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The Effects of Investment in Education and Training on Productivity Growth in the European Union

Iulia Siedschlag[a,b] and Juan Durán

a) Economic and Social Research Institute, Dublin, Ireland
b) Department of Economics, Trinity College Dublin, Dublin, Ireland

* Corresponding author Iulia.Siedschlag@esri.ie

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Iulia Siedschlag †[1, 2] and Juan Duran[1, 2]

[1]The Economic and Social Research Institute (ESRI)

[2]Department of Economics, Trinity College Dublin

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Abstract

This paper investigates the impact of on-the-job training on labour productivity, focusing on both the direct effects of training capital accumulation and its complementarity with other intangible capital assets. While previous research has highlighted the positive role of workplace training in enhancing productivity, we extend this literature by exploring how investments in training interact with other intangible assets such as software and data bases, innovation property, brand, and organizational capital. Using data from the EUKLEMS & INTANProd databases covering 17 industries across 27 EU countries, the UK, and the US between 1995 and 2021, we employ a difference-in-differences estimation approach within a production function framework augmented to include intangible capital. Our findings reveal that training significantly boosts labour productivity, with the effect being stronger in industries with higher training investment intensity. We also demonstrate that the complementarity between training and other intangible capital is most pronounced in business services and is mainly explained by the interaction between training and other firm-specific intangible assets such as branding and organisational capital.

Keywords— Investment in Training, Productivity Growth, Production Function Modelling

JEL Codes— E22, J24, O47

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†Corresponding author: iulia.siedschlag@esri.ie.

I. Introduction

Investment in education, reflected in the accumulation of human capital, is widely recognized as a key driver of productivity, innovation, and long-term economic growth (Lucas, 1988; Romer, 1990; Aghion & Howitt, 1997). While formal education plays a crucial role in skill acquisition, the need for lifelong learning systems is becoming increasingly important given the pace of rapidly evolving challenges such as climate change and technological advancements in information and communication technologies (ICT) (OECD, 2023). However, the contribution of education and skills to these economic benefits is likely to be underestimated given several measurement issues (Acemoglu, 2009). One possible source of mismeasurement is human capital quality, given significant differences in school and teacher quality within and across countries. A second source of mismeasurement is that most empirical macroeconomic growth models consider differences in human capital across countries as a result of differences in formal education. However, as shown by the model put forward by Ben-Porath (1967), human capital accumulation continues after individuals complete their formal education via on-the-job investment in training. This model suggests that the contribution of human capital to productivity growth might be underestimated.

A small body of literature has explored the impact of workplace training on productivity growth, generally finding positive direct effects (Bartel, 1994; Black & Lynch, 1996; Dearden et al., 2000; Barrett & O'Connell, 2001; Black & Lynch, 2001; Conti, 2005; Zwick, 2006). More recently, researchers have emphasized the role of continuous training as an intangible investment (Corrado et al., 2005; Timmer et al., 2010), contributing to human capital accumulation and output growth (O'Mahony, 2012) and boosting labour productivity both directly and indirectly, especially through interactions with ICT capital (O'Mahony & Peng, 2011). More broadly, the literature on intangible capital and labour productivity growth has integrated training within the economic competencies component, which also includes advertising, market research, and organizational capital (Corrado et al., 2005; Bontadini et al., 2023). Against this background, recent evidence shows that, among intangible capital assets, advertising and market research are the main drivers of labour productivity growth in Europe, the US, and Japan (Adarov & Stehrer, 2019).

This paper generates new knowledge on the effects of on-the-job training on productivity growth. Specifically, we estimate the direct impact of training capital accumulation and examine its complementarity with other types of intangible capital. This complementarity is particularly relevant in light of recent findings on the various reasons behind training provision (OECD, 2021). Beyond legal requirements related to health, safety, and security, firms invest in training to drive improvements in product market performance, organizational capabilities, client relationships, product quality, innovation, internal communication, and corporate culture. As a result, the benefits of training may also manifest indirectly by enhancing the productivity of other intangible capital assets such as advertising, market research, or organizational capital.

Using data from the EUKLEMS & INTANProd databases covering 17 industries across 27 EU countries and the UK from 1995 to 2021, we employ a cross-industry, cross-country difference-in-differences estimation approach within a production function framework augmented to include intangible capital. Our findings can be summarized as follows. First, consistent with previous research, we find that training capital significantly boosts labour productivity growth, measured by value-added per hour worked. Second, when considering training investment intensity (defined at industry level as training investment relative to industry value-added), we find robust evidence for the complementarity between training and other intangible capital. Specifically, the output elasticity of intangible capital is notably higher in industries with greater training investment intensity. Further analysis across sector groups and more disaggregated intangible capital types reveals that this complementarity is strongest in business services and primarily driven by the interaction between training and organisational capital.

The remainder of the paper is structured as follows: Section II. describes the data; Section III. discusses the empirical strategy; Section IV. presents the results and a range of robustness checks; and Section V. concludes.

II. Data

We use data from the 2025 release of the EUKLEMS & INTANProd database[1] on capital and labour accounts, along with the intangibles analytical module, providing information on value-added, number of workers, hours worked per worker, capital stocks, and investment flows at the 1-digit industry level. Our sample covers 17 sectors across the 27 EU countries and the UK between 1995 and 2021. Specifically, we include sectors A[2] to S excluding public administration and defence (O). When discussing the results, we consider different sector groups such as the market sectors -excluding education (P) and health (O)-, production sectors, and service sectors. Human capital is defined as the share of workers with tertiary education in total employment.[3] In line with recent literature, following Corrado et al. (2005), in this paper we analyse the impact of training capital on productivity growth and therefore we separate this intangible capital

[1]Bontadini et al. (2023) provide a detailed description of the EUKLEMS & INTANProd database.

[2]As in Chen et al. (2016), sector A+B combines agriculture, forestry and fishing, and mining and quarrying.

