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ABSTRACT

Advanced Digital Technologies and Investment in Employee Training: Complements or Substitutes?*

Using firm-level data covering the 27 EU countries, the UK and the US, we show that employers tend to reduce investment in training per employee after adopting advanced digital technologies (ADT). We estimate with a control function approach firm-level production functions augmented with two factors, the training stock per employee and digital technology use. We show that ADT use and employee training are substitutes in production, implying that an increase in the former negatively affects the marginal productivity of the latter, and that a decline in the cost of introducing ADT reduces employers' investment in training per employee. These findings point to challenges in realizing high levels of firm-sponsored training for employees in increasingly digital economies.

JEL Classification: D24, J24

Keywords: digitization, automation, training, productivity

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1. Introduction

The use of advanced digital technologies (ADT henceforth) – such as 3D printing, advanced robotics, augmented reality, drones, online platforms, internet of things, big data analytics and artificial intelligence (AI) – is spreading in developed countries, encouraged by declining costs[1] and most recently accelerated by the COVID-19 pandemic (Chernoff and Warman, 2021; EIB, 2022). ADT expand the set of tasks within the production process that can be performed by capital, which decreases the share of tasks performed by labor (Acemoglu and Restrepo, 2019; Acemoglu et al., 2022). The replacement of labor with cheaper capital can result in productivity gains, with uncertain effects on labor demand.[2]

Affected workers may need to re-skill or up-skill to adapt to the re-organization of tasks and the emergence of new tasks following the introduction of ADT, and to navigate transitions to new jobs. The impact of ADT on workers will depend on firm-level incentives to retain and retrain staff and on institutional factors, such as the general infrastructure for training and job-search available in the country, direct government funding, tax incentives and social benefit systems (Nedelkoska and Quintini, 2018; Lane and Saint-Martin, 2021).[3]

In a recent Accenture survey of 1,200 American CEOs and other top executives, 74 percent said that they plan to use artificial intelligence to automate tasks in their workplace over the next few years. Yet only 3 percent reported planning to significantly increase investments in training over the same period (Fitzpayne and

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[1] Over the past 30 years, the average robot price has fallen by half in real terms (Tilley, 2017; Graetz and Michaels, 2018; Battisti et al., 2021; Jurkat, Klump and Schneider, 2022), and the costs of ICT and internet access services have continuously declined (OECD, 2014; Byrne et al., 2020).

[2] The introduction of ADT is also expected to generate important shifts in the skills required in the workplace, by raising the demand for advanced technological skills, such as coding and programming (Bughin, Lund and Hazan, 2018; Acemoglu and Restrepo, 2022).

[3] Public programs that aim at strengthening workers' skills have been adopted to counteract the impact of an increasing automation risk. Schmidpeter and Winter Ebmer, 2021, observe that the UK government announced the creation of a nationwide scheme to enhance the skills of workers displaced by automation which has been rolled out since 2020. The Skills Future Credit offered by Singapore's government provides subsidies for participating in courses which help individuals to upgrade skills affected by technology and globalization.

Pollack, 2018). Since employers play a unique and vital role in workforce training, a relevant question is whether employers' investment in training and re-training per employee is encouraged or hampered by the introduction of ADT.

The answer to this question is not clear a priori.[4] On the one hand, training investment per employee could increase if the implementation of these technologies require significant worker retraining and the re-organization of production (see Draca, Sadun, Van Reenen, 2006).[5] On the other hand, introducing ADT may reduce the marginal productivity of training, for instance because the remaining tasks and employees require fewer skills, with negative effects on the incentive to invest in training.[6] Investment per employee may also decline if firms decide to obtain some of the skills associated with ADT – such as coding and programming – by hiring skilled labor rather than by training in-house,[7] if they increase the use of temporary workers, which typically receive less training, or if they choose to automate, among tasks that are equally complex, those that require more training (Feng and Graetz, 2020). Finally, since training investment is the product of unit costs by the quantity of training, the efficiency and cost of training could change, for instance because more digital companies might also be more inclined to use digital learning options.[8] Conditional on the quantity of training, investment per employee could decline because of lower costs.

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[4] Sieben et al., 2009, consider information and communication technologies (ICT) in call centres in 14 countries over the years 2003-2006 and conclude that ICT is associated with higher training participation, although not all types of technologies are associated with more training.

[5] Morikawa, 2017, uses Japanese survey data to show that the share of college graduates is higher in firms that adopt AI than in other firms. He interprets this evidence as suggestive of complementarity between automation and human capital.

[6] For instance, new technologies can "downgrade" the skill content of jobs. See Sieben et al., 2009, for a review of the relevant literature.

[7] Ransbotham et al., 2019, suggest that companies investing in AI bring in experienced AI talent from outside for technical leadership roles.

[8] The single largest cost of training is the cost of the staff attending the course (i.e., rather than doing their day job). It is generally agreed that e-learning is more cost effective than classroom-based training. Further cost savings include less downtime spent travelling to a venue, lower travel and subsistence costs, lower printing, and distribution costs, easier and faster to update as a result of legislation changes, and lower tutor and classroom costs. See, for example, https://www.ac-education.co.uk/benefits-of-e-learning/. See also Verhagen, 2021, for a discussion of the effects of artificial intelligence on the organization of training.

In this paper we address this question in two steps. First, we investigate whether and how real training investment per employee changed between time *t-1* and *t* following the introduction of ADT at time *t-1* or earlier. Second, after defining measures of digital use and intensity, we estimate production functions and ask whether these measures and the training stock per employee are substitutes or complements in production. With substitutability (complementarity), an exogenous decline in the cost of introducing ADT, which leads to more use and higher intensity, reduces (increases) the marginal productivity of training and training investment per employee.

Although much research has been done on the effects of ADT on employment and the distribution of tasks within firms, to our knowledge the question asked in this paper has received little attention so far.[9] One key reason is that it is difficult to find data on both employer training and the use of ADT. This information is available in the European Investment Bank Investment Survey (EIBIS), an employer survey that covers the years 2018-2020 and 27 European countries, the UK and the US.

We use these data to construct an index of digital use (U), which measures whether firms have implemented any of four different ADT specific to their sector, which are surveyed in EIBIS, and an index of digital intensity (D), which counts how many of these four sector-specific ADT are used by the employer. Adopting a selection on observables approach, we estimate the effect of U and D at time *t-1* on the percent change in average training investment per employee between time *t-1* and *t*. We find that firms that have introduced ADT invest less in training per employee than other firms. We verify whether this result is robust to the introduction of unobservables that are equally related to U or D as observables using the test developed by Oster, 2019, and conclude that accounting for unobservables does not change the direction of our results.

We estimate production functions that are augmented with digital use or intensity, the training stock per employee T and their interaction. We deal with the correlation

[9] An exception being the work by Sieben et al., 2009.

between unobserved productivity shocks and production factors using the control function approach proposed by Ackerberg, Caves and Frazer, 2015. We find that both digital use (intensity) and the training stock per employee increase productivity, and that U (D) and T are substitutes in production. This result implies that an increase in U (D) reduces the marginal productivity of training. Since we cannot reject the hypothesis of constant returns to scale with respect to capital and labor, substitutability is sufficient to establish that an exogenous decline in the cost of introducing ADT, which increases digital use (intensity), reduces the average training stock per employee. We find, however, that employment increases. Since this increase more than compensates the decline in the training stock per employee, the firm-level training stock increases.

Our paper speaks to two strands of empirical literature based on firm-level data. The first strand looks at the effects of automation and digitalization on productivity, employment and wages. While there is broad consensus that the effects on productivity are positive, the effect on employment is more ambiguous. Acemoglu, Lelarge and Restrepo, 2020, for instance, find that robot adoption by French firms reduced the labor share and the share of production workers but increased valued added and productivity. While the share of production workers declined, overall employment increased faster in firms that adopted robots.

Koch, Manuylov and Smolka, 2021, estimate that in Spain the adoption of robots in the production process raised firm-level output by almost 25 percent within four years, and employment by around 10 percent (see also Dinlersoz and Wolf, 2018; Dixon, Hong and Wu, 2018; Caselli et al., 2022). In contrast, Bonfiglioli et al., 2020, show that, while demand shocks generate a positive correlation between robot imports and employment, exogenous changes in automation lead to job losses. They also find that robot imports increase productivity and the employment share of high-skilled professions but have a weak effect on total sales. Finally, the effect of automation and digitalization on average wages is unclear, as some workers may gain and other workers may lose (Dinlersoz and Wolf, 2018; Lane and Saint Martin, 2021). We contribute to this literature by providing the first empirical evidence on the effects of automation on employer-provided training using firm-level data.

The second strand is the small literature that estimates the effects of training on productivity. Konings and Vanormelingen, 2015, use firm-level data from Belgium and find that a 10 percent increase in the share of trained workers raises productivity by 1.7 to 3.2 percent, depending on the specification. Almeida and Carneiro, 2009, estimate the effects of training on productivity using Portuguese firm-level data and find that 10 hours increase of training per employee per year triggers a 0.6 percent increase of current productivity.[10] The effects that we estimate, based on a much broader sample of countries, are closer to the latter than to the former contribution.

The remainder of this paper is organized as follows. Section 2 introduces the data. Section 3 illustrates our measures of digital use and intensity. In Section 4, we estimate the effects of adopting ADT on changes in training investment per employee. Section 5 presents an illustrative model that describes the effects of exogenous changes in the cost of introducing ADT on digital use (intensity), training per employee and employment. We discuss the method used to estimate production functions and describe our results in Section 6. Conclusions follow.

2. Data

We draw our data from the European Investment Bank Investment Survey (EIBIS). Since 2016, EIBIS is administered annually to a representative sample of firms in each of the 27 EU Member States and the UK. Since 2019, EIBIS also includes a sample of US firms. The respondents to the interviews are senior managers or financial directors with responsibility for investment decisions and how investments are financed – for example, the owner, chief financial officer or chief executive officer.

[10] Jones, Kalmi, and Kauhanen, 2012, use panel data for Finnish co-operative banks to study the impact of training on wages and performance. Unlike much of the existing literature, they find evidence that training improves worker wages more than organizational performance. Other papers in this literature include Zwick, 2006, and Martins, 2021. See also Fialho, Quintini and Vandeweyer, 2021, for a review.

EIBIS covers non-financial firms in manufacturing, construction, services and infrastructure.

Each year, the survey comprises a panel component and a top up sample, where panel firms (close to 40% in each wave) are firms that participated in a previous wave of the survey and consented to be re-contacted in the following wave. The top-up sample consists of firms that did not participate in the preceding wave. The firms included in the survey have at least five employees, with both full-time and part-time employees being counted as one employee, and employees working less than 12 hours per week being excluded. The EIBIS sample is stratified disproportionally by country, industry group and firm size class, and proportionally by region within each country.[11] Brutscher et al., 2020, provide evidence for the EU that this sample is representative of the business population as described by Eurostat Structural Business Statistics.

