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O'Mahony, Mary and Peng, Fei

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Mary O'Mahony
Fei Peng

University of Birmingham

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Corresponding author's e-mail address: m.omahony@bham.ac.uk

Abstract

This paper employs industry data, derived from linking the EU LFS to productivity accounts from EU KLEMS, to examine workforce training and productivity in European Union original members states. Training activities are modelled as intangible investments by firms and cumulated to stocks so their impact can be evaluated within a production function framework, including links to the use of information and communications technology (ICT). The results suggest significantly positive effects of training on productivity, both direct and interacted with ICT, with different impacts in services than in production industries. These results are robust to the use of instrumental variables methods, both lagged instruments and a set of variables that capture features of the operation of labour markets.

Keywords: Training, Intangible Capital, EUKLEMS, EU LFS

JEL codes: M53, D24, J24

1. Introduction

Remaining competitive in an increasingly globalised world requires that European nations maintain their comparative advantage in producing high quality output. This requires not only a highly skilled labour force, but also one that adapts fast to change. In the face of rapidly changing technology (for example, changes arising from information and communications technology - ICT), it is imperative that skills are appropriate and up to date. Providing basic skills is mostly the responsibility of the general education system but changing education provision is often time consuming. Firms or workers can instead make up for any skill shortfall by engaging in workplace training.

This paper investigates the impact of training on productivity, linking to a recent literature that emphasizes the need to invest in intangible assets when reorganising production following adoption of ICT. Organisational change alters the nature of work and is associated with retraining requirements. This paper utilises a new measure of firm specific human capital, which is richer than conventional measures of the proportion of the workforce that receives training, which combines both probability and duration of training with information on the characteristics of those trained.

The paper examines variation across EU15 members states and across industries, focusing especially on production versus market service sectors. It first reviews the literature on training, education, their links with use of information technology and their impacts on productivity. Section 3 presents a descriptive overview of training in the EU using the data from the EU Labour Force Survey (EU LFS)[1]. This section presents basic data by industry and country on the extent of training, who receives training and its duration. Section 4 presents details of the measurement of intangible training investments and capital stocks and

[1] European Commission, Eurostat, European Union Labour Force Survey, quarterly data. Eurostat has no responsibility for the results and conclusions which are those of the researchers.

presents growth accounting estimates. Section 5 is an econometric analysis of the impact of training on productivity. It tackles the important issue of endogeneity using a variety of instruments. Section 6 concludes.

2. Training, Education and Productivity

The importance of education and training as drivers of firm performance has long been recognised by both the human resource management and economics disciplines. Workplace learning and continuous improvement are considered essential for an organization to remain competitive (Salas and Cannon-Bowers 2001). When training does result in improvements in relevant knowledge and the acquisition of relevant skills, employee job performance should improve, provided that the skills learned in training transfer to the job (Baldwin and Ford 1988). In general, research finds that workplace training promotes good working practices. For example, Krueger and Rouse (1998) find that training had a positive association with the incidence of job bids, upgrades, performance awards, and job attendance. Many studies find a positive association between workplace training and productivity (Bartel 1994; Black and Lynch 1996; Conti 2005; Dearden et al. 2006; Vignoles et al, 2004, Zwick, 2006).

Human capital has long been seen as important in determining economic growth and countries may adopt and utilise technologies differently, depending on their skill endowments (Lewis 2005; Acemoglu 1998). Much research effort has been devoted to the issue of whether technical change is skill-biased and on the impact of information and communications technology (ICT) on the demand for skilled labour (e.g. Bartel and Lichtenberg 1987; Autor, Katz and Krueger 1998; Machin and van Reenen 1998). In a similar vein research has highlighted that organisational changes and other forms of intangible investment such as workforce training are necessary to gain significant productivity benefits from using ICT (Bertschek and Kaiser 2004; Bresnahan, Brynjolfsson and Hitt 2002; Brynjolfsson, Hitt and Yang 2002; Black and Lynch, 2001).

It is now well known that the acceleration in US productivity growth that emerged in the mid 1990s was not matched in the EU, O'Mahony and van Ark (2003), and that the differing performance in the two regions is linked to the knowledge economy, including use of ICT and skilled labour (van Ark, O'Mahony and Timmer, 2008). A comprehensive analysis of sources of productivity growth by country and industry is now possible following the construction of the EU KLEMS growth and productivity accounts database (see O'Mahony and Timmer, 2009, and Timmer et al. 2007 for details). This analysis suggests that much of the failure of Europe to match the US growth spurt can be traced to developments in market service sectors (Timmer et al. 2009), although the extent of this varies by country within the EU. These authors also highlight that the source of much of the difference between the US and EU labour productivity growth can be attributed to underlying multi-factor productivity (MFP), after accounting for the use of inputs of various kinds.

Since MFP is measured as a residual, less is known about the underlying drivers of productivity. A recent literature has tried to get beneath these differences by focusing on unmeasured intangible investments as sources of growth. The pioneering work in this respect is the paper by Corrado, Hulten and Sichel (2005) who attempted to measure intangibles for the US. These authors defined a number of types of intangible investments including software, scientific and non-scientific R&D, brand equity and firm specific expenditures such as on the job training and managing organisational changes. Estimates by the above authors suggest that these investments combined account for about 11% of US GDP and have been growing rapidly. Similar studies for the UK (Giorgio Marrano and Haskel 2006), Finland (Javala, Aulin-Amhavarra and Alanen 2007), Canada (Baldwin et al. 2008), the Netherlands (van Rooijen-Horsten et al. 2008), Japan (Fukao et al. 2007) and Jona-Lasinio, Iommi and Roth

(2009) for EU countries suggest also that intangibles are sizeable, although most account for lower proportions of GDP than in the US. Capitalisation of these assets and incorporating them in a growth accounting framework reduces MFP growth (e.g. Corrado, Hulten and Sichel, 2006, Giorgio Marrano, Haskel and Wallis, 2007), but this is true across all countries so that estimates to date suggest that unmeasured intangible inputs are unlikely by themselves to explain the EU-US productivity growth gap.

The above studies on intangible investments mainly refer to the aggregate economy, although a few report results by industry. Nevertheless comprehensive estimates by country and industry are some way off. As with the conventional sources of growth, it is likely that an examination of intangible investments by industry would be particularly beneficial in explaining why Europe failed to experience a US type productivity surge. This paper adds to the above literature by focusing on one type of intangible investment, work force training, using a harmonised data set, the EU LFS, that allows an investigation of cross industry and cross country differences.

3. Workforce Training in the EU

This section briefly examines the prevalence of workforce training across EU countries – further detail is given in Carmichael et al. (2009). The discussion employs the EU LFS as the main data source and presents an overview on training in the EU15. In 2007 in the EU as a whole approximately 11% of employees received some training in the 4 weeks prior to the quarterly survey (Table 1). The figures for the EU aggregate hide large variation across countries with high proportions in the Scandinavian countries, the Netherlands and the UK, and considerably lower proportions in the large continental EU-15 countries of France, Germany, Spain and Italy. The training proportion has been rising over time in the EU as a whole. Dividing by industry group shows that the percent of workers receiving training is generally higher in service sectors than in production industries and is highest for non-market services. The underlying data suggest that training proportions are particularly high in financial services – see Carmichael et al. (2009).