[3]This human capital measure is similar to labour quality measures used in other papers, see for example Black & Lynch (1996).

assets from the other intangible capital assets. Table A1 provides further details on the variables definitions.

Of crucial importance in this paper are the measures of continuous training. Following the seminal work of Corrado et al. (2005), several studies have understood continuous training paid by the firm as an investment rather than an intermediate consumption (O'Mahony, 2012). For European countries, EU KLEMS provides measures on investment in training estimated using vocational training and apprenticeships from the EU Continuing Vocational training Survey (CVTS) integrated with data from the EU Labour Cost Survey (EU LCS) (Bontadini et al., 2023). The CVTS provides information on the costs of continuing vocational training, defined as education or training courses that are financed in total or at least partly by the enterprise, for 2005, 2010, and 2015. The EU LCS provides information on the share of vocational training in the total labour costs for the years 2000, 2004, 2008, 2012 and 2016. In both cases, time series of expenditures were constructed by applying the shares of training to the compensation of employees from national accounts. Data for years between surveys were interpolated, and industry cost shares in the EU LCS were assumed to be the same as in 2000 for the period 1995-2000. Stocks are estimated assuming a capitalisation factor equal to one.

Using the provided series of training capital and investments flows, we define a training intensity measure computed as the ratio of investment in training to value-added adjusted for the inclusion of intangible capital in each industry. When discussing the estimation results, we test the sensitivity of the estimates to alternative training intensity measures using gross output and investment in all assets as denominators.

All monetary values are expressed in US dollars and deflated using value added price indices, except for training investment that is deflated using a labour earnings deflator following O'Mahony (2012). Table 1 reports the summary statistics of the main variables of interest across all countries, while Table A2 reports the means by country, where we also include the US as a non-European reference country. On average, investment in training represents 0.93% of the value-added per year. The countries with the highest average training capital intensities over the period are Ireland (1.54%), Denmark (1.47%), Finland (1.47%), and Germany (1.44%). Looking at the European average training intensity across industries (Fig. A1), the highest intensities are observed in Education (P), Professional, scientific and technical activities (M), Other services activities (S), and Financial and insurance activities (K).

In the empirical strategy, we use yearly growth rates of the variables of interest constructed using log changes. In order to avoid outliers, we exclude observations in the 1st and 99th percentiles per industry. Table 1 documents that the production input with the fastest mean growth is (other) intangible capital (1.7%), followed by human capital (0.98%), and tangible capital (0.59%).

In contrast, the training capital stock decreased by a mean annual rate of -2.18% over the studied period.

Table 1: Summary Statistics

	Obs.	Mean	SD	P25	P75
Adjusted value-added (USD mn)	10,920	32.881	66.208	2.237	30.279
Value-added per worker (USD th)	10,920	114.430	226.307	32.723	96.300
Value-added per hour (USD th)	10,920	0.089	0.225	0.023	0.072
Tangible capital stock per worker (USD mn)	10,920	0.866	3.478	0.038	0.193
Other intangible capital stock per worker (USD mn)	10,920	0.032	0.050	0.005	0.036
Training capital stock per worker (USD mn)	10,920	0.002	0.003	0.000	0.002
Training investment intensity (% VA)	10,920	0.886	1.016	0.283	1.145
Third-level emp. share (%)	10,920	24.343	22.814	0.000	38.651
Δ Value-added per worker (%)	10,920	0.797	8.606	-2.916	4.906
Δ Value-added per hour (%)	10,920	0.954	8.768	-3.030	5.168
Δ Third-level emp. share (%)	10,920	0.983	5.236	0.000	0.819
Δ Tangible capital (%)	10,920	0.590	8.136	-3.811	4.997
Δ Inangible capital (%)	10,920	1.701	8.200	-2.861	6.274
Δ Training capital (%)	10,920	-2.183	9.723	-7.707	3.235

Notes: Monetary values are expressed in thousands of 2015 US dollars deflated using industry-country price indices.

III. Empirical Strategy

We build on the extensive literature on productivity dynamics at the industry level and derive the empirical strategy by assuming an intangibles-augmented Cobb-Douglas production function with constant returns to scale:

$$Y_{jc,t} = A_{jc,t} \left(L_{jc,t}\right)^{\alpha_0} \left(H_{jc,t}\right)^{\alpha_1} \left(K^{Tan}_{jc,t}\right)^{\alpha_2} \left(K^{Int}_{jc,t}\right)^{\alpha_3} \left(K^{Tr}_{jc,t}\right)^{\alpha_4} \tag{1}$$

This implies that value-added (adjusted to include intangible capital, Y) is produced using labour (L) human capital (H), tangible capital (K^{Tan}), intangible capital excluding training (K^{Int}), and training capital (K^{Tr}) in industry j, country c, and time t. A is a parameter standing for the Hicks-neutral technical progress that increases the marginal productivity of all factors of production by the same proportion and α_i for $i = \{0, 1, 2, 3, 4\}$ denote the output elasticities with respect to input factors. Taking logs and first differences, and using the assumption of constant returns to scale we obtain the following equation:

$$\Delta\left(y_{jc,t}-l_{jc,t}\right)=\alpha_1\Delta\left(h_{jc,t}-l_{jc,t}\right)+\alpha_2\Delta\left(k^{Tan}_{jc,t}-l_{jc,t}\right)+\alpha_3\Delta\left(k^{Int}_{jc,t}-l_{jc,t}\right)$$
$$+\alpha_4\Delta\left(k^{Tr}_{jc,t}-l_{jc,t}\right)+\mu_{jc,t} \quad (2)$$

where $\mu_{jc,t}$ is an error term that includes the efficiency term $A_{jc,t}$, country-industry fixed effects, year fixed effects and an idiosyncratic component.