EIBIS is a rich source of information on investment in Europe and the US with several unique characteristics. First, the surveyed firms are matched to the ORBIS databank, which include detailed balance sheet data.[12] Second, EIBIS data are collected in a consistent manner from firms belonging to many countries and industries, thus permitting us to carry out comparative analysis. Third, the survey gathers data on many different aspects of investment and investment finance activities, which are often not available in standard official sources. Particularly important for the purposes of this paper is the information on the use of ADT and on

[11] The sampling methodology is described in Ipsos, 2019. An enterprise is defined as a company trading as its own legal entity. As such, branches are excluded from the target population. However, the definition is broader than in a typical enterprise survey given that some company subsidiaries are their own legal entities.

[12] The matching is done by Ipsos MORI, which provided anonymised data to the EIB. This means that EIBIS does not include the name, the address, the contact details or any additional individual information that could identify the firms in the final sample. Note that not every firm in EIBIS has complete information in ORBIS (e.g., ORBIS may have missing information on employment, while EIBIS does not).

annual investment in employee training.[13]

EIBIS has six waves, conducted from 2016 to 2021, and 68,852 observations. We retain the waves 2019-2021, which include US firms and a key question on the use of ADT, drop firms with a single observation, for which we cannot compute capital and training stocks, as defined below, and exclude observations with missing information on training investment or the use of ADT, ending up with a working sample of 7,899 firms and 15,546 observations.

3. Digital use, intensity and training investment

Starting with the 2019 wave, EIBIS respondents are asked about the use of four ADT that are specific to their sector. The relevant question is: "Can you tell me for each of the following digital technologies if you have heard about them, not heard about them, implemented them in parts of your business, or whether your entire business is organized around them?"

Firms in *manufacturing* are asked about the use of: (a) 3D printing, also known as additive manufacturing; (b) robotics, or automation via advanced robotics; (c) the internet of things, such as electronic devices that communicate with each other without human assistance; and (d) big data/artificial intelligence. Firms in *construction* reply about the use of: (a) 3D printing; (b) drones or unmanned aerial vehicles; (c) the internet of things; and (d) virtual reality, such as when information is integrated with real-world objects and presented using a head-mounted display. Firms in *services*[14] are surveyed about the use of: (a) virtual reality; (b) platforms or digital tools that connect customers with businesses or customers with other customers; (c) the internet of things; and (d) big data/artificial intelligence. Finally,

[13] Another survey that collects data on employer's training in Europe is the Continuous Vocational Training Survey (CVTS) by Eurostat, which runs every five years. See also CEDEFOP's European Skills and Jobs Survey.
[14] Services include wholesale and retail, accommodation, and food services.

firms in *infrastructure*[15] are asked about the use of: (a) 3D printing; (b) platforms; (c) the internet of things; and (d) big data/artificial intelligence.

Use occurs after the introduction of these technologies, which typically takes place at least one year earlier.[16] We define *digital use* as a binary variable taking the value 1 if the firm has implemented, either partially or totally, at least one of the four available ADT. Table 1 (upper panel) shows that the percentage of using firms in our working sample ranged in 2021 from 33.9 percent in construction to 55.2 percent in infrastructure. Internet of things is present in all the four sectors (manufacturing, construction, services and infrastructure), with a relatively high share of users. Artificial intelligence and 3D printers are present in three sectors out of four, with a relatively low share of users. While platforms are used in services and infrastructure, virtual reality is implemented in construction and services, and robots and drones are present only in manufacturing and construction respectively.[17] The frequencies reported in Table 1 are very similar to those in the original sample, which includes all surveyed firms (see Table A1).

We also define *digital intensity* (*D*) as a variable that counts the number of sector-specific ADT being implemented in part of the business or in the entire business. Digital intensity ranges from 0 to 4, with 0 assigned to firms that have implemented no technology and 4 assigned to the firms that have organized partially or totally their business around all the four available technologies. Intensity *D* is highest on average in infrastructure (0.84) and lowest in construction (0.47) (see

[15] Infrastructure includes electricity and gas, water supply and waste management, transportation and storage, information and communication.

[16] When asked about the timing of introduction of ADT, close to 40 percent of using firms selected the previous year and the rest selected earlier years.

[17] The frequencies reported in the table are based on firm-level weights, which align the number of firms in the sample to the number in the population. For Europe, the weights are constructed to reweight the original sample and make it representative of the population reported by Eurostat Structural Business Statistics (SBS). For the US, the reference data are those from the US Census Bureau and the US Bureau of Economic Analysis.

Table 1), highest in Slovenia (1.24) and lowest (0.20) in Hungary (see Figure 1).[18]

One feature of the index *D* is that it treats equally a firm that has implemented ADT partially or totally. To avoid this, we also define two alternative measures of intensity: *D1*, which counts the sector-specific technologies adopted only in parts of the business, and *D2*, which counts the technologies around which the firm has organized the entire business. Both measures range between 0 and 4. Table 1 shows that the index *D1* is always higher than *D2*, because most firms have adopted ADT only in part of their business. By construction, *D1*+*D2* = *D*.

For each firm in the sample, EIBIS has data on investment in land and business buildings, machinery and equipment and training of employees.[19] In real terms, average investment in training per employee in 2020, was equal to 240 euro, ranging from 20 euro in Bulgaria to 330 euro in Sweden (see Figure 1) and about 4 percent of average investment in land and equipment (5,320 euro).[20] Using firm-level weights, the percentage of firms that invested in employee training in 2020 was 44.5 – and average real training investment per employee conditional on doing any training was equal to 476 euro (ranging from 95 euro in Bulgaria to 619 euro in the US). Unfortunately, we do not observe how many workers received training or the hours of training per employee.[21]

Our data also include information on turnover, the capital stock, the (gross) wage bill, total employment and firm characteristics such as firm age and management practices. Although some of these variables are also available in the matched administrative ORBIS data, we prefer to use the survey information because there are

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[18] Table A2 in the Appendix presents the coefficients of linear regressions of digital use and intensity on country group, time, firm size and sector dummies, firm age, and dummies for the presence of financial constraints, pay for performance schemes and monitoring systems.

[19] The question on investment refers to the previous financial year. For example, the 2021 wave of EIBIS collects information on investment activities in the financial year 2020. In addition to data on investment in land and business buildings, machinery and equipment and training of employees, EIBIS also has information on investment in R&D; software, data, IT networks and website activities; organisation and business process improvements.

[20] Real values are obtained by dividing nominal values using the country–specific GDP deflator.

[21] We could obtain a rough estimate of the number of hours of training per employee by dividing the total investment in training by the cost of one hour of training, which is available for Europe in the 2015 wave of the Continuous Vocational Training Survey.

substantially fewer missing values.[22]

As shown in Table 2, firms that have implemented at least one advanced digital technology in 2020 have higher average real value added (2.43 versus 1.02 million euro), fixed assets (8.74 versus 2.98 million) and employment (37.2 versus 23.4 employees) than other firms. Digital firms also pay higher average gross wages (30.7 versus 28.7 thousand euro per year), have higher capital labor ratios (361.4 versus 221.5 thousand euro per year) and invest more in training per employee (240 versus 190 euro per year).

We proxy average labor quality in a firm with the average real wage during the years 2015 to 2017, before our working sample starts. This is only possible for close to 42 percent of the sample, but not at all for the US. We deal with missing values by defining a binary variable equal to 1 when the wage is missing and to zero otherwise, and by replacing missing values with mean values.

As highlighted in Table 2, firms using ADT have higher labor quality (29.5 thousand versus 25.6 thousand euro), are younger than other firms (15 percent have less than 10 years, versus 11 percent), are more likely to have implemented a formal business monitoring system (41 versus 20 percent) and to have adopted pay for performance schemes (70 versus 63 percent). They are also slightly less likely to be financially constrained (9 versus 10 percent).

4. The effect of introducing ADT on training investment per employee

Do firms invest more or less in training after the introduction of ADT? To investigate this question, we use an empirical approach similar to the one employed by Acemoglu and Restrepo, 2020, which consists of regressing firm specific changes in training investment on lagged digital use / intensity and a vector of covariates. We estimate the following empirical model over the financial years 2018-2020

[22] For the firms that have both survey and administrative information, the correlation between key variables such as employment and output is high (0.94 for the former and 0.84 for the latter).

$$\Delta \ln\left(1 + t_{e,i,t}\right) = \lambda_0 + \lambda_1 G_{i,t-1} + \lambda_2 lnE_{i,t-1} + \lambda_3 Q_{it} + v_{it} \tag{1}$$

where t_e is real training investment per employee, Δ is the change operator, G is either digital use U or digital intensity D, E is employment and Q is a vector that includes the following firm characteristics: the log average wage between 2015 and 2017, different indicator variables for firm age below 10, financial constraints, a strategic monitoring system and pay for performance schemes (all lagged by one period), indicator variables for missing values, as well as country by time, sector by time and country by sector fixed effects.

Eq. (1) investigates whether digital use or intensity in year *t-1* affects the change in training investment per employee between year *t-1* and *t*. We use a value-added specification (see Todd and Wolpin, 2003), which includes the lagged dependent variable to control for firm–specific characteristics (both observable and un-observable). We prefer this specification to one that uses firm fixed effects because our sample contains at most two consecutive observations per firm, and because the within standard deviation is relatively small compared to the total standard deviation.[23]

A potential concern with Eq. (1) is that, although we use a value-added specification and control for observable components of labor and managerial quality, firm-specific unobserved effects that are correlated with $G_{i,t-1}$ remain uncontrolled for and can therefore bias our estimates of λ_1. To attenuate this concern, we also estimate a specification that includes as additional control the first lag of predicted total factor productivity $\widehat{\omega}$, a function of unobserved labor and managerial quality, which we compute as the residuals of the production function estimated later in the paper.[24]

We present our estimates of Eq. (1) in Table 3, which consists of four columns, two for digital intensity and two for digital use. For each measure, we show the results of

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[23] Eq. (1) can be re-written as

$$\ln\left(1 + t_{e,i,t}\right) = \lambda_0 + \ln\left(1 + t_{e,it-1}\right) + \lambda_1 G_{i,t-1} + \lambda_2 lnE_{i,t-1} + \lambda_3 Q_{it} + v_{it}$$

The ratio between the within and the overall standard deviation ranges between 0.33 and 0.37, depending on whether we use U or D.

[24] Frazer, 2001, and Konings and Vanormelingen, 2015, use a similar approach to estimate the effects of training on wages.

a specification that either omits $\widehat{\omega}$ (columns (1) and (3)) or includes it (column (2) and (4).[25] We find that the use of at least one technology (U=1) reduces training investment by 1.3 to 1.7 percent. On the other hand, a one-unit increase in digital intensity, for instance from the use of one (D=1) to the use of two technologies (D=2), reduces training investment per employee by 0.4 to 0.8 percent.[26] While training per employee declines after firms adopt ADT, employment increases, as shown in Table A4, although the estimated effect is small (between 0.2 and 0.6 percent) and not statistically significant at the conventional level of confidence.[27]

We test whether our estimates are influenced by un-observables with the Oster test (Oster, 2019). This test establishes bounds to the true value of the key parameter under two polar cases. In the first case, there are no un-observables, and our estimates in Table 3 are consistent. We denote as $\hat{R}$ the estimated R squared in this case. In the second case, there are un-observables, but observables and un-observables are equally related to digital use or intensity (δ = 1 in Oster's notation). When un-observables are included, we assume, as suggested by Oster, that the R squared is equal to Rmax = min ($1.3\hat{R}$; 1). If zero can be excluded from the bounding set, then accounting for un-observables would not change the direction of our estimates. For digital use, we estimate that the bounding set is [-0.017, -0.016] when $\widehat{\omega}$ is excluded and [-0.014, -0.013] when it is included in the regression. For digital intensity, these sets are given by [-0.008, -0.007] and [-0.004, -0.004]. We conclude that allowing for un-observables that are equally related to the treatment as

[25] Since $\widehat{\omega}$ is a generated regressor, we bootstrap standard errors in columns (2) and (4) using 100 replications. The difference across columns in the sample size is because $\widehat{\omega}$ is derived from the production function estimates discussed below.

