

The Returns to General versus Job-Specific Skills: the Role of Information and Communication Technology

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Abstract

This paper examines the effect of information and communication technologies (ICT) on the return paid to two different types of skill: general skills, acquired through schooling and work experience, and job-specific skills, acquired by experience in a particular job. Using the UK Labour Force Survey we estimate skill returns in different industries over the period 1994-2001. We evaluate the marginal effect on these returns of the ICT intensity of industry capital and find that the shift towards ICT capital has been associated with a rise in the return to general skills and a reduction in the return to job-specific experience.

JEL Classification: J30; J31; O30.

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1 Introduction

It is widely believed that recent advances in technology, the development of information and communication technologies (ICT) in particular, have contributed to changes in the skill structure of employment and rising skill premia (see Acemoglu (2002) for a review of the arguments and Chennells and Van Reenen (2002) for a review of the empirical literature). The focus of this paper is on the relationship between ICT and the premium paid to general skills as opposed to job-specific skills. By general skills we mean those which are applicable in a wide variety of contexts, including the context of learning. Job-specific skills are applicable in a particular job only or at most in a limited set of jobs. Typically empirical studies have employed various educational or occupational hierarchies as measures of skill levels. The distinction between skill types made here has, as far as we are aware, not been made explicit in previous empirical analyses.

The paper is motivated by a number of observations. A growing set of theoretical models are based around the idea that technology adoption and diffusion require workers to learn and adapt (*e.g.* Greenwood and Yorukoglu, 1997; Aghion, 2002). Learning is costly and hence fast learners earn a premium at times of rapid or major technical change. In a similar set of models

new technologies are skill-biased if their use requires greater learning investments than old technologies. Individuals for whom learning investments are less costly (Caselli, 1999), perhaps because they have less to lose in terms of experience with older technologies (Helpman and Rangel, 1999), earn a premium when new technology is skill-biased. Krueger and Kumar (2004) develop a model to suggest that economies with education systems favoring general rather than specific skills are better able to adopt new technologies and hence grow more quickly in equilibrium. Central to these models are the assumptions that skills are not costlessly transferable from old to new technologies, such that in effect some skills are left obsolete with the introduction of new technology, and that general learning skills are necessary for technology implementation when technical change is either rapid or new technologies are skill-biased.

Quite separate from considerations about the role of general versus specific skills in the technology adoption and diffusion process is the possibility that ICT is intrinsically complementary to general rather than specific skills. Autor *et al.* (2003) present compelling evidence to suggest that this may be the case. They suggest that computers substitute for routine tasks, such as record-keeping and calculation, and complement non-routine tasks, such as

forming and testing hypotheses and managing others. Arguably the skills required to perform non-routine tasks are by their very nature of the general type. In a similar vein, the skills required to perform particular routine- or rule-based tasks, are less likely to be widely transferable between jobs.

Studies that employ other sometimes more sophisticated measures of skill than education or occupation are consistent with the hypothesis that the development and diffusion of ICT has been complementary to general rather than job-specific skills. Gould (2005) suggests that the returns to IQ and general, rather than sector-specific, unobserved ability were rising in the United States between 1978 and 1992. Murnane *et al.* (1995) find that an increase in the return to basic cognitive skills can explain much of the rise in the college wage premium in the United States between 1978 and 1986. More recently for the United Kingdom, Dickerson and Green (2004) suggest that the use of generic skills in the workplace increased between 1997 and 2001. Of these skills, high level communication skills and computer skills carried wage premia.

Finally, one of the striking features of the UK labor market in recent decades has been the rise in disability benefit claims and early retirement for older men (Disney, 1999; Nickell and Quintini, 2002). Older generations

usually have more job-specific experience than younger generations. If technology reduces the return to job-specific experience relative to general skills such as schooling, it will directly reduce the incomes of older in comparison to younger generations, all else being equal. Indirectly, this effect may be exacerbated as older cohorts may have relatively more to lose from re-skilling themselves. For example, the loss of wage income whilst acquiring further schooling has a relatively large effect on pensions income for older cohorts and the years over which the returns to such an investment can be capitalised is relatively short. Indeed, in a 1998 sample of French firms, Aubert *et al.* (2006) find that the use of information technologies and innovative workplace practices is biased against older workers.

In this paper we assess the effect of industry ICT intensity on industry specific returns to schooling and potential work experience, which serve as proxies for general skills, and job tenure, commonly used as a proxy for job-specific experience. Our analysis is based on annual observations from 1994 to 2001 for 16 industry groups comprising the entire market sector of the United Kingdom economy. Estimates of the return to different forms of human capital in different industries are obtained from a Mincerian type earnings equation using the UK Labor Force Survey. In comparison to many studies of

the relationship between ICT or technical change and skill premia our sample period is relatively recent and covers a period of rapid ICT implementation or diffusion. Between 1994 and 2001 the share of the UK market sector capital stock classified as ICT rose from 4% to $15\frac{1}{2}\%$.

We find that human capital returns display significant industry and time variation. In line with the literature we find that across industries the return to schooling increases with the ICT intensity of capital and that the magnitude and significance of this effect is reduced by efforts to control for various selection issues. We also find that the return to potential experience increases with ICT intensity. In contrast, the return to job-specific experience decreases with the ICT intensity of capital across industries. At the same time, the return to job-specific experience rises with the overall capital intensity of production. Our results lend support to the notion that ICT is biased towards general skills, which are useful in acquiring new skills and in performing a broad range of activities, and biased against skills that are less transferable between jobs. The findings reported here are consistent with the interpretation that recent technical change, although skill-biased, renders some job-specific skills obsolete. The results suggest that older workers, who are likely to have both more general and more job-specific experience than

younger workers, are adversely affected by ICT. The estimated positive effect of ICT on general experience is only half the magnitude of the estimated negative effect of ICT on job-specific experience.

