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

Christoph Weiss, European Investment Bank*

(with Giorgio Brunello, Désirée Rückert and Patricia Wruuck)

"The use of surveys for monetary and economic policy"

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*The views expressed in this presentation are those of the authors and do not reflect those of the European Investment Bank.

Outline

1. Motivation
2. Data on digital adoption and employee training: the EIB Investment Survey (EIBIS)
3. An illustrative model
4. Empirical framework and results
5. Conclusion

Research questions

- Q1. When firms adopt advanced digital technologies (ADT), do they invest more or less in employee training?
  - ADT: 3D printing, advanced robotics, drones, augmented or virtual reality, digital platforms, IoT, big data analytics and AI

- Q2. What are the implications for firm productivity?

- Investment in digitalisation accelerated by COVID-19 (EIB 2023)
  - 53% of EU firms made investments to become more digital as a response to COVID-19 (source: EIB Investment Survey)
  - to sell products and services online, prevent business disruption, organise remote work, and/or improve communication with customers, suppliers and employees

Structural increase in the use of advanced digital technologies (ADT)

- Rapid increase in the *use* of ADT and decline in the *price* over time
  - Brynjolfsson and McElheran (2016), Graetz and Michaels (2018), Acemoglu and Restrepo (2019), Klump et al. (2021)

- ADT expand the set of tasks within the production process that can be performed by capital
  - which decreases the share of tasks performed by labour, in particular for routine tasks (Acemoglu and Restrepo 2021, Acemoglu et al. 2022)

- Replacement of labour with cheaper capital can lead to productivity gains
  - can also reduce labour demand and put downward pressure on employment and wages

Answer to research question not obvious

- Adult learning considered as a crucial policy instrument for re-training and up-skilling of workers
  - especially for jobs affected by the adoption of ADT (Nedelkoska and Quintini 2018, EIB 2021)
  - employers key actors in the provision of training (Brunello et al. 2007)
- Digital adoption associated with changes in skills required and the reorganization of production
  - which may create incentives for higher investment in employee training
- At the same time, ADT may reduce the marginal productivity of training
  - some tasks may require lower skills after ADT adoption, which negatively affects the incentive to invest in employee training
  - less spending on training if firms decide to obtain skills associated with ADT (such as coding and programming) by hiring new skilled labour, instead of training in-house

What we do in the paper

- Q1. Investigate how investment in training per employee change between time *t-1* and *t* after the introduction of ADT at time *t-1*
  - using 3 years of firm-level data (financial years 2018-2020) from the EIB Investment Survey (EIBIS) in 29 countries: 27 EU countries, UK and US

- Q2. Estimate production function (value added, labour, capital) augmented with ADT, investment in employee training and their interaction
  - to investigate if ADT and training are substitutes or complements in production

- If digital adoption and training are substitutes (complements) in production, an exogenous decline in the cost of adopting ADT – which leads to more intensive use – reduces (increases) the marginal productivity of training
  - will result in less (more) investment in training per employee

Preview of the main findings

- Q1. We find that firms that have adopted advanced digital technologies (*A*) in the previous survey wave reduce their investment in training (*T*) after digital adoption
  - especially in countries where employment protection legislation is less severe
- Q2. We find that *A* and *T* are substitutes in production
  - which implies (with constant returns to scale in production) that an exogenous decline in the cost of adopting *A* decreases the marginal productivity of *T*

Dependent variable: value added	
Log employment (L)	0.898***
	(0.036)
Log capital stock (K)	0.145***
	(0.013)
Digital adoption (A)	0.053**
	(0.024)
Training stock per employee (T)	0.032***
	(0.008)
A x T	**-0.019****
	(0.009)
Sample size	15,546

Note: Panel firms in EIBIS waves 2019 to 2021. Firm productivity estimated following Ackerberg, Caves and Frazer (2015). The dependent and explanatory variables are residuals from regressions on country-sector, country-year, sector-year and firm size-year fixed effects. The regression also includes industry- and firm-level characteristics (average wage per employee, indicators of management practices, financial constraints, firm age and indicator variables for missing values). Bootstrap standard errors clustered by firm using 100 replications. One, two and three stars for statistical significance at the 10, 5 and 1 percent level of confidence.

