On-the-job training, wages and digitalisation: Evidence from European firms

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Abstract

This paper examines the differences in wage performance across European companies in relation to the digital content of their on-the-job training and production activities. Using cross-sectional data from three waves of the Continuing Vocational Training Survey (2005, 2010 and 2015), we estimate a wage premium of 8% paid by firms arranging training for IT skills-intensive workers. The wage premium associated with IT training is pervasive across sectors and is not confined to those firms more exposed to the digital transformation.

Keywords: training, IT upskilling, wage premium, European firms

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1. Introduction

Digitalization and the latest wave of digital technologies have been identified as disruptive forces that are compelling companies to undergo radical changes (Brynjolfsson and McAfee, 2014). One of the most significant impacts of this digital transformation is on the labour demand and workforce composition. With the arrival of new technologies, worker competencies become obsolete or even unsuitable. To address this challenge, companies must adjust the composition of their workforce and/or upgrade the skill set of their workers through training activities. However, the effectiveness of these policies varies depending on the characteristics of the firm, the nature of its production, and the content of training programs. While the impact of digital transformation on employment and wage dynamics has been extensively studied, the role of focused training programs on labour market outcomes has been largely unexplored. This paper seeks to fill this gap in the literature by investigating whether European firms that are more exposed to digital transformation and those providing targeted training for IT-skill intensive workers pay higher wages than companies with general training or firms without training programs.

A long stream of works has studied, both in theoretical and empirical terms, the interplay between digitalisation and labour demand. The introduction of computers and other digital technology has been linked to job-skill demands and wage inequality through several mechanisms. In a pioneering study, Krueger (1993) finds that workers using the computer earn 15% more than non-user workers and that the expansion of computer use explained one third of the wage premium of educated workers. Autor et. al (1998) find a persistent skill upgrading in the US economy, especially in more computer-intensive industries. Acemoglu (1998a and 1998b) explains these trends as a consequence of the long-term increase in educated labour supply which, endogenously, stimulates the development and the adoption of new technologies, such as ICT, which are human capital-intensive (see Acemoglu 2002 for an early review). In this initial wave of the literature, ICT and digitalisation are considered as a form of technological change complementary to high-skilled labour, forcing to job up-skilling (skill-bias technological change, SBTC). The SBTC literature therefore looks at the shift in the occupational distribution of employment, i.e., the increasing demand for high-skilled workers relative to lower skilled ones, and their effects on wages.

A later generation of studies (Autor et al. 2003) point out that the latest wave of digital technologies would displace workers performing routinized tasks, since they are repetitive and hence are codifiable in software. Digital technologies would require a greater number of skilled workers to manage them, such as programmers, technicians, and maintenance workers. Additionally, digital technologies generate vast amounts of information that require analysis by skilled workers, such as accountants, market researchers, and data analysts (Cedefop 2022). As a consequence, digital technologies would more easily automate tasks in middle-skill jobs, implying that technological change would be routine-biased (routine-biased technological change, RBTC) and would promote job polarisation (Goos et al. 2009).

Robots and highly automated machines are among the latest generations of digital technologies that have gain significant attention from economists, due to their displacement effects on manual and routinized jobs (Acemoglu and Restrepo 2022). However, automation is also argued to promote significant cost savings and business re-configurations, ultimately favouring the expansion of new tasks. Therefore, in the long run, both the occupational and wage effects of automation might not be as detrimental as often believed (Arntz et al. 2017, Bessen et al. 2020, Domini et al. 2022).

Recently, the emergence of cutting-edge technologies in the field of Artificial Intelligence (AI) has led to the adoption of novel productive systems capable to implement non-routine and cognitive tasks. This has increased the likelihood of displacement effects of automation even for high-skill jobs (Webb 2020, Goos et al. 2021). Fossen and Sorger (2022) study the effect of the exposure to computerisation and AI investment on employment conditions and wage dynamicsin the US. The study reveals that increased computerization leads to greater job instability, resulting in workers changing occupations or becoming unemployed, and to reduced wage growth. However, the study also reveals that AI investment has the opposite effect, improving job stability and increasing wage growth.

However, when examining the observed rates of firm adoption of new technologies, rather than just their exposure, it seems that the net employment effects of digital technologies are positive. This is due to the expansion of demand for high-skilled workers, which outweighs the job losses experienced by low-skilled workers.

Currently, the majority of employment impacts resulting from new technologies appear to be influenced by firm investment in machine-based digital technologies (robots, 3D printing, and the Internet of Things), and less by investment in non-machine-based digital technologies (ERP, e-commerce or cooperation support systems; see Balsmeier and Woerter 2019).

Recent evidence indicates that 16% of European workers is exposed to skill-displacing technical change and that this effect mostly transits through an increasing task complexity (McGuinness et al. 2021). Technical change is found to mostly affect highly educated workers, stimulating the company provision of training and workplace learning, and ultimately promoting workforce upskilling. According to Cedefop (2016), 71% of European workers claim to need basic or moderate ICT skills to implement their job, whilst another 14% require advanced digital skills. However, there is wide variation in the requirement of digital skills, especially advanced across various types of productions, from 51% of workers in the ICT sector to 5% in the Accommodation sector. A recent report by the European Investment Bank (EIB 2022) documents that companies using digital technologies are more likely to provide vocational training and that this investment increases with the complexity of the digital technologies adopted.

Training is seen as a tool for improving job opportunities and work conditions of employees, and for increasing company productivity (Becker 1964). The need for training increases with the pace of technological change, which makes the formal education of younger workers obsolete and the experience of more tenured employees unfit to contribute to company performance (Bartel and Sicherman 1998). In imperfect labour markets, namely when companies have monopsonistic power or employees are not mobile across companies and/or jobs, firms have incentives to bear the cost of training not only when it is designed to build firm-specific skills, but also when training targets more general competences as companies can capture part of the increased workers' productivity (Acemoglu and Pitschke 1998a and 1998b; 1999). The inefficiency associated with training could be higher when the company is expected to innovate as workers are willing to accept lower wages today expecting higher wages in the future (Acemoglu 1997).

The impact of training on wages has varied over time with technological advancements, that have rendered obsolete different types of skills. In a ground-breaking meta-analysis conducted by Haelermans and Borghans (2012), training is found to increase wages by an average of 2.6%. However, subsequent studies by Dearden et al. (2006) and Konings and Vanormelingen (2015) have shown that the wage increases resulting from training are lower than the productivity gains driven by training. This supports theories that explain training as a result of appropriation motives in imperfect competitive labour markets.[1] Recent research by Feng and Graetz (2020) has highlighted how the complexity of tasks and the required training can influence a firm's decision to automate production. Brunello et al. (2023) show

[1] The implementation of the training is not forced by changes in the supply conditions due to technological change but also on demand condition. Bertoni and Brunello (2022) find high counter-cyclicity of training programmes as companies finds less costly to organise training during recessions when the cost of foregone output of trained workers is smaller.

that advanced digital technologies and training are substitute, as the latter decrease after the introduction of the new technologies. However, there is still a lack of understanding in the literature regarding how training aimed at developing digital skills can impact labour market outcomes, particularly in terms of raising wage conditions for employees in companies that provide training.

To address this gap in the literature, this study aims to investigate the wage effect of employer-provided training in Europe. As long as training regenerates workers' competences, firms undertaking these measures should be able to pay higher wages compared to firms without training. On this basis, training can be seen as an intangible investment fuelling wage dispersion across companies. Our main goal is to ascertain (i) whether this process is related to the company exposure to the digitalisation process measured at industry level; and (ii) whether there is a differential effect between training targeted at digital skills-intensive jobs and training targeted at more general competences.

