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Abstract

This paper investigates the impact of training and education on productivity, in particular linking to a literature that emphasizes the need to reorganise production following adoption of ICT. The paper examines training at the total economy level and variation across industries, focusing especially on manufacturing versus market service sectors. It also examines the characteristics of those who receive training and outlines the incentives that underlie this.

Keywords: Training, Education, 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 having a highly skilled labour force. Workers not only need to be skilled, but also adapt fast to change. On-the-job training and education are therefore important sources of long-term competitiveness and means of adjustment. Indeed, as part of the "Growth and jobs strategy", the EU intends to "adapt education and training systems in response to new competence requirements". The "New skills for new jobs" initiative intends to understand better how these objectives can be met. In the face of rapidly changing technology (for example, changes arising from information and communications technology), 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 training.

This paper investigates the impact of training and education on productivity, in particular linking to a literature that emphasizes the need to reorganise production following adoption of ICT. The paper examines training at the total economy level and variation across industries, focusing especially on manufacturing versus market service sectors. It also examines the characteristics of those who receive training and outlines the incentives that underlie this.

This paper is organized as follows. It first reviews the literature on training, education, their links with use of information technology and their impacts on productivity and earnings. Section 3 presents a descriptive overview of training in the EU using the data from the EU Labour Force Survey (EU LFS). This section presents basic data by industry and country on the extent of training, who receives training, its duration and location and field of study. A sub section also considers the training of migrants. Following this section 4 contains an analysis of the impact of training and education on productivity and its links to ICT. This uses two complementary approaches – a growth accounting exercise that models training as intangible investments and an econometric analysis of the impact of training on productivity. Section 5 applies limited dependent variable regression methods to the EU LFS microdata on individuals to examine what factors characterize those who receive training, including an analysis by field of training. Section 6 reviews the existing evidence on incentives to train, focusing attention in particular on older workers. Finally section 7 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 & Ford, 1988). According to Ostroff and Bowen (2000), employees' collective attitudes, behaviours, and human capital should influence organizational performance. In turn, organizational performance should lead to positive financial outcomes for the organization (Becker and Huselid, 1998), mediating the relationship between human resource outcomes and financial performance. 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.

Human capital has long been seen as important in determining economic growth (Lucas, 1988). 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). Helpman and Rangel (1999) argue that technological changes may lead to an initial slow down because the diffusion process requires more education or training. Thus the overall skills of the workforce have to be higher for a successful diffusion, for which firms will have to replace the unskilled workers with the more skilled ones or with ones with higher educational qualifications. The literature on technology and organisational capital suggests that an important element of organisational change is retraining of the workforce.

There are many studies that 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). In one of the first papers on this issue Bartel (1994) finds that there is a positive association between training and labour productivity in US manufacturing firms. Deardon et al. (2006) find that the impact of training is about twice as high on productivity as on wages, which they interpret as suggesting external benefits from training not captured by workers. Ballot et al (2006) use firm level panel data to analyse the shares of firms and workers on returns to tangible (physical capital) and intangible assets (training, R&D). They find that returns to firms from investing in physical capital are higher than the returns from investing in training and R&D.

The literature also points to the need to distinguish the different types of training as much as possible, looking for instance at ICT training, or training of different lengths. Mabey and Ramirez (2005) analysed the impact of varying training types on productivity and find the significance of the impact depends on the type of training. Lynch and Black (1998) find that the higher the proportion of off-the-job training the higher the productivity in manufacturing, whereas in non-manufacturing sectors training on computer skills will increase productivity.

In addition it is important to emphasise that training and education are important but not sufficient for productivity growth (Mayhew and Neely, 2006). How much (if any) impact training has depends on the accompanying product and production strategies of the organization in which the training takes place. Plant productivity is found to be higher in businesses with more-educated workers or greater computer usage by non-managerial employees and the impact of ICT adoption on productivity can only be realised if the appropriate work practice has actually been implemented (Black and Lynch, 2001). Workers believe that their return to education and training will be high if firms adopt the new technology next period, thus they will certainly invest more in their training. Moreover, firms will hire more skilled labour while adopting IT related innovations (Bresnahan et al, 2002). Entrepreneurs will have more incentive to adopt the new technology if the level of education of workers is already high (Acemoglu, 1997). Hollenstein (2004) asserts that the willingness of firms to adopt ICT is subject to the relative benefits and costs involved. The firm will regard the adoption as beneficial if it helps to lower production costs; gain higher efficiency and flexibility; and/or increase product quality. In terms of the costs of adoption the usual arguments involve: (1) direct costs of investment (Goodacre and Tonks, 1995); (2) ICT related training and labour reshuffle costs (e.g. Leo, 2001); (3) Management readjustment costs (e.g. Eder and Igbaria, 2001).

Lee (2001) examines the impact of education on ICT adoption (PC per 1000 people) using cross section regressions for 80 countries in 1995 – 1998 and finds a significant relationship between education level and ICT adoption. He also finds that secondary and college level education is important to adopt ICT for a country. Furthermore, Gust and Marquez (2004) find a significant influence of the level of human capital on ICT adoption (ICT expenditure as per cent of GDP) for 13 industrial countries. In contrast some research finds no evidence that education is associated with the diffusion of ICT (For example, see, Hargittai (1999) for an investigation on the determinants of internet connectivity (internet hosts per capita) in 18 OECD countries and Norris (2001) for internet use in EU-15 in 1999). Nevertheless, one should note that different dependant variables (ICT proxies) were used in the above papers and it may be natural to expect that estimates of the impact would vary.

Training can upgrade workers' skills and may thus be linked to a faster adoption of ICT. Bresnahan et al (2002) find workers' skill is positively associated with ICT adoption. Hollenstein (2004) suggests that training will increase the absorptive capacity of the firm and hence the adoption procedures may be facilitated.

There is ample evidence that training impacts on worker's earnings (see e.g. Booth 1991 and Blundell, Dearden and Meghir 1996 for the UK, and Lynch 1992 and Bartel and Sicherman 1999 for the US). A typical result is Dearden et al. (2006) who find that a 1% increase in training is associated with an increase in hourly wages of about 0.3%. Vignoles et al. (2004) find that male workers in their mid career (age 33-42) experience the highest wage growth from training and that the firms often train the workers who are more able in the first place. Training may have different impacts on workers based on the characteristics of the worker (e.g. age, gender and education level) and whether they belong to public or private sector work place. For example, in public sectors women are found to have higher positive returns to job training than men, but the returns are insignificant for young workers (Greenberg et al, 2003). Blundell et al (1996) find that more educated people have higher chances of receiving training. It is also important to distinguish the funding body of the training – firm sponsored, or self sponsored? The different sponsors may have different interests in taking/providing training. Firms are more interested in investing types of training which increases the workers' productivity though skill improvement whereas workers want to see an increase in their wage rates after participating in training. In a perfect market wage rates are equal to the marginal productivity. However, imperfections in the labour market may produce situations where workers may gain very little in terms of wage increases from the value added they create, (Ballot et al, 2006). In fact, it is now generally accepted that firms and workers jointly invest in training programmes (workers sometimes invest with reduced wages) – that is, training is a joint decision.

Finally, macroeconomic conditions also affect the effectiveness of the training. For example, training will be less effective if the unemployment rate is high – particularly for young people (Greenberg, 2003).

3. Workforce Training in the EU

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, skill and nationality dimensions. This is followed by estimates of the impacts of training on productivity using both growth accounting and industry panel regression analysis.

3.1 Training in the EU: Descriptive analysis

3.1.1 Proportions of the workforce receiving 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. 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 of Carmichael et al (2009). 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 1. 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

Figure 1a shows the training proportions across industry groups in 2006 for the EU26. It suggests that the percent training is generally higher in service sectors than in production industries and is highest for financial services, education and health. The distribution across industries is similar in the EU15 and the NMS, except perhaps in financial services where the EU11 proportion is closer to the EU15 than is the case for other sectors.

Figure 1a. Training proportions by Industry: EU26

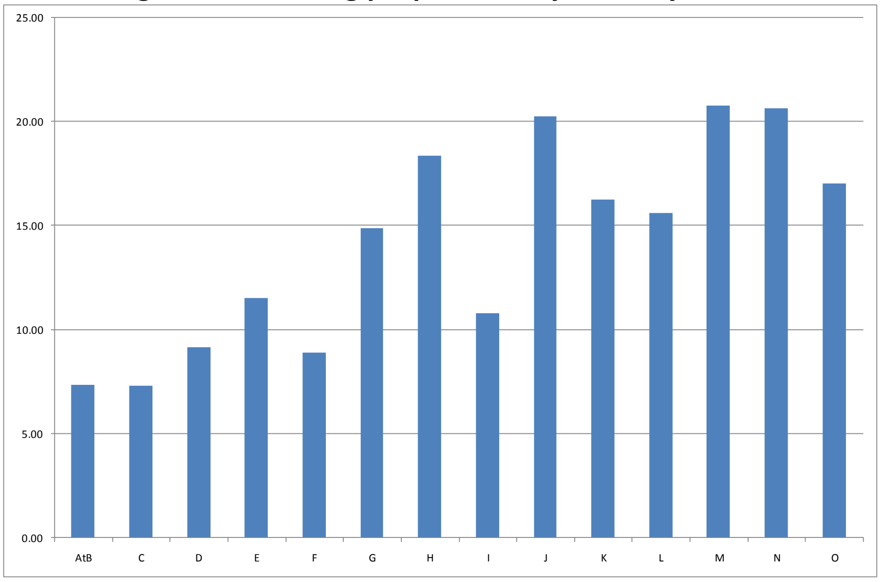
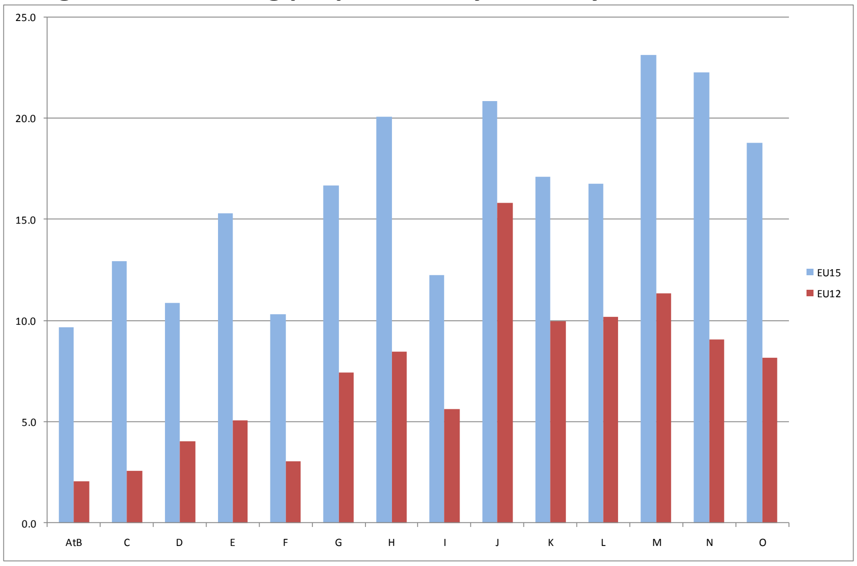


