EU KLEMS

Skill Bias, Age and Organisational Change

Working paper nr. 36

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EU KLEMS WORKING PAPER SERIES Product

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EU KLEMS Project
Productivity in the European Union: A Comparative Industry Approach

August 2008

This project is funded by the European Commission, Research Directorate General as part of the 6th Framework Programme, Priority 8, "Policy Support and Anticipating Scientific and Technological Needs".

Skill Bias, Age and Organisational Change

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Paper presented at the EUKLEMS final conference, June 19-20 2008

Abstract

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

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1. Introduction

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

Skill or educational attainment is only one dimension of worker's characteristics. Additional dimensions include gender and age but there are few studies that attempt to go beneath the skill classifications to consider these aspects. One important exception is Card and Lemieux (2001) which argues that the well known increase in the skill premium for college educated employees in the US in the 1980s was concentrated in younger age cohorts at that time. They argued that this was due to a low supply of graduates in the 1980s relative to previous cohorts, reflecting broader demographic trends. Daveri and Maliranta (2007) also consider links between age, seniority within the context of the ICT revolution.

The focus of this paper is on the age dimension, in particular demand for workers aged 50 and over. The paper begins by using EUKLEMS data to investigate the impact of ICT on demand for various types of workers, including a split by gender, three skill groups and age. We use the specification in O'Mahony, Robinson and Vecchi (2008) in this first analysis and consider results for 9 countries and 11 industry groups. These first results suggest there may be a bias against older male workers and specifically older males with university education arising from ICT. The second part of the paper attempts to delve more into the reasons why this might have occurred, focusing on training and organisational changes. This analysis uses data from the Labour Force Survey on training matched with EUKLEMS data for the UK. We consider whether training combined with ICT use affects wage premiums. We then consider if lower training for older workers appears to be driven by reluctance on the part of firms to train these people or reluctance of the workers themselves to undertake training.

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

2. Skill, Gender or Age Bias.

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

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

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

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

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

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

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

The analysis in this section uses data for 9 EU countries (Austria, Belgium, Denmark, Finland, Germany, Italy, the Netherlands, Spain and the UK). These are the countries for which labour composition data cross classified by gender, age and skill are available in EUKLEMS. The panel data used here are based on 11 industries that together make up the market economy and employs the EUKLEMS industry division into agriculture, forestry and fishing (AtB); ICT producing industries including computing equipment, electrical and electronic equipment, instruments and telecommunications equipment and services (ELECOM); a three way split of the remainder of manufacturing into consumer goods (Mcons), intermediate goods (Minter) and investment goods (Minves); a group combining mining, utilities and construction (Other G); wholesale and retail trade (50t52); transport (60t63); financial services (J); business services (71t74) and personal services including hotels and catering (PERS). The time periods differ by country, i.e. 1970-2005 for Finland, Italy and the UK; 1979-2005 for the Netherlands; 1980-2005 for Austria, Belgium, Denmark and Spain; and 1991-2005 for Germany.

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

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

A	**Aged 15-29**					
	Male			**Female**		
	High	Intermediate	Low	High	Intermediate	Low
K/Y	-0.0013**	-0.0063**	0.0033*	0.0036**	-0.0012	-0.0036**
	(0.0003)	(0.0012)	(0.0016)	(0.0003)	(0.0013)	(0.0008)
ICTK/K	0.0008**	0.0012	-0.0096**	0.0008**	-0.0066**	-0.0003
	(0.0002)	(0.0007)	(0.0010)	(0.0002)	(0.0007)	(0.0005)

B	**Aged 30-49**					
	Male			**Female**		
	High	Intermediate	Low	High	Intermediate	Low
K/Y	-0.0016	-0.0084**	0.0112**	0.0050**	0.0000	-0.0024*
	(0.0011)	(0.0023)	(0.0020)	(0.0007)	(0.0013)	(0.0011)
ICTK/K	0.0009	0.0168**	-0.0069**	0.0022**	-0.0036**	0.0038**
	(0.0006)	(0.0013)	(0.0011)	(0.0004)	(0.0008)	(0.0007)

C	**Aged 50+**					
	Male			**Female**		
	High	Intermediate	Low	High	Intermediate	Low
K/Y	-0.0025**	-0.0009	0.0033**	0.0012**	-0.0005	0.0011*
	(0.0006)	(0.0011)	(0.0010)	(0.0002)	(0.0004)	(0.0005)
ICTK/K	-0.0007*	0.0026**	-0.0045**	0.0003**	0.0008**	0.0020**
	(0.0003)	(0.0007)	(0.0006)	(0.0001)	(0.0002)	(0.0003)