[26] Since our proxy of labor quality is always missing in the US, we present in Table A3 in the Appendix the estimates of Eq. (1) when the US is excluded from the sample. Results are qualitatively similar to those discussed in the text.

[27] Our empirical results are qualitatively similar if we use entropy balancing (see Hainmueller, 2012) as a matching technique to achieve covariate balancing between the treatment group (which uses ADT) and the control group (which does not use ADT). We estimate that the effect of lagged use is -0.015 (standard error: 0.007) on the change of real training investment per employee and 0.008 (0.011) on the change of employment.

observables does not alter our estimates.[28]

The willingness to invest in training after introducing ADT may vary with labor market institutions. For instance, we expect that, in countries where employment protection legislation makes it less difficult to dismiss workers, firms may be less willing to train redundant workers following digital use or intensity than in countries where this legislation is more severe. To investigate this, we use the 2015 OECD index of employment protection legislation and divide the countries in our sample in two groups, according to whether their index is above the median or not.[29] We estimate separate regressions using either digital use or digital intensity as treatments and find (see Table 4) that the parameter λ_1 attracts a negative coefficient (-0.6 percent for intensity and -2 percent for use) in the countries with low employment protection and a positive coefficient (0.1 percent for intensity and 0.3 percent for use) in the group of countries with higher than median employment protection, in line with our expectations.[30]

We also expect the willingness of firms to train employees after introducing ADT to be affected by the generosity of public training subsidies to firms, which we measure with the share of public training expenditure on GDP, provided by the OECD for 2015. As for employment protection, we classify the countries for which we have data in countries with higher than median public training expenditure on GDP and other countries.[31] We estimate separate regressions using either digital use or digital intensity as treatments and find (see Table 5) that the parameter λ_1 attracts a negative coefficient (-0.6 percent for intensity and -1.6 percent for use) in the countries with relatively low public training expenditure, and a positive coefficient

[28] We also find that selection on un-observables would need to be between 6.2 (for digital use) and 14.6 (for digital intensity) times as large as selection on observables to explain away our results. Setting Rmax = min (1.5$\hat{R}$; 1) does not change our qualitative results.

[29] See https://www.oecd.org/els/emp/oecdindicatorsofemploymentprotection.htm. The countries with higher than median strictness of employment protection are: Belgium, Czechia, Finland, France, Greece, Italy, Lithuania, Latvia, Luxemburg, Netherlands, Portugal and Sweden.

[30] The number of observations is smaller than in Table 3 because the information on employment protection legislation is missing for Cyprus, Croatia, Malta, Bulgaria and Romania.

[31] The countries with higher than median public training expenditure are Austria, Denmark, Finland, France, Germany, Italy, Luxemburg and Portugal.

(1.4 percent for intensity and 2 percent for use) in the countries with higher than median training expenditure, which confirms our expectations.[32]

A candidate reason why training investment per employee declines in firms that have introduced ADT is that the implementation of these technologies reduces the marginal productivity of training, which is equivalent to saying that digital use or intensity and training are substitutes in production. We explore this possibility in the rest of the paper by introducing an illustrative model and by estimating production functions that are augmented with both the training stock and digital use or intensity.

5. An illustrative model

In this section, we propose an illustrative model that describes the effects of changes in the cost of introducing ADT on digital use or intensity, the training stock per employee and employment. Consider an economy populated by monopolistically competitive firms with demand function

$$Y_{it} = P_{it}^{-\sigma} \tag{2}$$

where the indices i and t are for the firm and time and σ is the elasticity of substitution between goods in utility. We assume that $\sigma > 1$ (Blanchard and Kiyotaki, 1987).[33] Each firm operates the following production function (see Konings and Vanormelingen, 2015)

$$Y_{it} = L_{it}^{\alpha} K_{it}^{\delta} \exp(q_{it}) \exp(\varepsilon_{it}) \tag{3}$$

where Y denotes value added, L labor in efficiency units, K the capital stock, q technical efficiency that shifts the production function, and ε is a disturbance term. Taking logs of (2) and defining $y = \ln(Y), l = \ln(L), k = \ln(K)$ we obtain

[32] The number of observations is smaller than in Table 3 because the information on public training expenditure is missing for Cyprus, Croatia, Malta, Bulgaria, Romania, the UK and the US.

[33] Blanchard and Kiyotaki, 1987, justify this assumption because it guarantees the existence of an equilibrium with monopolistic competition. The assumption is also necessary to have non-negative marginal benefits of employment, capital, training and digital intensity.

$$y_{it} = \alpha l_{it} + \delta k_{it} + q_{it} + \varepsilon_{it} \quad (4)$$

As in Bartel, 2000, and Konings and Vanormelingen, 2015, we assume that labor efficiency increases with the average stock of training per employee T,[34] observed labor and managerial quality S and unobserved labor and managerial quality Z. Therefore

$$L_{it} = E_{it}(1 + \gamma_T T_{it} + \gamma_S S_{it} + Z_{it}) \quad (5)$$

where E is employment. Taking logs and using the approximation $\ln(1 + x) \cong x$, we obtain that $l_{it} = e_{it} + \gamma_T T_{it} + \gamma_S S_{it} + Z_{it}$, where $e = \ln(E)$. We capture S with the average (lagged) wage and with binary variables indicating the presence of a formal business monitoring system, pay for performance schemes and financing constraints.[35]

Let the variable G denote either digital use U or digital intensity D. We further assume that technical efficiency q depends on G, its interaction with training T and a vector of controls X

$$q_{it} = \beta_0 + \beta_G G_{it} + \beta_{GT}(G_{it}\, x\, T_{it}) + \lambda X_{it} \quad (6)$$

Using (5) and (6) in (4) we obtain

$$y_{it} = \alpha e_{it} + \beta_T T_{it} + \beta_S S_{it} + \beta_G G_{it} + \beta_{GT}(G_{it}\, x\, T_{it}) + \delta k_{it} + \lambda X_{it} + \omega_{it} + \varepsilon_{it} \quad (7)$$

where $\beta_T = a\gamma_T$, $\beta_S = a\gamma_S$ and $\omega_{it} = \beta_0 + aZ_{it}$. The error component ω_{it} – or total factor productivity (TFP) – is a function of unobserved labor and managerial quality Z and is correlated with the profit-maximizing choices of employment, the capital stock, training and digital intensity (see Konings and Vanormelingen, 2015). The disturbance term ε is instead assumed to be orthogonal to the right-hand side variables in (7).

In this setup, both G and the training stock per employee T affect productivity, the former by improving technical efficiency, and the latter by improving both labor and

[34] The training stock is obtained from training investment using the perpetual inventory formula, as described in the next section.
[35] Popov, 2014, argues that the presence of financial constraints may signal poor managerial quality.

technical efficiency. Digital use (or intensity) G and the training stock per employee T are complements in production if $\partial^2 Y / \partial T \partial G = Y[\beta_{GT} + (\beta_G + \beta_{GT} T)(\beta_T + \beta_{GT} G)] > 0$ and substitutes if $\partial^2 Y / \partial T \partial G < 0$ (see Seidman, 1989). With complementarity (substitutability), an increase in G (T) raises (reduces) the marginal productivity of T (G). If β_T and β_G are positive, as we assume, for substitutability β_{GT} must not only be negative but also larger in absolute value than $(\beta_G + \beta_{GT} T)(\beta_T + \beta_{GT} G)$. A sufficient condition for complementarity is instead that $\beta_{GT} \geq 0$.

Firms maximize profits with respect to E, K, T and G by taking factor prices w (wages) and r (cost of capital) as given. Assuming that the cost of training per employee and the cost of introducing ADT are convex in T and G, (real) profits are defined as

$$\pi_{it} = \left[L_{it}^{\alpha} K_{it}^{\delta} \exp(q_{it}) \exp(\varepsilon_{it})\right]^{1-1/\sigma} - w_{it} E_{it} - r_{it} K_{it} - \frac{\theta}{2} {G_{it}}^2 - \frac{\phi}{2} {T_{it}}^2 E_{it} \tag{8}$$

where parameters θ and ϕ are the marginal costs of increasing G and T by one unit. We show in the Appendix that a reduction in θ increases G if

$$\left[\frac{\alpha}{T} - (\beta_T - \beta_{GT} G)\right]\left[\alpha + \delta - 1 - 1/\sigma\,(\alpha + \delta)\right] < 0 \tag{9}$$

and the training stock T if

$$\left[(\alpha + \delta - 1) - \frac{1}{\sigma}(\alpha + \delta)\right]\beta_{GT} < 0 \tag{10}$$

Therefore, the effect of θ on T depends upon: a) the sign of parameter β_{GT}; b) the returns to scale with respect to labor and capital;[36] c) the elasticity of substitution between goods in utility σ. With constant returns to scale, condition (10) simplifies to $-\frac{1}{\sigma}\beta_{GT}$ and the sign of the effect of θ on T depends exclusively on the sign of β_{GT}.

We also show that employment E increases when θ declines if

$$\left[(1 - \alpha - \delta) + \frac{1}{\sigma}(\alpha + \delta)\right]\beta_{GT} + \left(1 - \frac{1}{\sigma}\right)(\beta_G + \beta_{GT} T)\left[(\beta_T + \beta_{GT} D) - \alpha/T\right] < 0 \tag{11}$$

[36] $\alpha + \delta = 1$ if returns are constant, $\alpha + \delta > 1$ with increasing returns and $\alpha + \delta < 1$ with decreasing returns. The introduction of *ADT* affects both the marginal benefits and the marginal costs of training, by affecting T and E.

6. Estimation of the production function

6.1 Methods and data

The evaluation of the effects of changes in the cost of digitalization on training (and digital intensity) requires that we estimate the parameters of the production function (7). This estimate is complicated by the fact that factor input choices (capital and labor) as well as the choice of training and digital use / intensity, are correlated with the error term ω_{it}. To address this problem, we estimate (7) using the control function approach proposed by Olley and Pakes, 1996, and refined by Ackerberg, Caves and Frazer (ACF henceforth), 2015.

The basic idea of this approach is that the endogeneity problem originates from the fact that ω_{it} is unobserved by the analyst. If some invertible function can tell us what ω_{it} is, making it observable, the problem can be eliminated. ACF, 2015, assume that the cost of intermediate materials is an invertible function of the state variables, employment and unobserved ω_{it}. We describe ACF's approach in more detail in the Appendix. Its implementation requires that we treat the capital stock, the training stock per employee, digital intensity and the interaction between *T* and *G* as state variables that are determined by decisions taken at time *t-1*.

