Skill bias, age and organizational change

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Abstract

This paper considers evidence on the impact of ICT on demand for different types of workers, focusing in particular on the age dimension. It first examines data from EUKLEMS using regressions standard in the literature and suggests ICT may have adversely affected older workers, in particular high skilled males aged 50 and over. The paper then uses data from the EU Labour Force Survey, linked to EUKLEMS, to examine whether the observed differences by worker type could be due to variations in on the job training. It shows that training linked to ICT use can explain some of the wage variation and that reluctance by older men to undertake training has a role as well as lower offers of training by firms.

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1. Introduction

Since the introduction of ICT there has been a vast literature on whether this new technology is skill biased. On balance the evidence that emerged from studies at industry and firm levels and for a wide range of countries suggests that ICT has indeed favoured the more highly skilled (see e.g. Autor, Katz and Krueger (1998) and Chennells and Van Reenen (1999) for a survey). In general this literature considers the high skill/low skill wage premium and links this to a measure of ICT use, most commonly use of computers or investment in ICT capital..

Skill or educational attainment is only one dimension of worker's characteristics. Additional dimensions include gender and age but there are few studies that attempt to go beneath the skill classifications to consider these aspects. Exceptions include Card and Lemieux (2001) which argues that the well known increase in the skill premium for college educated employees in the US in the 1980s was concentrated in younger age cohorts at that time, due to a low supply of graduates in the 1980s relative to previous cohorts. In addition Daveri and Maliranta (2007) consider links between age, seniority and wages and information technology.

The focus of this paper is on the age dimension (in particular demand for workers aged 50 and over) incorporating organisational changes such as training. According to human capital theory (Becker, 1964; Mincer, 1962, 1974) the decision to invest in human capital is based on cost-benefit considerations for both employers and employees, and these determine their decisions on whether to offer or undertake training. For workers, the main benefits from participating in training are likely to be increased chances of promotion, greater opportunities for career development, more choice in employment and higher earnings. The latter in particular will depend on the type of job or occupation to which the training relates; higher potential earners will have more incentive for training.

In relation to the effectiveness of training, human capital theory predicts that lower levels of ability lead to lower productivity in the workplace and that therefore a worker with higher ability will command a higher wage. It follows that any given human capital investment or more specifically training, is associated with a higher rate of return (in terms of both higher productivity and higher earnings) the more able the worker. Thus if learning ability declines with age, training effectiveness, in terms of the potential gains to the employer from higher productivity and consequently higher earnings for the trainee, would be lower for older workers (as well as lower ability workers). This would lead to both lower offers of training for older workers and less incentive for them to accept any offers that came their way. Furthermore, lower levels of learning ability will also raise the costs of training, in terms of effort and time, for the trainee and therefore have an additional negative impact on their motivation to train. However, while it is commonly assumed that learning ability deteriorates with age the related evidence is very mixed (see Wooden et al, 2001; Waldman and Avolio, 1986).

The paper begins by using EUKLEMS data to investigate the impact of ICT on demand for various types of workers, including a split by gender, three skill groups and age. We use the specification in O'Mahony, Robinson and Vecchi (2008) in this first analysis and consider results for 9 countries and 11 industry groups. These first results suggest there may be a bias against older male workers and specifically older males with university education arising from ICT. The second part of the paper attempts to delve more into the reasons why this might have occurred, focusing on training and organisational changes. This analysis uses data from the EU Labour Force Survey (EU LFS) on training matched with EUKLEMS data. We consider whether training combined with ICT use affects wage premiums. We then consider if lower training for older workers appears to be driven by reluctance on the part of firms to train these people or reluctance of the workers themselves to undertake training.

The next section presents the basic results on the impact of technical change using available EUKLEMS data for EU countries. Section 3 considers why firms and workers retrain, discussed in the context of the introduction of a new technology such as ICT, describes the training data available from the EU LFS and links with ICT. Section 4 provides results of econometric analysis on associations between wage and training. Section 5 considers whether training, or lack of it, is driven by behaviour of firms or workers. Section 6 concludes.

2. Skill, Gender or Age Bias.

The basic specification follows O'Mahony, Robinson and Vecchi (2008) which considers a wage share equation that depends on the capital output ratio and the share of ICT capital in total capital. A standard way to analyse the impact of technology on the wage shares of skilled workers is to express total cost in industry *i* at time *t* as a function of the average wage of the different groups of workers, the stock of quasi-fixed capital and real output:

(1) $$LC_{it} = f(p_{1t}....p_{nt},.K_{it},Y_{it}),$$

where p_j is the wage rate for each of the labour groups *j*, K is total capital, and Y is real output. Assuming a Translog cost function, labour cost share equations for each category of workers can be derived as:

(2) $$\left(\frac{W_{jit}}{WT_{it}}\right) = \beta_i + \sum \beta_{wj} \ln\left(\frac{p_{jit}}{p1_{it}}\right) + \beta_K \ln\left(\frac{K_{it}}{Y_{it}}\right) + \varepsilon_{it}.$$

W_{ji} is the wage bill of labour group *j* in industry *i*, WT_i is the total wage bill for a particular industry, *p* are wage rates and *p1* is the wage of the numeraire group of workers, and the other terms are as described above. The capital output ratio captures the degree of capital skill complementarity. Existing evidence has shown the presence of capital-skill complementarity ($\beta_K > 0$) for skilled workers (Berman et al. 1994, Machin and Van Reenen 1998, Chun 2003). A direct evaluation of the impact of technological change on the wage premium can be derived by augmenting equation (2) with an indicator of technology. Following O'Mahony et al. (2008) we use the ratio of ICT capital over total capital ($\frac{ICT_i}{K_i}$) as a technology indicator. We therefore re-write equation (2) as follows:

(3) $$\left(\frac{W_{jit}}{WT_{it}}\right) = \beta_i + \beta_K \ln\left(\frac{K_{it}}{Y_{it}}\right) + \beta_{IT} \ln\left(\frac{IT_{it}}{K_{it}}\right) + \eta_t D_t + \varepsilon_{it}$$

In this equation the relative wage term has been replaced by time dummies (D_t) following a common practice in the related literature to deal with the problem that wages are endogenous (Machin and Van Reenen 1998, Berman et al. 1994, Chennells and Van Reenen 1999, Chun 2003). Technology is biased in favour of labour type s if $\beta_{IT} > 0$ for this group.

The analysis in this section uses data for eight EU countries (Austria, Belgium, Denmark, Finland, Germany, the Netherlands, Spain and the UK). These are the countries for which labour composition data cross classified by gender, age and skill are available in EUKLEMS. The panel data used here are based on 11 industries that together make up the market economy and employs the EUKLEMS industry division into agriculture, forestry and fishing (AtB); ICT producing industries including computing equipment, electrical and electronic equipment, instruments and telecommunications equipment and services (ELECOM); a three way split of the remainder of manufacturing into consumer goods (Mcons), intermediate goods (Minter) and investment goods (Minves); a group combining mining, utilities and construction (Other G); wholesale and retail trade (50t52); transport (60t63); financial services (J); business services (71t74) and personal services including hotels and catering (PERS). The time periods differ by country, i.e. 1970-2005 for Finland and the UK; 1979-2005 for the Netherlands; 1980-2005 for Austria, Belgium, Denmark and Spain; and 1991-2005 for Germany.