Using data for 112 thousand European companies, collected from three waves of the EU Continuing Vocational Training Survey (2005, 2010, and 2015), we document wide gaps in wage (and occupational) levels among companies in relation to the digital content of their production and training activities. Specifically, we estimate a wage premium of 9% for companies undertaking training and an additional 8% for those firms arranging training for IT skills-intensive workers.

Admittedly, the main caveat of our analysis is to use company-level data to infer the effect of training on workers' remuneration. In other words, we quantify the effect of training policies on the average wage paid by the firm, which covers both trainees and workers not engaged in training. This implies that the estimated impact is a *net effect* across workers and that, for instance, it may be affected by substitution effects (hires and fires). On the other hand, company-level data is less affected by selectivity issues than employee-level data. Indeed, skilled workers respond to wage differences and move across jobs and firms paying higher wages, increasing the company incentives to offer training in order to keep them.

Our work makes a threefold contribution to the literature. First, we provide novel evidence on the drivers of wage effect in Europe focusing on the role played by training in the digitizing economy. Complementary evidence is offered by Brunello and Wruuck (2020) who review the main training policies pursued by European companies, identifying the main factors hindering investment in training. Second, we shed light on the differential effect on wages of IT training with respect to other forms of training. Prior works focusing on wage premia (O'Mahony et al. 2008) or wage polarisation (Michael et al. 2014) looked at the earlier diffusion of ICT. More recent studies look at the labour market effects of automation (Acemoglu and Restrepo 2018) and the diffusion of AI (Webb 2020, Acemoglu et al. 2022). Lastly, we complement with company-level evidence the stream of industry-level studies assessing the economic impact of training, defined as intangible investment, through growth accounting methods (O'Mahony 2012, Squicciarini et al. 2015).

The paper is organised as follows. Section 2 lays down the empirical model. Section 3 describes data. Section 4 presents the econometric results and, finally, Section 5 concludes.

2. Empirical model

In order to assess the influence of training on wages, we have conducted a thorough regression analysis, that takes into account the type of training received, distinguishing between general training and training for IT-intensive skills. Furthermore, we have taken into consideration the level of digitalization in production activities, differentiating between highly digitalized and low digitalized industries.

The regression analysis is performed pooling together three different nation-representative samples of European companies for which information on continuing vocational training is available from the waves of the EU Continuing Vocational Training Survey (CVTS) for the years 2005, 2010 and 2015.

In our baseline model (eq. (1)), we regress the average wage (in logs) against a variable, *T*, capturing the training policy implemented by the firm. In eq. (1), *i* denotes the firm, *t* years. *T* is mainly defined as a binary indicator reflecting whether the company has arranged vocational training activities for its employees. We also try to identify the wage effect of training by considering three continuous proxies for the training effort of the company, namely the ratio of training costs to total labour expenses, the share of workers under training out of the total workforce and, finally, the average number of training hours per trainee. As we discuss more extensively below, such continuous measures of training are more likely to be affected by reverse causality issues, making the binary indicator our preferred measure for identifying the wage impact of training. We also assess whether the way in which these activities are organised, i.e., whether training is internally managed by the company or is provided by external specialised trainers, such as private companies, education institutions and government agencies, has a differential impact on workers' remuneration. In this regard, we consider a set of dummies identifying companies with internal training only (T^I), companies with external training only (T^E), and companies pursuing both modes of training (T^B). These variables are mutually exclusive. Furthermore, we utilize an extra set of binary indicators to distinguish companies that participate in external training programs offered by educational institutions such as universities, as well as public training centers. Additionally, we identify companies that have contractual agreements with social partners that mandate the implementation of training. This information allows us to gain a more comprehensive understanding of the training practices of companies in our study.

Eq. (1) defines our baseline regression model. X_i is a vector of company characteristics whose effect may be confused with that of training. d_s, d_c, d_t denote industry-, country- and time-specific fixed effects. d_s should capture wage differences depending on the technology conditions of production. d_c should neutralise the effect associated with country-specific differences in training legislation, as well as in other relevant institutional (national) characteristics. d_t should capture the effect on wages generated by common technology shocks, business cycle, etc.[2] ε is the error term.

$$\ln w_i = \alpha + \beta T_i + \gamma X_i + d_s + d_c + d_t + \varepsilon_i \tag{1}$$

In our main estimation we assume that *T* is exogenous with respect to the outcome variable and hence β can be regarded as an average treatment effect (ATE): β identifies, in essence, the average impact of training on wages on the total sample of firms, which includes both companies with training and companies without training.

Next, we expand our specification (see eq. (2)) to assess whether the effect of training changes with given characteristics of the company (C). In this context, the parameter δ will identify the wage premium granted by companies with given characteristics, with respect to the main effect of training found for all other companies without these characteristics (β):

$$\ln w_i = \alpha + \beta\ T_i + \delta\ T_i \times C_i + \gamma C_i + \theta X_i + d_s + d_c + d_t + \varepsilon_i \tag{2}$$

Specifically, we explore whether returns to training are related to how these activities are organised, namely trough: (i) internal training; (ii) external training; (iii) external training provided by education institutions; and (iv) external training provided by government-funded institutions:

To mitigate omitted-variable bias, in identifying the wage effect of training, we enrich our regression models with controls for (*X*): (i) the intensity in the labour use;

[2] The deterministic components of the model are also used to purge out the effect of price differences among industries, countries and years as wages are expressed in euro at current prices.

(ii) the company size; (iii) the gender diversity of the workforce; (iv) the implementation of other forms (non-vocational) of training.

3. Data

3.1 Data sources

The analysis is conducted using company-level data extracted from the waves of the EU Continuing Vocational Training Survey (CVTS) for the years 2005, 2010 and 2015. We use the version of the CVTS dataset releasing information on the sector of production at a 2-digit level (Nace Rev. 2 classification). The dataset provides information on nation-wide representative samples of companies with a number of employees ranging from 10 to 999, from the following European countries: Bulgaria, Czech Republic, Germany, Denmark, Estonia, Spain, Finland, France, Italy, Latvia, Norway and United Kingdom.[3]

Our study focuses on the average wage paid by firms (our dependent variable), which we calculate by dividing total labour costs by the number of employees. To determine the impact of training on wages, we use two main explanatory variables. The first is a binary measure of general training, which we define as any continuous vocational training provided by a company, whether internal or external, regardless

[3] For info on the CVTS dataset see: https://ec.europa.eu/eurostat/web/microdata/continuing-vocational-training-survey .
This dataset covers enterprises with 10 or more employed in the business sector for the years 2010 and 2015, and companies in the industry and service sectors for the year 2005. A larger version of the dataset includes microdata from 24 countries (Belgium, Bulgaria, Czechia, Denmark, Germany, Estonia, Spain, France, Italy, Cyprus, Latvia, Lithuania, Luxembourg, Hungary, Malta, Poland, Portugal, Romania, Slovenia, Slovakia, Finland, Sweden, United Kingdom and Norway) but with an industry breakdown to one-digit level only.

of the specific skills targeted by the training. The second variable is a binary indicator for IT training, which we define as any training focused on general IT skills or IT professional skills. It is important to note that IT training is just one sub-category of general training. Other types of training include courses focused on management skills, team working skills, customer handling skills, problem solving skills, office administration skills, foreign language skills, technical or job-specific skills, oral or written communication skills, numeracy or literacy skills, and other.

We quantify the wage disparities that arise due to the organization of training. We use a set of binary indicators to identify companies that rely on both internal and external training providers, as well as those that use only internal or external sources. For firms that access external training, we distinguish between those whose training providers are educational institutions, such as schools, colleges, universities, and other higher education institutions, and those whose training providers are public training institutions funded by the government, such as adult education centers.

