	yes	yes	yes
Region FE	yes	yes	yes	yes
Sector FE	yes	yes	yes	yes
Observations	9332	9332	9332	9332
Kleibergen-Paap LM stat	7.029*	7.029*	7.029*	7.029*
Kleibergen-Paap Wald F stat	80.148	80.148	80.148	80.148
Anderson-Rubin Wald Chi-sq stat	19.47***	19.47***	19.47***	19.47***
Hansen J stat	3.380	1.254	2.079	0.377

Notes: The dependent variable is the difference in the share of employees with permanent contracts between 2014 and 2017 in column (1), the difference in the share of employees with temporary contracts between 2014 and 2017 in column (2), the difference in the share of employees with apprenticeship contracts between 2014 and 2017 in column (3), and the difference in the share of employees with on-demand contracts between 2014 and 2017 in column (4). Firm controls include the log of the total number of employees in 2014, total sales in 2014, the log of firm age in 2014, the log of the number of plants in 2014, a dummy equal to one if the firm belongs to a group in 2014, a dummy equal to one if the firm is owned by a family in 2014, a dummy equal to one if the firm is owned by a financial company in 2014, and a dummy equal to one if the firm completed a capital operation in the period 2015-2017. Workforce controls include the share of white-collar workers in 2014, the share of blue-collar workers in 2014, a dummy equal to one if the firm provides on-the-job training in 2014, and a dummy equal to one if the firm employs agency workers. Manager controls include gender, age, and dummies for the level of education of the top manager in 2014, a dummy equal to one if the top manager is a member of family owning the firm, and dummies for the top manager's remuneration scheme. Other investments includes two dummies equal to one if the firm makes investment in marketing, advertising, land, buildings, and other types of investment in 2014 and 2017. No. patents in other technologies includes the change in the worldwide stock of patents that fall neither in ODT nor in IDT at the 4-digit industry level (2000-2014) and its interactions with the shares of blue-collar and white-collar workers. All regressions are estimated with the 2SLS estimator. The instruments are the change in the worldwide stock of patents in ODT (2000-2014) and its interaction with the share of white-collar workers, and the change in the worldwide stock of patents in IDT (2000-2014) and its interaction with the share of blue-collar workers. Standard errors clustered at the 4-digit industry level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

that on-the-job training is often provided to help workers transition to new tasks within the same firm, but less so when their activities may eventually be replaced. Also Pedota et al. (2023) conclude that there is a stronger association between ICT upskilling and investment in 4IR technologies for firms that adopt IDT; however, unlike us, they find a positive (though milder) association in the case of ODT.

In summary, while some training activities appear to be important for both types of technological investment, they are targeted at different types of workers and tasks in firms with different innovation strategies.

Table 4: Effect of investment in digital technologies on training

	Training, IT-related (1)	Training, task-specific (2)
Investment in ODT	0.135	0.425**
	(0.121)	(0.180)
Investment in IDT	0.411***	-0.122
	(0.147)	(0.259)
Firm controls	yes	yes
Workforce controls	yes	yes
Manager controls	yes	yes
Other investments	yes	yes
No. patents in other technologies	yes	yes
Region FE	yes	yes
Sector FE	yes	yes
Observations	9332	9332
Kleibergen-Paap LM stat	7.029*	7.029*
Kleibergen-Paap Wald F stat	80.148	80.148
Anderson-Rubin Wald Chi-sq stat	19.47***	19.47***
Hansen J stat	3.636	4.948

Notes: The dependent variable is a dummy equal to one if the firm provides IT-related training in 2017 in column (1), and a dummy equal to one if the firm provides task-specific technical training in 2017 in column (2). Firm controls include the log of the total number of employees in 2014, total sales in 2014, the log of firm age in 2014, the log of the number of plants in 2014, a dummy equal to one if the firm belongs to a group in 2014, a dummy equal to one if the firm is owned by a family in 2014, a dummy equal to one if the firm is owned by a financial company in 2014, and a dummy equal to one if the firm completed a capital operation in the period 2015-2017. Workforce controls include the share of white-collar workers in 2014, the share of blue-collar workers in 2014, a dummy equal to one if the firm provides on-the-job training in 2014, and a dummy equal to one if the firm employs agency workers. Manager controls include gender, age, and dummies for the level of education of the top manager in 2014, a dummy equal to one if the top manager is a member of family owning the firm, and dummies for the top manager's remuneration scheme. Other investments includes two dummies equal to one if the firm makes investment in marketing, advertising, land, buildings, and other types of investment in 2014 and 2017. No. patents in other technologies includes the change in the worldwide stock of patents that fall neither in ODT nor in IDT at the 4-digit industry level (2000-2014) and its interactions with the shares of blue-collar and white-collar workers. All regressions are estimated with the 2SLS estimator. The instruments are the change in the worldwide stock of patents in ODT (2000-2014) and its interaction with the share of white-collar workers, and the change in the worldwide stock of patents in IDT (2000-2014) and its interaction with the share of blue-collar workers. Standard errors clustered at the 4-digit industry level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Due to the binary nature of the training variables, we cannot estimate the impact of digital technology adoption on the intensive margin of training-related investment per employee. Nor can we examine whether firms prefer to hire more skilled workers from outside or to train them in-house.[21] However, our results provide evidence that firms

[21] Brunello et al. (2023) show that advanced digital technologies and training can be substitutes.

adopting IDT are more likely to invest in IT-related training than non-investing firms, while firms adopting ODT are more likely to invest in task-specific technical training than non-investing firms. This confirms the importance of distinguishing between IT-related training and other forms of training (Jona-Lasinio and Venturini, 2023), as well as between IDT and ODT.

4.3.3 Agency workers

Employment agencies act as intermediaries between firms and workers. While they often play a coordinating role, they also facilitate firms' use of atypical contracts. The estimates in Table 5 suggest that firms investing in robotics are more likely to use agency workers, while those investing in IDT have a lower ratio of agency workers to total employees. This provides additional evidence of the differential impact of ODT and IDT, with the latter being associated with more stable contracts and employment conditions.