We further explore to what extent the output elasticity of human or intangible capital is higher in more training intensive industries by adopting a difference-in-differences approach inspired by the seminal contribution of Rajan & Zingales (1998) and interact each production input with the training investment intensity γ_j^{Tr}:

$$\Delta\left(y_{jc,t}-l_{jc,t}\right)=\left[\Delta\left(h_{jc,t}-l_{jc,t}\right)+\Delta\left(k^{Tan}_{jc,t}-l_{jc,t}\right)+\Delta\left(k^{Int}_{jc,t}-l_{jc,t}\right)+\Delta\left(k^{Tr}_{jc,t}-l_{jc,t}\right)\right]$$
$$\cdot\left(\boldsymbol{\alpha}+\boldsymbol{\beta}\gamma_j^{Tr}\right)+\varepsilon_{jc,t} \quad (3)$$

Building on Chen et al. (2016), we also include the interaction between tangible capital and training intensity to prevent omitted variables bias and demean the interaction terms.

In terms of identification, there are two important concerns when estimating Eq. 3. First, input levels are likely to be endogenous due to unobserved shocks affecting both labour productivity and input use. Second, and related, the training investment intensity can be endogenous to unobserved industry characteristics. We address these potential issues using two methods employed in the literature. To deal with the simultaneity bias, we include country-industry fixed effects, which account for time-invariant industry confounding factors systematically affecting both input use and labour productivity, and year fixed effects, which absorb time-varying shocks common to all industries.

Regarding the training intensity, we instrument the average training investment intensity using the initial values in a country selected as a benchmark. These estimators have been widely used in the cross-industry cross-country literature and the US is typically employed as a benchmark being a technological leader and having a more flexible regulation framework (Rajan & Zingales, 1998; Raddatz, 2006; Nunn, 2007; Ciccone & Papaioannou, 2009; Bassanini et al., 2009; Michaels et al., 2014; Chen et al., 2016). In the context of training, we use Finland as a benchmark being one of the economies with the highest training investment intensities. Alternatively, we set the US as benchmark to test the sensitivity of this modelling choice since the country is in the top quartile of the training investment intensity distribution. Aside from providing benchmarks with different occupational structures, these countries also had different funding systems back in 1995.

IV. Estimation Results

A. *Baseline Results*

Table 2 presents the estimation results of our baseline specifications when the outcome variable is the growth in value-added per worker (Panel A) and value-added per hour worked (Panel B). In the first set of columns (1)-(3), we estimate the output elasticities without considering heterogeneity in training intensity across industries, by fitting the model described by Eq. 2. The results in Panel A indicate that tangible capital is the most significant driver of labour productivity growth in column (1). However, this effect diminishes substantially when intangible capital is included in the model (columns 2 and 3). Specifically, the estimates in column (3) show that intangible capital is the main contributor to labour productivity growth with an ouput elasticity of 0.34, followed by tangible capital with an output elasticity of 0.28. In contrast, human capital (labour quality), as proxied by the share of university graduates in employment, and training capital are not significantly linked to labour productivity growth across any of these specifications.

Next, we examine the model's estimates when we incorporate differential effects using the average training investment intensity measure, as reported in columns (4)-(6). Column (4) shows the OLS estimates, while columns (5)-(6) present IV estimates where the capital training intensity is instrumented with initial intensity values from Finland and the US. When instrumenting $\overline{\gamma}_j^{Tr}$, we drop the benchmark country from the sample when applicable. Initial values for Finland are highly correlated with the average training intensity measure, as indicated by Kleibergen-Paap rk Wald F statistic above 13. The IV estimates align with the OLS results, but suggest an upward bias in the interaction terms vs a downward bias of the direct effects. Taken together, these findings suggest that the output elasticity of intangible capital (other than training capital) is stronger in industries with higher training intensity, as evidenced by the positive and statistically significant interaction term. In contrast, the interaction between tangible capital and average training intensity is negative, suggesting either a substitution effect or a reflection of the fact that the output elasticity of tangible capital is lower in training-intensive industries compared to other manufacturing or non-tradable service sectors. Finally, regarding human capital, we find no robust evidence of the complementarity between the share of university graduates in employment and training investment intensity.

Comparing the results when labour productivity is measured as the value-added per hour worked (Panel B of Table 2), all our findings hold but we also find that the direct effect of training capital is positive and statistically significant in all of these specifications, with an estimated output elasticity of 0.021 to 0.026.

To illustrate the implications of the differential effects, we estimate the marginal effects of intangible capital with respect to training intensity in Fig. 1, based on the baseline OLS specification (column 4 of Table 2).[4] The estimated output elasticity of intangibles (other than training capital) ranges between 0.32-0.36, reflecting the direct effect for an industry with average training intensity. Notably, the marginal effect of intangibles increases as training intensity rises. Specifically, the output elasticity ranges between 0.27-0.31 in industries at the 25th percentile of demeaned training investment intensity (-0.14) and 0.36-0.40 in those at the 75th percentile (0.16). When considering the 10th-90th percentiles, the difference in output elasticity becomes even more pronounced, increasing from 0.09-0.14 to 0.44-0.47.

[4] In particular, marginal effects are calculated as $\hat{\alpha} + (\hat{\beta} \cdot \gamma_j^{Tr})$, where $\hat{\alpha}$ is the output elasticity of intangible capital, $\hat{\beta}$ is the interaction term between intangible capital growth and average training intensity, and Tr_j is the country-industry demeaned training intensity.