Figure 1b. Training proportions by Industry: EU15 and EU11



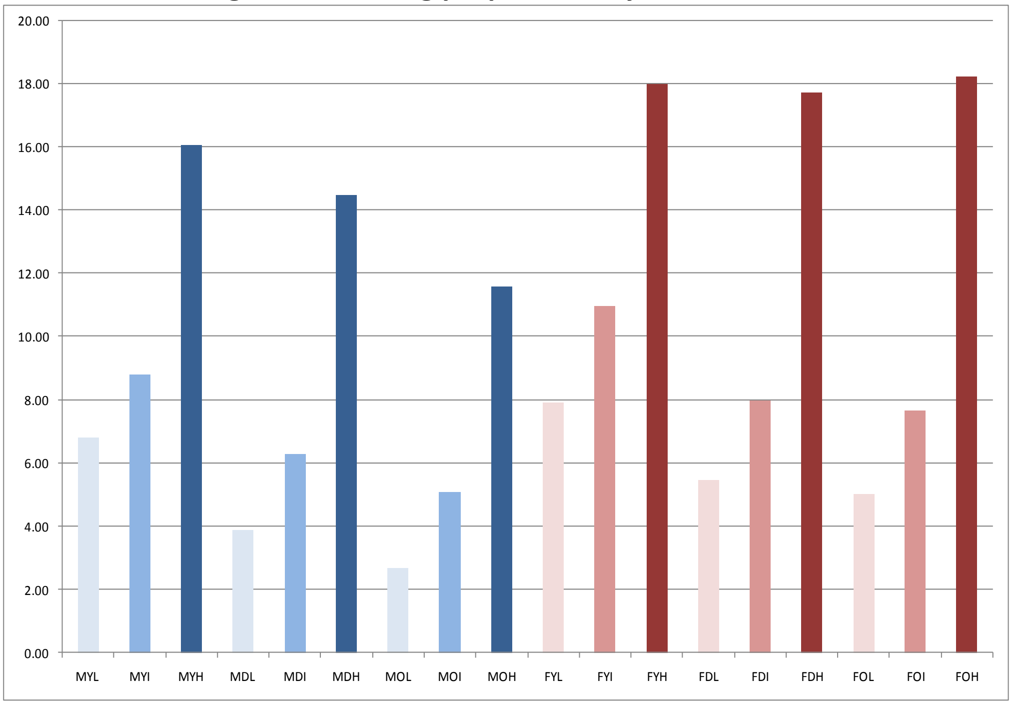
Notes: AtB = Agriculture, Forestry & Fishing; C= Mining; D = Manufacturing; E = Electricity, Gas & Water; F = Construction; G = Distribution; H = Hotels & Catering; I = Transport and Communications; J = Financial Services; K = Business Services; L = Public Administration; M = Education; N = Health and Social Services; and O = Other Personal Services.

3.1.2 Characteristics of workers who receive training

We next consider the characteristics of those receiving training. O'Mahony and Peng (2008), using UK data, presented evidence that propensity to receive training decreased with age and increased with skill level, with males slightly less likely to receive training on average than females. Below we summarise this information for the EU as a whole for 2006, dividing into 18 separate groups, using the notation in the footnote to the Table. 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.

There are some differences across countries in this general pattern, with some showing far less variation across the groups than others. Table 2 shows the coefficient of variation of the training proportion across the 18 characteristic groups by EU country. This 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.

Figure 2. 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.

Table 2. Coefficient of variation in training proportions across 18 characteristic groups, 2006

AT	0.59		IT	0.75		CZ	0.99
BE	0.59		LU	0.47		EE	0.85
DE	0.78		NL	0.40		HU	0.88
DK	0.30		PT	0.63		LT	1.15
ESP	0.55		SE	0.42		LV	0.87
FI	0.42		UK	0.35		PL	1.01
FR	0.40					RO	1.05
EL	0.89		BG	1.19		SI	0.70
IE	0.52		CY	0.76		SK	1.04

Similar patterns to those in Figure 2 are apparent if we divide by industry group, although the sample sizes tend to be very small for some industries. 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.

3.1.3. Quality of Training

This section considers a number of measures that yield information on the quality of training received. These include purpose of training, duration of training, whether training occurs during working hours and field of training. These questions 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 3. On average workers who receive training in the past 4 weeks are trained for about 12 hours or about 1.5 days in the EU as a whole. 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 1 and 3 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).

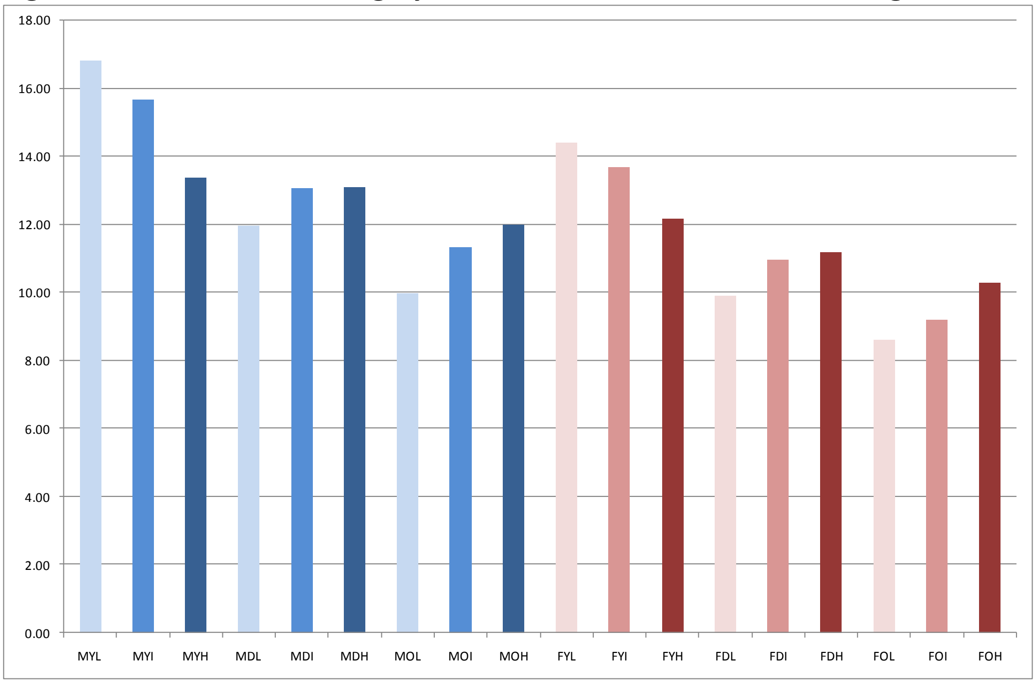
Table 3. Average duration of training (hours),average 2003-06

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 3 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 for the youngest age group, 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 2 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 3. 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 Carmichael et al. 2009. As the response rate is also low for this question and the number of categories is large, we have aggregated to six groups described in Table 4. 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 SSE or SSBL.

Table 4. 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

3.1.4. Training of migrants

This section considers the training experience of migrants versus nationals. Given the transient nature of many migration decisions it might be expected that migrants receive less training than other workers as firms are less likely to reap the benefits of training these workers. Table 5 shows the proportion of workers trained in 2006 cross classified by migration status (national versus non-nationals) and skill level for the total across 17 EU countries for which data are available (EU15 minus Greece and Ireland, plus the Czech Republic and Hungary).

Looking first at the total economy, nationals are more likely to be trained than non-nationals although the difference is not large. Dividing by skill level shows that significant differences in training propensity by nationality only occurs for the lowest skill group. Division by industry group highlights some interesting results. In manufacturing and market services the differences between nationals and non-nationals likelihood of receiving training is larger than for the total economy, with the largest differences again in the lowest skill group. In contrast in non-market services and especially in health, non-nationals are more likely to receive training with the difference most pronounced for those with high level skills. Carmichael et al. (2009) present data by country. This shows a wide range of experience. In Austria, France, Germany, Italy and Spain, non nationals are far less likely to receive training whereas in the UK and Denmark and the Czech Republic training of non-nationals is significantly greater.

Table 5. Training proportions by migrant status and skill, EU, 2006.

	Total all Workers	Total Nationals	Nationals			Total non-nationals	Non-nationals		
			High skill	Medium skill	low skill		High skill	Medium skill	low skill
Total Economy	15.5	15.7	21.2	14.2	12.7	12.5	20.1	13.6	7.2
Manufacturing	10.2	10.4	15.6	8.8	9.8	8.1	12.3	7.8	6.6
Market Services	16.2	16.4	19.4	15.8	14.8	13.9	18.7	15.6	8.9
Non-market services	20.3	20.1	24.8	17.6	14.1	25.5	30.1	26.7	13.9
Health	*21.6*	*21.4*	*28.1*	*18.4*	*15.9*	*25.6*	*33.2*	*25.9*	*13.1*

The EULFS microdata do not use consistent definitions of migrants through time to allow a complete split between EU nationals and others. Up to 2004 EU nationals were defined in the survey as citizens of EU-15 countries. Table 6 shows the proportion trained in 2004 dividing migrants into those working in an EU country who were nationals of another EU-15 country and migrants from all other countries. In total migrants who are EU-15 nationals were marginally more likely to receive training than other migrants but this occurred primarily in manufacturing. In both market and non-market services migrants from the rest of the world were more likely to receive training. This difference was most pronounced in Health and probably reflects recognition of medical qualifications within EU member states and additional training requirements for those coming from outside the EU.

Table 6. Proportions of migrants receiving training: EU nationals and other, 2004

	EU-15 nationals	Rest of the world	Nationals
Total	13.5	12.3	15.6
D	9.3	7.9	10.5
MS	13.4	14.6	16.5
NMS	22.8	25.8	19.8
Health	*23.3*	*26.7*	*20.7*

4. Training, Wages and Productivity

4.1 Training as an Intangible Investment

Investments were frequently referred to as the 'missing input' in the literature - 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. The pioneering work by Corrado, Hulten and Sichel (2005, 2006) attempted to measure intangibles for the US, defining a number of categories 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, Giorgio Marrano, Haskel and Wallis, 2007), Finland (Jalava, Aulin-Amhavarra and Alanen, 2007), Canada (Baldwin et la. 2008), the Netherlands (van Rooijen-Horsten et al. 2008) and Japan (Fukao et al. 2007) suggest also that intangibles are sizeable, although most account for lower proportions of GDP than in the US.

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 Carmichael et al. (2009). This is followed by a description of the importance of these intangible investments as shares of outputs. Then growth accounting is used to estimate the impact of intangible investments in training on output growth.

The following equation is employed to calculate intangible investments by firms in training in industry i, country j and time period t:

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

Where TI = nominal expenditures on investments in training, TR is the proportion of workers trained, HRT = hours spent training per worker, PRC is the proportion of training costs borne by firms and C is the cost of an hour's training. TR is estimated from the EULFS data summarised in Table 1 above, EMP is employment from EU KLEMS and HRT is the hours of training duration summarised in Table 3. Since hours are reported for the previous 4 weeks, this is converted to an annual basis, allowing for time lost due to holidays and other forms of absence. Hourly costs C will have two elements, the direct costs of training (costs of running courses or external fees) and the opportunity costs due to production foregone while. The latter is estimated by the average labour compensation of employees taken from EU KLEMS.

There is much less information available to estimate the direct cost. Here we assume the ratio of total to opportunity costs is equal to two, which is based on UK survey data reported in Giorgio-Marrano and Haskel (2006). Finally, in a measure of intangible investments by firms it is important to exclude any cost borne by the workers themselves. Although we lack direct evidence on this we assume 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 - PRC(firm) is therefore estimated as the proportion of respondents who replied that training occurred entirely or mostly during working hours. Table 7 shows intangible investments as a share of value added.