We assume this to be the case for *G*, as there is at least one-year lag between the introduction and the use of ADT in the workplace. For *K* and *T*, we compute both the capital and the training stock using the perpetual inventory formula

$$X_{it} = x_{it-1} + (1-\delta)X_{i,t-1} \tag{12}$$

where *X* is the stock, *x* the flow and δ is the depreciation rate. Since it takes time for physical and human capital to be installed, we use lagged rather than current flows.[37]

The flow *x* in (12) is the (real) investment in land, business building, machinery and equipment in the case of the capital stock and the (real) investment in training in the case of the training stock. We set the depreciation rate at 4.6 percent for physical

[37] In the few cases where there are gaps in the years, we replace the lagged flow with the closest year.

capital (see ECB, 2006), and at 17 percent for training (see Almeida and Carneiro, 2009). For the capital stock, the initial value is the one associated with the first available year (starting with 2015). For the training stock, we follow Jones, Kalmi and Kauhanen, 2012, and use the first available training flow t_0 (starting in 2015) and the assumption that the initial stock T_0 is given by $T_0 = \frac{t_0}{\delta+g}$, where g is the steady state rate of growth of human capital, which we set at 5 percent, as in Jones, Kalmi and Kauhanen, 2012. Using this procedure, we find that the average training stock in 2020 was equal to 1.79 thousand euro per employee in firms adopting ADT and to 1,28 thousand euro in the remaining firms.

EIBIS has no data on the cost of intermediate materials, which we require to apply ACF's approach to the estimation of production functions. For many firms, we obtain this cost by matching the data from EIBIS to the ORBIS database, which contains firm balance sheet data. For firms with missing data,[38] we regress by sector the cost of materials on sales over the period 2015-2020 using ORBIS data and predict the cost of intermediate materials by applying the estimated sector-specific coefficient to EIBIS data on turnover. Value added is obtained as the difference between turnover and the cost of materials.[39]

6.2 Baseline results

The firms in our unbalanced panel have different size and belong to different countries and sectors. To control for unobserved sector, country and size effects as well as for country, sector and size specific shocks, we regress the variables of interest on country by time, sector by time, country by sector and size by time fixed effects and use the residuals (plus the constant term) to estimate production functions, adopting the control function approach discussed in the previous section.

Table 6 reports the ACF estimates of Eq. (7) when we use digital use U (column (1)),

[38] The missing rate is close to 55 percent, partly due to the fact that financial data in Orbis are missing for missing firms for the financial year 2020.

[39] For many firms this value is provided by ORBIS. To limit the effect of outliers, we replace the values of capital, employment, value added and the training stock above and below the 99th and 1st percentile with the 99th and the 1st percentiles.

digital intensity *D* (column (2)) and the two indicators of intensity *D1* and *D2* (column (3)).[40] In each column, the standard errors are clustered by firm and bootstrapped (100 iterations) to take into account the fact that we use generated regressors. We find that digital use (intensity) U (*D)* and the training stock per employee T increase productivity, and that their interaction attracts a negative and statistically significant coefficient. Focusing on columns (1) and (2), the sign of the second partial derivative $\frac{\partial^2 Y}{\partial T \partial G}\frac{1}{Y} = [\beta_{GT} + (\beta_G + \beta_{GT}T)(\beta_T + \beta_{GT}G)]$, evaluated at sample means (reported in Table A5), is negative and equal to -0.018 and -0.007 respectively. Thus, there is evidence that digital use (intensity) U (*D)* and the training stock T are substitutes in production, and that the introduction of ADT reduces the marginal product of training.

Substitutability could arise if the use of ADT not only replaces unskilled labor with capital but also modifies the residual tasks filled by this type of labor in such a way that the marginal product of training per employee declines. The marginal productivity of training could also fall if employers find it more difficult to fill the new skilled positions associated with ADT technologies by training incumbents in-house than by hiring from the market.[41]

There is also evidence that productivity is higher in firms that have higher labor quality, captured by the average wage between 2015 and 2017, and have adopted a formal strategic monitoring system and pay for performance incentives. Productivity is instead lower in financially constrained firms. We estimate that the combination of coefficients $\alpha + \delta - 1$ ranges from 0.009 in column (3) to 0.043 in column (1). In all cases, we cannot reject the hypothesis of constant returns to scale with respect to capital and labor at the five percent level of confidence.

Using the results in column (2) and evaluating marginal effects at the sample mean

[40] Table A6 reports the OLS estimates of Eq. (7) and Table A7 replicates Table 6 for the sub-sample that excludes the US, for which our measure of labor quality is missing. We find that that results are qualitatively similar.

[41] Substitutability also implies that an increase in the training stock per employee reduces the marginal productivity of adopting ADT.

values of the relevant variables, we estimate that, ceteris paribus, the introduction of one ADT, either used in part or in all the business, which corresponds to a one-unit increase in digital intensity D, raises real value added per head by 2.4 percent (0.031-0.007 x 0.96). The same productivity increase could be obtained by raising the training stock per employee by 1.13 thousand euro, which corresponds to a 117.8 percent increase with respect to the sample mean, a sizeable amount.[42]

With constant returns to scale with respect to capital and labor, a reduction in the cost of introducing ADT increases digital use / intensity if $[\frac{\alpha}{T} - (\beta_T + \beta_{TG} G)] > 0$, which holds for the estimates in first two columns of Table 6.[43] In addition, $\partial T/_{\partial \theta} > 0$ if $\beta_{GT} < 0$, which also holds using these estimates. Therefore, a decline in the cost of introducing ADT increases the incentive to use these technologies but reduces the real training stock and training investment per employee, consistent with the findings in Table 3, which show that firms using ADT reduce their training investment per employee.

The estimates in column (2) of Table 6 can be used to show that $\partial E/_{\partial \theta} < 0$, as condition (11) under constant returns to scale is equal to $-0.033 + 0.026 \frac{1}{\sigma}$, a negative expression because $\sigma > 1$. We conclude that firm-level employment increases when the cost of introducing ADT falls and digital intensity increases, consistent with the empirical findings of Acemoglu and Restrepo, 2020 and Koch, Manuylov and Smolka, 2021. Although the training stock per employee declines when θ falls, the firm-specific training stock T increases because the positive effect on employment more than compensates the negative effect on T. In particular, $\partial TE/_{\partial \theta} = -0.0317 + \frac{0.0114}{\sigma}$, a negative value since $\sigma > 1$.

Turning to column (3) of Table 6, we find that both $D1$ and $D2$ affect positively

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42 Raising T by 1 thousand euro would increase productivity by 2.1 percent [0.026-0.007 x 0.69] x 100. Therefore, a 2.4 percent increase can be obtained by increasing T by 1.13 thousand euro. We also estimate that, ceteris paribus, a 10 percent increase in the training stock with respect to the mean raises real value added per head by 0.20 percent.

43 Evaluated at sample means, this expression is equal to 0.91 when we use the estimates in column (1) and to 0.90 when we use the estimates in column (2).

productivity, but that the effect is larger for *D2* than for *D1*. When evaluated at sample means, we estimate that $\frac{\partial^2 Y}{\partial T \partial D_1}\frac{1}{Y} = \left[\beta_{D_1T} + \left(\beta_{D_1} + \beta_{D_1T}T\right)\left(\beta_T + \beta_{D_1T}D_1 + \beta_{D_2T}D_2\right)\right]$ is equal to -0.004 and that $\frac{\partial^2 Y}{\partial T \partial D_2}\frac{1}{Y} = \left[\beta_{D_2T} + \left(\beta_{D_2} + \beta_{D_2T}T\right)\left(\beta_T + \beta_{1T}D_1 + \beta_{D_2T}D_2\right)\right]$ is equal to -0.020. We conclude from this that the degree of substitutability between digital intensity and the training stock is higher when firms organize their business around the new technologies than when the use of ADT is only partial.

It is useful to compare our estimates of the impact of training on productivity with those obtained by Konings and Vanormelingen, 2015, for Belgium and by Almeida and Carneiro, 2009 for Portugal. Both studies estimate the effect of an hour of training per employee on productivity. Konings and Vanormelingen find a 0.76 percent increase, while Almeida and Carneiro estimate a much lower effect, ranging between 0.06 to 0.13 percent. We convert the training stock per employee in training hours by using, as an approximation, the average cost of an hour of training in Europe (including the UK), which according to Eurostat was 63 euro in 2015, the closest available date (see CVTS, 2015). We estimate that one thousand euro spent on training per employee corresponds to roughly 16 hours of training. Since this expenditure raises productivity by 2.6 to 3.2 percent (see columns (1) and (2) of Table 6), we conclude that an hour of training increases productivity in European firms by 0.16 to 0.2 percent, a value closer to Almeida and Carneiro than to Konings and Vanormelingen

6.3 Heterogeneous effects

In this sub-section, we focus for brevity on digital intensity *D* and allow the effects of *D* and *T* on productivity to vary across groups of countries and sectors. First, since Central and Eastern European countries are at a different stage of economic development compared to the rest of Europe and the US, we estimate separate production function regressions for the two groups and report our findings in Table A8. We find that a one-unit increase in digital intensity *D* and a one thousand-euro increase in *T* raise productivity by 4.4 and 2.8 percent in Central and Eastern Europe, and by 3.1 and 2.6 percent in the rest of Europe and the US. In addition, while D and T are substitute in production in Western and Southern Europe and the US, the coefficient associated with the interaction between D and T is equal to zero and too imprecisely estimated to allow us to draw any conclusion. Second, we present in Table A9 the results by sector of activity, distinguishing between manufacturing and infrastructure and construction and services. Our estimates indicate that D and T are substitutes in production in both groups of sectors.[44]

So far, we have assumed that all ADT (which include robots, platforms, drones, virtual reality and 3D printers) have the same impact on productivity. This may be restrictive, as AI and internet of things may differ from other automation technologies, such as industrial robots and other automated machinery, for instance because of their greater potential to expand the range of tasks that can be automated. In addition, while low skilled occupations are highly exposed to ADT in general, high skilled occupations are also increasingly exposed to AI (Nedelkoska and Quintini, 2018; Lane and Saint-Martin, 2021).

To address this concern, we classify ADT in two groups: I (internet of things, artificial intelligence and big data, platforms and augmented reality) on the one hand and R (drones, robots and 3D printers) on the other hand. We compute digital use and intensity for both groups (G_I and G_R respectively) and estimate a version of Eq. (7) that includes both G_I and G_R and their interaction with T. As shown in Table 7, we find that the effect of digital use / intensity on productivity is larger for drones, robots and 3D printers than for the other technologies.[45] Although the degree of substitutability between ADT and T appears to be higher for R than for I, the difference is not statistically significant at the conventional levels of confidence.[46]

[44] Because of the relatively small sample size, we refrain from presenting estimates by sector.

[45] The difference between the coefficients associated with G_I and G_R is equal to -0.007 (standard error: 0.033) in the first column of Table 7 and to -0.052 (standard error: 0.030, statistically significant at the 10 percent level of confidence) in the second column.

[46] The difference between the coefficients associated with the interaction of T with G_I and G is equal to -0.009 (standard error: 0.013) in the first column of Table 7 and to 0.008 (standard error: 0.016) in the second column.

