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WHO GAINS WHEN WORKERS TRAIN?
TRAINING AND CORPORATE PRODUCTIVITY IN A
PANEL OF BRITISH INDUSTRIES

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March 2000

Abstract

There is a vast empirical literature of the effects of training on wages that are taken as an indirect measure of productivity. This paper is part of a smaller literature on the effects of training on *direct* measures of industrial productivity. We analyse a panel of British industries between 1983 and 1996. Training information (and other individual productivity indicators such as education and experience) is derived from a question that has been asked consistently over time in the Labour Force Survey. This is combined with complementary industry-level data sources on value added, wages, labour and capital. We use a variety of panel data techniques (including system GMM) to argue that training significantly boosts productivity. The existing literature has underestimated the full effects of training for two reasons. First, it has tended to treat training as exogenous whereas in reality firms may choose to re-allocate workers to training when demand (and therefore productivity) is low. Secondly, our estimates of the effects of training on wages are about half the size of the effects on industrial productivity. It is misleading to ignore the pay-off firms take in higher profits from training. The effects are economically large. For example, raising the proportion of workers trained in an industry by 5 percentage points (say from the average of 10% to 15%) is associated with a 4 per cent increase in value added per worker and a 1.6 per cent increase in wages.

Keywords: Productivity, training, wages, panel data

JEL Classifications: J31; C23; D24

Acknowledgements

Financial support from the Economic and Social Research Council, award no. R000222382 and the Leverhulme Trust, is gratefully acknowledged. The authors would like to thank Amanda Gosling, Lisa Lynch, Rachel Griffith, Nicholas Bloom and participants in the IFS seminar for helpful comments and suggestions. We are grateful to the Office for National Statistics for supplying the Census of Production data and to the OECD for supplying the ISDB data. Material from the Labour Force is Crown Copyright; have been made available by the Office for National Statistics through the ESRC Data Archive and has been used by permission. Neither the ONS nor the Data Archive bear any responsibility for the analysis or interpretation of the data reported here. The views expressed in this report are solely those of the authors and not those of the IFS, which has no corporate views.

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1. Introduction

For some time in the UK, there has been a widely-held view that there needs to be an expansion of vocational and work-related training in order to increase the skill level of the workforce and to ensure stronger long-term economic performance.¹ Running parallel to this there has been a perception that British industry has been suffering from a ‘productivity gap’², with lower output per worker than her main industrialised competitors. Given that low productivity is often seen as a malady affecting UK performance and training as one of the cures for the problem, the main aim of this study is to assess whether training has an impact on various measures of corporate productivity.

This is not a new question in itself. As we show in Section 2, there is a small (but growing) empirical literature on the link between training and industrial performance. There is a rather larger literature in the closely related field of the impact of training on the wages of individual employees.

This study breaks new ground in several ways. First, very few papers have access to *longitudinal* information on training and productivity. This is important if one wishes to control for unobserved fixed effects and potential endogeneity of training (and other variables) in production functions. Britain is fortunate in that the national Labour Force Survey has asked a consistent question on training since 1984 that we use to construct an industry level panel dataset. As far as we know, Only Black and Lynch (1999) have used panel data with repeated training

¹ See, for example, Green and Steedman (1997) for an appraisal from the academic perspective; and the first report of the National Skills Task Force (1998) for a perspective on the UK’s skill position commissioned by a government department.

² This view is articulated by HM Treasury (1998). See Griffith and Simpson (1998) for an exploration of the ‘productivity gap’ claim.

questions over time, and even this exists only for a survey they administered themselves for two years. As Lynch (1998, p.406) emphasises for the U.S. “We have no aggregate measurement of the stock of post-school training in the economy that parallels the information we have on the average educational attainment of workers”³. Secondly, although there are several studies of the impact of training on wages in the UK there is no econometric work which examines directly the link between training and productivity.

A third novel feature of this paper is that we explicitly compare the production function estimates with wage equations. It is important to examine if training differentially benefits firms and employers. Only the simplest models of perfectly competitive labour markets with general training imply that wage equations alone will be adequate in gauging the productivity effects of training. In models of specific human capital where the costs and benefits of training are split between firms and workers, examining earnings alone will underestimate the full return to training. In modern models of training under imperfect information (e.g. Acemoglu and Pischke, 1999) or under bargaining (e.g. Booth et al, 1999) the returns to training are not fully appropriated by employees.

We conduct our analysis of the effects of training on corporate productivity at an industry level, rather than at the level of the firm or individual. Aggregation has pros and cons that we discuss. On the positive side, if there are important spillovers to training within an industry (e.g. through a faster rate of innovation) then a firm level analysis will potentially miss out these linkages and underestimate the return to human capital⁴. On the negative side, there may be aggregation biases at the sectoral level which could lead to negative or positive

³ The CPS asked training questions for on-the job training in supplements for only two years (1983 and 1991). The NLSY has consistent training questions only between 1979-86 and is, of course, only for young people.

⁴ For example, O'Mahony (1998) finds that the coefficient on labour skills in a production function is more than twice that assumed by traditional growth accounting from relative wages.

biases. We follow Grunfeld and Griliches (1960) in claiming that the pros outweigh the cons⁵.

The format of the paper is as follows. Section 2 presents a guide to the previous literature on the effects of training on productivity and earnings. Section 3 describes the data and Section 4 outlines a simple empirical model of productivity and training. The results are in section 5 and we offer concluding comments in section 6. The main result is that we find a statistically and economically significant effect of training on industrial productivity. A 5 percentage point increase in training is associated with a four percent increase in productivity and a 1.6 per cent increase in hourly wages. The productivity effect of training is over twice as large as the wage effect, implying that existing estimates have underestimated the benefits of training by focusing on wages. Failure to accounting for the endogeneity of training also leads to an underestimation of the true economic returns. We argue that this may be because firms re-allocate workers to training activities when demand and productivity are low.