Table 1. Proportion of the workforce receiving training in the past four weeks, EU15.[1]

Year		***Worker characteristic*** *(2007)*	
		Skill Group	
1995	8.5	High[5]	18.3
1999	9.1	Intermediate[6]	9.5
2003	10.9	Low[7]	5.2
2007	11.2	***Gender***	
		Male	9.7
		Female	12.8
Industry group (2007)		***Age Group***	
Production[2]	7.0	15-29	13.1
Market Services[3]	10.1	30-49	11.0
Non-market services[4]	16.2	50+	9.4

Notes: 1. From 2003 this is based on the variable 'COURATT' which ask respondents 'did you attend any courses, seminars, conferences or received private lessons or instructions outside the regular education system in the past 4 weeks. Time series are constructed by linking in an overlapping year to the variable 'EDUC4WN' – education or training received during the previous 4 weeks.
2. Agriculture, Forestry & Fishing; Mining; Manufacturing; Electricity, Gas & Water and Construction;
3.Distribution; Hotels & Catering; Transport and Communications; Financial Services; Business Services; Other Personal Services; 4. Public Administration; Education; Health and Social Services.
5.(ISCED 5-6) University degree or equivalent; 6. (ISCED 3-4) Academic and vocational qualifications above intermediate secondary; 7. (ISCED 1-2) secondary qualifications at age 16 or below
Source EU LFS

Training is also varies by worker characteristic. The figures in Table 1 suggest that females are more likely to receive training than males, training proportion decline with age and rise with skill level. The division by skill group is particularly pronounced – in fact in the EU-15 the share of all workers receiving training who have 'high' qualification levels was much higher (44%) than this group's share of the total workforce (15%).

The proportion of workers trained is a crude measure of countries propensity to invest in training not least because training durations can vary considerably. On average workers who receive training in the past 4 weeks are trained for about 17 hours which is a sizeable length of time. Thus workplace training is not dominated by relatively short courses but rather represents activities that are likely to add substantially to the human capital of those being trained and to the costs of firms undertaking the training. However not all training costs are borne by firms. An important indicator of the commitment of firms to training, and of the cost to firms as used in the intangible investment calculations below, is the extent to which training occurs during normal working hours. The EULFS asks respondents if the training occurred always or mostly during working hours. In the EU countries for which data were available, about 67% of respondents said training occurred wholly or mostly during working hours. Similar proportions were observed in production and services sectors but the variation was greater across countries. In Finland, France and the UK more than 75% of training occurred during working hours whereas in Belgium, Ireland, Italy and the Netherlands the proportion was about 50% and was under 40% in Greece.

4. Training as Intangible Capital

As noted in section 2, much of the recent literature on the productivity effects of new technologies emphasises the need to invest in organisational changes and other firm specific changes in production processes. These changes required firms to expend some resources, which collectively are termed intangible investments. The literature frequently referred to these intangible investments as the 'missing input' that potentially could explain the apparent rise in MFP growth some time after the introduction of technologies such as ICT. As intangibles are difficult to observe and measure by definition, their impact was mainly captured by the MFP component in analyses of sources of growth.

This section analyses training as an intangible investment, using the information on proportions of workers trained and the duration of training. It first sets out a brief description of the methodology employed – further details and sensitivity analysis are given in O'Mahony (2010). This is followed by a description of the importance of these intangible investments as shares of outputs and a discussion of growth accounting impacts. In this paper we only present estimates for the market economy since non-market services are not included in our regressions due to well known problems in estimating real output in these sectors.[2]

Estimating intangible investments by firms requires a monetary valuation of the number of hours of training received by workers. The estimates presented here are calculated as hours trained multiplied by the average hourly cost to firms aggregated to industry level as the source data on training does not have information on wages. Therefore intangible investments by firms in training in industry i, country j and time period t are calculated by:

$$(1) \qquad TI_{i,j,t} = HTR_{i,j,t} C_{i,j,t} PRC(firm)_{i,j,t}$$

Where TI = nominal expenditures on investments in training, HTR = total hours spent training per worker, C is the cost of an hour's training and PRC is the proportion of training costs borne by firms. Hourly costs C will have two elements, the direct costs of training (costs of running courses or external fees) and the opportunity costs of the time foregone due to time spent training. Time away from production is valued at the market wage, as in Jorgenson and Fraumeni (1992). In this analysis hourly costs were estimated as:

$$(2) \qquad C_{i,j,t} = DR + \overline{w}adj$$

Information on hourly direct costs (DR) was taken from the Eurostat Continuous Vocational Training Surveys (CVTS) surveys, which were carried out in 1999 and 2005, averaged across the two years to take account of small sample sizes. We used the variable 'the ratio of direct to opportunity costs (wages)' in these surveys. This variable is available by country and industry. Examination of the data suggests that these ratios vary significantly across industry so we calculate just two ratios for each country, dividing into production industries (NACE C to F) and market services (NACE G to K and O). The first component in equation (2) was estimated as the average labour compensation of employees, taken from EU KLEMS, multiplied by the ratio of direct to opportunity costs from CVTS.

[2] Estimates for the entire economy, including the non-market sectors are presented in O'Mahony (2010).

The second term in the hourly costs equation is the opportunity cost. This is set equal to the average wage but adjusting for the composition of those being trained; data are again taken from EU KLEMS. Due to small samples we estimate proportions trained by skill, age and gender groups for the two broad sectors, production industries and market services, and we apply the average proportion for 2003-2007 to all years. In most countries the proportions of workers with university degrees or equivalent is higher for those trained than for employment so this adjustment is positive. The one exception appears to be Italy. The adjustments are positive for both production industries and market services but much lower in the latter reflecting the relatively greater employment of females in services industries. On average, taking account of the characteristics of those trained leads to an upward adjustment of the opportunity cost terms by 10%-15% for EU15 countries and by closer to 25% for new member states.

Finally, in a measure of intangible investments by firms it is important to exclude any cost borne by the workers themselves. Although there is no direct evidence on this it is assumed that it can be proxied by the extent to which training occurs during working hours. Training occurring outside usual hours arguably has zero opportunity cost for the firm; therefore PRC (firm) is estimated as the proportion of respondents who replied that training occurred entirely or mostly during working hours.[3]

Table 2 presents intangible investments as a share of value added, averaged across the years 2003-2007. In the EU15, intangible investments in training represent 1.55 of GDP. These investments represent a lower share of production industry value added than in market services. Table 2 also shows the results for individual countries, sorted from highest to lowest for the total market economy. It shows the UK as the country most willing to spend on

[3] This variable was not reported for a few countries, most notably Germany and Spain. The EU15 average values were used for countries where data were not available.

training. In general intangible investment in training is a lower share of GDP in smaller countries but the share is much smaller for Italy than other large EU15 countries. .

Table 2. Intangible investments in Training as a % of GDP, average 2003-07

	Market Economy	***Production Industries***	***Market Services***
EU15	**0.98**	**0.86**	**1.06**
UK	2.45	2.21	2.57
Denmark	1.62	1.45	1.74
Sweden	1.40	1.15	1.58
Finland	1.24	1.01	1.46
Netherlands	1.14	0.75	1.37
France	1.12	1.32	1.02
Luxembourg	0.71	0.48	0.78
Germany	0.67	0.60	0.71
Spain	0.65	0.60	0.69
Austria	0.65	0.54	0.72
Belgium	0.44	0.47	0.43
Ireland	0.21	0.15	0.28
Portugal	0.16	0.12	0.18
Italy	0.11	0.13	0.10
Greece	0.05	0.04	0.05

In order to estimate the impact of these investments on productivity it is necessary to convert investment values to volumes and construct capital stocks. As both the direct and indirect components of the hourly costs vary with wages through time it seems natural to use an earnings index as a deflator. In all such exercises the perpetual inventory method that cumulates investments and deducts depreciation is employed to convert real investments to capital stocks. The most common assumption employed on the form of the depreciation function is geometric decay – this is largely due to the relative simple calculations this entails. If we let I denote investment, K denote capital and d the depreciation rate, geometric decay allows capital at time t to be estimated as:

(3) $K_t = K_{t-1}(1- d) + I_t$

Geometric decay implies that proportionally more of the asset is depreciated early in its use. It is common in the intangibles literature to employ relatively high depreciation rates to take account of the idea that many of these investments are associated with new technologies that change rapidly. In this study we employ a 25% depreciation rate - sensitivity of the estimates to this assumption is discussed below.