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

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

Table 2. Coefficients on ICT/K by country

A	**Aged 15-29**					
	Male			**Female**		
	High	Intermediate	Low	High	Intermediate	Low
Austria	-0.0016** (0.0003)	0.0076** (0.0018)	-0.0014 (0.0008)	-0.0004 (0.0003)	-0.0035* (0.0017)	-0.0093** (0.0017)
Belgium	0.0012* (0.0006)	0.0120** (0.0038)	0.0010 (0.0046)	-0.0002 (0.0008)	-0.0050** (0.0017)	-0.0019 (0.0032)
Denmark	0.0004 (0.0003)	0.0000 (0.0036)	-0.0023 (0.0034)	-0.0013** (0.0002)	0.0164** (0.0029)	0.0034* (0.0016)
Finland	0.0023** (0.0004)	0.0072** (0.0009)	-0.0114** (0.0009)	0.0006 (0.0004)	0.0027** (0.0006)	0.0065** (0.0009)
Germany	-0.0005 (0.0003)	0.0034 (0.0020)	0.0126** (0.0018)	0.0001 (0.0002)	-0.0095** (0.0015)	0.0062** (0.0010)
Italy	0.0023** (0.0005)	-0.0067** (0.0025)	0.0005** (0.0002)	0.0077** (0.001)	-0.0021 (0.0027)	-0.0001 (0.0001)
Netherlands	-0.0009 (0.0006)	0.0149** (0.0030)	0.0039** (0.0009)	-0.0006 (0.0004)	-0.0069** (0.0022)	0.0004 (0.0004)
Spain	0.0041** (0.0011)	-0.0108** (0.0041)	0.0034 (0.0037)	0.0010 (0.0011)	-0.0003 (0.0021)	0.0051 (0.0035)
UK	0.0039** (0.0009)	0.0004 (0.0043)	-0.0448** (0.0073)	0.0013* (0.0006)	-0.0206** (0.0038)	-0.0250** (0.0041)

B	**Aged 30-49**					
	Male			**Female**		
	High	Intermediate	Low	High	Intermediate	Low
Austria	-0.0097** (0.0016)	-0.0016 (0.0030)	0.0084** (0.0022)	0.0000 (0.0007)	0.0004 (0.0015)	0.0005 (0.0015)
Belgium	-0.0078** (0.0022)	0.0064 (0.0084)	0.0213** (0.0062)	-0.0001 (0.0019)	0.0014 (0.0026)	0.0093** (0.0021)
Denmark	-0.0049** (0.0020)	0.0015 (0.0054)	-0.0046 (0.0046)	-0.0063** (0.0010)	0.0078** (0.0026)	0.0084** (0.0020)
Finland	-0.0047** (0.0012)	0.0089** (0.0020)	-0.0114** (0.0018)	-0.0066** (0.0010)	0.0008 (0.0007)	0.0056** (0.0013)
Germany	-0.0159** (0.0035)	-0.0352** (0.0046)	0.0248** (0.0047)	0.0041** (0.0011)	-0.0090** (0.0025)	0.0169** (0.0027)
Italy	0.0116** (0.0021)	-0.0234** (0.0039)	0.0076** (0.0028)	0.0026** (0.0005)	0.0119** (0.0026)	-0.0039** (0.0013)
Netherlands	-0.0100** (0.0020)	-0.0086* (0.0048)	0.0082** (0.0022)	-0.0021** (0.0009)	-0.0031 (0.0023)	-0.0019** (0.0005)
Spain	0.0108** (0.0037)	0.0052 (0.0052)	-0.0463** (0.0102)	-0.0037 (0.0028)	0.0052* (0.0024)	-0.0022 (0.0024)
UK	0.0045 (0.0034)	0.0053 (0.0053)	0.0447** (0.0036)	0.0017 (0.0012)	0.0132** (0.0024)	0.0019 (0.0030)

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

C	Aged 50+					
	Male			**Female**		
	High	Intermediate	Low	High	Intermediate	Low
Austria	-0.0014 (0.0011)	0.0063** (0.0017)	0.0055** (0.0015)	0.0005** (0.0002)	0.0008 (0.0006)	-0.0010 (0.0006)
Belgium	-0.0098** (0.0012)	-0.0149** (0.0019)	-0.0039 (0.0021)	-0.0015** (0.0004)	-0.0066** (0.0011)	-0.0008* (0.0004)
Denmark	-0.0028** (0.0006)	-0.0024 (0.0031)	-0.0096** (0.0028)	-0.0010** (0.0002)	-0.0083** (0.0017)	0.0054** (0.0010)
Finland	-0.0010* (0.0005)	0.0017** (0.0007)	-0.0014** (0.0006)	-0.0011* (0.0005)	0.0005* (0.0003)	0.0007 (0.0005)
Germany	-0.0056** (0.0012)	-0.0092** (0.0019)	0.0077** (0.0016)	0.0019** (0.0004)	0.0019 (0.0012)	0.0053** (0.0010)
Italy	-0.0008** (0.0001)	-0.0047** (0.0006)	0.0000 (0.0006)	-0.0003* (0.0002)	-0.0015** (0.0004)	-0.0008** (0.0001)
Netherlands	-0.0002 (0.0010)	0.0086** (0.0025)	-0.0035** (0.0012)	0.0008** (0.0003)	0.0022** (0.0009)	-0.0011** (0.0003)
Spain	0.0061** (0.0024)	0.0082** (0.0018)	0.0089* (0.0041)	-0.0010* (0.0005)	0.0013* (0.0006)	0.0048** (0.0020)
UK	-0.0046** (0.0013)	0.0149** (0.0051)	0.0007 (0.0015)	-0.0006* (0.0003)	0.0008 (0.0012)	0.0021** (0.0006)