The structure of the paper is as follows. In the next section we review the data and discuss measurement issues. In section III we set out our strategy for identifying the effects of ICT on different forms of human capital and the estimation procedure. Results are reported in section IV and a final section concludes.

2 Data and measurement

Here we briefly review the two data sources we use to obtain information on ICT capital and the premia paid to various measures of skill. We discuss our proxies for general and specific skills and a number of measurement issues.

2.1 Human capital and earnings

We use the United Kingdom Labor Force Survey (LFS) over the period 1994 to 2001 to estimate returns to general and specific human capital in different industries and years. The LFS is a quarterly survey of approximately 61,000

households across the United Kingdom with a 5-quarter rolling panel design. For the purposes of this paper we use information at the individual level; this translates to all adults within the household. The LFS is particularly suitable in the current context due to its relatively rich information on individuals' characteristics, including employment and earnings, its frequency and large sample size. The latter is important since we wish to obtain estimates of skill returns disaggregated by industry and time.

Earnings questions have been included in the LFS since the fourth quarter of 1992. From the fourth quarter of 1993 industry recordings switched from Standard Industrial Classification (SIC) 1980 to SIC 1992. We restrict our analysis to the period from 1994 onwards to avoid problems with different industry classifications. Before the end of 1996 earnings questions were asked of respondents only in the fifth and final survey wave. Since 1997 earnings questions have been asked in both the first and fifth waves of the survey, effectively doubling the quarterly sample of earnings data. We include in our sample wave 5 respondents only to avoid issues of differential attrition bias. We exclude the approximately 2,000 responding households in Northern Ireland as their inclusion otherwise restricts the time period available.

Our sample comprises employees of working age, defined as 16-64 for

men and 16-59 for women, who are not in full-time education and who have responded with a positive value for earnings and hours worked. Using these variables we are able to derive an hourly earnings variable, which we deflate to 2000 prices using the UK National Accounts consumer expenditure deflator. Following Anderson *et al.* (2001) and Manning (2003) we restrict our sample to those whose hourly earnings were greater than or equal to £1 and less than or equal to £100 in 2000 prices. We apply the adjustment procedure proposed by Wilkinson (1998) to correct for the discrepancies between self-reported earnings and proxy respondents in the LFS. We use each quarter of the LFS to boost annual sample sizes and to maximize the industry detail. This restricts the available control variables somewhat. For example, we are unable to control for union membership as this is only asked of respondents in the third quarter of the LFS.

We proxy general skills by years of schooling, defined as years spent in continuous full-time education, and years of potential work experience, defined as current age minus age left full-time education as in Manning (2003) and Harmon, Oosterbeek and Walker (2003). We proxy job-specific skills by tenure, defined as continuous years served with current employer. An important question that arises is whether years of schooling and work experience

provide good proxies for general skills and whether years of job-specific experience provide a good proxy for job-specific skills? A related concern is whether or not these proxies are adequately measured.

As regards the first question, it is obvious that none of these proxies capture general or job-specific skills perfectly. Indeed, it is probably not very sensible to think of skills as being either useful in all jobs or useful in a few jobs only. These two cases lie at opposite extremes and most skills will fall somewhere in between. Similarly, the skill measures used here should be thought of as capturing a more or a less general set of skills.

Taking each proxy measure in turn, schooling provides individuals with a number of basic skills such as reading and writing skills, it increases general knowledge and enhances individuals' ability to learn. These are skills which are general in the sense that they are applicable in a broad range of jobs. Schooling may also provide individuals with a number of specific skills that may be suitable to particular jobs only, but the important point is that schooling provides a range of these. Work experience should provide individuals with a set of skills that are important in the workplace, some of which are likely to be suitable to a restricted set of jobs only. Equally, others are likely to be more widely applicable, such as the ability to interact

and communicate in a workplace, to meet deadlines, and to give and follow instructions. When contrasted with job-specific experience, work experience accumulated over an individual's entire career is likely to be more general in nature.

Concerning the second question, there are a number of measurement issues that need mentioning. Years spent in continuous full-time education may not fully capture the amount of time spent in education. For example, a respondent may have taken a gap year after finishing secondary education and before beginning tertiary education. To get around this problem we could employ individuals' highest educational qualification, also recorded in the LFS, as an indicator of general skills rather than years of schooling. However, years of schooling is an attractive measure since it is more easily comparable to years of potential or job-specific experience. We also avoid the problem of somewhat arbitrary rankings or groupings of different qualifications.

Using the LFS we are limited to measuring work experience as potential rather than actual work experience. This is a standard problem. Potential experience is likely to be a better proxy for work experience than is age. Also, in terms of the effect on the estimated return to schooling in the framework we

employ below, potential experience is very similar to actual work experience, whereas age is not (Harmon, Oosterbeek and Walker, 2003).

Tenure, our proxy for job-specific experience, also suffers some measurement error. It is common in the literature to think of job tenure as job-specific experience (see *e.g.* Topel, 1991). Nevertheless, an individual may have done the same job with different employers, in which case our proxy underestimates job-specific experience. Also, an individual may have worked in different jobs with the same employer, in which case our proxy overestimates job-specific experience.

2.2 ICT capital

We use the National Institute Sectoral Productivity (NISEC) dataset to construct measures of industry capital and ICT intensity. The UK data within NISEC are developed from UK National Accounts investment data, which are also used to create official estimates of industry capital stocks. However, the capital stock data published by the Office for National Statistics do not include a separate measure of ICT capital. The NISEC data include measures of ICT capital (computers, software and other ICT technology) and non-ICT capital (structures, vehicles and non-ICT equipment) constructed

using the perpetual inventory method assuming asset specific depreciation rates, as described in O'Mahony and Vecchi (2005). These data are available as annual observations 1950-2001 for 26 UK industries covering the entire UK economy.