Table 3 shows growth in training intangible capital stocks and its contribution to value added growth. The results suggest that intangible capital growth from on the job training was strong in the period since 2001 and was higher in market services than in production industries. To place this in perspective the growth rate of real tangible physical capital for the market economy in the EU15 was only 2.65% per annum in the same period.[4] The contribution of intangible training capital in the EU15 is small but significant. This compares to 0.20 percentage point contribution from labour composition which in turn is mainly driven by up-skilling of the workforce arising from general education. In a number of countries, namely, Denmark, Spain, Finland, France, the Netherlands, Sweden and the UK these high growth rates translate into small but significant contributions to value added growth (see O'Mahony (2010) for details by country and broad sector.

[4] This number refers to the aggregate across countries for whom growth accounts were available in EUKLEMS and includes some intangible capital in the form of software. See O'Mahony and Timmer (2009) for more details of capital growth rates in the EU.

Table 3. Intangible Training capital and output growth, 2001-2007, Market economy

	Growth in intangible training capital (% p.a.)	Contribution of intangible training capital to value added growth[1]
Market Economy		
EU15	5.56	0.06
Production industries		
EU15	3.71	0.03
Market Services		
EU15	6.52	0.06

1. Growth from column 1 times share in value added.

While these 'growth accounting' estimates can yield a 'ball park' figure for the contribution of training capital to value added growth, they suffer from a number of deficiencies, as discussed in O'Mahony (2010). In particular they are dependent on the market clearing assumptions underlying all such exercises and cannot take account of complementarities between inputs. We now turn to an econometric analysis of the impact of training and links with ICT.

5. Training and Productivity: Econometric Analysis

5.1 Empirical specification and methods

In this section we model labour productivity as depending on capital inputs including both tangible and intangible components. The following log form equation for labour productivity (*lnlp*) is estimated for both measures of training:

$$(4)\ lnlp_{cit} = \beta_1 \ln(intkh)_{cit} + \beta_2 ln(capith)_{cit} + \beta_3 \ln(intkh)_{cit} \times ln(capith)_{cit} + \beta_4 ln(capnith)_{cit} + \sum \beta_{5j}\ labchar_{citj} + \beta_c + \beta_i + \beta_t + e_{cit}$$

where $ln(intkh)_{cit}$ is intangible training capital per hour as measured in the previous section, in industry i, (i=1…11), of country c, (c=1..14), in year t, (t=1995…2007). Control variables include both ICT and non-ICT capital per hour worked, i.e. $ln(capith)_{cit}$ and $ln(capnith)_{cit}$ and j measures of characteristics of the labour force *labchar*$_{citj}$.[5] Country, industry and time dummies are used to control the unobservable time-invariant effects and the business cycle. Our regressions are weighted by average employee compensation (*COMP*) share of each industry over the period 1995-2007, a standard approach in the literature to take account of industry heterogeneity (see e.g. Kahn and Lim, 1998). Equation (4) is estimated first with just intangible training capital included, and then with the training-ICT interaction term.

We compare the results from this specification with one where the measure of training is the proportion of workers receiving training (*tr*), the specification employed in many previous papers such as Deardon et al. (2006). This measure does not take account of duration of training or the composition of those trained and so suffers from being a relatively crude measure.

We then need to consider whether our estimates are subject to endogeneity bias, i.e. the possibility that training and the unobserved error term in equation (4), e_{cit}, are likely to be correlated. To get around this problem, we need instruments to isolate the exogenous variation in training. The most widely-used alternative strategy is to use generalized method of moments (GMM) as developed by Arellano and Bond (1991) for dynamic panels. This method employs lagged values as instruments and has been used, for example, by Black and Lynch (2001) and Deardon et al. (2006) when addressing similar issues of the impact of

[5] The labour characteristics included are proportions of males (*male*), age below 29 (*age<29*), age between 29 and 49 (*age29-49*), medium educated workers with certificates below degree (*Ed_medium*) and highly educated workers with degree equivalent or above (*Ed_high*). We also tried an aggregated labour composition index estimated as the difference between wage share weighted and employment share weighted hours worked that distinguishes gender, age and qualification levels, a standard measure used in growth accounting. As this did not change the coefficients on the other variables in the equations we report the results including the proportions of workers of various types, which are free of the marginal productivity assumptions underlying the growth accounting measure.

workplace and practices and training on productivity to those covered in this paper. However recent literature has shown that there are possible statistical problems associated with the above approach. When the regressors are persistent it can be shown that lagged levels of the explanatory variables are weak instruments. Asymptotically, the use of weak instruments implies that the variance of the coefficient increases and in small samples the coefficients can be biased (Staiger and Stock 1997, Durlauf et al. 2005, MacDonald et al. 2010).

Lagged values are often used due to the lack of 'cross section' instruments. A more satisfactory approach might be to use variables that capture features of the labour markets that differentiate industries as instruments. However the dataset underlying the training measures is also a rich source of information on the underlying labour markets which might also serve as valid instruments. Therefore, we included four additional variables from EU LFS that describe the labour market conditions in each industry. Our choice of which variables to employ as instruments was guided by the analysis of the same dataset by Carmichael and Ercolani (2010) who examined the determinants of training propensities, as well as data availability by country, industry and time. We sought variables that previous analysis suggested were correlated with training but whose variation across industry was largely determined by historically given conventions on modes of production and the use of flexible work practices. Four variables were chosen as possible measures of workplace practices: *hmwk* (employees who work at home), *satsunwk* (employees who work on Saturday or Sunday), *pt* (employees who are part time workers), and *y1unem* (employees who were unemployed one year ago). Thus we rely on variation across industry in the extent to which flexible working predominates as the exogenous factors. Instrument validity tests are employed to determine which, if any, of these instruments can be used in our analysis.

Average values of the instrumental variables by country and year are calculated and shown in Appendix Table A1. Countries with relatively flexible labour markets such as the

UK and Denmark tend to have high proportions of their workforce who work at home, at weekends or part-time, but low proportions of workers unemployed one year ago. Differences in labour market institutions across countries might affect labour productivity directly and so affect the validity of our chosen instruments. However such institutions tend to be slow to change and so may not impact on the validity of our instruments in the short time period covered in this paper. Our choice of which of these instruments to employ are determined by statistical tests as discussed further below.

5.2 Industry Panel Data

The econometric analysis combines the training proportions and intangible training capital with data on output and inputs from EU KLEMS. The analysis in this section uses data for 14 of the EU15 group of countries, with Greece omitted due to lack of data on ICT capital. The panel data employed in this analysis cover eleven industries, five of which are production sectors; agriculture, forestry and fishing (AtB), Mining and quarrying (C) manufacturing (D), Electricity, gas and water supply (E), Construction (F), and six of which are providers of services; Trade (G), Hotels and restaurants (H), Transport, storage and communication (I), Financial intermediation (J), renting and business activities (K excluding real estate), and Other community, social and personal services (O). We exclude the non-market sectors of as the Public admin and defence (L), Education (M) and Health and Social work (N), given well known problems in estimating output of these sectors. All variables are transformed into US dollars by using price ratios for outputs and inputs developed by Inklaar and Timmer (2008). Hence, all productivity and wage variables in regressions are comparable across countries and industries.