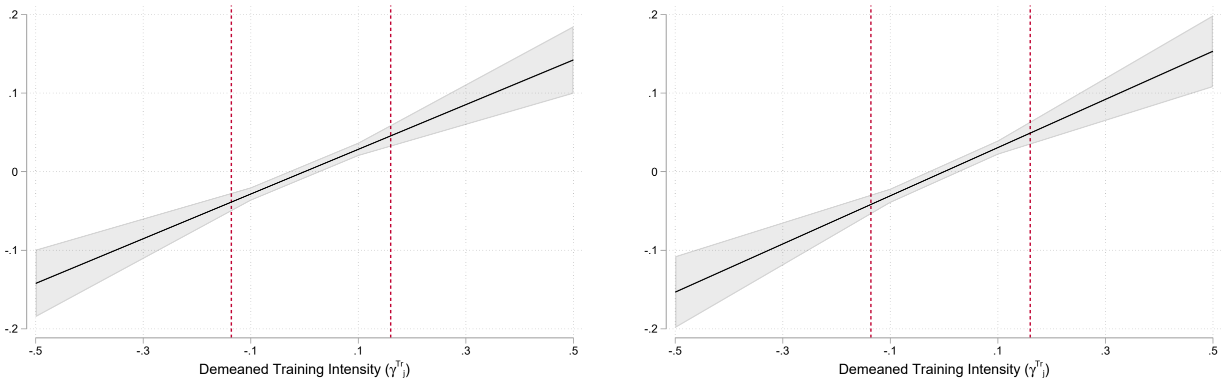
Table 2: Baseline Estimates

	Outcome variable: Value-added per worker					
	OLS	OLS	OLS	OLS	IV	IV
Panel A	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta h_{jc,t}$	-0.003	-0.000	-0.001	-0.008	-0.004	-0.015
	(0.019)	(0.018)	(0.018)	(0.020)	(0.023)	(0.019)
$\Delta k^{Tan}_{jc,t}$	0.507***	0.277***	0.281***	0.281***	0.281***	0.266***
	(0.018)	(0.020)	(0.020)	(0.019)	(0.019)	(0.020)
$\Delta k^{Intan}_{jc,t}$		0.335***	0.341***	0.350***	0.347***	0.359***
		(0.020)	(0.021)	(0.021)	(0.022)	(0.023)
$\Delta k^{Tr}_{jc,t}$			-0.017	-0.021	-0.020	-0.031**
			(0.013)	(0.013)	(0.013)	(0.013)
$\Delta h_{jc,t} \times \overline{\gamma}^{Tr}_j$				0.042	0.016	0.063**
				(0.026)	(0.092)	(0.031)
$\Delta k^{Tan}_{jc,t} \times \overline{\gamma}^{Tr}_j$				-0.278***	-0.285***	-0.254***
				(0.042)	(0.087)	(0.065)
$\Delta k^{Intan}_{jc,t} \times \overline{\gamma}^{Tr}_j$				0.284***	0.238***	0.126**
				(0.044)	(0.088)	(0.063)
N	10920	10920	10920	10920	10478	9637
Adjusted R^2	0.316	0.387	0.388	0.393	0.271	0.266
Country-industry groups	470	470	470	470	453	415
Instrument					Finland	US
F-stat excluded instruments					13.700	71.410

	Outcome variable: Δ Value-added per hour worked					
	OLS	OLS	OLS	OLS	IV	IV
Panel B	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta h_{jc,t}$	-0.003	0.031	0.032	0.022	0.027	0.021
	(0.019)	(0.019)	(0.019)	(0.021)	(0.026)	(0.020)
$\Delta k^{Tan}_{jc,t}$	0.507***	0.283***	0.277***	0.278***	0.278***	0.260***
	(0.018)	(0.020)	(0.020)	(0.019)	(0.019)	(0.020)
$\Delta k^{Intan}_{jc,t}$		0.310***	0.301***	0.314***	0.313***	0.319***
		(0.021)	(0.021)	(0.020)	(0.021)	(0.022)
$\Delta k^{Tr}_{jc,t}$			0.026**	0.021*	0.023*	0.015
			(0.013)	(0.013)	(0.013)	(0.012)
$\Delta h_{jc,t} \times \overline{\gamma}^{Tr}_j$				0.052*	0.030	0.049
				(0.030)	(0.105)	(0.035)
$\Delta k^{Tan}_{jc,t} \times \overline{\gamma}^{Tr}_j$				-0.235***	-0.246***	-0.223***
				(0.045)	(0.086)	(0.065)
$\Delta k^{Intan}_{jc,t} \times \overline{\gamma}^{Tr}_j$				0.307***	0.285***	0.141**
				(0.047)	(0.084)	(0.069)
N	10920	10920	10920	10920	10478	9637
Adjusted R^2	0.316	0.319	0.319	0.325	0.227	0.215
Country-industry groups	470	470	470	470	453	415
Instrument					Finland	US
F-stat excluded instruments					13.700	71.410

Notes: The dependent variable is the log change of value added in model (1) and of intangibles-adjusted value-added in models (2)-(6). All interactions are demeaned. Training intensity in model (5)-(6) is instrumented using industry intensities for Finland and the US in 1995. All models include country-industry and year fixed-effects. Standard errors clustered at the country-industry level in parentheses. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Figure 1: Marginal Effects of Intangible Capital



Panel A: Value-added per worker | Panel B: Value-added per hour worked

Notes: The graph plots the marginal effects of intangible capital accumulation on labour productivity growth for different initial average training intensities at the industry-level along with the 95% confident interval (grey area). The red dotted lines correspond to the 25th and 75th percentiles of the demeaned training intensity.

B. *Alternative Measures and Samples*

We test the robustness of our results with alternative measures of training investment intensity. Specifically, we calculate the mean intensity $\overline{\gamma}_j^{Tr}$ as the ratio of training investment to gross output and to investment in all capital assets. Table A3 reports the estimation results for both OLS and IV (using Finland's initial values) specifications with these alternative measures. In all models, the interaction term between intangible capital and training intensity remains positive and statistically significant.

Next, to ensure our results are not driven by any specific country in the sample, we estimate the baseline differential effects specification while repeatedly dropping each country from the sample. Figure A2 presents the leave-one-out estimates, demonstrating that our findings are robust across this cross-validation approach.

We also conduct separate estimations for various sector groups, as shown in Table 3, by excluding education and health services, and examining production (A-G), services (H-Q), and business services (J-N) independently. Overall, the results remain robust across these sector groupings. The direct effects of training, along with the complementarity between intangibles and training investment intensity, are notably stronger in services—especially in business services—compared to the production sectors.

