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ADVANCED DIGITAL TECHNOLOGIES AND INVESTMENT IN EMPLOYEE TRAINING

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Advanced Digital Technologies and Investment in Employee Training

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Abstract

Using firm-level data covering 25 EU countries, the UK and the US and a difference-in-differences approach, we show that employers adopting advanced digital technologies reduce their investment in training per employee. Compared to non-adapting firms, this reduction is negligible on impact but increases to -11.3 and -13.8 percent of the pre-treatment mean two and three years after adoption. It can be decomposed into two contrasting effects: the increase in the probability of investing in training and the reduction in investment by firms with positive training. We argue that a candidate reason for the decline in investment in training per employee is that the use of advanced digital technologies and employee training are substitutes in production, implying that an increase in the former negatively affects the marginal productivity of the latter. Our findings point to challenges in realizing high levels of firm-sponsored training for employees in increasingly digital economies.

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1. Introduction.

The use of advanced digital technologies (ADT henceforth) – such as 3D printing, advanced robotics, drones, digital platforms, internet of things (IoT), virtual reality, big data analytics and artificial intelligence (AI) – is spreading, encouraged by declining costs.[1] It has also been accelerated by the COVID-19 pandemic (Chernoff and Warman (2021); EIB (2022)).

ADT expands 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)). The replacement of labor with cheaper capital can result in productivity gains, with uncertain effects on labor demand (Acemoglu et al. (2022)).[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 (Brunello et al, (2024)). 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 an Accenture survey of 1,200 American CEOs and other top executives, 74 percent said that they plan to use AI to automate tasks in their workplace over the next few years (Fitzpayne and Pollack (2018)). Yet only 3 percent reported planning to significantly increase investments in training over the same period. Since employers

[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); Jurkatet al. (2022)), and the costs of ICT and internet access services have continuously declined (Byrne et al. (2017)).

[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 (Bughinet al. (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.

play a unique and vital role in workforce training, a relevant question is whether employers' investment in training and re-training is encouraged or hampered by the introduction of ADT.[4]

The answer to this question is not clear a priori.[5] On the one hand, investment in training per employee could increase if the implementation of these technologies requires significant worker retraining and the re-organization of production (see Draca et al. (2006)).[6] 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.[7]

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,[8] if they increase the use of temporary workers, who 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)).[9] Finally, since training investment is the product of unit costs and the quantity of training, the efficiency and cost of training could change, for instance because more digital companies may also be more inclined to use digital learning options. Conditional on the quantity of training, investment per employee could decline because of lower costs.

[4] In 2016, participation by the adult population aged 25-64 in job-related education and training in the EU was 43.7%, the vast majority of which (87.9%) was sponsored by the employer (Guner and Nurskl (2023)).

[5] Sieben et al. (2009) consider information and communication technologies (ICT) in call centers 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.

[6] 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.

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

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

[9] 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. See also Verhagen (2021) for a discussion of the effects of AI on the organization of training.

We study whether adopting ADT encourages or hampers investment in training by comparing investment in firms adopting ADT with non-adopting firms, using a difference -in - differences framework. We also estimate production functions and investigate whether ADT adoption and the training stock per employee are substitutes or complements in production. With substitutability (complementarity), ADT adoption reduces (increases) the marginal productivity of training, with negative (positive) implications for investment in training.

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 so far little attention, and with controversial results. On the one hand, Hess et al. (2023) use a German survey of individuals and find that workers who are exposed to substitution by automation are 15 percentage points less likely to participate in training than those who are not exposed to it. On the other hand, Gathman et al. (2023) also use survey data for Germany at the time of the COVID 19 pandemic and find evidence of complementarity between the adoption of digital technologies and training needs in areas such as leadership and IT skills.[10]

One key reason for the scarcity of research in this area is that it is difficult to find microdata on both employer training and the adoption of ADT. One source of firm-level data is the European Investment Bank Investment Survey (EIBIS), an employer survey that covers the financial years 2015-2023 and the 27 EU countries, the UK and the US. This survey contains information both on the adoption of ADT between 2018 and 2023 and on employers' investment in training per employee.

We use EIBIS data on digital adoption, which measures whether firms have implemented ADT that are specific to their sector. We compare firms that adopted ADT between 2018 and 2023 with non-digital firms, which did not adopt ADT during the same period. We estimate the effects of adoption at time *t* on training per employee between time *t* and *t+5*. Since the selected period includes the COVID-19 pandemic,

[10] See also Sieben et al. (2009).

we explicitly control for the effects of the pandemic using both time fixed effects and firm-specific data on the impact of the pandemic on business activities that are available in EIBIS. We also present estimates that omit 2020, the year of the lockdown.

We find that firms adopting ADT invest less in training per employee than non-adopting firms. This effect is negligible on impact but increases to -11.3 and -13.8 percent of the pre-treatment mean two and three years after adoption and consists of two contrasting effects: the increase in the probability of investing in training and the reduction in investment by firms with positive training. When we estimate the separate effects of adopting different ADT, namely AI, IoT, digital platforms and virtual reality on the one hand and robots, drones and 3D printers on the other hand, we find that the reduction of investment in training is due to the adoption of the former group of technologies.

We estimate production functions that are augmented with digital adoption, the training stock per employee and their interaction. We deal with the correlation between unobserved productivity shocks and production factors using the control function approach proposed by Levinsohn and Petrin, 2003. We find that both digital adoption and the training stock per employee increase productivity, and that they are substitutes in production. This result implies that adopting ADT reduces the marginal productivity of training, and therefore the incentive to train.

Using Italian firm level data that has information on both training investment and training incidence (the percentage of employees receiving training), we show that investment and incidence are positively correlated. This evidence, although only suggestive, helps dispelling the concern that the observed decline in training investment may be driven entirely by a potential reduction in training costs.

Our paper speaks to the strand of empirical literature based on firm-level data that looks at the effects of automation and digitalization on productivity, employment and wages. While there is a broad consensus that the effects on productivity are positive, the effect on employment is more ambiguous. Acemoglu et al. (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 et al. (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 et al. (2018); Caselli et al. (2022)). In contrast, Bonfiglioli et al. (2020), argue 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 output. 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 empirical evidence on the effects of automation on employer-provided training using firm-level data.

The remainder of this paper is organized as follows. Section 2 introduces the data. Section 3 illustrates our measures of digital adoption. In Section 4, we estimate the effects of adopting ADT on training investment per employee using a difference - in - differences approach. We estimate the effect of ADT and the training stock on productivity in Section 5. Finally, Section 6 looks at the relationship between investment in training and the quantity of training. Conclusions follow.

2. Data.

We draw our data from the European Investment Bank Investment Survey (EIBIS). Since 2015, EIBIS is administered annually to a representative sample of firms in all 27 EU Member States and the UK, asking them questions about their investment activities in the previous financial year.[11] Since 2018, EIBIS has included questions on the use of ADT and a sample of US firms. The respondents to the interviews are senior managers

[11] Data for the UK cover the period 2015-2020.

or financial directors with responsibility for investment decisions and how investment is financed – for example, the owner, chief financial officer or chief executive officer. EIBIS covers non-financial firms in manufacturing, construction, services and infrastructure.[12]

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.[13] Brutscher et al. (2020), provide evidence for the EU that EIBIS 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 data on balance sheet and profits and loss accounts, which we use in our estimates of production functions.[14] 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 aspects of investment and investment finance activities, which are often not available in standard official sources. Particularly important for the purpose of this

[12] Manufacturing includes firms in NACE sector C, construction firms in NACE sector F, services firms in NACE sectors G and I, and infrastructure firms in NACE sectors D, E, H and J.

[13] 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.

[14] The matching is done by Ipsos MORI, which provided anonymized 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 – for example ORBIS may have missing information on employment or sales, while EIBIS does not.

paper is the information on the adoption of ADT and on annual investment in employee training.[15]

3. Digital adoption and investment in training.

Starting in 2018, EIBIS respondents are asked about the implementation 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 adoption of: (a) 3D printing, also known as additive manufacturing; (b) robotics, or automation via advanced robotics; (c) the internet of things (IoT), such as electronic devices that communicate with each other without human assistance; and (d) big data analytics and artificial intelligence (AI). Firms in the construction sector reply about the adoption of: (a) 3D printing; (b) drones or unmanned aerial vehicles; (c) IoT; and (d) augmented or virtual reality, such as when information is integrated with real-world objects and presented using a head-mounted display. Firms in services are surveyed about the adoption of: (a) virtual reality; (b) platforms or digital tools that connect customers with businesses or customers with other customers; (c) IoT; and (d) big data/artificial intelligence. Finally, firms in infrastructure are asked about the adoption of: (a) 3D printing; (b) digital platforms; (c) IoT; and (d) big data analytics and AI.