5.3 OLS results

Results for the total sample are presented in Table 4 using the OLS estimator. Training has a large positive impact on labour productivity both on its own and interacted with ICT. Since the coefficient of training-ICT interaction term is significant for total sample, the interaction specification could be a better estimation method than the specification of training capital alone. Note the coefficient on intangible training capital is much higher than the growth accounting results presented earlier. These results are consistent with Hempell and Zwick's (2008) argument that ICT fosters product and process innovations by facilitating employee participation, which is enhanced by horizontal employee communication and ICT training.

We next explore the impact of training when we divide the sample into production industries (the five industries covered by NACE AtB-F) and market services (the six industries covered by NACE G-K, O). These show similarly positive and significant direct impacts from training and from training interacted with ICT, but the latter is much larger in market services than in production industries. We test the equality of coefficients of intangible training capital (and training-ICT interaction term) in the production and services sectors using the Chi2 statistics in the Seemingly Unrelated Estimation (*SUEST*, Weesie 1999). Chi2 statistics show that coefficients of intangible training capital in the specification of intangible training capital alone are not significantly different in both sectors (chi2 =0.22). However, intangible training capital and training-ICT interaction term jointly have significantly different coefficients in both sectors (chi2 =5.36). Thus, the division of two sectors is necessary for our estimation.

At the end of Table 4, the marginal effects of training variable are interpreted conditionally on the interaction with ICT capital (Friedrich 1982). We follow Dreher and Gassebner (2007) and Potrafke (2009) evaluating the marginal effects at various points of the distribution of ICT, namely at the 5th, 25th, median, 75th, 95th percentiles and maximum of the interacted variable (log form ICT capital per hour, i.e. *lncapith*).[6] Using this method we can distinguish between the impact of training on labour productivity when the levels of ICT capital are low and high. For the total sample, the marginal effect of training capital at the 5th percentile of ICT capital is significantly positive. An increase in the training capital by 1% increases the labour productivity by about 0.067%, consistent with the growth accounting magnitudes reported in Table 3 above. At the maximum level of ICT capital, the effect of training is also significantly positive and very large: an increase in the training capital by 1% increases the labour productivity by about 0.324%. The marginal effects of training capital conditional on ICT capital increase faster in services than in the production sector, suggesting a stronger association with ICT capital.

Table 4. Regression Results. OLS, Intangible training capital, 1995-2007 (Country, Industry and Year dummies included in all regressions)

	Total sample		Production		Services	
Training Capital	0.101***	0.107***	0.090***†	0.112***††	0.111***†	0.119***††
	0.017	***0.017***	***0.018***	***0.018***	***0.026***	***0.025***
Training Capital* ICT Capital		0.032***		0.030***††		0.053***††
		0.004		***0.004***		***0.007***
ICT Capital	0.030*	0.100***	0.005	0.076***	0.074***	0.188***
	0.016	***0.018***	***0.016***	***0.019***	***0.027***	***0.03***
Non-ICT Capital	0.339***	0.344***	0.617***	0.673***	0.237***	0.226***
	0.025	***0.025***	***0.037***	***0.037***	***0.034***	***0.033***
Male	-0.692***	-0.722***	1.916***	1.639***	-1.451***	-1.602***
	0.201	***0.198***	***0.301***	***0.295***	***0.291***	***0.284***
Age < 29	-0.013	0.133	0.993***	1.286***	0.029	0.303
	0.277	***0.273***	***0.339***	***0.332***	***0.433***	***0.423***
Age29-49	1.004***	1.179***	0.678**	1.053***	1.284**	1.373***
	0.338	***0.334***	***0.341***	***0.335***	***0.51***	***0.496***
Ed_High	1.383***	1.352***	1.305***	0.919***	1.774***	1.743***
	0.178	***0.175***	***0.268***	***0.266***	***0.282***	***0.274***
Ed_medium	0.756***	1.100***	0.331*	0.713***	1.150***	1.589***
	0.121	***0.128***	***0.172***	***0.176***	***0.183***	***0.188***
R-squared	0.692	0.702	0.786	0.799	0.71	0.726
N	1726	1726	772	772	954	954

[6] We use the 5th percentile to replace the minimum ICT capital, which is an extremely small value (less than 0.02 US dollar per hour) and hence not representative.

Marginal effects of training proportions at percentile levels of ICT capital						
	Total sample					
ln (ICTcapital)	5%(-1.23)	25% (-0.05)	50% (0.57)	75% (1.17)	95% (2.12)	Max (6.81)
Marginal effects	0.067***	0.105***	0.125***	0.144***	0.174***	0.324***
	0.017	***0.017***	***0.017***	***0.018***	***0.019***	***0.034***
	Production					
Marginal effects	0.075***	0.110***	0.129***	0.147***	0.176***	0.317***
	0.017	***0.018***	***0.018***	***0.019***	***0.021***	***0.038***
	Services					
Marginal effects	0.054**	0.116***	0.149***	0.180***	0.230***	0.478***
	0.026	***0.025***	***0.026***	***0.027***	***0.030***	***0.056***

Notes: Standard errors are below coefficients. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

† Coefficients of intangible training capital in the specification of intangible training capital alone are not significantly different in both sectors (*SUEST)*: chi2 (1) =0.22, Prob>chi2=0.643.

†† Coefficients of intangible training capital and training-ICT interaction term are significantly different in both sectors (*SUEST)*: chi2 (2) = 5.36, Prob > chi2 = 0.069.

It is interesting to compare these results with those using the proportions of the workforce who receive training as this is the measure most commonly employed in previous research – the results are shown in Appendix Table A.2. These show that when labour productivity is regressed on training alone the results were insignificant. When training is interacted with ICT capital the coefficient on interaction becomes significantly positive, suggesting an important role for training when combined with ICT investments but suggests little or no benefit of training not linked to the new technology. The results for the production industries in Table A.2 suggest that training on its own has a large significant impact on output and this is not dependent on the use of ICT capital. In contrast, in market services training appears only to impact positively on output when combined with ICT use, with the direct effect having an implausibly large negative coefficient. Chi2 statistics show significant different effect of training capital between the production and services in both specifications.

Measuring the impact of intangible training as an investment decision by firms is a conceptually more satisfactory when examining links with other firm level decisions such as the use of ICT, than a crude measure of proportions of the work force trained. Thus, we concentrate on this measure in the next section. Before doing so it is worth mentioning some additional robustness tests to the underlying measurement framework. Estimates of intangible training capital were also estimated using alternative assumptions on the depreciation rates and deflators (e.g. using the 40% depreciation rate and GDP deflator employed by Corrado, Hulten and Sichel, 2005) but the results in Table 4 were not appreciably altered. Therefore we conclude that the results are not especially sensitive to the methods employed to convert investments to capital stocks.

5.4 Instrumental variables estimates

Although the fixed-effects estimator corrects for the omitted-variable bias associated with unobserved time-invariant factors in the cross section estimation, the fact that current values of training may be simultaneously determined with output can lead to biased estimates (Black and Lynch 2001).[7] We first considered correcting for these potential biases using conventional GMM techniques with lagged values as instruments for training (see Table A.3. in Appendix). Endogeneity tests (C chi-square statistic) indeed confirm that intangible training capital is endogenous. Hansen J tests of over-identification do not reject the validity of our instruments. Compared with the OLS results, the GMM estimates lead to higher and significant coefficients of intangible training capital. This increase in the coefficients implies a greater impact of training on output, both the direct effect and the impact through interaction with ICT, than the coefficients reported in Table 4. Again impacts are higher in market services than production, especially for the interaction with ICT capital. The marginal effects of training capital conditional on the interaction with ICT capital are always significantly positive and stronger than in OLS.