Results from fixed effect regressions across the entire pooled sample are presented in Table 1. These regressions are weighted by average employee compensation (COMP) share of each industry over the period 1970-2005, again a standard approach in the literature to take account of industry heterogeneity. The results for the capital output ratio are mixed. For the highest skill group capital appears to be complementary for females but substitutes for males. The reverse is true for the lowest group with positive coefficients for males and the more usual negative for females. The technology term suggests that ICT increases the wage shares of the highly skilled at the expense of the unskilled, consistent with previous literature (e.g O'Mahony et al. 2008). A notable exception is workers aged over 50 (both males and females). In general, technology also favours female workers, the only exception being the youngest group with intermediate skills and the oldest group with high skills.

Table 1 Estimation of wage equations in all eight EU countries, 11 industries 1970-2005

A	**Aged 15-29**					
	Male			**Female**		
	High	Intermediate	Low	High	Intermediate	Low
K/Y	-0.0018**	-0.0028*	0.0067**	0.0033**	-0.0041**	-0.0039**
	(0.0004)	(0.0013)	(0.0017)	(0.0003)	(0.0011)	(0.0009)
ICTK/K	0.0009**	0.0009	-0.005**	0.0007**	-0.0051**	-0.0016
	(0.0002)	(0.0008)	(0.0011)	(0.0002)	(0.0007)	(0.0006)

B	**Aged 30-49**					
	Male			**Female**		
	High	Intermediate	Low	High	Intermediate	Low
K/Y	-0.0034**	-0.0157**	0.0142**	0.0060**	0.0052**	-0.0033**
	(0.0011)	(0.0021)	(0.0021)	(0.0008)	(0.0011)	(0.0012)
ICTK/K	0.0039**	0.0029*	-0.0040*	-0.0008	-0.0008	0.0058**
	(0.0007)	(0.0014)	(0.0014)	(0.0005)	(0.0007)	(0.0008)

C	Aged 50+					
	Male			Female		
	High	Intermediate	Low	High	Intermediate	Low
K/Y	-0.0016**	-0.0035**	0.0033**	0.0012**	-0.0002	0.0003
	(0.0006)	(0.0013)	(0.0011)	(0.0003)	(0.0004)	(0.0006)
ICTK/K	-0.0049*	0.0028**	-0.0006	-0.0005**	-0.0001	0.0023**
	(0.0004)	(0.0008)	(0.0007)	(0.0002)	(0.0003)	(0.0004)

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

These results however pool across countries and industries. Although dummy variables are included to account for both, this is unlikely to capture the full diversity. Therefore we also ran regressions by country. Table 2 summarises the coefficient on the ICT term by country; full results are available on request from the authors.

Table 2. Coefficients on ICT/K by country

A	Aged 15-29					
	Male			Female		
	High	Intermediate	Low	High	Intermediate	Low
Austria	-0.0016** (0.0003)	0.0076** (0.0018)	-0.0014 (0.0008)	-0.0004 (0.0003)	-0.0035* (0.0017)	-0.0093** (0.0017)
Belgium	0.0012* (0.0006)	0.0120** (0.0038)	0.0010 (0.0046)	-0.0002 (0.0008)	-0.0050** (0.0017)	-0.0019 (0.0032)
Denmark	0.0004 (0.0003)	0.0000 (0.0036)	-0.0023 (0.0034)	-0.0013** (0.0002)	0.0164** (0.0029)	0.0034* (0.0016)
Finland	0.0023** (0.0004)	0.0072** (0.0009)	-0.0114** (0.0009)	0.0006 (0.0004)	0.0027** (0.0006)	0.0065** (0.0009)
Germany	-0.0005 (0.0003)	0.0034 (0.0020)	0.0126** (0.0018)	0.0001 (0.0002)	-0.0095** (0.0015)	0.0062** (0.0010)
Netherlands	-0.0009 (0.0006)	0.0149** (0.0030)	0.0039** (0.0009)	-0.0006 (0.0004)	-0.0069** (0.0022)	0.0004 (0.0004)
Spain	0.0041** (0.0011)	-0.0108** (0.0041)	0.0034 (0.0037)	0.0010 (0.0011)	-0.0003 (0.0021)	0.0051 (0.0035)
UK	0.0039** (0.0009)	0.0004 (0.0043)	-0.0448** (0.0073)	0.0013* (0.0006)	-0.0206** (0.0038)	-0.0250** (0.0041)

Table 2. Coefficients on ICT/K by country (continued)

B	**Aged 30-49**					
	Male			**Female**		
	High	Intermediate	Low	High	Intermediate	Low
Austria	-0.0097** (0.0016)	-0.0016 (0.0030)	0.0084** (0.0022)	0.0000 (0.0007)	0.0004 (0.0015)	0.0005 (0.0015)
Belgium	-0.0078** (0.0022)	0.0064 (0.0084)	0.0213** (0.0062)	-0.0001 (0.0019)	0.0014 (0.0026)	0.0093** (0.0021)
Denmark	-0.0049** (0.0020)	0.0015 (0.0054)	-0.0046 (0.0046)	-0.0063** (0.0010)	0.0078** (0.0026)	0.0084** (0.0020)
Finland	-0.0047** (0.0012)	0.0089** (0.0020)	-0.0114** (0.0018)	-0.0066** (0.0010)	0.0008 (0.0007)	0.0056** (0.0013)
Germany	-0.0159** (0.0035)	-0.0352** (0.0046)	0.0248** (0.0047)	0.0041** (0.0011)	-0.0090** (0.0025)	0.0169** (0.0027)
Netherlands	-0.0100** (0.0020)	-0.0086* (0.0048)	0.0082** (0.0022)	-0.0021** (0.0009)	-0.0031 (0.0023)	-0.0019** (0.0005)
Spain	0.0108** (0.0037)	0.0052 (0.0052)	-0.0463** (0.0102)	-0.0037 (0.0028)	0.0052* (0.0024)	-0.0022 (0.0024)
UK	0.0045 (0.0034)	0.0053 (0.0053)	0.0447** (0.0036)	0.0017 (0.0012)	0.0132** (0.0024)	0.0019 (0.0030)