Table 7. Intangible investments in Training as a % of GDP, average 2003-06

	Total	*Manufacturing*	*Market Services*	*Non-market services*
EU24*	**1.36**	**1.01**	**1.27**	**2.36**
EU15	**1.50**	**1.15**	**1.39**	**2.54**
EU9*	**0.42**	**0.24**	**0.41**	**0.91**
UK	2.69	1.99	2.50	4.62
DK	2.60	2.08	2.40	4.24
NL	2.25	1.43	2.37	3.24
FI	2.22	1.59	2.14	4.01
SE	1.90	1.23	1.89	2.96
FR	1.77	1.59	1.62	2.55
DE	1.62	1.50	1.47	2.28
SI	1.30	0.66	1.48	2.32
ES	1.02	0.76	0.80	2.60
AT	0.87	0.77	0.77	1.46
BE	0.84	0.60	0.72	1.44
LU	0.82	0.60	0.84	1.18
LV	0.75	0.35	0.50	2.25
EE	0.69	0.27	0.61	2.06
PT	0.57	0.26	0.45	1.25
LT	0.51	0.25	0.51	1.41
PL	0.49	0.35	0.47	1.01
IE	0.47	0.16	0.42	1.04
CY	0.45	0.14	0.43	0.85
SK	0.36	0.13	0.42	0.82
IT	0.33	0.17	0.27	0.81
CZ	0.20	0.14	0.16	0.57
HU	0.20	0.06	0.20	0.42
GR	0.11	0.01	0.13	0.17

*Excluding Bulgaria, Malta and Romania

Here we confine attention to 24 EU countries as industry value added data are not available for Bulgaria and Romania. In the EU 15 intangible investments in training represent 1.55 of GDP but only a third as large in the new member states. These investments represent a lower share of manufacturing GDP than in the total economy but the latter is heavily influenced by relatively high training propensities in non-market sectors such as health and education. Appendix Table A.4 in Carmichael et al. (2009) shows the share of intangible training investments of GDP for 1 digit sectors. This shows that training investments tend to be relatively high in Financial services and Business services but in many countries are also sizeable in wholesale and retail trade.

Table 7 also shows the results for individual countries, sorted from highest to lowest for the total economy. It shows the UK as the country most willing to spend on training – the figure for that country is comparable a little higher than that share of 2.45% in 2004 estimated by Giorgio-Marrano and Haskel (2006), especially since these authors' value added figures include an upward adjustment to add many types of intangible investments to output. The figure for Finland is a little higher than that estimated by Jalava, Aulin-Amhavarra and Alanen, 2007, of about 1.5% in 2005. In general intangible investment in training is a lower share of GDP in smaller countries and in new member states. However the share is much smaller for Italy than other large EU-15 countries and the figure for Slovenia, a small new member state, is comparable to Spain. The cross country pattern by broad sector is similar to that for the total economy, with some marginal differences in ranking – for example France ranks 4th in manufacturing but only 7th in non-market services.

In order to estimate the impact of these investments on productivity it is necessary to convert investment values to volumes and construct capital stocks. Following the convention in the literature set by Corrado, Hulten and Sichel (2005) we use the GDP deflator to construct volume measures and the perpetual inventory method using geometric decay and a 40% depreciation rate to construct stocks – see Carmichael et al. (2007a and 2007b) for further details. Table 8 shows growth in training intangible capital stocks and its contribution to value added growth. As a point of comparison it also shows the percentage point contribution to output growth of labour composition where it is available in EU KLEMS.

The results in Table 8 suggest that intangible capital growth from on the job training was very high in the period since 2001 in the EU15 and also relatively high in the new member states. To place this in perspective the growth rate of real tangible physical capital in the EU15 was only 2.5% per annum in the same period.[1] The contribution of intangible training capital in the EU15 is only a little below the 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, Slovenia and the UK these high growth rates translate into small but significant contributions to value added growth. Of these countries, contributions from training are above those from labour composition in France and Denmark and close in Finland and the Netherlands. Interestingly, in many countries where labour composition changes are very high, e.g. Ireland, Portugal and Hungary, the contribution of intangible training capital is small.

[1] This number, derived from EU KLEMS data, 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 8. Intangible Training capital and output growth, 2001-2005

	Growth in intangible training capital (% p.a.)	Contribution of intangible training capital to value added growth[1]	Contribution of Labour Composition to output growth[2]		Growth in intangible training capital (% p.a.)	Contribution of intangible training capital to value added growth[1]	Contribution of Labour Composition to output growth[2]
EU24	9.15	0.12		**LU**	14.06	0.12	
EU15	9.25	0.14		**NL**	17.91	0.40	0.48
EU15ex[3]	9.48	0.15	0.19	**PT**	0.80	0.00	0.85
EU9	6.01	0.03		**SE**	5.08	0.10	0.33
				UK	8.94	0.24	0.39
AT	2.94	0.03	0.21				
BE	6.68	0.06	0.16	**CY**	17.16	0.08	
DE	2.46	0.04	0.12	**CZ**	2.77	0.01	0.37
DK	5.84	0.15	0.15	**EE**	5.14	0.04	
ES	17.93	0.18	0.49	**HU**	9.07	0.02	0.93
FI	8.67	0.19	0.26	**LT**	15.29	0.08	
FR	21.60	0.38	0.26	**LV**	7.80	0.06	
GR	20.30	0.02		**PL**	3.49	0.02	
IE	8.41	0.04	0.63	**SI**	15.90	0.21	0.76
IT	8.60	0.03	0.21	**SK**	8.31	0.03	

1. Column 1 times share in value added; 2. Source EU KLEMS; 3. Aggregate across EU15 countries for which growth accounts are available in EU KLEMS.

Table 9 shows growth in intangible training capital and contributions to output growth by broad sector. Training capital is most important in non-market sectors - in the EU aggregates and all individual countries the contributions are greater in non-market services than in the total economies. The Table also shows that contributions are significantly higher in market services than manufacturing in the EU and in all countries other than the Czech Republic. Growth rates of intangible training capital and contributions to value added in individual sectors are shown in Appendix Table A.5 and A.6, of Carmichael et al. (2009), respectively. These show the highest contributions in Health as expected, with intangible training capital also important in financial services, business services and wholesale and retail trade.

Table 9. Intangible Training capital and output growth, 2001-2005, sector

	Growth in intangible training capital (% p.a.)			Contribution of intangible training capital to value added growth		
	Manufacturing	**Market Services**	**non-market services**	**Manufacturing**	**Market Services**	**non-market services**
EU24	5.97	9.88	10.04	0.06	0.13	0.24
EU15	6.03	9.97	10.13	0.07	0.14	0.26
EU9	3.73	6.73	6.99	0.01	0.03	0.06
AT	2.67	3.51	6.01	0.02	0.03	0.09
BE	4.88	6.13	9.18	0.03	0.04	0.13
CY	14.03	12.89	23.00	0.02	0.06	0.20
CZ	4.54	0.99	3.92	0.01	0.00	0.02
DE	1.43	2.86	3.68	0.02	0.04	0.08
DK	2.24	6.37	6.60	0.05	0.15	0.28
EE	6.14	9.83	1.86	0.02	0.06	0.04
ES	17.90	17.17	17.89	0.14	0.14	0.47
FI	6.71	8.50	9.71	0.11	0.18	0.39
FR	23.57	23.39	19.30	0.37	0.38	0.49
GR	18.05	17.37	19.74	0.00	0.02	0.03
HU	5.38	8.28	10.53	0.00	0.02	0.04
IE	-0.80	8.06	10.16	0.00	0.03	0.11
IT	2.12	7.04	12.51	0.00	0.02	0.10
LT	16.74	20.69	11.30	0.04	0.11	0.16
LU	6.23	16.04	11.71	0.04	0.13	0.14
LV	2.79	8.06	7.28	0.01	0.04	0.16
NL	16.01	15.60	23.27	0.23	0.37	0.75
PL	0.95	4.55	5.02	0.00	0.02	0.05
PT	-5.96	-2.65	4.70	-0.02	-0.01	0.06
SE	2.65	5.22	5.77	0.03	0.10	0.17
SI	16.94	15.43	15.48	0.11	0.23	0.36
SK	4.42	7.67	8.56	0.01	0.03	0.07
UK	5.10	10.34	8.18	0.10	0.26	0.38

The estimates above will be sensitive to the assumptions underlying equation (1) on estimating investments and on the assumptions employed to capitalise these assets. These issues are discussed in more detail in Carmichael et al. (2009). An important sensitivity test is the impact of alternative depreciation rates – the results show a relatively small impact from changing the assumption on the depreciation rate.

4.2 Training, Wages and Productivity: Econometric Analysis

An alternative to employing growth accounting is to use econometric methods to freely estimate the impact of training on productivity and to compare with impacts on earnings. In this section we largely follow the specification in Deardon et al (2006). Thus we firstly estimate the following log form equation for labour productivity (*lnlp*),

(3) $\text{lnlp}_{cit} = \alpha + \beta\, \text{tr}_{cit} + \gamma\, \text{tr}_{cit} \cdot \ln(\text{capit/h})_{cit} + \mu \ln(\text{capit/h})_{cit} + \lambda \ln(\text{capnit/h})_{cit}$ + 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.

The analysis in this section uses data for the 17 EU countries for which input, output and productivity data at industry level are available in the EU KLEMS database.[2] This provides data on value added (VA), hours worked, labour compensation, a breakdown of capital into ICT- and non-ICT assets, and derived variables such as total factor productivity (TFP) at industry level (O'Mahony and Timmer 2009). All these input, output and productivity variables are transformed into the US dollar in 1997 by using the volume index at industry level (also provided by EU KLEMS) and 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.

The panel data employed in this analysis cover nine industries, using the EU KLEMS industry division into manufacturing (D), Electricity, gas and water supply (E), Construction (F), Trade (G), Hotels and restaurants (H), Transport, storage and communication (I), Financial intermediation (J), Real estate, renting and business activities (K), and Other community, social and personal services (O). We exclude agriculture, forestry and fishing (AtB), Mining and quarrying (C) as the proportions trained in these sectors are small and variable and the public administration sectors such as the Public admin and defence (L), Education (M) and Health and Social work (N) in order to focus on the market economy.

Productivity, wage, labour and capital inputs variables are from EU KLEMS, while training and all workforce characteristics variables are from the EU LFS. Our regressions are weighted by the average employee compensation share of each industry over the period 1995-2005, a standard approach in the literature to take account of industry heterogeneity.

Similar equations are estimated for total factor productivity (*lntfp*) and hourly wage rates (*lnw*). Labour productivity at industry level is measured as the value added per hour within the industry, hourly wage rates at industry level are measured as labour compensation per hour within the industry. Labour and capital input variables are not included in the TFP equations as they are already accounted for in the measurement of that variable.[3] Data availability on training varies by time period – see Carmichael et al. 2009 for details – hence estimations are carried out on an unbalanced panel.

The regressions were carried out using both the OLS within estimator and GMM. The latter was used to take account of the possibility of endogeneity of the explanatory regressors in growth regressions. Nickell (1981) revealed 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

[2] Austria, Belgium, Czech Republic, Denmark, Spain, Finland, France, Germany, Hungary, Ireland, Italy, Luxemburg, the Netherlands, Portugal, Slovenia, Sweden and the United Kingdom.

[3] See O'Mahony and Timmer (2009) for details of output, input and productivity measures at the industry level in the EU KLEMS database.

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) and Deardon et al (2006) also apply GMM techniques to instrument labour, capital, materials and work place practices. Their results show this approach can yield a more accurate association between the productivity growth and explanatory variables.

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. 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 and the Hansen-Sargan tests of over-identifying restrictions do not suggest misspecification of the model (see Carmichael et al 2009 for details).

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.

Turning first to the GMM regressions shown in Table 10, the effect of training alone is significant and positively associated with labour productivity and wages but is insignificant with TFP. When training is interacted with ICT capital the results for labour productivity (0.131), TFP (0.066) and wage (0.129) were all positive and significant. Note these effects were much smaller than those using the within estimator. The results in Table 10 show an important role for training when combined with ICT investments. The impact of training interacted with ICT is very similar in the labour productivity (0.131) and wage (0.129), and is much higher than in the TFP equation (0.066). Therefore these results do not support the external benefits from training arguments put forward by Deardon et al. (2006).

The proportions of workers with high education (*eduhprop*) significantly increases both labour productivity and wage (0.235), but the proportions of workers with medium education (*edumprop*) are insignificant or even negative. When high education proportions are interacted with the training proportion, the coefficients are negative for all of labour productivity, wage and TFP. Training interacted with age and gender show mixed results.