Contribution to the literature

- Substantial research on the effects of ADT on firm productivity, employment, wages, distribution of tasks within firms, management practices, labour share, competition and income inequality
  - Autors and Salomon (2018), Graetz and Michaels (2018), Acemolgu and Restrepo (2019, 2021), Acemoglu et al. (2020), Bessen et al. (2020), Cette et al. (2021), Koch et al. (2021), Dauth et al. (2021), among others

- But to our knowledge the questions asked in this paper, where we focus on the links with employee training, have not yet been addressed

- Our paper is also related to the (smaller) literature on training and firm productivity
  - Dearden et al. (2006), Almeida and Carneiro (2009), Konings and Vanormelingen (2015), Fialho et al. (2019), Martins (2021)

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The EIB Investment Survey (EIBIS)

- Since 2016, annual survey of about 13,350 firms in all 27 EU countries, the UK, and the US (since 2019)
  - non-financial enterprises with 5+ employees
  - NACE categories C to J: manufacturing, construction, services (wholesale and retail trade, accommodation and food services), and infrastructure (electricity and gas, water supply and waste management, transportation and storage, information and communication)
  - each year, sample size ranges from 180 firms in Cyprus, Luxembourg and Malta to 600 in France, Germany, Italy, Spain and the UK, and 800 in US
- Information on firm characteristics and performance, past investment activities and future plans, sources of finance, and challenges that businesses face
- EIBIS waves 4-6 conducted in 2019-2021: phone interviews between March and July (between May and August in 2020)
- Since wave 4, EIBIS includes questions on the adoption of digital technologies

EIBIS - sampling strategy

- Interviews of senior persons with responsibility for investment decisions and how they are financed (owner, CEO or CFO)
  - administrated by phone using computer-assisting telephone interviewing (CATI) by the market research company Ipsos MORI on behalf of the EIB

- EIBIS sample stratified disproportionally by country, industry group (sector) and firm size classes, and stratified proportionally by region within each country
  - EIBIS firms then weighted (for example, with value added) to make them representative of the population reported by Eurostat SBS

- Each year, EIBIS includes a panel component and a top-up sample
  - panel firms (approx. 40% in each wave): participated in a previous wave of the survey, and consented to be re-contacted in the following wave
  - top-up sample: firms that did not participate in the preceding wave

EIBIS - question on the use of advanced digital technologies (ADT)

- "Can you tell me for each of the following [four] 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 organised around them?"

A. Manufacturing: 3D printing, automation via advanced robotics, internet of things (IoT), big data analytics and artificial intelligence (AI)

B. Construction: 3D printing, augmented or virtual reality, IoT, drones

C. Services: augmented or virtual reality, platform technologies, IoT, big data/AI

D. Infrastructure: 3D printing, platform technologies, IoT, big data/AI

Adoption of advanced digital technologies (ADT) in 2021 (% of firms)

	Manufacturing	Construction	Services	Infrastructure
A (adoption: at least 1 tech)	40.5	33.9	46.4	55.2
3D printing	14.2	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	-	-	32.6	39.2
D (intensity: 0 to 4 techs)	0.564	0.469	0.707	0.837

Note: Panel firms in EIBIS waves 2019 to 2021. Weighted averages, using weights that align the number of firms in the sample to the number of firms in the business population.

EIBIS - question on training of employees

- "In the [last] financial year, how much did your business invest in each of the following with the intention of maintaining or increasing your company's future earnings?"

1. Land, business buildings and infrastructure
2. Machinery and equipment
3. Research and Development (including the acquisition of intellectual property)
4. Software, data, IT networks and website activities
5. **Training of employees**
6. Organisation and business process improvements

- Training of employees: 11% of total investment in financial year 2020
- EUR 210 per employee (EUR 480 among firms with positive training investment), but with considerable heterogeneity across EU countries