Our working sample consists of all the countries in the dataset, with the exception of Malta and Cyprus, which we exclude due to the small size of their economies. We define advanced digital technology adoption D_{it} as an indicator variable taking the value 1 if the firm i in year t has implemented at least one digital technology in parts or in the entire business, and 0 otherwise.

[15] 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.

Table 1 shows that the percentage of adopting firms in our working sample ranged in 2023 from 44 percent in construction to 65.9 percent in infrastructure. IoT is present in all the four sectors (manufacturing, construction, services and infrastructure), with a relatively high share of users. AI and 3D printers are present in three sectors out of four, with a relatively low share of users. While digital 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.[16]

For each firm in the sample, EIBIS has data on investment in land and business buildings, machinery and equipment, and training of employees. Average training investment per employee in 2023 was equal to 260 euro in real terms, ranging from 29 euro in Greece to 453 euro in Belgium.[17] Total investment in training in 2023 was equal on average to 8.19 thousand euro, close to 2 percent of average investment in land and equipment (376 thousand euro). 56.3 percent of firms invested in employee training in 2023, and average training investment per employee conditional on doing any training was equal to 461 euro (ranging from 119 euro in Lithuania to 642 euro in Belgium). Unfortunately, we do not observe in EIBIS data how many employees received training or the hours of training per employee.

Our data also includes information on turnover, the capital stock, the (gross) wage bill, the number of employees and other 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 substantially fewer missing values.[18]

As shown in Table 2, firms that have adopted at least one advanced digital technology

[16] 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 business 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.

[17] Throughout the paper, investment, output, capital and material costs are reported in real terms. Real values are obtained by dividing nominal values by the country–specific GDP deflator.

[18] 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).

in 2023 have higher levels of average output (8.70 versus 6.85 million euro), fixed assets (4.95 versus 2.69 million euro) and employment (35.2 versus 21.4 employees) than other firms. They also invest more in training per employee (320 versus 180 euro per year). The positive association between adoption of ADT and training per employee is presumably driven by the fact that bigger firms are more likely both to use ADT and to invest in training (Brunello et al. (2007)).

Table 3 reports the results of the OLS regression of the probability of adopting ADT during the period 2018-2023 on observed firm-level characteristics. We find that this probability is lower in Central and Eastern Europe than elsewhere,[19] higher in large than in small firms, highest in information and communication and lowest in construction, and highest in firms adopting strategic monitoring systems and pay for performance schemes.

4. The effect of adopting ADT on investment in training per employee.

Does the adoption of ADT lead to an increase or a decrease in training per employee? To investigate this question, we compare firms that adopted ADT during the period 2018 to 2023 ($ADOPT_i$= 1) with firms that never adopted ADT during the same period ($ADOPT_i$= 0). The binary variable $ADOPT_i$ is the treatment, adopting firms are treated firms and non-adopting firms are control firms.[20]

Using a difference – in – differences approach, we compare the change in investment in training per employee before and after adoption by firms that introduced ADT between 2018 and 2023 with the change experienced by firms that did not adopt ADT. For each treated firm in our sample, we assume that adoption occurred in the year when it was first reported (conditional on the firm reporting no adoption in the previous year),[21] and define the year when ADT was first adopted as year t=0, the years after adoption as year $t \geq 1$ and the years before adoption as year $t \leq -1$). In

[19] In this paper, the countries belonging to Central and Eastern Europe are: Bulgaria, Croatia, Czechia, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia and Slovenia.
[20] Compared to the dummy D_{it}, which varies over time, the dummy $ADOPT_i$ varies only across firms, as it refers to the first year in which firms started using ADT.
[21] We further discuss this assumption in Section 4.2.

our data the index t ranges between -4 and 5. Our final sample consists of 41,012 observations and 11,406 firms, with an average of 3.6 observations per firm.

4.1 Difference - in - differences estimates.

We estimate the following two-way fixed effects model:

$$y_{it} = \delta + \sum_{j=-4}^{-2} \alpha_j \, (ADOPT_i \times t = j) + \sum_{j=0}^{5} \beta_j \, (ADOPT_i \times t = j) + \gamma_1 C19_{it} + \theta_i + \delta_t + \varepsilon_{it} \qquad (1)$$

where the subscripts i and t denote the firm and the year, y is the dependent variable, $ADOPT_i$ is the treatment variable, θ_i and δ_t are firm-specific and time fixed effects, $C19_{it}$ is a control for the effects of the COVID-19 pandemic and β_j are the differential effects of the adoption of ADT on treated firms, compared to control firms.

Firm-specific fixed effects absorb the entire cross-sectional variability of the treatment. Conditional on these effects, we treat the interactions of the treatment $ADOPT_i$ with the year fixed effects as exogenous. In this staggered setting, where different firms start their adoption of ADT at different points in time between 2018 and 2023, we assign to the control group only non-digital firms, which did not adopt ADT between 2018 and 2023 (see Baker et al. (2021)).

We include in equation (1) the component $\sum_{j=-4}^{-2} \alpha_j \, (ADOPT_i \times t = j))$ to verify whether, during the pre-treatment period, training per employee moved in parallel in treated and control firms. This parallel trends hypothesis is a necessary requirement to interpret our estimates as causal.[22] We also allow the effect of the treatment to vary during the post-treatment period, and estimate (1) by clustering standard errors at the firm level.

Since our sample includes the year 2020, we need to control for the effects of the COVID-19 pandemic, which affected many firms in that year and made training activities in physical presence difficult. We do so in three ways: first, we use time fixed effects to control for the aggregate impact of the pandemic, as well as for other aggregate effects. Second, we control for the differential impact of COVID-19 across

[22] As is customary in this approach, we do not include in the specification the last year before the treatment (year t-1).

firms by including in equation (1) the binary variable $C19_{it}$, which is equal to 1 if the firm reported to have experienced lower sales or to have reduced investment because of COVID-19 in the year 2020, and 0 otherwise.[23] Third, we replicate our estimates by excluding the year 2020 from the sample.

Another source of concern is that our estimates could be driven by the contemporaneous increase in part-time employment, rather than by the introduction of ADT. This would lead to both lower average investment in training per employee and higher employment. Since our data does not have information on part time employment, we address this issue by augmenting our regressions with country-specific data on the share of part time employment for the years 2018 to 2023, using data from Eurostat and the OECD. If growing firms also adopt ADT, one could argue that the observed changes in training are driven by growth rather than by adoption. The time-invariant component of firm growth is picked up in our regressions by firm fixed effects. To capture the time varying component, we augment our estimates with output per employee.

Letting $E[TE]$ be the expected investment training per employee, this expectation is equal to $E[TE] = E[TE \mid TE > 0] * \Pr(TE > 0)$, where $E[TE \mid TE > 0]$ is the conditional expectation for firms with positive investments in training – or the intensive margin - and $\Pr(TE > 0)$ is the probability of positive training – or the extensive margin. Since the introduction of ADT can affect expected investment in training by influencing either margin, we estimate equation (1) using three dependent variables: investment in training per employee TE, a binary variable equal to 1 for positive investment in training and 0 otherwise, and investment in training per

[23] We combine the following two questions, asked in the 2020 wave of the survey: (a) "What has been the impact so far of the COVID-19 pandemic on your company's sales or turnover compared to the beginning of 2020". (b) "You mentioned revising your investment plans due to the COVID-19 pandemic. Did you revise them upward or downward?" We assign to C19 the value 1 if the firm had lower sales or revised investment plans downwards because of the pandemic inn 2020, and 0 otherwise. The percentage of firms reporting to have lower sales or reduced investment plans in 2020 is 56% for treated firms and 58.4% for control firms.

employee for firms with positive training.[24]

We report our estimates in Table 4, which is organized in three columns, one for each dependent variable. We find that the interactions of the treatment variable $ADOPT_i$ with the pre-treatment years are never statistically significant in any of the three columns, implying that we cannot reject the parallel trends hypothesis. Column (1) of the table and Figure 1 show that the impact of the treatment on training is close to zero at time $t=0$, negative at $t>0$ and statistically significant at the 10 percent level of confidence at $t+2$ and $t+3$. These findings indicate that training per employee declines with respect to the pre-treatment average of 0.238 by 11.3 percent (-0.027/0.238) and 13.8 percent (-0.033/0.238) two and three years after treatment. These are sizeable effects.[25]

Column (2) in Table 4 and Figure 2 consider the extensive margin and show that the interactions of the treatment with all post-treatment years are positive and statistically significant at the 5 percent level of confidence. Expressing these estimated effects as a percentage of the average probability of positive training before the treatment (0.474), the probability of training increases by 8.8 percent in the year of the treatment, by 15.6 percent three years after the treatment and by 12.8 percent five years after the treatment. Again, these effects are sizeable.