Table 10 Productivity, Wage and Training, GMM

	Lnlp		lntfp		lnw	
	(1)	(2)	(3)	(4)	(5)	(6)
tr1	0.704**	0.602*	0.354	0.353*	0.988**	0.948**
	0.384	***0.339***	***0.248***	***0.227***	***0.521***	***0.507***
tr1lnicth		0.131***		0.066**		0.129***
		0.045		***0.032***		***0.048***
lncapith	0.013	0.000			0.027***	0.014
	0.010	***0.012***			***0.008***	***0.010***
lncapnith	0.322***	0.333***			0.190***	0.197***
	0.026	***0.027***			***0.024***	***0.024***
tr1eduh	-0.191	-0.555**	-0.351	-0.508**	-1.079***	-1.501***
	0.270	***0.280***	***0.235***	***0.260***	***0.494***	***0.555***
eduhprop	0.078	0.146**			0.169*	0.235**
	0.073	***0.073***			***0.101***	***0.108***
tr1edum	-0.045	-0.215	-0.429**	-0.556***	0.340*	0.194
	0.239	***0.250***	***0.210***	***0.217***	***0.210***	***0.222***
edumprop	-0.088	-0.058			-0.290***	-0.257***
	0.067	***0.068***			***0.061***	***0.063***
tr1age29	-0.848**	-0.390	-0.375	-0.273	-1.317***	-1.044***
	0.368	***0.343***	***0.259***	***0.246***	***0.436***	***0.396***
age29prop	0.185**	0.142*			0.132	0.098
	0.089	***0.091***			***0.099***	***0.099***
tr1age49	-0.890**	-0.850**	-0.148	-0.180	-1.127**	-1.132**
	0.416	***0.432***	***0.252***	***0.260***	***0.597***	***0.588***
age49prop	0.154*	0.164*			0.307***	0.286***
	0.088	***0.094***			***0.108***	***0.107***
tr1male	-0.038	0.050	0.057	0.132	-0.073	0.024
	0.258	***0.245***	***0.206***	***0.199***	***0.203***	***0.201***
maleprop	-0.090	-0.114			-0.037	-0.056
	0.076	***0.076***			***0.068***	***0.067***
Country Dummy	No	No	No	No	No	No
Industry Dummy	No	No	No	No	No	No
Year Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Obvs	1115	1115	1077	1077	1115	1115

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

To explore the training effect in different education systems, a more sophisticated specification is applied on this framework. Drawing from the work of Estevez-Abe et al (2001, Table 4.3, p170), we categorize the education systems of the EU15 countries into three groups: Vocational-oriented (Austria, Germany, Sweden and Finland), Academic-oriented (Italy, France, Ireland, the UK, Spain and Luxemburg) and Mixed (Belgium, Netherlands, Denmark and Portugal) and include a fourth group which we term new-comers (Hungary, Czech Republic and Slovenia).[4] Dummy variables for these four groups are cd1-cd4 respectively, which are interacted with training (and training interacted with ICT capital) variables. The vocational-oriented group is used as the baseline group. Since vocational and

[4] Estevez-Abe et al. (2001) do not categorise all countries for which data are available in this report. Based on discussions with researchers from these countries, we classified Spain to the academic group and Portugal to the mixed group.

academic-oriented groups include all big economies in the EU, they dominate the overall tendency in our estimation. The results of these regressions are shown in Carmichael et al. (2009). Here we report just a summary of the coefficients on the training terms (Table 11).

Table 11. Training and Education Systems. Summary of GMM results

Training	labour productivity		TFP		Wages	
Vocational	0.433	0.576	0.377	0.497	0.665	0.909
Academic	0.938***	0.744	0.751***	0.650	0.841	0.768
Mixed	0.605**	0.590	0.490	0.566	0.894**	1.044
New comers	0.171**	0.251***	0.140*	0.271*	0.837	1.021
Training interacted with ICT						
Vocational		-0.004		0.037		0.068
Academic		0.250***		0.152*		0.302***
Mixed		0.081*		0.058		0.072
New comers		0.219***		0.104		0.187*

Notes: ***, ** and * denote significance difference relative to base (vocational) group at 1%, 5% and 10% levels, respectively.

The effect of training alone on labour productivity is insignificant for the vocational-oriented group. However, training alone has a much higher effect in the academic-oriented group and a little higher in the mixed group. The effect of training is relatively small for the new comers. When training is interacted with ICT capital, all groups have higher impacts than the vocational group and especially so for the academic group. The coefficient on the interaction term is also relatively high for the new comers, compensating to some extent for the low value for training on its own. Similar results tend to hold for the TFP and wage equations, although values for the mixed group are not significantly difference from those for the vocationally oriented group. In no country grouping do we find much higher impacts on productivity than on earnings, again casting doubt on the external benefits from training argument of Deardon et al. (2006).

Therefore, focusing on the more theoretically defensible GMM results yields some interesting conclusions. Firstly, training alone has positive or insignificant overall effect on labour productivity, TFP and wage. Positive effects of training alone on productivity and wage are more evident for academic-oriented and mixed groups, but much less in the new members. Secondly, training combined with ICT capital has a significantly positive effect on productivity and wage in all specifications. The academic-oriented group can benefit more from training combined with ICT capital than other groups. Finally, new member states also have higher effects from training combined with ICT capital than the vocational oriented group of countries. It suggests that even with a lower overall effect of training on productivity and wage, the ICT investment combined with training can help them to catch up with the advanced economies in Europe.

4.3 Training and ICT

An alternative to looking at interactions between training and ICT in a production function is to consider the direct impact of training on adoption and use of ICT. Cross country, cross industry and cross firm analyses show how important a successful adoption of the ICT is for the competitiveness of firms and the development of a country as a whole. In general, ICT is found to contribute positively to GDP growth (O'Mahony and Vecchi, 2005;

Oulton, 2002); and firm's productivity (Matteucci et al, 2005; Gust and Marquez, 2004). At the macro level, researchers have analysed the determinants for the adoption and diffusion of ICT, which include the overall educational level of the population, real per capita income, openness, industrial structure, geographical location and relative price of the adoption across countries (for a detailed discussion, see Pohjola, 2003). On the micro side, research is often concerned with quantifying the impact of such determinants as firm level human capital (number or proportion of skilled labour), workplace organisation, benefits and costs of adoption, absorptive capacity induced mainly by training as well as initial human capital, competition and other firm specific fixed effects (see Hollenstein (2003), for a survey of literature). However, the industry or micro-level determinants of ICT adoption and diffusion are not so widely investigated due to lack of data in the past. The combination of EU LFS and EU KLEMS data allows an examination of the direct link between ICT and training.

We estimate a series of industry level short-run demands for ICT using the following OLS (with fixed effects) mode, for industry I and country j:

$$(ICT/K)_{i,j,t} = TR_{i,j,t-1} + EDU_{i,j,t} + AGE_{i,j,t} + GENDER_{i,j,t} + \mathrm{X}_{i,j,t-1} + \varphi_i + \gamma_j + \eta_t + \varepsilon_{ijt}$$

where ICT/K is the proportion of ICT capital, *TR* is the proportion of workers who undertake training during the last four weeks; *EDU* has three categories: proportions of workers with lower secondary, upper secondary and third level education; *AGE* comprises three categories, proportions of young (15-29), medium aged (30-49) and older (50+) workers; *Gender* is the proportion of male workers; ***X*** includes production function variables, namely, log of value added, log of capital and log employment. Industry (φ), country (γ) and year (η) dummies are included in the estimation and ε_{ijt} is the usual disturbance term.

Estimations using only the current level variables may be subject to the problem of endogeneity either because ICT investment and training decisions are made simultaneously by the management. Therefore, we use lagged explanatory variables. Carmichael et al. (2009) also report results when current values are used – these do not alter the conclusions. The regression results are presented in Table 12. The overall fit of the model is good with about 70% of the variation explained. As expected, the skill and human capital indicators are the strong predictors of ICT adoption. A one percentage point increase in the training proportion can predict about half a percentage point increase in the ICT adoption. The contribution of educational attainment to ICT adoption increases substantially by education level. Age and gender profiles within an industry do not seem to have individual impacts, but there is an indication that ICT adoption is more prevalent in industries where the majority of the workers are young (aged 15 – 29). Value added is positively correlated with ICT adoption, a finding consistent with Bresnahan et al. (2002), possibly indicating that ICT adoption at the industry level is related to greater success of the firms within the entire industry. The level of capital investment shows no effect on the ICT adoption, but the number of employees, usually an indicator of the size of an industry, has a significant negative impact on the ICT adoption.

The cross products introduced in the regression reveal that the impact of training and education is gender and age specific. In general, training males appears to be beneficial for the ICT adoption. But the training of different aged workers doesn't seem to matter even though there is an indication that training the older workers (aged 50+) is negatively correlated with ICT adoption. An interesting finding is that training provided to the workers with higher educational attainment yields less contribution to the ICT adoption than the training provided to the workers with low educational attainment. The possible reason is that the marginal benefit from training the less educated workers may be higher – they gain greater amount of skill per training provided – than their highly educated counterparts, and so, firms which train less educated workers may increase the overall skill level of the workforce in greater margins which aids in adoption of ICT.

As mentioned earlier, higher proportion of male workers aged 50+ in a given industry is associated with lower proportion of ICT capital. However, the most puzzling result is that higher proportion of male workers with higher educational attainment is also found to be contributing less to the ICT adoption. When we put these two impacts together, it will be obvious that the older male workers with high educational attainment appear to have a negative association with ICT adoption. O'Mahony and Peng (2008) find that ICT adoption adversely affects the wage share of high skilled males aged 50+. They argue that faster skill depreciation, less training opportunity and less willingness of training take-up at old ages can partly explain the reason. They find that older males tend to refuse the training offer more frequently than younger males and females of the same age, particularly when they have higher degrees. This finding can be helpful for us to interpret the puzzle. If older male workers tend to refuse more training offers, they will then accumulate less modern skills which are preconditions to adopt ICT. Firms with less modern skilled employees will tend to have less incentive to adopt new technology (Chander et al, 2004).

Table 12. ICT demand as a function of human capital (1995 – 2005)
Dependant Variable: ICT/K, (No. Obs = 1957)

	Coefficient	Std. Error		Coefficient	Std. Error
TRAINING	0.419***	2.72	TRAINING * MALE	0.323***	3.43
EDU- (medium level)	0.180***	2.93	TRAINING * AGE (30-49)	0.028	0.12
EDU- (high level)	0.143*	1.83	TRAINING * AGE (50+)	-0.325	-1.24
MALE	-0.062	-0.4	TRAINING * EDU (medium level)	-0.676***	-3.48
AGE- (30-49)	-0.025	-0.17	TRAINING * EDU (high level)	-0.315**	-2.06
AGE- (50+)	0.355**	2.59	MALE * AGE (30-49)	0.238	1.09
Ln (Value Added)	0.010*	1.70	MALE * AGE (50+)	-0.384*	-1.84
Ln (Capital)	-0.001	-0.34	MALE * EDU (medium level)	-0.260***	-3.77
Ln (Employment)	-0.049***	-6.95	MALE * EDU (high level)	-0.270**	-2.34
Adjusted R^2 = 0.705					

Notes: ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

5. What affects on-the-job training?

Having explored the impact of on-the-job training on employment and wages we now turn our attention to what factors affect individual employees' decision to train. There is a considerable previous literature which considers this question for a range of time periods and countries. One of the seminal papers for on-the-job training is provided by Mincer (1962), who uncovered some socio-economic patterns. These are that lower on-the-job training is undertaken by women, blacks, those with lower incomes and those with lower levels of education. Lynch (1992) uses the youth cohort of the US National Longitudinal Survey to explore the on-the-job training experiences of young employees. She finds that on-the-job training has a substantial impact on subsequent earnings. She also finds that females and non-whites experience a significantly lower incidence of on-the-job training. Similarly Lynch and Black (1998) using a 1994 survey of US employers find that employer-provided training was greater for employers with larger numbers of employees, for capital intensive production and for employees with existing higher levels of educational attainment. Sussman (2002) focuses on various socio-economic characteristics that affect access to job-related training in Canada.