As we are limited by small cell sizes in the LFS we aggregate these data into 16 industry groupings excluding all non-market services: agriculture and non-manufacturing production, 7 manufacturing industries (chemicals and allied products; basic metals; machinery; electrical and optical equipment; transport; food, drink and tobacco; other), construction, wholesale and retail, hotels and restaurants, non-manufacturing transport, communications, business services, and personal services. Excluded non-market services are made up of health, education and public sector administration. Using these data we construct annual estimates of industry ICT shares of total capital. In combination with National Accounts data for levels of gross value-added by industry, deflated to be comparable in volume terms to the capital stock data, we obtain annual estimates of industry capital-output ratios.

Restricting our attention to 1994-2001, the period we use in estimation, the mean ICT share of capital across industries and years is 8.9%, varying from 0.6% to 53.6%. The mean capital-output ratio is 1.5, varying from 0.3

to 3.5. Variation in both the ICT share of capital and the capital-output ratio occurs mostly across industries, rather than over the time dimension. The capital-output ratio displays particularly little variation over time.

3 Empirical strategy

We investigate the effect of ICT on the returns to general and specific human capital in an industry panel. First, we describe the way in which we obtain estimates of human capital returns. Second, we describe our panel analysis of the relationship between ICT and these returns.

3.1 Estimating the returns to human capital

We estimate the returns to human capital in different industries and years, within a standard model of earnings, by allowing the coefficients on the human capital terms to vary by these two dimensions. We estimate the returns to the three measures of skill discussed in the previous section: potential experience (P), schooling (S), and job tenure (T). The first two are measures of general skills and job tenure is a measure of job-specific skills. We use a standard Mincer-type earnings function, augmented with quadratic terms

for all human capital types to capture non-constant returns, of the form

$$\ln Y_i = \alpha + \sum_{H=P,S,T} [\beta^{H1} H_i + \beta^{H2} H_i^2] + \gamma X_i + \varepsilon_i \quad (1)$$

where $\ln Y_i$ is the log hourly wage deflated to 2000 prices, α is a constant term, H_i is years of human capital type P , S or T , X_i is a vector of explanatory variables and ε_i is an error term for individual i . The quadratic term in potential experience is standard. The importance of relaxing the assumption of linearity in schooling is discussed in *e.g.* Heckman *et al.* (2003) and Trostel (2004). We follow Cingano (2003) by relaxing the assumption of linearity in tenure. We extend this earnings function to allow the coefficients on the human capital terms (β^{Hi} , $H = P, S, T; i = 1, 2$) to vary both by industry and year, denoted by subscripts j and t respectively. Then H_{ijt} is years of human capital type P , S or T , for individual i employed in industry j at time t . Since we observe each individual at one point in time in one job only, an individual with $H_{ijt} > 0$ for $jt = JT$ has $H_{ijt} = 0$ for $jt \neq JT$. We include industry-year specific fixed effects, δ_{jt} . Without these, industry-time specific demand or supply shocks and/or composition effects would be absorbed in our estimates of industry-year specific human capital returns, which would

then be biased. Thus our model becomes:

$$\ln Y_i = \alpha + \sum_j \sum_t \sum_{H=P,S,T} [\beta_{jt}^{H1} H_{ijt} + \beta_{jt}^{H2} H_{ijt}^2] + \gamma X_i + \delta_{jt} + \varepsilon_i \quad (2)$$

Evaluated at industry-year sample means, the marginal return in industry j at time t to one additional year of human capital accumulation is given by:

$$\omega_{jt}^{\bar{H}} = \beta_{jt}^{H1} + 2\beta_{jt}^{H2} \bar{H}_{jt} \quad (3)$$

where $\bar{H}_{jt} = \frac{1}{N_{jt}} \sum_i H_{ijt}$ and N_{jt} denotes the number of individuals employed in industry j at time t .

We have two selection problems. The first is the problem of endogenous schooling choice when the error term in (2) is likely to capture individual unobserved ability. Since high ability individuals are more likely to invest in schooling the error term and years of schooling are correlated. A common solution is to use instrumental variables (IV) to control for ability bias (see *e.g.* Card (1999) and Harmon, Oosterbeek and Walker (2003) for a review of the literature). However, as discussed in Harmon, Oosterbeek and Walker (2003), there are problems finding suitable instruments and the available evidence suggests that IV estimates may be biased upwards, particularly for the UK. Harmon, Hogan and Walker (2003) conclude that the effect of measurement error and ability bias on OLS estimates of returns to education

may cancel each other out. With these considerations in mind we simply apply OLS to (2). Furthermore, rather than the level it is the variation in schooling returns across industry and time that is central to the objectives in this paper.

This latter point raises a separate endogeneity issue; the possibility that individuals with certain human capital characteristics self-select into particular industries. If this is the case then the industry variation in individuals' human capital is endogenous and the estimated coefficients on human capital, indexed by industry and year, may be biased. For example, suppose the ability premium is relatively high in ICT intensive industries. In this case high ability individuals select into ICT intensive industries and the estimated return to schooling will be biased upwards in these. Note that in this paper schooling is used to represent a general set of skills, and therefore the bias that arises from the correlation of schooling with ability is not as problematic as it may initially seem, since ability is a general skill. To take another example, suppose that the return to job-specific experience is relatively low in ICT intensive workplaces so that individuals with much job-specific experience switch out of these and appear instead as low-tenure individuals in workplaces that are less ICT intensive. These individuals may bias the esti-

mated return to tenure upwards in ICT intensive industries, where more ICT intensive workplaces are likely to be concentrated, since it is those individuals who are most adversely affected that are likely to leave. At the same time, since tenure is an imperfect measure of job-specific experience and is likely to capture other attributes that may carry a premium in the labor market such as *e.g.* loyalty and reliability, these individuals may bias the estimated return to tenure downwards in less ICT intensive industries, where less ICT intensive workplaces are likely to be concentrated. If individuals switch to less ICT intensive workplaces within the same industry, they may bias the estimated return to tenure downwards in ICT intensive industries as well. In what follows we assess the robustness of our results to some of these issues by excluding from the sample individuals who have been in their current job for less than 2 years. In other words, we restrict our attention to those individuals who are less likely to have self-selected into a particular industry because of recent changes in the use of ICT across industries. The cut-off point of 2 years is admittedly somewhat arbitrary.