6.4 Training investment and quantity

Our finding that firms using ADT spend less on training per employee may be a source of concern for those in policy circles who argue that more adult learning per capita is required to address the labor market consequences of digitization. Yet, since real training investment per employee is the product of the unit cost of training by the quantity of training per employee, a decline in investment does not necessarily imply a reduction in the quantity of training. This could happen, for instance, if the efficiency of training expenditure increases with the use of ADT, cutting costs rather than quantities. For example, training modes could increasingly shift from the traditional classroom to online learning, with firms more at the forefront of digital technologies also taking stronger advantage of digital learning options.

To determine the effects of ADT on the quantity of training per employee, we need data on training costs and quantities, which are not available in the current dataset. As a first step in this direction, we collapse our firm-level data on digital intensity by country, sector and year and merge them with data from the European Labor Force Survey (ELFS), which covers all EU member states and the UK. The ELFS is an employee survey, which has information on the percentage of individuals undertaking any training (Z_0), job-related training (Z_1) and engaging in training mostly or exclusively during working hours (Z_2) during the four weeks before the interview.[47] Interpreting Z_0, Z_1 and Z_2 as a rough indicators of training quantity, we proceed as in Eq. (1) and regress the change of log(1+Z_0), log(1+Z_1) and log(1+Z_2) on lagged digital intensity, country by time, sector by country and sector by time fixed effects. As shown in Table A10, we find that a one-unit increase in digital intensity D reduces the share engaged in any training, professional training and

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[47] The relevant questions in the survey are: a) did you attend any courses, seminars, conferences or received private lessons or instructions outside the regular education system (hereafter mentioned as taught learning activities) within the last 4 weeks; b) purpose of the most recent taught learning activity; c) did the most recent taught learning activity take place during paid working hours? We define Z_0 as the percentage doing any training, Z_1 as the share doing professional training and Z_2 as the share doing training mostly or entirely during working hours. The information for the last two measures is not available for Sweden, Denmark, Ireland, Luxembourg and Portugal.

training during working time by 2.4, 2.5 and 1.9 percent respectively. These results suggest that the introduction of ADT reduces not only training investment per employee but also training incidence, a measure of training quantity.[48]

We also have access to data from the Italian Longitudinal Survey on Firms and Employment (*Rilevazione Longitudinale su Imprese e Lavoro)*, which includes information on employment, training investment and number of trained employees in 2010, 2014 and 2017 for more than 20 thousand Italian firms. We regress the change in the share of employees being trained – a proxy of the quantity of training – on the change in real training investment per employee, firm and year fixed effects, and find that the estimated coefficient is 1.149 (standard error: 0.032), suggesting a strong positive association between the two variables. We infer from this evidence that the observed reduction in training investment per employee among firms adopting ADT is unlikely to be entirely due to a decline in training costs. We recognize, however, that a more thorough analysis would require better and more detailed data, a task that we leave to future research.

Conclusions

There is much concern in policy circles about the labor market consequences of automation and digitization. Several studies have stressed the importance of re-training and up-skilling workers whose jobs are being affected by technology. Adult learning is often seen as a useful antidote to navigate the troubled waters of modern labor markets. Since substantial training is employer-provided (see Brunello, Garibaldi and Wasmer, 2007), it is important to understand whether and how the increased use of automation and digitization technologies affects employers' incentives to invest in the training of their employees.

We have addressed this question by using rather unique firm-level data that cover

[48] Using the same dataset which includes the share of temporary workers (source: ELFS) we find no evidence of a statistically significant relationship between digital use or intensity and the share of temporary workers.

the 27 EU countries, the UK and the US and include information both on the use of ADT and on training investment. We have shown that employers adopting these technologies have reduced their investment in training per employee, especially in countries where employment protection legislation is less severe or where public training expenditure as share of GDP is lower. We have argued that the observed reduction is unlikely to reflect only a decline in the cost of training but is also a reduction in the percentage of individuals undertaking job-related training.

We have argued that a mechanism explaining this result is that ADT and training investment per employee are substitutes in production, which implies that a higher use of the former reduces the marginal product of the latter. This could happen because ADT not only replace unskilled labor with capital but also modify the remaining tasks filled by labor in such a way that the productivity of training declines. For example, the remaining tasks could be more focused on social interaction and communication, requiring different types of training and often informal learning, which is not captured by data on training investment. Firms using ADT could also fill the skilled positions associated with these technologies by hiring rather than by training in-house, thereby reducing training needs. This explanation would also be in line with persistently high shortages for digital experts observed on labor markets in recent years. Although average training investment per employee has declined with automation, total firm-specific investment has increased because of the positive employment effects.

We have shown that the decline of training investment per employee with digital use and intensity is typical of countries with a relatively low public training expenditure (as a share of GDP). In countries that spend more on training policies – which include subsidies to employers - employers' training investment per employee does not fall with digital use or intensity.

On the one hand, these results are worrisome with respect to countries where there is little investment in active labor market policies and limited investment in training by employers. Here, the risk of widening inequalities linked to digitalization might be most pronounced. On the other, the findings point to the potential of positive complementarities between public and private sector. Where spending on active labor market policies focusing on training is higher, firms also appear more likely to continue higher levels of training investment. This is particularly important in the current environment characterized by automation and digitization to foster re-skilling and up-skilling, not only because they provide training opportunities for the displaced and unemployed, but also because they stimulate employers to invest more. The combination could help to maintain high levels of employment against the background of accelerating digitalization as it facilitates adaptation to changing tasks and ways of work within firms and offering those having lost their jobs better opportunities for labor market reintegration. Finally, the combination would raise skill levels across the workforces, thereby helping to mitigate skill gaps.

Tables and figures

Table 1. Share of firms using partially or fully a digital technology. Working sample. Financial year 2020.

	Manufacturing	Construction	Services	Infrastructure
Digital use	40.5	33.9	46.4	55.2
3 D printers	14.1	5.7	-	2.9
Advanced robotics	15.9	-	-	-
Internet of things	22.0	17.8	24.7	30.3
Artificial intelligence	4.4	-	7.7	11.3
Augmented reality	-	5.0	5.6	-
Drones	-	18.4	-	-
Platforms	-	-	32.7	39.2
Digital intensity	0.564	0.469	0.707	0.837
	(0.769)	(0.780)	(0.919)	(0.919)
Digital intensity - partial	0.517	0.436	0.619	0.713
	(0.749)	(0.714)	(0.889)	(0.867)
Digital intensity - full	0.047	0.033	0.088	0.124
	(0.266)	(0.186)	(0.338)	(0.423)

Note. Weighted frequencies, using EIBIS firm-level weights, which align the number of firms in the sample to the number of firms in the population. Standard errors within parentheses.

Table 2. Average firm characteristics. By use of at least one of the four advanced digital technologies. Financial year 2020, weighted means.

	Use (U=1)	Do not use (U=0)
Real gross wage (thousand euro)	30.73 (21.61)	28.70 (21.99)
Real capital labor ratio (thousand euro)	361.37 (2,541.78)	221.48 (2,695.08)
Real value added (million euro)	2.43 (10.66)	1.02 (4.25)
Real capital stock (million euro)	8.74 (51.66)	2.98 (19.01)
Real material costs (million euro)	8.65 (37.08)	3.48 (14.49)
Employment	37.15 (134.54)	23.38 (89.66)
Training investment per employee (thousand euro)	0.24 (0.49)	0.19 (0.47)
Training stock per employee (thousand euro)	1.79 (3.03)	1.28 (2.61)
Firm age less than 10	0.15	0.11
Real average wage during 2015-17 (thousand euro)	29.52 (20.73)	25.62 (19.61)
Firm uses formal strategic monitoring system	0.41	0.20
Firm adopts pay for performance systems	0.70	0.63
Financially constrained	0.09	0.10

Note: weighted averages using EIBIS firm-level weights, which align the number of firms in the sample to the number of firms in the population. Excluding missing values. Standard errors within parentheses.

Table 3. Estimated effects of digital intensity and use on the change of real training investment per employee. Ordinary least squared estimates. Dependent variable: change in $\ln(1 + t_e)$. Financial years 2018-20.

	(1)	(2)	(3)	(4)
Digital intensity (lagged)	-0.008***	-0.004**	-	-
	(0.003)	(0.002)	-	-
Digital use (lagged)	-	-	-0.017***	-0.013***
	-	-	(0.006)	(0.004)
Log employment (lagged)	0.007***	0.007***	0.007***	0.007***
	(0.002)	(0.002)	(0.002)	(0.002)
Total factor productivity (lagged)	-	-0.005**	-	-0.005*
	-	(0.003)	-	(0.003)
Financial constraints (lagged)	0.001	0.006	0.000	0.006
	(0.009)	(0.008)	(0.009)	(0.008)
Strategic monitoring system (lagged)	-0.006	-0.007**	-0.006	-0.006
	(0.006)	(0.004)	(0.006)	(0.005)
Pay for performance schemes (lagged)	-0.017***	-0.016***	-0.017***	-0.016***
	(0.006)	(0.005)	(0.006)	(0.005)
Log average wage between 2015 and 2017	-0.009**	-0.010**	-0.009**	-0.010***
	(0.004)	(0.005)	(0.004)	(0.004)
Number of observations	9,086	7,612	9,086	7,612

Note: t_e: real training investment per employee. Each regression includes a constant, country by time, country by sector, sector by time dummies, dummies for missing values and a dummy equal to 1 if the age of the firm is lower than 10 years and to 0 otherwise. Standard errors are clustered at the firm level. Bootstrapped standard errors (100 iterations) in column (2). One, two and three stars for statistical significance at the 10, 5 and 1 percent level of confidence. The number of observations differs across columns because of the missing values in total factor productivity, a generated regressor.

Table 4. Estimated effects of lagged digital intensity and use on the change of real training investment per employee. Ordinary least squared estimates. Dependent variable: change in $\ln(1+t_e)$. Financial years 2018-20. By level of country-specific employment protection.

	High employment protection	Low employment protection	High employment protection	Low employment protection
Digital intensity (lagged)	0.001	-0.006	-	-
	(0.001)	(0.004)	-	-
Digital use (lagged)	-	-	0.003	-0.020**
	-	-	(0.003)	(0.009)
Log employment (lagged)	0.000	0.009***	0.000	0.009***
	(0.001)	(0.001)	(0.001)	(0.001)
Total factor productivity (lagged)	-0.000	-0.005	-0.000	-0.005
	(0.002)	(0.004)	(0.002)	(0.004)
Financial constraints (lagged)	-0.029***	0.015**	-0.030***	0.016***
	(0.007)	(0.007)	(0.007)	(0.007)
Strategic monitoring system (lagged)	0.005	-0.005	0.005	-0.004
	(0.006)	(0.006)	(0.006)	(0.007)
Pay for performance schemes (lagged)	-0.023***	-0.021***	-0.023***	-0.021***
	(0.003)	(0.006)	(0.004)	(0.006)
Log average wage between 2015 and 2017	-0.006**	-0.013***	-0.006**	-0.013***
	(0.003)	(0.006)	(0.003)	(0.004)
Number of observations	3,267	3,195	3,267	3,195

Note: t_e: real training investment per employee. Each regression includes a constant, country by time, country by sector, sector by time dummies, dummies for missing values and a dummy equal to 1 if the age of the firm is lower than 10 years and to 0 otherwise. Standard errors are clustered at the firm level. One, two and three stars for statistical significance at the 10, 5 and 1 percent level of confidence. Countries with high employment protection: Belgium, Czechia, Finland, France, Greece, Italy, Latvia, Lithuania, Luxemburg, Netherlands, Portugal and Sweden. Countries with low employment protection: Austria, Denmark, Estonia, Germany, Hungary, Poland, Slovakia, Slovenia, Spain, UK and US. Missing countries: Cyprus, Croatia, Malta, Bulgaria and Romania.

