The returns to schooling and job-specific experience: the role of ICT technology

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30 January 2004

Abstract
We use the United Kingdom Labour Force Survey to estimate the returns to schooling and job-specific experience in different industries, over the period 1994-2001. Regressing these returns on measures of the capital intensity of production and the ICT intensity of capital, we find that ICT intensity increases the return to general skills, acquired through schooling, relative to the return to job-specific experience. Controlling for the effect of industry schooling levels on the industry return to job-specific experience, we find that the ICT intensity of capital devalues the return to job-specific experience.

JEL classification:
J30; J31; O30

Keywords:
Skill-biased technical change; return to human capital; technology adoption.

Acknowledgements:
We are grateful to participants at an ESRC user group seminar, held at NIESR in October 2003, for helpful comments and suggestions and to Mary O'Mahony for assistance with the NISEC database. We gratefully acknowledge the financial support received from the ESRC under grant L138250122.

Introduction

We investigate empirically the effect of technology on the return to different types of human capital. A number of studies have found that recent technical change and innovation has been biased towards skilled labour, resulting in a rise in the skill premium for a given skill composition of employment.[1] Typically these studies analyse trends in wage bill shares or relative wages, for different occupation or qualification groupings, and how they relate to measures of technical change, determining the shift in the relative demand for skills that can be attributed to technology. Here we look at the effect of technology on the return to general skills, acquired through schooling, versus job-specific skills, which are less transferable across different jobs and technologies. While, essentially, the complementarity of physical capital and recent technologies to human capital is a stylised fact (see Goldin & Katz (1998) for a review of the literature), the complementarity of these factors of production to different types of human capital has received less attention.

The effect of technical change on the returns to general versus job-specific skills is important from several perspectives. It is likely to have implications for the intergenerational distribution of labour market outcomes. Older generations typically have more job-specific experience than younger generations. If technology reduces the return to job-specific experience relative to 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 would have relatively more to lose from re-skilling themselves. In addition, generations closer to retirement age may have less incentive to undertake certain types of human capital investment in comparison to younger generations. For example, the loss of wage income whilst acquiring further schooling has a relatively large effect on pensions income for these generations and the years over which the returns to such an investment can be capitalised is relatively short. Indeed, one of the striking features of the UK labour market in recent decades has been the rise in disability benefit claims and early retirement for older men (Disney, 1999; Nickell and Quintini, 2002).

Others have emphasised the importance of the learning process in adapting to new technologies and the way in which this affects the adjustment of the aggregate economy to the arrival of new technology. For instance, Greenwood and Yorukoglu (1997) suggest that if skill biased technical change is associated with significant diversion of skilled resources to learning, advances in technology may be associated with an initial slowdown in productivity growth. If more experienced workers have less incentive to upgrade their skills because switching to the use of new technology devalues job-specific experience, any initial slowdown in productivity growth associated with learning is more muted and technology absorption occurs more gradually (Helpman and Rangel, 1998).[2]

[1] These include amongst others Bound and Johnsen (1992), Berman *et al.* (1994), Machin (1996), Machin and Van Reenen (1998), Haskel and Heden (1999), Haskel and Slaughter (2001 and 2002).
[2] Heckman *et al.* (1998) also study the role of human capital formation, distinguishing between on-the-job learning and formal education, on the effects of skill-biased technical change on the economy.

We use the UK Labour Force Survey from 1994-2001 to estimate the return to schooling and job-specific experience, as a proxy for the return to general and technology-specific skills, allowing the returns to vary by industry and year. Next, we regress the estimated returns on industry-year measures of capital intensity and the ICT share of the capital stock. The latter is our measure of new technology. Our results suggest that new technologies are biased towards general skills, which are useful in acquiring new skills, but not towards skills that are less transferable. Indeed, controlling for the effect of general skills levels on the industry return to job-specific experience our results are consistent with the interpretation that recent skill biased technologies may render job-specific skills obsolete.

The returns to schooling and job-specific experience across industry and year

We estimate the returns to schooling and job-specific experience across industries and years, within a standard model of earnings, by allowing the coefficients on these measures of skill to vary accordingly. We use a standard Mincer-type earnings function, augmented with quadratic terms in both schooling and job-specific experience to capture non-constant returns, of the form

$$\ln Y_i = \alpha + \beta_{S1} S_i + \beta_{S2} S_i^{\ 2} + \beta_{T1} T_i + \beta_{T2} T_i^{\ 2} + \gamma X_i + \varepsilon_i \qquad (1)$$

where $\ln Y_i$ is the log hourly wage, deflated to 2000 prices[3], α is a constant term, S_i is years of schooling, T_i is years of job-specific experience, X_i is a vector of explanatory variables and ε_i is an error term for individual *i*. We extend this standard earnings function to allow the returns to schooling and job-specific experience to vary both by industry and year, denoted by subscripts *j* and *t* respectively. We also include industry and year specific dummy variables, denoted as η_{ijt} , to control for any industry-year specific effect on earnings that may bias our estimates of the industry and year specific return to schooling and job-specific experience. This could include industry and time specific demand or supply shocks or composition effects. Thus our model becomes:

$$\ln Y_i = \alpha + \beta_{S1jt} S_{ijt} + \beta_{S2jt} S_{ijt}^{\ 2} + \beta_{T1} T_{ijt} + \beta_{T2jt} T_{ijt}^{\ 2} + \gamma_{0jt} \eta_{ijt} + \gamma X_i + \varepsilon_i \qquad (2)$$