Her main finding is that being too busy is the main constraint to employees undertaking additional training. Rubenson (2007) finds, using Canada's Adult Education and Training Surveys, that the strongest impact of on-the-job training is made by the existing level of education of the employee. Other papers that address this issue include Krueger and Rouse (1998), Wooden et al (2001),

Vignoles et al (2004), using the individual-level panel data from the UK National Child Development Study (NCDS), find that there is a great deal of selection by employers as to which employees to engage in on-the-job (lifelong) training. Employers seem able to select those employees who benefit the most, in terms of their wage, from their training. This implicitly also means it is those employees whose productivity can increase the most who are selected for on-the-job training. In our research, we are interested in identifying those demographic and economic characteristics that are, for a sample of EU countries, consistently associated with a higher probability of on-the-job training.

We address this question by carrying out an econometric analysis on individual-level employee data from the European Union Labour Force Surveys (EU LFS) for the years 2003 to 2007. The dependent variable is ECUD4WN which records if the employee undertook any training in the previous four weeks is our indicator of on-the-job training. The dependent variable is binary zero-one, so Probit regressions are used for the analysis and marginal (probability) effects are also reported to aid the interpretation. The explanatory variables include as many demographic and economic characteristics as are important and are consistently available in the dataset. Country-specific Probit regressions are run for a representative sample of EU member states, these are: Austria (AT), Belgium (BE), Germany (DE), Denmark (DK), Spain (ES), Finland (FI), France (FR), Italy (IT), Netherlands (NL), Sweden (SE) and the United Kingdom (UK). The next sub-section reviews the EU LFS data, followed by the discussion of the Probit marginal effects.

5.1 The EU Labour Force Survey Data

Our analysis is based on individual-level data from the EU LFS, from 2003 where we select only employees. The dependent variable, EDUC4WN, has been summarised in the descriptive section 3 above. In this section we present a short summary of the explanatory variables (regressors) and the reasons why they are included – further details are available in Carmichael et al. (2009). To clarify the exposition we divide our regressors into three broad categories: Demographic, Economic and Temporal.

Regressors: Demographic Characteristics

Variable	Min	Max	Description
AGE_	0	1	Ten 5 yearly age bands
FEMALE	0	1	Female employee.
MARITAL_MARRIED			Marital status: married.
MARITAL_W_S_D			Marital status: widowed, separated or divorced.
MARITAL_SINGLE			Marital status: single.
EDUCATION_L	0	1	Education low : ISCED 0(no formal), 1(primary), 2(lower secondary), 3c(<2years).
EDUCATION_M	0	1	Education mid : ISCED 3abc(upper secondary), 4(post secondary)
EDUCATION_H	0	1	Education high: ISCED 5ab(1st stage secondary), 6(2nd stage secondary)
URBAN_DENSE	0	1	Densely-populated area.
URBAN_INTERM	0	1	Intermediately-populated area.
URBAN_THIN	0	1	Thinly-populated area.
NATIONAL_HOME	0	1	Nationality of home country.
NATIONAL_FOREIGN	0	1	National of foreign country.

The AGE_ variables are included in order to model the expected non-linear decline in training that occurs with age. The impact of being female on training may vary by country according to various other factors, such as the level of female participation in the labour market. In terms of urbanisation, our prior is that more densely populated urban areas will have easier access to educational facilities for on-the-job training.

Regressors: Economic Characteristics

Variable	Min	Max	Description
TENURE	1	52	Number of years with current employer.
TENURESQ	1	2704	TENURE squared
HWUSUAL	1	80	Number of hours per week usually worked in first job
PARTTIME	0	1	Part-time employee.
TEMPORARY	0	1	Temporary employee.
LOOKOJ	0	1	Looking for another job.
HOMEWK_USUALLY	0	1	Usually works from home.
HOMEWK_SOMETIMES	0	1	Sometimes works from home.
HOMEWK_NEVER	0	1	Never works from home.
ISCO_0	0	1	0: Armed forces.
ISCO_1	0	1	1: Legislators, senior officials and managers
ISCO_2	0	1	2: Professionals
ISCO_3	0	1	3: Technicians and associate professionals
ISCO_4	0	1	4: Clerks
ISCO_5	0	1	5: Service employees and shop and market sales employees
ISCO_6	0	1	6: Skilled agricultural and fishery employees
ISCO_7	0	1	7: Craft and related trades employees
ISCO_8	0	1	8: Plant and machine operators and assemblers
ISCO_9	0	1	9: Elementary occupations. This is the excluded/control category in the regressions.

TENURE and TENURESQ are variables capturing the number of years the employee has been with the current employer.. We expect the probability of undertaking training to increase with tenure but at a decreasing rate. We therefore expect a concave quadratic profile with a positive parameter on TENURE and a negative parameter on TENURESQ. Note that age is already controlled for in the Probit regressions. Temporary employees may have higher probabilities of having had training if this is self-financed but a lower probability of receiving firm-paid training. Unfortunately, we do not know from the data who it was that paid for the training. Looking for another job may discourage training if it takes up too much time. Conversely looking for another job may encourage training if it improves the respondent's outside employment opportunities. ISCO_0to9=0,1 are ten binary variables capturing one-digit categories for the European Union variant of the "International Standard Classifications of Occupations", the ISCO-COM (88). With the exception of ISCO_0=1 that captures those in the military, the other categories can be interpreted as a rough measure of status in the occupation with ISCO_1=1 having the highest status and ISCO_9=1 having the lowest status. These nine binary variables can also be viewed as a rough proxy for earnings, which are not available in the EU LFS datasets. The excluded control category in these regressions is the lowest status ISCO_9. We have no strong prior on the effect of these ISCO variables on the probability of training. It may be that higher status occupations are associated with more training opportunities. Conversely, the highest status occupations may have already achieved all the training required for the occupation and may feel no further need to train. The existing literature suggests that the probability of on-the-job training should increase with the job status of the employee.

In addition we also include some temporal dummy variables. QUARTER_(1/2/3/4)=0,1 are binary variables capturing the quarter corresponding to the survey reference week and are intended to capture if there is a seasonal cycle to when individuals are likely to undertake on-the-job training. For example, QUARTER_3 may be a quarter when less on-the-job training is undertaken because employees are more likely to be on holiday. Conversely, it may be associated with a higher probability of training if employees see the holiday period as an opportunity to train. YEAR_(2003/2004/2005/2006/2007)=0,1 are binary variables capturing the year of the interview reference week. The excluded control year is 2007 and we can see from the regression results which other years have been excluded from the regression because of data unavailability.

5.2 Probit regression results

Since EDUC4WN is a binary 0/1 variable, limited dependent variable regression rather than OLS is the appropriate statistical tool for the analysis. The analysis in this section employs a probit estimation, details of which are given in Carmichael et al. 2009. The estimated parameters are difficult to interpret directly, so the discussion below is in terms of marginal effects which provide a measure of the change in the probability of the regressand from changes in the regressors. If the regressors are binary, the marginal effects provide a measure for the change in the binary variable on the probability of a positive outcome on the regressand. For example, they give the change in the probability of being trained (EDUC4WN=1) for a woman as compared to a man (FEMALE=1). If the regressors are continuous (i.e. TENURE, TENURESQ and HWUSUAL in our estimates) the marginal effects give the slope of these functions with respect to the probability, e.g. the estimated parameter on HWUSUSAL gives the change in the probability of being trained from working an extra hour. Marginal effects can be calculated for any set of characteristics but they are most often, as here, based on the mean characteristics for the sample under analysis.

The marginal effects from country-specific Probit regressions are given in Appendix Table 1. The AGE dummies are significant in the Probit regressions for every country - the young have the highest probability of undertaking training and this probability declines, at a diminishing rate, with age. The effect of being FEMALE is mixed, associated with a lower probability of undertaking on-the-job training in Germany, Spain, France, Italy and the Netherlands, and associated with a higher probability of undertaking on-the-job training in Denmark, Finland, Sweden and the UK. It is likely these results reflect the degree of female labour market participation within each respective country. The results for marital status show no clear patterns although the parameter estimates for most countries are statistically significant but with different signs.

EDUCATION_H and EDUCATION_M seem to have the effect of increasing the probability of undertaking on-the-job training when compared to EDUCATION_L for the vast majority of countries. This suggests that on-the-job training is a complement to existing educational attainment. One exception is Denmark where the results are mixed with EDUCATION_M reducing the probability of undertaking more training and EDUCATION_H increasing this probability. The other notable exception is Germany with EDUCATION_H and EDUCATION_M begin associated with a lower probability of undertaking on-the-job training, suggesting it may act as a substitute to compensate for lower previous educational attainment rather than a complement to it.

A dense urban environment is associated in most cases with a higher probability of undertaking on-the-job training in most countries. This result seems reasonable if dense urban areas have easier geographic access to adult educational facilities. However, this pattern is not universally true such as in the cases of: Spain, Sweden and the United Kingdom.

Being a foreign national (NATIONAL_ FRGN) is almost universally associated with a significantly reduced probability of undertaking on-the-job training. It is easy to envisage situations where nationals of the home country have better access to on-the-job training facilities. The three exceptions to this general result are Denmark, the Netherlands and the United Kingdom. In these three countries being a NATIONAL_ FRGN is actually associated with a higher probability of undertaking on-the-job training. This situation could possibly come about if Denmark, the Netherlands and the United Kingdom attract a large number of non-EU nationals who simultaneously undertake both paid work and studies, this may be explained by the existence of a large number of non-EU students in higher education. As noted above it can also reflect the high usage of foreign workers in the health sectors in some countries, most notably the UK.

The results for the parameter estimates on TENURE and TENURESQ indicate for most countries a concave function with respect to on-the-job training - the probability of on-the-job training is increasing with the length of tenure but at a decreasing rate. This, obviously, suggests that the longer an employee has been in a job the higher the probability of undertaking on-the-job training. Note that the effect of age has been controlled for by the included age variables.

Longer usual hours of work, HWUSUAL, are associated in every country with a reduced probability of undertaking on-the-job training and tThe significant positive parameter estimates on PARTTIME (except for Sweden) indicate part-time employees have a higher probability of undertaking on-the-job training. Being a TEMPORARY employee is in every country associated with a higher probability of undertaking on-the-job training. This result is evidently supported if the current employment is perceived as a transitional job in expectation of undertaking better employment once the on-the-job training is successfully completed.

The impact of looking for another job (LOOKOJ) varies a great deal by country. In some cases it is not significant but in some cases it can have a significant positive or negative impact of having undertaken on-the-job training in the previous four weeks. Evidently, in some countries undertaking on-the-job search is a complement to on-the-job training while in other countries these two activities are substitutes.

Working from work (HOMEWK_USUALLY /SOMETIMES =1) has the almost universal strong effect of increasing the probability of undertaking on-the-job training. The flexible working practices associated with being able to work from home may be correlated with increased training opportunities. However the results also suggest that those employees who <u>usually</u> work from home actually have lower on-the-job training opportunities that those who only <u>sometimes</u> work from home.

The ISCO dummies capture the "status" of the occupation and are highly correlated with earnings and/or wealth. ISCO_9 (elementary occupations) is the excluded category and is the one associated with the lowest earnings. The probability of on-the-job training increases monotonically as we move from ISCO_8 to ISCO_2 (professionals). ISCO_1 (legislators, senior officials and managers) has a probability of on-the-job training that is slightly lower than ISCO_2. The parameter on ISCO_0 varies from country to country regressions, indicating different impacts on training for different national armed forces.

Finally no systematic patterns emerge with respect to the QUARTER dummies, other than QUARTER_3 (July to September) is typically associated with a lower probability of on-the-job training.