Table 3: Results by Different Sector Groups

	Market economy A-S, ex. P, Q	Production A-G	Services H-Q	Business services J-N
Panel A	Outcome variable: Δ Adjusted value-added per worker			
	(1)	(2)	(3)	(4)
$\Delta h_{jc,t}$	-0.020	-0.009	-0.008	0.003
	(0.023)	(0.059)	(0.021)	(0.027)
$\Delta k^{Tan}_{jc,t}$	0.269***	0.348***	0.292***	0.257***
	(0.020)	(0.031)	(0.023)	(0.036)
$\Delta k^{Intan}_{jc,t}$	0.371***	0.251***	0.384***	0.382***
	(0.022)	(0.034)	(0.025)	(0.039)
$\Delta k^{Tr}_{jc,t}$	-0.019	0.041	-0.036**	0.046**
	(0.014)	(0.025)	(0.015)	(0.022)
$\Delta h_{jc,t} \times \overline{\gamma}^{Tr}_j$	-0.004	0.017	0.034	-0.045
	(0.045)	(0.101)	(0.028)	(0.049)
$\Delta k^{Tan}_{jc,t} \times \overline{\gamma}^{Tr}_j$	-0.358***	-0.070	-0.353***	-0.475***
	(0.051)	(0.092)	(0.048)	(0.060)
$\Delta k^{Intan}_{jc,t} \times \overline{\gamma}^{Tr}_j$	0.393***	0.234**	0.243***	0.377***
	(0.049)	(0.100)	(0.050)	(0.054)
N	9621	3189	7082	3204
Adjusted R^2	0.400	0.367	0.434	0.501
Country-industry groups	414	137	305	138
Panel B	Outcome variable: Δ Adjusted value-added per hour worked			
	(1)	(2)	(3)	(4)
$\Delta h_{jc,t}$	0.014	0.005	0.016	0.034
	(0.024)	(0.064)	(0.023)	(0.029)
$\Delta k^{Tan}_{jc,t}$	0.266***	0.344***	0.291***	0.256***
	(0.020)	(0.034)	(0.024)	(0.037)
$\Delta k^{Intan}_{jc,t}$	0.336***	0.230***	0.346***	0.366***
	(0.022)	(0.036)	(0.025)	(0.038)
$\Delta k^{Tr}_{jc,t}$	0.028**	0.053*	0.011	0.089***
	(0.014)	(0.028)	(0.014)	(0.024)
$\Delta h_{jc,t} \times \overline{\gamma}^{Tr}_j$	0.007	-0.069	0.056*	-0.035
	(0.051)	(0.115)	(0.033)	(0.056)
$\Delta k^{Tan}_{jc,t} \times \overline{\gamma}^{Tr}_j$	-0.300***	-0.015	-0.320***	-0.417***
	(0.056)	(0.108)	(0.048)	(0.067)
$\Delta k^{Intan}_{jc,t} \times \overline{\gamma}^{Tr}_j$	0.423***	0.280**	0.255***	0.418***
	(0.051)	(0.108)	(0.054)	(0.060)
N	9621	3189	7082	3204
Adjusted R^2	0.330	0.298	0.359	0.420
Country-industry groups	414	137	305	138

Notes: All interactions are demeaned. All models include country-industry and year fixed-effects. Standard errors clustered at the country-industry level in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

C. *Disaggregated Capital Types*

A critical question is which specific type of intangible asset drives the complementarity between training investment intensity and other intangible assets. To explore this, we build on Chen et al. (2016) and present OLS estimation results for different capital types in Table 4. In column (1), we distinguish between ICT (computing and communications equipment) and non-ICT tangible capital, while columns (2)-(5) further break down intangible capital into three aggregate categories: economic competencies other than training (i.e. organisational capital and brands), software and databases, and innovation property.

Our key findings are as follows. First, both ICT and non-ICT tangible capital are significantly associated with labour productivity growth. The negative interaction effect between tangible capital and training investment intensity observed in the baseline specification is driven by non-ICT capital, while we find no robust evidence of complementarity between ICT capital and training.

Second, the complementarity between training investment intensity and intangible capital is primarily driven by other economic competencies assets and, to a lesser extent, innovation property assets. In contrast, we find no evidence of complementarity between training investment and software and databases. Interestingly, the direct effect of training capital accumulation becomes statistically insignificant when we include all dissagregated capital assets, suggesting that training's effect on productivity occurs indirectly through its complementarity with other economic competencies and innovation property assets. Further regressions, disaggregating the intangible assets even more finely, reveal that this finding is primarily driven by the interaction between training and organisational capital (Table A4).