We estimate (2) using OLS. There has been much discussion in the literature about the use of instrumental variables to control for ability bias (see Card, 1999 and Harmon *et al*., 2003b for a review of the literature). There is evidence from a number of countries that the use of the instrumental variables approach to estimate the returns to education produces higher results that the simple OLS approach. However, as discussed in Harmon *et al*. (2003b) there are problems with finding instruments that are not only uncorrelated with wages, but that are actually correlated with schooling. It has also been suggested that estimates using the instrumental variables approach may be in themselves biased upwards, and the effect of

[3] The hourly wages were deflated to 2000 prices using the UK National Accounts consumption expenditure deflator.

measurement error and ability bias on OLS estimates of returns to education cancel themselves out (see Harmon *et al*., 2003a).

Data

To estimate (2) we use data from the United Kingdom Labour Force Survey (LFS) from 1994 to 2001. The LFS is a quarterly sample survey of approximately 61, 000 households across the United Kingdom with a 5-quarter rolling panel design[4]. For the purposes of this paper we use information at the individual level; this translates to all adults within the household. The LFS has included questions on earnings since the fourth quarter of 1992, but we restrict our analysis to the period from 1994 onwards to avoid problems with classifying industries[5]. From 1992 to the end of 1996 the earnings questions were only asked of respondents in the fifth and final survey wave. Since 1997 the earnings questions have been asked in both the first and fifth waves of the survey, effectively doubling the quarterly sample of earnings data. We have restricted our sample to wave 5 respondents to avoid issues of differential attrition bias over our sample period.

Our sample comprises employees of working age who are not in full-time education who have responded with a positive value for earnings and hours worked[6]. We have restricted our sample to those whose hourly earnings were greater than or equal to £1 and less than or equal to £100 in 2000 prices. Using these variables we are able to derive an hourly earnings variable. Wilkinson (1998) compares both the LFS and New Earnings Survey (NES) earnings data and presents the discrepancies between the two. The NES is a one per cent sample of employees in Great Britain and collects data direct by employers' payroll records. Wilkinson (1998) suggests that there may be an element of error in answers by LFS respondents, in particular by proxy respondents, and suggests an adjustment procedure for the earnings data from the LFS depending on whether the proxy respondent is a spouse or non-spouse proxy respondent to correct for this error. We have applied these adjustments to our measure of hourly earnings.

(Table 1 here)

(Table 2 here)

The characteristics of our sample are reported in table 1. Table 2 shows the distribution of the sample across industries and years. We use each quarter of the LFS to boost annual sample sizes and to maximise 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 autumn quarter of the LFS.

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[4] There is a sample of approximately 2, 000 responding households in Northern Ireland that have not been included in this analysis. Thus we use only the 59, 000 households from Great Britain as our sample.
[5] From Winter 1993 the LFS records industry using the Standard Industrial Classification 1992. Before then industry is classified by Standard Industrial Classification 1980.
[6] Working age is defined as 16-64 for men and 16-59 for women.

We proxy general skills by years of schooling, defined as years spent in continuous full-time education. We proxy job-specific skills by tenure, defined as continuous years served with the current employer. These are interacted with industry and year to obtain estimates of industry-year specific returns to schooling and tenure, allowing us to estimate the effect of the capital intensity of production and the ICT intensity of capital on the returns to schooling and tenure, discussed in the next section.

Results

Table 3 gives OLS estimates of the model in (2). We control for a quadratic in potential experience[7], sex, birth cohort (through nine cohort dummy variables), the seventeen industries examined[8], quarter, region of residence[9], size of the establishment where the individual works, cohabiting status, full-time status (defined as greater than or equal to 30 hours per week, excluding overtime) and private sector employee. The coefficient estimates in table 3 are generally significantly different from zero and have the expected signs.

(Table 3 here)

The coefficients on the industry-year dummy variables and the industry-year specific coefficients on schooling and tenure, and schooling and tenure squared, are not reported in table 3. Instead we plot the estimated marginal return to one additional year of schooling and tenure in charts one and two respectively, together with their 95 per cent confidence intervals. These are evaluated at industry-year sample means, $\bar{S}_{jt} = \frac{1}{N_{jt}} \sum_i S_{ijt}$ and $\bar{T}_{jt} = \frac{1}{N_{jt}} \sum_i T_{ijt}$, where N_{jt} denotes the number of individuals employed in industry *j* at time *t* (reported in table 2). The standard errors used to calculate confidence intervals for the marginal returns estimates take into parameter uncertainty only, treating the industry-year sample means as given. Letting $\hat{\omega}^S{}_{jt}$ denote the estimated return to schooling in industry *j* at time *t* we have

$$\hat{\omega}^S{}_{jt} = \hat{\beta}_{S1jt} + 2\hat{\beta}_{S2jt}\bar{S}_{jt} \qquad (3)$$

and

$$\operatorname{var}(\hat{\omega}^S{}_{jt}) = \operatorname{var}(\hat{\beta}_{S1jt}) + 4\bar{S}_{jt}{}^2 \operatorname{var}(\hat{\beta}_{S2jt}) + 4\bar{S}_{jt} \operatorname{cov}(\hat{\beta}_{S1jt}, \hat{\beta}_{S2jt}) \qquad (4)$$

Similar expressions can be derived for the marginal returns to job-specific experience. The quadratic in both schooling and tenure in (2) complicates the marginal returns expression in (3) and its variance in (4), but, F-tests suggest that both the squared terms in schooling and tenure should be included. Our results in the next section are robust to the restricted specification of (2) where $\beta_{S2jt} = 0 \forall j,t$ and $\beta_{T2jt} = 0 \forall j,t$.