As argued above the use of lagged values as instruments may not adequately deal with the endogeneity issue due to persistence of the regressors. The extremely high F test values in

[7] See Card (2001) for a theoretical treatment of the interpretation of instrumented variables and the practical application in STATA (Baum et al. 2003).

the first stage regressions reported in Table A.3. reveal the persistence problem and cast doubt on lagged values as legitimate instruments. We therefore tried the work practices instruments described earlier in this paper and tested their validity. First, in order to reduce the cross-country heterogeneity of instrumental variables, we transform these variables into relative variables in our regressions, that is, industry level ratios to the country average. Average relative instrumental variables (over the period of 1995-2007) by industry are presented in Appendix Table A.4. Employees in the industries of Agriculture, forestry and fishing (AtB), renting and business activities (K excluding real estate), and other community, social and personal services (O) are more likely to work at home than other industries; Hotels and restaurants (H), Transport, storage and communication (I) and Other community, social and personal services (O) have higher proportions of weekend workers and part timers; Agriculture, forestry and fishing (AtB) and Transport, storage and communication (I) have higher workers being unemployed one year ago. Our choice of which of these instruments to employ are determined by statistical tests as discussed further below.

Secondly, we apply the Generalized IV method country by country to overcome the possible over-identification and heteroscedasticity problem. This is a 2 Stage Least Square (2SLS) procedure. In the first stage, we regress training intangible capital on instruments and get the 1SLS estimator by country. Then we calculate the predicted values of training intangible capital for each country. In order to avoid the predicted values of training intangible capital are distorted by large industries such as manufacturing, we drop weights in the first stage and use unweighted estimation of coefficients to predict training intangible capital. Hence, the variable of training intangible capital can be decomposed into two components: a linear combination of instruments (predicted training intangible capital) and a random component. In stage 2, we estimate equation (4) using the predicted training intangible capital; this is the GIV estimator. Results of the first step by country are reported in Table 5. We find the linear combination of instruments fit training intangible capital quite well in Austria, Belgium, Finland, France, Luxembourg, the Netherlands, Portugal, Sweden and the UK. The F statistics for IVs are significant in these countries. However, predictions of training intangible capital are also seriously affected by the missing values of four instruments in the EU LFS data for three countries: Germany (all four instruments are only available after 2002), Ireland (*Y1unem* missing after 1997) and the Netherlands (6 years of *Satsunwk* and *Y1unemp* missing).[8] In order to test the validity of IVs in the first stage regressions country by country, we stack the 14 country-specific regressions using SUEST again and test whether coefficients of these IVs significantly different from zero. The Chi2 test easily reject the hypothesis that the four IVs are not significantly associated with training capital: chi2(56) = 277.49, Prob > chi2 = 0.0000. Hence, we regard these four work practices variables are valid instrumental variables for training capital.

Table 5 GIV first stage regression by country (Industry and Year dummies included)

	Austria	Belgium	Denmark	Spain	Finland	France	Germany
rhmwk	0.275**	0.076**	0.067	-0.025	-0.02	0.009	-0.237
	0.109	*0.035*	*0.058*	*0.016*	*0.028*	*0.028*	*0.626*
rsatsunwk	-0.218	-0.025	-0.113	0.143	-0.211***	-0.261**	0.462
	0.193	*0.034*	*0.089*	*0.088*	*0.073*	*0.129*	*1.014*
rpt	-0.01	-0.038*	0.009	-0.113*	0.085**	0.146*	0.176
	0.092	*0.022*	*0.061*	*0.062*	*0.04*	*0.074*	*0.878*
ry1unem	0.019	-0.018	-0.016	0.146*	0.029**	-0.133**	-0.081
	0.087	*0.016*	*0.034*	*0.077*	*0.013*	*0.056*	*0.307*
F statistic for IVs	2.68**	2.65**	0.78	1.58	5.4***	2.81**	0.06
Prob > F	0.041	0.038	0.544	0.192	0.001	0.031	0.992
R-squared	0.956	0.804	0.646	0.865	0.443	0.518	0.701
N	86	129	99	88	132	109	31
	Ireland	Italy	Luxembourg	Netherlands	Portugal	Sweden	UK
rhmwk	-0.041	-0.052	0.146**	-0.013	0.058	0.019	0.412***
	0.088	*0.038*	*0.07*	*0.036*	*0.048*	*0.025*	*0.123*

[8]Our choice of which of these instruments to employ are determined by statistical tests as in the first step regressions. As a robustness check, we also tried dropping of those insignificant instrumental variables in the first step regressions, but this does not change our basic conclusions.

rsatsunwk	-0.195	-0.061	0.271**	0.797*	-0.098	-0.106***	-0.12
	1.568	*0.137*	*0.107*	*0.424*	*0.08*	*0.04*	*0.203*
rpt	1.742**	0.034	-0.004	0.768**	-0.06	0.005	-0.052
	0.7	*0.076*	*0.086*	*0.315*	*0.045*	*0.029*	*0.039*
ry1unem	-0.409	-0.048	-0.033	-0.110*	-0.073	0.01	-0.025
	0.261	*0.069*	*0.068*	*0.055*	*0.062*	*0.017*	*0.031*
F statistic for IVs	1.99	0.7	3.8***	3.57**	2.43*	2.05*	8.05***
Prob > F	0.180	0.596	0.009	0.025	0.055	0.098	0.000
R-squared	0.052	0.508	0.463	0.013	0.287	0.883	0.599
N	33	143	77	44	111	98	132

Notes: Standard errors are below coefficients. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively. Control variables include ICT and non-ICT capital per hour, proportions of males (*male*), age below 29 (*age<29*), age between 29 and 49 (*age29-49*), medium educated workers with certificates below degree (*Ed_medium*) and highly educated workers with degree equivalent or above (*Ed_high*).
The SUEST Chi2 test: null hypothesis (all IVs are not significantly associated with training capital in 14 countries), chi2(56) = 277.49, Prob > chi2 = 0.0000.

Finally, we put predicted training intangible capital (and its interaction with ICT capital) into equation (4). Results of the second stage are presented in Table 6. The results using these instruments yield lower coefficients values on the direct training measures in the OLS estimates and Table A.3., but very similar to the growth accounting results. Training capital alone and interaction with ICT capital are still significantly positive in all regressions except the last column, lower than in the OLS results and again more prominent for training*ICT interaction term in the service sector. The marginal effects of training capital conditional on ICT capital confirm our findings in OLS and GMM. For the total sample: while the effect of training is insignificant at the 5th percentile of ICT capital, at the 25th percentile of ICT capital, the effect of training is positive and significant. An increase in the training capital by 1% increases the labour productivity by about 0.042%. After that, the marginal effects of training become higher as ICT capital increases and becomes 0.278% at the maximum value of ICT. The marginal effects of training in the production sector are positive and significant (but insignificant in services) at low levels of ICT capital. Similarly, as ICT capital increases, the positive marginal effects of training in both sectors become higher. The marginal effects of training in services grow faster than in the production sector, suggesting more benefit from the links to ICT capital. Therefore, the GIV estimation using work practices instruments shows that indeed training, especially complemented with ICT capital have positive and large impacts on labour productivity. In summary, the results employing instrumental variables suggest that the OLS estimates if anything overestimate the impact of training on labour productivity, especially through its interaction with ICT.