The analysis presented was extended to take account of different systems of education provision by comparing Austria and Germany to France and the UK. In Austria and Germany the general education systems place high emphasis on vocational training whereas in France and the UK general education is recognized as being largely academic in nature. Without any prior pre-conceptions, we wish to investigate whether the vocational versus academic nature of education affects the probability of undertaking on-the-job training. The results of this extension are presented in Carmichael et al. (2009) and are just summarised here.

First adding a 'Vocational' dummy, taking the value 1 if the observations comes from Austria or Germany has the effect of reducing the probability of undertaking on-the-job training. Specifically, all other things being equal, for the mean respondent being in a country with vocational-oriented education systems, training is associated with a 3.92 percent lower probability of undertaking on-the-job training. Including interactions between the vocational dummy and other variables also yields some interesting conclusions. For example this indicates that being female in a country with vocational training is associated with a much lower probability of undertaking on-the-job training. Individuals in countries with vocational education systems tend to undertake more education the younger they are while those in countries with academic educational systems undertake more education the older they are. For those with an existing higher or medium level of education the probability of undertaking additional on-the-job training is actually lower in vocational oriented countries. Against this the results for the occupational dummies suggest that in countries with vocational educational systems the positive association between job status and on-the-job training is magnified.

This interesting result on lower probabilities of training in more vocationally oriented countries could come about if much of what is taught in general vocational training in countries such as Austria and Germany needs to be learned on the job in countries where the school curriculum focus on more academic subjects. However it could also be consistent with other explanations such as lower willingness to undertake training by workers or a proxy for different types of labour market institutions.

5.3 Determinants of the field of training

The analysis was further developed to explore the determinants of training participation by type or field of training. In this analysis we examine in more detail the relationships between training field and (i) educational systems (whether a country is more vocationally or more academically orientated); (ii) age; (iii) education and; (iv) gender. The sample for this part of the research was restricted to those who had attended informal training courses within the last 4 weeks. The research methodology involved the estimation of multinomial logit estimations (see Carmichael et al. 2009 for details of the method) for which the categorical dependent variable, field of training, was constructed as follows:

Outcome 0: General: General programmes and arts; the base outcome
Outcome 1: Social Science: Social science, business and law
Outcome 2: Science: Science and engineering
Outcome 3: Computing: Computer science and use
Outcome 4: Health: Health (including agriculture and veterinary) and education
Outcome 5: Services

The data set comprises annual series (2004-2006) for the UK, France, Austria and Germany. Regressions were run including the dummy variable VOCATIONAL (= 1 for Germany and Austria) and including interactions terms with the VOCATIONAL dummy variable. The independent variables included in the estimations closely mirror those in the training participation estimations; e.g. variables indicating individual characteristics (e.g. age and marital status) and controls for job specific characteristics (e.g. TENURE, TEMPORARY, PARTTIME and ISCO1D occupational dummies). In addition, industry sector dummy variables for current economic activity were also included.

The results of the multinominal regressions are reported in Carmichael et al. (2009). The main conclusions that emerged from this are as follows. The odds ratios associated with the vocational dummy variable are consistently less than one and significant. This implies that relative to general training the odds of an individual undertaking training in any of the other fields is significantly less in the more vocationally orientated countries (Germany and Austria) compared with the more academically orientated countries (the UK and France). These differences are most pronounced for training in social sciences and are also large for science and computing. The difference is less in relation to training in health and even smaller in relation to services. These results appear to be consistent with the notion that vocational training at school level can substitute for specific skills required in the workplace.

Some interesting results also emerge regarding the demographic variables. The results indicate that the relationship between age and training participation depends to some extent on the type of training being undertaken since the impact of age varies according to training field. For example the odds of training in social science, science and services (relative to general training) are less than 1 for all age groups over 42 (indicating that older workers are less likely to be involved in these fields of training relative to general training). However, the relative odds of training in computing and health appear to be higher for some older people below 60. The results indicate that, compared with general training, males are significantly more likely than females to undertake any kind of specialised training.

Looking at education variables, for social science and science training, educational attainment has no significant effect (at the 5% level or above) on participation relative to the base category. However, having attained a higher level of education lowers the relative odds of participating in computer related training and having attained either an intermediate or higher level of education lowers the relative odds of participating in services training (even after controlling for industry sector). In contrast, the odds of undertaking health related training (relative to general training) are higher for those who have attained a higher level of education.

In summary the results indicate that participation in training is conditioned by type or field of training since, for trainees, participation in alternative training fields is not random. For example, while the overall relationship between age and training participation is clearly negative, among trainees, workers over 44 are more likely to participate in general training and training in health and computing. In contrast, younger trainees are more likely to be involved in services training although they are also more likely to be involved in general training. Female trainees are more likely than males to be involved in general training while male trainees are more likely to be involved in any other kind of training than either general training or training in health. More educated trainees are most likely to be involved in health and social science related training and least likely to be involved in training in computing and services. Regardless of age, gender or educational attainment, trainees in more academically orientated countries are more likely to be engaged in non-general training than trainees in more vocationally orientated countries and the latter are more likely to be involved in general and services training than any other kind of training.

This analysis helps policy makers identify which characteristics affect the probability of undertaking on-the-job training. We must, however, be cautious in not automatically assuming this means we must recommend increases in on-the-job training. There is a much more subtle question as to the effectiveness of this on-the-job training on the efficiency of the workforce. Until the EU LFS microdata releases a measure of labour efficiency, such as the wage, this remains a challenging question to address directly.

6. Incentives and disincentives to train for older and less skilled workers

This section explores reasons for lower training rates among older and less skilled workers. It sets out theoretical perspectives on incentives in terms of the costs and benefits of training and then relates these theoretical ideas to empirical evidence on barriers to training.

6.1 *Theoretical considerations; the costs and benefits of 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. For unemployed workers who participate in training, the expected gains may additionally derive from enhanced employability. The costs of training for the individual will vary according to a number of factors which will include whether or not training takes place on the job or not, whether the employer pays the direct costs of training, the duration of the training, how arduous or how difficult the training is and how much effort is involved. If training is not fully incorporated into time at work then individuals may also incur forgone or lower earnings and loss of leisure time. The net benefits of training will therefore vary according to the type of training being considered, the employment to which it is relevant, the characteristics of the individual concerned and the duration of time over which the benefits of training can be earned and therefore compensate for costs incurred.

For employers, the benefits from training derive from expected increases in productivity leading to higher profits. Employers accrue training costs in the form of course fees, payments to instructors, supervision costs and foregone output while an employee participates in training. As these costs will vary to some extent depending on the characteristics of trainees, they will tend to provide more training opportunities for those workers for whom they perceive the costs of training are lower and the long-term benefits from increases in productivity are higher

Human capital theory predicts that the extent of any net benefits from job-related training (to either or both employees and employers) will critically depend on the likely length of tenure of the employee, the return to training in terms of higher wages and the effectiveness of training. All of the factors potentially have a negative impact on the incentives of older people to undertake training while the latter also has implications for low skilled workers of any age if these are attributable to lower ability.

In relation to length of tenure, the earlier any training is undertaken the greater the likely return to both the trainee and the employer. This follows since the period during which the gains from higher productivity, and the consequent flow of higher, discounted earnings are received will be longer. Since older employees have fewer years of employment to recoup any training costs (for themselves or their employer), human capital theory predicts that older workers will not only be less motivated to accept any offers of training that come their way but they will also be less likely to be offered training in the firs place. Against this there is a general perception that older workers exhibit greater employment stability than younger employees, so that expected years with the firm will not be synonymous with years to retirement. Also, where depreciation rates for investment in training are very high, the impact of age will be relatively minor.

Since there is a positive relationship between age and earnings (due to career progression and seniority), any forgone earnings costs associated with training will increase with age. This will act as a further disincentive for older people to invest in human capital since it reduces the rate of return to such investments. However, for older workers in low skilled jobs where there is little or no reward to seniority, age will be less of a factor in determining willingness to accept offers of training. Nevertheless, the direct costs of any training that is not financed by employers or the government, will be higher (relative to their income and wealth) for generally less well-off, lower skilled workers (of any age). Therefore, training costs are more likely to impact negatively on the training incentives of lower skilled workers. However, while these costs may be similar for all low skilled workers, the net effect on the motivation to train will be greater for older workers since, as discussed above, they have less time in which to recoup such costs.

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 above arguments indicate that the lower training rates observed among older people as well as less skilled people, as outlined in section 2.1 above, 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 (1999) 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, 1990). 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. This point is developed further below.

6.2 Empirical evidence: barriers to training

A number of studies from a range of countries have reported evidence on lower training participation rates among older and less skilled workers related to barriers to training. These may either reduce individuals' incentive to take up training offers or the employers' incentives to offer training to particular groups. As such, barriers to training are factors that either restrict opportunities for training or, if training is available, they raise the perceived costs of training or reduce the benefits of training making it more likely that an offer of training is rejected. Three main types of barriers to participation in job-related training can be identified in the literature (Sussman, 2002), as follows:

- *Situational barriers:* Barriers associated with a person's situation in life at a given time e.g. being too busy at work, financial constraints, family responsibilities or lack of child care, language, health problems, lack of relevant education, insufficient ability
- *Institutional barriers :* Barriers associated with established practices that exclude or discourage participation in training e.g. high training fees, entrance requirements, limited course offerings, inconvenient times or locations, ageist attitudes of employers
- *Dispositional/or psychological barriers:* Barriers attributable to negative attitudes and opinions towards learning or negative perceptions of oneself as a learner

All three types of barriers to training raise the perceived or actual costs associated with training. Situational and dispositional barriers are perhaps more likely to explain why a particular individual (or group of individuals) has relatively low incentives to train and therefore is more likely to reject an offer of training. Institutional barriers are most likely to explain why a person or group of individuals is not offered training by employers. However, none of these categories are mutually exclusive as they can overlap or act together to reinforce barriers, e.g. if the location is not convenient, the costs associated with the training are likely to be higher.

The degree to which barriers to training impact on actual training outcomes has been explored by Sussman (2002), who reviews evidence from the 1998 and 1994 Adult Education and Training Surveys (AETS), supplements to the respective Canadian Labour Force Surveys. Respondents were asked if there was any training or education they needed to take for job-related or career reasons *but did not.* If the answer to this question was yes, then they were asked to identify all the barriers to training they faced. The main barriers identified by those who did perceive an unmet need for training were: 1.too busy at work (situational); 2 training was too expensive (situational/institutional); 3. the inconvenience of time and location if training was available (institutional); 4. the unavailability of a course or training programme (institutional); 5. lack of employer support (institutional); 6. family responsibilities (situational). Sussman (2002) found that among those who reported unmet needs for training the two most important reasons given were being too busy at work and expense, but also important were lack of an offer of training or the inconvenience of location or time if training was offered, lack of employer support and family responsibilities (especially for women). Insufficient qualifications or prerequisites and health reasons were only important for a small minority. Among those who perceived unmet needs for training but who *had* taken some job-related training the main barriers to more training were also being too busy at work, inconvenient time or location and the unavailability of a course. For those who had taken training, finance was not an important issue.

Cully et al. (2000) report on data from the Australian surveys of Training and Education Experience (ATEE) which interviewed only employed respondents. In this data three types of training are examined; in-house, external and unstructured. This study additionally identifies fear of training as a dispositional or psychological barrier to participation in training that is particularly demotivating for older people.

Chapman et al (2003) suggest that the expense of training (particularly in the context of credit constraints among the unemployed) is an important barrier to training for older people in Australia. They found that 50-60 year olds were less likely than younger cohorts to have participated in self-financed training although they were no less likely to have had taken part in assisted training. They also implicate lack of employer support as a further disincentive for training among older people. Similarly, Lundberg and Marshallsay (2007) who report on evidence from survey based studies on the perspectives of older workers (aged over 45) in three industry sectors; finance, care work for the aged in the health sector and construction. They report that about 20% of respondents thought that that their employer had negative attitudes towards supporting training for older workers (specifically beyond retirement age).