C	**Aged 50+**					
	Male			**Female**		
	High	Intermediate	Low	High	Intermediate	Low
Austria	-0.0014 (0.0011)	0.0063** (0.0017)	0.0055** (0.0015)	0.0005** (0.0002)	0.0008 (0.0006)	-0.0010 (0.0006)
Belgium	-0.0098** (0.0012)	-0.0149** (0.0019)	-0.0039 (0.0021)	-0.0015** (0.0004)	-0.0066** (0.0011)	-0.0008* (0.0004)
Denmark	-0.0028** (0.0006)	-0.0024 (0.0031)	-0.0096** (0.0028)	-0.0010** (0.0002)	-0.0083** (0.0017)	0.0054** (0.0010)
Finland	-0.0010* (0.0005)	0.0017** (0.0007)	-0.0014** (0.0006)	-0.0011* (0.0005)	0.0005* (0.0003)	0.0007 (0.0005)
Germany	-0.0056** (0.0012)	-0.0092** (0.0019)	0.0077** (0.0016)	0.0019** (0.0004)	0.0019 (0.0012)	0.0053** (0.0010)
Netherlands	-0.0002 (0.0010)	0.0086** (0.0025)	-0.0035** (0.0012)	0.0008** (0.0003)	0.0022** (0.0009)	-0.0011** (0.0003)
Spain	0.0061** (0.0024)	0.0082** (0.0018)	0.0089* (0.0041)	-0.0010* (0.0005)	0.0013* (0.0006)	0.0048** (0.0020)
UK	-0.0046** (0.0013)	0.0149** (0.0051)	0.0007 (0.0015)	-0.0006* (0.0003)	0.0008 (0.0012)	0.0021** (0.0006)

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

These results suggest that in most countries technology appears to be biased against older high skilled males, the only exception is Spain. There is less uniformity as regards older skilled females, although the majority show significant negative coefficients.

3. Organisational changes and on the job-training

3.1. The need for training

The relationship between age, seniority on the one hand and productivity and labour costs on the other are discussed in Daveri and Maliranta (2007), with an empirical application to manufacturing firms in Finland. They cite evidence from psychology that cognitive ability decreases beyond some threshold age and the rate of decline accelerates from about age 50 and then argue that rapid technical progress accelerates the depreciation of skills that occur naturally as workers age. They consider firms located in three distinct sectors, forestry, industrial machinery and electronics and show that only the electronics sector shows a productivity profile that first increases with age but turns negative beyond a certain level of seniority. Note these authors suggest it is seniority rather than age that impacts most on productivity since older workers who have been a long time in a job exhaust learning potential. The seniority impact is even more pronounced on labour costs since in many countries senior workers appear to get a premium over their productivity contributions due to collective bargaining or deferred payment arrangements.

Why should new technology be detrimental to the relative earnings of older workers. One possible direct channel is that older workers find it difficult to use the new technology. While this might be an explanation in the early years of its development, it is less likely in recent years as the technology became more codified and accessible. In addition Daveri and Maliranta (2007) distinguish 'fluid abilities' - capacities to relate speedily to new material and 'crystallized abilities' – verbal meaning and word fluency. They argue that in sectors that demand considerable mathematical skills such as ICT production, skills depreciate rapidly with age, hence their focus on the electronics sector. But functions that benefit from experience are unlikely to lead to significant skill depreciation, an argument also put forward by Autor et al (2003).

An alternative argument that might provide a link between technical change and depreciation of skills with aging is through the need to reorganise production following adoption of ICT. Organisational capital is an intangible capital, distinct from the concepts of human or physical capital in the standard growth model. It is the organisational capability to enhance the productivity of workers and includes the organisational structure, task allocation, decisionmaking distributions, relations with suppliers and major customers, and the culture of the company. One strand of the literature treats organisational capital as embodied in the firm's workers or in their matches to tasks within the firm, defining it as firm specific human capital. Organisational changes alter the nature of work and if sufficiently radical might favour ability to adapt to new surroundings than capabilities related to experience. The balance between these two is, in turn, likely to depend on the extent to which workers undertake retraining.

A key paper which demonstrates the link between productivity and organisational changes associated with flexible specialisation is Black and Lynch (2001). They use a detailed firm level dataset for the US (the Educational Quality of the Workforce, National Employers Survey), matched into the LRD to estimate cross sectional and panel production functions which incorporate measures of workplace practices and technology. Their analysis covers the period 1987-1993, a period of rapid adoption of ICT particularly in the US and just before the resurgence of US productivity growth (O'Mahony and van Ark, 2003). Their findings highlight the importance of establishing the extent to which firms actually engage in new management practices, not simply whether they supposedly have the system in place.

Firm level analysis has also taken place in the UK. A more recent paper by Crespi, Criscuolo, and Haskel (2007) examines in detail the relationships between productivity growth, IT investment and organisational change using UK firm panel data for 1998 and 2000. They find evidence of organisational change positively affecting productivity growth through a complementary interaction with ICT investment. The study goes further and finds organisational change is affected by competition and that ownership affects the propensity to implement changes. In their conclusions, they speculate that the EU slowdown relative to the US is possibly a combination of later IT investment and less organisational change.

Organisational change is likely to affect productivity indirectly by raising individual workers productivity, particularly the higher skilled workforce. Skill Biased Organisational Change (SBOC) is the hypothesis that organisational change increases the demand for skilled workers relative to unskilled workers since skilled workers are more able to handle information, have superior communication skills, are more receptive to retraining, and are more autonomous and as a result, organisational change measures are more cost effective to implement. In terms of empirical evidence supporting the existence of skill biased organisational change, a study comparing France with the UK by Caroli and van Reenen (2001) proposes that organisational change and skilled labour are complements for one another. Using data from the UK WIRS and the French RESPONSE survey they find that organisational change leads to greater productivity increases in establishments with larger initial skill endowments.

Bresnahan (1999) argues that Skill-Biased Organisational Change (SBOC) and Skilled-Biased Technical Change (SBTC) are effectively the same phenomena viewed from different perspectives. This is supported by Giuri et al (2008) who find in their study of Italian manufacturing weak evidence of SBOC when measured alongside SBTC (for which they report strong evidence). This is consistent with the findings of Piva et al (2005) who find that upskilling is more a function of organisational change than a consequence of technological change alone. Some evidence of an additive effect of technological and organisational change on the skill composition of employment emerges, which they argue is consistent with the theoretical hypothesis of a co-evolution of technology and organisation.

3.2 Training in the EU

The arguments above suggest that an important element of organisational change is retraining of the workforce. This section examines the prevalence of workforce training across EU countries and how training affects productivity. This uses EU LFS as the main data source, linked to data from EUKLEMS. It begins with an overview on training in the EU, both the quantity and quality of training provided and information on who receives training, looking at gender, age and skill. Our training variable is the proportion of workers received training, which is derived from the question of "Training or education in the last 4 weeks?" in the EU LFS 1995-2005. The EU LFS also provide information about training quality including purpose of training, duration of training, whether training occurs during working hours and field of training.

In 2006 in the EU as a whole approximately 14% of the employees received some training in the 4 weeks prior to the quarterly survey. In Table 3, the training proportions are significantly higher in the EU-15 than in the group of new member states and higher in market services than manufacturing. There appears to be a slightly higher growth between 2003 and 2006 in manufacturing than in market services. The figures for the EU aggregates hide large variation across countries – shown in Appendix Table A.1. The proportions are very high in the Scandinavian countries, the Netherlands and the UK, but are considerably lower in the large continental EU-15 countries of France, Germany, Spain and Italy. Some EU-15 countries (Portugal, Greece) have as low training densities as some of the smaller new member states

(NMS). The training proportions show a tendency to rise over time; this is especially apparent in countries for which long run data are available.