Table 6. Regression Results. GIV second stage, Intangible training capital, 1995-2007 (Country, Industry and Year dummies included in all regressions)

	Total sample		Production		Services	
Linear prediction of Training Capital	0.045***	0.039***	0.067***†	0.071***††	0.056***†	0.016††
	0.007	***0.008***	***0.008***	***0.008***	***0.012***	***0.016***
Linear prediction of Training Capital * ICT Capital		0.009**		0.008*††		0.028***††
		0.004		***0.004***		***0.007***
ICT Capital	0.033*	0.045**	0.024	0.031*	0.055*	0.110***
	0.018	***0.019***	***0.016***	***0.016***	***0.032***	***0.035***
Non-ICT Capital	0.282***	0.276***	0.560***	0.579***	0.147***	0.149***
	0.03	***0.03***	***0.038***	***0.039***	***0.042***	***0.042***
Male	-0.458**	-0.461**	1.733***	1.675***	-0.974***	-1.111***
	0.231	***0.23***	***0.298***	***0.299***	***0.34***	***0.338***
Age < 29	0.601*	0.572*	0.627*	0.690**	0.262	0.301
	0.31	***0.31***	***0.338***	***0.339***	***0.484***	***0.479***
Age29-49	1.524***	1.505***	0.376	0.497	1.945***	1.826***
	0.377	***0.376***	***0.338***	***0.343***	***0.578***	***0.573***
Ed_high	2.138***	2.104***	2.249***	2.063***	2.579***	2.651***
	0.226	***0.226***	***0.309***	***0.323***	***0.351***	***0.348***
Ed_medium	1.083***	1.201***	0.782***	0.865***	1.785***	2.041***
	0.128	***0.137***	***0.17***	***0.175***	***0.199***	***0.208***
R-squared	0.707	0.708	0.82	0.821	0.725	0.73
N	1333	1333	601	601	732	732
Marginal effects of training capital at a minimum and maximum level of ICT capital.						
	Total sample					
ICT Capital	5%(-1.23)	25% (-0.05)	50% (0.57)	75% (1.17)	95% (2.11)	Max (6.81)
Marginal effects	0.001	0.042***	0.063***	0.084***	0.116***	0.278***
	0.009	***0.007***	***0.008***	***0.009***	***0.012***	***0.032***
	Production					
Marginal effects	0.029***	0.063***	0.080***	0.097***	0.123***	0.256***
	0.009	***0.008***	***0.008***	***0.009***	***0.011***	***0.029***
	Services					
Marginal effects	-0.021	0.052***	0.090***	0.127***	0.185***	0.475***
	0.015	***0.012***	***0.012***	***0.015***	***0.020***	***0.055***

Notes: Standard errors are below coefficients. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

† Coefficients of training proportions in the specification of training proportions alone are not significantly different in both sectors (*SUEST)*: chi2 (1) =0.47, Prob>chi2=0.495.
†† Coefficients of intangible training capital and its interaction with ICT capital are significantly different in both sectors (*SUEST)*: chi2 (2) = 9.51, Prob > chi2 = 0.0086.

We tried a number of variants as sensitivity tests for the GIV results. We first fitted training intangible capital using estimation based on a pooled sample of all countries. This estimation suggests a strong assumption that there is no cross-country heterogeneity in training capital's associations with instrumental variables. It is highly unlikely from our Chi2 tests using the SUEST. Moreover, the F test of IVs shows a weak fit even with much larger sample size than country by country estimation (F tests 2.42, Prob > F =0.0465) which is lower than the reference F test level (around 10) in Staiger and Stock (1997). In second stage regression, the fitted training capital alone from the first stage regressions of all countries is insignificantly associated with labour productivity, while the training*ICT interaction terms are still positive and significant. We also tried more specifications with country*year, country*industry dummies in the first stage regressions for the pooled sample of all countries to test country-specific business cycle or country*industry fixed effects. All specifications with country*year or country*industry dummies gave much higher (and unrealistic) 2nd stage coefficients maybe due to loss of too many degrees of freedom. Therefore, we think our main results are not overstating the case.

6. Conclusions

This paper linked the microdata underlying the EU LFS to industry data from EU KLEMS to examine links between productivity and workforce training. Modelling training activities as intangible investments by firms allows us to compare the extent of these investments across countries. The econometric analysis suggests training has a significantly positive impact on productivity, especially when combined with investment in ICT. This is consistent with a recent literature that emphasises the role of organisational changes and associated retraining of the workforce in diffusing new technology. Moreover, division of the sample into production and service sectors highlights some interesting differences. The results suggest that firm specific intangible investments may be more important in services than in production industries, when interacted with ICT. It therefore is important to caution against drawing too strong conclusions based on estimates for the aggregate economy alone.

Returning to Europe's poor productivity record relative to the US, the results here are suggestive that failure to capture intangible inputs and their interactions with information technology may go some way towards providing an explanation. Existing estimate show that levels of ICT capital and overall intangible inputs are much higher in the US than in most European countries. The results here suggest these inputs might explain most of the difference in growth performance. However we have to be cautious in drawing such conclusions since in this paper we only attempt to measure one form of intangible input; further work is required to see the results hold true for other types of intangibles.

Table A.1 EU LFS based Instruments, per cent of employees
Average 1995-2007

Country	hmwk	satsunwk	pt	y1unemp
Austria	9.7	40.7	12.7	1.4
Belgium	6.5	30.1	14.4	2.5
Denmark	10.6	44.0	16.1	1.8
Spain	0.5	32.5	4.8	8.0
Finland	7.0	35.0	9.5	3.9
France	3.3	43.0	11.2	4.0
Germany	5.2	46.5	13.3	2.4
Ireland	4.9	55.9	11.3	3.5
Italy	2.0	46.3	7.3	5.7
Luxembourg	4.2	34.8	9.9	1.6
Netherlands	1.1	38.3	29.9	1.4
Portugal	2.6	36.4	2.8	3.5
Sweden	4.1	32.7	15.6	2.9
UK	18.7	63.1	17.7	2.2

Data source: EU LFS 1995-2007.

Table A2. Regression Results, OLS, Training proportions, 1995-2007 (Country, Industry and Year dummies included in all regressions)

	Total sample		Production		Services	
Training proportion	-0.32	-1.948***	0.996***†	0.796**††	-0.559†	-3.541***††
	0.281	***0.315***	***0.35***	***0.361***	***0.388***	***0.426***
Training proportion * ICT Capital		0.946***		0.232**††		1.720***††
		0.092		***0.106***		***0.134***
ICT Capital	0.043***	-0.036**	0.011	-0.01	0.084***	-0.067**
	0.016	***0.017***	***0.016***	***0.019***	***0.027***	***0.028***
Non-ICT Capital	0.345***	0.378***	0.617***	0.623***	0.243***	0.276***
	0.026	***0.025***	***0.037***	***0.037***	***0.035***	***0.032***
Male	-0.786***	-0.987***	1.866***	1.834***	-1.382***	-1.743***
	0.201	***0.196***	***0.301***	***0.301***	***0.294***	***0.272***
Age < 29	0.03	-0.333	0.948***	0.986***	-0.02	-0.377
	0.28	***0.274***	***0.339***	***0.339***	***0.438***	***0.405***
Age29-49	0.955***	0.311	0.672**	0.667**	1.217**	-0.583
	0.34	***0.336***	***0.34***	***0.339***	***0.517***	***0.497***
Ed_High	1.356***	1.554***	1.197***	1.185***	1.755***	1.998***
	0.178	***0.174***	***0.27***	***0.269***	***0.284***	***0.263***
Ed_medium	0.912***	1.312***	0.484***	0.616***	1.354***	1.791***
	0.119	***0.122***	***0.17***	***0.18***	***0.178***	***0.167***
R-squared	0.686	0.704	0.781	0.782	0.705	0.75
N	1749	1749	795	795	954	954
Marginal effects of training proportions at percentile levels of ICT capital						
	Total sample					
ln (ICTcapital)	5%(-1.23)	25% (-0.05)	50% (0.57)	75% (1.17)	95% (2.12)	Max (6.81)
Marginal effects	-3.12***	-1.99***	-1.41***	-0.84***	0.05	4.50***
	0.38	***0.32***	***0.29***	***0.28***	***0.27***	***0.54***
	Production					
Marginal effects	0.51	0.79**	0.93***	1.07***	1.29***	2.37***
	0.41	***0.36***	***0.35***	***0.35***	***0.37***	***0.72***
	Services					
Marginal effects	-5.66***	-3.62***	-2.56***	-1.53***	0.10***	8.17***
	0.53	***0.43***	***0.39***	***0.37***	***0.36***	***0.77***