4.3.4 Recruitment plans

The analysis so far has focused on changes in the composition and training of the workforce. However, investment in digital technologies is also likely to have an impact on future recruitment decisions. RIL includes detailed questions about the job profiles that firms are looking for. This allows us to investigate whether, after investing in digital technologies, firms are more or less likely to hire workers with certain profiles than non-investing firms.

The estimates are shown in Table 6, where each column corresponds to a different profile. The results show that firms investing in IDT actively look for scientists and specialised workers involved in the construction, repair or maintenance of artefacts, objects and machines. These conclusions are in line with Harrigan et al. (2021), who find a positive impact of firms' technological adoption on the so-called techies, i.e., workers involved in the design, installation and maintenance of information and computer technology and other technologies. In turn, firms investing in IDT are less likely than non-investing firms to look for workers referred to as qualified, i.e., machine operators involved in the manage-

Table 5: Effect of investment in digital technologies on agency workers

	Use of agency workers (1)	Share of agency workers (2)
Investment in ODT	0.499*	0.118
	(0.273)	(0.077)
Investment in IDT	0.052	-0.084**
	(0.193)	(0.035)
Firm controls	yes	yes
Workforce controls	yes	yes
Manager controls	yes	yes
Other investments	yes	yes
No. patents in other technologies	yes	yes
Region FE	yes	yes
Sector FE	yes	yes
Observations	9332	9332
Kleibergen-Paap LM stat	7.029*	7.029*
Kleibergen-Paap Wald F stat	80.148	80.148
Anderson-Rubin Wald Chi-sq stat	19.47***	19.47***
Hansen J stat	3.519	0.906

Notes: The dependent variable is a dummy equal to one if the firm employs agency workers in 2017 in column (1), and the share of agency workers over total employment in 2017 in column (2). Firm controls include the log of the total number of employees in 2014, total sales in 2014, the log of firm age in 2014, the log of the number of plants in 2014, a dummy equal to one if the firm belongs to a group in 2014, a dummy equal to one if the firm is owned by a family in 2014, a dummy equal to one if the firm is owned by a financial company in 2014, and a dummy equal to one if the firm completed a capital operation in the period 2015-2017. Workforce controls include the share of white-collar workers in 2014, the share of blue-collar workers in 2014, a dummy equal to one if the firm provides on-the-job training in 2014, and a dummy equal to one if the firm employs agency workers. Manager controls include gender, age, and dummies for the level of education of the top manager in 2014, a dummy equal to one if the top manager is a member of family owning the firm, and dummies for the top manager's remuneration scheme. Other investments includes two dummies equal to one if the firm makes investment in marketing, advertising, land, buildings, and other types of investment in 2014 and 2017. No. patents in other technologies includes the change in the worldwide stock of patents that fall neither in ODT nor in IDT at the 4-digit industry level (2000-2014) and its interactions with the shares of blue-collar and white-collar workers. All regressions are estimated with the 2SLS estimator. The instruments are the change in the worldwide stock of patents in ODT (2000-2014) and its interaction with the share of white-collar workers, and the change in the worldwide stock of patents in IDT (2000-2014) and its interaction with the share of blue-collar workers. Standard errors clustered at the 4-digit industry level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

ment and control of industrial machines and automated or robotised systems, and with a level of qualification between specialised and unqualified workers. These results are consistent with the idea that IDT are introduced to revise the way in which firms control and manage the machines involved in the production process: these technologies shift labour demand from profiles associated with simple machine operations to those involved in the construction, repair or maintenance of the machines. This is consistent with a reading of technological adoption that does not focus on labour-saving objectives, but rather on improving productivity, and is accordingly accompanied by changes in the organisational process and in the composition and training of the workforce (Battisti et al., 2023; Cirillo et al., 2021). These results also suggest that IDT investment may displace people performing simple cognitive activities associated with automation, but may enhance other specialised activities, in line with the theoretical prediction of simultaneous displacement and reinstatement effects (Acemoglu and Restrepo, 2019).

Our estimates also show that firms investing in ODT are less likely than non-investing firms to look for unqualified workers, who perform simple and repetitive physical activities that do not require a specific qualification. This suggests a displacement effect for this type of unskilled workers, as suggested by Dauth et al. (2021), who examine new hiring in German firms investing in robotics. On the other hand, firms investing in ODT are just as likely as non-investing firms to look for other profiles.

5 Closing remarks

This paper contributes to the literature on the impact of investments in new digital technologies on firms' workforce. By developing a new empirical methodology to identify the casual effects of different technological investments at the firm level, it provides new evidence on the observed evolution of firms' labour demand.

Methodologically, our novel empirical strategy to identify the causal effects of technological investment is based on IV-2SLS estimations with exogenous instrumental variables that affect firms' employment only through their impact on the probability of investing in ODT and IDT. We rely on global technological progress in ODT and IDT at the industry level, which is proxied by the lagged change in the worldwide stock of patents at the 4-digit industry level. Worldwide patent development is exogenous to each firm in our sample. In addition, we interact changes in patent stocks with predetermined firm-level variables in order to capture the variation in investment across firms within the same industry. This approach makes it possible to identify the effects of ODT and IDT on firm employment separately, despite the high correlation between these investment

Table 6: Effect of investment in digital technologies on the types of profiles to recruit