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

The paper by Card and Lemieux (2001) referred to above suggests reduced supply of the highly skilled younger age cohorts can explain the increase in their relative wages. An alternative way of looking at the evidence is to use the Katz Murphy demand and supply analysis which looks at the inner product between changes in wages and changes in equilibrium employment (Katz and Murphy (1992). We test the Katz and Murphy (1992) hypothesis (that fluctuations of labour supply combined with stable or steadily growing labour demand decided wage movements, hence a negative association between employment and wage changes), and the Machin (2001) hypothesis (that fluctuations of labour demand combined with steady changes of labour supply decided wage changes, hence a positive association between employment and wage changes).
The discrete version of the estimating equation is given by:

$$(4) \qquad (\frac{W_t}{A_t}-\frac{W_{t-1}}{A_{t-1}})'\left\{(X_t-X_{t-1})-[D(\frac{W_{t-1}}{A_{t-1}},Z_t)-D(\frac{W_{t-1}}{A_{t-1}},Z_{t-1})]\right\} \quad \leq 0$$

W_t is wage in year t; A_t is the total factor productivity (TFP) decided by the neutral technology, that is, an index of the productivity level of the whole economy in year t; X_t is labour input employed; in addition, Z_t is labour demand shifts induced by exogenous factors such as technology, international competition and institutions. To simplify the calculation, we follow Katz and Murphy (1992) to assume a stable growing labour demand. Hence the above equation can be rewritten as $(\frac{W_t}{A_t}-\frac{W_{t-1}}{A_{t-1}})'\{X_t-X_{t-1}\} \leq 0$.

We categorize the data of each year into 198 (2×3×3×11) distinct labour cells, distinguished by two gender, three skill levels (high skilled, intermediate skilled and unskilled), three age groups (15-29, 30-49 and 50+) and eleven industries described as above. The average labour input share of each cell is calculated firstly as the fixed weight. Then, we use the fixed weighted average wage as the index of the productivity level of the whole economy in year t (A_t). The average level of relative wage of each cell (W_t/A_t) over the entire period is regarded as the efficiency units of this cell. Finally, we use efficiency units as weights to calculate the relative labour input of each cell (X_t) and the inner product of changes of relative wage (W_t/A_t- W_{t-1}/A_{t-1}) and changes of relative labour input (X_t-X_{t-1}).

The Katz Murphy decomposition was undertaken industry by industry for the UK – the results for high skilled males are shown in Table 3. The values are generally negative for the younger age groups suggesting supply shifts can explain wage behaviour. The values are positive for the remaining two groups, suggesting a role for demand shifts and are particularly large for the middle age group. The positive values for older males are consistent with a situation of negative demand shifts outweighing any supply shifts.

Table 3 High skilled Males: Katz Murphy cross terms, UK

	aged 15-29	Aged 30-49	Aged 50 and over
ELECOM	-0.0007	0.0377	0.0095
Mcons	-0.0042	0.0345	0.0063
Minter	0.0016	0.0362	0.007
Minvest	-0.0024	0.0243	-0.0002
Other G	-0.0001	0	-0.0108
AtB	0.0007	0.0035	0.0001
50t52	0.004	0.0047	0.0241
60t63	0.0012	0.0138	0.0059
J	-0.0023	0.0766	0.0039
71t74	-0.0005	-0.0413	0.0175

3. Organisational changes and on the job-training

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

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

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

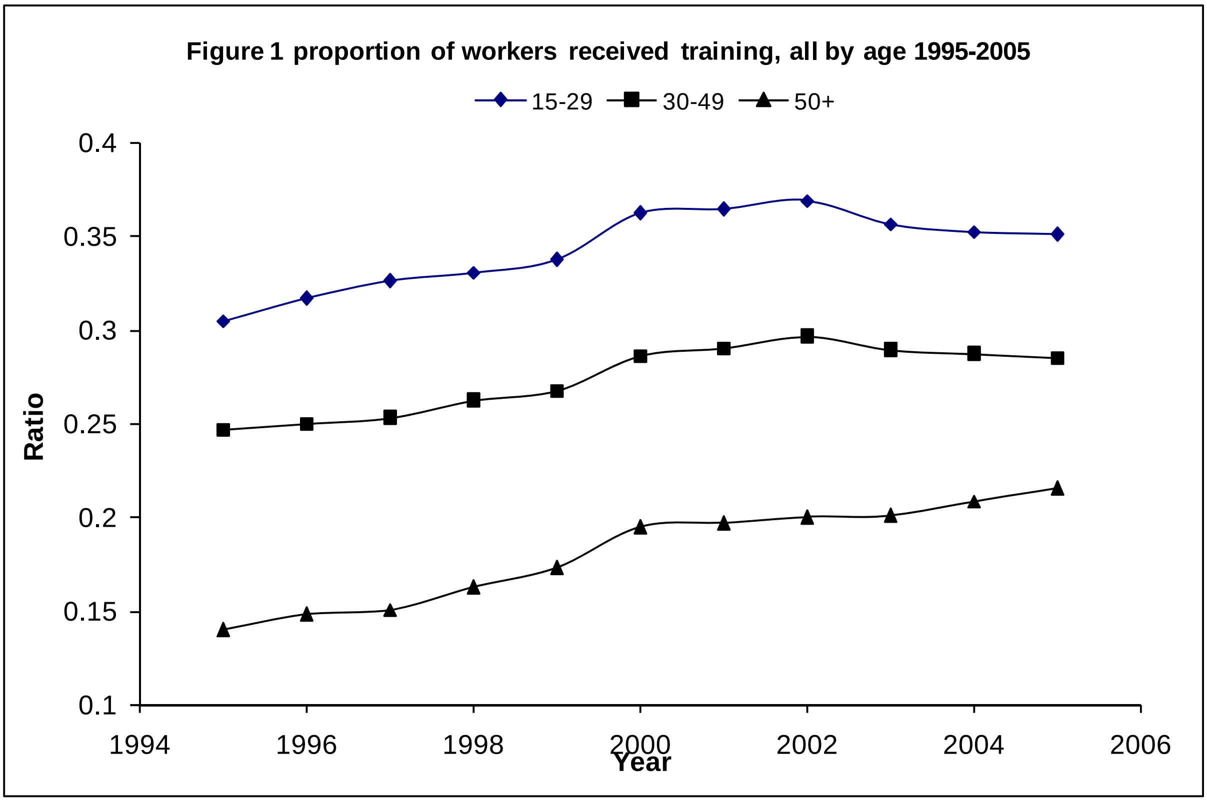
A key paper which demonstrates the link between productivity and organisational changes associated with flexible specialisation is Black and Lynch (2003). They use a detailed firm level dataset for the US (the Educational Quality of the Workforce, National Employers Survey), matched into the LRD to estimate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