Notes: Standard errors are in parentheses; ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

† Coefficients of training proportions in the specification of training proportions alone are not significantly different in both sectors (*SUEST)*: chi2 (1) =4.57, Prob>chi2=0.033.

†† Coefficients of intangible training capital and its interaction with ICT capital are significantly different in both sectors (*SUEST)*: chi2 (2) = 46.33, Prob > chi2 = 0.000.

Table A3. Regression Results. GMM, Intangible training capital, 1995-2007 (Country, Industry and Year dummies included in all regressions)

	Total sample		Production		Services	
Training Capital	0.319***	0.318***	0.329***	0.406***	0.413***	0.507***
	0.05	***0.048***	***0.065***	***0.063***	***0.085***	***0.094***
Training Capital*ICT Capital		0.056***		0.054***		0.127***
		0.009		***0.01***		***0.02***
ICT Capital	0.060**	0.164***	0.008	0.121***	0.164***	0.386***
	0.023	***0.028***	***0.018***	***0.025***	***0.05***	***0.06***
Non-ICT Capital	0.277***	0.297***	0.560***	0.667***	0.172***	0.152***
	0.036	***0.035***	***0.058***	***0.073***	***0.04***	***0.043***
Male	-0.781**	-0.789**	1.884***	1.447***	-2.106***	-2.170***
	0.311	***0.309***	***0.359***	***0.359***	***0.413***	***0.466***
Age < 29	-0.062	0.084	1.209***	1.600***	0.244	0.867
	0.388	***0.384***	***0.438***	***0.418***	***0.714***	***0.744***
Age29-49	1.977***	1.853***	1.403***	1.901***	3.253***	2.590***
	0.479	***0.474***	***0.395***	***0.386***	***0.78***	***0.823***
Ed_high	1.208***	1.286***	0.986**	0.389	1.701***	1.853***
	0.28	***0.284***	***0.448***	***0.48***	***0.373***	***0.411***
Ed_medium	0.237	0.923***	-0.363	0.321	0.622	1.535***
	0.302	***0.32***	***0.31***	***0.331***	***0.398***	***0.438***
R-squared	0.656	0.656	0.74	0.711	0.666	0.601
N	1258	1258	562	562	696	696
First stage F test: Training Capital	103.94 ***	92.39***	34.02***	24.65***	43.69***	43.32***
Training Capital*ICT Capital		1232.16***		495.94***		410.64***
C chi-sq statistic	32.87***	37.84***	21.53***	29.05***	27.46***	37.77***
Chi-sq P-val	0	0	0	0	0	0
Hansen J statistic	0.36	4.33	0.14	0.66	0.58	4.31
Chi-sq P-val	0.55	0.11	0.71	0.72	0.45	0.12
Marginal effects of training capital at percentile levels of ICT capital.						
	Total sample					
Ln(ICT capital)	5%(-1.23)	25% (-0.05)	50% (0.57)	75% (1.17)	95% (2.11)	Max (6.81)
Marginal effects	0.249***	0.315***	0.349***	0.383***	0.436***	0.698***
	0.045	***0.048***	***0.051***	***0.053***	***0.058***	***0.091***
	Production					
Marginal effects	0.340***	0.404***	0.437***	0.470***	0.521***	0.774***
	0.062	***0.062***	***0.064***	***0.065***	***0.069***	***0.097***
	Services					
Marginal effects	0.350***	0.501***	0.579***	0.656***	0.776***	1.374***
	0.084	***0.094***	***0.101***	***0.108***	***0.121***	***0.201***

Notes: Standard errors are below coefficients. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively. 3/4 lagged values of intangible training capital and its interaction with ICT capital are used as instruments for the GMM estimator.

Table A.4 Relative instruments by industry, ratios to country average, 14 countries average over 1995-2007

Industry	rhmwk	rsatsunwk	rpt	ry1unemp
AtB	1.61	1.27	1.58	1.97
C	0.94	1.34	0.81	1.04
D	0.74	0.92	0.33	0.62
E	1.06	0.84	0.59	0.82
F	1.12	0.80	0.48	0.75
G	0.83	0.87	0.76	1.47
H	0.95	1.51	2.22	1.42
I	0.62	1.63	2.47	1.76
J	0.95	1.11	0.89	0.90
K	1.63	0.68	1.15	0.71
O	1.61	1.31	2.31	1.07

Data source: EU LFS 1995-2007.

References

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

Arellano, Manuel, and Stephen Bond (1991). “Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations.” *Review of Economic Studies*, 58, 2, 277-97.

Autor, David H, Lawrence F Katz, and Alan B Krueger (1998). “Computing Inequality: Have Computers Changed the Labour Market?” *Quarterly Journal of Labour Economics*, 113, 4, 1169-1213.

Baldwin, Timothy T, and J. Kevin Ford (1988). “Transfer of Training: A Review and Directions for Future Research.” *Personnel Psychology*, 41, 1, 63-105.

Baldwin, John, Wulong Gu, Amélie Lafrance, and Ryan Macdonald. (2008), “Intangible capital in Canada: R&D, Innovation, Brand and Mining, Oil and Gas Exploration expenditures." paper presented to the 2008 IARIW conference, Slovenia, Statistics Canada.

Bartel, Ann P, and Frank R Lichtenberg (1987). "The Comparative Advantage of Educated Workers in Implementing New Technologies." *Review of Economics and Statistics*, 69, 1, 1-11.

Bartel, Ann P (1994). "Productivity Gains from the Implementation of Employee Training Programmes." *Industrial Relations*, 33, 4, 411-425.

Baum, Christopher F, Mark E Schaffer, and Steven Stillman (2003). "Instrumental variables and GMM: Estimation and testing," *Stata Journal*, StataCorp LP, vol. 3, 1, 1-31.

Bertschek, Irene, and Ulrich Kaiser (2004). "Productivity effects of organisational change: Microeconometric evidence." *Management Science*, 50, 3, 394-404.

Black, Sandra E, and Lisa M Lynch (1996). "Human capital investments and productivity." *American Economic Review*, 86, 2, 263-267.

Black, Sandra E, and Lisa M Lynch (2001). "How to Compete: The Impact of Workplace Practices and Information Technology on Productivity." *The Review of Economics and Statistics*, 83, 3, 434-445.

Bresnahan, Timothy F, Erik Brynjolfsson, and Lorin M Hitt (2002). "Information Technology, Workplace Organization, and the Demand for Skilled Labor: Firm-Level Evidence." *Quarterly Journal of Economics*, 117, 1, 339 – 376.