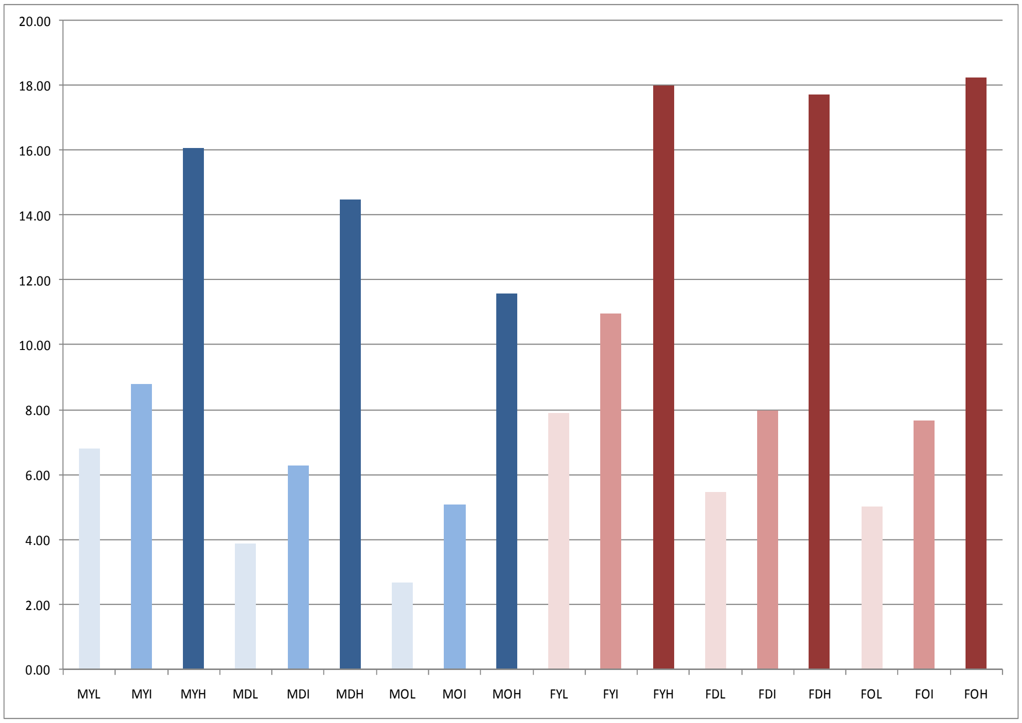
Table 3. Proportion of the workforce receiving training in the past four weeks.

	Total Economy			Manufacturing			Market Services	
	2003	**2006**		**2003**	**2006**		**2003**	**2006**
EU-26*	13.5	14.4		8.1	9.2		15.2	15.5
EU-15	15.3	16.2		9.8	10.9		16.7	17.1
EU-11*	6.6	6.8		3.9	4.1		8.2	8.1

*Excluding Malta

We next consider the characteristics of those receiving training. Below we summarise this information for the EU as a whole for 2006, dividing into 18 separate groups, using the notation in Figure 1. Thus, for example, MOI is male, aged 50+ with intermediate level qualifications. The height of the bars are greater in the right hand side indicating more females are trained than males and this is true for all age-skill combinations. The proportion trained rises with skill level (from light to dark) and significantly so comparing those with university degrees or equivalent with other groups. The height of the bars also declines with age, comparing bars of the same colour, with the exception of the female high skill group. There is a similar cross characteristic pattern in both the EU15 and EU11 groups of countries, except that for the high skilled group in the EU11 (both males and females), those in the age group 30-49 were more likely to receive training than in the younger age group. Similar patterns to those in Figure 1 are apparent if we divide by industry group – in both the EU-15 and the EU-11 groups, the decline in training with level of skill in manufacturing appears to be much steeper than for the economy as a whole, in particular for males.

Figure 1. Training proportions by worker characteristic EU27



Notes: M=Males; F = Females; Y = aged 15-29; D=aged 30-49; O=aged 50+; L = low skill; I = intermediate skill; H= high skill.

There are some differences across countries in this general pattern, with some showing far less variation across the groups than others. The variation tends to be lower for countries with high training proportions – the correlation between the average per cent trained and the coefficient of variation across characteristics equals -0.75 for the EU26 group and -0.74 for the EU15. The proportions are much more variable in the new member states but this partly reflects the smaller sample sizes of those who receive training. In most countries the group receiving the lowest training intensity is low skilled males aged 50 plus. In the Czech Republic and Slovenia the group least likely to be trained are low skilled females aged 50 plus, in Finland it is low skilled young males and in the Netherlands it is low skilled young females.

Questions regarding quality of training were only asked since 2003 or 2004, depending on the country and the response rate was relatively low so the numbers presented below are all based on average values over the period 2003-2006. EU LFS Respondents were asked if the purpose of the training was mainly professional or mainly personal/social. In the EU as a whole 84% said the training was mainly professional. There was some small variation by type of worker – the most salient being that the low skilled were more likely to say the training was for personal reasons (25%) against only 14% for the highest skill group. The percent of workers saying training was for professional reasons was similar across gender and across age groups. There were also some differences across country and industry but in general the response rate on this question was quite low so these differences are unlikely to be significant.

A more revealing quality dimension is the average length of training, shown in Table 4. On average workers who receive training in the past 4 weeks are trained for about 12 hours or about 1.5 days. This is a significant length of time suggesting a reasonable quality of training. There is some variation across country with hours generally larger in new member states than in the EU15. Comparison of the numbers in Tables 3 (and Appendix Table A.1) and 4 suggest an inverse relationship between length of training and percent trained – indicating a possible trade off between quantity and quality of training. The correlation between duration and proportions trained is significantly negative (-0.57, -0.64 and -0.49, for the EU26, EU15 and EU11, respectively).

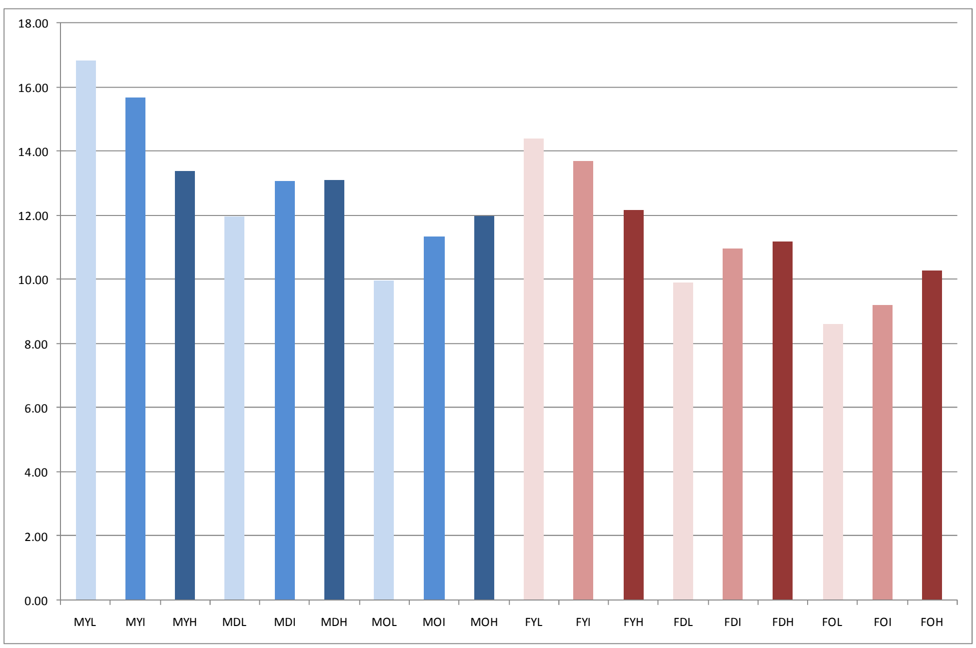
Table 4. Average duration of training (hours), average 2003-06