3.2 Evaluating the effect of ICT on human capital returns

To estimate the effect of ICT technology on the return to general and job-specific skills we regress the industry and year specific estimates of human capital returns obtained from model (2) on the ICT share of capital, controlling for the overall capital intensity of production, as well as industry specific and time specific fixed effects. As illustrated in eq. (3), estimated human capital returns depend on human capital levels, which themselves may determine the ICT share of capital. To bypass this potential endogeneity problem, we evaluate the effect of ICT on the return to general and job-specific skills at given skill levels. To do this we regress estimates of β_{jt}^{Hi} from model (2), rather than ω_{jt}^H given by eq. (3), on the ICT share of capital and other controls. We have:

$$\beta_{jt}^{Hi} = \lambda_k^{Hi} k_{jt} + \lambda_{ICT}^{Hi} ICT_{jt} + \theta_j^{Hi} + \eta_t^{Hi} + \varepsilon_{jt}^{Hi},$$

$$H = P, S, T; \quad i = 1, 2; \tag{4}$$

where j denotes industry and t denotes year as above, k is the capital-output ratio, ICT is the ICT share of the capital stock, θ_j is a set of industry fixed effects, η_t is a set of year fixed effects, and ε_{jt} is an error term. Observations

on the dependent variable in eq. (4) are obtained by estimating eq. (2). From this initial estimation exercise we also obtain estimates of the variances of these observations. These are not homogeneous across industries and years. To correct for the implied heteroscedastic error structure in eq. (4), we follow Saxonhouse (1976) and weight each observation on all variables by the inverse of the estimated standard errors of the dependent variable. We then estimate this 6 equation system using SUR. Given the weighting procedure just described this is more efficient than least squares applied to the individual equations and allows us to test cross equation restrictions.

Within this model we can evaluate the marginal effect of ICT intensity on the return to general and specific human capital, assuming exogenous human capital levels. If $q_{ICT}^{\bar{H}} \equiv \left. \frac{\partial \omega^H}{\partial ICT} \right|_{\bar{H}}$, then we have from eqs (3) and (4):

$$q_{ICT}^{\bar{H}} = \lambda_{ICT}^{H1} + 2\lambda_{ICT}^{H2} \bar{H} \quad (5)$$

where we have fixed human capital at its total sample mean, $\bar{H} = \sum_i H_i$. An expression for the effect of the capital intensity of production on the return to human capital can be similarly derived. Rejection of the null $H_0 : q_{ICT}^{\bar{H}} = 0$ against the alternative $H_1 : q_{ICT}^{\bar{H}} \neq 0$ implies a non-zero effect of ICT on the return to human capital type H . We assess this for general skills as proxied by years of potential experience, P , and schooling, S , and for job-specific

skills as proxied by years of tenure, T . We also test for differences in the effect of ICT on returns to the three different human capital types.

4 Results

4.1 Industry-specific returns to human capital

Table 1 gives OLS estimates of the model in eq. (2), where $j = 1 - 16$ and $t = 1 - 8$. We control for sex, birth cohort (nine cohort dummy variables), region of residence based on the August 1998 definition of Government Office Regions, size of the establishment where the individual works, marital status, and full-time status (defined as greater than or equal to 30 hours per week, excluding overtime). We also include separate dummy variables for each sex that control for private sector employment. There is econometric evidence that women suffer a pay penalty when working in the private sector, whereas for men there is a pay penalty for working in the public sector (Anderson *et al.*, 2001). The regression also includes a full set of industry-year dummies and sample quarter dummies. Industry-year specific returns to human capital as derived in eq. (3) are illustrated in figures 1 to 3.

Table 1: OLS earnings estimates

Dependent variable: log hourly wages	Coefficient	t-statistic
Male	0.079	11.63
Born 1940-1944	-0.033	4.06
Born 1945-1949	-0.035	3.19
Born 1950-1954	-0.044	3.12
Born 1955-1959	-0.020	1.16
Born 1960-1964	0.026	1.32
Born 1965-1969	0.081	3.79
Born 1970-1974	0.082	3.53
Born 1975-1983	-0.004	0.17
North East	0.032	6.67
Yorkshire & Humberside	0.011	2.28
East Midlands	0.022	4.30
West Midlands	0.015	3.15
East	0.046	7.83
London	0.239	45.95
South East	0.171	38.32
South West	0.030	6.06

Table 1: OLS earnings estimates - continued

	Coefficient	t-statistic
Wales	-0.021	3.72
Scotland	0.030	6.10
25-49 employees at workplace	0.082	25.42
50 or more employees	0.154	67.01
Don't know but over 24	0.081	7.04
Private sector (male)	0.036	7.49
Private sector (female)	-0.085	15.00
Cohabiting	0.061	27.06
Full-time hours	0.146	45.61
Constant	-0.633	1.11
Sample size		184044
F(924,183119)		155.92

Notes: t-statistics calculated using robust standard errors; Industry-year dummy variables included; Sample quarter dummies included; Industry-year specific coefficients on human capital terms are illustrated in figures 1 to 3; Reference category is female, born 1929-1939, resident in North West, <25 employees at workplace, sampled 1994Q1, employed in the agriculture or non-manufacturing production sector.