Brynjolfsson, Erik, Lorin M Hitt, , and ShinkYu Yang (2002). "Intangible Assets: Computers and Organisational Capital." *Brookings paper on Economic Activity*, 1, 137-181.

Card, David (2001). "Estimating the Return to Schooling: Progress on Some Persistent Econometric Problems", *Econometrica*, 69, 5, 1127–1160.

Carmichael, Fiona, Marco Ercolani, Lili Kang, Yasheng Maimaiti, Mary O'Mahony, Fei Peng, and Catherine Robinson (2009). "Education, Training and Productivity." *Report for the European Commission*, University of Birmingham

Carmichael, Fiona, and Marco Ercolani (2010). "Age-training gaps in the European Union: Evidence from the European Labour Force Surveys 2004-2007." Paper presented at CREW conference, University of Birmingham

Conti, Gabriella (2005). "Training, productivity and wages in Italy." *Labour Economics*, 12, 4, 557-576.

Corrado, Carol, Charles Hulten, and Daniel Sichel (2005). "Intangible Capital and Economic Growth.Measuring capital and technology: an expanded framework in C. Corrado, C. Hulten and D. Sichel eds, *Measuring Capital in the New Economy, Studies in Income and Wealth Vol. 65,* Chicago, The University of Chicago Press.

Corrado, Carol, Charles Hulten, and Daniel Sichel (2006). "Intangible Capital and Economic Growth." *NBER Working Paper* 11948.

Dearden, Lorraine, Howard Reed, and John van Reenen (2006). "The Impact of Training on Productivity and Wages: Evidence from British Panel Data." *Oxford Bulletin of Economics and Statistics*, 68, 4, 397-421.

Dreher, Axel, and Martin Gassebner (2007). "Greasing the wheels of entrepreneurship? The impact of regulations and corruption on firm entry." *CESifo Working Paper No 2013*.

Durlauf, Steven N, Paul A Johnson, and Jonathan R. W Temple (2005). "Growth Econometrics." in: Philippe Aghion & Steven Durlauf (ed.), *Handbook of Economic Growth*, edition 1, volume 1, chapter 8, pp 555-677, Elsevier

Friedrich, Robert J. (1982). "In Defense of Multiplicative Terms in Multiple Regression Equations." *American Journal of Poltical Science*, 26, 4, 797-833.

Fukao, Kyoji, Sumio Hamagata, Tsutomu Miyagawa, and Konomi Tonogi (2007). "Intangible Investment in Japan: Measurement and Contribution to Economic Growth" Discussion papers 07034, Research Institute of Economy, Trade and Industry (RIETI).

Giorgio-Marrano, Mauro, and Jonathan Haskel (2006). "How much does the UK invest in intangible assets?" Dept of Economics, working paper No. 578, Queen Mary University of London.

Giorgio-Marrano, Mauro, Jonathan Haskel, and Gavin Wallis (2007). "What happened to the knowledge economy? ICT, intangible investment and Britain's productivity record revisited." Dept of Economics, working paper No. 603, Queen Mary University of London.

Griliches, Zvi. and Jerry A Hausman (1986). "Errors in Variables in Panel Data." *Journal of Econometrics*, 31, 93–118.

Hempell, Thomas, and Thomas Zwick (2008). "New Technology, Work Organisation, and Innovation", *Economics of Innovation and New Technology,* 17, 4, 331-354.

Inklaar, Robert C, and Marcel Timmer (2008). "GGDC Productivity Level Database: International Comparisons of Output, Inputs and Productivity at the Industry Level", Groningen Growth and Development Centre Research Memorandum GD-104, Groningen: University of Groningen.

Jalava, Jukka, Pirkko Aulin-Amhavarra, and Aku Alanen. (2007). "Intangible capital in the Finnish Business sector, 1975-2005". ETLA - The Research Institute of the Finnish Economy, discussion paper no. 1103

Jona-Lasinio, Cecilia, Massimiliano Iommi, and Felix Roth (2009). "Report on gathering information and estimations for the Innodrive project – macro approach." mimeo, Innodrive project.

Jorgenson, Dale W.. and Barbara M Fraumeni (1992). "The Output of the Education Sector." in Zvi Griliches ed. *Output Measurement in the Services Sector*, University of Chicago Press, Chicago.

Kahn, James A. and Lim, Jong-Soo (1998). Skill labour augmenting technical progress in U.S. manufacturing. Quarterly Journal of Economics 113, 1281-1308.

Krueger, Alan, and Cecilia Rouse (1998). "The effect of workplace education on earnings, turnover and job performance." *Journal of Labor Economics*, 16, 1, 61-94

Lewis, Ethan (2005). "Immigration, skill mix and the choice of technique. " Centre for Economic Studies, US Census Bureau Working Paper no. 05-04.

MacDonald, Ronald, Aderbal Damasceno, and Flávio Vieira, (2010). "The role of institutions in cross-section income and panel data growth models: a deeper investigation on the weakness and proliferation of instruments." Working Papers Department of Economics, University of Glasgow.

Machin, Stephen, and John Van Reenen (1998). "Technology and changes in skill structure: evidence from seven OECD countries." *Quarterly Journal of Economics,* 113, 4, 1215-44.

O'Mahony, Mary (2010). "Human Capital Formation and Continuous Training: Evidence for EU countries." paper presented to the IARIW conference, St Gallen, Switzerland.

O'Mahony, Mary, and Bart van Ark (2003), editors, *EU Productivity and Competitiveness: A Sectoral Perspective. Can Europe Resume the Catching-up Process?* The European Commission, November

O'Mahony, Mary, and Marcel P Timmer (2009). "Output, Input and Productivity Measures at the Industry Level: the EU KLEMS Database." *Economic Journal*, 119 (June), F374–F403

Potrafke, Niklas (2009). "Did globalization restrict partisan politics? An empirical evaluation of social expenditures in a panel of OECD countries." *Public Choice* 140: 105–124

Salas, Eduardo, and Janis A Cannon-Bowers (2001). "The science of training: A decade of progress." *Annual Review of Psychology*, 52: pp. 471–499

Staiger, Douglas, and James H Stock (1997). "Instrumental Variables with Weak Instruments." *Econometrica*, 65, 3, 557–586.

Timmer, Marcel P, Mary O'Mahony, and Bart van Ark (2007). *EU KLEMS Growth And Productivity Account: An Overview*, March, available at www.euklems.net

Timmer, Marcel P, Robert C Inklaar, Mary O'Mahony, and Bart van Ark (2009). "The European Economy in Comparative Perspective, forthcoming, Cambridge University Press.

van Ark, Bart, Mary O'Mahony, and Marcel P Timmer (2008). "The productivity gap between Europe and the U.S.: Trends and causes." *Journal of Economic Perspectives*, 22, 1, 25–44.

van Rooijen-Horsten, Myriam, Dirk van den Bergen, and Murat Tanriseven (2008). "Intangible capital in the Netherlands: A benchmark." Statistics Netherlands, Discussion paper no. 08001.

Vignoles, Anna, Fernando Galindo-Rueda, and Leon Feinstein (2004). "The labour market impact of adult education and training: A cohort analysis." *Scottish Journal of Political Economy*, 51, 2, 266-280.

Weesie, Jeroen (1999). "sg121: Seemingly unrelated estimation and the cluster-adjusted sandwich estimator." Stata Technical Bulletin 52: 34–47. Reprinted in Stata Technical Bulletin Reprints, vol. 9, pp. 231–248. College Station, TX: Stata Press.

Zwick, Thomas (2006). "The Impact of Training Intensity on Establishment Productivity." *Industrial Relations*, 45, 1, 26-46.