	Executive (1)	Scientific (2)	Technical (3)	Administrative (4)	Sales (5)	Specialised (6)	Qualified (7)	Unqualified (8)
Investment in ODT	-0.047	-0.156	0.203	-0.084	-0.087	0.334	0.029	-0.055**
	(0.065)	(0.135)	(0.355)	(0.142)	(0.125)	(0.317)	(0.044)	(0.026)
Investment in IDT	0.131	0.350**	0.584	0.171	0.220	0.288***	-0.079**	-0.031
	(0.111)	(0.166)	(0.378)	(0.203)	(0.146)	(0.102)	(0.039)	(0.025)
Firm controls	yes	yes	yes	yes	yes	yes	yes	yes
Workforce controls	yes	yes	yes	yes	yes	yes	yes	yes
Manager controls	yes	yes	yes	yes	yes	yes	yes	yes
Other investments	yes	yes	yes	yes	yes	yes	yes	yes
No. patents in other technologies	yes	yes	yes	yes	yes	yes	yes	yes
Region FE	yes	yes	yes	yes	yes	yes	yes	yes
Sector FE	yes	yes	yes	yes	yes	yes	yes	yes
Observations	9332	9332	9332	9332	9332	9332	9332	9332
Kleibergen-Paap LM stat	7.029*	7.029*	7.029*	7.029*	7.029*	7.029*	7.029*	7.029*
Kleibergen-Paap Wald F stat	80.148	80.148	80.148	80.148	80.148	80.148	80.148	80.148
Anderson-Rubin Wald Chi-sq stat	19.47***	19.47***	19.47***	19.47***	19.47***	19.47***	19.47***	19.47***
Hansen J stat	2.374	0.773	3.585	2.758	2.192	2.103	0.484	0.801

Notes: The dependent variables are dummies equal to one if the firm is aiming to recruit at the time of the interview (2018). *Executive* profiles are defined as “planning and coordination of corporate strategies”. *Scientific* profiles are defined as “analysis of complex situations and development of new knowledge”. *Technical* profiles are defined as “control of production processes and application of operational protocols”. *Administrative* profiles are defined as “acquisition, processing, storage and transmission of information”. *Sales* profiles are defined as “assistance to customers, consumers, citizens”. *Specialised* profiles are defined as “construction, repair or maintenance of artefacts, objects and machines”. *Qualified* profiles are defined as “management and control of industrial machines and automated or robotised systems”. *Unqualified* profiles are defined as “simple and repetitive activities for which a particular qualification is not required”. Firm controls include the log of the total number of employees in 2014, total sales in 2014, the log of firm age in 2014, the log of the number of plants in 2014, a dummy equal to one if the firm belongs to a group in 2014, a dummy equal to one if the firm is owned by a family in 2014, a dummy equal to one if the firm is owned by a financial company in 2014, and a dummy equal to one if the firm completed a capital operation in the period 2015-2017. Workforce controls include the share of white-collar workers in 2014, the share of blue-collar workers in 2014, a dummy equal to one if the firm provides on-the-job training in 2014, and a dummy equal to one if the firm employs agency workers. Manager controls include gender, age, and dummies for the level of education of the top manager in 2014, a dummy equal to one if the top manager is a member of family owning the firm, and dummies for the top manager’s remuneration scheme. Other investments includes two dummies equal to one if the firm makes investment in marketing, advertising, land, buildings, and other types of investment in 2014 and 2017. No. patents in other technologies includes the change in the worldwide stock of patents that fall neither in ODT nor in IDT at the 4-digit industry level (2000-2014) and its interactions with the shares of blue-collar and white-collar workers. All regressions are estimated with the 2SLS estimator. The instruments are the change in the worldwide stock of patents in ODT (2000-2014) and its interaction with the share of white-collar workers, and the change in the worldwide stock of patents in IDT (2000-2014) and its interaction with the share of blue-collar workers. Standard errors clustered at the 4-digit industry level are reported in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

decisions. In particular, the joint estimation of the effects of these different technologies would not be possible with other identification methods, such as the propensity score matching at the firm level.

The empirical analysis shows that ODT and IDT have different effects on firm employment and on the composition of the workforce within firms, confirming the non-neutrality of technology. Investment in ODT does not have a relevant effect on overall firm employment levels, but it leads to a more flexible structure of the workforce through temporary contracts at the expense of permanent ones and agency workers. Firms investing in ODT are no more likely that non-investing firms to develop training programmes, but they are particularly focused on training activities that cover task-specific technical aspects. Firms investing in ODT are also less likely to look for new workers for simple and repetitive activities that do not require a specific qualification. Taken together, these findings on ODT investment suggest the existence of a partial displacement of workers performing simple and repetitive activities, a limited engagement of firms in general and IT-related training and their reliance on a more flexible workforce.

On the contrary, investment in IDT has a positive and significant effect on firm employment, driven by an increase in the share of apprenticeship contracts at the expense of temporary workers and agency workers. This tendency to upgrade and upskill the workforce is also reflected in the greater likelihood that firms investing in IDT provide more training, especially more IT-related training. Moreover, these firms are more likely to look for new workers with qualified scientific profiles and workers involved in the construction, repair or maintenance of artefacts, objects and machines.

These results show the coexistence of displacement and reinstatement effects within firms, with a relative increase in the demand for highly skilled workers capable of interacting with new IDT, and flexibility enhancing effects in firms investing in ODT. Our findings confirm those theoretical models and empirical studies that suggest that the employment effects of investment in new digital technologies are highly heterogeneous across technological domains and workers' occupations, and thus strengthen the case for more empirical research that looks at effects measured at a granular level.

The differential impact of ODT and IDT calls for great care in interpreting the empirical results obtained in empirical studies that combine many different technologies.[22] The distinction between ODT and IDT is justified by their different role in and expected impact on the production process: while ODT tend to replace human tasks associated with repetitive movements in space, IDT tend to accompany a more comprehensive revision of the organisation with the aim of optimising the process and the products, thanks to the data collected with the new digital artefacts. This is in line with the increased importance of IT-related knowledge and advanced skills that firms investing in IDT tend to have.

Projecting our firm-level findings to a higher level, it appears that the diffusion of IDT is accompanied by firms' investment in the development of new skills and IT-related knowledge. This positive impact on workers' knowledge and skills, together with the positive impact on employment in adopting firms, casts a positive light on the labour-related effects of IDT in the 4IR paradigm.

Finally, a word of caution is in order. There are risks in stretching the interpretation of our results. Our results are to be interpreted as LATE, not average treatment effects on the treated, and we cannot estimate spillover effects in non-adopting firms. Also, the set of 4IR technologies covered in RIL is limited, as the data do not provide information on the adoption of artificial intelligence, additive manufacturing, simulation, and cloud computing. Nevertheless, our analysis provides compelling and novel evidence on the heterogeneous effects of different digital technologies on firms' labour demand and human resource management.