EU26	**12.3**		FR	18.7		CY	13.9
EU15	**12.0**		GR	22.5		CZ	11.7
EU11	**15.6**		IE	13.1		EE	16.2
			IT	14.7		HU	24.1
AT	16.6		LU	16.2		LT	15.9
BE	14.8		NL	15.5		LV	16.2
DE	17.4		PT	19.6		PL	16.6
DK	15.7		SE	9.7		RO	19.8
ESP	22.6		UK	12.0		SI	15.6
FI	11.5		BG	24.8		SK	15.4

Figure 2 shows duration of training by worker characteristic. It suggest that females receive less hours training on average than males and that duration of training falls marginally with skill level, compensating to some extent for the reverse findings for proportions of workers trained in these two dimensions. However duration of training falls with age, reinforcing the findings for this group in Figure 1 above so that both the quantity and quality of training appears to be lower for older age groups.

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 manufacturing (70%), distribution (60%), financial and business services (72%) and health (68%), but were smaller in some sectors such as hotels (43%) and education (49%). The variation was greater across countries. In Finland, France and the UK more than 75% of training occurred during working hours; in Belgium, Ireland, Italy, the Netherlands and Poland the proportion was about 50% whereas in many new member states and Greece the proportion was under 40%. However it should be noted that this variable was not reported for many countries including Germany and Spain.

Figure 2. Duration of training by worker characteristic, EU26, average 2003-06.



In terms of worker characteristics, all groups showed very similar proportions except low skilled young persons for whom about 50% of training occurred outside normal working hours. This variable is the one most likely correlated with commitment by the firm, since the opportunity costs of lost production will be larger for those trained during working hours than those who undertake training outside normal hours, even if the firm pays the direct costs of both. The opportunity costs in terms of production foregone are lowest for the group of young unskilled since they have the lowest relative earnings but these are also likely to be relatively mobile. The results are suggestive that the latter effect dominates.

The final quality dimension which we examine is the field in which the training occurred. The EULFS divides this variable into 15 separate categories which are shown in Appendix Table A.2. As the response rate is also low for this question and the number of categories is large, we have aggregated to six groups described Table 5. This shows that training directly related to computing, is a small proportion of total training. However we should not conclude from this that ICT is a minor element of training since many fields will involve some use of ICT as part of their training. The table shows some differences comparing the EU15 with the group of new member states with language training and teacher training more prevalent in the latter and computer use and services training in the former. Science and engineering fields are more common in manufacturing and social sciences, business and law in market services. Finally the summary data show only small differences by worker characteristic although there is some suggestion that low skilled older workers are more likely to be trained in computer use and less likely to receive training in either SSE or SSBL.

Table 5. Training by field of study: shares of fields in total training

	EU15	EU11	EU26	Manufacturing	Market services
GAL: General, arts and languages (000,200,222)	19.1	25.7	18.3	24.0	20.0
SSBL: Social science, business and law (300)	22.2	20.5	23.8	19.0	32.6
SE: Science and engineering (400,420,440,460,500)	9.7	11.5	9.7	20.5	8.8
COMP: Computing (481,482)	11.2	7.7	11.3	12.6	12.6
HVE: Health, veterinary, education (100,600,700)	20.0	21.2	20.6	5.7	7.2
SERV: Services (800)	16.9	12.3	16.3	18.3	18.7

4. Econometric Analysis

We utilise the data described in the previous section, together with industry data on wages from EU KLEMS, to see if there is evidence that received training can explain wage changes and then look at its impact through use of ICT. In this section we largely follow the specification in Deardon et al (2006). Thus we estimate the following log form equation for real hourly wage rates (*lnw*):

(4) $\ln w_{cit} = \alpha + \beta\, tr_{cit} + \gamma\, tr_{cit} \cdot \ln(capit/h)_{cit} + \mu \ln(capit/h)_{cit} + \lambda \ln(capnit/h)_{cit}$ + labour type controls (interactions with tr_{cit}) + country, industry and time dummies.

where tr_{cit} is the proportion of workers receiving training in the industry i (i=1…9) of country c (c=1..17), in year t (t=1995…2005). Control variables include both ICT and non-ICT capital (*lncapith* and *lncapnith*), and characteristics of the workforce, namely, the proportions of males (*maleprop*), aged 15-29 (*age29prop*), age between 30-49 (*age49prop*), high educated (*eduhprop*) and medium educated (*edumprop*) workers in total employees, and their interactions with training. Country, industry and time dummies are used to control the unobservable time-invariant effects and the business cycle. Wage, labour and capital input variables are from EU KLEMS, while training and all workforce characteristics variables are from the EU LFS. Hourly wage rates at industry level are measured as labour compensation per hour within the industry, i.e. employee compensation (COMP) divided by total working hours (H_EMPE). Our regressions are weighted by average employee compensation (COMP) share of each industry over the period 1995-2005, a standard approach in the literature to take account of industry heterogeneity.

More details of training variable are worthy of mention, given variation in data availability. Hence, the time periods of the training variable differ by country, i.e. 1995-2005 for Austria, Belgium, Denmark, Spain, France, Italy, Luxemburg, the Netherlands and Portugal; 1996-2005 for Finland, Slovenia and Sweden; 1997-2005 for Hungary; 1999-2005 for United Kingdom; 2002-2005 for Germany, Ireland and Czech Republic. We lose 270 (=30×9) observations of training variable. Hence, as above specification is applied on the framework of 17 countries × 9 industries × 11 years, we have an unbalanced panel data of training variable.