The coefficient estimates in Table 1 are generally significantly different from zero and have the expected signs. The reported t-statistics are calculated using robust (White corrected) standard errors. There is a significant wage premium paid to men. The gender pay gap widens in the private sector, where women suffer a significant pay penalty and men receive a significant pay premium. As expected we find quite a considerable pay premium for employees resident in the London and South East regions. The premium to working full-time is also very significant, with full-time employees earning almost 15% more per hour than those defined as working part-time. Also as expected we find that large employers pay more than smaller employers, and that there is a positive pay premium associated with marriage.

The coefficients on the industry-year dummy variables and the industry-year specific coefficients on potential experience, schooling, and job-specific experience (and the squared terms in these) are not reported in table 1. Instead we plot the estimated marginal return to one additional year of each of these human capital types in figures 1 to 3 respectively, together with their 95% confidence intervals. Returns are evaluated at industry-year sample means as in eq. (3). The standard errors used to calculate confidence intervals for these take into account parameter uncertainty only,

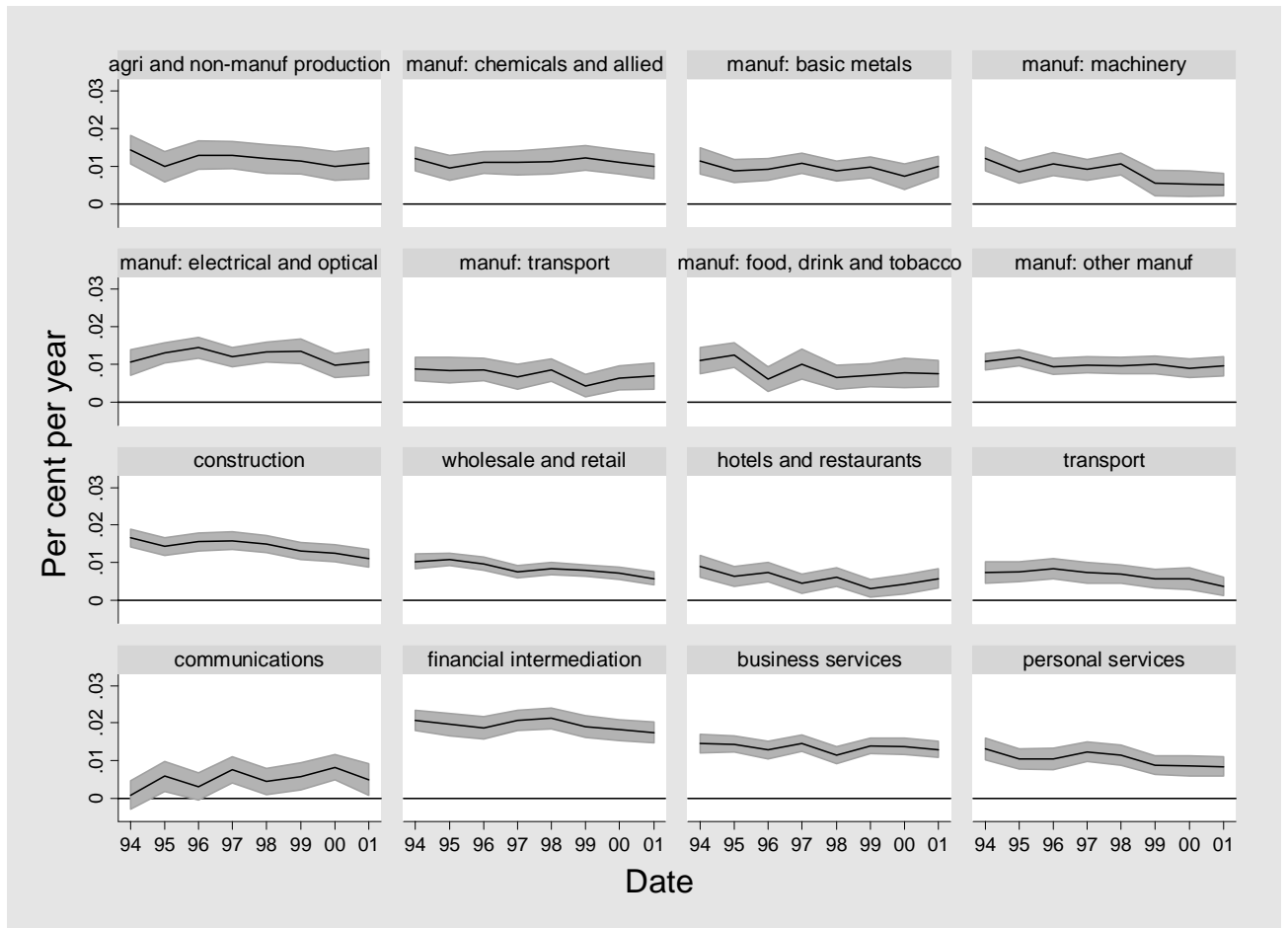


Figure 1: Return to potential experience by industry, 1994-2001

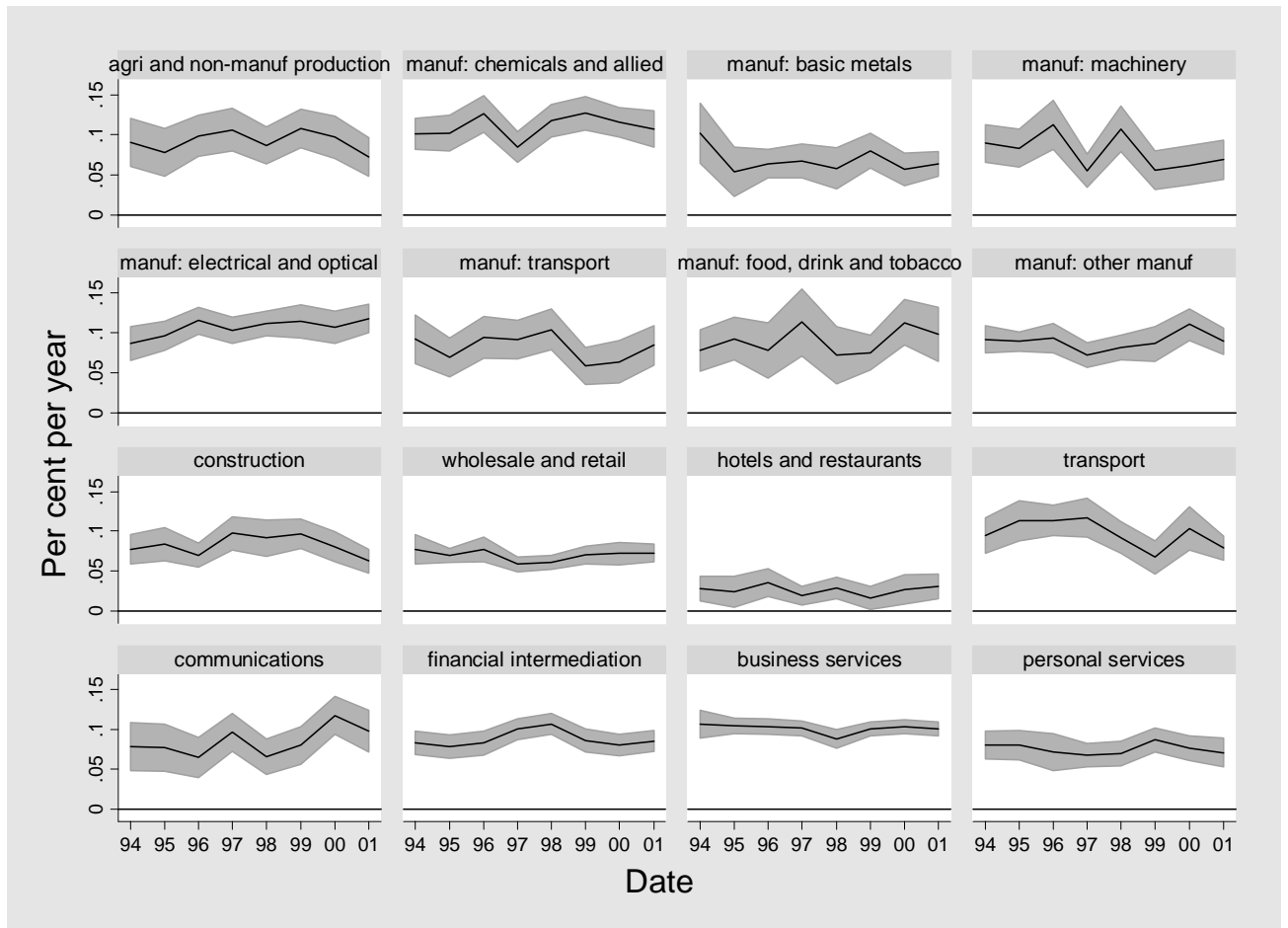


Figure 2: Return to schooling by industry, 1994-2001

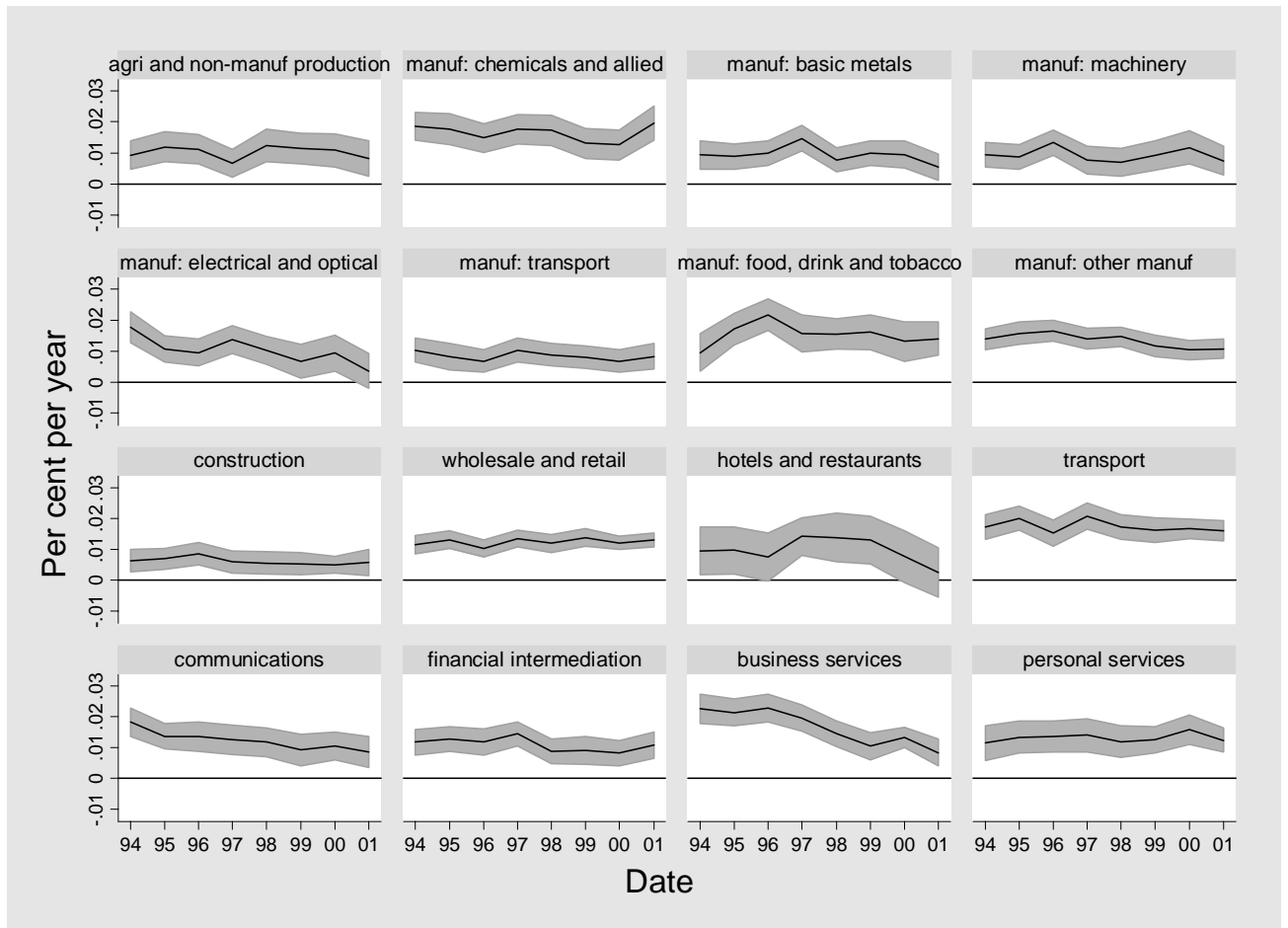


Figure 3: Return to job-specific experience by industry, 1994-2001

treating the industry-year sample means as given. The quadratic in human capital in (2) complicates the marginal returns expression in (3) and its variance, but F-tests suggest that the squared terms should be included ($F(128, 183119) = 16.34$ (P); 6.99 (S); 5.76 (T)).