[7] Defined as current age minus age left full-time education.
[8] See appendix for details on the industry breakdown.
[9] The regional classification is based on the August 1998 definition of Government Office Regions. Residents of Northern Ireland were not included in the sample.

Chart one shows the return to schooling over the period 1994 to 2001 for each of the seventeen industries analysed. A line has been drawn in the charts at zero returns to schooling to highlight those estimates that were not significantly different from zero at the 95 per cent level. It is clear from the chart that all our estimates of the return to schooling were significant at the 95 per cent level. With the 95 per cent confidence intervals plotted we can determine if the return to schooling in each industry have been stable over time. There is no clear statistically significant rise or fall in the return to schooling over our sample period in any of the industries examined. Overall, the estimated returns to schooling within each industry are reasonably stable over the sample period as a whole. It is clear from the chart that the lowest returns to schooling are concentrated in the hotels & restaurants, construction and the manufacture of basic metals, and machinery industries. The returns to schooling are greatest in the manufacture of chemicals and allied products, the manufacture of electrical and optical equipment and communications industries. The transport sector also has a high return to schooling relative to the other industries, although the return does decline somewhat in 1999. The business services sector also exhibits a relatively high return to schooling in comparison to most of the other industries.

(chart 1 here)

(chart 2 here)

Chart two shows the return to job-specific experience over the period 1994 to 2001 for each of the seventeen industries analysed. It is clear that the return to an additional year of job-specific experience is lower relative to an additional year of schooling. In chart 2 a horizontal line has been produced for zero returns to job-specific experience. Non-significant coefficients are only apparent in the hotels and restaurants industry. The estimated return to job-specific experience in this industry is not statistically different from zero in any of the sample years. This may be a consequence of the short-term and seasonal nature of a portion of this industry. The manufacturing of chemical and allied products industries exhibit the highest returns to job-specific experience, while the construction and transport manufacturing industries exhibit the lowest returns after the hotels and restaurants industry. In comparison to the first four years in our sample, the return to tenure is statistically lower in the last four years in the business services sector, providing evidence of a decline in the return to job-specific experience over our sample period

The effect of ICT technology on the returns to schooling and job-specific experience

To estimate the effect of ICT technology on the return to general and job-specific skills we regress separately the industry and year specific estimates of the return to schooling and tenure obtained from model (2) on measures of the capital intensity of production and the ICT intensity of capital:

$$\omega_{jt} = \alpha + \beta_1 \nu_{jt} + \beta_2 \theta_j + \beta_3 \eta_t + \varepsilon_{jt} \qquad (5)$$

where ω_{jt} is the return to either schooling or tenure in industry *j* at year *t* (defined in the previous section), α is a constant, v_{jt} is a vector of industry and year specific controls, including capital and technology intensity measures (capital stock-output ratio and ICT capital stock-total capital stock ratio), θ_j is a set of industry dummy variables, η_t is a set of year dummy variables and ε_{jt} is an error term. We estimate this model using OLS.

Data

We use the National Institute Sectoral Productivity (NISEC) dataset for measures of capital stock levels and UK National Statistics data for levels of gross value-added to construct capital stock-output ratios and ICT-total capital stock ratios for each of the 17 industries and 8 years in our sample[10]. The NISEC capital stock data is derived using National Statistics investment data, used to create National Statistics estimates of capital stocks by industry. However, the capital stock data from National Statistics does not include a separate measure of ICT capital. The NISEC data contains measures of ICT capital (computers, software and other ICT technology) constructed using asset specific depreciation rates. Consequently we rely on NISEC rather than National Statistics capital stocks data for the purposes of this paper. Non-ICT capital includes structures, vehicles and non-ICT equipment. The capital stock data in the NISEC dataset has been produced up to 2001 and is in constant 1995 volumes. We use the most recent output data, from the 2003 edition of the *Blue Book*, and deflate the data from 2000 prices to 1995 prices, to construct capital-output ratios.

Charts 3 and 4 graph the capital intensity of production (capital-output ratios) and the ICT intensity of capital (ICT share of the total capital stock) over time for each of the seventeen industries.