Table 4: Results by Different Capital Types

Outcome variable:	Δ Adjusted value-added per hour worked				
	(1)	(2)	(3)	(4)	(5)
$\Delta h_{jc,t}$	-0.003	0.003	0.008	0.001	0.009
	(0.021)	(0.021)	(0.022)	(0.024)	(0.024)
$\Delta h_{jc,t} \times \overline{\gamma}_j^{Tr}$	0.051*	0.060*	0.045	0.036	0.052
	(0.030)	(0.031)	(0.036)	(0.036)	(0.035)
$\Delta k_{jc,t}^{ICT}$	0.018***	0.019***	0.023***	0.024***	0.015**
	(0.005)	(0.006)	(0.007)	(0.007)	(0.008)
$\Delta k_{jc,t}^{ICT} \times \overline{\gamma}_j^{Tr}$	0.016	0.014	0.008	0.020*	0.013
	(0.012)	(0.013)	(0.015)	(0.012)	(0.014)
$\Delta k_{jc,t}^{NICT}$	0.301***	0.334***	0.498***	0.413***	0.332***
	(0.021)	(0.021)	(0.020)	(0.023)	(0.023)
$\Delta k_{jc,t}^{NICT} \times \overline{\gamma}_j^{Tr}$	-0.173***	-0.154***	0.027	-0.098*	-0.197***
	(0.055)	(0.052)	(0.049)	(0.055)	(0.055)
$\Delta k_{jc,t}^{Intan}$	0.283***				
	(0.021)				
$\Delta k_{jc,t}^{Intan} \times \overline{\gamma}_j^{Tr}$	0.291***				
	(0.054)				
$\Delta k_{jc,t}^{Tr}$	0.018	0.039***	0.053***	0.027*	0.021
	(0.014)	(0.014)	(0.015)	(0.015)	(0.015)
$\Delta k_{jc,t}^{EC}$		0.220***			0.181***
		(0.020)			(0.024)
$\Delta k_{jc,t}^{EC} \times \overline{\gamma}_j^{Tr}$		0.258***			0.229***
		(0.044)			(0.049)
$\Delta k_{jc,t}^{SDB}$			0.014**		0.005
			(0.006)		(0.006)
$\Delta k_{jc,t}^{SDB} \times \overline{\gamma}_j^{Tr}$			0.011		0.003
			(0.012)		(0.012)
$\Delta k_{jc,t}^{Innov}$				0.135***	0.086***
				(0.017)	(0.015)
$\Delta k_{jc,t}^{Innov} \times \overline{\gamma}_j^{Tr}$				0.171***	0.104**
				(0.046)	(0.046)
N	8445	8419	7771	7042	6816
Adjusted R^2	0.333	0.332	0.332	0.338	0.373
Country-industry groups	352	351	321	295	283

Notes: All interactions are demeaned. All models include country-industry and year fixed-effects. Standard errors clustered at the country-industry level in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

V. Conclusion

This paper studies the role of training in driving labour productivity growth, both through the direct impact of training capital accumulation and its complementarity with other intangible capital assets. Our analysis, using data from the EUKLEMS & INTANProd databases covering a wide range of industries across the EU and the UK, demonstrates that investment in training significantly enhances labour productivity growth, as measured by value-added per hour worked. In particular, our findings highlight that industries with higher training investment intensity experience a larger output elasticity with respect to intangible capital, illustrating the important synergies between training and other intangible assets, particularly organisational capital. These results are robust to alternative measures of training intensity and sample composition in terms of countries and industries. The direct and indirect effects of training on productivity growth are found to be stronger in business services than in production sectors, in line with findings by O'Mahony & Peng (2011).

Our results indicate that the main effect of training occurs indirectly through the complementarity between training and organisational capital. We argue that this complementarity is particularly relevant in light of recent findings on the various reasons behind training provision (OECD, 2021). Beyond legal requirements related to health, safety, and security, firms report improvements in product market performance, organizational capabilities, client relationships, product quality, innovation, internal communication, and corporate culture as the main reasons behind training provision.

Taken together, our results highlight the importance of investment in on-the-job training as a source of productivity growth. From a policy perspective, this new evidence supports the case for measuring accurately intangible assets and integrate them in analytical economic frameworks to inform pro-growth policies in an era of increasingly knowledge-intensive economy.

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Appendix

A *Data*

Table A1: Variables Definition and Data Sources.

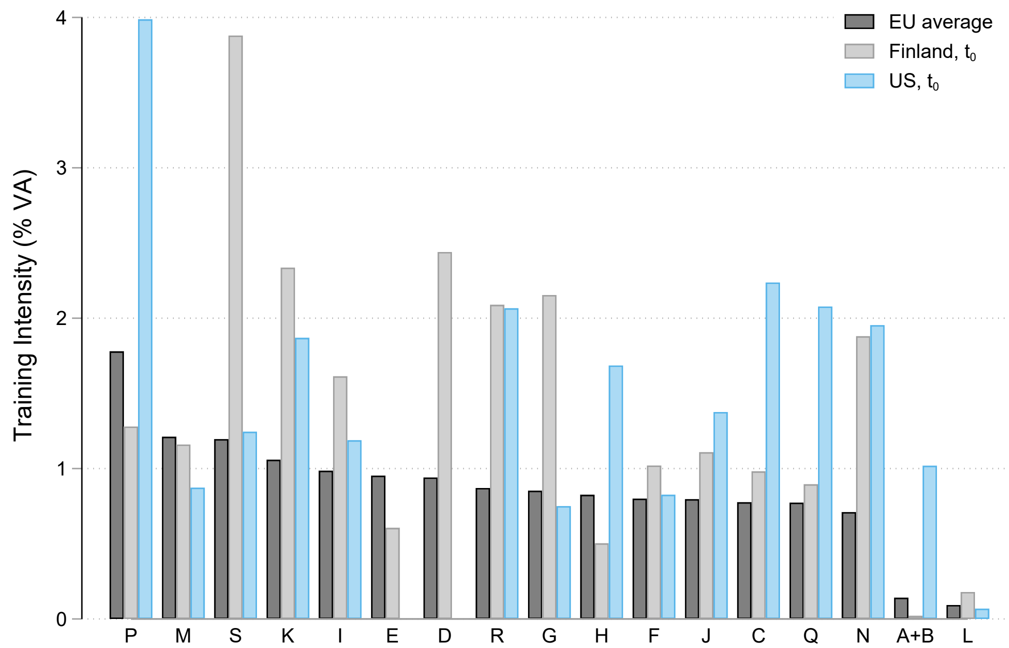
Variable	Description	Database
Value-added ($Y_{jc,t}$)	Gross value-added and intangibles-adjusted gross value added, USD billions.	EUKLEMS & INTANProd
Human capital ($H_{jc,t}$)	Share of workers with tertiary education in total employment.	
Tangible capital ($K_{jc,t}^{Tan}$)	Computing equipment, communications equipment, transport equipment, other machinery and equipment, residential structures, and total residential structures investment net capital stocks.	
Intangible capital ($K_{jc,t}^{Intan}$)	Economic competencies (design, brand, organisational capital and new financial products excluding training), computer software and databases, and other innovativation properties net capital stocks.	
Training capital ($K_{jc,t}^{Tr}$)	Training net capital stock.	
Training intensity ($\overline{\gamma}_{j}^{Tr}$)	Training investment (% of intaingibles-adjusted value-added), sample average over 1995-2021.	