Figures 1-3 show that marginal returns to human capital (and their standard errors) vary significantly across the sixteen industry groups in the sample. They also vary over time (the period 1994 to 2001), but most of the variation occurs across industries. With the exception of the communications industries in 1994 and 1996, the marginal return to an additional year of experience is positive and significant at the 5% level in all industries and years, and averages around 1% (figure 1). The marginal return to job-specific experience (figure 3) is generally a little higher than the return to experience and is greatest in the manufacture of chemicals and allied products; it shows quite significant declines over the sample period in both the manufacture of electrical and optical equipment and in business services. The return to an additional year of schooling (figure 2) is significantly higher than the return to an additional year of experience, be it job-specific or general. Averaging across industries and time our estimates are consistent with those found elsewhere in the literature (Harmon, Oosterbeek and Walker, 2003). Schooling

returns are lowest in the hotels and restaurants industries and highest in the manufacture of chemicals and allied products and in business services. In the next section we discuss how this variation in human capital returns is related to the capital-output share and the ICT intensity of capital.

4.2 Industry ICT intensity and human capital returns

Estimates of λ_k^{Hi} and λ_{ICT}^{Hi} in eq. (4) are reported in Table 2. The dependent variables are the estimated coefficients on the human capital terms in (2). We also show the associated estimates of the marginal effect of ICT or capital on the return to an additional year of skill accumulation as expressed in (5), and differences in these between skill types.

The results in Table 2 suggest that the ICT intensity of capital has a positive and significant effect on the constant term in the expression for the return to potential experience and schooling (see eq. (3)) and a negative and significant effect on the secondary term, although the effects on the schooling terms are only significant at the 20% level. In contrast, ICT intensity has a negative and significant effect on the constant term in the expression for the return to job-specific experience and a positive and significant effect on the secondary term. Evaluated at sample means this estimated model implies