[22]It could be argued that this observation requires the separation of the individual IDT that we have put together. While this is true in theory, it is difficult to put into practice. Not only is the adoption of these technologies highly correlated, but it is also more difficult to identify valid instrumental variables for each technology separately. The same problem would also affect those studies that use difference-in-difference estimation and propensity score matching to analyse the impact of one technology at a time: these methods would require the identification of some technology-specific variables that would allow a good matching between investing and non-investing firms.

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A Appendix

A.1 Methodological details

Table A1: Identification of patents

Technology	CPC classes	Keywords
Robotics	B25J19/0016, B25J7/00, B25J19/0079, B25J9/0093, B25J15/0253, B25J19/0012, G01B5/25, B25J9/1612, B65G47/90, B25J19/06, B25J18/025, B25J9/109, B23P19/102, B25J9/1065, H05K13/0408, B21D43/105, B25J9/107, B25J9/161, G05B19/4083, B25J19/0029, B25J19/002, G05B2219/45213, A61B2019/464, A47L2201/00, H01L21/6838, B23P19/105, B05B13/0431, A63H11/00, B62D57/032, A61B2019/2296, H01L21/681, B25J19/023, H01L21/67742, B25J15/0616, B25J17/0275, B25J9/042, G01L5/228, A61B19/2203, G05B19/427, A61B2019/223, B25J19/021, B25J9/026, G05D1/0255, G05B2219/45083, A61B2019/2292, A61F2002/701, B25J15/0491, G01N29/265, A61B19/5212, B25J9/14, B25J9/00, B25J9/1692, B05B13/0452, B25J17/0266, B25J9/04, B23K9/0956, B05B12/14, B23Q7/04, B25J15/0009, B25J9/101, A61B2019/2242, F22B37/003, B25J13/082, B25J15/04, B25J18/02, B25J9/1697, B25J15/0019, B25J9/08, B25J9/046, B25J17/0208, B25J13/084, B25J17/0258, G05B19/41825, B25J9/1671, H05K13/0413, G05B19/4207, B25J17/0241, G05D1/0272, B25J9/1682, A61B2019/5259, B25J9/102, B23Q3/002, B23Q1/38, B23K9/287, B25J15/02, G06N3/008, B25J9/1689, B25J19/0008, H01L21/68707, B25J9/06, B25J9/104, B25J15/00, B05B13/0292, B23K9/1274, B25J15/0206, B25J17/0283, B25J9/10, G05B19/425, B65G61/00, B23Q1/5462, B25J19/0025, B25J13/085, B25J19/063, G05B19/4182, G21C17/01, B23P19/12, A61B19/22, G05B2219/37572, B25J9/041, G05D1/0225, B25J9/0084, G01N27/902, G01B7/008, G05B19/416, B25J9/1045, B65G47/91, B25J9/045, A61B2019/2223, G05B19/42, G05B2219/45104, B25J9/023, B25J9/0081, B25J15/103, G05D1/0274, Y10S901	robot, cobot, [self driving, self-driving, driveless, autonomous, automated, automated guided, automated-guided, unmanned]*[cell, car, vehicle, automobile, aircraft, airplane, aeroplane, marine]

(continued)

Table A1 – continued

Technology	CPC classes	Keywords
Big data	A61B5/72-A61B5/7296, A61B6/581, A61B8/4472, A61B8/56-A61B8/565, A61B8/582, A63B24/00-A63B2024/0096, B05C11/10-B05C11/105, B60S5/02, B60S5/06, B60W10/00-B60W10/30, B60W30/00-B60W2030/206, B60W50/00-B60W50/16, B60W60/00-B60W60/007, B61L15/00-B61L15/02, B61L23/00-B61L23/34, B61L27/00-B61L27/04, B61L3/00-B61L3/246, B64C2201/12-B64C2201/128, B64C39/024, B64F1/228, B64F5/40-B64F5/45, B64F5/60, D06F33/00, E05C17/58, E21B44/00-E21B44/10, E21B47/00-E21B47/24, F01K13/02-F01K13/025, F01N11/00-F01N11/007, F01N2900/04-F01N2900/0422, F01N9/00-F01N9/007, F02C9/00-F02C9/58, F02D1/00-F02D41/408, F02K9/00-F02K9/978, F02N11/08-F02N2011/0896, F02N2200/00-F02N2200/14, F02P5/00-F02P5/1558, F03B15/00-F03B15/22, F03D17/00, F03D7/042-F03D7/048, F04B49/06-F04B49/065, F04B51/00, F04C14/00-F04C14/28, F04C28/00-F04C28/28, F04D27/00-F04D27/0292, F05D2270/00-F05D2270/71, F16D66/00-F16D66/028, F22B35/00-F22B35/16, F22B35/18, F22D5/00-F22D5/36, F23N5/00-F23N5/265, F24D19/10-F24D19/1096, F24F11/00-F24F11/89, F24S50/00-F24S50/80, F25B49/00-F25B49/046, F25D21/006, F25D29/00-F25D29/008, F25J1/0244-F25J1/0256, F28F27/00-F28F27/02, G03G15/00-G03G15/5095, G05B15/00-G05B15/02, G05B19/00-G05B19/427, G05B23/02-G05B23/0297, G05D23/00-G05D23/32, G06F11/22-G06F11/277, G06F11/30-G06F11/3495, G06F11/36-G06F11/3696, G16B5/00-G16B45/00, G16C20/00-G16C20/90, G16C60/00, G06K9/00-G06K9/82, G06Q10/04-G06Q10/047, G06Q10/06-G06Q10/067, G06Q50/10-G06Q50/265, G07C5/00-G07C5/12, G08G1/00-G08G1/22, H02J13/00-H02J13/0089, H04N17/00-H04N17/06, G06F17/18	online analytical process, multi-dimensional analytic, tensor, dimensionality reduction, reduce dimension, reducing dimension, multilinear subspace learn, massively parallel, clustered file system, big data, [cloud, parallel]*[comput, process], [data]*[capture, storage, mining, integration, lake, warehouse], [distributed]*[parallel architecture, file system, cache, data]