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

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

Bresnahan (1999) argues that Skill-Biased Organisational Change (SBOC) and Skilled-Biased Technical Change (SBTC) are effectively the same phenomena viewed from different perspectives. This is supported by Giuri et al (2008) who find in their study of Italian manufacturing weak evidence of SBOC when measured alongside SBTC (for which they report strong evidence). This is consistent with the findings of Piva et al (2003) who find that upskilling is more a function of organisational change than a consequence of technological change alone. Some evidence of an additive effect of technological and organisational change on the skill composition of employment emerges, which they argue is consistent with the theoretical hypothesis of a co-evolution of technology and organisation.

The arguments above suggest that an important element of organisational change is retraining of the workforce. We now examine information on training through linking data from the UK labour Force Survey (LFS) to EUKLEMS. The Labour Force Survey (LFS) is a quarterly sample survey of households living at private addresses in Great Britain. Our training variable is the proportion of workers received training, which is derived from the question of "Job related training or education in the last 3 months?" in the LFS 1995-2005. The LFS also provide information about training offered from employer (" Education or training offered, if not received in the last 3 month?"). We will use the offered training variable for further analysis later in this paper. These questions were asked of all workers and so can be divided by gender, age and skill. A summary of the data is illustrated by the following charts. First Figure 1. shows that a greater proportion of younger than older workers receive training. Figs 2 and 3 show this is true for both males and females but that males aged 50+ receive the least training. Over the ten year period on average only 15% of males aged 50+ received training compared to 33% for males aged <29, and 25% for males aged 30-49. In all age groups females receive more training than males, 36%, 30% and 21% respectively for age groups <29, 30-49 and 50+. In addition there is a more pronounced upward trend for females than males.