Results

Table 4 shows OLS estimates of model (5) where the dependent variable is the marginal return to schooling. Table 5 shows OLS estimates of model (5) where the dependent variable is the marginal return to job-specific experience. We show 6 separate models. Models 3 and 4 include industry dummies. Models 2, 3 and 6 include year dummies. Models 1 and 5 include neither and are our preferred models. We have controlled for industry and year specific effects in estimating (2), to correct for any bias in our estimates of the industry and year specific returns to schooling and job-specific experience that could arise from industry and time specific demand or supply shocks or composition effects. Thus, arguably, we do not need to include industry and year dummies in (5). Nevertheless we report the results of including industry and year dummies, separately and together, to give an indication of the robustness of our findings. Models 5 and 6 include average job-specific experience by industry-year in the schooling regressions and average schooling levels by industry-year in the job-experience regressions. Here we attempt to control for the effect on the return to one

[10] For further details on the NISEC dataset refer to O'Mahony and de Boer (2002).

type of human capital that may arise from the presence of another type of human capital. This may occur at the individual level or at the industry level. For example, Green *et al.* (2001) find that individuals' work-based skills depend on both work experience and schooling, but also on the interaction between the two. At the industry level it is easy to envisage a situation where the return to job-specific experience is enhanced by the general level of schooling amongst its employees.

(table 4 here)

(table 5 here)

Our preferred models suggest that the ICT intensity of capital raises the return to schooling, but not to job-specific experience. These results are not robust to the inclusion of industry dummies, but are robust to the inclusion of year dummies. However, in all models 1 through 6, the ICT intensity of capital appears to be associated with a rise in the return to schooling measured relative to the return to job-specific experience. In models 5 and 6, controlling for the interaction between the two types of human capital we analyse, we find that schooling and job-specific skills are complementary to one another. Controlling for this complementarity in model 5, ICT technology appears to devalue the returns to job-specific experience.

Conclusions

We have attempted to provide more evidence on the nature of 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 to job-specific skills in the form of job-specific experience (tenure). We find evidence of variations in the returns to these two skill measures across industries and the years of our sample. Our standard earnings function suggests the return to an extra year of schooling is greater relative to an extra year of job-specific experience. Using data on capital stocks from the NISEC dataset we have then been able to regress these returns on measures of capital and technology intensity. In line with the literature, we find evidence of technology-skill complementarity.

Taken together our results are consistent with the hypothesis that new ICT technologies are biased towards more general skills, such as those achieved through schooling, in comparison to technology specific skills. General skills are arguably more useful in acquiring the new skills that may be required in adapting to new technologies. In addition, controlling for the interaction between schooling and job-specific experience, our results would indicate that ICT technologies are associated with a reduction in the return to job-specific skills, measured here as tenure with current employer, which are likely to be less transferable to new technologies.

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Tables and charts

Table 1: Earnings function sample characteristics

Number of observations	260220
Sample means:	
Log hourly wage	1.946
Age	38.763
Years of continuous full-time education	12.252
Years of tenure with current employer	7.868
Potential experience	21.491
Potential experience squared	602.947
Male	0.500
Born 1929-1939 (reference category)	0.046
Born 1940-1944	0.082
Born 1945-1949	0.128
Born 1950-1954	0.126
Born 1955-1959	0.135
Born 1960-1964	0.152
Born 1965-1970	0.145
Born 1970-1974	0.111
Born 1975-1983	0.074
Agriculture and non-manufacturing production (reference category)	0.022
Manufacturing: chemicals and allied products	0.025
Manufacturing: basic metals	0.024
Manufacturing: machinery	0.021
Manufacturing: electrical and optical equipment	0.029
Manufacturing: transport	0.024
Manufacturing: food, drink and tobacco	0.021
Manufacturing: other manufacturing	0.058
Construction	0.047
Wholesale and retail	0.142
Hotels and restaurants	0.035
Transport	0.044
Communications	0.023
Financial intermediation	0.051
Business services	0.094
Personal Services	0.047
Non-market services	0.293
Year sample is 1994 (reference category)	0.125
Year sample is 1995	0.129
Year sample is 1996	0.129
Year sample is 1997	0.130
Year sample is 1998	0.130
Year sample is 1999	0.126
Year sample is 2000	0.119
Year sample is 2001	0.113
Resident in the North west (reference category)	0.055
North east	0.106
Yorkshire & Humberside	0.091
East Midlands	0.075

West Midlands	0.095
East	0.044
London	0.101
South east	0.204
South west	0.087
Wales	0.046
Scotland	0.097
<25 employees at workplace (reference category)	0.316
25-49	0.123
50 or more	0.552
Don't know but over 24	0.009
Private sector employee	0.710
Cohabiting	0.619
Full-time hours	0.771
Quarter1 (reference category)	0.247
Quarter2	0.251
Quarter3	0.251
Quarter4	0.251