(continued)

Table A1 – continued

Technology	CPC classes	Keywords
IoT	G16Y, H04L29/08, H04L12/28, H04L29/06, G06F15/16, G05B19/418, H04W84/18, H04W4/00, G08C17/02, H04W72/04, H04B7/26, H04W4/70, Y02B70/3, Y02B90/20	iot, internet of thing, web of thing, internet of everything, ambient intelligence, ubiquitous comput, [car, vehicle, device, machine, peer]*[-, 2, to]*[car, vehicle, infrastructure, server, device, machine, peer, anything, something], [inter, connected, networked, smart]*[car, vehicle, device, machine, grid, home]

(continued)

Table A1 – continued

Technology	CPC classes	Keywords
Virtual reality	A61B2017/00115-A61B2017/00128, A61B34/25-A61B2034/258, A63B71/06-A63B71/0697, A63F2300/00-A63F2300/8094, B60K35/00, B60K37/06, B64D45/00-B64D45/08, D06F34/28, G02B27/01-G02B2027/0198, G10L13/00-G10L2013/105, G10L15/00-G10L15/34, G10L17/00-G10L17/26, G10L19/00-G10L19/265, G10L21/00-G10L21/18, G10L25/00-G10L2025/937, G06F40/20-G06F40/58, G06T19/00-G06T19/20	data eyeglass, google glass, data spectacle, data display, display helmet, [head, wearable]*[mount, display], [augment, augmented, virtual, mixed, enhanced, mediated]*[reality, environment, world]

(continued)

Table A1 – continued

Technology	CPC classes	Keywords
IT security	G06F21/00-G06F21/88, H04L63/00-H04L63/308, H04L9/00-H04L9/38, H04W12/00-H04W12/128	cybersecurity, access control, cryptography, encryption, firewall, mobile secure gateway, secure sockets layer, [it, information technology, information-technology, application, app, computer, data, information, endpoint, end-point, cyber, transport layer, transport-layer, cloud]*security, anti*[virus, malware, spyware]

Table A2: Overlapping patents

	Robotics	Big data	IoT	Virtual reality	Cybersecurity
Robotics	-	0.0001	0	0.0001	0.0002
Big data	0.0016	-	0.0008	0	0.0024
IoT	0	0.0007	-	0	0.0042
Virtual reality	0.0005	0	0	-	0.0008
Cybersecurity	0.0002	0.0002	0.0004	0.0002	-

Notes: The table indicates the proportion of patents included in the digital technologies in each row that are also included in the digital technologies in each column.

A.2 Additional descriptive statistics

Table A3: Descriptive statistics, dependent variables

	Mean	SD
Growth no. employees (2014-2017)	0.04	0.21
Difference share of employees with permanent contract (2014-2017)	-0.02	0.17
Difference share of employees with temporary contract (2014-2017)	0.02	0.15
Difference share of employees in apprenticeship (2014-2017)	0.00	0.09
Difference share of employees on demand (2014-2017)	0.00	0.05
Training, task-specific (2017)	0.37	0.48
Training, IT-related (2017)	0.11	0.31
Use of agency workers (2017)	0.16	0.37
Share of agency workers (2017)	0.02	0.15
Recruitment, executive (2018)	0.01	0.07
Recruitment, scientific (2018)	0.02	0.16
Recruitment, technical (2018)	0.07	0.26
Recruitment, administrative (2018)	0.03	0.17
Recruitment, sales (2018)	0.04	0.18
Recruitment, specialised (2018)	0.07	0.26
Recruitment, qualified (2018)	0.03	0.17
Recruitment, unqualified (2018)	0.02	0.13

Notes: Growth no. employees (2014-2017) is calculated as the difference of the log of the number of employees between 2017 and 2014. Training, task-specific is a dummy equal to one if the firm provides task-specific technical training in 2017. Training, IT-related is a dummy equal to one if the firm provides IT-related training in 2017. Use of agency workers is a dummy equal to one if the firm employs agency workers in 2017. Share of agency workers is the share of agency workers over total employment in 2017. Recruitment, *type* are dummies equal to one if the firm is aiming to recruit profile *type* at the time of the interview (2018).

Table A4: Descriptive statistics, control variables

	Mean	SD
No. employees (2014)	65.91	222.52
Total sales (2014)	32.43	702.73
Firm age (2014)	28.26	14.82
No. plants (2014)	1.78	11.53
Part of group (2014)	0.15	0.36
Owned by family (2014)	0.83	0.38
Owned by financial group (2014)	0.09	0.29
Performed capital operations (2015-2017)	0.05	0.22
Manager type, family owner (2014)	0.87	0.34
Manager gender, female (2014)	0.13	0.34
Manager age, 50+ (2014)	0.70	0.46
Manager education, upper secondary and higher (2014)	0.81	0.40
Manager remuneration, variable (2014)	0.44	0.50
Training, any (2014)	0.57	0.49
Use of agency workers (2014)	0.20	0.40
Other investments (2014)	0.19	0.40
Other investments (2017)	0.18	0.38
No. patents in other technologies (2000-2014) $\times$1000	0.24	0.74

Notes: Total sales is the amount in millions of Euros of total sales in 2014. Training, any is a dummy equal to one if the firm provides any on-the-job training in 2014. Use of agency workers is a dummy equal to one if the firm employs agency workers in 2014. Other investments are two dummies equal to one if the firm makes investment in marketing, advertising, land, buildings, and other types of investment in 2014 and 2017. No. patents in other technologies (2000-2014) is the change in the worldwide stock of patents that fall neither in ODT nor in IDT at the 4-digit industry level (2000-2014, $\times$1000).