Additionally the right hand variables including training in above specification may not be exogenous. Much of the empirical growth literature addressed the endogeneity of the explanatory regressors in growth regressions. Nickell (1981) reveals that within-groups estimate of a dynamic panel data model can be badly biased for small T, even as N goes to infinity. The endogeneity problem matters since it may affect the consistency of the regression estimates. The most widely-used alternative strategy is to difference the model to eliminate the fixed effects, and then use two stage least squares or generalized method of moments (GMM) to address the correlation between the differenced lagged dependent variable and the induced MA(1) error term. Arellano and Bond (1991) develop the GMM approach to dynamic panels; their technique includes methods suitable for unbalanced panels and specification tests. Thereafter, recent literature on the links between ICT capital and productivity such as Barro and Lee (1994), Caselli, Esquivel and Lefort (1996), Stiroh (2002) and O'Mahony and Vecchi (2005) apply panel dynamic method in their estimation. Black and Lynch (2001) apply GMM techniques to instrument labour, capital, materials and work place practices (training) and address omitted variable and endogeneity bias. Deardon et al (2006) explicitly allow training to be a choice variable by using GMM estimators developed to deal with endogenous variables in production functions. Their results show this approach can yield a more accurate association between the productivity growth and explanatory variables. Thus, it has become increasingly common to avoid the within-groups estimator when estimating dynamic models.[1] We follow this way and apply the GMM specification on effect of training:

(5) $\Delta \ln w_{cit} = \alpha + \xi \ln w_{cit-2} + \beta \Delta tr_{cit} + \gamma\ \Delta tr \ln(capit/h)_{cit} + \mu\ \Delta \ln(capit/h)_{cit} + \lambda\ \Delta \ln(capnit/h)_{cit} +$ Δlabour type controls (Δ interactions with tr_{cit}) + time dummies.

The GMM approach is typically based on using lagged levels of the dependent variable as instruments for lagged first differences. If the error terms in the levels equation are serially uncorrelated then lagged first difference can be instrumented using earlier lagged levels. This corresponds to a set of moment conditions that can be used to estimate the first-differenced equation by GMM. Since our time period is not very long, we choose only one lag for the instrumental variable.[2]

We use two different methods of estimation. The baseline specification only considers the overall effect of training on productivity for all 17 European countries in our regression, while the more sophisticated specification involves allowing for the different education systems in European countries. Results from the baseline specification are presented in Table 6. The first two columns use data of average real hourly wage within industry regressed on industry training proportions (*tr*) and the ICT capital per hour interacted with training (*trlnicth*). This specification is based on the framework of 17 countries × 9 industries × 11 years. When wage is regressed on training alone the results were significantly negative (-1.762). This surprising result is not consistent with authors such as Dearden et al (2006) and Vignoles et al (2004) find positive impacts. When training is interacted with ICT capital the results were positive and significant (0.273). The next two columns provide more accurate GMM results of trainings. The effect of training alone was significantly positive. As training is interacted with ICT capital the results were

[1]See more discussion on the GMM techniques in the growth econometrics in Durlauf et al (2005).
[2]More generally, the GMM approach relies on a lack of serial correlation in the error terms of the growth equation (before differencing). We test this assumption using the methods developed in Arellano and Bond (1991). The Arellano and Bond tests of autocorrelation do not suggest misspecification of the model.

positive and significant (0.129). The results in Table 6 suggest an important role for training especially when combined with ICT investments and linked to the new technology.

Table 6 Training and wage, 1995-2005

	OLS		GMM	
	(1)	(2)	(3)	(4)
tr	-1.762*	-1.606	0.988*	0.948*
	(0.906)	***(0.899)***	***(0.521)***	***(0.507)***
trlnicth		0.273**		0.129**
		(0.059)		***(0.048)***
lncapith	0.041**	0.004	0.027**	0.014
	(0.009)	***(0.012)***	***(0.008)***	***(0.010)***
lncapnith	0.079**	0.077**	0.190**	0.197**
	(0.015)	***(0.015)***	***(0.024)***	***(0.024)***
treduh	-2.221**	-2.981**	-1.079**	-1.501**
	(0.467)	***(0.492)***	***(0.494)***	***(0.555)***
eduhprop	1.234**	1.417**	0.169	0.235*
	(0.114)	***(0.120)***	***(0.101)***	***(0.108)***
tredum	0.801	0.406	0.340	0.194
	(0.631)	***(0.632)***	***(0.210)***	***(0.222)***
edumprop	0.248**	0.362**	-0.290**	-0.257**
	(0.087)	***(0.090)***	***(0.061)***	***(0.063)***
trage29	-0.571	0.389	-1.317**	-1.044**
	(0.936)	***(0.951)***	***(0.436)***	***(0.396)***
age29prop	-0.357	-0.752**	0.132	0.098
	(0.264)	***(0.276)***	***(0.099)***	***(0.099)***
trage49	4.609**	3.152**	-1.127*	-1.132*
	(1.212)	***(1.244)***	***(0.597)***	***(0.588)***
age49prop	-1.226**	-1.211**	0.307**	0.286**
	(0.311)	***(0.308)***	***(0.108)***	***(0.107)***
trmale	-0.898**	-0.085	-0.073	0.024
	(0.417)	***(0.450)***	***(0.203)***	***(0.201)***
maleprop	1.019**	0.835**	-0.037	-0.056
	(0.117)	***(0.123)***	***(0.068)***	***(0.067)***
Country Dummy	Yes	Yes	No	No
Industry Dummy	Yes	Yes	No	No
Year Dummy	Yes	Yes	Yes	Yes
Obvs	1349	1349	1115	1115

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

To explore the training effect in different education systems, a more sophisticated specification is applied on this framework. According to Estevez-Abe et al (2001, Table 4.3, p170), we categorize the education systems of the 17 European countries in our regression into four groups: Vocational-oriented (Austria, Germany, Sweden and Finland), Academic-oriented (Italy, France, Ireland, Spain the UK and Luxemburg), Mixed (Belgium, Netherlands, Denmark and Portugal) and New-comers (Hungary, Czech Republic and Slovenia). Dummy variables of these four groups are cd1-cd4 respectively, which are interacted with training (or training interacted with ICT capital) variables. The vocational-oriented group is used as the baseline group. The results of these regressions are shown in Table 7.

In the OLS estimation, the training variable alone shows insignificant effect in vocational-oriented countries, and significantly positive incremental effect in other countries except the academic-oriented countries. It suggests that training alone can significantly increase more wage in the Mixed and new member groups. Furthermore, when we interact the training variable with ICT capital, the interaction can work very well in the Academic-oriented countries (0.222). However, the mixed group shows a less effect of training interacted with ICT capital (-0.129). Thus, these results show a very interesting pattern that training is positively associated with wage in the mixed and new member countries, while only is combined with ICT investments in academic and vocational-oriented countries.