Table 2: Distribution of industries by year

	1994	1995	1996	1997	1998	1999	2000	2001	Total Sample
Agriculture and non-manufacturing production	0.026	0.025	0.024	0.021	0.021	0.021	0.021	0.020	0.022
Manufacturing: chemicals and allied products	0.027	0.025	0.026	0.028	0.025	0.026	0.024	0.022	0.025
Manufacturing: basic metals	0.024	0.025	0.027	0.024	0.025	0.022	0.022	0.022	0.024
Manufacturing: machinery	0.023	0.022	0.023	0.020	0.020	0.020	0.019	0.019	0.021
Manufacturing: electrical and optical equipment	0.030	0.031	0.032	0.030	0.030	0.026	0.027	0.027	0.029
Manufacturing: transport	0.025	0.023	0.025	0.023	0.023	0.025	0.025	0.023	0.024
Manufacturing: food, drink and tobacco	0.021	0.023	0.025	0.021	0.022	0.020	0.018	0.017	0.021
Manufacturing: other manufacturing	0.064	0.062	0.062	0.062	0.059	0.054	0.050	0.049	0.058
Construction	0.043	0.043	0.042	0.048	0.051	0.048	0.051	0.051	0.047
Wholesale and retail	0.144	0.144	0.143	0.145	0.140	0.143	0.142	0.137	0.142
Hotels and restaurants	0.035	0.037	0.036	0.036	0.036	0.036	0.031	0.032	0.035
Transport	0.042	0.044	0.042	0.043	0.045	0.044	0.045	0.044	0.044
Communications	0.023	0.023	0.022	0.023	0.022	0.024	0.024	0.026	0.023
Financial intermediation	0.053	0.053	0.051	0.052	0.051	0.049	0.050	0.052	0.051
Business services	0.082	0.088	0.087	0.094	0.096	0.102	0.100	0.104	0.094
Personal Services	0.047	0.046	0.046	0.046	0.047	0.045	0.047	0.047	0.046
Non-market services	0.291	0.287	0.289	0.284	0.288	0.295	0.303	0.307	0.293
Total	32593	33539	33517	33771	33830	32752	30932	29286	260220

Table 3: OLS earnings estimates

	Coefficient	t-statistic
Female (reference category)		
Male	0.187	100.66
Born 1929-1939 (reference category)		
Born 1940-1944	-0.029	-5.04
Born 1945-1949	-0.035	-4.58
Born 1950-1954	-0.048	-4.87
Born 1955-1959	-0.032	-2.68
Born 1960-1964	-0.002	-0.13
Born 1965-1970	0.039	2.45
Born 1970-1974	0.020	1.11
Born 1975-1983	-0.062	-3.01
Resident in the North west (reference category)		
North east	0.027	6.65
Yorkshire & Humberside	0.010	2.40
East Midlands	0.018	4.01
West Midlands	0.013	3.17
East	0.038	7.49
London	0.221	52.40
South east	0.141	37.45
South west	0.021	4.81
Wales	-0.016	-3.20
Scotland	0.035	8.43
<25 employees at workplace (reference category)		
25-49	0.066	25.02
50 or more	0.138	73.00
Don't know but over 24	0.066	8.01
Private sector	-0.075	-26.72
Cohabiting	0.052	28.38
Full-time hours	0.138	63.26
Quarter1 (reference category)		
Quarter2	0.003	1.48
Quarter3	0.005	2.03
Quarter4	0.005	2.15
Constant	-0.047	-0.14
Sample size	260220	
Adjusted R^2	0.426	
MSE	0.158	

Notes: Industry-year dummy variables were included but not reported here.
For the industry-year specific coefficients on the schooling and tenure variables see charts 1 and 2.