As control variables, we consider: (i) a measure of the intensity of labor usage, which is defined by the average number of hours worked by employees (measured in logs); (ii) a set of binary indicators that distinguish between small, medium, and large-sized firms (i.e. companies with less than 50 employees, between 50 and 249 employees, and 250 or more employees, respectively); (iii) the proportion of male workers in the total workforce, which serves as a proxy for gender diversity; and (iv) a dummy variable that indicates whether a firm provides internal apprenticeships. The last variable is particularly important, as it allows us to capture the wage effect of baseline skills that are developed through learning in school and training in a company. This effect can be confounded with the impact of vocational training.

Since we are interested in the company response to the digital transformation, we classify firms in relation to the digitalisation of their production, using the taxonomy provided by OECD (Calvino et al. 2018, Table 3). We use the global classification of digitalised sectors built for the period 2001-03, which precedes the time interval covered by our analysis thus mitigating reverse causality problems as companies with training may self-select and move towards sectors involved in a more intensive digitalisation process. Another possibility is that firms operating in highly digitalised industries are structurally more productive, can afford to pay higher wages and invest more resources in training to keep up with the advances in digital technologies. The OECD categorisation reflects the intensity in the usage and exploitation of digital technologies *at industry level* along different dimensions: the share of ICT tangible and intangible (i.e. software) investment; the share of purchases of intermediate ICT goods and services; the per-worker stock of installed robots; the share of ICT specialists out of the total workforce; and the share of turnover from online sales. We consider as highly digitalised those sectors lying at the top quartile of the usage of the four types of ICT technologies described, and as lowly digitalised those at the bottom quartile (see Table 3, Calvino et. al 2018). The remaining industries (i.e., those at the second and third quartile) have an intermediate degree of digitalisation and are regarded as reference sectors in the regression analysis.[4] To ensure the accuracy of our findings, we conduct robustness checks using alternative industry categorizations. Specifically, we examine two key dimensions of digitalization intensity in production and consider the industry positioning (1st and 4th quartile) in software investment or the workforce share of ICT specialists. These are two prior components of the general categorisation developed by Calvino et al. (2018, Table 1) and seems more relevant to characterise the later wave of digitalisation, which relies heavily on software and IT systems, rather than on the adoption of industrial robots. By considering these factors, we can better understand the impact of training on wages in the digital age.

3.2 Summary statistics

Table 1 presents the proportion of companies undertaking training (without distinguishing its purposes) and those with a training programme focused on IT skill-intensive job positions (general IT and professional IT skills). Our sample consists of a pool of 112 thousand companies, 65% of which undertake training defined in

[4] The group of highly digitalised sectors (top quartile) includes: Computer, electronic and optical products (NACE rev. 2 category 26); Machinery and equipment n.e.c. (28); Transport equipment (29) Telecommunications (61); IT and other information services (62-63); Finance and insurance (64-66); Real estate (68); Legal and accounting activities, etc. (69-71); Advertising and market research; other business services (73-75); Administrative and support service activities (77-82). The group of lowly digitalised industries includes: Agriculture, forestry, fishing (01-03); Mining and quarrying (05-09); Food products, beverages and tobacco (10-12); Electricity, gas, steam and air conditioning (35); Water supply; sewerage, waste management (36-39); Construction (41-43); Transportation and storage (49-53); Accommodation and food service activities (55-56).

general terms (73 thousand firms).[5] This share increased from 54% in 2005 to 76% in 2015. A greater incidence can be found in highly digitalised industries, where the percentage of firms with training is 78% and denotes a rapid increase between 2005 and 2015. An upward trend can also be found in lowly digitalised industries (from 54 to 79%) in which, however, the proportion of companies with training remains smaller.

Table 1. Proportion of firms with training

	All years		2005	2010	2015
	#	%	%	%	%
	(1)	(2)	(3)	(4)	(5)
			Training		
All companies	73,070	65.0	53.7	60.8	75.7
High digital	12,669	77.8	64.8	75.5	84.5
Low digital	16,256	67.2	53.6	63.7	79.2
			IT Training		
All companies	23,169	20.6	24.2	23.8	15.4
High digital	5,486	33.7	35.6	41.7	26.1
Low digital	4,280	17.7	22.4	19.6	12.3

Notes: The figures consist in the absolute number of firms covered by analysis in all years (col. (1)) and the percentage of those with training (col. (2)). Columns (3)-(5) report the percentage of companies with training out of the total number covered by each wave of the CVTS.

The proportion of companies with IT training is one third of all companies with training programmes (21 vs 65%). The need to train workers in IT skill-intensive positions seems to be partly explained by the company exposure to digitalisation, as the proportion of firms with IT training rises to 34% in highly digitalised industries.

[5] We trim the sample excluding from the analysis companies at the extreme tails of wage distribution (below 1 and above 99% percentiles), thus mitigating problems related to censoring in employment data. Our main regression results that will be shown below are robust to the trimming procedure and also to excluding the smallest companies (those with less than 20 employees). All unreported results are available upon request.

It should be noted, however, that the share of companies with IT training has dropped in all branches of the economy since 2005, revealing that the disruptive effect of digitalisation on workforce skills may have been more pronounced in the first half of the sample period.

Table 2. Proportion of firms with training by country (%)

	# Firms	Training	IT training	Training		IT training	
		All sectors	All sectors	Highly digitalised	Lowly digitalised	Highly digitalised	Lowly digitalised
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Bulgaria	5,648	26.2	7.1	40.4	33.4	14.8	6.2
Czech Rep.	15,326	81.5	19.7	89.6	82.6	34.0	16.8
Germany	8,063	66.3	33.1	76.3	64.6	41.9	30.5
Denmark	3,307	76.0	32.2	81.4	79.9	42.9	30.4
Estonia	4,136	68.1	16.5	74.9	70.1	25.1	15.7
Spain	22,993	71.3	25.0	82.7	70.0	41.9	19.8
Finland	2,930	77.5	25.4	85.9	76.1	37.8	23.0
France	3,861	83.7	13.4	86.9	84.3	21.0	10.5
Italy	35,155	57.4	15.1	72.6	64.5	27.5	13.1
Latvia	3,453	40.5	8.7	54.9	47.0	16.6	7.5
Norway	876	57.2	34.2	63.1	58.6	36.9	34.9
UK	6,651	66.8	36.3	71.3	69.7	44.2	36.7
TOTAL	112,399	65.0	20.6	77.8	67.2	33.7	17.7

Notes: The figures consist in the absolute number of firms covered by analysis per country (col. (1)), the percentage of those with training (col. (2)), with IT training (col. (3)), and those active in highly digitalised sectors (col. (4)) or in lowly digitalised sectors (col. (5)).
Source: Authors' own elaboration.

Table 2 reports the breakdown of our sample by country, showing for each European economy the percentage share of firms with training/IT training and their distribution across digital sectors. The highest proportion of firms with training can be found in France (84%); companies with IT training are prevalent in the UK, Norway, Germany and Denmark, where one third of all firms undertake programmes focused on advanced digital skills. Focusing on the major countries, it can be observed that, in highly digitalised sectors, the incidence of firms with training is below the European average (78%) in Italy and the United Kingdom; the latter country, however, excels in the highest proportion of firms with IT training which achieves 44% of the national sample.

Next, we quantify investment in training, expressing the cost of these activities as percentage ratio to total labour cost (Table 3). Due to data restrictions along all three waves of the CVTS survey, we can accurately quantify only costs for total training, without distinguishing company expenditure by type of training (IT skills vs the rest). As training costs, we consider both direct expenses for training and the implicit cost associated with the working hours lost by employees during training.[6] The relative incidence of training investment is 1.5%, and 1.7% if we restrict to firms with IT training. The latter group of companies invests more in training in almost all countries. If we consider all firms with training, the cost share of this investment looks relatively low in lowly digitalised sectors (0.9% of labour costs). If we consider firms with IT training, the investment share looks relatively high in highly digitalised sectors (2%).