Finally, column (3) and Figure 3 report the effects of the treatment on training per employee for firms with positive training. We find that these effects are negative, statistically significant at the 5 percent level of significance and sizeable. Expressed as a percentage of average training before the treatment (0.501), we estimate that the adoption of ADT reduces training intensity for firms with positive training by 6.3 percent on impact, by 17.3 percent three years after adoption and by 17.9 percent five years after adoption. These effects are larger in absolute value than those found for the

[24] Following Chen and Roth (2023), we prefer to use the level of training per employee rather than log(1 + training per employee).

[25] Five years after the treatment, the estimated effect is imprecisely estimated but similar to the one three years after the treatment.

extensive margin.

The estimates in Table 4 indicate that the negative impact of adopting ADT on real training per employee reported in column (1) is the outcome of two contrasting and statistically significant effects, positive for the extensive margin and negative for the intensive margin. With the exception of $t=0$, the negative effects are always larger than the positive effects.

The expected negative impact on training of the 2020 lockdown due to the COVID-19 pandemic is captured in Table 4 by the negative coefficients associated with the variable C19. In addition, we find that the time effect for the year 2020 (not reported in the table) attracts large negative coefficients (-0.064 in column (1), -0.126 in column (2) and -0.052 in column (3)). We further investigate whether our results are driven by the 2020 pandemic by running our estimates in the sub-sample that excludes the year 2020. Although the results in Table 5 are less precise than those in Table 4, they are qualitatively similar, suggesting that the results in Table 4 are not driven by the lockdown induced by the COVID-19 pandemic.

4.2 Robustness checks and heterogeneous effects.

We identify the year when ADT was first adopted in firm i by setting it at t when the firm states that it adopted ADT at time t but not at time $t-1$. In many cases, however, adoption is reported in the first available observation. For these cases, we have assumed that the year of first adoption coincides with the first observation. Since a potential concern is that this assumption can induce measurement error in the year of first adoption, we have re-estimated equation (1) by excluding all firms stating that they were using ADT in their first available observation. When we do so, our results are qualitatively unchanged (see Appendix Table A1).

The countries in our sample include economies at different level of development, with Central and Eastern European countries lagging the rest of Europe and the US. We verify in Tables 6 whether our estimates change significantly when we restrict the sample to a more homogeneous group of countries by excluding Central and Eastern

Europe and find that our results are qualitatively similar but somewhat more precise than those reported in Table 4.[26]

Finally, we investigate whether the effects of adopting ADT on training vary with the type of technology by distinguishing between two groups of treatment: 1) AI, IoT, digital platforms and virtual reality; 2) robots, drones and 3D printers. For each group, we use as controls non-adopting firms. The first group of technologies is used in all sectors, but only marginally in infrastructure. Firms in the services sector are not asked about the second group of technologies and are therefore excluded from the regression for this group. Our estimates in Table 7 report the effects of adopting ADT on training per employee by type of technology. For the first group, we find that these effects are negative and statistically significant in most post-treatment periods. For the second group, the estimated effects are generally small, often positive and not statistically different from zero. We conclude that our key results are driven by the first group of technologies.

5. Training, digital adoption and firm productivity.

A candidate reason why training per employee declines over time in firms that have implemented ADT (compared to other firms) is that the adoption of these technologies reduces the marginal productivity of training, which is equivalent to saying that digital adoption and training are substitutes in production. We explore this possibility by estimating production functions that are augmented with both the training stock and digital adoption.

5.1 Augmented production functions.

We assume that firms operate the following production function (see Konings and Vanormelingen (2015))

$$Y_{it} = L_{it}^{\gamma}[\exp(\rho D_{it}) K_{it}]^{\delta} M_{it}^{\eta} \exp(q_{it}) \exp(\varepsilon_{it}) \quad (2)$$

where Y denotes output, L labor in efficiency units, K capital, M intermediate

[26] We also estimate Eq. (1) by dropping one country at a time but find little variation in the key estimated coefficients. The results are available from the authors upon request.

materials, q technical efficiency that shifts the production function, and ε is a disturbance term. Since ADT can expand the set of tasks within the production process that can be performed by capital, we assume that the adoption of ADT, captured by the binary variable D, increases the productivity of capital by the factor $\exp(\rho D_{it})$.

Taking logs of equation (2) and defining $y = \ln(Y), l = \ln(L), k = \ln(K)$ and $m = ln(M)$ we obtain

$$y_{it} = \gamma l_{it} + \delta\rho D_{it} + \delta k_{it} + \eta m_{it} + q_{it} + \varepsilon_{it} \quad (3)$$

As in Bartel (2000) and Konings and Vanormelingen (2015), we assume that labor efficiency increases with the average stock of training per employee TS[27] and unobserved labor and managerial quality Z. Therefore

$$L_{it} = E_{it}(1 + \rho_T TS_{it} + Z_{it}) \quad (4)$$

where E is employment. Taking logs and using the approximation $\ln(1 + x) \cong x$, we obtain that $l_{it} = e_{it} + \rho_T TS_{it} + Z_{it}$, where $e = \ln(E)$.

We further assume that technical efficiency q depends on advanced digital technology adoption D_{it}, its interaction with training TS and a vector of controls X

$$q_{it} = \beta_0 + \beta_D D_{it} + \beta_{DT}(D_{it}\ x\ TS_{it}) + \lambda X_{it} \quad (5)$$

Using equations (5) and (4) in (3) we obtain

$$y_{it} = \gamma e_{it} + \beta_T TS_{it} + [\beta_D + \delta\rho]D_{it} + \beta_{DT}(D_{it}\ x\ TS_{it}) + \delta k_{it} + \eta m_{it} + \lambda X_{it} + \omega_{it} + \varepsilon_{it} \quad (6)$$

where $\beta_T = \gamma\rho_T$ and $\omega_{it} = \beta_0 + \gamma Z_{it}$. 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 assumed instead to be orthogonal to the right-hand side variables in equation (6).

In this setup, both advanced digital technology adoption D_{it} and the training stock

[27] The training stock is obtained from training investment using the perpetual inventory formula, as described in the next sub-section.

per employee TS_{it} affect productivity, the former by improving technical efficiency and the productivity of capital, and the latter by improving both labor and technical efficiency. Advanced digital technology adoption D_{it} and the training stock per employee TS_{it} are complements in production if $\partial^2 y / \partial TS \partial D = \beta_{DT} > 0$ and substitutes if $\partial^2 y / \partial TS \partial D = \beta_{DT} < 0$ (see Seidman (1989)). With complementarity (substitutability), an increase in D_{it} (TS_{it}) raises (reduces) the marginal productivity of TS_{it} (D_{it}).

5.2 Estimation.

The estimation of the parameters in equation (6) is complicated by the fact that factor input choices (capital, materials, and labor) as well as the choice of training and digital adoption are correlated with the error term ω_{it}. To address this problem, we use the control function approach proposed originally by Olley and Pakes (1996) and refined by Levinsohn and Petrin (2003) (LP in short).

The basic idea of this approach is that the endogeneity problem originates from the fact that ω_{it} is unobserved by the analyst. If an invertible function can make ω_{it} observable, the problem can be solved. Following LP (2003), we assume that the cost of intermediate materials m_{it} is an invertible function of the state variables Γ_{it} (the capital stock, the training stock per employee, digital intensity and the interaction between *TS* and D_{it}) and unobserved ω_{it}, or $m_{it} = f(\Gamma_{it}, \omega_{it})$. Invertibility implies that $\omega_{it} = f^{-1}(m_{it}, \Gamma_{it})$, which can be substituted in equation (6) and approximated with a polynomial in m_{it} and Γ_{it}. Further details on this method are described in the Appendix. Its implementation requires that we treat the state variables as determined by decisions taken at time *t-1*.