Chart 1: Returns to schooling by industry, 1994-2001

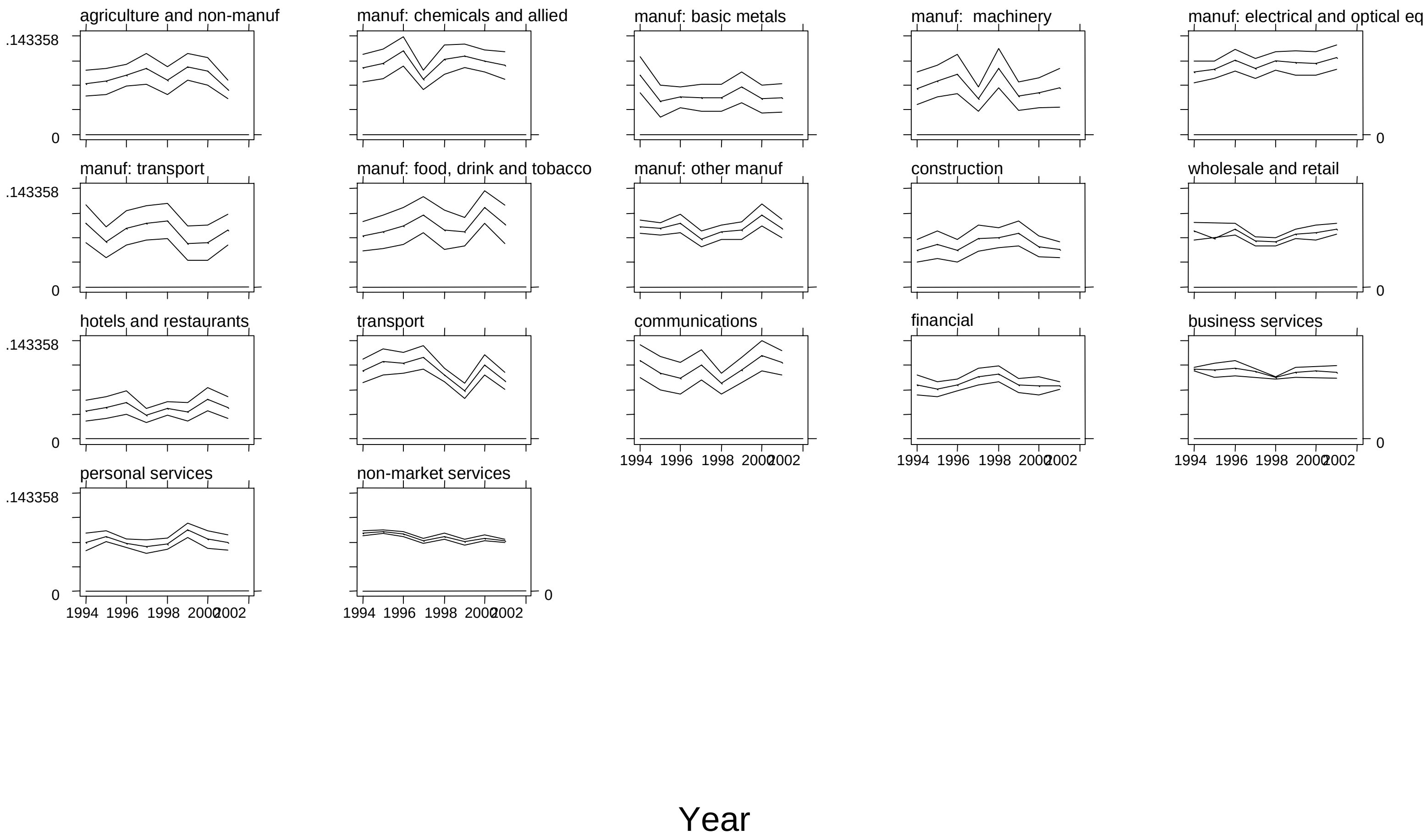


Chart 2: Returns to