2. Previous Literature⁶

Employers may fully or partially fund the training of workers in the hope of gaining a profitable return on this investment. In practice, however, it is very difficult to measure this return and most studies have looked at wages. Most studies looking at the private return to work-related training find that training results in workers receiving higher real wages⁷. Good examples of previous UK

⁵ Of course, combining firm level and industry level data on training would be the best strategy. Unfortunately there is no company dataset with any serious time dimension that currently allows one to perform this exercise.

⁶ We are not addressing here the large literature on the impact of formal qualifications on wages or labour productivity. See Card (1999) for a survey of the former or Sianesi and Van Reenen (1999) for a survey of the latter.

⁷ Studies of government-related training schemes tend to produce much lower returns.

work are Greenhalgh and Stewart (1987) looking at the 1975/76 National Training Survey, Booth (1991) who uses the 1987 British Social Attitudes Survey and Booth (1993) who looks at the 1987 British National Survey of 1980 Graduates and Diplomas. An important point about all these papers is that they all use cross-sectional data sources rather than longitudinal data (although in many cases the data have a retrospective element). A recent study by Blundell et. al. (1996) using panel data from the British National Child Development Survey (NCDS) to look at the returns to different types of work-related training controlling for a host of individual and background characteristics. The authors find that work-related training has a significant impact on the earnings prospects of individuals, adding some 5 per cent to their real earnings over the ten years between 1981 and 1991.⁸

In a more comparative vein, Tan et. al. (1992) use data from the US, UK and Australia and found that in all three countries company based training (As opposed to training outside the firm) provided the largest returns followed by off-the-job training. They also found that the size of the returns to training in the US were substantially larger than those in Britain and Australia⁹. Lynch (1992) uses data from the US NLSY to estimate the returns to training. She finds that receiving on-the-job, off-the-job and apprenticeship training results in higher wages for young people. She finds, however, that on-the-job training only has a

⁸ Note that estimates of the effects of a year in a job which included some training on wage growth are not comparable to effects of an additional year of schooling at the average level of education, since job training is not a full-time (full-year) activity (Mincer, 1994). Lillard and Tan (1992) note that there is not one kind of training, but various kinds for different purposes. Some kinds of training are relevant in the context of technological change, and some are not. Some actively complement formal schooling, and some do not.

⁹ For instance they found that company training was associated with an initial increase in wages of around 18 per cent in the US compared with around 8 per cent in Australia and 7 per cent in Britain.

significant impact on wages if it was provided by the person's current employer and concludes that on-the-job training is quite firm specific.

Other recent studies include Lillard and Tan (1992) on US panel data, Blanchflower and Lynch (1992) using UK and US panel data, Winkelmann (1994) using German data and Bartel (1995) looking within a large US manufacturing company. All of these studies find statistically significant positive returns to training.

Although these studies are informative, they only tell half the story. The relationship between wage increases and productivity gains can vary according to the structure of the labour and product markets and according to who actually pays the costs of training. In a simple neoclassical view of the labour market where the market is perfectly competitive wages will be equal to the value of marginal product. Thus the wage can be taken as a direct measure of productivity. However even in this case there can be a divergence between observed earnings and productivity if the employee receives an element of non-financial remuneration or, especially, if the employer is providing training but the employee is paying part or all of the costs of training. An employee may implicitly pay the costs of a training scheme to the employer in the form of lower wages whilst being trained, which then rise after training is completed. If this is the case, then we might see a greater increase in *observed* wages than in productivity due to training costs driving a wedge between (net) earnings and productivity.¹⁰

If the labour market is characterised by imperfect competition then the strict link between wages and productivity can be broken. Employees can find themselves being paid less (or more) than their marginal revenue product, and there may be scope for bargaining and rent-sharing. However, it is still the case that,

¹⁰ Another possibility however is that employees' wages are lower during training because they are not contributing to firm productivity whilst actually being trained. This could be the case even if firms were actually paying for training.

conditional on a given degree of rent-sharing between firms and workers, increases in wages have to be paid out of productivity gains and therefore we can assert the general principle that these real wage increases should provide a lower bound on the likely size of productivity increases.¹¹ In practice, however, the productivity gains are likely to be higher than this. For instance, when training has a large firm-specific component (i.e. training providing firm-specific knowledge and skills which has little or no value when an employee leaves the firm that provided the training) and, more generally, when labour mobility is effectively restricted, there may be productivity gains from training that are not passed on to the employee in terms of wages but are only reflected in direct measures of productivity¹².

Even if the link between earnings and productivity holds over the duration of an employee's stay with a given firm, but not in a given period, there may be a substantial discrepancies between earnings and productivity *measured at a given period in time*. This could be the case for instance if firms offered deferred compensation packages, where the employee's remuneration is 'backloaded' towards later years as a means of ensuring loyalty and/or effort early in the employee's tenure.¹³ Backloading could lead to increases in wages which outstripped increases in productivity.

¹¹ An exception to this would occur if training actually strengthened employees' bargaining position in some way and hence increased employees' ability to appropriate rents (perhaps due to increasing the accumulation of specific human capital).

¹² Following Becker (1975), economic theory distinguishes training according to its portability between firms. The two polar forms are specific training and general training, the latter generating extremely versatile skills, equally usable or marketable in any other firm that might employ the worker concerned. A standard result based on the general-specific distinction concerns training finance. General training will not be financed by the firm due to the risk of its training investment being poached away by other firms; hence it is workers receiving general training who will bear the cost of it, either directly or in the form of reduced wages during the training period. As for firm-specific training, the firm may be willing to fund part of its costs, while reaping part of its benefits.