Table 2: Determinants of industry-year specific returns to human capital

		K/Y		ICT/K	
Equation:	β^P	.0028	(0.53)	.0432	(3.40)***
	β^S	.0346	(0.46)	.2782	(1.52) \sim
	β^T	.0063	(1.28)	-.0410	(3.44)***
	β^{P^2}	-.0001	(0.49)	-.0006	(2.34)**
	β^{S^2}	-.0013	(0.46)	-.0091	(1.40) \sim
	β^{T^2}	-.0003	(1.85)*	.0006	(1.74)*
Marginal effect on the return to human capital:	q^P	.0005	(0.30)	.0160	(4.24)***
	q^S	.0046	(0.33)	.0612	(1.71)*
	q^T	.0021	(0.65)	-.0317	(4.09)***
Differences in marginal effects:	$q^P - q^T$	-.0016	(0.41)	.0477	(4.94)***
	$q^S - q^T$.0026	(0.17)	.0929	(2.49)**
	$q^S - q^P$.0042	(0.32)	.0452	(1.34) \sim

Notes: |z-statistics| in parentheses; Significant \sim at 20%, * at 10%, ** at 5%, *** at 1%; 768 obs. (6 eqs.*16 industries*8 years); observations weighted by the inverse of $se(\beta_{jt}^{Hk})$ estimated from the individual earnings equation; 6 eqs estimated by SUR; All models incl. time dummies and industry dummies; Log-likelihood=6328; Means used in calculating marginal effects: $\bar{P} = 21.0$; $\bar{S} = 12.0$; $\bar{T} = 7.5$.

that a 10 percentage point rise in the ICT share of capital is associated with a 0.16 and 0.61 %points increase in the return to potential experience and schooling respectively. The effect on experience returns is significant at the 1% level and the effect on schooling returns is significant at the 10% level. The estimated effect of a 10 percentage point rise in the ICT share of capital is also to reduce the return to job-specific experience by 0.32 %points. This effect is significant at the 1% level. Thus, our results suggest that industry ICT intensity is associated with positive premia for our two proxies of general skills, and with a penalty for job-specific experience. Estimated differences in the effect of ICT on potential experience versus job tenure and on schooling versus job tenure are both statistically significant (also reported in table 2). There is a less statistically significant difference between the ICT premia paid to schooling and potential experience. There are no significant effects on skill returns from the capital intensity of production.