Table A2: Summary Statistics - Means per Country

	VA /hour (USD th)	VA /worker (USD th)	Tangible K /worker (USD mn)	Intan. K /worker (USD mn)	3rd level emp. share (%)	Training K /worker (USD mn)	Train. inv. /VA (%)
Austria	0.08	109.35	0.85	0.02	29.11	0.0018	0.811
Belgium	0.16	188.04	1.67	0.06	22.74	0.0039	1.034
Bulgaria	0.03	37.11	0.15	0.01	24.23	0.0010	1.122
Croatia	0.07	87.36	0.79	0.01	15.88	0.0007	1.261
Cyprus	0.08	104.19	1.06	0.01	24.08	0.0008	0.420
Czechia	0.05	65.06	0.40	0.02	14.47	0.0007	0.607
Denmark	0.13	176.23	1.34	0.09	18.32	0.0042	1.398
Estonia	0.03	51.16	0.28	0.01	27.38	0.0008	0.761
Finland	0.11	150.75	1.26	0.05	39.41	0.0032	1.388
France	0.10	130.18	0.86	0.06	36.77	0.0026	1.133
Germany	0.10	110.17	0.84	0.04	29.24	0.0027	1.361
Greece	0.15	159.99	1.47	0.02	19.02	0.0003	0.262
Hungary	0.03	50.97	0.33	0.02	17.44	0.0007	0.771
Ireland	0.16	210.59	2.14	0.02	24.56	0.0032	1.436
Italy	0.17	151.87	1.36	0.03	19.56	0.0016	0.846
Latvia	0.02	31.57	0.23	0.01	19.69	0.0003	0.356
Lithuania	0.02	40.54	0.31	0.01	24.54	0.0006	0.793
Luxembourg	0.18	196.64	1.03	0.03	19.19	0.0048	1.196
Malta	0.05	72.05	0.54	0.02	19.49	0.0008	0.656
Netherlands	0.11	131.97	1.03	0.05	34.35	0.0033	1.339
Poland	0.03	47.01	0.15	0.01	24.78	0.0004	0.462
Portugal	0.06	107.96	0.96	0.01	19.61	0.0006	0.509
Romania	0.05	87.88	0.51	0.02	23.69	0.0005	0.497
Slovakia	0.04	59.21	0.54	0.01	17.27	0.0007	0.656
Slovenia	0.06	74.79	0.68	0.02	23.98	0.0010	0.794
Spain	0.09	117.82	1.04	0.03	42.80	0.0015	0.545
Sweden	0.11	163.59	0.91	0.09	18.63	0.0032	0.687
United Kingdom	0.12	175.43	0.63	0.06	24.58	0.0031	1.177
United States	0.12	164.67	0.81	0.08	.	0.0030	1.073

Notes: Monetary values are expressed in thousands of 2015 US dollars deflated using industry-country price indices.

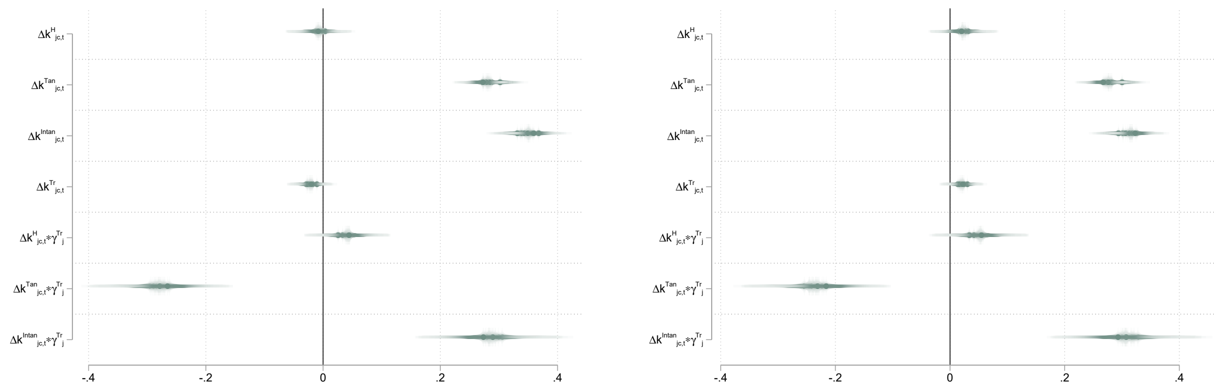
Figure A1: Training Investment Intensity by Industry



Notes: The graph plots training investment as a share of adjusted value-added. Dark grey bars correspond to EU averages between 1995-2021, light grey and blue bars correspond to Finland and the US in 1995.

B *Estimation Results*

Figure A2: Robustness: Leave-one-out Estimates



Panel A: Value-added per worker

Panel B: Value-added per hour worked

Notes: The graph plots the estimated OLS coefficients of Eq. 3 using the average training investment intensity and repeatedly leaving each country out from the sample.