We assume this to be the case for D_{it}, as it takes time to install new technologies. For *K* and *TS*, we compute both the capital and the training stock using the perpetual inventory formula:

$$X_{it} = x_{it-1} + (1-\delta) X_{i,t-1} \tag{7}$$

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.[28]

The flow x in equation (7) is investment in land, business building, machinery and equipment for the capital stock and investment in training per employee for the training stock. We set the depreciation rate at 4.6 percent for physical 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 et al. (2012), and use the first available training flow t_0 (starting in 2015) and the assumption that the initial stock TS_0 is given by $TS_0 = \frac{t_0}{\delta+g}$, where g is the steady state rate of growth of human capital, which we set at 5 percent, as in Jones et al. (2012). Using this procedure, we find that the average training stock in 2023 was equal to 1.59 thousand euro per employee in firms adopting ADT and to 0.92 thousand euro in non-adopting firms (see Table 2).

Unfortunately, EIBIS has no data on the cost of intermediate materials, which we require to apply LP's approach to the estimation of production functions. For many firms in our sample, we obtain this cost by matching the data from EIBIS to the ORBIS database, which contains firm balance sheet data and profit and loss accounts. For the firms with no information on material costs in ORBIS we use EIBIS data on profits and the wage bill to obtain an estimate of value added.[29] The cost of materials is then obtained as the difference between turnover and value added.[30]

5.3 Results.

Table 8 reports the LP estimates of equation (6) for the period 2018-2023, under the assumption that the function $f^{-1}(m_{it}, \Gamma_{it})$ is approximated by a fourth order polynomial. Standard errors are clustered by firm and bootstrapped with 50 iterations. We find that digital adoption D_{it} and the training stock per employee TS increase

[28] In the few cases where there are gaps in the years, we replace the lagged flow with the closest year.
[29] These firms are 41 percent of the sample.
[30] To avoid that our estimates are affected by outliers, we replace the values of capital, employment, output and the training stock above and below the 99th and 1st percentile with the 99th and the 1st percentiles.

productivity, and that their interaction attracts a negative and statistically significant coefficient, implying that digital adoption D_{it} and the training stock TS_{it} are substitutes in production, and that the introduction of ADT reduces the marginal product of training.

Substitutability could arise if the implementation 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.[31]

6. Investment in training and the quantity of training

Our finding that the adoption of ADT reduces training investment 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 investment in training per employee is the product of the unit cost of training and the quantity of training per employee, a decline in investment does not necessarily imply a reduction in the quantity of training. This could happen 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 EIBIS survey. As a first step in this direction, we use firm data from the Italian Longitudinal Survey on Firms and Employment (*Rilevazione Longitudinale su Imprese e Lavoro),* which includes information on employment, investment in training and number of trained employees

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

in 2010, 2014 and 2017 for more than 20 thousand Italian firms.[32] If the observed changes in investment in training per employee were driven exclusively by changes in the costs of training, we should find that the correlation between training incidence (defined as the share of trained employees) and investment in training is close to zero. Yet Figure 4 shows that the correlation between firm-specific changes in training investment per employee and training incidence is positive (and equal to 0.64), suggesting that changes in the quantity of training are an important part of the variation in investment in training induced by the adoption of ADT.

Conclusions.

There is much concern in policy circles about the labor market consequences of automation and digitalization. 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 a substantial share of employee training is provided by employers (see Brunello et al (2007)), it is important to understand whether and how the increased use of automation and digital technologies affects employers' incentives to invest in the training of their workers.

We have addressed this question using unique firm-level data that cover 25 EU countries, the UK and the US and include information both on the use of ADT and on investment in training. We have shown that, compared to non-adopting firms, employers adopting these technologies are more likely to train their employees. However, investment in training per employee for firms with positive training declines after digital adoption. As a result of these contrasting effects, the adoption of ADT reduces average investment in training per employee.

Using Italian firm level data, we have shown that the observed reduction of average investment in training per employee is unlikely to reflect only a decline in the cost of training but also involves a reduction in average training incidence, as documented

[32] This survey is managed by INAPP (Istituto Nazionale per l'Analisi delle Politiche Pubbliche).

also by Hess et al (2023) for Germany.

We have argued that a mechanism explaining our results is that ADT and investment in training 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 replaces unskilled labor with capital but also modifies 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 investment in formal training. Firms using ADT could also fill the skilled positions associated with these technologies by hiring new employees rather than by training in-house, thereby reducing training needs.

Adult reskilling and upskilling are seen as natural remedies against the effects of introducing ADT. Since employers adopting these technologies are investing less in training, government policies that stimulate workers to undertake further training can play a very important role. However, a side effect of substitutability between training and ADT is that policies that manage to increase employee training may also reduce the marginal productivity of ADT and therefore contribute to slowing down its adoption. Our findings thus point to challenges in realizing high levels of firm-sponsored training for employees in increasingly digital economies.

An example of policies that could work are individual learning accounts (ILA), that encourage savings for education while providing vouchers to people interested in pursuing training. In France, for instance, the French Compte Personnel de Formation (Personal Training Account – CPF), were introduced in 2015 and reformed in 2018. This is an individualized scheme for financing training that is open to all economically active people, and is fully transferable throughout the individual's working life, from the time they enter the labor market until they retire. Recent data covering the years 2021 and 2022 show a surge in the take-up of this measure, with more than 1.6 million users per year (out of an active population of 30 million), suggesting that this type of intervention could be useful to foster a culture of training, even though reaching out to the low educated groups remains a challenge (see Brunello et al. (2024)).

Tables and figures.

Table 1. Share of firms implementing advanced digital technologies (ADT). Financial year 2023.

	Manufacturing	Construction	Services	Infrastructure
Digital adoption	49.8	44.0	59.7	65.9
3 D printers	22.5	7.1	-	4.3
Advanced robotics	21.5	-	-	-
Internet of things	30.1	28.3	31.1	36.8
Artificial intelligence	15.6	-	15.6	22.7
Augmented reality	-	7.1	6.1	-
Drones	-	21.9	-	-
Platforms	-	-	45.2	48.2

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

Table 2. Firm characteristics, by digital adoption status. Financial year 2023.

	Adopting firms	Not adopting firms
Output (million euro)	8.70 (36.43)	6.85 (31.77)
Fixed assets (million euro)	4.95 (22.71)	2.69 (15.83)
Material costs (million euro)	7.26 (28.29)	6.53 (31.75)
Employment	35.20 (122.19)	21.42 (65.00)
Investment in training per employee (thousand euro)	0.32 (0.59)	0.18 (0.41)
Investment in training (thousand euro)	11.06 (48.54)	4.07 (24.67)
Training stock per employee	1.59 (2.86)	0.92 (2.00)
Share of manufacturing firms	0.17	0.21

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

Table 3. Factors affecting digital adoption. Financial years 2018-23. Linear regressions. Dependent variable: binary variable D (digital adoption).

	Digital adoption
Central and Eastern Europe	-0.042*** (0.006)
2019	0.022*** (0.007)
2020	0.019*** (0.007)
2021	0.141*** (0.008)
2022	0.148*** (0.008)
2023	0.162*** (0.009)
10-49 employees	0.053*** (0.007)
50-249 employees	0.150*** (0.008)
250+ employees	0.276*** (0.009)
Electricity	0.062*** (0.019)
Water	-0.029** (0.015)
Construction	-0.103*** (0.008)
Wholesale and Retail Trade	0.026*** (0.008)
Transportation	0.009*** (0.009)
Accommodation & hotels	0.012 (0.016)
Information & Communication	0.270*** (0.011)
Firm age is less than 10 years	0.005 (0.009)
Firm uses a strategic business monitoring system	0.168*** (0.005)
Firm uses pay for performance schemes	0.072*** (0.007)
Number of observations	42,702

Note: Central and Eastern Europe: Bulgaria, Croatia, Czechia, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia and Slovenia. Omitted categories: Western Europe and the US, financial year 2018, small firms with 5-9 employees and manufacturing. Standard errors clustered at the firm level in parentheses. One, two and three stars for statistical significance at the 10, 5 and 1 percent.

Table 4. The differential effect of adopting ADT on investment in training per employee. Event study. Financial years 2018-23. Dependent variables: investment in training per employee, probability of training and training per employee for firms with positive training.