[6] The implicit costs of training, defined as Personal Absence Cost (PAC), is computed as "Paid working time (in hours) spent on all CVT courses" multiplied by "Average labour cost per hour worked". Figures in Table 3 use sampling weights reflecting the representativeness of surveyed companies on national universes.

Table 3. Total training cost relative to labour costs, by firm types and country (%)

	Firms with Training	Firms with IT training	Firms with Training		Firms with IT Training	
			Highly digitalised	Lowly digitalised	Highly digitalised	Lowly digitalised
Bulgaria	2.1	2.8	1.0	0.4	3.3	2.1
Czech Republic	1.2	1.6	1.3	0.9	1.9	1.2
Germany	1.4	1.6	1.4	0.8	2.1	1.5
Denmark	1.4	1.5	1.1	1.1	1.5	1.4
Estonia	1.6	2.0	2.0	0.8	2.8	1.9
Spain	1.5	1.8	1.5	0.9	1.9	1.5
Finland	1.3	1.7	1.4	1.1	2.0	1.9
France	2.0	2.0	1.8	1.7	2.0	2.1
Italy	1.4	1.6	1.2	0.8	1.8	1.4
Latvia	0.6	0.9	0.5	0.2	1.7	0.5
Norway	2.2	2.4	1.7	1.2	2.5	2.7
UK	1.9	1.9	1.6	1.3	2.1	2.1
TOTAL	1.5	1.7	1.4	0.9	2.0	1.5

Notes: The figures consist in the cost of training expressed as a percentage ratio of total labour costs, distinguishing across firms with training, with IT training, and those active in highly and lowly digitalised sectors.
Source: Authors' own elaboration.

We now provide a descriptive overview of the wage differences associated with training (Table 4). Firms with training pay wages one third higher than companies without training. This pattern is common to all countries. In particular, in all the major European economies (Germany, France, Italy, Spain), the size of the wage differential is substantial and similar (roughly 8 thousand euro). As the right-hand side of Table 4 illustrates, firms with IT training pay even more than the reference group of companies without any type of training. Taken as a whole, the biggest continental economies in Europe denote the largest wage differentials (in absolute terms) with respect to the firms without training.

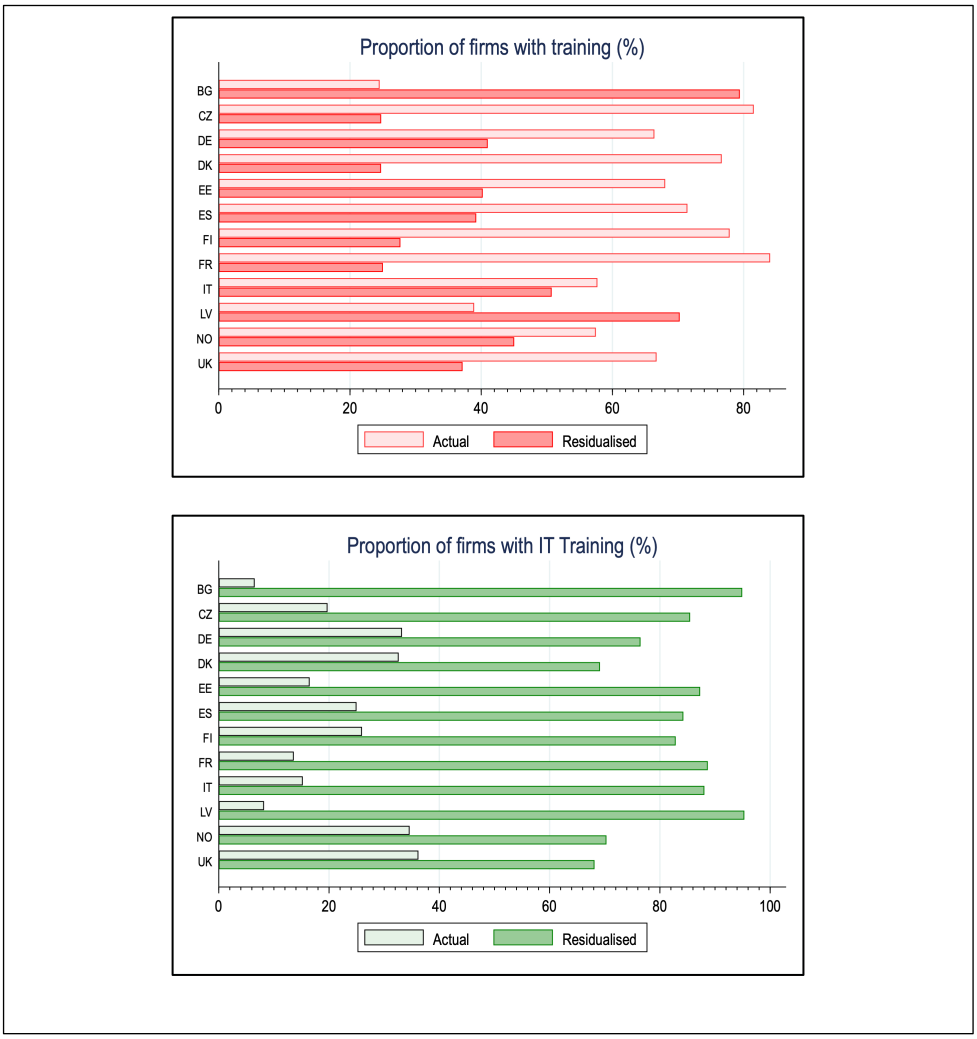
Table 4. Wage differences for training firms

	Training			IT Training		
	No	Yes	t-statistic difference	No	Yes	t-statistic difference
Bulgaria	2,748	4,110	***	2,748	4,988	***
Czech Rep.	11,319	14,904	***	11,319	17,254	***
Germany	30,013	39,028	***	30,013	41,869	***
Denmark	45,816	52,331	***	45,816	54,275	***
Estonia	9,474	13,800	***	9,474	15,834	***
Spain	23,440	31,682	***	23,440	35,057	***
Finland	39,992	46,418	***	39,992	49,062	***
France	38,777	44,695	***	38,777	48,331	***
Italy	30,442	38,747	***	30,442	41,123	***
Latvia	3,491	5,734	***	3,491	8,174	***
Norway	43,309	48,125	***	43,309	50,180	***
UK	23,117	27,600	***	23,117	28,630	***
TOTAL	23,295	31,169	***	23,295	34,632	***

Notes: The stars denote the level of significance for the t-statistics on the mean difference between groups of firms for each country. ***,**, * significant at 1, 5 and 10%.
Source: Authors' own elaboration.

One important point to note regarding the data presented in Table 3 and Table 4 is that variations in training efforts across different countries may be attributed to differences in the skill levels of their respective workforces, industry structures, or government policies and incentives. In order to determine the extent to which idiosyncratic firm behaviour contributes to variation in training, we compute residualised values for our three primary explanatory variables: training, IT training, and training cost. This is achieved through a series of regressions in which each indicator is regressed against country, industry, and year (or wave) fixed effects, using sampling weights. By doing so, we are able to isolate the portion of training effort that is not influenced by common factors among companies at the country, industry, and year levels. This approach allows for a more accurate understanding of the impact of a firm's idiosyncratic behaviour on overall variation of training. To obtain the residualised values for the dummy variables of training (general training and IT training), a probit regression is utilized, from which we recover the probability complementary to one. On the other hand, for the continuous training variables (training costs over total labour costs), the residualised values are calculated as residuals of an OLS regression.