In estimating eq. (4) we have controlled for industry and time fixed effects. These capture industry and time effects that directly influence the return to human capital, whereas the industry-year fixed effects in eq. (2) capture industry-time effects that influence earnings more generally. We note that exclusion of the industry and time fixed effects in eq. (4) results in a

larger and statistically very significant effect of ICT on the return to schooling (not shown). This sensitivity of the results is well-known in the literature. For example, looking beyond the cross-section and controlling for fixed effects Doms *et al.* (1997) find that the impact of ICT on the return to skill in US manufacturing plants is much reduced and becomes statistically insignificant. Similarly, using a panel dataset of individuals in the UK during the 1990s, Dolton and Makepeace (2004) find a significant computer premium in the cross-section, which disappears using simple fixed effects estimates. We also note that the estimated ICT effect on the return to potential experience is only significant at the 20% level when we exclude industry fixed effects in eq. (4). It is of course important to include industry fixed effects and the model reported in table 2 does. The results there are consistent with other studies that assess the effect of technology on the return to general experience (see Allen, 2001; Weinberg, 2004). These find a positive effect of technology on the return to experience. The impact of ICT on the return to job tenure is also statistically insignificant if we exclude industry fixed effects.

While estimated ICT effects on human capital returns are sensitive to the inclusion or exclusion of industry fixed effects, the estimated difference between the ICT effect on general versus specific skills is less so. The ICT

effect on the return to schooling and job-specific experience is positive and statistically significant regardless of the inclusion or exclusion of industry fixed effects. However, the estimated differential between the ICT effect on the return to potential and job-specific experience is statistically insignificant when we exclude industry fixed effects.

As discussed in section 3.1, to address the problem of industry selection, we also report results where we have excluded workers with job tenures less than 2 years (table 3). As expected, the magnitude and significance of the ICT effect on the return to schooling diminish. We emphasize that this does not necessarily imply a weaker effect of ICT on general skills (see section 3.1). There is little change in the estimated effect of ICT on the return to potential and job-specific experience. The direction of the bias of these parameter estimates that arises from individual selection across industries was *a priori* unclear.

In terms of the overall picture we get of the effect of ICT on general versus specific skills the results reported in table 3 are little different from those in table 2. In contrast to the results based on the full sample, the restricted sample results show a larger and statistically more significant role for the capital intensity of production.

Table 3: Determinants of industry-year specific returns to human capital
(restricted sample)

		K/Y		ICT/K	
Equation:	β^P	.0044	(0.69)	.0500	(3.29)***
	β^S	.1688	(1.79)*	-.0015	(0.01)
	β^T	.0164	(2.96)***	-.0433	(3.21)***
	β^{P^2}	-.0000	(0.28)	-.0007	(2.19)**
	β^{S^2}	-.0066	(1.94)*	.0021	(0.27)
	β^{T^2}	-.0006	(3.53)***	.0006	(1.57) [~]
Marginal effect on the return to human capital:	q^P	.0027	(1.54) [~]	.0171	(4.13)***
	q^S	.0129	(0.72)	.0485	(1.10)
	q^T	.0053	(1.64)*	-.0314	(4.15)***
Differences in marginal effects:	$q^P - q^T$	-.0026	(0.65)	.0485	(5.16)***
	$q^S - q^T$.0076	(0.42)	.0799	(1.79)*
	$q^S - q^P$.0102	(0.59)	.0314	(0.74)

Notes: |z-statistics| in parentheses; Significant [~]at 20%, * at 10%, ** at 5%, *** at 1%; 768 obs. (6 eqs.*16 industries*8 years); observations weighted by the inverse of $se(\beta_{jt}^{Hk})$ estimated from the individual earnings equation; 6 eqs estimated by SUR; All models incl. time dummies and industry dummies; Log-likelihood=6265; Means used in calculating marginal effects: $\bar{P} = 22.8$; $\bar{S} = 11.9$; $\bar{T} = 9.9$.

5 Conclusions

This paper provides more evidence on the nature of ICT and skill-biased technical change commonly discussed in the literature. Using pooled cross-sections of the UK LFS we have estimated the return to general skills in the form of schooling and general experience and to job-specific skills in the form of job-specific experience (tenure). We find evidence of variations in the returns to these measures of human capital across industry groups and the years 1994-2001. A standard earnings function suggests the return to an extra year of schooling is greater relative to an extra year of job-specific experience in most industries. An additional year of job-specific experience is valued more highly than an additional year of general career experience in most industries.

Using data on asset specific capital from the NISEC dataset we have regressed these returns on measures of capital and technology intensity. In line with the literature, we find evidence of technology-skill complementarity. But, it would appear that this bias of ICT is towards more general skills, achieved either through schooling or career experience. Our results indicate that ICT is associated with an increase in the return to two separate measures of general skill. Furthermore, ICT is associated with a reduction in the

return to job-specific experience, which is likely to be less transferable to new technologies. Note that this finding does not rule out the possibility that for the subset of jobs which yield experience in the use of ICT itself, job-specific experience is more rewarding. This is what one might predict on the basis of models that emphasize the importance of learning with new technologies (*e.g.* Caselli, 1999; Aghion, 2002). Indeed, the study by Entorf and Kramarz (1997) suggests that experience with computer technologies carries a distinct premium.

General skills are arguably more useful in acquiring the new skills that may be required in implementing new technologies. In this sense the results in this paper could be interpreted as evidence of a learning process in implementing ICT. Alternatively, the results presented here may be interpreted to suggest that ICT is complementary to general skills rather than specific skills, as implied by the work of Autor *et al.* (2003). We also note that the analysis may capture the effect of ICT more widely. As suggested in Bresnahan *et al.* (2002), increased ICT use is likely to go hand in hand with a number of other innovations, including organizational change.

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