¹³ for a theoretical exposition see, for example, Lazear (1979).

There is far less work on the impact of training on directly measured productivity. Some interesting evidence on the links between the skill composition of the workforce of a firm and labour productivity is provided by the National Institute of Economic and Social Research. In their work they take a number of UK manufacturing firms and match them with Continental firms producing similar products. This allowed them to carry out direct productivity comparisons of these matched samples of manufacturing plants¹⁴. All the case studies found evidence of a productivity gap between the UK and European plants that was partly attributable to poor skills. Not all of these skills were due to the training system, however, and although suggestive, it is unclear how general this qualitative evidence is.

On the econometric side several micro studies have found impacts of training on subjective measures of performance. In the US, Bartel (1995) found a significant relationship between formal on-the-job training and the subjective performance ratings of professional employees by using the 1986-1990 personnel records of a large US manufacturing company. Also on US data, Barron et al. (1989) find that a 10% increase in training is associated with a 3% increase in the growth of a subjective productivity scale, while Russel et al. (1985) find similar results for a sample of retail stores.

Using more objective measures of performance, Holzer et al (1993) found that firms receiving training grants in Michigan state had significantly faster growth in labour productivity than those who applied but did not get grants. Bartel (1994) used another survey of U.S. employers and also uncovered faster productivity growth for firms instituting training programmes.

¹⁴ A range of different industries was covered: engineering (metalworking) — Dali, Hitchens and Wagner (1985) and Mason and van Ark (1994); wood furniture — Steedman and Wagner (1987); clothing manufacture — Steedman and Wagner (1989); food manufacture — Mason, van Ark and Wagner (1994); and a service sector: hotels — Prais, Jarvis and Wagner (1989).

Using Dutch firm level data, de Koning (1994) found that external training has a significant positive effect on productivity, while internal training an insignificant effect. The effect of training is small - a doubling of the training effort increases productivity by about 10%. Somewhat larger effects are found by Boon and ven der Eijken (1997) who use training expenditures to construct a stock measure¹⁵. A significantly positive (but small) impact of training is also found for a sample of large Spanish firms by Alba-Ramirez (1994). Barrett and O'Connell (1998) also uncover significant effects of "general" (but not specific) training for a surveyed sample of Irish firms.

One general problem with these studies is that they tend to be rather specific samples. Black and Lynch have managed to construct a more representative sample of U.S. establishments matched to the LRD (Longitudinal Research Database, an administrative data source). In the cross section (Black and Lynch, 1995) they identified some effects of the type of training on productivity, but they could find no effects at all when they controlled for plant specific effects (Black and Lynch, 1996). Ichinowski et al (1997) argue that training per se is likely to be less important than the overall combination of complementary human resource practices. They demonstrate this in their panel of steel finishing mills. Black and Lynch (1996) and Bartel (1995) do not find strong evidence of such interactions in their data.

Despite many important contributions, the overall impression is that the micro literature has had difficulties in establishing a strong link between training and productivity. Black and Lynch point to several sources of measurement difficulties such as the low signal to noise ratio in the training indicator when using the

¹⁵ They get a value added to human capital stock elasticity of 0.38. They do not control for education or occupation, however, which will be highly correlated with training.

'within' dimension of short panels. This suggests using panel data with a longer time dimension to smooth out some of the measurement error.

Another problem is that training is potentially endogenous. Firms have choices over when workers can train. Part of this is controlled for by examining the same firms over time. But transitory shocks may also have an impact on training decisions and none of the studies properly control for this. In particular, there is a lot of evidence that training programmes are introduced when firms are faced by negative demand shocks. Since production is slack there is an incentive to re-allocated workers to training activities. Black and Lynch (1997) argue that employers decide to adopt a new workplace practice, like a training programme, in times of trouble, and Bartel (1991) finds that those firms that were operating below average productivity were more likely to implement formal training than those firms with average or above average productivity. In a similar vein, Nickell and Nicolitsas (1996) offer some British evidence on how 'bad times' encourage firms to introduced HRM practices that cost time, but save money. The upshot of this is that we are likely to underestimate the effect of training unless we treat it as a choice variable¹⁶.

Our contribution in this paper is to advance the literature in at least three ways. First, we build a panel with a long time series dimension across the bulk of the UK economy based on representative data. The will deal with the issue of non-random selection and potentially with measurement error from short panels. Second, we explicitly allow for endogeneity and fixed effects using GMM techniques. Third, we combine information from the production function literature with the wage equation literature?

¹⁶ Of course there are arguments suggesting that endogeneity will lead to an upward bias. If good times generate free cash flow and firms are financially constrained in their training investments, then we will tend to overestimate the effect of training unless it is treated as endogenous.

3.Data

3.1 Data Construction

This paper uses data from several different complementary datasets. The reason for this is that no one British dataset contains the required data on training and measures of corporate performance that are needed for the analysis.

The main dataset is the Labour Force Survey (LFS). LFS is a large-scale household interview based survey of individuals in the UK which has been carried out on varying bases since 1973¹⁷. Around 60,000 households have been interviewed per survey since 1984. The LFS data are useful for our purposes as they contain detailed information on:

- the extent and types of training undertaken by employees in the survey;
- personal characteristics of interviewees (e.g. age, sex, region);
- the skills of individuals (educational qualifications and occupation);
- some basic workplace characteristics (e.g. employer size, industry);
- job characteristics of employees (e.g. job tenure, hours of work).