tenure by industry, 1994-2001

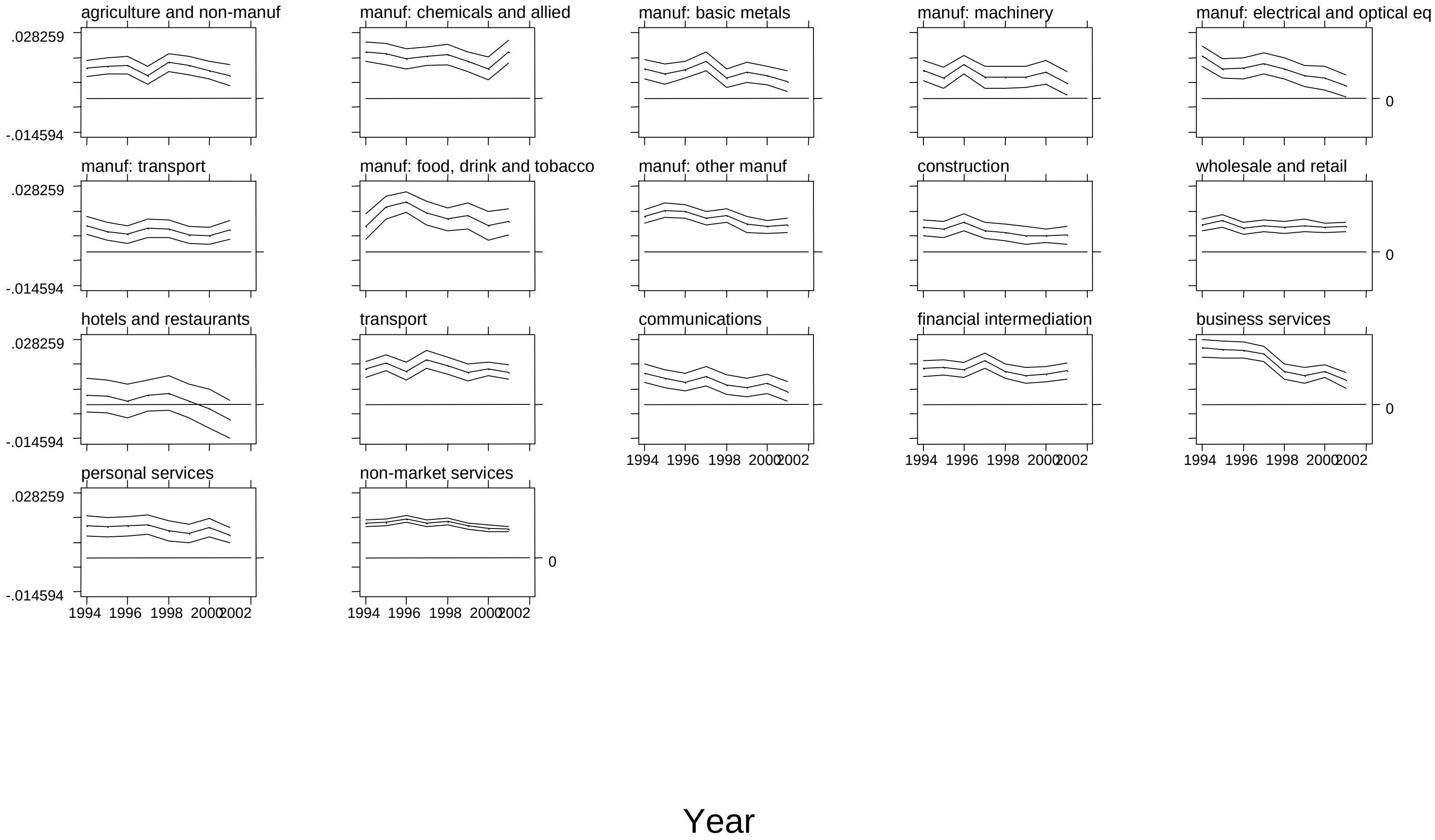
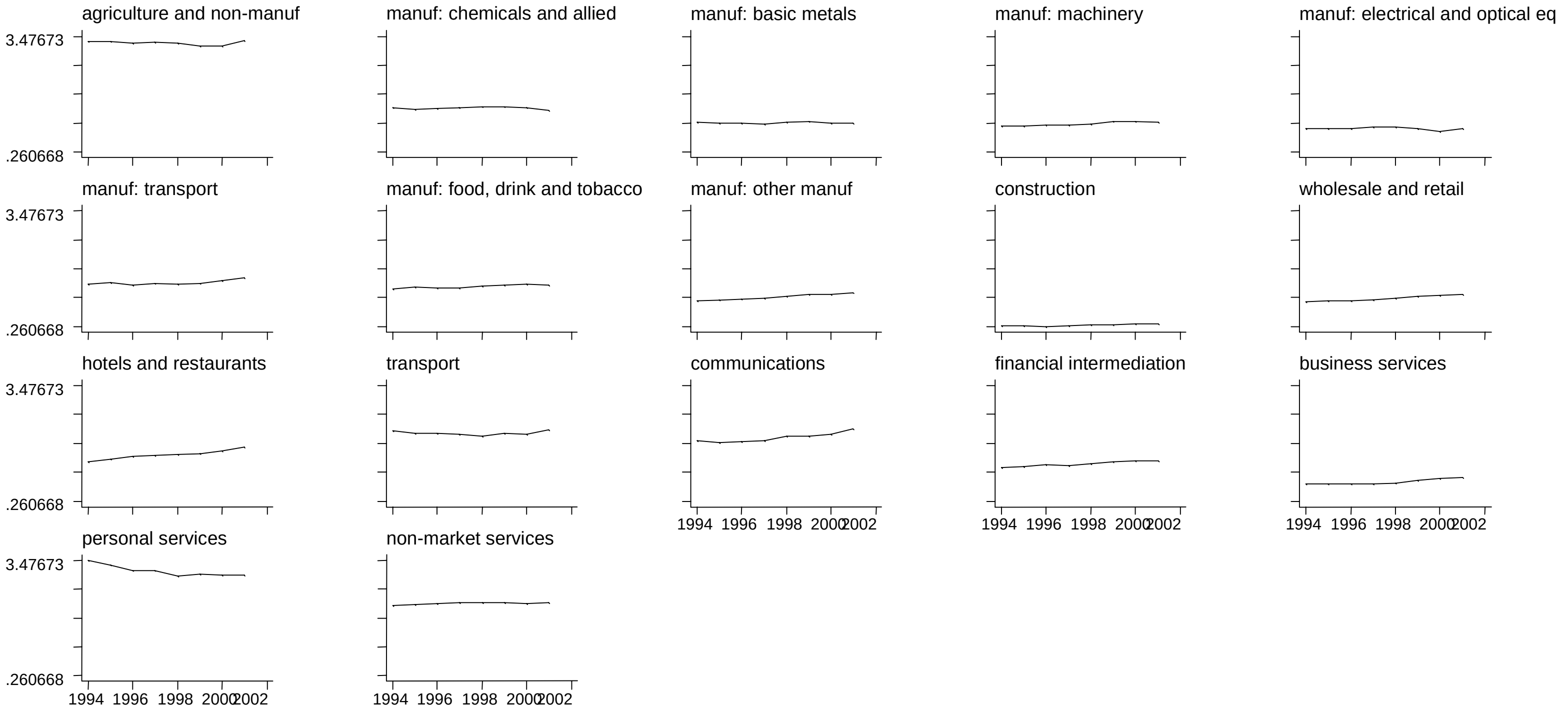