A.3 OLS

Table A5: Effect of investment in digital technologies on total employment growth, OLS

	(1)	(2)	(3)
Investment in ODT	0.030***	0.027***	0.027***
	(0.008)	(0.008)	(0.008)
Investment in IDT	0.030***	0.025***	0.026***
	(0.005)	(0.005)	(0.005)
Firm controls	yes	yes	yes
Workforce controls	yes	yes	yes
Manager controls	yes	yes	yes
Other investments	no	yes	yes
No. patents in other technologies	no	no	yes
Region FE	yes	yes	yes
Sector FE	yes	yes	yes
Observations	9332	9332	9332

Notes: The dependent variable is the difference in the log of the total number of workers between 2014 and 2017. Firm controls include the log of the total number of employees in 2014, total sales in 2014, the log of firm age in 2014, the log of the number of plants in 2014, a dummy equal to one if the firm belongs to a group in 2014, a dummy equal to one if the firm is owned by a family in 2014, a dummy equal to one if the firm is owned by a financial company in 2014, and a dummy equal to one if the firm completed a capital operation in the period 2015-2017. Workforce controls include the share of white-collar workers in 2014, the share of blue-collar workers in 2014, a dummy equal to one if the firm provides on-the-job training in 2014, and a dummy equal to one if the firm employs agency workers. Manager controls include gender, age, and dummies for the level of education of the top manager in 2014, a dummy equal to one if the top manager is a member of family owning the firm, and dummies for the top manager's remuneration scheme. Other investments includes two dummies equal to one if the firm makes investment in marketing, advertising, land, buildings, and other types of investment in 2014 and 2017. No. patents in other technologies includes the change in the worldwide stock of patents that fall neither in ODT nor in IDT at the 4-digit industry level (2000-2014) and its interactions with the shares of blue-collar and white-collar workers. All regressions are estimated with the OLS estimator. Standard errors clustered at the 4-digit industry level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

A.4 First stage

Table A6: First stage

	Investment in ODT	Investment in IDT
	(1)	(2)
No. patents in ODT ×1000	0.054***	0.042***
	(0.008)	(0.008)
No. patents in IDT ×1000	-0.008	0.048***
	(0.017)	(0.008)
No. patents in ODT ×	-0.148**	0.064
Share of white-collar workers	(0.070)	(0.047)
No. patents in IDT ×	-0.006	0.067***
Share of blue-collar workers	(0.042)	(0.021)
Firm controls	yes	yes
Workforce controls	yes	yes
Manager controls	yes	yes
Other investments	yes	yes
No. patents in other technologies	yes	yes
Region FE	yes	yes
Sector FE	yes	yes
Observations	9332	9332
Sanderson-Windmeijer Chi-sq stat	188.03***	323.82***
Sanderson-Windmeijer F stat	62.14***	107.01***
Kleibergen-Paap LM stat	7.029*	7.029*
Kleibergen-Paap Wald F stat	80.148	80.148
Anderson-Rubin Wald Chi-sq stat	19.47***	19.47***
Hansen J stat	0.807	0.807

Notes: The dependent variable is investment in operational digital technologies (ODT) in the period 2015-2017 in column (1) and investment in information digital technologies (IDT) in the period 2015-2017 in column (2). Firm controls include the log of the total number of employees in 2014, total sales in 2014, the log of firm age in 2014, the log of the number of plants in 2014, a dummy equal to one if the firm belongs to a group in 2014, a dummy equal to one if the firm is owned by a family in 2014, a dummy equal to one if the firm is owned by a financial company in 2014, and a dummy equal to one if the firm completed a capital operation in the period 2015-2017. Workforce controls include the share of white-collar workers in 2014, the share of blue-collar workers in 2014, a dummy equal to one if the firm provides on-the-job training in 2014, and a dummy equal to one if the firm employs agency workers. Manager controls include gender, age, and dummies for the level of education of the top manager in 2014, a dummy equal to one if the top manager is a member of family owning the firm, and dummies for the top manager's remuneration scheme. Other investments includes two dummies equal to one if the firm makes investment in marketing, advertising, land, buildings, and other types of investment in 2014 and 2017. No. patents in other technologies includes the change in the worldwide stock of patents that fall neither in ODT nor in IDT at the 4-digit industry level (2000-2014) and its interactions with the shares of blue-collar and white-collar workers. Standard errors clustered at the 4-digit industry level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

A.5 Robustness checks

Table A7: Effect of investment in digital technologies on total employment growth, Heckman correction

	Observed in 2015 & 2018	Investment in ODT	Investment in IDT	Growth no. employees
Observed in 2010	0.162***			
	(0.018)			
No. patents in ODT	0.004	0.054***	0.042***	
	(0.031)	(0.014)	(0.014)	
No. patents in IDT	0.003	-0.008	0.048***	
	(0.034)	(0.018)	(0.018)	
No. patents in ODT ×	0.115	-0.143**	0.086	
Share of white-collar workers	(0.141)	(0.068)	(0.090)	
No. patents in IDT ×	0.069	-0.003	0.079	
Share of blue-collar workers	(0.085)	(0.040)	(0.050)	
Inverse Mills Ratio		0.067	0.300***	0.025
		(0.052)	(0.100)	(0.051)
Investment in ODT				-0.069
				(0.110)
Investment in IDT				0.238**
				(0.098)
Firm controls	yes	yes	yes	yes
Workforce controls	yes	yes	yes	yes
Manager controls	yes	yes	yes	yes
Other investments	yes	yes	yes	yes
No. patents in other technologies	yes	yes	yes	yes
Region FE	yes	yes	yes	yes
Sector FE	yes	yes	yes	yes
Observations	23483	9332	9332	9332
Sanderson-Windmeijer Chi-sq stat		179.08***	319.70***	
Sanderson-Windmeijer F stat		59.17***	105.64***	
Kleibergen-Paap LM stat		6.705*	6.705*	6.705*
Kleibergen-Paap Wald F stat		76.834	76.834	76.834
Anderson-Rubin Wald Chi-sq stat		21.88***	21.88***	21.88***
Hansen J stat		0.847	0.847	0.847