We work with this information aggregated into proportions and/or averages by (broadly) three digit SIC80 industry¹⁸. Our sample includes all employed men and women aged between 16 and 64 inclusive (i.e. employees plus the self-employed) for whom there was information on the industry under which their employment was classified.

¹⁷ Between 1975 and 1983 the survey was conducted every two years; from 1984 until 1991 it was conducted annually. Since 1992 the Labour Force survey has been conducted every three months in a five-quarter rolling panel format.

¹⁸ See Appendix A for more information on how the data are aggregated into the 1980 Standard Industrial Classification (SIC80) categories.

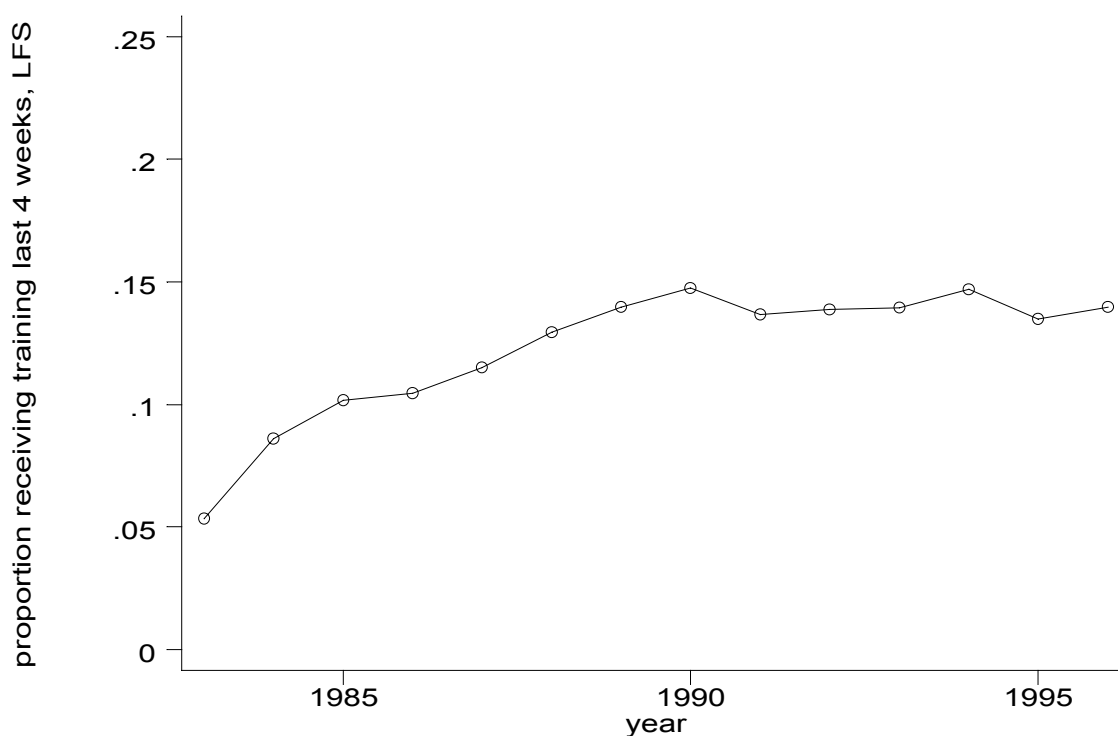
The main training question asked to employees in the Labour Force Survey between 1983 and 1996 was, “over the 4 weeks ending Sunday ... have you taken part in any education or training connected with your job, or a job that you might be able to do in the future ... ?” Figure 3.1 below shows the average proportions of employees undertaking training in each year of the LFS sample. Figure 3.1 shows a reasonably steady increase in the proportion of employees in the LFS receiving training in the 1980s¹⁹. From 1990 onwards, the proportion of employees receiving training stabilises at around 14% and stays at or around this level for the rest of the sample period.

We did some simple decomposition analyses to investigate whether the increase in aggregate training was due to the growth in size of industries which are (and always have been) relatively more training intensive. It turns out that this is only a minor factor: over 95% of the increase in aggregate training is due to an increase within a large number of different sectors²⁰. This is consistent with the findings of other papers which have found that the aggregate growth of education or occupational skills is essentially a within industry phenomenon (e.g. Machin and Van Reenen, 1998).

¹⁹ It should be noted that the figure of around 5% for 1983 is almost certainly an underestimate because in 1983 the 4 week training question was only asked of employees under 50, whereas in all subsequent years it was asked of employees over 50 and under 65 as well. However, even if the training measure is calculated as the proportion of employees aged under 50 receiving training in every year, the figure for 1983 is still lower than for 1984.

²⁰ The change of training propensity over a given period. can be decomposed into a *within-industry* and a *between-industry* component: $\Delta T = \sum_i \Delta S_i \bar{T}_i + \sum_i \Delta T_i \bar{S}_i$ where T = proportion of workers undertaking training, S = share of industry i in total employment, a bar denotes a mean over time and the delta is the difference over the same two time periods.