Chart 3: Capital intensity of production by industry, 1994-2001



Year

Chart 4: ICT intensity of capital by industry, 1994-2001

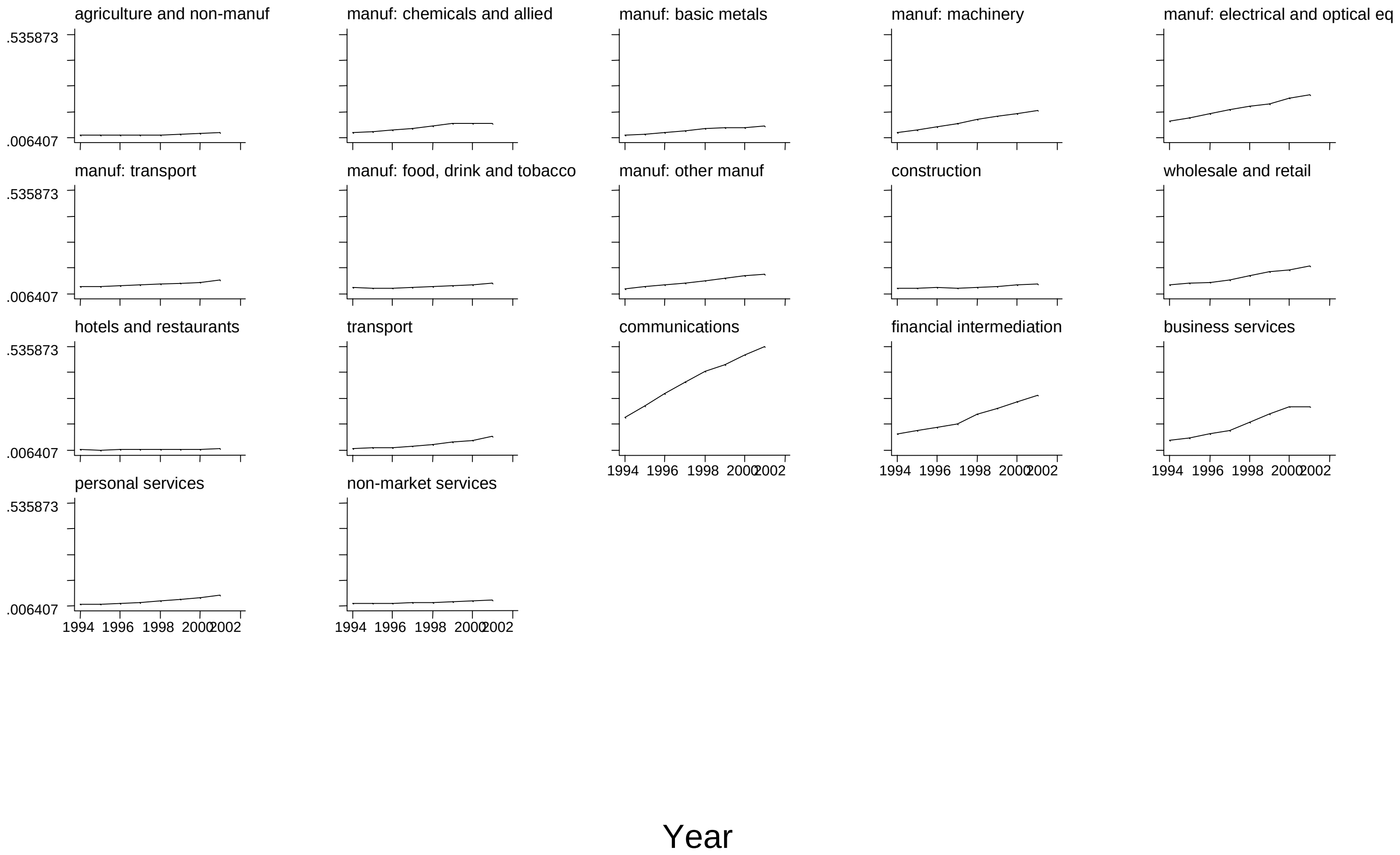


Table 4: OLS estimates of the effect of ICT technology on the returns to schooling

Dependent variable: Estimated return to one additional year of schooling	model 1		model 2		model 3		model 4		model 5		model 6	
Constant	0.0705	(18.68)	0.0731	(13.49)	0.0814	(1.56)	0.0911	(1.81)	0.0576	(7.99)	0.0609	(7.19)
K/Y	0.0031	(1.60)	0.0034	(1.71)	0.0008	(0.05)	-0.0023	(0.15)	0.0022	(1.11)	0.0025	(1.25)
Tech/K	0.0782	(4.80)	0.0870	(5.02)	0.0114	(0.34)	0.0089	(0.34)	0.0724	(4.44)	0.0804	(4.59)
Job experience									0.0018	(2.10)	0.0016	(1.87)
Years			Included		Included						Included	
Industries					Included		Included					
Sample size	136		136		136		136		136		136	
Adjusted R^2	0.1420		0.1252		0.6609		0.6671		0.1635		0.1423	
Root MSE	0.0179		0.0181		0.0113		0.0112		0.0177		0.0179	

Notes: K/Y is capital intensity of production; Tech/K is ICT intensity of capital; |t-statistics| in parentheses; 17 industries and 8 years (1994-2001)

Table 5: OLS estimates of the effect of ICT technology on the returns to job-specific experience

Dependent variable: Estimated return to one additional year of job-specific experience												
	model 1		model 2		model 3		model 4		model 5		model 6	
Constant	0.0124	(12.36)	0.0133	(9.71)	0.0241	(2.37)	0.0319	(3.01)	-0.0216	(2.46)	-0.0269	(3.26)
K/Y	0.0002	(0.46)	0.0004	(0.80)	-0.0030	(0.98)	-0.0056	(1.73)	-0.0002	(0.39)	-0.0001	(0.20)
Tech/K	-0.0048	(1.10)	0.0008	(0.19)	-0.0126	(1.90)	-0.0296	(5.28)	-0.0099	(2.30)	-0.0043	(1.04)
Schooling									0.0029	(3.90)	0.0035	(4.93)
Years			Included		Included						Included	
Industries					Included		Included					
Sample size	136		136		136		136		136		136	
Adjusted R^2	-0.0034		0.0723		0.7882		0.7551		0.0935		0.2172	
Root MSE	0.0048		0.0046		0.0022		0.0024		0.0045		0.0042	

Notes: K/Y is capital intensity of production; Tech/K is ICT intensity of capital; |t-statistics| in parentheses; 17 industries and 8 years (1994-2001)