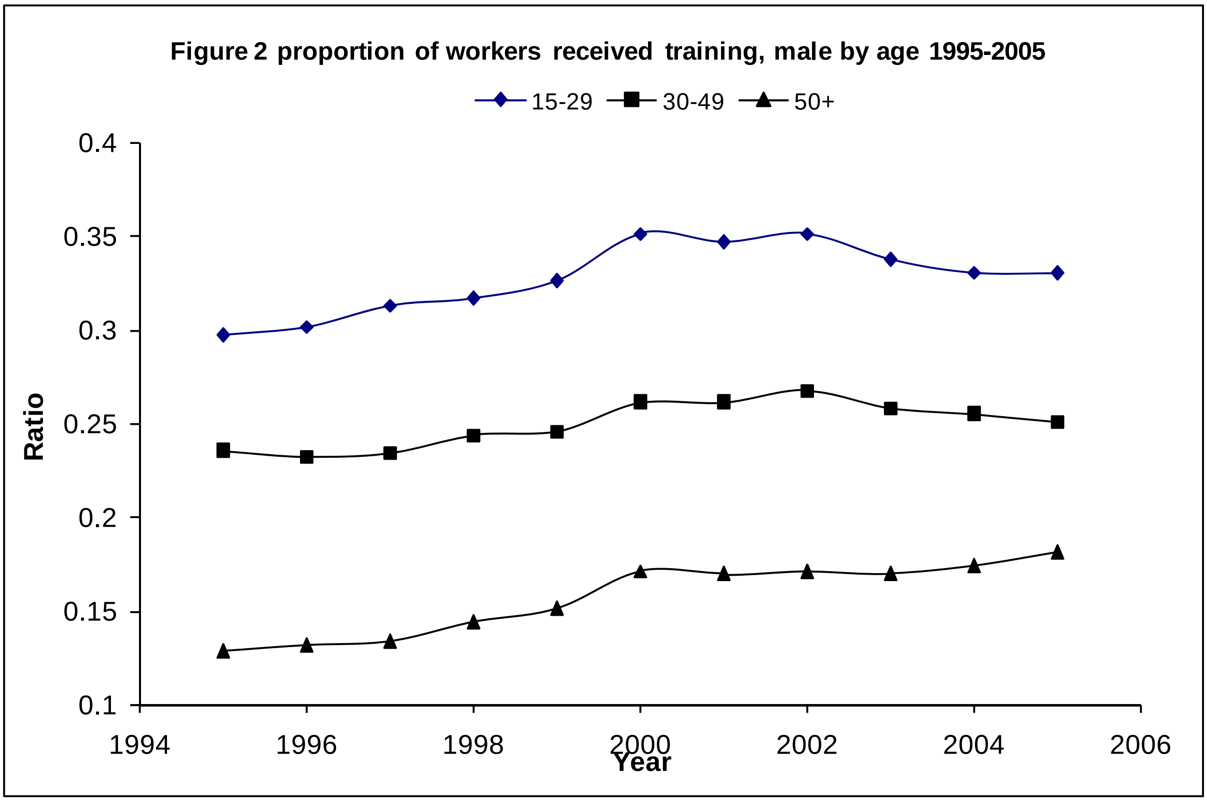


Figure 2 proportion of workers received training, male by age 1995-2005
15-29
30-49
50+
Ratio
0.4
0.35
0.3
0.25
0.2
0.15
0.1
1994
1996
1998
2000
2002
2004
2006
Year

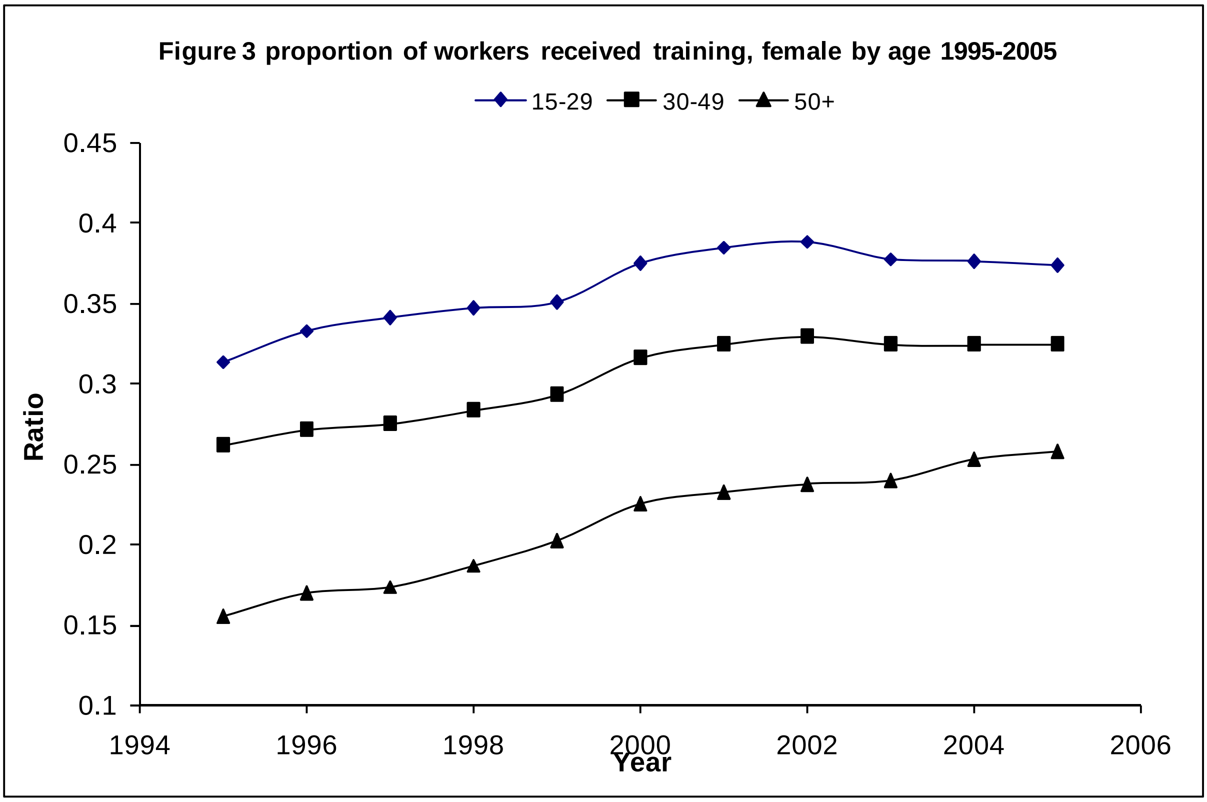


Figure 3 proportion of workers received training, female by age 1995-2005
15-29
30-49
50+
Ratio
0.45
0.4
0.35
0.3
0.25
0.2
0.15
0.1
1994
1996
1998
2000
2002
2004
2006
Year

Training also increases with educational attainment/qualification for all age groups and both genders. Thus, for males in 2005, 36% of those with degree or above received training compared to a very low 8% for the unskilled. Table 4 shows the proportions receiving training in that year. In all skill groups training is higher for females than males and higher for younger than older workers. This pattern is apparent throughout the time period for which training data are available, 1995-2005.