Notes: Column (1) corresponds to the selection equation, columns (2) and (3) correspond to the first stage of the 2SLS estimation and column (4) corresponds to the second stage of the 2SLS estimation. The dependent variable is a dummy equal to one if the firm is observed in the 2015 and 2018 waves in column (1) (Observed in 2015 & 2018), two dummies equal to one if the firm invests in ODT and IDT between 2015 and 2017 in columns (2) and (3) (Investment in ODT, Investment in IDT), and the difference in the log of the total number of workers between 2014 and 2017 in column (4) (Growth no. employees). Observed in 2010 is a dummy equal to one if the firm is observed in the 2010 wave. Firm controls include the log of the total number of employees in 2014, total sales in 2014, the log of firm age in 2014, the log of the number of plants in 2014, a dummy equal to one if the firm belongs to a group in 2014, a dummy equal to one if the firm is owned by a family in 2014, a dummy equal to one if the firm is owned by a financial company in 2014, and a dummy equal to one if the firm completed a capital operation in the period 2015-2017. Workforce controls include the share of white-collar workers in 2014, the share of blue-collar workers in 2014, a dummy equal to one if the firm provides on-the-job training in 2014, and a dummy equal to one if the firm employs agency workers. Manager controls include gender, age, and dummies for the level of education of the top manager in 2014, a dummy equal to one if the top manager is a member of family owning the firm, and dummies for the top manager's remuneration scheme. Other investments includes two dummies equal to one if the firm makes investment in marketing, advertising, land, buildings, and other types of investment in 2014 and 2017. No. patents in other technologies includes the change in the worldwide stock of patents that fall neither in ODT nor in IDT at the 4-digit industry level (2000-2014) and its interactions with the shares of blue-collar and white-collar workers. The regression in column (4) is estimated with the 2SLS estimator. The instruments are the change in the worldwide stock of patents in ODT (2000-2014) and its interaction with the share of white-collar workers, and the change in the worldwide stock of patents in IDT (2000-2014) and its interaction with the share of blue-collar workers. Bootstrapped standard errors (500 iterations) are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A8: Effect of investment in digital technologies on total employment growth, sensitivity to sample

	(1)	(2)
Investment in ODT	-0.059	-0.067
	(0.068)	(0.097)
Investment in IDT	0.228***	0.237***
	(0.071)	(0.090)
Firm controls	yes	yes
Workforce controls	yes	yes
Manager controls	yes	yes
Other investments	yes	yes
No. patents in other technologies	yes	yes
Region FE	yes	yes
Sector FE	yes	yes
Observations	9183	8860
Kleibergen-Paap LM stat	5.861	6.955*
Kleibergen-Paap Wald F stat	77.771	59.855
Anderson-Rubin Wald Chi-sq stat	19.89***	18.58***
Hansen J stat	0.848	0.919

Notes: The dependent variable is the difference in the log of the total number of workers between 2014 and 2017. The sample in column (1) excludes NACE sector C28 (Manufacture of machinery and equipment). The sample in column (2) excludes large firms (with more than 250 employees). Firm controls include the log of the total number of employees in 2014, total sales in 2014, the log of firm age in 2014, the log of the number of plants in 2014, a dummy equal to one if the firm belongs to a group in 2014, a dummy equal to one if the firm is owned by a family in 2014, a dummy equal to one if the firm is owned by a financial company in 2014, and a dummy equal to one if the firm completed a capital operation in the period 2015-2017. Workforce controls include the share of white-collar workers in 2014, the share of blue-collar workers in 2014, a dummy equal to one if the firm provides on-the-job training in 2014, and a dummy equal to one if the firm employs agency workers. Manager controls include gender, age, and dummies for the level of education of the top manager in 2014, a dummy equal to one if the top manager is a member of family owning the firm, and dummies for the top manager's remuneration scheme. Other investments includes two dummies equal to one if the firm makes investment in marketing, advertising, land, buildings, and other types of investment in 2014 and 2017. No. patents in other technologies includes the change in the worldwide stock of patents that fall neither in ODT nor in IDT at the 4-digit industry level (2000-2014) and its interactions with the shares of blue-collar and white-collar workers. All regressions are estimated with the 2SLS estimator. The instruments are the change in the worldwide stock of patents in ODT (2000-2014) and its interaction with the share of white-collar workers, and the change in the worldwide stock of patents in IDT (2000-2014) and its interaction with the share of blue-collar workers. Standard errors clustered at the 4-digit industry level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A9: Effect of investment in digital technologies on total employment growth, LASSO

	(1)	(2)
Investment in ODT	-0.047	-0.047
	(0.085)	(0.085)
Investment in IDT	0.219***	0.121**
	(0.080)	(0.047)
Region FE	yes	yes
Sector FE	yes	yes
Observations	9332	9332
Weak identification F stat	77.85	55.27

Notes: The dependent variable is the difference in the log of the total number of workers between 2014 and 2017. All regressions are estimated with the IV-LASSO estimator. Region and sector fixed effects are partialled out, so they are not penalised by LASSO. The covariates that are not penalised by LASSO are the share of white-collar workers in 2014 and the share of blue-collar workers in 2014. The instruments that are not penalised by LASSO are the change in the worldwide stock of patents in ODT (2000-2014) and its interaction with the share of white-collar workers, and the change in the worldwide stock of patents in IDT (2000-2014) and its interaction with the share of blue-collar workers. In column (1), LASSO selects covariates from the full set of variables available in the 2015 wave of RIL. In column (2), LASSO selects IVs from the full set of interactions between the IVs that are not penalised and the variables available in the 2015 wave of RIL. Standard errors clustered at the 4-digit industry level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A10: Effect of investment in digital technologies on total employment growth, separate treatments

	(1)	(2)
Investment in ODT	0.047	
	(0.057)	
Investment in IDT		0.211***
		(0.050)
Firm controls	yes	yes
Workforce controls	yes	yes
Manager controls	yes	yes
Other investments	yes	yes
No. patents in other technologies	yes	yes
Region FE	yes	yes
Sector FE	yes	yes
Observations	9332	9332
Kleibergen-Paap LM stat	1.688	4.651*
Kleibergen-Paap Wald F stat	28.325	58.150
Anderson-Rubin Wald Chi-sq stat	7.99**	14.61***
Hansen J stat	4.835	0.290