Digital firms tend to perform better and train more

	Did not implement (A = 0)	Implemented (A = 1)
Value added (EUR m)	1.02 (4.25)	2.43 (10.66)
Capital stock (EUR m)	2.98 (19.01)	8.74 (51.66)
Number of employees	23.38 (89.66)	37.15 (134.54)
Material costs (EUR m)	3.48 (14.49)	8.65 (37.08)
Training investment per employee (EUR k)	**0.19 (0.47)**	**0.24 (0.49)**
Training stock per employee (EUR k)	1.28 (2.61)	1.79 (3.03)
Average wage per employee in 2015-17 (EUR k)	25.62 (19.61)	29.52 (20.73)
Strategic monitoring system with KPIs	0.20	0.41
Use of performance pay schemes	0.63	0.70
Financially constrained	0.10	0.09
Firm age less than 10	0.11	0.15

Note: Panel firms in EIBIS waves 2019 to 2021. Weighted averages, using weights that align the number of firms in the sample to the number of firms in the business population.

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Q1. Effect of introducing ADT on investment in training per employee

- Change in training investment per employee between time *t-1* and *t* following the introduction of ADT at time *t-1*
  - similar approach as in Acemoglu and Restrepo (2020)
  - pooled data over financial years 2018-2020 in 29 countries

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

where $t_{e,i,t}$: investment in training per employee of firm *i* at time *t*

Δ: change operator

A: digital adoption

E: number of employees

Q: vector of firm characteristics (and country by time, sector by time and country by sector fixed effects)

υ_{it}: disturbance term

Digital adoption associated with a decrease in training investment per employee

Dependent variable: Change in training investment per employee		Controlling for productivity
Digital adoption (lagged)	**-0.017***** **(0.006)**	**-0.013***** **(0.004)**
Log employment (lagged)	0.007*** (0.002)	0.007*** (0.002)
Total factor productivity (lagged)	- -	-0.005* (0.003)
Log average wage between 2015 and 2017	-0.009** (0.004)	-0.010*** (0.004)
Strategic monitoring system with KPIs (lagged)	-0.006 (0.006)	-0.006 (0.005)
Use of performance pay schemes (lagged)	-0.017*** (0.006)	-0.016*** (0.005)
Financially constrained (lagged)	0.000 (0.009)	0.006 (0.008)
Sample size	9,086	7,612

Note: Panel firms in EIBIS waves 2019 to 2021. Firm productivity estimated following Ackerberg, Caves and Frazer (2015). The regression also includes indicator variables for missing values and country-sector, country-year, and sector-year fixed effects. Bootstrap standard errors clustered by firm using 100 replications in column (2). One, two and three stars for statistical significance at the 10, 5 and 1 percent level of confidence.

Digital adoption negatively associated with investment in training per employee, in countries with low employment protection

Dependent variable: Change in training investment per employee	High employment protection	Low employment protection
Digital adoption (lagged)	**0.003**	**-0.020****
	(0.003)	**(0.009)**
Log employment (lagged)	0.000	0.009***
	(0.001)	(0.001)
Total factor productivity (lagged)	-0.000	-0.005
	(0.002)	(0.004)
Financial constraints (lagged)	-0.030***	0.016***
	(0.007)	(0.007)
Strategic monitoring system (lagged)	0.005	-0.004
	(0.006)	(0.007)
Pay for performance schemes (lagged)	-0.023***	-0.021***
	(0.004)	(0.006)
Log average wage between 2015 and 2017	-0.006**	-0.013***
	(0.003)	(0.004)
Sample size	3,267	3,195

Note: Panel firms in EIBIS waves 2019 to 2021. Firm productivity estimated following Ackerberg, Caves and Frazer (2015). The regression also includes indicator variables for missing values and country-sector, country-year, and sector-year fixed effects. Bootstrap standard errors clustered by firm using 100 replications. One, two and three stars for statistical significance at the 10, 5 and 1 percent level of confidence.