Table 4. Proportion of workers receiving training, UK, average 1995-2005

	Degree and above	Intermediate	Low
Male			
15-29	43.7	32.1	16.0
30-49	38.1	23.3	8.0
50+	29.8	15.1	5.3
Female			
15-29	47.1	34.4	18.8
30-49	45.8	29.6	11.1
50+	42.5	24.0	7.6

We utilise these data to see if there is evidence that received training can explain wage changes and then look at its impact through use of ICT. We follow Deardon, Reed and Van Reenen (2006) by relating wages to the proportion of workers trained (TR) and other control variables. Here we are interested in whether ICT affects wages through training so we interact Training with the ratio of ICT capital to total capital (ICT/K). We also include proportions of workers of various types as regressors.

Deardon et al.(2006) suggest estimating an equation that allows for different relative wages for each type of labour k due to training, but their regression results are presented for average training impacts and include labour type proportions as controls. We follow this method by including labour type proportions or group dummy variables in the regressions. Thus we estimate the following:

(5) $\ln(w) = \alpha + \beta\, TR + \gamma\, TR \ln(ICT/K)$ + labour type controls, time dummies

We use two different methods of estimation. The first uses data on industry average wages regressed on industry training proportions and the ratio of ICT to total capital interacted with training. This specification is rather limited as it is based on only 121 (11 years X 11 industries) observations. This specification also includes proportions of workers of various types. To increase the number of observations in the second approach we include data on wages and training for each type of labour k, but keep industry values for ICT/K and include group dummy variables. The results of these regressions are shown in Table 5.

Table 5 Training and wage, the UK, 11 industries 1995-2005

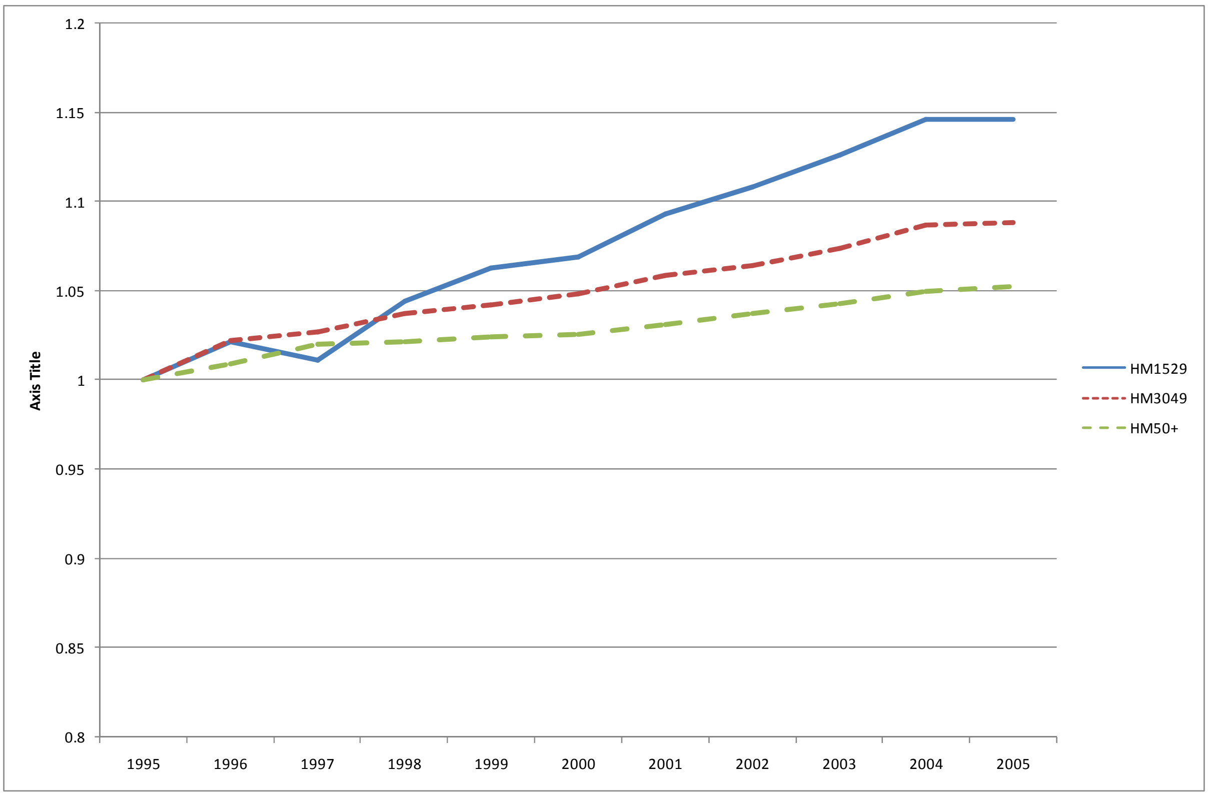
	Industry Panel		Group Panel	
	(1)	(2)	(3)	(4)
TR1	-0.49 (0.62)	-0.03 (0.597)	-0.0001 (0.056)	-0.068 (0.063)
TR1*ln(ICT/H)	-	1.95** (0.134)	-	0.328* (0.145)
Male	-0.002 (0.005)	-0.743 (0.451)	-	-
High skill	0.031** (0.008)	1.845** (0.763)	-	-
Medium skill	0.002 (0.004)	1.283* (0.419)	-	-
Age15-29	0.013* (0.006)	0.615 (0.517)	-	-
Age30-49	-0.001 (0.007)	0.512 (0.645)	-	-
Industry dummy	yes	yes	yes	yes
Year dummy	yes	yes	yes	yes
Group dummies	no	no	yes	yes
Observations	121	121	2177	2177