Wooden et al (2001) and Cully et al (2000) both report on ATEE data and show that the likelihood of training was much lower among older employees. The main reasons cited by the authors for the lower training participation of older workers were fewer training offers, differential learning ability and the attitudes of older workers themselves. Fewer offers of training are made to older workers because they are either perceived to be more costly to train or because of less specific, negative and potentially ageist attitudes of employers towards older workers. Wooden et al. (2001) and Culley et al. (2000) found that the probability of undertaking training was positively related to educational attainment. Since older workers generally have lower levels of educational attainment, these authors both suggest that this is likely to be an important explanation for lower training rates among older workers. Culley et al. (2000) use regression analysis to explore this relationship and find that much of the differences in age and participation in training are unexplained by the data, attributing this to unobservable characteristics of older workers and age discrimination.

The attitudes of older workers themselves can constitute a dispositional or psychological barrier to training if for instance they result in a fear of training or a lack of a perceived need for training. Cully et al. (2000) argue that fear of training is associated with lack of confidence in the ability to succeed on a training programme. Among older workers, fear of training can be attributed to either negative self-perceptions in relation to an expectation of low training performance or low ability, unfamiliarity with the training environment or fear of being unable to compete with younger and possibly more educated trainees. Fear of training raises the psychological costs of training and consequently lowers motivation to train.

Lack of perceived need is potentially a major reason for a lack of motivation for training among older people. In terms of the human capital perspective, a lack of a perceived need for training suggests that the perceived benefits from training are either low (relative to the costs) or non-existent. Sussman (2002) found that while a majority of all respondents in the AETS Canadian data had not participated in any training, a majority of these did not perceive a need for training which may suggest a lack of motivation. Older people in particular were *less* likely to report unmet needs for training as were women, those with less than a high school education, part-time workers and workers in agriculture and other primary industries and construction. Relatedly, these groups of people were found to report fewer barriers to training. Similarly, Cully et al. (2000) found that among respondents to the ATEE data, *no need for training* was more likely to be cited by older workers; similar findings are also reported in US research by Guthrie and Schwoerer (1996) and Lundberg and Marshalsay (2007). A perceived lack of need for training would be consistent with beliefs that there will be insufficient reward from participating in training either because the individual has already accumulated sufficient skills and experience or because training will do little to enhance future promotion prospects or employability. As such, training utility will be conditioned by age because, as discussed above, the longer-term benefits of training are reduced by looming retirement.

There is some evidence that it is not a perceived lack of need for training in itself that characterizes older workers, but rather, a perceived lack of need for the type of training that is currently on offer. This possibility is explored further by Lundberg and Marshallsay (2007) who found that a majority of respondents in their sample thought that training in computing skills would be the most useful in enabling them to continue work after retirement. As stressed by Lundberg and Marshallsay (2007:16) reiterating the recommendations of Pillay et al (2003) and Sheen (2000) 'there is a need to understand how workers perceive their work' in order to adopt practices that will result in 'increased productivity' as well as 'long-term career benefits'. Qualitative studies are well suited to such a task.

Wooden et al (2001) conducted focus groups with employed and unemployed people over 45 as well as Human Resource managers. The main barriers identified were attitudinal, specifically resistance to change and fear of ICT. However, ageist attitudes of managers (particularly younger managers) rather than trainers were identified as culpable by this group. For example, older workers thought that managers perceived older workers as being incapable of change or as a threat because of their willingness to challenge managers' decisions. The research by Carmichael et al (2007(a) and (b)) was based on a small scale, in depth study with 56 people between 50 and 68 in the North West of England. Among this sample there was a general appreciation of the value of training and a majority of the respondents said that they had undertaken some job-related training since leaving full-time education; some more vocational than others, some more intensive than others and some quite limited. Nearly half of the respondents had been involved in training related to computing/IT. Some of this training was perceived to be inadequate but in several cases it had lead to career changes. Carmichael et al. identify five main barriers to training in addition to lack of opportunity. Two of these were dispositional; lack of motivation associated with the lack of perceived need for training and resistance to training and the acquisition of new skills. Lack of a perceived need for training was noted above as an important determinant of lower training rates among older workers. Among this sample it was sometimes attributable to the inappropriateness of the training in question or lack of motivation for training was related to looming retirement. Resistance to training was possibly symptomatic of a more general resistance to change (also noted by Wooden et al, 2001). Additional barriers identified in this research was the expense of training, lack of time for training and prior and negative experiences of training (e.g. due to general unpleasantness, difficulty, inadequacies or the ineffectiveness of training) with the latter acting as a disincentive for undertaking further training. In addition, this research identifies three possible incentives for training. First of all, self-motivation was identified as an important driver for learning and training. Secondly, employers attitudes were seen as a critical determinant of whether or not an employee undertook training. Lastly, while negative experiences of training could act as a disincentive to train, pleasant, enjoyable experiences could have the opposite effect.

7. Conclusions

Access to the microdata underlying the EU LFS has allowed for the first time a comprehensive examination of various aspects of employee training in the EU. These include its impact on productivity and earnings, links with ICT adoption and use and determinants of who is trained and their field of training. Modelling training activities as intangible investments by firms allows us to compare the extent of these investments across countries while econometric analysis permits an evaluation of links with ICT. Detailed probit analysis on what factors affect who receives training is possible given the very large samples available. The main conclusions that emerge from this analysis are as follows:

In a small number of countries, intangible capital from investing in training is a significant contributor to output growth, and in some the impact of training is on a par with contributions from upskilling through the general education system. In other countries, however, the contribution of this type of investment is relatively small. The econometric analysis suggests training has most impact when combined with investment in ICT, in particular in countries with a more 'academic' general education system. This is consistent with a recent literature that emphasises the role of organisational changes and associated retraining of the workforce in diffusing new technology. Training also appears to have a direct impact on adoption and use of ICT although the impact is gender, age and skill specific. An interesting finding is that training provided to the workers with higher educational attainment yields less contribution to the ICT adoption than the training provided to the workers with low educational attainment.

A number of factors affect who is likely to receive training and confirms earlier analysis for the UK in O'Mahony and Peng (2008) that lower skilled and older workers are less likely than other workers to receive training. This analysis also highlights that training increases with job tenure and so has the implication that labour market systems that promote long term relationships between firms and workers might have positive impacts on human capital accumulation, a point frequently emphasised by the ILO (see e.g. Storm and Naastepad, 2007).

The analysis of field of training also highlights some interesting findings in respect of worker characteristics. While the overall relationship between age and training participation is clearly negative, among trainees, workers over 44 are more likely to participate in general training and training in health and computing. Males are more likely to be trained in specific rather than general areas and more educated trainees are most likely to be involved in health and social science related training and least likely to be involved in training in computing and services. Regardless of age, gender or educational attainment, trainees in more vocationally orientated countries are more likely to be engaged in general and services training than trainees in more academically orientated countries.

A number of policy implications follow for dealing with barriers to training outlined in section 5. For example, lack of confidence, fear of, or resistance to training could be addressed by adopting particular training methods that are suited to specific groups of workers. Training providers need to ensure that prospective trainees can realistically expect tangible benefits from that training that translate into incentives to train e.g. by making the purpose of training clear, closely linking training to specific employment opportunities But the lack of a perceived value of training is more difficult to address. Wooden et al (2001) suggest that this could require a rise in the retirement age and more emphasis on a 'throughout career' requirement for accreditation.

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APPENDIX TABLES

Table B1a. Marginal Effect estimates.
Regressand (dependent variable): EDUC4WN

	(1)	(2)	(3)	(4)	(5)	(6)
Country:	AT	BE	DE	DK	ES	FI
FEMALE	-0.0136***	-0.0110***	-0.0151***	0.0352***	-0.00592***	0.0251***
	(-8.76)	(-5.89)	(-15.8)	(11.8)	(-3.97)	(7.05)
AGE_17	0.531***	0.361***	0.630***	0.541***	0.195***	0.512***
	(89.9)	(24.6)	(116)	(85.4)	(22.8)	(55.8)
AGE_22	0.115***	0.0333***	0.215***	0.265***	0.0819***	0.234***
	(29.8)	(6.89)	(57.9)	(34.2)	(18.1)	(26.2)
AGE_27	0.0538***	0.0106***	0.0813***	0.107***	0.0349***	0.0829***
	(16.8)	(2.95)	(33.0)	(16.7)	(10.3)	(11.1)
AGE_32	0.0193***	0.000437	0.0228***	0.0153***	0.00919***	0.0282***
	(7.25)	(0.14)	(12.2)	(2.91)	(3.21)	(4.13)
AGE_37	0.00468**	-0.00597**	0.00801***	-0.00751	0.00760***	0.000990
	(1.98)	(-2.08)	(4.90)	(-1.53)	(2.80)	(0.16)
AGE_47	-0.00593**	-0.00744**	-0.00853***	-0.0110**	-0.00690***	-0.00991
	(-2.49)	(-2.56)	(-5.31)	(-2.23)	(-2.59)	(-1.63)
AGE_52	-0.0262***	-0.0154***	-0.0192***	-0.0246***	-0.0250***	-0.0273***
	(-10.2)	(-4.93)	(-11.6)	(-4.92)	(-8.95)	(-4.42)
AGE_57	-0.0625***	-0.0319***	-0.0383***	-0.0549***	-0.0430***	-0.0716***
	(-22.5)	(-9.27)	(-22.1)	(-10.8)	(-14.6)	(-11.3)
AGE_62	-0.0891***	-0.0412***	-0.0564***	-0.0895***	-0.0528***	-0.113***
	(-20.4)	(-7.64)	(-27.5)	(-14.2)	(-14.9)	(-13.7)
MARITAL_W_S_D	-0.00843***	-0.00473	-0.00707***	0.00954*	-0.00256	-0.000990
	(-3.18)	(-1.49)	(-4.08)	(1.73)	(-0.78)	(-0.16)
MARITAL_SINGLE	-0.0222***	-0.0110***	-0.0286***	-0.00679*	-0.0259***	0.00973**
	(-12.4)	(-5.08)	(-24.3)	(-1.92)	(-13.9)	(2.33)
EDUCATION_HIGH	0.0425***	0.0534***	-0.000614	0.0499***	0.0777***	0.0483***
	(13.6)	(16.8)	(-0.37)	(10.2)	(32.2)	(8.11)
EDUCATION_MED.	-0.00812***	0.0246***	-0.0389***	0.0181***	0.0743***	0.0408***
	(-3.77)	(9.19)	(-26.8)	(4.55)	(29.8)	(8.13)
URBAN_INTERM	-0.0136***	-0.00836***	-0.0114***	-0.0290***	0.00222	-0.0137***
	(-8.32)	(-4.98)	(-12.5)	(-9.26)	(1.32)	(-3.02)
URBAN_THIN	-0.0292***	-0.0266***	-0.0101***	-0.0349***	-0.00268*	-0.0392***
	(-19.3)	(-10.1)	(-9.22)	(-10.7)	(-1.68)	(-10.7)
NATIONAL_FOREIG.	-0.0384***	0.0171***	-0.0268***	-0.0311***	-0.0258***	-0.0294**
	(-16.0)	(5.32)	(-16.4)	(-3.99)	(-8.70)	(-2.14)
TENURE	0.00129***	-0.000366	0.00229***	0.00443***	0.000614**	0.00148**
	(5.10)	(-1.11)	(13.9)	(9.06)	(2.04)	(2.36)
TENURESQ	0.00000616	0.0000153	-0.0000309***	-0.0000911***	-0.00000597	-0.00000198
	(0.84)	(1.63)	(-6.80)	(-6.35)	(-0.70)	(-0.11)
HWUSUAL	-0.000970***	0.000889***	-0.00181***	-0.00514***	-0.00239***	-0.00340***
	(-10.4)	(7.49)	(-23.8)	(-24.3)	(-18.1)	(-12.0)
PARTTIME	0.0347***	0.0357***	-0.00331*	-0.00463	0.0212***	0.0143**
	(12.4)	(11.7)	(-1.72)	(-1.00)	(5.55)	(2.03)
TEMPORARY	0.220***	0.0525***	0.183***	0.0953***	0.0264***	0.0648***
	(58.4)	(14.0)	(78.3)	(19.2)	(14.0)	(12.8)
LOOKOJ	0.00407	0.0125***	-0.0380***	-0.0427***	0.0430***	0.0141**
	(1.00)	(3.41)	(-23.9)	(-8.99)	(12.8)	(2.44)
HOMEWRK_USUAL.	0.0985***	0.0516***	0.0290***	0.0734***	0.0622***	0.0556***
	(28.0)	(11.6)	(9.31)	(11.2)	(7.41)	(7.78)
HOMEWRK_SOMET.	0.0846***	0.0576***	0.0473***	0.0705***	0.0335***	0.0835***
	(33.3)	(15.1)	(25.4)	(17.4)	(4.96)	(11.5)
ISCO_0	0.177***	0.0935***	-0.00564	0.157***	0.0850***	0.150***
	(11.1)	(6.63)	(-1.10)	(6.74)	(7.79)	(5.47)
ISCO_1	0.174***	0.107***	0.160***	0.143***	0.111***	0.205***