Table 5. Estimated effects of lagged digital intensity and use on the change of real training investment per employee. Ordinary least squared estimates. Dependent variable: change in $\ln(1 + t_e)$. Financial years 2018-20. By level of country-specific public training expenditure on GDP.

	High public training / GDP	Low public training / GDP	High public training / GDP	Low public training / GDP
Digital intensity (lagged)	0.014***	-0.006***	-	-
	(0.004)	(0.002)	-	-
Digital use (lagged)	-	-	0.020**	-0.016***
	-	-	(0.008)	(0.005)
Log employment (lagged)	0.002**	0.007**	0.003***	0.007**
	(0.001)	(0.003)	(0.001)	(0.003)
Total factor productivity (lagged)	0.001	-0.002	0.000	-0.002
	(0.004)	(0.003)	(0.004)	(0.002)
Financial constraints (lagged)	-0.020***	0.001	-0.018***	0.001
	(0.004)	(0.009)	(0.004)	(0.009)
Strategic monitoring system (lagged)	-0.004	-0.014***	-0.003	-0.014***
	(0.004)	(0.005)	(0.004)	(0.005)
Pay for performance schemes (lagged)	-0.015***	-0.019***	-0.015***	-0.019***
	(0.003)	(0.005)	(0.003)	(0.005)
Log average wage between 2015 and 2017	-0.009**	-0.006	-0.009*	-0.005*
	(0.006)	(0.006)	(0.005)	(0.006)
Number of observations	2,612	3,030	2,612	3,030

Note: t_e: real training investment per employee. Each regression includes a constant, country by time, country by sector, sector by time dummies, dummies for missing values and a dummy equal to 1 if the age of the firm is lower than 10 years and to 0 otherwise. Standard errors are clustered at the firm level. One, two and three stars for statistical significance at the 10, 5 and 1 percent level of confidence. Countries with high training / GDP: Austria, Denmark, Finland, France, Germany, Italy, Luxemburg and Portugal. Countries with low training /GDP: Belgium, Czechia, Estonia, Greece, Hungary, Ireland, Latvia, Lithuania, Netherlands, Poland, Slovakia, Slovenia, Spain and Sweden. Missing countries: Cyprus, Croatia, Malta, Bulgaria, Romania, UK and US.

Table 6. Effects of digital use / intensity and training on productivity. ACF estimates. Dependent variable: log real value added. Financial years 2018-2020.

	(1)	(2)	(3)
Log employment	0.898***	0.888***	0.864***
	(0.036)	(0.035)	(0.038)
Log capital stock	0.145***	0.143***	0.146***
	(0.013)	(0.014)	(0.017)
Training stock per employee (T)	0.032***	0.026***	0.021***
	(0.008)	(0.007)	(0.009)
Digital use	0.053**	-	-
	(0.024)	-	-
Digital intensity	-	0.031***	-
	-	(0.007)	-
Digital intensity – partial	-	-	0.032***
	-	-	(0.013)
Digital intensity – full	-	-	0.057***
	-	-	(0.015)
T x digital use	-0.019**	-	-
	(0.009)	-	-
T x digital intensity	-	-0.007***	-
	-	(0.004)	-
T x digital intensity – partial	-	-	-0.005
	-	-	(0.006)
T x digital intensity – full	-	-	-0.020**
	-	-	(0.010)
Log average wage between 2015 and 2017	0.240***	0.243***	0.255***
	(0.018)	(0.016)	(0.023)
Firm uses strategic monitoring system	0.045***	0.041***	0.042***
	(0.013)	(0.012)	(0.013)
Firm uses pay for performance	0.117***	0.117***	0.120***
	(0.018)	(0.019)	(0.018)
Firm is financially constrained	-0.124***	-0.127***	-0.126***
	(0.031)	(0.032)	(0.033)
Returns to scale: $\alpha + \delta - 1$	0.043	0.031	0.009
	(0.076)	(0.074)	(0.081)
Number of observations	15,546	15,546	15,546

Note: ACF: Ackerberg, Caves and Frazer, 2015. The dependent and explanatory variables are residuals from regressions of the raw variables on country by year, sector by year, firm size by year and country by sector fixed effects. Standard errors within parentheses are clustered by firm and bootstrapped using 100 replications. Each regression includes also a constant, dummies for missing values and a dummy equal to 1 if the age of the firm is lower than 10 years and to 0 otherwise. Returns to scale are constant if $\alpha + \delta - 1 = 0$. One, two and three stars for statistical significance at the 10, 5 and 1 percent level of confidence.

Table 7. Effects of digital use / intensity and training on productivity. ACF estimates. Dependent variable: log real value added. Financial years 2018-2020. By type of technology.

Log employment	0.872***	0.897***
	(0.040)	(0.030)
Log capital stock	0.146***	0.160***
	(0.017)	(0.013)
Training stock per employee (T)	0.029***	0.037***
	(0.009)	(0.007)
Internet of things & artificial intelligence (G_I) – digital use	-	0.035
	-	(0.032)
Drones, robots and 3D printers (G_R) – digital use	-	0.087***
	-	(0.015)
Internet of things & artificial intelligence (G_I) – digital intensity	0.030***	-
	(0.012)	-
Drones, robots and 3D printers (G_R) – digital intensity	0.037	-
	(0.025)	-
T x G_I – digital use	-	-0.016
	-	(0.011)
T x G_R – digital use	-	-0.024*
	-	(0.013)
T x G_I – digital intensity	-0.005	-
	(0.006)	-
T x G_R – digital intensity	-0.014	-
	(0.011)	-
Firm uses strategic monitoring system	0.040***	0.056***
	(0.012)	(0.010)
Firm uses pay for performance	0.115***	0.106***
	(0.019)	(0.018)
Log average wage between 2015 and 2017	0.257***	0.231***
	(0.036)	(0.017)
Firm is financially constrained	-0.0130***	-0.128***
	(0.030)	(0.015)
Returns to scale: $\alpha + \delta - 1$	0.018	0.056
	(0.085)	(0.080)
Number of observations	15,546	15,546

Note: ACF: Ackerberg, Caves and Frazer, 2015. The dependent and explanatory variables are residuals from regressions of the raw variables on country by year, sector by year, firm size by year and country by sector fixed effects. Standard errors clustered by firm and bootstrapped using 100 replications. Each regression includes also a constant, dummies for missing values and a dummy equal to 1 if the age of the firm is lower than 10 years and to 0 otherwise. Returns to scale are constant if $\alpha + \delta - 1 = 0$. One, two and three stars for statistical significance at the 10, 5 and 1 percent level of confidence.

Table A1. Share of firms using partially or entirely a digital technology. Original sample. Financial year 2020.

	Manufacturing	Construction	Services	Infrastructure
Digital use	41.1	33.3	43.8	56.2
3 D printers	14.3	5.2	-	5.1
Advanced robotics	18.8	-	-	-
Internet of things	22.3	15.8	22.2	28.9
Artificial intelligence	6.9	-	7.5	14.7
Augmented reality	-	5.4	4.3	-
Drones	-	15.8	-	-
Platforms	-	-	31.4	40.7
Digital intensity	0.619	0.448	0.650	0.886
	(0.887)	(0.745)	(0.865)	(0.966)
Digital intensity – partial	0.545	0.414	0.583	0.708
	(0.810)	(0.703)	(0.834)	(0.869)
Digital intensity – full	0.074	0.035	0.066	0.179
	(0.335)	(0.189)	(0.292)	(0.496)

Note: Weighted frequencies, using EIBIS firm-level weights, which align the number of firms in the sample to the number of firms in the population. Standard errors within parentheses.

Table A2. Factors affecting digital use and intensity. Financial years 2018-20. Linear regressions.

	Digital use	Digital intensity
Eastern Europe	-0.038*** (0.010)	-0.089*** (0.021)
Southern Europe	-0.001 (0.012)	-0.004 (0.025)
2019	0.032*** (0.008)	0.084*** (0.015)
2020	0.007 (0.009)	0.033* (0.017)
10-49 employees	0.055*** (0.012)	0.098*** (0.021)
50-249 employees	0.151*** (0.013)	0.322*** (0.024)
250+ employees	0.284*** (0.016)	0.726*** (0.037)
Electricity	-0.002 (0.013)	0.076 (0.061)
Water	-0.030 (0.026)	-0.164*** (0.046)
Construction	-0.091*** (0.013)	-0.235*** (0.025)
Wholesale and Retail Trade	0.028** (0.013)	0.021 (0.027)
Transportation	0.033** (0.015)	-0.010 (0.030)
Accommodation & hotels	0.040 (0.025)	0.011 (0.048)
Information & Communication	0.300*** (0.019)	0.741*** (0.051)
Firm age	-0.002 (0.013)	0.016 (0.025)
Firm uses strategic monitoring system	0.172*** (0.009)	0.382*** (0.017)
Firm uses pay for performance schemes	0.068*** (0.009)	0.129*** (0.017)
Firm is financially constrained	0.007 (0.014)	0.015 (0.028)
Number of observations	15,546	15,546

Note: Omitted categories: Western Europe and the US, year 2018, small firms with 5-9 employees and manufacturing. Standard errors are clustered at the firm level. One, two and three stars for statistical significance at the 10, 5 and 1 percent level of confidence.

Table A3. Estimated effects of digital intensity and use on real training investment per employee. Ordinary least squared estimates. Dependent variable: change in $\ln(1+t_e)$. Financial years 2018-20. Excluding the US.

	(1)	(2)	(3)	(4)
Digital intensity (lagged)	-0.006**	-0.003	-	-
	(0.003)	(0.002)	-	-
Digital use (lagged)	-	-	-0.013***	-0.010***
	-	-	(0.005)	(0.004)
Log employment (lagged)	0.008***	0.007***	0.007***	0.008***
	(0.002)	(0.001)	(0.002)	(0.001)
Total factor productivity (lagged)	-	-0.006**	-	-0.007**
	-	(0.003)	-	(0.003)
Financial constraints (lagged)	0.002	0.009	0.002	0.009
	(0.009)	(0.008)	(0.009)	(0.008)
Strategic monitoring system (lagged)	-0.007	-0.007	-0.007	-0.006
	(0.006)	(0.006)	(0.006)	(0.006)
Pay for performance schemes (lagged)	-0.014**	-0.014***	-0.014**	-0.014***
	(0.006)	(0.004)	(0.006)	(0.004)
Log average wage between 2015 and 2017	-0.009**	-0.009**	-0.009**	-0.009**
	(0.004)	(0.004)	(0.004)	(0.004)
Number of observations	8,500	7,087	8,500	7,087

Note: t_e: real training investment per employee. Each regression includes a constant, country by time, country by sector, sector by time dummies, dummies for missing values and a dummy equal to 1 if the age of the firm is lower than 10 years and to 0 otherwise. Standard errors are clustered at the firm level. Bootstrapped standard errors (100 iterations) in column (2). One, two and three stars for statistical significance at the 10, 5 and 1 percent level of confidence.