Q2. Estimation of firm productivity augmented with digital adoption, training and their interaction

- To evaluate the effects of changes in the cost of digitalisation on training (and digital adoption), estimate the parameters in the equation:

$$y_{it} = \alpha e_{it} + \beta_T T_{it} + \beta_S S_{it} + \beta_A A_{it} + \beta_{AT}(A_{it}\ x\ T_{it}) + \delta k_{it} + \lambda X_{it} + \omega_{it} + u_{it}$$

- But factor input choices (capital and labour) as well as the choice of training and digital adoption can be correlated with the error term ω_{it}
  - we estimate firm productivity following Ackerberg et al. (2015)
- We need to treat the capital stock, the training stock per employee, digital intensity and interaction between *T* and *A* as state variables that are determined by decisions taken at time *t-1*
  - for digital adoption A, we use the lagged value of the use of digital adoption
  - for *K* and *T*, we compute the capital and training stock using the perpetual inventory formula: $X_{it} = x_{it-1} + (1-\delta)\ X_{it-1}$, where *X* is the stock, *x* the flow and δ the depreciation rate
  - flow for physical capital: investment in land, business building, machinery and equipment (from EIBIS), depreciation rate at 4.6%, and material costs from Orbis
  - flow for training capital: investment in employee training (EIBIS), and depreciation rate at 17% (Almeida and Carneiro, 2009)

Effect of digital adoption on firm productivity

Dependent variable: value added	
Log employment (E)	0.898***
	(0.036)
Log capital stock (K)	0.145***
	(0.013)
Training stock per employee (T)	0.032***
	(0.008)
Digital adoption (A)	0.053**
	(0.024)
T x A	**-0.019****
	(0.009)
Log average wage between 2015 and 2017	0.240***
	(0.018)
Strategic monitoring system with KPIs	0.045***
	(0.013)
Use of performance pay schemes	0.117***
	(0.018)
Financially constrained	-0.124***
	(0.031)
Sample size	15,546

Note: Panel firms in EIBIS waves 2019 to 2021. Firm productivity estimated following Ackerberg, Caves and Frazer (2015). The dependent and explanatory variables are residuals from regressions on country-sector, country-year, sector-year and firm size-year fixed effects. The regression also includes industry- and firm-level characteristics (firm age and indicator variables for missing values). Bootstrap standard errors clustered by firm using 100 replications. One, two and three stars for statistical significance at the 10, 5 and 1 percent level of confidence.

Comparing the estimated coefficient on training with other studies

- Konings and Vanormelingen (2015), for Belgium: effect of an hour of training per employee on productivity is 0.76%
- Almeida and Carneiro (2009), for Portugal: ranging between 0.06 to 0.13%

- EIBIS data: training investment per employee
  - approximate training expenditure per hour using average cost of an hour of training in Europe (including UK): according to Eurostat, EUR 63 in 2015 (latest year available)
  - EUR 1,000 investment in training: approx. 16 hours of training (1,000/63)
  - In previous table, estimated coefficient on training *T* is 0.032, suggesting that an additional hour of training increases productivity in EU firms by 0.2% (which is closer to the estimates of Almeida and Carneiro, 2009)

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Main findings

- We find that firms that have adopted advanced digital technologies (*A*) in the previous year reduce their investment in employee training (*T*) after digital adoption
- We find that *A* and *T* are substitutes in production
  - which implies (with constant returns to scale in production) that an exogenous decline in the cost of adopting *A* decreases the marginal productivity of *T*

Dependent variable: value added	
Log employment (L)	0.898***
	(0.036)
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Note: Panel firms in EIBIS waves 2019 to 2021. Firm productivity estimated following Ackerberg, Caves and Frazer (2015). The dependent and explanatory variables are residuals from regressions on country-sector, country-year, sector-year and firm size-year fixed effects. The regression also includes industry- and firm-level characteristics (average wage per employee, indicators of management practices, financial constraints, firm age and indicator variables for missing values). Bootstrap standard errors clustered by firm using 100 replications. One, two and three stars for statistical significance at the 10, 5 and 1 percent level of confidence.

Limitations of our study

- No data on cost of digital technologies adopted
- No data on distribution of wages within the firm
- No data on distribution of skills within the firm
- No data on how many workers received training or the hours of training per employee
  - no data on which workers received training
  - no information on type of training provided

Conclusion

- Why are digital adoption A and the training stock T substitutes in production?
- Digital adoption may not only replace unskilled labor with capital but also modify the residual tasks filled by unskilled labor
  - in such a way that marginal product of training per employee declines
- Productivity of training could also fall if firms find it more difficult to fill the new (skilled) positions associated with ADT with in-house training
  - and they then prefer to hire new skilled workers directly from the market
  - for example, with skills in coding or programming
- Changes in tasks may also require different types of training
  - for example, for new job profiles with more social interaction components
  - and possibly at lower costs (or harder to measure)

Thank you for your attention!