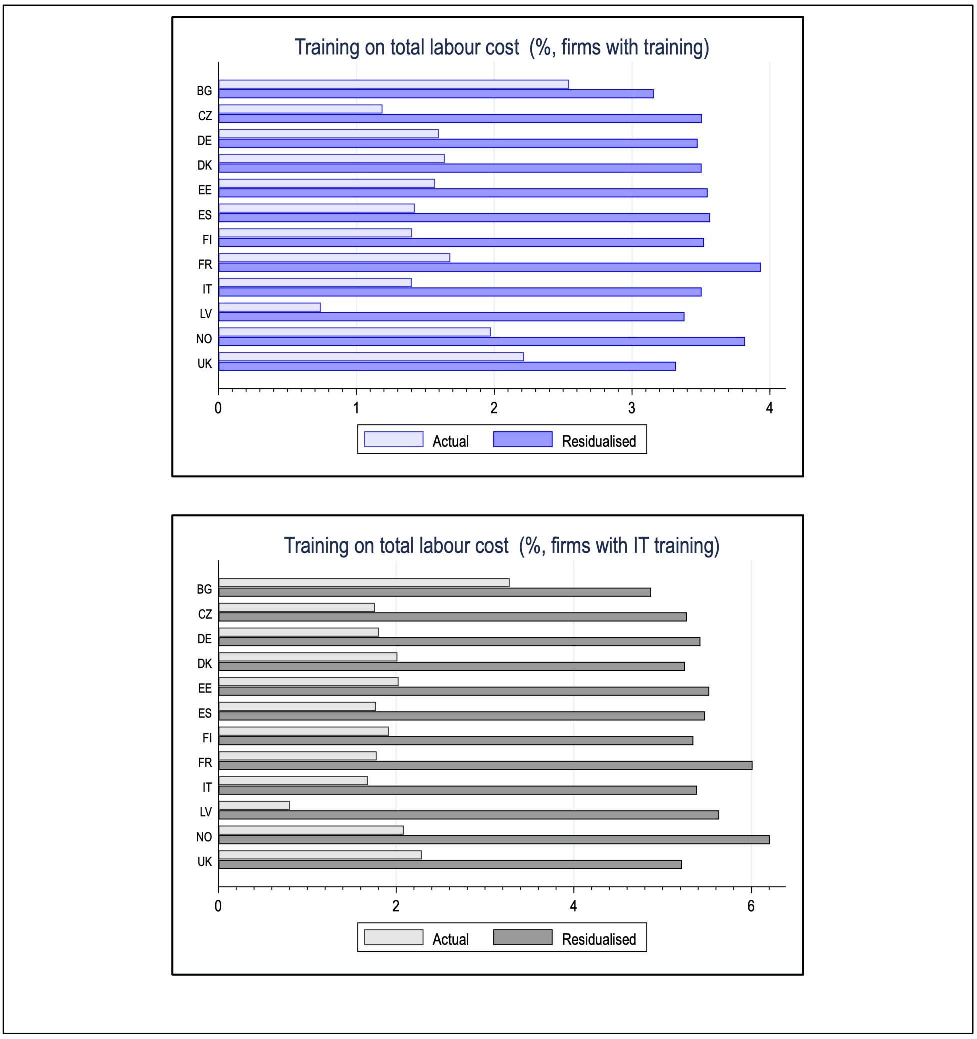
Figure 1. Actual and residualised values of training probabilities (%)



Source: Authors' own elaboration.

In Figure 1, we present the residualised values for the probability of training variables and compare them with the observed proportions of firms with training and IT training, as shown in columns 2 and 3 of Table 2.

Figure 2. Actual and residualised values of training cost over total labour costs



Source: Authors' own elaboration.

By removing the deterministic sources of variation, we find that the probability of general training is lower than the observed one. Additionally, cross-country differences in the proportion of firms with general training remain significant, ranging from 20% to 80%. Conversely, after controlling for country, industry, and fixed effects, the proportion of firms with IT training is much higher than the actual value, and the results are similar across European economies, ranging from 60% to 80%. This suggests that companies are recognizing the need to upskill their workforce in digital competencies more than in general skills.

Figure 2 displays the residualised values of training costs for companies with general training and those with IT training. In both cases, these values are significantly higher than the observed values and are more consistent across countries. Among companies with training (defined in general terms), Italy and Norway have the highest proportion of training costs in relation to total labor costs. Norwich and French companies are at the top of the European ranking.

Table 5 presents comprehensive summary statistics for all variables utilised in the regression analysis. Our sample primarily consists of small and medium-sized enterprises, accounting for 82% and 16%, respectively. Additionally, 10% of the companies in our study operate in highly digital-intensive industries, while 20% operate in low-intensive digital skills sectors. The remaining 70% belong to sectors that require an intermediate level of digital skills. Upon examining the most significant control variables, we note that European companies have a predominant share of male workers, accounting for 64% of the workforce. Furthermore, only a small proportion of these companies undertake apprenticeship programs (35%) or are subject to contract agreements for the implementation of vocational training (19%).

Table 5 Summary statistics

		Mean	SD	Min	Max
Wage	Continuous	29,977.9	14,539.4	1,116.0	90,421.3
Training	Dummy	0.60	0.49	0.00	1.00
IT training	Dummy	0.20	0.40	0.00	1.00
Training costs	Percentage	0.96	1.90	0.00	98.54
Trainees	Percentage	47.21	32.20	0.00	100.00
Training hours per trainee	Continuous	24.00	48.71	0.00	2,000.00
Internal training	Dummy	0.07	0.26	0.00	1.00
External training	Dummy	0.26	0.44	0.00	1.00
Int. and external training	Dummy	0.26	0.44	0.00	1.00
Government training	Dummy	0.05	0.22	0.00	1.00
Education training	Dummy	0.04	0.21	0.00	1.00
Highly digitalised industry	Dummy	0.10	0.29	0.00	1.00
Lowly digitalised industry	Dummy	0.20	0.40	0.00	1.00
Hours per worker	Continuous	1,665.1	3,780.0	0.75	833,074
Small firm	Dummy	0.82	0.39	0.00	1.00
Medium firm	Dummy	0.16	0.36	0.00	1.00
Large firm	Dummy	0.03	0.16	0.00	1.00
Male workers	Percentage	63.63	27.17	0.00	100.00
Agreement	Dummy	0.19	0.39	0.00	1.00
Apprenticeship	Dummy	0.35	0.48	0.00	1.0

Notes: Mean values are obtained using sampling weights.
Source: Authors' own elaboration.

4.2 Baseline regression

Table 6 illustrates the findings of OLS regression for our baseline model.[7] Column (1) reports estimation results for our most conservative specification which includes only training – defined as dummy variable – and the full set of industry-, country- and time-effects. The coefficient of the explanatory variable indicates that, once the effects of all the deterministic components of the model have been accounted for, there is a wage difference of 19% between companies with and without training.

[7] All regressions use standard errors clustered at industry-by-country level.

In column (2), we introduce the set of control variables reflecting the structural characteristics of the company. As expected, wages are significantly higher in medium and large-sized companies, which have more funds to allocate to investments compared to smaller firms; wages are also higher in companies having a larger share of male workers and in those with a larger number of hours worked per employee. Column (2) allows us to check whether the coefficient of our key explanatory variable captures the effect of other idiosyncratic characteristics correlated with training activities, some of which may ultimately depend on the organisational capabilities of the company.