	Training per employee	Probability of training	Training per employee for firms with positive training
ADOPT x (t= - 4)	-0.014	-0.000	-0.014
	(0.030)	(0.037)	(0.039)
ADOPT x (t= - 3)	-0.024	-0.044	0.003
	(0.022)	(0.027)	(0.030)
ADOPT x (t= - 2)	-0.016	-0.007	-0.007
	(0.015)	(0.018)	(0.026)
ADOPT x adoption year	-0.004	0.042***	-0.032**
	(0.009)	(0.010)	(0.015)
ADOPT x (t= + 1)	-0.018	0.043***	-0.057***
	(0.011)	(0.013)	(0.019)
ADOPT x (t = + 2)	-0.027*	0.055**	-0.076***
	(0.014)	(0.016)	(0.023)
ADOPT x (t = + 3)	-0.033*	0.074***	-0.087***
	(0.017)	(0.020)	(0.028)
ADOPT x (t = + 4)	-0.015	0.067***	-0.070**
	(0.021)	(0.024)	(0.035)
ADOPT x (t = + 5)	-0.035	0.061**	-0.090**
	(0.026)	(0.029)	(0.042)
C19	-0.016*	-0.040***	-0.002
	(0.009)	(0.010)	(0.015)
Number of observations	41,012	41,012	25,984

Note: ADOPT: treatment variable; C19: binary variable equal to 1 if the firm had lower sales or reduced investment in 2020 due to COVID-19, and to 0 otherwise. All regressions include output per employee, an indicator for missing values on output per employee, the share of part time workers by country and year, and year and firm fixed effects. Standard errors clustered at the firm level in parentheses. One, two and three stars for statistical significance at 10, 5 and 1 percent

Table 5. The differential effect of adopting ADT on investment in training per employee. Event study. Financial years 2018-19 and 2021-23. Dependent variables: investment in training per employee, probability of investing in training, and training per employee for with positive investment.

	Training per employee	Probability of training	Training per employee for firms with positive training
ADOPT x (t= - 4)	0.001	0.008	0.010
	(0.032)	(0.038)	(0.043)
ADOPT x (t= - 3)	-0.013	-0.062*	0.026
	(0.027)	(0.032)	(0.036)
ADOPT x (t= - 2)	-0.002	0.006	0.041
	(0.020)	(0.023)	(0.030)
ADOPT x adoption year	-0.001	0.049***	-0.028
	(0.011)	(0.012)	(0.018)
ADOPT x (t= + 1)	-0.018	0.040***	-0.042*
	(0.014)	(0.015)	(0.022)
ADOPT x (t = + 2)	-0.025	0.066**	-0.074***
	(0.017)	(0.019)	(0.027)
ADOPT x (t = + 3)	-0.036*	0.080***	-0.094***
	(0.019)	(0.022)	(0.031)
ADOPT x (t = + 4)	-0.017	0.077***	-0.069*
	(0.024)	(0.027)	(0.038)
ADOPT x (t = + 5)	-0.034	0.066**	-0.086*
	(0.028)	(0.032)	(0.046)
Number of observations	33,179	33,179	21,566

Note: ADOPT: treatment variable. All regressions include output per employee, an indicator for missing values of output per employee, the share of part-time workers by country and year, year and firm fixed effects. Standard errors clustered at the firm level in parentheses. One, two and three stars for statistical significance at 10, 5 and 1 percent.

Table 6. The differential effect of adopting ADT on investment in training per employee. Event study. Financial years 2018-23. Excluding Central and Eastern Europe. Dependent variables: investment in training per employee, probability of investing in training, and training per employee for firms with positive investment

	Training per employee	Probability of training	Training per employee for firms with positive training
ADOPT x (t= - 4)	0.032	0.064	0.047
	(0.054)	(0.050)	0.062
ADOPT x (t= - 3)	-0.010	-0.032	0.031
	(0.035)	(0.036)	(0.050)
ADOPT x (t= - 2)	-0.011	0.026	-0.001
	(0.023)	(0.023)	(0.038)
ADOPT x adoption year	-0.011	0.034**	-0.041*
	(0.014)	(0.013)	(0.022)
ADOPT x (t= + 1)	-0.029*	0.039**	-0.066***
	(0.017)	(0.016)	(0.027)
ADOPT x (t = + 2)	-0.039*	0.058***	-0.094***
	(0.021)	(0.021)	(0034)
ADOPT x (t = + 3)	-0.067**	0.059**	-0.117***
	(0.026)	(0.026)	(0.042)
ADOPT x (t = + 4)	-0.038	0.044	-0.088*
	(0.033)	(0.032)	(0.052)
ADOPT x (t = + 5)	-0.063	0.030	-0.103
	(0.041)	(0.039)	(0.064)
C19	-0.019	-0.042***	0.0000
	(0.013)	(0.013)	(0.020)
Number of observations	25,655	25,655	16,912

Note: ADOPT: treatment variable; C19: binary variable equal to 1 if the firm had lower sales or reduced investment in 2020 due to COVID-19, and to 0 otherwise. All regressions include output per employee, an indicator for missing values of output per employee, the share of part time workers by country and year, year and firm fixed effects. Standard errors clustered at the firm level in parentheses. One, two and three stars for statistical significance at 10, 5 and 1 percent.

Table 7. The differential effect of adopting ADT on investment in training per employee. Event study. Financial years 2018-23. Dependent variables: investment in training per employee. By type of investment.

	Training per employee – AI, IoT, digital platforms and virtual reality	Training per employee – Robots, drones and 3D printers
ADOPT x (t= - 4)	-0.02	-
	(0.028)	-
ADOPT x (t= - 3)	-0.034*	-0.032
	(0.021)	(0.034)
ADOPT x (t= - 2)	-0.022	-0.003
	(0.015)	(0.025)
ADOPT x adoption year	-0.009	-0.002
	(0.009)	(0.017)
ADOPT x (t= + 1)	-0.025**	-0.004
	(0.011)	(0.019)
ADOPT x (t = + 2)	-0.037***	0.012
	(0.014)	(0.021)
ADOPT x (t = + 3)	-0.035**	0.008
	(0.017)	(0.025)
ADOPT x (t = + 4)	-0.027	0.011
	(0.021)	(0.029)
ADOPT x (t = + 5)	-0.046*	0.020
	(0.026)	(0.038)
C19	-0.016*	-0.021*
	(0.009)	(0.011)
Number of observations	41,001	31,187

Note: ADOPT: treatment variable; C19: binary variable equal to 1 if the firm had lower sales or reduced investment in 2020 due to COVID-19, and to 0 otherwise. All regressions include output per employee, an indicator for missing values of output per employee, the share of part-time workers by country and year, year and firm fixed effects. We exclude the services sector and the few observations with *t* = -4 in column 2. Standard errors clustered at the firm level in parentheses. One, two and three stars for statistical significance at 10, 5 and 1 percent.

Table 8. Effects of digital use and training on productivity. Levinsohn and Petrin method. Dependent variable: log value added. Financial years 2018-2023.

	Log value added
Log employment	0.894***
	(0.005)
Log capital stock	0.118***
	(0.006)
Training stock per employee (TS)	0.056***
	(0.006)
ADT adoption (D)	0.120***
	(0.011)
TS x D (binary)	-0.023***
	(0.006)
Number of observations	28,143

Note: D: binary variable equal to 1 if the firm adopted ADT and to 0 otherwise. All regressions include indicator variables for Central and Eastern Europe and Southern Europe, an indicator for the manufacturing sector and year fixed effects. Standard errors clustered at the firm level in parentheses. One, two and three stars for statistical significance at 10, 5 and 1 percent.

Figure 1. Estimated effects of the treatment ADOPT on investment in training per employee.