Table A4. Estimated effects of digital intensity and use on the change of employment. Ordinary least squared estimates. Dependent variable: change of employment. Financial years 2018-20.

	(1)	(2)	(3)	(4)
Digital intensity (lagged)	0.002	0.006	-	-
	(0.007)	(0.005)	-	-
Digital use (lagged)	-	-	0.004	0.006
	-	-	(0.004)	(0.011)
Log employment (lagged)	-0.025***	-0.028***	0.025***	-0.028***
	(0.003)	(0.004)	(0.004)	(0.004)
Total factor productivity (lagged)	-	0.050***	-	0.050***
	-	(0.006)	-	(0.006)
Financial constraints (lagged)	-0.026**	-0.016	-0.026**	-0.015
	(0.012)	(0.013)	(0.012)	(0.013)
Strategic monitoring system (lagged)	0.011	0.000	0.010	0.002
	(0.007)	(0.012)	(0.007)	(0.011)
Pay for performance schemes (lagged)	0.016**	0.014*	0.015**	0.014*
	(0.007)	(0.008)	(0.007)	(0.008)
Log average wage between 2015 and 2017	0.013***	0.019**	0.013**	0.018**
	(0.005)	(0.007)	(0.005)	(0.007)
Number of observations	9,086	7,612	9,086	7,612

Note: Each regression includes a constant, country by time, country by sector, sector by time dummies, dummies for missing values and a dummy equal to 1 if the age of the firm is lower than 10 years and to 0 otherwise. Standard errors are clustered at the firm level. Bootstrapped standard errors (100 iterations) in column (2). One, two and three stars for statistical significance at the 10, 5 and 1 percent level of confidence.

Table A5. Summary statistics of the main variables used to estimate Eq. (7).

Ln real value added – residuals + constant	5.99 (1.12)
Ln employment – residuals + constant	2.12 (0.38)
Ln real capital – residuals + constant	5.97 (1.65)
Ln real materials – residuals + constant	6.22 (1.27)
Training stock – residuals + constant	0.96 (0.48)
Digital use – residuals + constant	0.42 (0.47)
Digital intensity – residuals + constant	0.69 (0.86)
Digital intensity D1 – residuals + constant	0.65 (0.80)
Digital intensity D2 – residuals + constant	0.04 (0.33)

Note: Weighted averages using EIBIS firm-level weights. Excluding missing values. Standard errors within parentheses.

Table A6. Effects of digital intensity / use and training on productivity. OLS estimates. Dependent variable: log real value added. Financial years 2018-2020.

	(1)	(2)	(3)
Log employment	0.880***	0.878***	0.877***
	(0.021)	(0.021)	(0.021)
Log capital stock	0.038***	0.140***	0.140***
	(0.008)	(0.008)	(0.008)
Training stock per employee (T)	0.038***	0.039***	0.039***
	(0.008)	(0.007)	(0.007)
Digital use	0.059***		
	(0.019)		
Digital intensity		0.044***	
		(0.010)	
Digital intensity – partial			0.041***
			(0.011)
Digital intensity - full			0.068***
			(0.025)
T x digital use	-0.018**		
	(0.009)		
T x digital intensity		-0.012***	
		(0.004)	
T x digital intensity – partial			-0.008**
			(0.004)
T x digital intensity - full			-0.024***
			(0.008)
Log average wage between 2015 and 2017	0.248***	0.247***	0.247***
	(0.025)	(0.025)	(0.025)
Firm uses strategic monitoring system	0.090***	0.086***	0.086***
	(0.018)	(0.018)	(0.018)
Firm uses pay for performance	0.126***	0.125***	0.124***
	(0.018)	(0.018)	(0.018)
Firm is financially constrained	-0.186***	-0.186***	-0.186***
	(0.029)	(0.028)	(0.029)
Returns to scale: $\alpha + \delta - 1$	0.021	0.018	0.018
	(0.019)	(0.019)	(0.019)
Number of observations	15,546	15,546	15,546

Note: OLS: ordinary least squares. The dependent and explanatory variables are residuals from regressions of the raw variables on country by year, sector by year, firm size by year and country by sector fixed effects. Standard errors clustered by firm within parentheses. Each regression includes also a constant, dummies for missing values and a dummy equal to 1 if the age of the firm is lower than 10 years and to 0 otherwise. Returns to scale are constant if $\alpha + \delta - 1 = 0$. One, two and three stars for statistical significance at the 10, 5 and 1 percent level of confidence.

Table A7. Effects of digital intensity and training on productivity. Dependent variable: log real value added. Financial years 2018-2020. ACF estimates. Excluding the US.

	(1)	(2)	(3)
Log employment	0.910***	0.909***	0.905***
	(0.024)	(0.056)	(0.052)
Log capital stock	0.129***	0.129***	0.128***
	(0.007)	(0.013)	(0.012)
Training stock per employee (T)	0.036***	0.031***	0.028***
	(0.010)	(0.011)	(0.013)
Digital use	0.059***		
	(0.021)		
Digital intensity		0.036***	-
		(0.012)	-
Digital intensity – partial		-	0.038***
		-	(0.013)
Digital intensity – full		-	0.056*
	-0.020*	-	(0.031)
T x digital use	(0.011)		
T x digital intensity		-0.008***	-
		(0.003)	-
T x digital intensity – partial		-	-0.008*
		-	(0.005)
T x digital intensity - full		-	-0.024***
		-	(0.008)
Log average wage between 2015 and 2017	0.248***	0.227***	0.236***
	(0.031)	(0.049)	(0.051)
Firm uses strategic monitoring system	0.046**	0.045***	0.045***
	(0.021)	(0.013)	(0.014)
Firm uses pay for performance	0.107***	0.110***	0.113***
	(0.011)	(0.013)	(0.013)
Firm is financially constrained	-0.131***	-0.136***	-0.136***
	(0.034)	(0.028)	(0.028)
Returns to scale: $\alpha + \delta - 1$	0.039	0.038	0.033
	(0.025)	(0.065)	(0.072)
Number of observations	14,597	14,597	14,597

Note: ACF: Ackerberg, Caves and Frazer, 2015. The dependent and explanatory variables are residuals from regressions of the raw variables on country by year, sector by year, firm size by year and country by sector fixed effects. Standard errors clustered by firm and bootstrapped using 100 replications. Each regression includes also a constant, dummies for missing values and a dummy equal to 1 if the age of the firm is lower than 10 years and to 0 otherwise. Returns to scale are constant if $\alpha + \delta - 1 = 0$. One, two and three stars for statistical significance at the 10, 5 and 1 percent level of confidence.

Table A8. Effects of digital intensity on productivity. Dependent variable: log real value added. Financial years 2018-20. By group of countries. ACF estimates

	Western, Southern Europe and US (1)	Central and Eastern Europe (2)
Log employment	0.858***	0.966***
	(0.076)	(0.064)
Log capital stock	0.151***	0.123***
	(0.017)	(0.028)
Training stock per employee (T)	0.026***	0.028
	(0.011)	(0.026)
Digital intensity	0.031**	0.044**
	(0.014)	(0.020)
T x Digital intensity	-0.009*	0.000
	(0.005)	(0.011)
Log average wage between 2015 and 2017	0.328***	0.251***
	(0.023)	(0.091)
Firm uses strategic monitoring system	0.029	0.061**
	(0.021)	(0.028)
Firm uses pay for performance	0.071***	0.184***
	(0.021)	(0.035)
Firm is financially constrained	-0.131***	-0.122***
	(0.040)	(0.038)
Returns to scale: $\alpha + \delta - 1$	0.009	0.089*
	(0.071)	(0.050)
Number of observations	10,512	5,034

Note: ACF: Ackerberg, Caves and Frazer, 2015. The dependent and explanatory variables are residuals from regressions of the raw variables on country by year, sector by year, firm size by year and country by sector fixed effects. Standard errors clustered by firm and bootstrapped using 100 replications. Each regression includes also a constant, dummies for missing values and a dummy equal to 1 if the age of the firm is lower than 10 years and to 0 otherwise. Returns to scale are constant if $\alpha + \delta - 1 = 0$. One, two and three stars for statistical significance at the 10, 5 and 1 percent level of confidence.

Table A9. Effects of digital intensity on productivity. Dependent variable: log real output. Financial years 2018-20. By sector. ACF estimates

	Manufacturing and infrastructure (1)	Construction and services (2)
Log employment	0.934***	0.887***
	(0.068)	(0.153)
Log capital stock	0.161***	0.109***
	(0.016)	(0.029)
Training stock per employee (T)	0.037***	0.015
	(0.012)	(0.011)
Digital intensity	0.009	0.076***
	(0.009)	(0.021)
T x Digital intensity	-0.010**	-0.005
	(0.004)	(0.006)
Log average wage between 2015 and 2017	0.163***	0.305**
	(0.049)	(0.134)
Firm uses strategic monitoring system	0.007	0.088***
	(0.017)	(0.030)
Firm uses pay for performance	0.135***	0.083***
	(0.017)	(0.009)
Firm is financially constrained	-0.137***	-0.109***
	(0.026)	(0.031)
Returns to scale: $\alpha + \delta - 1$	0.096	0.004
	(0.059)	(0.158)
Number of observations	8,368	7,178