Figure 3.1. Overall Training Incidence, Labour Force Survey, 1983-96

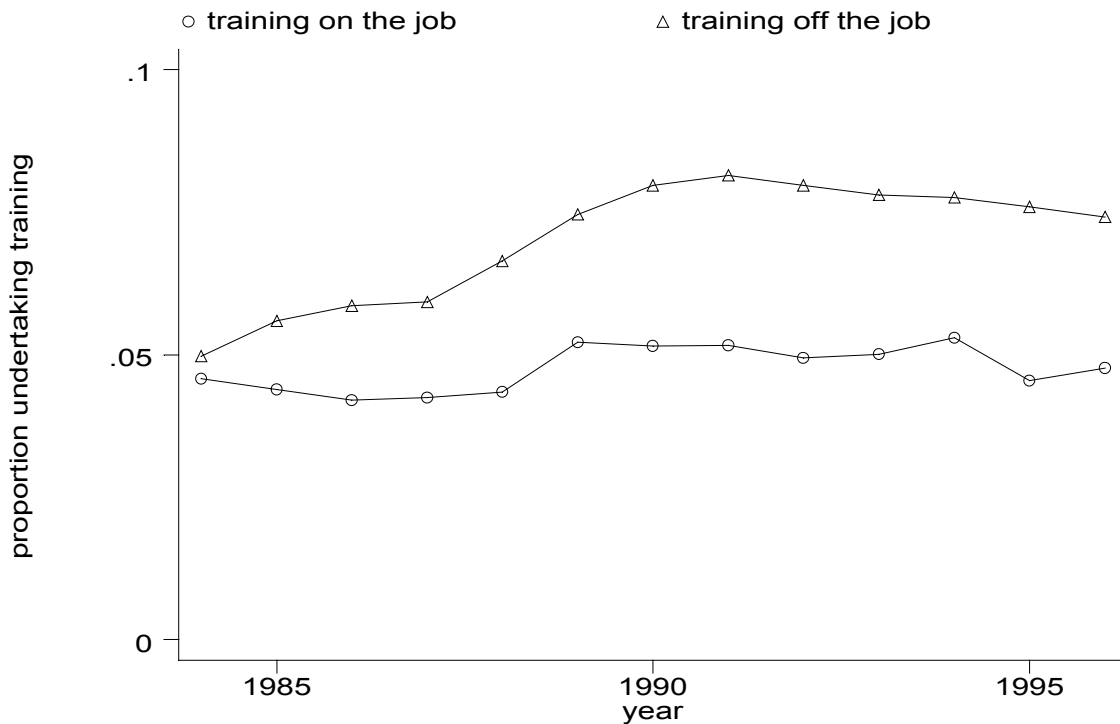


LFS also has further information on the type of training received (although not all of these are asked in each year). For example, Figure 3.2 shows the incidence of training on-the-job and off-the-job. In the LFS, “on-the-job” training is defined as learning by example and practice whilst actually doing the job, whilst “off-the-job” training refers to training which is conducted as a formal training course (such as a classroom or training section).²¹

The time series of these training variables is presented for the period 1984 to 1996 only, as the definition of the variable in 1983 was somewhat incompatible.

²¹ It is important to note that the on-the-job/off-the-job distinction is to do with the formality or informality of training rather than the location. A training course could be conducted at an employer’s premises and still be ‘off-the-job training’ on the LFS definition. In some years, the LFS data do provide information on the location of the training course, but there is not enough of a consistent time series on training location to allow us to make use of this variable.

Figure 3.2. The incidence of on-the-job and off-the job training, 1984-96



Interestingly, the overall increase in recorded levels of training between 1984 and 1996 seems to be almost completely accounted for by an increase in off-the-job training. The incidence of on-the-job training over the time period has been more or less constant.

Other indicators of training (not asked in every year) include the duration of training, whether it was employer funded, whether it was completed or still ongoing. In the results section we examined whether there were differential productivity effects for all these different types of training.

It is useful to address the subject of data quality with regard to the training question. Although the question which has been asked to employees in the LFS is consistently phrased over time, the measure takes no account of the intensity

or length of the training course (except insofar as a longer training course is more likely to fall within the 4-week period prior to the survey). Furthermore, there is some evidence both from our own investigative data analysis and from other sources that the average length of a training course has been falling since the late 1980s²². Unfortunately our attempts to identify differential effects of training courses according to the length of the most recent training course undertaken were hampered by the fact that this question is not defined consistently over time and there is a lot of non-response to the duration question. However, some comfort is provided by the fact that when we estimate training effects separately for each year of the LFS sample, the magnitude of the training effect does not differ significantly over time; one might expect a decrease in the productivity effect of the training measure for the later years if the average quality of training courses has declined (see Section 5.1 for the details of this procedure).

The second major dataset we use is the Annual Census of Production (ACOP). This gives production statistics on capital, labour and output for industries in the manufacturing, energy and water sectors (collectively known as the production sector of the economy). It is based on the ARD (Annual Respondents Database) which is a survey of all production establishments (plants) in the UK with 100 or more employees, plus a subset of establishments with less than 100 employees.²³ We use the COP data on value added, gross output, investment, employment and wages for industries in the manufacturing sector and the energy and water industries.

Capital stocks were calculated using the perpetual inventory method drawing on NIESR's estimates on initial capital stocks (see O'Mahony and Oulton, 1990). All the nominal measures were deflated with three digit industry price indices from

²² For a detailed analysis see Felstead *et al* (1997).

²³ for more details see Griffith (1999).

ONS. For the services industries we drew on the ISDB (intersectoral Database) compiled by the OECD.

There was a change in SIC classification in 1992 which forced us to aggregate some of the industries and prevented us from using some of the industries after the change. Additionally, we insisted on having at least 25 individuals in each cell in each year. After matching the aggregated individual data from LFS we were left with 94 industry groupings over (a maximum of) 14 years. Full details of this process are in the Appendices A and B.

3.2 Data Description

Armed with this dataset we present various descriptive statistics by industry. First we ranked all industries by their propensity to train. From Table 3.1 we see that the highest-training industries are generally high tech - pharmaceuticals, aerospace, chemicals and computers. Another important group are the energy industries including electricity and especially nuclear fuel, which is the top-ranked training. This is to be expected, given that, given that these industries include a lot of specialised equipment and stringent safety requirements.