Table A3: Alternative Training Intensity Measures

Panel A	Outcome variable: Δ Value-added per worker			
Training intensity:	% Gross output		% Total investment	
	OLS (1)	IV (2)	OLS (3)	IV (4)
$\Delta h_{jc,t}$	-0.014	-0.018	-0.002	-0.000
	(0.021)	(0.031)	(0.018)	(0.019)
$\Delta k^{Tan}_{jc,t}$	0.282***	0.281***	0.281***	0.280***
	(0.019)	(0.019)	(0.019)	(0.019)
$\Delta k^{Intan}_{jc,t}$	0.347***	0.345***	0.348***	0.343***
	(0.021)	(0.022)	(0.020)	(0.021)
$\Delta k^{Tr}_{jc,t}$	-0.020	-0.020	-0.021	-0.019
	(0.013)	(0.013)	(0.013)	(0.013)
$\Delta h_{jc,t} \times \overline{\gamma}^{Tr}_{j}$	0.065**	0.076	0.004	-0.001
	(0.029)	(0.117)	(0.004)	(0.010)
$\Delta k^{Tan}_{jc,t} \times \overline{\gamma}^{Tr}_{j}$	-0.291***	-0.383***	-0.028***	-0.039***
	(0.056)	(0.133)	(0.006)	(0.009)
$\Delta k^{Intan}_{jc,t} \times \overline{\gamma}^{Tr}_{j}$	0.296***	0.305**	0.028***	0.027***
	(0.068)	(0.136)	(0.006)	(0.009)
N	10920	10478	10920	10478
Adjusted R^2	0.391	0.268	0.392	0.268
Country-industry groups	470	453	470	453
F-stat excluded instruments		15.686		11.474
Panel B	Outcome variable: Δ Value-added per hour worked			
Training intensity:	% Gross output		% Total investment	
	OLS (1)	IV (2)	OLS (3)	IV (4)
$\Delta h_{jc,t}$	0.015	0.019	0.029	0.034*
	(0.022)	(0.034)	(0.019)	(0.021)
$\Delta k^{Tan}_{jc,t}$	0.279***	0.280***	0.279***	0.278***
	(0.019)	(0.020)	(0.019)	(0.019)
$\Delta k^{Intan}_{jc,t}$	0.310***	0.311***	0.312***	0.309***
	(0.021)	(0.022)	(0.020)	(0.020)
$\Delta k^{Tr}_{jc,t}$	0.022*	0.023*	0.020	0.023*
	(0.013)	(0.013)	(0.013)	(0.013)
$\Delta h_{jc,t} \times \overline{\gamma}^{Tr}_{j}$	0.074**	0.060	0.005	-0.002
	(0.033)	(0.133)	(0.005)	(0.012)
$\Delta k^{Tan}_{jc,t} \times \overline{\gamma}^{Tr}_{j}$	-0.253***	-0.343***	-0.023***	-0.033***
	(0.054)	(0.130)	(0.006)	(0.009)
$\Delta k^{Intan}_{jc,t} \times \overline{\gamma}^{Tr}_{j}$	0.326***	0.394***	0.031***	0.032***
	(0.072)	(0.130)	(0.006)	(0.008)
N	10920	10478	10920	10478
Adjusted R^2	0.323	0.224	0.323	0.224
Country-industry groups	470	453	470	453
F-stat excluded instruments		15.686		11.474

Notes: All models include industry-year and country-year fixed-effects. Standard errors clustered at the country-industry level in parentheses. * p<0.1, ** p<0.05, *** p<0.01. All interactions are demeaned. Training intensity in models (2) and (4) is instrumented using industry intensities for Finland in 1995.

Table A4: Results by Different Capital Types

Outcome variable:	Δ Value-added per hour worked			
	(1)	(2)	(3)	(4)
$\Delta h_{jc,t}$	0.025	0.019	0.017	0.019
	(0.022)	(0.022)	(0.024)	(0.024)
$\Delta h_{jc,t} \times \overline{\gamma}_j^{Tr}$	0.064*	0.064*	0.058	0.059
	(0.037)	(0.037)	(0.040)	(0.041)
$\Delta k_{jc,t}^{ICT}$	0.016**	0.018**	0.021***	0.017**
	(0.008)	(0.007)	(0.007)	(0.008)
$\Delta k_{jc,t}^{ICT} \times \overline{\gamma}_j^{Tr}$	0.007	0.011	0.017	0.011
	(0.017)	(0.016)	(0.016)	(0.017)
$\Delta k_{jc,t}^{NICT}$	0.405***	0.376***	0.430***	0.332***
	(0.024)	(0.025)	(0.024)	(0.026)
$\Delta k_{jc,t}^{NICT} \times \overline{\gamma}_j^{Tr}$	-0.134**	-0.157**	-0.120**	-0.220***
	(0.058)	(0.063)	(0.056)	(0.064)
$\Delta k_{jc,t}^{Tr}$	0.039***	0.029*	0.033**	0.021
	(0.015)	(0.015)	(0.016)	(0.016)
$\Delta k_{jc,t}^{SDB}$	0.012*	0.014**	0.012*	0.006
	(0.007)	(0.007)	(0.006)	(0.006)
$\Delta k_{jc,t}^{SDB} \times \overline{\gamma}_j^{Tr}$	0.007	0.009	0.008	0.000
	(0.015)	(0.016)	(0.015)	(0.015)
$\Delta k_{jc,t}^{RD}$	0.012**	0.011**	-0.007	-0.000
	(0.005)	(0.005)	(0.006)	(0.006)
$\Delta k_{jc,t}^{RD} \times \overline{\gamma}_j^{Tr}$	0.031**	0.032**	-0.001	0.010
	(0.014)	(0.014)	(0.017)	(0.017)
$\Delta k_{jc,t}^{Org}$	0.150***			0.098***
	(0.022)			(0.022)
$\Delta k_{jc,t}^{Org} \times \overline{\gamma}_j^{Tr}$	0.199***			0.132***
	(0.046)			(0.045)
$\Delta k_{jc,t}^{Adv}$		0.183***		0.112***
		(0.025)		(0.030)
$\Delta k_{jc,t}^{Adv} \times \overline{\gamma}_j^{Tr}$		0.219***		0.096
		(0.055)		(0.059)
$\Delta k_{jc,t}^{Inno}$			0.134***	0.061***
			(0.019)	(0.018)
$\Delta k_{jc,t}^{Inno} \times \overline{\gamma}_j^{Tr}$			0.203***	0.118*
			(0.060)	(0.060)
N	7270	7270	6428	6428
Adjusted R^2	0.366	0.368	0.368	0.383
Country-industry groups	316	316	279	279

Notes: All interactions are demeaned. All models include country-industry and year fixed-effects. Standard errors clustered at the country-industry level in parentheses. * p<0.1, ** p<0.05, *** p<0.01.