For instance, firms may pursue wider training policies like those for initial apprenticeship, with the risk that the coefficient of the vocational training is upward biased. Companies may also undertake training programmes as these are imposed by the contract agreement between the organisations of employers and employees, implying that the coefficient of training does not specifically reflect the company decision to pursue this policy. Overall, accounting for all these factors does marginally influence our main estimates (0.117), despite control variables being significant and with the expected sign.

Table 6. Impact of training on wages: baseline estimation

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
Training	Dummy	0.189***	0.117***					
		(0.008)	(0.007)					
Training costs	Percentage			0.015***				
				(0.002)				
Trainees	Percentage				0.001***			
					(0.000)			
Avg training hours	Log					0.037***		
						(0.004)		
Internal training	Dummy						0.040***	0.041***
							(0.008)	(0.008)
External training	Dummy						0.091***	0.088***
							(0.008)	(0.008)
Int. and ext. training	Dummy						0.186***	0.181***
							(0.010)	(0.010)
Government training centre	Dummy							0.017
								(0.014)
Education training centre	Dummy							0.036***
								(0.014)
Hours per worker	Log		0.543***	0.557***	0.542***	0.542***	0.540***	0.540***
			(0.044)	(0.044)	(0.045)	(0.043)	(0.043)	(0.043)
Medium-sized	Dummy		0.111***	0.132***	0.125***	0.120***	0.097***	0.096***
			(0.010)	(0.009)	(0.009)	(0.009)	(0.010)	(0.010)
Large-sized	Dummy		0.182***	0.210***	0.194***	0.194***	0.147***	0.145***
			(0.018)	(0.018)	(0.016)	(0.015)	(0.018)	(0.018)
Males	Percentage		0.003***	0.003***	0.003***	0.003***	0.003***	0.003***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Agreement	Dummy		0.043***	0.058***	0.044***	0.048***	0.036***	0.036***
			(0.007)	(0.007)	(0.006)	(0.006)	(0.007)	(0.007)
Apprenticeship	Dummy		0.013*	0.020**	0.002	-0.001	0.008	0.007
			(0.008)	(0.008)	(0.008)	(0.008)	(0.007)	(0.007)
Observations		112,399	112,399	112,399	71,662	71,509	112,399	112,399
R-squared		0.755	0.797	0.795	0.728	0.731	0.799	0.799

Notes: The dependent variable is the average wage (in logs). OLS estimates. The dependent variable is the log of wage. Standard errors clustered at industry-by-country level. Year-, Industry-, and Country-fixed effects are included in all regressions. ***,**, * significant at 1, 5 and 10%.
Source: Authors' own elaboration.

Next, we assess the sensitivity of these results to alternative training measures. As described above, we use the ratio of training expenses to total labour costs (col. (3)), the share of trainees out of the total workforce (col. (4)) and average number of training hours (col. (5)). These variables turn out to be largely significant and with a positive coefficient. Parameters in columns (3)-(4) are semi-elasticities, therefore suggesting that a 1% increase in training costs or the share of workers under training is associated with a 1.5% and 0.1% wage increase, respectively. The positive coefficient associated with the share of trainees suggests that wage spillovers might occur when a larger number of workers is involved in training as these activities could enhance complementarities among trainees and workers without training, making them more productive and leading to higher wages. The coefficient of training in col. (5) is an elasticity indicating that a one percent increase in the number of training hours translates into a 0.037% wage premium. Since the average number of training hours (per trainee) is 24 per year, with 2.5 additional hours of training (roughly a 10% increase) the average salary would be expected to rise by 0.5%, i.e.,150 euro as average for all workers.

Finally, we explore whether the wage premium associated with training varies in relation to how this activity is organised, i.e., whether it is internally managed by the company, it is outsourced to external bodies or the firm adopts both forms of training. We find that a 19% wage premium is associated with companies adopting a hybrid training policy (both internal and external training), whilst the wage premium associated with external or internal training only amounts to 9 and 4%

respectively (column (6)). The larger effect found for companies having training programmes organised both internally and externally may reveal that trainees become more productive, because they develop a larger or a more effective set of skills when they learn competences developed within the company combined with more general skills acquired through specialized centres or companies. Our study therefore reveals that companies that rely on both internal and external training providers tend to have higher wages compared to those that use only one source.

In column (7), we refine the latter estimates by exploring whether the wage premium associated with the implementation of external training depends on the nature of the training centre. We therefore include two dummy variables capturing whether the training provider is a public training institution (i.e., financed or led by the government) or an education institution (schools, colleges, universities and other higher education institutions). Our estimation shows that only companies with training provided by an education institution pay wages higher than the reference group. Overall, this check does not change the main pattern of our results.

4.3 Extended regression: IT sectoral pattern

In this part of the work, we investigate in what respect the training policy pursued by the European companies is affected by digitalisation and whether the company response to such transformations, in terms of IT-related training content, helps explain the wage differentials existing across firms. This analysis is developed in

Table 7 where, in column (1), we report the main results of the previous set of regressions as reference (i.e., col. (2), Table 6). All estimations in Table 7 include the same set of controls used above but are not shown here for the sake of brevity. In col. (2), we include a binary indicator identifying firms undertaking training targeted to develop IT-related competences (general IT skills and professional IT skills). To discern the wage effect of this variable from the general tendency of a company to pay higher (or lower) wages in relation to its exposure to digitalisation, we include two dummies for those companies active in industries identified as highly digitalised or lowly digitalised (1st and 4th quartile of the ICT ranking developed by ICT).

Companies that provide IT training to their employees offer a higher wage compared to those that offer training in more general competencies (0.087 vs 0.092). This trend is prevalent across various sectors of the economy and is not limited to specific sectoral patterns of digitalization. These findings align with the evidence provided by Michaels et al. (2014) who, analysing industry-by-country data from the early 1970s, highlight the wage polarization resulting from the IT revolution. Additionally, it is noteworthy that firms operating in highly digitalized or lowly digitalized sectors tend to pay statistically higher wages than those in other sectors (i.e., medium-high and medium-low digitalised sectors, 2nd and 3rd quartile). In particular, a 53% higher wage is found for highly digitalised firms with respect to the reference group, and a 14% higher wage for firms in lowly digitalised sectors.

Table 7. Impact of training on wages: IT sectoral pattern and IT training

	(1) All sectors	(2) All sectors	(3) Highly digitalised sectors	(4) Lowly digitalised sectors	(5) Highly digitalised sectors	(6) Lowly digitalised sectors	(7) Highly digitalised sectors	(8) Lowly digitalised sectors
			(all assets)		(software investment)		(ICT specialists)	
Training	0.117***	0.092***	0.107***	0.082***	0.108***	0.098***	0.104***	0.085***
	(0.007)	(0.007)	(0.017)	(0.012)	(0.016)	(0.012)	(0.013)	(0.010)
IT training		0.087***	0.060***	0.082***	0.074***	0.126***	0.056***	0.117***
		(0.009)	(0.012)	(0.018)	(0.015)	(0.015)	(0.012)	(0.016)
High digitalised sector		0.530***						
		(0.058)						
Low digitalised sector		0.136***						
		(0.028)						
CONTROLS	YES	YES	YES	YES	YES	YES	YES	YES
Observations	112,399	112,399	16,276	24,203	28,010	37,023	23,473	47,919
R-squared	0.797	0.798	0.761	0.817	0.806	0.761	0.770	0.782

Notes: The dependent variable is the average wage (in logs). OLS estimates. Standard errors clustered at industry-by-country level. Year-, Industry, and Country-fixed effects are included in all regressions. All estimates include the control variables used in Table 6, namely hours per worker, size dummies, share of male workers, and the binary indicators for the companies with contract agreement for training and those with workers under apprenticeship. ***,**,*significant at 1, 5 and 10%.
Source: Authors' own elaboration.