Table 3.1: Propensities to train ranked by industry

Rank	Industry SIC80 code and description	% undertaking training in last 4 weeks in industry , LFS
1.	152: nuclear fuel	22.35
2.	330: office machinery (including computers)	19.06
3.	810-29: financial services	18.75
4.	257: pharmaceuticals	18.12
5.	251: basic chemicals	17.55
6.	161: electricity	17.37
7.	162-3: other energy	17.04
8.	170: water	16.18
9.	256: specialised chemicals	14.83
10.	900-999: miscellaneous services	14.53
11.	364-5: aerospace	14.19
12.	362-3: trains & cycles	14.03
13.	830-899: real estate & business services	13.75
14.	140: mineral oil processing	13.27
15.	344: telecommunications equipment	13.06
16.	790-9: communications services	12.72
17.	371: measuring instruments	12.70
18.	372: medical equipment	12.07
19.	258: soap	12.00
20.	329: small arms	11.61
21.	345: other electronics	11.57
22.	255: paints etc.	11.51
23.	351: vehicles & engines	11.50
24.	343: batteries etc.	11.41
25.	325: mining machinery	11.20
26.	259-60: man-made fibres	11.12
27.	361: shipbuilding	11.02
28.	210-221: iron & steel	10.96
29.	373-4: clocks & optical	10.76
30.	427: brewing	10.60
31.	342: basic electrical equipment	10.15
32.	326: power transmission equipment	10.08
33.	327: printing machinery	9.92
34.	321: tractors etc.	9.88
35.	328: other machinery	9.86
36.	323-4: textile & chemical machinery	9.75
37.	322: machine tools	9.66
38.	428-9: soft drinks/tobacco	9.66
39.	353: vehicle parts	9.56
40.	481-2: rubber products	9.55
41.	224: non-ferrous metals	9.46
42.	420-1: sugar & chocolate	9.27
43.	346: domestic appliances	9.17
44.	341: wires & cables	9.11
45.	422: animal feed	8.94
46.	320: industrial plant	8.83
47.	610-59, 670-99: distribution & vehicle repair	8.70
48.	244-6: stoneworking, asbestos	8.69
49.	710-779: transport	8.54
50.	312: forging etc.	8.35
51.	242-243: cement & plaster	8.32
52.	471: paper	8.28
53.	111-120: solid fuels	8.18
54.	223: drawing steel	8.05

Rank	Industry SIC80 code and description	% undertaking training in last 4 weeks in industry , LFS
55.	247: glass	8.00
56.	241: clay products	7.86
57.	483: plastics	7.83
58.	492-3: musical instruments & photography	7.81
59.	424-6: spirits & wine	7.73
60.	472: paper conversion	7.68
61.	463: carpentry/joinery	7.54
62.	475: printing/publishing	7.53
63.	500-599: construction	7.52
64.	660-9: restaurants/hotels	7.49
65.	222: steel tubes	7.34
66.	314: metal doors/windows	7.09
67.	494: toys	6.94
68.	347: lighting	6.91
69.	352: vehicle bodies	6.85
70.	418-9: bread & starch	6.76
71.	316: hand tools	6.61
72.	248: ceramic goods	6.58
73.	415-6: fish & grain	6.31
74.	311: foundries	6.31
75.	464-6: wooden items	6.14
76.	441-2: leather	6.07
77.	491: jewelry/coins	5.96
78.	467: wooden furniture	5.95
79.	0-99: agriculture	5.78
80.	231-9: other mineral extraction	5.52
81.	411-2: animal products	5.34
82.	432-5: natural fibres	5.22
83.	495: miscellaneous manufacturing	5.19
84.	414: fruit & vegetables	5.11
85.	455-6: textiles & fur	4.82
86.	313: nuts & bolts	4.76
87.	438: carpets	4.59
88.	431: woolen goods	4.43
89.	453: clothing	4.27
90.	461-2: wood processing equipment	3.99
91.	436: hosiery	3.90
92.	439: miscellaneous textiles	3.83
93.	451: footwear	3.76
94.	437: textile finishing	2.72

Notes

These are derived from the LFS matched to our 94 industry groupings 1984-1996.

Financial services and banking (where IT equipment is intensively used) are also highly ranked. At the low end of the table come several industries associated with low-paid, low-skilled labour such as textiles, footwear and clothing, all with less than 5% of employees being trained.

To begin the analysis we simply plot the scatterplot of labour productivity (log real value added per worker) against training propensity in Figure 3.3. There is a strong positive correlation. Figure 3.4 repeats the exercise for log hourly wages. The correlation is somewhat weaker (a result which is repeated in the econometric analysis) but still clearly positive. These are the essential patterns in the data that we will be testing more rigorously in Section 5.

The outliers in both graphs tend to be in the service sector. Further analysis revealed that the series for value added and capital stocks tended to be rather unreliable in the service sector and (to a lesser extent) in the non-manufacturing parts of the production sector. For example in banking and financial services real value added per person declined every year between 1983 and 1996 according to the ISDB! Measuring productivity and prices is an inherently difficult problem in these sectors. Although we only have 91 observations in these sectors they are large and since we weight by the size of the industry, they have a large influence on the results. Given the poor quality of the data we decided, somewhat reluctantly, to focus the econometric part of the analysis on the production side of the economy (some results for non-production are given in section 5).