	(31.1)	(14.8)	(29.2)	(16.7)	(14.0)	(20.6)
ISCO_2	0.216***	0.0924***	0.160***	0.148***	0.109***	0.189***
	(39.2)	(16.5)	(38.5)	(21.1)	(24.2)	(23.0)
ISCO_3	0.178***	0.0818***	0.143***	0.134***	0.0731***	0.150***
	(46.6)	(14.1)	(41.7)	(22.6)	(18.4)	(19.8)
ISCO_4	0.137***	0.0615***	0.125***	0.0957***	0.0619***	0.0956***
	(34.7)	(12.2)	(33.9)	(14.5)	(16.0)	(11.1)
ISCO_5	0.123***	0.0515***	0.0969***	0.0806***	0.0515***	0.0553***
	(31.4)	(9.68)	(27.4)	(13.7)	(15.8)	(7.92)
ISCO_6	0.0592***	0.00449	0.0440***	0.0314**	0.0466***	0.0204
	(6.57)	(0.37)	(7.05)	(2.19)	(4.63)	(1.42)
ISCO_7	0.0753***	0.0156***	0.0574***	0.0427***	0.00150	-0.0315***
	(19.3)	(3.12)	(18.1)	(6.35)	(0.50)	(-4.26)
ISCO_8	0.0474***	0.00371	0.0241***	-0.0230***	0.0141***	-0.0411***
	(10.6)	(0.74)	(7.08)	(-3.18)	(3.87)	(-5.22)
QUARTER_2	0.00726***	0.000385	0.00214	-0.0153***	-0.00499*	0.0154
	(3.82)	(0.16)	(1.25)	(-4.14)	(-1.92)	(1.48)
QUARTER_3	-0.0518***	-0.0548***	-0.0193***	-0.109***	-0.0470***	-0.0913***
	(-29.9)	(-28.6)	(-12.4)	(-29.9)	(-24.2)	(-9.87)
QUARTER_4	0.00978***	-0.00338	0.00415**	0.0284***	0.00108	0.0351***
	(5.12)	(-1.48)	(2.45)	(7.42)	(0.42)	(3.17)
YEAR_2006	0.00344**	0.00240	-0.00543**	0.00917***	-0.00727***	-0.0144*
	(2.06)	(1.11)	(-2.01)	(2.70)	(-3.99)	(-1.76)
YEAR_2005	0.00128	0.0157***	0.000872	-0.0107***	-0.0790***	-0.0143*
	(0.77)	(7.00)	(0.42)	(-3.17)	(-40.1)	(-1.76)
YEAR_2004	-0.0129***	0.0197***	-0.00251	-0.0440***	-0.0703***	-0.00728
	(-4.29)	(5.04)	(-1.05)	(-7.65)	(-34.8)	(-0.89)
YEAR_2003	-0.0596***	0.0103***	-0.0214***	-0.112***		-0.0857***
	(-25.0)	(2.66)	(-9.67)	(-20.9)		(-11.4)
Observations	278230	124061	445534	111689	173556	74209
PseudoR2	0.218	0.093	0.324	0.128	0.170	0.116

t statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B1b. Marginal Effect estimates.
Regressand (dependent variable): EDUC4WN

	(7)	(8)	(9)	(10)	(11)
Country:	FR	IT	NL	SE	UK
FEMALE	-0.00275*	-0.000184	-0.0280***	0.0703***	0.0508***
	(-1.95)	(-0.25)	(-16.4)	(50.1)	(20.3)
AGE_17	0.564***	0.208***	0.541***	0.332***	0.422***
	(64.1)	(33.7)	(94.6)	(55.1)	(70.2)
AGE_22	0.136***	0.0579***	0.177***	0.124***	0.0950***
	(28.1)	(22.7)	(41.3)	(33.1)	(16.9)
AGE_27	0.0497***	0.0195***	0.0555***	0.0587***	0.0212***
	(15.0)	(11.2)	(17.9)	(19.4)	(4.44)
AGE_32	0.0272***	0.00429***	0.0151***	0.00372	-0.00223
	(9.78)	(3.17)	(5.89)	(1.48)	(-0.53)
AGE_37	0.00967***	0.00126	0.00434*	-0.00848***	0.00303
	(3.89)	(1.04)	(1.82)	(-3.60)	(0.76)
AGE_47	-0.00786***	-0.00325***	-0.0136***	-0.0114***	-0.00848**
	(-3.37)	(-2.72)	(-5.71)	(-4.73)	(-2.09)
AGE_52	-0.0219***	-0.0140***	-0.0384***	-0.0223***	-0.0280***
	(-9.20)	(-11.5)	(-15.7)	(-9.21)	(-6.67)
AGE_57	-0.0484***	-0.0281***	-0.0816***	-0.0462***	-0.0578***
	(-20.4)	(-22.3)	(-32.7)	(-19.3)	(-13.4)
AGE_62	-0.0664***	-0.0356***	-0.126***	-0.0795***	-0.106***
	(-16.7)	(-19.8)	(-36.0)	(-31.6)	(-19.8)
MARITAL_W_S_D	0.0102***	0.00112	0.0138***	-0.00112	0.00221
	(3.78)	(0.71)	(4.54)	(-0.48)	(0.54)
MARITAL_SINGLE	-0.00204	-0.0141***	-0.0282***	0.00221	-0.0258***
	(-1.30)	(-15.1)	(-15.7)	(1.42)	(-8.47)
EDUCATION_HIGH	0.0458***	0.0862***	0.0597***	0.108***	0.138***
	(19.4)	(41.2)	(24.0)	(38.6)	(38.4)
EDUCATION_MED.	0.0237***	0.0443***	0.0484***	0.0425***	0.0799***
	(13.5)	(46.0)	(25.2)	(20.0)	(27.7)
URBAN_INTERM	-0.000781	-0.00606***	-0.0127***	0.00750***	-0.00202
	(-0.57)	(-8.21)	(-9.19)	(3.59)	(-0.74)
URBAN_THIN	-0.0121***	-0.00726***	-0.00555	-0.000166	-0.0132***
	(-6.55)	(-8.59)	(-1.38)	(-0.10)	(-4.53)
NATIONAL_FOREIG.	-0.0151***	-0.0187***	0.0197***	-0.0154***	0.0437***
	(-4.87)	(-10.9)	(4.14)	(-4.65)	(8.70)
TENURE	0.00315***	0.00113***	-0.00355***	0.00281***	-0.00165***
	(12.0)	(7.84)	(-13.0)	(12.5)	(-3.90)
TENURESQ	-0.0000489***	-0.0000143***	0.0000734***	-0.0000447***	0.0000442***
	(-6.82)	(-3.47)	(9.36)	(-7.57)	(3.44)
HWUSUAL	-0.000112	-0.000634***	-0.00188***	-0.00552***	-0.00152***
	(-1.32)	(-13.0)	(-13.6)	(-44.4)	(-10.7)
PARTTIME	0.0221***	0.0182***	0.00475*	-0.0408***	0.0333***
	(9.64)	(13.0)	(1.92)	(-18.9)	(8.12)
TEMPORARY	0.0852***	0.0209***	0.0261***	0.00979***	0.0340***
	(32.6)	(17.4)	(10.1)	(4.69)	(7.03)
LOOKOJ	-0.00710**	0.00316**	0.00533*	0.0122***	0.0224***
	(-2.47)	(2.22)	(1.91)	(5.03)	(5.11)
HOMEWRK_USUAL.	0.00605**	0.0587***	-0.0208***	0.0291***	0.0116
	(2.42)	(14.2)	(-3.29)	(5.29)	(1.16)
HOMEWRK_SOMET.	0.0226***	0.0270***		0.0469***	0.0922***
	(8.35)	(6.10)		(15.8)	(30.1)
ISCO_0	0.0656***	0.0578***	0.189***	0.108***	0.242***
	(8.56)	(12.0)	(17.0)	(8.01)	(12.1)
ISCO_1	0.117***	0.119***	0.116***	0.114***	0.0777***
	(19.7)	(24.0)	(23.9)	(23.0)	(14.9)

ISCO_2	0.115***	0.0937***	0.141***	0.105***	0.139***
	(23.6)	(28.4)	(32.0)	(27.6)	(24.7)
ISCO_3	0.0991***	0.0727***	0.126***	0.0839***	0.145***
	(25.1)	(32.2)	(30.8)	(24.2)	(27.2)
ISCO_4	0.0595***	0.0376***	0.0671***	0.0458***	0.0829***
	(15.5)	(17.2)	(16.4)	(12.6)	(17.0)
ISCO_5	0.0538***	0.0455***	0.0659***	0.0421***	0.119***
	(14.3)	(19.9)	(15.9)	(13.0)	(24.8)
ISCO_6	0.00443	-0.00853*	0.0234***	-0.0142**	0.0301
	(0.67)	(-1.75)	(3.15)	(-2.05)	(1.64)
ISCO_7	0.0305***	-0.0112***	0.0418***	-0.0108***	0.0418***
	(8.02)	(-6.71)	(9.89)	(-3.01)	(6.87)
ISCO_8	0.0197***	-0.00966***	0.0150***	-0.0258***	0.000741
	(5.25)	(-5.25)	(3.41)	(-7.65)	(0.12)
QUARTER_2	0.00176	-0.000286	-0.00300	-0.0413***	-0.0377***
	(0.90)	(-0.32)	(-1.45)	(-22.1)	(-13.7)
QUARTER_3	-0.0364***	-0.0239***	-0.0474***	-0.109***	
	(-21.0)	(-29.0)	(-24.5)	(-65.1)	
QUARTER_4	0.00862***	0.00483***	0.00148	-0.00519***	
	(4.31)	(5.28)	(0.71)	(-2.75)	
YEAR_2006	-0.000222	-0.00136*	-0.0169***	-0.00300*	0.0592***
	(-0.087)	(-1.71)	(-6.69)	(-1.93)	(17.8)
YEAR_2005	-0.00743***	-0.00347***	-0.000127	-0.000399	0.0641***
	(-3.78)	(-4.37)	(-0.062)	(-0.23)	(18.3)
YEAR_2004	-0.00637**		0.00802***	0.188***	0.133***
	(-2.46)		(2.74)	(57.9)	(36.4)
YEAR_2003	-0.0105***		0.0143***	0.168***	0.00820**
	(-4.12)		(4.68)	(52.9)	(2.47)
Observations	231346	529218	352370	418708	173585
PseudoR2	0.119	0.114	0.083	0.096	0.106

t statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1