Next, we inspect whether the effect of training changes across sectors in relation to the digitalisation of their production. Accordingly, we run our regression model separately for companies active in highly digitalised and lowly digitalised sectors (cols. (3) and (4)). The coefficient size of general and IT training variables does not appear very different between these two types of industries compared to what we found for the pool of firms in col. (2). In order to determine the reliability of our findings regarding the impact of training on wages, we replicate estimates classifying industries along two main dimensions of the digital transformation: investment in software (columns (5) and (6)) and the percentage of ICT specialists (columns (7) and (8)). The wage effect of both forms of training remains consistent in highly digitalized industries, regardless of the type of industry classification used. However, we find that the wage premium associated with general and IT training is significantly higher in industries with lower levels of digitalization, as measured by our refined metrics of digital transformation in production. This suggests that there is a greater incentive to invest in upskilling the workforce in industries where software and ICT specialists are less prevalent.

As a final step of the work, in Table 8 we explore whether the impact of training is influenced by how these activities are arranged. This dimension, as previously mentioned, can only be explored in the context of general training. In column (2), we examine firms that offer internal training, external training, and both, which are identified by binary indicators. In this regression, we observe that the coefficient of IT training experiences only a slight reduction and remains highly significant. It is worth noting that all variables related to the organization of general training are significant, and their cumulative impact is greater than the coefficient of the baseline dummy for training. This suggests that there may be important complementarities between the various forms of organization of training that cannot be captured by a single binary indicator.

Table 8. Impact of the organisation of training on wages

		(1)	(2)	(3)	(4)
		All sectors	**All sectors**	**All sectors**	**All sectors**
Training	Dummy	0.092***			
		(0.007)			
IT training	Dummy	0.087***	0.072***		
		(0.009)	(0.008)		
Internal training	Dummy		0.023***	0.024***	0.024***
			(0.008)	(0.008)	(0.008)
External training	Dummy		0.072***	0.068***	0.064***
			(0.008)	(0.008)	(0.008)
Internal and external training	Dummy		0.155***	0.161***	0.154***
			(0.008)	(0.009)	(0.009)
Internal training × IT training	Dummy			0.058***	0.078***
				(0.008)	(0.009)
External training × IT training	Dummy			0.070***	0.069***
				(0.012)	(0.012)
Int. and external training. × IT training	Dummy			0.090***	0.105***
				(0.010)	(0.010)
Government training centre	Dummy		0.032**	0.033**	0.066***
			(0.013)	(0.014)	(0.013)
Education training centre	Dummy		0.013	0.013	0.039**
			(0.014)	(0.012)	(0.016)
Govern. training centre × IT training	Dummy				-0.073***
					(0.013)
Educ. training centre × IT training	Dummy				-0.070***
					(0.014)
CONTROLS		YES	YES	YES	YES
Observations		112,399	112,399	112,399	112,399
R-squared		0.798	0.800	0.801	0.800

Notes: The dependent variable is the average wage (in logs). OLS estimates. Standard errors clustered at industry-by-country level. Year-, Industry, and Country-fixed effects are included in all regressions. All estimates include the control variables used in Table 7, namely hours per worker, size dummies, share of male workers, and the binary indicators for the companies with contract agreement for training and those with workers under apprenticeship, and the binary indicators identifying firms operating in highly and low digitalised sectors. ***,**,*significant at 1, 5 and 10%.
Source: Authors' own elaboration.

In column (3), we interact IT training with the three variables identifying the organisational modes of training. We find that IT training companies with standalone external training provision, or those combining both internal and external training, pay statistically higher wages than companies without training (general reference group) and compared to companies with general training. Finally, in column (4) we introduce an interaction term between IT training and the dummy variable identifying firms with external training provided by government-funded institutions and firms with external training provided education training centres. These estimates reveal that the wage premium of IT training is not associated with these forms of provisions but, more likely, with training provided by private companies or organised internally.

4.4 Endogeneity issues

One concern with our estimates is that the sample of firms with training (treated) may not be randomly selected, but both training and wage performance may depend on some unobservable characteristics or, worse, that the direction of causality runs in the opposite direction to what is assumed here, namely that companies with higher wages may be endowed with more productive workers that employers seek to keep through training and other activities promoting firm-specific human capital. All this would raise concerns about the consistency of our estimates due to selectivity and simultaneity issues.

To address these important issues, there are two potential approaches at hand. The first method involves utilizing a matching procedure, such as the propensity score matching (PSM), to determine whether selectivity issues affect the estimated wage impact of training. This non-parametric method compares the mean difference in wages (measured in the log scale) between companies that provide training and those that do not. The identifying assumption of PSM is that, once observable characteristics are controlled for ("selection on observables"), any difference in the outcome variable between treated and untreated companies (the control group) can be ascribed solely to training (the treatment variable). However, it is important to note that if there are unobservable characteristics that influence a firm's likelihood of providing training programs to their employees, matching methods may produce biased estimates, as the treatment variable would be endogenous ("selection on unobservables"). In our specific context of analysis, the lack of comprehensive information on the workforce's characteristics increases the likelihood of obtaining biased estimates from PSM.[8]

The second method mitigates the risk of bias associated with "selection on unobservables," and mostly consists of two procedures. The first is the difference-in-differences (DiD) approach, which requires a panel dimension of the data. The second is instrumental-variables (IV) regression, which imposes a set of assumptions, including independence, relevance condition, and exclusion restrictions. However, these assumptions may be difficult to satisfy with our data.

For example, independence assumes that the benefits of training do not depend on the level of public support received to implement training programs. However,

[8] Ci et al. (2015) study the impact of the mid-carrier (on-the-job) training in Canada comparing estimates obtained with OLS and propensity score matching (see also Frölich 2007).

a firm's knowledge of public schemes to support training may depend on the incentives firms have to invest in training. Although individual firms cannot affect legislation, the firm's knowledge of public schemes to support training may itself depend on firm incentives to invest in training.

On the basis of this comprehensive discussion, we keep OLS as our preferred method of regression, acknowledging however that the resulting estimates may be subject to selectivity and reverse causality bias.[9]

4. Conclusions

This paper has investigated the company-level wage effect of training in selected European countries, by taking into account the different exposure to digitalisation and the digital content of training activities. Digital transformation forces firms to adopt measures for upgrading the skill structure of the workforce. This need is particularly strong for jobs based on digital skills (IT upskilling). Based on a large company-level dataset (112 thousand companies), obtained by merging three different waves of the EU Continuing Vocational Training Survey, we have illustrated that there are significant differences in the wage performance related to training across European companies. According to our estimates, a wage premium of 9% is associated with companies undertaking training, defined in general terms, and an additional 8% is paid by firms providing IT training. Since information technologies

[9] We gratefully acknowledge one referee for providing valuable insights that have been instrumental in developing the discussion of the econometric issues.

are highly pervasive, are employed in a wide range of sectors and act as general-purpose technologies, the wage effect of the digital transformation channelled by the IT upskilling is broad-based and not strictly confined to those productions more exposed to digitalisation.

Our analysis offers useful insights for academics and policymakers interested in understanding the consequences of digitalisation and how to tackle its possible adverse effects. A wide literature has looked at the change in labour demand, wage levels and dispersion, as well as employment prospects associated with the diffusion and adoption of new digital technologies, but little is known about which company-level policy is more effective to tackle this process. This study helps to fill this important gap in our understanding. On aggregate, however, there is also the risk that wage differences across firms are likely to widen if falling-behind companies are not able to systematically organize policies for workplace learning and training, especially for some key job positions. Our findings complement recent evidence on the widening productivity gap between frontier and laggard companies in Europe and other advanced countries (Andrews et al. 2019), and on the fact that acting in the new technological fields may help reduce the distance from the most productive companies (Pompei and Venturini 2022).