Figure 3.1 Labour Productivity and Training in British Industries

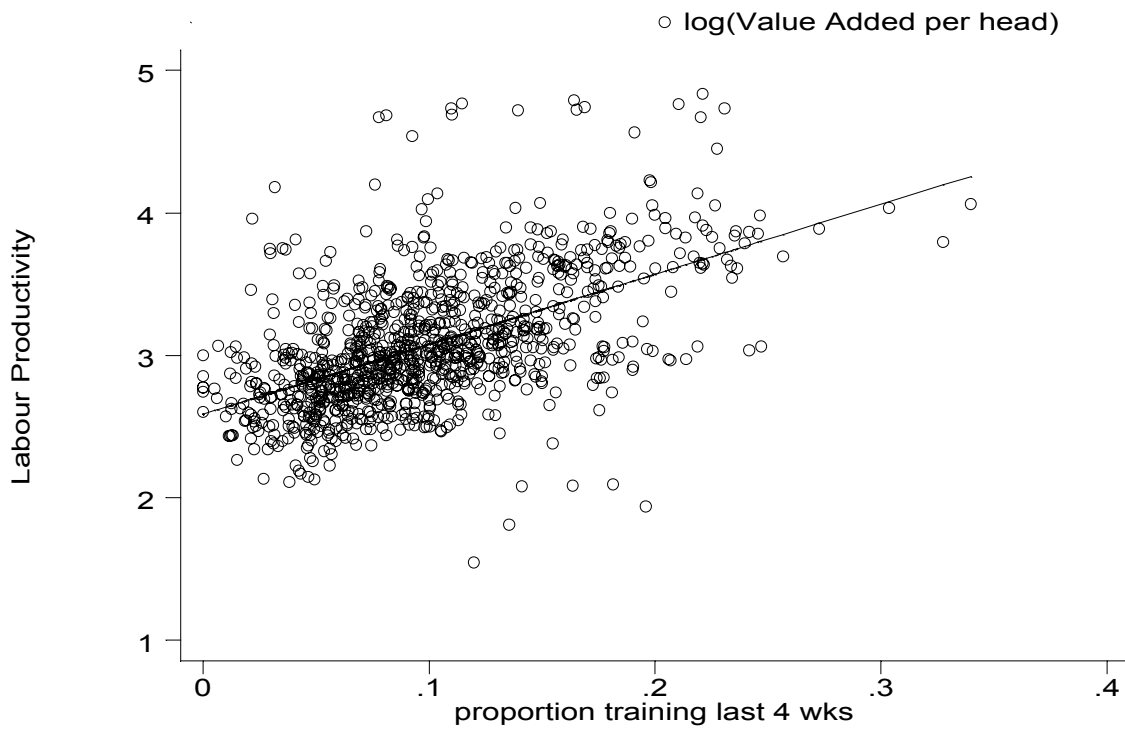
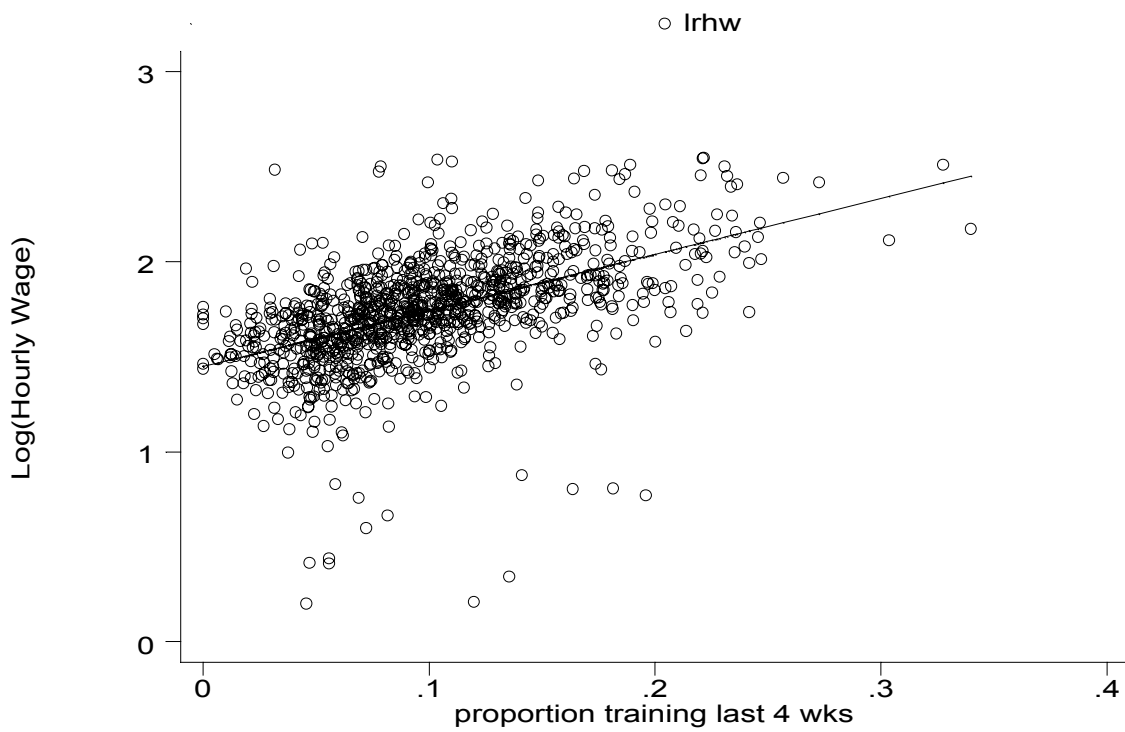


Figure 3.2 Wages and Training in British Industries



Notes to Figures 3.1 and 3.2

1. Each point is an industry-year observation
2. The OLS regression line has a slope of 4.91 for productivity and 2.95 for wages
3. Labour productivity is $\log(\text{Value added per employee})$ from Census of Production
4. Wages are \log hourly wages from the Census of Production (wages) and the LFS (hours)
5. Training is the proportion of workers involved in training from the LFS

For descriptive purposes we split industries into 'high-training' and 'low-training' based on whether they are above or below the median training propensity (8.7%). Industries ranked 1 through 47 fall into the 'high-training' category. Table 3.2 gives the mean characteristics of the high and low training industries. High training industries are characterised by being more productive and paying high wages as we expected. Furthermore, they are more capital intensive, conduct more research and development, employ more workers of higher skills (managers/professionals and those with more qualifications) and longer tenure. They also employ more men and have fewer small firms.