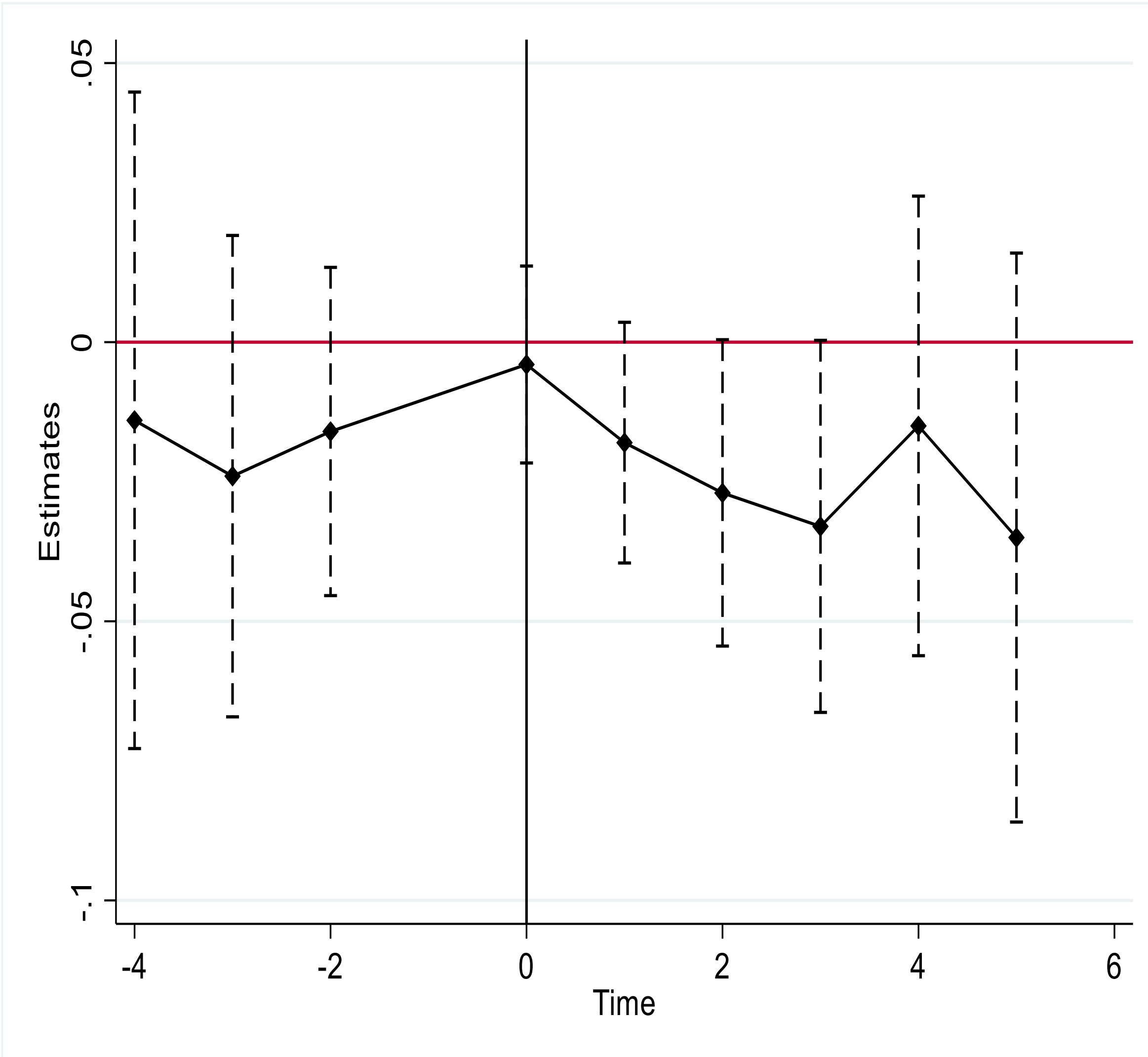


Figure 2. Estimated effects of the treatment ADOPT on the probability of training.

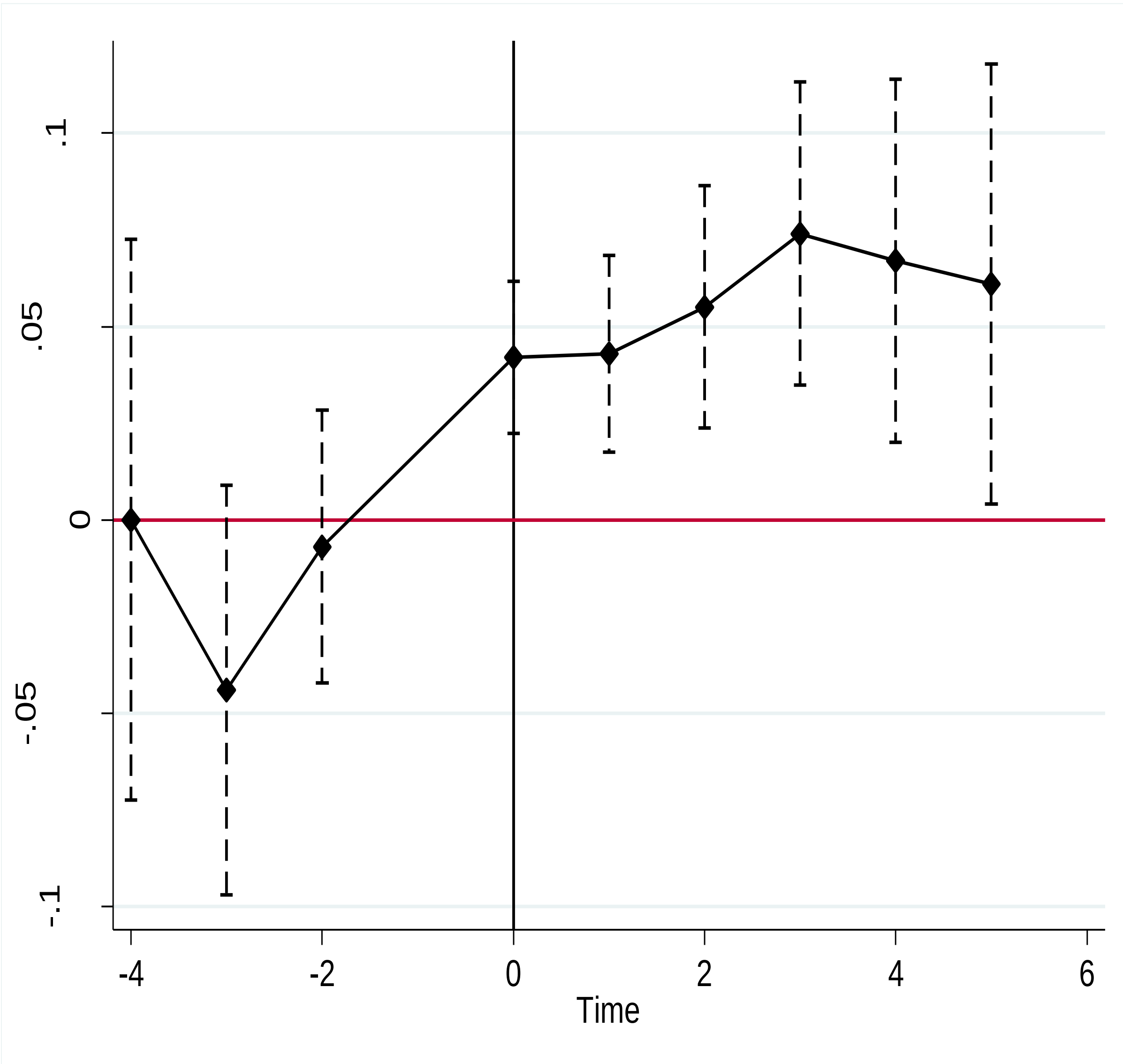


Figure 3. Estimated effects of the treatment ADOPT on investment in training per employee in firms with positive training.