References

Acemoglu, D. (1998a). Training and innovation in an imperfect labour Market. *Review of Economic Studies* 64(3), 445-464.

Acemoglu, D. (1998b) Why do new technologies complement skills? Directed technical change and wage inequality. *Quarterly Journal of Economics* 113(4), 1055–1089.

Acemoglu, D. (2002). Technical change, inequality, and the labor market. Journal of Economic Literature, 40(1), 7–72.

Acemoglu, D. and Pischke, J. (1998a). Why do firms train? Theory and evidence. Quarterly Journal of Economics 113(1), 79-119.

Acemoglu, D. and Pischke, J. (1998b). The structure of wages and investment in general training. *Journal of Political Economy* 539–572.

Acemoglu, D., Pischke, J. (1999). Beyond Becker: Training in imperfect labor markets. *Economic Jourrnal* 109, F112-F142.

Acemoglu, D. and Restrepo, P., (2018) The race between man and machine: Implications of technology for growth, factor shares and employment. *American Economic Review* 108(6), 1488–1542.

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

Acemoglu, D., Autor., D., Hazel., D and Restrepo, P. (2022) Artificial Intelligence and jobs - Evidence from online vacancies. *Journal of Labor Economics*, 40(S1), S293-S340.

Andrews, D., Criscuolo, C. and Gal., P.N., (2019). The best versus the rest: Divergence across Firms during the Global Productivity Slowdown. CEP Discussion Paper No 164. https://cep.lse.ac.uk/pubs/download/dp1645.pdf

Autor, D.H., Katz, L.F. and Krueger, A.B. (1998) Computing inequality: Have computers changed the labor market? *Quarterly Journal of Economics* 113(4) 1169–1213.

Autor, D.H, Levy, F. and Murnane, R. J. (2003). The skill content of recent technological Change: An empirical exploration. *Quarterly Journal of*

Economics 118(4), 1279–1333.

Balsmeier, B. and Woerter, M. (2019). Is this time different? How digitalization influences job creation and destruction. *Research policy*, 48 (8), 103765.

Bartel, A. and Sicherman, N. (1998). Technological change and the skill acquisition of young Workers. *Journal of Labour Economics* 16(4), 718-755.

Becker, G. (1964). *Human capital*. University of Chicago Press, Chicago.

Bertoni, M. and Brunello, G. (2022). Training during recessions: recent European evidence. *IZA Journal of Labor Policy,* 12(1) 1-17

Bessen, J., Goos, M., Salomons, A., and van den Berge, W. (2020). Firm-Level Automation: Evidence from the Netherlands. *AEA Papers and Proceedings*, 110 389-93.

Brynjolfsson, E. and McAfee, A. (2014). The second machine age: Work, progress, and prosperity in a time of brilliant technologies, New York: W. W. Norton and Company, 1st ed.

Brunello, G. and Wruuck, P. (2020). Employer-provided training in Europe: Determinants and obstacles. *IZA Discussion Paper No.* 12981

Brunello, G., Rückert, D., Weiss, C., and Wruuck, P. (2023). Advanced digital technologies and investment in employee training: Complements or Substitutes?. IZA Discussion Paper No. 15936

Calvino, F., Criscuolo, C., Marcolini, L. and Squicciarini, M. (2018). A taxonomy of digital intensive sectors. *OECD Science, Technology and Industry Working Papers, No. 2018/14,* OECD Publishing, Paris, https://doi.org/10.1787/f404736a-en

Cedefop (2016). The great divide: Digitalisation and digital skill gaps in the EU workforce. *#ESJsurvey Insights, No* 9, Thessaloniki: Greece.

Cedefop (2022). Setting Europe on course for a human digital transition: new evidence from Cedefop's second European skills and jobs survey. Luxembourg: Publications Office. Cedefop reference series; No 123

Ci, W., Galdo, J. C., Voia, M. and Worswick, C., (2015). Wage returns to mid-career investments in job training through employer-supported course enrollment: Evidence for Canada. *IZA Discussion Papers 9007*, Institute of

Labor Economics (IZA).

Dearden, L, Reed, J., Van Reenen, J. (2006). Training and corporate productivity: Evidence from a panel of UK industries. *Oxford Bulletin of Economics and* Statistics 68(4), 397-421.

Dauth, W., Findeisen, S., Südekum, J., Woessner, N., (2017). German robots - The impact of industrial robots on workers. CEPR Discussion Papers 12306, C.E.P.R. Discussion Papers.

Domini, G., Grazzi, M., Moschella, M., Treibich, M., (2022). For whom the bell tolls: The firm-level effects of automation on wage and gender inequality. *Research Policy* 51(7), 104533

EIB (2022). Digitalisation in Europe 2021-2022: Evidence from the EIB Investment Survey. *European Investment Bank, Economics Department*, https://www.eib.org/attachments/publications/digitalisation_in_europe_2021_2022_en.pdf

Feng, A., and Graetz, G., (2020). Training Requirements, Automation, and Job Polarisation. *Economic Journal* 130(631), 2249–2271.

Fossen, F., and Sorgner, A. (2022). New digital technologies and heterogeneous wage and employment dynamics in the United States: Evidence from individual-level data. *Technological Forecasting and Social Change* 175, 121381

Frölich, M. (2007). Propensity score matching without conditional independence assumption—with an application to the gender wage gap in the United Kingdom. *The Econometrics Journal* 10(2), 359–407.

Gal, P., Nicoletti, G., Renault, T., Sorbe, S. and Timiliotis, C. (2019). Digitalisation and productivity: In search of the holy grail – Firm-level empirical evidence from EU countries. *OECD Economics Department Working Papers, No. 1533*, OECD Publishing, Paris.

Goos, M. Manning, A. and Salomons, A. (2009). Job polarization in Europe. *American Economic Review* 99, 58-63.

Goos, M., Rademakers, E., and Röttger, R., (2021). Routine-biased technical change: Individual-level evidence from a plant closure. *Research Policy* 50(7) 104002.

Haelermans, C. and Borghans, L. (2012). Wage effects of on-the-job training: A meta-analysis. *British Journal of Industrial Relations* 50, 502-528.

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

Krueger, A. B. (1993). How computers have changed the wage structure: Evidence from microdata, 1984-1989. *Quarterly Journal of Economics* 108(1), 33–60.

McGuinness, S., Pouliakas, K. and Redmond, P. (2021). Skills-displacing technological change and its impact on jobs: challenging technological alarmism?. *Economics of Innovation and New Technology*, 1-23

Michaels, G., Natraj, A. and Van Reenen, J., (2014). Has ICT polarized skill demand? Evidence from eleven countries over 25 Years. *Review of Economics and Statistics* 96(1) 60–77.

O'Mahony, M., Robinson C. and Vecchi, M. (2008). The impact of ICT on the demand for skilled labour: A cross-country comparison. *Labour Economics* 15(6), 1435-1450.

O'Mahony, M. (2012). Human capital formation and continuous training: Evidence for EU countries. *Review of Income and Wealth* 58(3), 531-549.

Pompei, F. and Venturini, F. (2022). Firm level productivity and profitability effects of managerial and organisational capabilities and innovations. *Untangled Research Papers No. 02/2022.* https://projectuntangled.eu/untangled-research-papers/

Squicciarini, M., Marcolin, L. and Horvat, J., (2015). Estimating cross-country investment in training: An experimental methodology using PIAAC data. *OECD Science, Technology and Industry Working Papers 2015/09*

Webb, M. (2020). The Impact of Artificial Intelligence on the labor market. *Stanford University*, mimeo.