Contact: c.weiss@eib.org

Additional slides

The EIB Investment Survey (EIBIS)

EIBIS - matched to Orbis

- An enterprise is defined as a company trading as its own legal entity: branches excluded from the target population
  - but definition broader than a typical enterprise survey, given that some company subsidiaries are their own legal entities
- Minimum number of employees is 5
  - with full-time and part-time employees being counted as one employee, and employees working less than 12 hours per week excluded
- ORBIS dataset of Bureau van Dijk used as the sampling frame
  - EIBIS matched to data on balance sheet and profit and loss statements
  - match done for each firm by Ipsos MORI, which then sends anonymised data to EIB
  - the EIB does not have the name, address, contact details or any additional individual information that could identify the firms surveyed in EIBIS

EIBIS – representativeness

- ORBIS is a popular source of administrative data for cross-country analyses at the firm level
  - majority of information comes from business registers collected by local chambers of commerce to fulfil legal and administrative requirements
  - Bureau van Dijk organises the data and arranges them in a standard “global” format to facilitate company comparisons across countries
  - Kalemli-Ozcan et al. (2015) and Bajgar et al. (2020): discussion of the (dis)advantages of using ORBIS for economic analysis of firm dynamics
- Brutscher, Coali, Delanote and Harasztosi (2020): evidence on representativeness of EIBIS for the business population of interest
  - comparison with the population of firm-level data in Eurostat SBS (e.g. average firm size, labour productivity, etc.)
  - comparisons with CompNet (extracted from confidential firm-level datasets available within National Central Banks or National Statistical Institutes)
  - comparisons with random samples from ORBIS (e.g. sales growth, cash flow ratio, leverage, returns on assets, etc.)

Additional slides

An illustrative model

An illustrative model

- Assume firms operate a Cobb-Douglas production function

$$Y_{it} = L_{it}^{\alpha} K_{it}^{\delta} \exp(q_{it}) \exp(\varepsilon_{it}) \qquad (1)$$

  - where *Y* denotes value added, *L* labour in efficiency units, *K* the capital stock, *q* (Hicksian neutral) technical efficiency, and *ε* is a disturbance term
  - taking logs (and using lower-case letters):

$$y_{it} = \alpha l_{it} + \delta k_{it} + q_{it} + \varepsilon_{it} \qquad (2)$$

- Following Frazer (2001) and Konings and Vanormelingen (2015), we assume

$$L_{it} = E_{it}(1 + \gamma_T T_{it} + \gamma_S S_{it} + Z_{it}) \qquad (3)$$

  - E_{it}: number of employees
  - labour efficiency increases with stock of training per employee *T*, observed labour and managerial quality *S,* and unobserved labour and managerial quality *Z*
  - taking logs and using the approximation $\ln(1 + x) \cong x$

$$l_{it} = e_{it} + \gamma_T T_{it} + \gamma_S S_{it} + Z_{it} \qquad (4)$$

Firm productivity augmented with digital adoption, training and their interaction

- We also assume that technical efficiency *q* depends on digital adoption *A*, its interaction with training *T* and a vector of controls *X:*

$$q_{it} = \beta_0 + \beta_A A_{it} + \beta_{AT}(A_{it}\, x\, T_{it}) + \lambda X_{it} \qquad (5)$$

  - both digital adoption *A* and *T* can impact on firm productivity: *A* by improving technical efficiency, and *T* by improving both labour and technical efficiency

- Using equations (4) and (5) in (2):

$$y_{it} = \alpha e_{it} + \beta_T T_{it} + \beta_S S_{it} + \beta_A A_{it} + \beta_{AT}(A_{it}\, x\, T_{it}) + \delta k_{it} + \lambda X_{it} + \omega_{it} + u_{it} \qquad (6)$$

  - ω_{it} (TFP): function of unobserved labor and managerial quality Z and correlated with profit-maximizing choices of capital stock, employment, training and digital intensity
  - u_{it}, instead, assumed to be orthogonal to the right-hand side variables