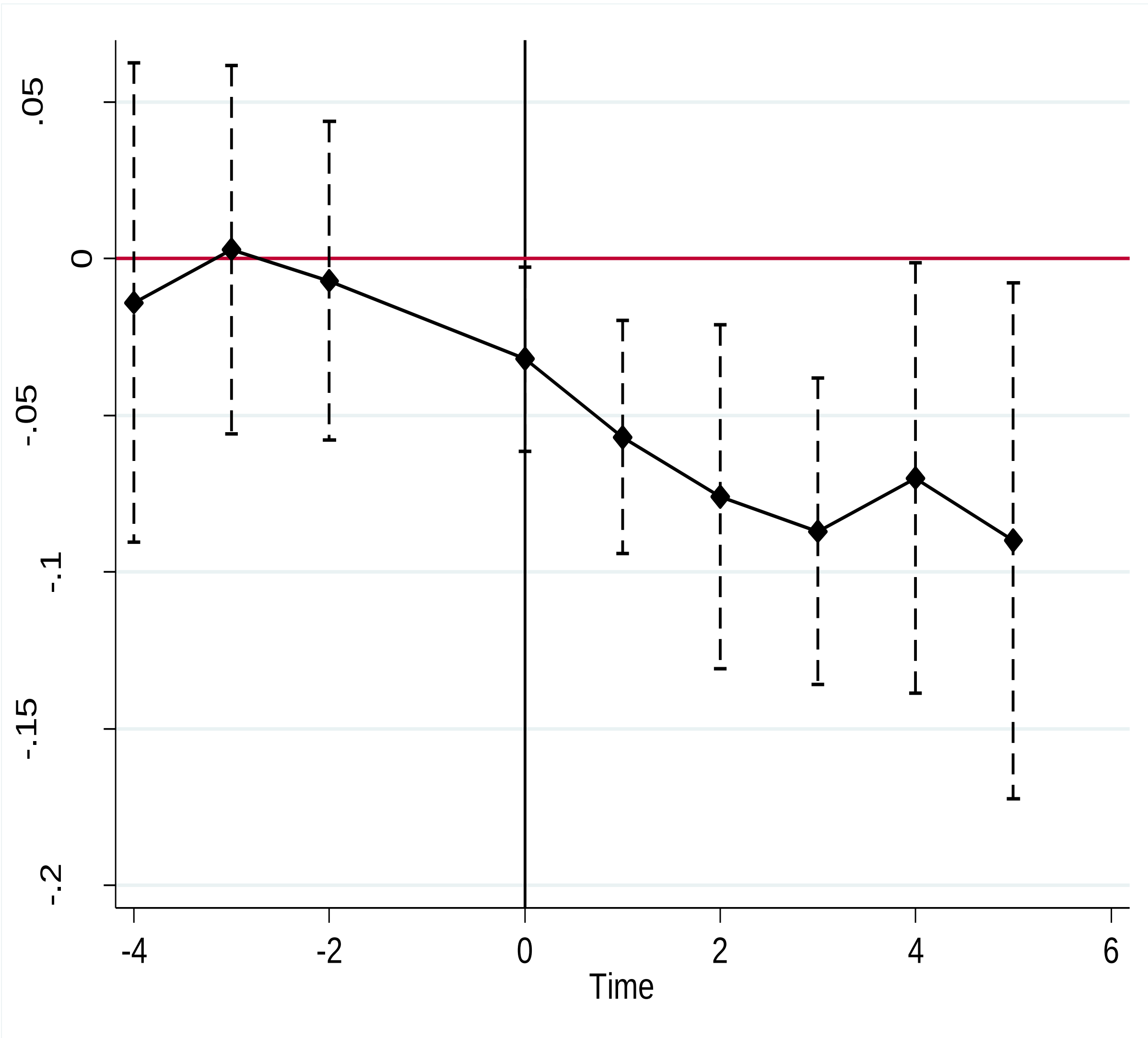
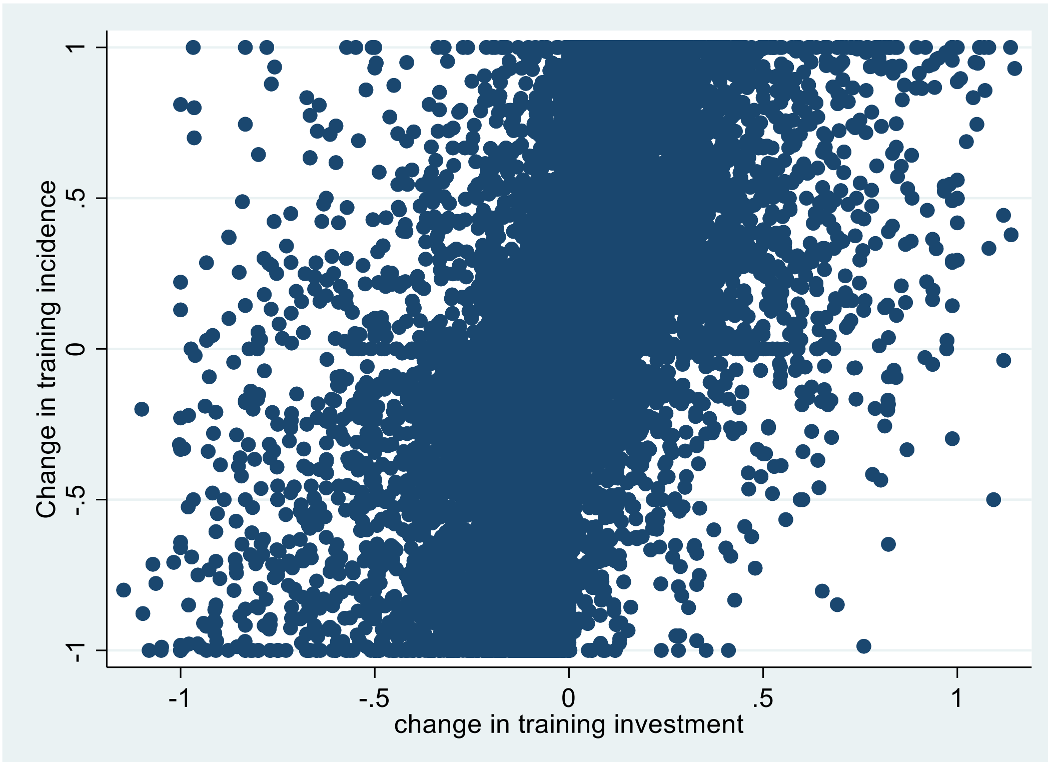


Figure 4. Changes in investment in training per employee and in the share of trained employees. Italy 2010-2017



Source: RIL survey waves 2010, 2014 and 2017

References

Acemoglu, D., Lelarge, C. and Restrepo, P. (2020). Competing with robots: Firm-level evidence from France. *AEA Papers and Proceedings*, 110, 383–88.

Acemoglu, D. and Restrepo, P. (2019). Automation and new tasks: How technology displaces and reinstates labor. *Journal of Economic Perspectives,* 33(2), 3–30.

Acemoglu, D. and Restrepo, P. (2022). Tasks, automation, and the rise in U.S. wage inequality. *Econometrica*, 90(5), 1973-2016.

Acemoglu, D., Anderson, G., Beede, D., Buffington, C., Childress, E., Dinlersoz, E., Foster, L., Goldschlag, N., Haltiwanger J., Kroff, Z., Restrepo, P. and Zolas, N. (2022). Automation and the workforce: A firm-level view from the 2019 Annual Business Survey. NBER Working Paper No. 30659.

Almeida, R. and Carneiro, P. (2009). The return to firm investments in human capital. *Labour Economics* 16(1), 97–106.

Baker, A., Larcker, D. and Wang, C. (2021). How much should we trust staggered differences-in-differences estimates? Harvard Business School working paper 21-112

Bartel, A.P. (2000). Measuring the employer's return on investments in training: Evidence from the literature. *Industrial Relations*, 39, 502-524.

Battisti, M., Del Gatto, M., Gravina, A. and Parmeter, C. (2021). Robots versus labor skills: A complementarity/substitutability analysis. CRENOS Working Paper No. 2021/4.

Bonfiglioli, A., R. Crinò, H. Fadinger and Gancia, G. (2019). Robot imports and firm level outcomes. CEPR Working Paper No. 14593.

Brunello, G., Garibaldi, P. and Wasmer, E. (2007). *Education and Training in Europe*. Oxford University Press.

Brunello, G., Rückert, D. and Wruuck, P. (2024). Adult learning: the employers' provision of retraining and re-skilling, in Carcillo, S and Scarpetta, S. *Handbook on Labour Markets in Transition*, forthcoming.

Brutscher, P., Coali, A., Delanote, J. and Harasztosi, P. (2020). EIB group survey on investment and investment finance: A technical note on data quality. EIB working paper No 2020/08.

Bughin, J., Lund, S. and Hazan, E. (2018). Automation will make lifelong learning a necessary part of work. *Harvard Business Review*, May 24, 2018.

Byrne, D. and Corrado, C., (2017). ICT Prices and ICT Services: what do they tell us about Productivity and Technology, Finance and Economics Discussion Paper No. 2015-015, Board of Governors of the Federal Reserve System.

Caselli, M., Fracasso, A., Scicchitano, S., Traverso, S. and Turdis, E. (2022). Stop worrying and love the robot? An activity-based approach to assess the impact of robotization on employment dynamics. Unpublished manuscript.

Chen, J and Roth, J (2023). Logs with zero? Some problems and solutions, *Quarterly Journal of Economics*, 139,2, 1-46.

Chernoff, A. and Warman, C. (2021). COVID-19 and implications for Automation. Bank of Canada Staff Working Papers No. 21-25.