Table 7 Training, Education and Wage

	OLS		GMM	
	(1)	(2)	(3)	(4)
tr	-0.779	0.290	0.665	0.909
	(0.904)	***(0.898)***	***(0.520)***	***(0.535)***
trcd2	-0.436**	-0.869**	0.176	-0.141
	(0.219)	***(0.239)***	***(0.187)***	***(0.214)***
trcd3	0.694**	0.661**	0.229*	0.135
	(0.244)	***(0.278)***	***(0.117)***	***(0.113)***
trcd4	2.603**	2.819**	0.172	0.112
	(0.668)	***(0.810)***	***(0.130)***	***(0.148)***
trlnicth		0.185**		0.068
		(0.068)		***(0.057)***
trlnicthcd2		0.222**		0.234**
		(0.052)		***(0.082)***
trlnicthcd3		-0.129*		0.004
		(0.066)		***(0.066)***
trlnicthcd4		0.033		0.119
		(0.401)		***(0.069)***
lncapith	0.040**	0.002	0.029**	0.015
	(0.009)	***(0.012)***	***(0.008)***	***(0.010)***
lncapnith	0.084**	0.087**	0.183**	0.195**
	(0.014)	***(0.014)***	***(0.025)***	***(0.025)***
treduh	-2.404**	-2.904**	-0.706	-1.089
	(0.460)	***(0.480)***	***(0.514)***	***(0.594)***
eduhprop	1.265**	1.431**	0.138	0.186
	(0.112)	***(0.119)***	***(0.103)***	***(0.110)***
tredum	0.069	0.435	0.398	0.082
	(0.637)	***(0.647)***	***(0.229)***	***(0.251)***
edumprop	0.385**	0.468**	-0.276**	-0.238**
	(0.090)	***(0.094)***	***(0.066)***	***(0.067)***
trage29	-1.159	-1.130	-1.328**	-1.090
	(0.998)	***(1.044)***	***(0.514)***	***(0.502)***
age29prop	-0.179	-0.577**	0.113	0.096
	(0.265)	***(0.276)***	***(0.107)***	***(0.111)***
trage49	3.864**	0.691	-1.019**	-1.118
	(1.211)	***(1.257)***	***(0.616)***	***(0.630)***
age49prop	-0.957**	-0.726**	0.262**	0.256*
	(0.309)	***(0.304)***	***(0.112)***	***(0.111)***
trmale	-1.188**	-0.445	0.016	0.010
	(0.415)	***(0.455)***	***(0.194)***	***(0.194)***
maleprop	0.99**	0.805**	-0.057	-0.049
	(0.115)	***(0.119)***	***(0.066)***	***(0.067)***
Country Dummy	Yes	Yes	No	No
Industry Dummy	Yes	Yes	No	No
Education group Dummy	Yes	Yes	No	No
Year Dummy	Yes	Yes	Yes	Yes
Obvs	1349	1349	1115	1115

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

This argument can be strengthened by the GMM estimation. In the next two columns, the effect of training alone on wage is not much different among all countries except that the mixed up group still can benefit more from training (0.229), which suggests that there is only insignificant benefit of training not linked to the new technology. Only the academic-oriented group shows significantly positive association with training interacted ICT capital (0.234). Therefore, especially for those academic-oriented countries, the strong incremental positive effect of training reflects the important role for training when combined with ICT investments.[3]

5. Training and ICT: Receipts versus Offers

Given that older workers in fact receive relatively little training, and this is associated with ICT, there remains an issue of what is driving the lower training. Is it that firms are less willing to train workers or that older workers themselves are less willing to undertake the necessary training? From the perspective of the firm, the costs of training will be weighed against the benefits. In deciding who to train firms will consider whether costs vary by type of worker and the benefit in terms of the probability that the person trained will stay in the firm. The benefits of training are likely to be positively related to worker characteristics such as education/qualification on the grounds that the more educated are best placed to absorb the new knowledge. Firms deciding on whom to train will have little information on the inherent ability of individuals to benefit from training but might well use education as a signal. The sign of the impact of other characteristics such as age and gender is unclear. Again faced with asymmetric information the firm might decide that flexibility and ability to train may first rise and then decline with age. Vignoles et al (2004) present evidence that firms do cherry pick which workers to train and suggest given this that there should be no presumption that if all workers were trained their wages would necessarily rise. The probability of staying in a job is likely to rise with age whereas the length of time the worker remains in the firm is a positive function of age up to retirement. Costs of training will also depend on characteristics with again these likely to be lower for the better educated. If we assume a hump shape for benefits by age, then the firm is most likely to offer training to those in young to mid age groups.

The individual worker will undertake training if the benefits to them outweigh the costs. Benefits are likely to be dominated by pay but might also include non pecuniary benefits that include

[3] There is much less observation in the GMM estimation. Especially for the new member countries, data are more recent and even less. Hence GMM results for the new member countries should be used with caveats.

working conditions. Since training leads to productivity increases and, in a competitive market, increased pay we would expect workers to accept training if offered. However the sociological literature and the results shown below suggest that not all workers accept training and the ratio of acceptances to offers rises education and declines with age.

The UK LFS can provide information about training offered from employer ("Education or training offered, if not received in the last 3 month?").[4] Hence, it allows examination of these issues as it includes information on offers of training as well as uptake. Table 8 summarises these data. The first panel shows the proportion of workers not offered training. This decreases with skill level but increases with age for males for given skill group. Comparing those aged 50 and over with the middle age group, the highest skill group shows the greatest proportional disadvantage. This is consistent with the idea that firms are less likely to train older workers for given skill levels. A similar conclusion applies to females but the differences are not as great as for males. The second panel shows the take-up rate for training offers. This declines with age suggesting some role for a reluctance of older workers to undertake training. For males in the higher skill group, the difference between the over 50s and the middle age group is not large suggesting that reluctance on the part of firms to provide training dominates for the higher skill group.

Table 8. Training: Receiving and Offers, UK, average 1995-2005

	Degree and above	Intermediate	Low
% of workers not offered training			
Male			
15-29	31.7	44.9	66.2
30-49	32.5	48.8	72.7
50+	45.2	60.0	76.8
Female			
15-29	28.9	41.6	63.4
30-49	26.7	40.9	67.1
50+	33.2	45.7	70.1

[4] Hence, our training variable here is also the proportion of workers received training, which is derived from the question of "Job related training or education in the last 3 months?" rather than "in the last 4 weeks" in the British LFS 1995-2005.

workers receiving training as a % of offered training			
Male			
15-29	64.0	58.3	47.3
30-49	56.4	45.5	29.3
50+	54.4	37.8	22.8
Female			
15-29	66.2	58.9	51.4
30-49	62.5	50.1	33.7
50+	63.6	44.2	25.4

Sources: UK LFS 1995-2005

Similar analysis is not possible using the EU LFS data, as the harmonised data only contain information on those who took up offers of training. An interesting avenue for future research might be to examine country specific surveys to see if the low take up rate observed for older workers in the UK also hold for other EU countries. The arguments in section 2 indicate that the lower training rates observed among older people as well as less skilled people are consistent with the predictions of human capital theory, additionally implying that decisions to reject an offer of training may be entirely rational. Nevertheless, lower training rates will impact negatively on employability in the mid to long-term, particularly if an older person becomes unemployed, since the value of human capital depreciates. For example, Groot (1998) has estimated that the value of skill depreciates at rates of between 11 per cent and 17 per cent annually. In addition, some beliefs regarding the relationship between the costs and benefits of training and age may be based on incorrect or stereotypical and ageist attitudes to older workers. Specifically, ageist perceptions may reinforce employers' disinclination to invest in training for older workers (Lundberg and Marshallsay, 2007; Cabinet Office 2000; McKay and Middleton, 1998; Thompson, 1991). This could therefore be part of the explanation for the lower incidence of training among older workers but in this case, the decisions made by both employers and employees in relation to training would not necessarily be correct ones.