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

When wage rates were regressed on training alone the results were negative in both the industry panel and group panel, although none are significant. This was surprising given that authors such as Dearden et al (2006) and Galindo-Rueda and Vignoles (2004) find positive impacts, although the latter only for middle aged males. When training was interacted with ICT capital the results were positive, and significant in both the industry and group panels. The coefficients on the labour type dummy variables are mostly insignificant in the industry panel and not sensible signs for the youngest age group where we expect lower average earnings than for older workers.

Combining the low training proportions with the rise in ICT capital would therefore in both equations suggest lower growth in earnings among older workers. This would be counterbalanced to some extent by the negative TR coefficient which will decrease earnings more for workers with higher training. The following chart shows the predicted wages for high skilled males using the group panel regression results. This shows that wages of the oldest age group have indeed suffered from lack of ICT linked training.

Figure 4: Predicted wages



4. Training and ICT: Received versus offers

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

The individual worker will undertake training if the benefits to them outweigh the costs. Benefits are likely to be dominated by pay but might also include non pecuniary benefits that include working conditions. Since training leads to productivity increases and, in a competitive market, increased pay we would expect workers to accept training if offered. However the sociological literature and the results shown below suggest that not all workers accept training and the ratio of acceptances to offers rises education and declines with age.

The LFS allows examination of these issues as it includes information on offers of training as well as uptake. Table 6 summarises these data. The first panel shows the proportion of workers not offered training. This decreases with skill level but increases with age for males for given skill group. Comparing those aged 50 and over with the middle age group, the highest skill group shows the greatest proportional disadvantage. This is consistent with the idea that firms are less likely to train older workers for given skill levels. A similar conclusion applies to females but the differences are not as great as for males. The second panel shows the take-up rate for training offers. This declines with age suggesting some role for a reluctance of older workers to undertake training. For males in the higher skill group, the difference between the over 50s and the middle age group is not large suggesting that reluctance on the part of firms to provide training dominates for the higher group.

Table 6. Training: Receiving and Offers, UK, average 1995-2005

	Degree and above	Intermediate	Low
% of workers not offered training			
Male			
15-29	31.7	44.9	66.2
30-49	32.5	48.8	72.7
50+	45.2	60.0	76.8
Female			
15-29	28.9	41.6	63.4
30-49	26.7	40.9	67.1
50+	33.2	45.7	70.1
workers receiving training as a % of offered training			
Male			
15-29	64.0	58.3	47.3
30-49	56.4	45.5	29.3
50+	54.4	37.8	22.8
Female			
15-29	66.2	58.9	51.4
30-49	62.5	50.1	33.7
50+	63.6	44.2	25.4

It is interesting to consider to what extent wages would have increased if those offered training had in fact accepted training. We calculated the 'counterfactual' increase in wages using the group panel coefficients above, and substituting the proportion of the workforce offered training for proportion receiving training. The ratio of this to wage growth based on received training is shown in Table 7. This suggests that lower skill and older age groups would have benefited relatively more if they had taken up training offers than highly skilled and younger workers.

However among highly skilled males, those aged 50 and over would not have benefited much more than the middle aged group suggesting the relative performance of these two groups is driven more by the behaviour of firms offering lower training to highly skilled older workers.

This raises the question of why individuals might engage in what appears to be irrational behaviour. One possibility is that the training offered but turned down is not of the same quality as that taken up. The LFS has some information that may allow us to consider this in future work, e.g. on whether training is external or internal to the firm and the duration of training.

Table 7. Ratio of predicted annual growth in wages, Offered versus received training.

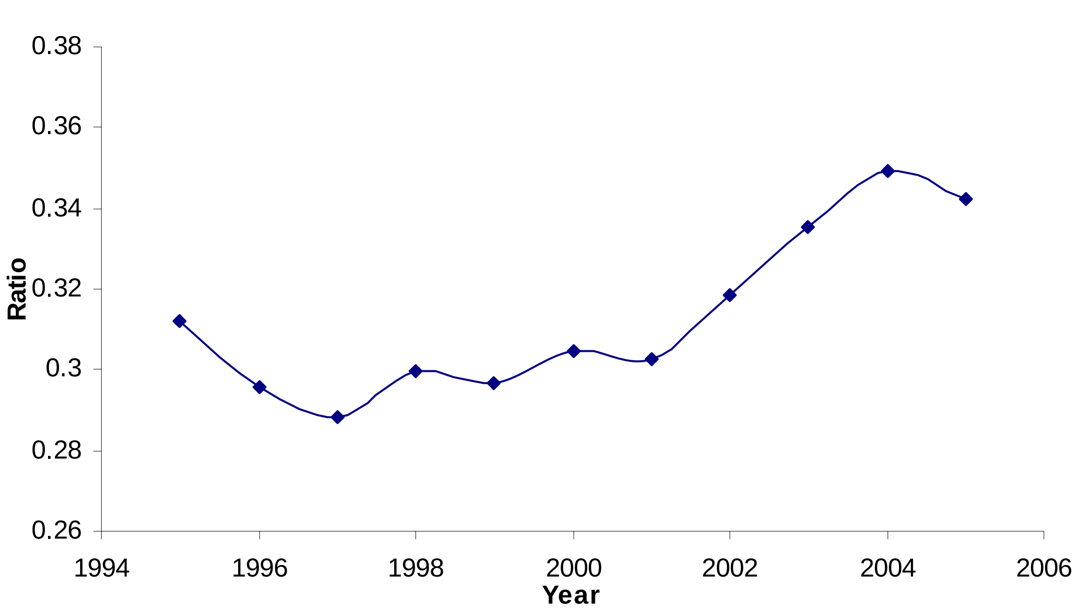
Male			
15-29	1.56	1.72	2.11
30-49	1.77	2.20	3.41
50+	1.84	2.65	4.39
Female			
15-29	1.51	1.70	1.95
30-49	1.60	2.00	2.97
50+	1.57	2.26	3.94