- If *A* and *T* are substitutes (complements) in production, an increase in *A* (*T*) reduces (increases) the marginal productivity of *T* (A)
  - complements if $\partial^2 Y / \partial T \partial A = Y[\beta_{AT} + (\beta_A + \beta_{AT} T)(\beta_T + \beta_{AT} A)] > 0$
  - substitutes if $\partial^2 Y / \partial T \partial A < 0$

Effect of a change in the cost of digital adoption θ on training *T* (1/2)

- Firms maximize profits with respect to *E*, *K*, *T*, and *A*

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

  - taking factor *w* (wages) and *r* (cost of capital) as given
  - σ is the elasticity of substitution
  - parameters θ and ϕ are the marginal costs of increasing *A* and *T* by one unit
  - cost of digital adoption and cost of training per employee convex (and separable) in *A* and *T*

- In the paper, we show that, with constant returns to scale ($\alpha + \delta = 1$), the sign of the effect of θ on training *T* depends exclusively on the sign of β_{AT} (the coefficient on the interaction term between *A* and *T*)
  - if β_{AT} is negative, *A* and *T* are substitutes in production
  - an exogenous decline in the cost of adopting *A* will then decrease the marginal productivity of training *T*

Effect of a change in the cost of digital adoption θ on training T (2/2)

- In the Appendix of the paper, we show that a reduction in θ
  - increases digital adoption A if $\left[\frac{\alpha}{T} - (\beta_T - \beta_{AT} A)\right] [\alpha + \delta - 1 - {}^1/_\sigma (\alpha + \delta)] < 0$
  - increases the training stock T if $\left[(\alpha + \delta - 1) - \frac{1}{\sigma}(\alpha + \delta)\right] \beta_{AT} < 0$

- The effect of θ on T thus depends on:
  i. the sign of parameter β_{AT}
  ii. the returns to scale with respect to labor and capital (α and δ)
  iii. the elasticity of substitution σ

- With constant returns to scale ($\alpha + \delta = 1$), this simplifies to $-\frac{1}{\sigma}\beta_{AT}$
  - the sign of the effect of θ on T depends exclusively on the sign of β_{AT}

Additional slides

Heterogeneous effects of digital technologies

Heterogeneous effects of digital technologies

Dependent variable: value added		
Log employment (L)	0.897***	0.888***
	(0.030)	(0.035)
Log capital stock (K)	0.160***	0.143***
	(0.013)	(0.014)
Training stock per employee (T)	0.037***	0.026***
	(0.007)	(0.007)
IoT & AI (A_I) - adoption	0.035	
	(0.032)	
Robots, 3D printers and drones (A_R) - adoption	0.087***	
	(0.015)	
T x A_I	-0.016	
	(0.011)	
T x A_R	**-0.024***	
	(0.013)	
Digital intensity (I) - number of techs adopted (0 to 4)		0.031***
		(0.007)
T x I		**-0.007*****
		(0.004)
Sample size	15,546	15,546

Note: Panel firms in EIBIS waves 2019 to 2021. Firm productivity estimated following Ackerberg, Caves and Frazer (2015). The dependent and explanatory variables are residuals from regressions on country-sector, country-year, sector-year and firm size-year fixed effects. The regression also includes industry- and firm-level characteristics (average wage per employee, indicators of management practices, financial constraints, firm age and indicator variables for missing values). Bootstrap standard errors clustered by firm using 100 replications. One, two and three stars for statistical significance at the 10, 5 and 1 percent level of confidence.

Additional slides

Decreases in the cost of training?

Decrease in the costs of training?

- Investment per employee: product of the unit cost of training x quantity of training per employee
- In principle, a decline in investment does not necessarily mean a reduction in the quantity of training
  - could happen if the efficiency of training expenditure increases after the digital adoption, cutting training costs rather than quantity
  - digital adoption, for instance, could encourage firms to shift training modes from the traditional classroom to online learning
- We use data from the European Labor Force Survey (ELFS) on training incidence to have a measure of training quantity
  - combine it with EIBIS at aggregated sectoral level
  - find evidence that digital adoption also reduces training incidence
  - suggesting that the reduction in training investment is likely not to be due to a reduction in training costs