6. Conclusions

This paper considered evidence that ICT may have been associated with reductions in the relative wages of older workers, in particular males aged 50 and over. Both the EUKLEMS data and EU LFS information appear to support this conjecture. The LFS data suggests that low levels of training linked to ICT may be an explanatory factor. The LFS data in the UK also highlight puzzling trends in workers unwillingness to engage in training when offered. There is some suggestion from LFS data that the quality of the training offered is lower for older than younger workers but this is far from conclusive so that direct measures of the quality of training for those offered but declining training is required. In addition it would be useful to directly link training to organisational changes stemming from ICT.

Appendix A

Table A. 1. Proportion of the workforce receiving training in the past four weeks.

	Total Economy			Manufacturing			Market Services		
	1995	**2003**	**2006**	**1995**	**2003**	**2006**	**1995**	**2003**	**2006**
AT	12.4	12.8	19.1	10.6	11.6	15.6	12.6	12.7	18.4
BE	3.5	8.9	8.9	2.7	6.5	6.4	4.0	8.6	8.5
BG	-	1.7	2.1	-	0.9	1.0	-	2.6	3.2
CY	-	11.4	9.9	-	7.2	4.1	-	12.5	10.3
CZ	-	6.4	6.6	-	3.8	4.5	-	6.8	6.3
DE	-	11.8	13.6	-	9.3	11.0	-	12.0	13.7
DK	26.1	29.0	36.8	19.1	20.0	28.2	31.1	32.0	39.9
EE	-	10.0	9.6	-	4.3	4.0	-	11.7	10.6
ESP	4.8	5.4	12.7	2.6	3.5	8.7	5.0	6.2	13.2
FI	-	27.3	30.0	-	20.5	21.9	-	28.6	31.7
FR	4.5	10.6	11.4	2.7	8.8	9.6	4.7	11.0	11.7
EL	1.4	4.8	2.6	0.8	2.3	1.3	2.1	5.8	3.3
HU	-	6.3	4.5	-	3.5	2.9	-	7.3	5.1
IE	9.6	11.1	11.7	7.2	6.6	7.0	10.5	12.4	13.0
IT	3.6	3.9	6.7	2.6	2.3	3.3	3.5	4.0	6.5
LT	-	6.3	7.2	-	3.1	3.7	-	7.8	9.1
LU	4.6	7.2	9.4	2.4	4.9	6.5	5.2	7.4	9.1
LV	-	12.9	10.0	-	6.3	4.1	-	12.6	10.7
NL	21.8	27.4	26.4	17.1	19.0	19.0	26.1	31.2	31.1
PL	-	10.0	10.2	-	7.0	6.5	-	12.0	12.3
PT	5.0	4.0	4.0	3.4	1.9	2.6	5.9	5.3	4.5
RO	-	1.5	2.1	-	0.6	1.0	-	2.0	2.8
SE	-	33.2	20.0	-	23.8	14.1	-	32.1	19.6
SI	-	18.9	20.2	-	11.9	13.7	-	21.6	22.8
SK	-	5.0	5.3	-	2.7	2.9	-	5.8	6.3
UK	23.9	30.9	33.3	18.5	20.4	22.7	25.8	30.5	32.7
EU-26*	-	13.5	14.4	-	8.1	9.2	-	15.2	15.5
EU-15	-	15.3	16.2	-	9.8	10.9	-	16.7	17.1
EU-11*	-	6.6	6.8	-	3.9	4.1	-	8.2	8.1

*Excluding Malta

Table A.2. Training by field of study: shares of fields in total training

	EU15	EU11	EU27	Manufact-uring	Market services
000 General programmes	4.8	1.5	4.6	4.8	4.7
100 Teacher training and education science	5.6	10.5	5.9	1.0	1.3
200 Humanities, languages and arts	8.1	3.0	6.0	5.1	6.5
222 Foreign languages	6.2	21.2	7.7	14.1	8.8
300 Social sciences, business and law	22.2	20.5	23.8	19.0	32.6
400 Science, mathematics and computing	0.0	0.8	0.1	0.1	0.1
420 Life science	0.5	0.9	0.5	0.5	0.4
440 Physical science	0.6	0.6	0.6	1.0	0.6
460 Mathematics and statistics	0.4	0.3	0.4	0.4	0.2
481 Computer science	4.0	4.0	3.9	4.2	5.1
482 Computer use	7.1	3.8	7.4	8.3	7.6
500 Engineering, manufacturing and construction	8.1	9.0	8.1	18.5	7.6
600 Agriculture and veterinary	0.9	1.1	0.8	0.5	0.7
700 Health and welfare	14.4	10.7	13.8	4.2	5.3
800 Services	16.9	12.3	16.3	18.3	18.7
	100	100	100	100.0	100
GAL: General, arts and languages (000,200,222)	19.1	25.7	18.3	24.0	20.0
SSBL: Social science, business and law (300)	22.2	20.5	23.8	19.0	32.6
SE:Science and engineering (400,420,440,460,500)	9.7	11.5	9.7	20.5	8.8
COMP:Computing (481,482)	11.2	7.7	11.3	12.6	12.6
HVE: Health, veterinary, education (100,600,700)	20.0	21.2	20.6	5.7	7.2
SERV: Services (800)	16.9	12.3	16.3	18.3	18.7
	100	100	100	100	100

Appendix B. EU LFS Variables

EDUC4WN: In education or training, formal or informal in the past four weeks.
COURATT: Attended any courses outside the formal education system in past four weeks

Field of training: COURFILD
The base outcome is no training. Outcomes 1 -10 are as follows:
Outcome 1: general programmes
Outcome 2: teacher training and education science
Outcome 3: humanities, languages and arts
Outcome 4: foreign languages
Outcome 5: social sciences, business and law
Outcome 6: science, mathematics and computing - life science, physical science, mathematics and statistics
Outcome 7: computer science and use
Outcome 8: engineering, manufacturing and construction
Outcome 9: agriculture and veterinary
Outcome 10: health and welfare
Outcome 11: services

Hours of training: COURLEN
The base outcome is no training. Outcomes 1-4 are as follows:
Outcome 1: 1-20 hours
Outcome 2: 21-50 hours
Outcome 3: 51-100 hours
Outcome 4: 101-300 hours

Whether training took place during working hours: COURWORH
The base outcome is no training. Outcomes 1-5 are as follows:
Outcome 1: training only took place during work hours
Outcome 2: training was mostly during work hours
Outcome 3: training was mostly outside work hours
Outcome 4: training only took place outside work hours
Outcome 5: trainee did not have a job at the time

Purpose of training: COURPURP
The base outcome is no training. Outcomes 1-2 are as follows:
Outcome 1: mostly job related
Outcome 2: mostly personal/social

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