5. Quality of Training

This section considers other training variables available in the LFS that might give some additional information on the quality of the training offered. The variables considered are duration of training, time spent on training and whether the training was offered on or off the job. An important qualification attached to using these data is that the questions are only put to those who undertook some training in the four weeks before the quarterly survey. This raises a number of issues. The first is that the training variable employed above is the proportion of workers trained in the three months before the survey so the additional questions are asked of only a sub sample of the positive respondents to the initial training question. However over 50% of those trained received some training in the past 4 weeks and this ratio has remained stable since 1995. Therefore the effect is likely to be to lower the sample size rather than impart any biases. A related issue is the questions on time spent training is only asked of those who had some training in the reference week and so the sample size is very small. A third issue is that those offered but declining training are not asked the additional questions but as the discussion above we are particularly interested in these workers. This means that we need to assume that the type of training is the same for acceptors and decliners – this assumption is discussed further below.

The question on length of training course, TRNLEN, is divided into bands of weeks and the total length of the course was recorded not just the part that has so far been completed. For persons engaged on day or block release the total length of training is given. For persons who have "dropped out" of a course the time spent on the course, not the length is recorded. The chart below shows the proportion of 'short' courses, i.e. those lasting 1 week or less. These represent about 30% of training courses overall and shows a slight tendency to rise since 1995.

Figure 5 Proportion of less than one week



The following Table shows the proportion of short courses according to the demographic/skill breakdown. It suggests that younger workers are likely to receive longer training and this is true for both males and females. Somewhat surprisingly the proportion receiving short courses is much greater for those with university degrees than other skill groups and the difference is most pronounced for the youngest age group. This suggests that firms are more willing to invest resources in training the younger workers with lower skill levels, possibly as these workers have less outside options and so are less mobile and less likely to leave the firm than those with degrees. Nevertheless there is a significant difference in the incidence of short courses among older workers than the very young. This finding is reinforced by Table 8.b which shows average length of training, which is about 3 times for younger than older workers.

Table 8a % of workers offered training lasting one week or less

Average 2003-05

	Degree and above	Intermediate	Low
% of workers offered training lasting one week or less			
Male			
15-29	38.1	17.4	12.9
30-49	55.7	49.2	39.0
50+	64.4	58.7	65.6
Female			
15-29	39.2	20.2	14.1
30-49	55.4	42.5	33.0
50+	62.9	54.8	51.7

Table 8b Average length of training course (weeks), average 2003-05

	Degree and above	Intermediate	Low
Average length of training course (weeks)			
Male			
15-29	48.1	90.7	68.0
30-49	23.9	23.8	24.3
50+	12.6	11.4	8.5
Female			
15-29	44.9	85.1	63.1
30-49	26.8	34.4	30.5
50+	17.1	16.8	13.5

The second variable we consider is on the job training, JOBTRN, which according to the LFS definitions means learning by example and practice while actually doing the job. Any training conducted in a classroom or training section, even if on the employers' premises is not "on the job training". The chart below shows that the proportion of those trained receiving this on the job is rising over time and represents about 30% of all training on average in the sample period.

The table below shows the per cent of workers receiving 'on the job training' only which can be interpreted as a relatively low cost and hence lower quality type of training. Here we see that the main distinction is across the skill dimension with the lowest qualified less likely to be offered external courses. For those with intermediate skills older workers appear on average to be more likely to be only offered training on the job but the reverse is true for those with degrees and there is no apparent difference in the low skilled group between the very young and those aged over 50.

Table 9 % of workers offered on the job training only, average 2003-05

	Degree and above	Intermediate	Low
% of workers offered on the job training only			
Male			
15-29	32.9	33.0	58.6
30-49	27.3	36.8	52.6
50+	27.5	40.3	57.6
Female			
15-29	32.2	33.8	53.2
30-49	25.8	34.3	52.0
50+	27.8	37.9	59.9

The data on quality of training suggests it might be the case that the training offered to older workers is of a relatively lower quality but the evidence is far from conclusive. The most important caveat is that we can only observe these quality dimensions for those who in fact take up the offer of training and the selectivity bias could obviously be very significant.

6. Conclusions

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

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