Notes: The dependent variable is the difference in the log of the total number of workers between 2014 and 2017. Firm controls include the log of the total number of employees in 2014, total sales in 2014, the log of firm age in 2014, the log of the number of plants in 2014, a dummy equal to one if the firm belongs to a group in 2014, a dummy equal to one if the firm is owned by a family in 2014, a dummy equal to one if the firm is owned by a financial company in 2014, and a dummy equal to one if the firm completed a capital operation in the period 2015-2017. Workforce controls include the share of white-collar workers in 2014, the share of blue-collar workers in 2014, a dummy equal to one if the firm provides on-the-job training in 2014, and a dummy equal to one if the firm employs agency workers. Manager controls include gender, age, and dummies for the level of education of the top manager in 2014, a dummy equal to one if the top manager is a member of family owning the firm, and dummies for the top manager's remuneration scheme. Other investments includes two dummies equal to one if the firm makes investment in marketing, advertising, land, buildings, and other types of investment in 2014 and 2017. No. patents in other technologies includes the change in the worldwide stock of patents that fall neither in ODT nor in IDT at the 4-digit industry level (2000-2014) and its interactions with the shares of blue-collar and white-collar workers. All regressions are estimated with the 2SLS estimator. The instruments are the change in the worldwide stock of patents in ODT (2000-2014) and its interaction with the share of white-collar workers, and the change in the worldwide stock of patents in IDT (2000-2014) and its interaction with the share of blue-collar workers. Standard errors clustered at the 4-digit industry level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A11: Effect of investment in digital technologies on total employment growth, 2009 shares

	(1)	(2)	(3)
Investment in ODT	0.153*	0.139*	0.158*
	(0.080)	(0.081)	(0.085)
Investment in IDT	0.305**	0.303**	0.320**
	(0.139)	(0.123)	(0.128)
Firm controls	yes	yes	yes
Workforce controls	yes	yes	yes
Manager controls	yes	yes	yes
Other investments	no	yes	yes
No. patents in other technologies	no	no	yes
Region FE	yes	yes	yes
Sector FE	yes	yes	yes
Observations	3441	3441	3441
Kleibergen-Paap LM stat	4.038	3.920	4.188
Kleibergen-Paap Wald F stat	8.791	17.395	14.148
Anderson-Rubin Wald Chi-sq stat	14.35***	16.65***	17.51***
Hansen J stat	1.513	1.729	1.579

Notes: The dependent variable is the difference in the log of the total number of workers between 2014 and 2017. Firm controls include the log of the total number of employees in 2014, total sales in 2014, the log of firm age in 2014, the log of the number of plants in 2014, a dummy equal to one if the firm belongs to a group in 2014, a dummy equal to one if the firm is owned by a family in 2014, a dummy equal to one if the firm is owned by a financial company in 2014, and a dummy equal to one if the firm completed a capital operation in the period 2015-2017. Workforce controls include the share of white-collar workers in 2009, the share of blue-collar workers in 2009, a dummy equal to one if the firm provides on-the-job training in 2014, and a dummy equal to one if the firm employs agency workers. Manager controls include gender, age, and dummies for the level of education of the top manager in 2014, a dummy equal to one if the top manager is a member of family owning the firm, and dummies for the top manager's remuneration scheme. Other investments includes two dummies equal to one if the firm makes investment in marketing, advertising, land, buildings, and other types of investment in 2014 and 2017. No. patents in other technologies includes the change in the worldwide stock of patents that fall neither in ODT nor in IDT at the 4-digit industry level (2000-2014) and its interactions with the shares of blue-collar and white-collar workers. All regressions are estimated with the 2SLS estimator. The instruments are the change in the worldwide stock of patents in ODT (2000-2014) and its interaction with the share of white-collar workers in 2009, and the change in the worldwide stock of patents in IDT (2000-2014) and its interaction with the share of blue-collar workers in 2009. Standard errors clustered at the 4-digit industry level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A12: Effect of investment in digital technologies on total employment growth, pre-trend

	(1)
Investment in ODT	0.143
	(0.194)
Investment in IDT	0.341
	(0.217)
Firm controls	yes
Workforce controls	yes
Manager controls	yes
Other investments	yes
No. patents in other technologies	yes
Region FE	yes
Sector FE	yes
Observations	3441
Kleibergen-Paap LM stat	6.537*
Kleibergen-Paap Wald F stat	4.370
Anderson-Rubin Wald Chi-sq stat	21.84***
Hansen J stat	2.086

Notes: The dependent variable is the difference in the log of the total number of workers between 2009 and 2014. Firm controls include the log of the total number of employees in 2014, total sales in 2014, the log of firm age in 2014, the log of the number of plants in 2014, a dummy equal to one if the firm belongs to a group in 2014, a dummy equal to one if the firm is owned by a family in 2014, a dummy equal to one if the firm is owned by a financial company in 2014, and a dummy equal to one if the firm completed a capital operation in the period 2015-2017. Workforce controls include the share of white-collar workers in 2014, the share of blue-collar workers in 2014, a dummy equal to one if the firm provides on-the-job training in 2014, and a dummy equal to one if the firm employs agency workers. Manager controls include gender, age, and dummies for the level of education of the top manager in 2014, a dummy equal to one if the top manager is a member of family owning the firm, and dummies for the top manager's remuneration scheme. Other investments includes two dummies equal to one if the firm makes investment in marketing, advertising, land, buildings, and other types of investment in 2014 and 2017. No. patents in other technologies includes the change in the worldwide stock of patents that fall neither in ODT nor in IDT at the 4-digit industry level (2000-2014) and its interactions with the shares of blue-collar and white-collar workers. All regressions are estimated with the 2SLS estimator. The instruments are the change in the worldwide stock of patents in ODT (2000-2014) and its interaction with the share of white-collar workers, and the change in the worldwide stock of patents in IDT (2000-2014) and its interaction with the share of blue-collar workers. Standard errors clustered at the 4-digit industry level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.