Dinlersoz, E. and Wolf, Z. (2018). Automation, labor share, and productivity: Plant-level evidence from U.S. Manufacturing. CES Working Paper No. 18-39.

Dixon, J., Hong, B. and Wu, L. (2019). The employment consequences of robots: Firm-level evidence. Unpublished manuscript.

Draca, M., Sadun, R. and Van Reenen, J. (2006). Productivity and ICT: A review of the evidence. CEP Discussion Paper No. 749.

ECB (2006). *Monthly Bulletin, May 2006*. Frankfurt am Main: European Central Bank.

EIB (2022). *Investment Report 2021/2022: Recovery as a springboard for change.* Luxembourg: European Investment Bank.

Feng, A. and Graetz, G. (2020). Training requirements, automation and job polarization. *Economic Journal*, 130, 2249-2271.

Fitzpayne, A. and Pollack, E. (2018). Lifelong learning and training accounts: Helping workers adapt and succeed in a changing economy. Issue Brief, May 2018, The Aspen Institute.

Gathman,C., Kagerl, C., Pohlan, L. and Roth, D. (2023), The Pandemic push: digital technologies and workforce adjustment, IZA Discussion Paper #16062.

Graetz, G. and Michaels, G. (2018). Robots at work. *Review of Economics and Statistics*, 100(5), 753-768.

Guner, D. and Nursk, L. (2023). Understanding barriers and resistance to training in the European Union, Bruegel. https://www.bruegel.org/blog-post/understanding-barriers-and-resistance-training-european-union.

Hess, P., Janssen, S. and Leber, U. (2023), The effect of automation technology on workers' training participation, *The Economics of Education Review*, 96

Ipsos (2019). EIB Group survey on investment and investment finance: Technical report. Luxembourg: European Investment Bank.

Jones, D., Kalmi, P. and Kauhanen, A. (2012). The effects of general and firm-specific training on wages and performance: Evidence from banking, *Oxford Economic Papers*, 64, 151-175.

Jurkat, A., Klump, R. and Schneider, F. (2022). Tracking the rise of robots: The IFR database. *Jahrbücher für Nationalökonomie und Statistik*, 242, 669-689.

Koch, M., Manuylov I. and Smolka, M. (2021). Robots and firms. *Economic Journal*, 131, 2553-2584.

Konings, J. and Vanormelingen, S. (2015). The impact of training on productivity and wages: Firm-level evidence. *Review of Economics and Statistics* 97(2), 485–497

Lane, M. and Saint Martin, A. (2021). The impact of artificial intelligence on the labor market: What do we know so far. OECD Social, Employment and Migration Working Paper No. 256.

Levinsohn, J. and Petrin, A. (2003), Estimating Production Functions using Inputs to control for Unobservables, *The Review of Economic Studies*, 70, 317-341

Morikawa, M. (2017). Firms' expectations about the impact of AI and robotics: Evidence from a survey. *Economic Inquiry*, 55(2), 1054–1063.

Nedelkoska, L. and Quintini, G. (2018). Automation, skills use and training. OECD Social, Employment and Migration Working Paper No. 202

Olley, G.S. and Pakes, A. (1996). The dynamics of productivity in the telecommunications equipment industry. *Econometrica*, 64(6), 1263–97.

Ransbotham, S., Khodabandeh, S., Fehling, R., LaFountain B. and Kiron, D. (2019). Winning with AI, *The Sloan Management Review*, October 15, 2019.

Rovigatti, G. and Mollisi, V. (2018). Theory and practice of TFP estimation: The control function approach using Stata. *Stata Journal*, 18(3), 618-662.

Schmidpeter, B. and Winter-Ebmer, R. (2021). Automation, unemployment and the role of labor market training. *European Economic Review*, 137, 103808.

Seidman, L. (1989). Complements and substitutes: The importance of minding q's and p's. *Southern Economic Journal*, 56(1), 183-190.

Sieben, I., De Grip, A., Longen, J. and Sorensen, O. (2009). Technology, selection and training in call centers. *Industrial and Labor Relations Review*, 62(4), 553-573.

Tilley, J. (2017). Automation, robotics and the factory of the future. McKinsey, September 7, 2017.

Verhagen, A. (2021). Opportunities and drawbacks of using AI for training. OECD Social, Employment and Migration Working Paper No. 266.

Appendix Tables

Table A1. The differential effect of adopting ADT on investment in training per employee. Event study. Financial years 2018-23. Dependent variables: investment in training per employee.

	Training per employee	Probability of training	Training per employee for firms with positive training
ADOPT x (t= - 4)	-0.016	-0.003	-0.017
	(0.031)	(0.037)	(0.039)
ADOPT x (t= - 3)	-0.027	-0.044	-0.000
	(0.022)	(0.027)	(0.031)
ADOPT x (t= - 2)	-0.020	-0.007	-0.011
	(0.016)	(0.018)	(0.027)
ADOPT x adoption year	-0.005	0.044***	-0.035**
	(0.010)	(0.011)	(0.017)
ADOPT x (t= + 1)	-0.030**	0.031*	-0.067***
	(0.013)	(0.016)	(0.022)
ADOPT x (t = + 2)	-0.008	0.061***	-0.051
	(0.021)	(0.023)	(0.034)
ADOPT x (t = + 3)	-0.006	0.077**	-0.055
	(0.033)	(0.031)	(0.048)
ADOPT x (t = + 4)	-0.044	0.119***	-0.139***
	(0.030)	(0.039)	(0.042)
C19	-0.021*	-0.040**	-0.001
	(0.012)	(0.016)	(0.023)
Number of observations	18,853	18,853	18,853

Note: ADOPT: treatment variable; C19: indicator variable equal to 1 if the firm had lower sales or reduced investment in 2020 due to COVID-19, and to 0 otherwise. All regressions include output per employee, an indicator for missing values of output per employee, the share of part-time workers by country and year, year and firm fixed effects. Standard errors clustered at the firm level in parentheses. One, two and three stars for statistical significance at 10, 5 and 1 percent.

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:

$$y_{it} = \alpha + w_{it}\beta + x_{it}\gamma + \omega_{it} + \varepsilon_{it} \quad \text{(A1)}$$

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

$$\omega_{it} = g(\omega_{it-1}) + \psi_{it} \quad \text{(A2)}$$

Where ψ_{it} is a productivity shock, uncorrelated with ω_{it} and the vector x. Levinsohn and Petrin, 2003, proposes to estimate (A7) by using an observable variable, expenditure on intermediate materials m, as proxy for ω. They further assume

a) $m_{it} = f(x_{it}, \omega_{it})$, where the function f is invertible in ω, and intermediate materials m are 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 m and x are orthogonal and that $m_{it} = f(x_{it}, \omega_{it})$ can be inverted to yield

$$\omega_{it} = f^{-1}(m_{it}, x_{it}) \quad \text{(A3)}$$

Plugging this in equation (A8) we obtain

$$y_{it} = \alpha + w_{it}\beta + \Phi_{it}(m_{it}, x_{it}) + e_{it} \quad \text{(A4)}$$

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

Equation (A4) can be parametrically estimated approximating $\Phi_{it}(m_{it}, x_{it})$ by an nth order polynomial. This yields an estimate of β.

To estimate γ, rewrite the model as

$$y_{it} - w_{it}\hat{\beta} = \alpha + x_{it}\gamma + g(\omega_{it-1}) + e_{it} \quad \text{(A5)}$$

where $e_{it} = \varepsilon_{it} + \psi_{it}$. Since $\omega_{it} = \Phi_{it} - x_{it}\gamma$, equation (A5) becomes

$$y_{it} - w_{it}\hat{\beta} = \alpha + x_{it}\gamma + g(\Phi_{it-1} - x_{it-1}\gamma) + e_{it} \quad \text{(A6)}$$

Assuming that the function g follows a random walk, equation (A6) can be written as

$$y_{it} - w_{it}\hat{\beta} = \alpha + (x_{it} - x_{it-1})\gamma + \widehat{\Phi}_{it-1} + e_{it} \quad \text{(A7)}$$

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

$$E\left[e_{it}x_{it}^{j}\right] = 0 \quad \text{(A8)}$$

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

The estimate of γ is obtained as

$$\gamma^{*} = argmax\left\{-\sum_{k}(\sum_{i}\sum_{t} e_{it}x_{it}^{j})^{2}\right\}$$

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