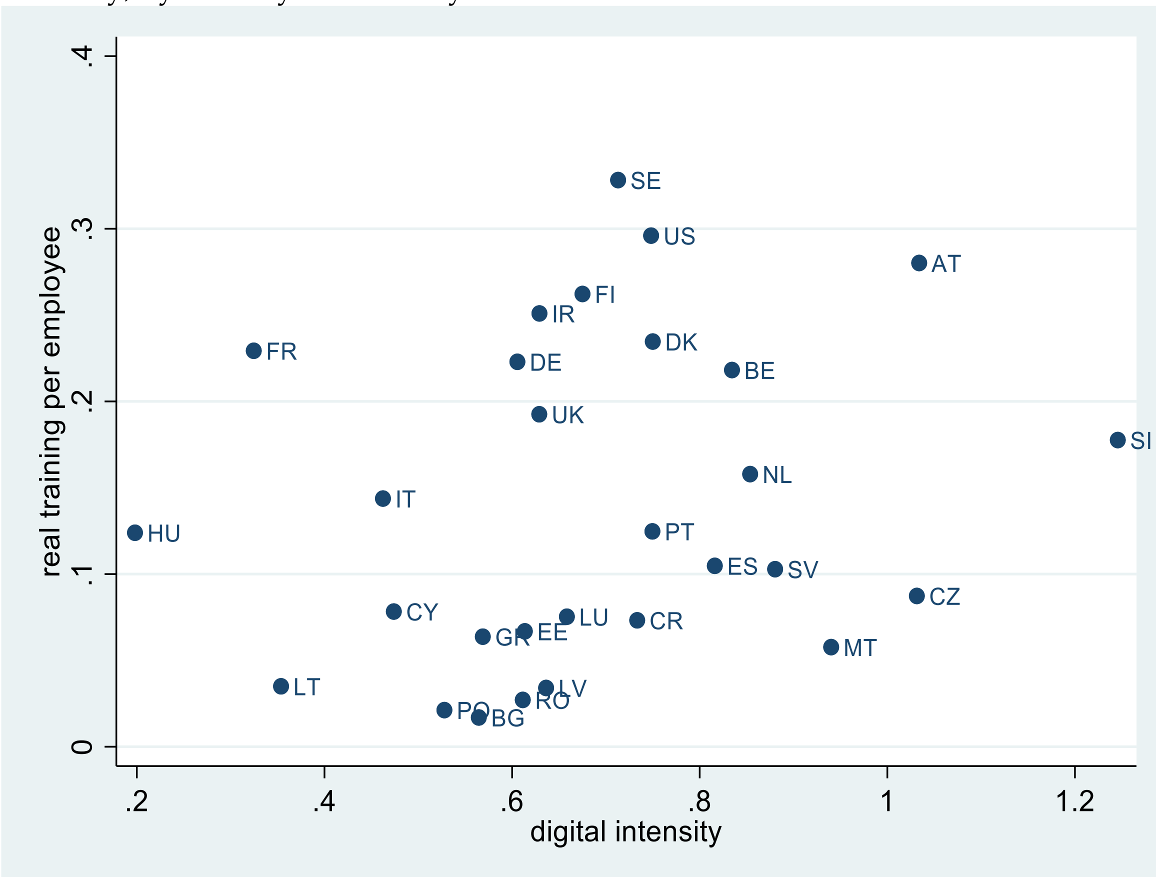
Note: ACF: Ackerberg, Caves and Frazer, 2015. The dependent and explanatory variables are residuals from regressions of the raw variables on country by year, sector by year, firm size by year and country by sector fixed effects. Standard errors clustered by firm and bootstrapped using 100 replications. Each regression includes also a constant, dummies for missing values and a dummy equal to 1 if the age of the firm is lower than 10 years and to 0 otherwise. Returns to scale are constant if $\alpha + \delta - 1 = 0$. One, two and three stars for statistical significance at the 10, 5 and 1 percent level of confidence.

Table A10. Estimated effects of digital intensity on the change in the share of individuals engaged in professional training and in the share doing training mostly or entirely during working time. European countries. Ordinary least squared estimates. Dependent variable: change in $\ln(1+Z_1)$ and in $\ln(1+Z_2)$. Financial years 2018-20.

	$\Delta\ln(1+Z_0)$	$\Delta\ln(1+Z_1)$	$\Delta\ln(1+Z_2)$
Digital intensity (lagged)	-0.024**	-0.025***	-0.019**
	(0.011)	(0.010)	(0.008)
Country x sector effects	Y	Y	Y
Country x time effects	Y	Y	Y
Sector by time effects	Y	Y	Y
Number of observations	439	359	359

Note: Robust standard errors within parentheses. One, two and three stars for statistical significance at the 10, 5 and 1 percent level of confidence. The number of observations differs across columns because professional training and training during working hours are available only for a subset of European countries.

Figure 1. Average real training investment per employee and average digital intensity, by country. Financial year 2020.



Notes: training per employee in thousand euro. AT: Austria; BE: Belgium; BG: Bulgaria; CY: Cyprus; CR: Croatia; CZ: Czech Republic; DE: Germany; DK: Denmark; EE: Estonia; FI: Finland; FR: France; GR: Greece; CR: Croatia; HU: Hungary; IE: Ireland; IT: Italy; LT: Lithuania; LU: Luxembourg; LV: Latvia; MT: Malta; NL: Netherlands; PL: Poland; PT: Portugal; RO: Romania; SE: Sweden; SI: Slovenia; SV: Slovakia; ES: Spain; GB: Great Britain.

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Appendix

A1. Profit maximization

Omitting subscripts for convenience, the first order conditions for a local maximum are:

$$\left(1 - {}^{1}/_{\sigma}\right)P\, {}^{\partial Y}/_{\partial E} - w - {}^{\phi}/_{2}\, T^2 = 0 \quad \text{(A1)}$$

$$\left(1 - {}^{1}/_{\sigma}\right)P\, {}^{\partial Y}/_{\partial T} - \phi T E = 0 \quad \text{(A2)}$$

$$\left(1 - {}^{1}/_{\sigma}\right)P\, {}^{\partial Y}/_{\partial G} - \theta G = 0 \quad \text{(A3)}$$

$$\left(1 - {}^{1}/_{\sigma}\right)P\, {}^{\partial Y}/_{\partial K} - r = 0 \quad \text{(A4)}$$

Totally differentiating (A1) - (A4) with respect to *E*, *T*, *D*, *K* and ϕ, defining Δ as the determinant of the Jacobian matrix and using Cramer's rule, we obtain that

$$ {}^{\partial G}/_{\partial \theta} = \frac{P^3 Y^3 \left(1 - {}^{1}/_{\sigma}\right)^3 \delta \mathrm{G}(\beta_\mathrm{T} + \beta_\mathrm{TG}\mathrm{G})}{\Delta \mathrm{K}^2 E^2} \left[\tfrac{\alpha}{T} - (\beta_\mathrm{T} + \beta_\mathrm{TG}\mathrm{G})\right]\left[\alpha + \delta - 1 - {}^{1}/_{\sigma}\,(\alpha + \delta)\right] \quad \text{(A5)}$$

Since the determinant of the Jacobian matrix is positive because of the second order conditions for a maximum, ${}^{\partial G}/_{\partial \theta} < 0$ if $\left[\frac{\alpha}{T} - (\beta_\mathrm{T} + \beta_\mathrm{TG}\mathrm{G})\right]\left[\alpha + \delta - 1 - {}^{1}/_{\sigma}\,(\alpha + \delta)\right] < 0$.

We also have

$$ {}^{\partial T}/_{\partial \theta} = \frac{P^3 Y^3 \left(1 - {}^{1}/_{\sigma}\right)^3 \alpha \delta G}{\Delta \mathrm{K}^2 E^2} \left[\alpha + \delta - 1 - {}^{1}/_{\sigma}\,(\alpha + \delta)\right]\beta_{GT}$$

(A6)

Therefore, ${}^{\partial T}/_{\partial \theta} > 0$ if $\left[(\alpha + \delta - 1) - \frac{1}{\sigma}(\alpha + \delta)\right]\beta_{GT} < 0$

Finally, we establish that

$$ {}^{\partial E}/_{\partial \theta} = \frac{P^3 Y^3 \left(1 - {}^{1}/_{\sigma}\right)^3 \delta \mathrm{G}(\beta_\mathrm{T} + \beta_\mathrm{TG}\mathrm{G})}{\Delta \mathrm{K}^2 E^2} \begin{Bmatrix} \left[1 - \alpha - \delta + {}^{1}/_{\sigma}\,(\alpha + \delta)\right]\beta_{DT} \\ +\left(1 - {}^{1}/_{\sigma}\right)(\beta_\mathrm{T} + \beta_\mathrm{TG}\mathrm{G})\left[(\beta_\mathrm{G} + \beta_\mathrm{TG}\mathrm{T}) - {}^{\alpha}/_{T}\right] \end{Bmatrix}$$

so that ${}^{\partial E}/_{\partial \theta} < 0$ if the term in braces is negative.

A2. The estimation of production functions using the control function approach

We provide a brief overview of the estimation of production functions using a control function approach, which draws from Rovigatti and Mollisi, 2018.

Consider a Cobb Douglas production function for firm i at time t:

$$y_{it} = \alpha + w_{it}\beta + x_{it}\gamma + \omega_{it} + \varepsilon_{it} \tag{A7}$$

Where y denotes output, w is a vector of free variables (in logs), x a vector of state variables (in logs), ω is the unobservable productivity shock and ε is a white noise shock. In the current application, the vector w includes employment and the vector x includes the capital stock, the stock of training, digital intensity and their interaction.

The productivity shock evolves according to a first order Markov process

$$\omega_{it} = g(\omega_{it-1}) + \psi_{it} \tag{A8}$$

Where ψ_{it} is a productivity shock, uncorrelated with ω_{it} and the vector x. Olley and Pakes, 1996, proposes to estimate (A7) by using an observable variable, investment s, as proxy for ω. They further assume

a) $s_{it} = f(x_{it}, \omega_{it})$, where the function f is invertible in ω, and investment s is a monotonic function of ω;

b) The state variables evolve according to decisions taken at *t-1*;

c) The variables in w are chosen at time t after ω is realized.

These assumptions imply that s and x are orthogonal and that $s_{it} = f(x_{it}, \omega_{it})$ can be inverted to yield

$$\omega_{it} = f^{-1}(s_{it}, x_{it}) \tag{A9}$$

Plugging this in (A8) we obtain

$$y_{it} = \alpha + w_{it}\beta + \Phi_{it}(s_{it}, x_{it}) + e_{it} \tag{A10}$$

Where $\Phi_{it}(s_{it}, x_{it}) = x_{it}\gamma + f^{-1}(s_{it}, x_{it})$

Equation (A10) can be parametrically estimated approximating $\Phi_{it}(s_{it}, x_{it})$ by an nth order polynomial. This yields an estimate of β.

To estimate γ, rewrite the model as

$$y_{it} - w_{it}\hat{\beta} = \alpha + x_{it}\gamma + g(\omega_{it-1}) + e_{it} \tag{A11}$$

Where $e_{it} = \varepsilon_{it} + \psi_{it}$. Since $\omega_{it} = \Phi_{it} - x_{it}\gamma$, Eq. (A11) becomes

$$y_{it} - w_{it}\hat{\beta} = \alpha + x_{it}\gamma + g(\Phi_{it-1} - x_{it-1}\gamma) + e_{it} \tag{A12}$$

Assuming that the function g follows a random walk, (A12) can be written as

$$y_{it} - w_{it}\hat{\beta} = \alpha + (x_{it} - x_{it-1})\gamma + \widehat{\Phi}_{it-1} + e_{it} \tag{A13}$$

Residual e_{it} can be used to build a GMM estimator exploiting the moment condition

$$E\left[e_{it}x_{it}^{j}\right] = 0 \tag{A14}$$

for any j, where j is an element of the vector x.

The estimate of γ is obtained as

$$\gamma^{*} = argmax\left\{-\sum_k\left(\sum_i\sum_t e_{it}x_{it}^{j}\right)^2\right\}$$

Ackerberg, Caves and Frazer (ACF), 2015, substitute investment with the cost of materials m and propose an alternative approach based on the following assumptions:

a) $m_{it} = p(x_{it}, l_{it}, \omega_{it})$ is invertible in ω_{it} and m_{it} is monotonically increasing in ω_{it};

b) The state variables are decided at *t-b*;

c) Labor *l* is decided at *t-z*, where $z < b$;

d) The production function is value added in the sense that the intermediate input *m* does not enter the production function.

The implementation of the ACF correction is based on the routine "prodest" developed by Rovigatti and Mollisi, 2018.