We also analysed the time series trends of these variables split by high and low training industries. The relative differences appeared to be very persistent over time, although there was some tendency for the older individuals to increase their training more than the younger individuals.

Since most of these characteristics are associated with higher productivity the scatterplots of Figures 3.1 and 3.2 could merely represent the fact that high training industries happen to employ workers who are more productive. We need to turn to an explicit econometric model to investigate whether there is a causal effect of training per se on productivity.

Table 3.2
Means of Variables by High and Low Training Industries

Variable	Mean (low training industries)	Mean (high training industries)
proportion of male employees	62.4%	80.9%
proportion aged: 16-24	22.7%	15.5%
: 25-34	24.5%	25.4%
: 35-44	22.2%	24.0%
: 45-54	19.1%	22.1%
: 55-64	11.1%	12.8%
proportion in occupation:		
:professional/managerial	14.7%	27.1%
:clerical	8.5%	10.9%
:security/personal	1.9%	1.6%
:sales	3.4%	2.5%
:other occupations	71.5%	58.0%
highest qualification:		
:degree	2.6%	7.3%
:sub-degree level	3.7%	9.2%
:A level / equivalent	15.5%	22.5%
:O level/ equivalent	15.6%	14.3%
:other/none/missing	62.7%	46.7%
tenure in current job:		
:less than 6 months	10.9%	7.1%
:6 months – 1 year	8.4%	5.8%
:1 year – 2 years	11.1%	8.0%
:2 years – 5 years	21.6%	17.8%
:5 years – 10 years	18.8%	19.7%
:10 years – 20 years	18.0%	24.3%
:more than 20 years	9.0%	16.5%
proportion in small firm	21.2%	12.6%
average log capital-labour ratio	2.22	3.02
average log real value added per worker	2.76	3.19
average log gross output per worker	3.80	4.27
average log hourly wages	1.56	1.84
average hours worked	39.1	40.2
average R&D spend as proportion of output	0.52	2.99

Notes to Table 3.2

'High Training' industries are those that trained on average more than 8.7% of employees (the sample median).

4. A Model of training and productivity

Following Bartel (1995), consider a simple Cobb-Douglas production function - this should be thought of as a first order approximation to a more complicated functional form (we discuss alternatives below).

$$Q = AL^\alpha K^\beta \quad (1)$$

Where Q is value added, L is effective labour, K is capital and A is a Hicks neutral efficiency parameter. Effective labour will depend on many aspects of the organisation of the firm. If we assume that training improves the amount of effective labour then write effective labour as

$$L = N^U + \gamma N^T \quad (2)$$

where N^U are untrained workers and N^T are trained workers (we expect $\gamma > 1$). Substituting equation (2) into (1) gives:

$$Q = A(N^U + \gamma N^T)^\alpha K^\beta$$

which can be re-expressed as

$$Q = A(1 + (\gamma - 1)TRAIN)^\alpha N^\alpha K^\beta \quad (3)$$

where $TRAIN = N^T/N$, the proportion of trained workers in an industry. If $(\gamma - 1)TRAIN$ is small we can use the approximation $\ln(1+x) = x$ and re-write the production function in logarithmic form as

$$\log Q = \log A + \alpha(\gamma - 1)TRAIN + \alpha \log N + \beta \log K \quad (4)$$

If the industry exhibits constant returns to scale then equation (4) can be re-written in terms of labour productivity as

$$\log(Q/N) = \log A + (1 - \beta)(\gamma - 1)TRAIN + \beta \log(K/N) \quad (5)$$

If the trained are no more productive than the untrained ($\gamma=1$) then the coefficient on TRAIN will be zero. Of course, there are a large number of other influences on productivity captured in A. In the empirical work below we consider a large vector of other variables. In particular we will allow for other dimensions of worker heterogeneity by including standard proxies for human capital (education, occupation, age and tenure). Furthermore, we allow for differential hours, worker turnover rates, innovation (as proxied by R&D intensity), gender, regional composition and the proportion of small firms. Finally we will examine the returns to different types of training (e.g. off the job and on the job).

Despite the presence of these additional observables to control for factors affecting productivity there remain several econometric problems. Firstly, there are likely to be unobservable factors that are correlated with our regressors that we have not measured. For example, some industries may have a higher rate of technological progress which requires a larger amount of training. It is the unobserved technical change which boosts productivity and not training per se. Unless we control for these fixed effects we may overstate the importance of training for productivity. There are a variety of methods to control for this problem. Since we have a long panel (1983-1996) we deal with it by including a full set of industry dummies (fixed effects). The within groups bias should not be large with a time series of this dimension but we are careful to check by examining the fully balanced data and examining other estimation strategies (see below).

A second major problem is that of endogeneity. Transitory shocks could raise productivity and induce changes in training activity (and of course in the other inputs, labour and capital). For example, faced with a downturn in demand in its industry, a firm may reallocate idle labour to training activities ('the pit stop theory'). This would mean that we underestimate the productivity effects of training because human capital acquisition will be high when demand and production is low²⁴.

To deal with this problem one needs to use sets of instrumental variables that are correlated with training, but not with the productivity shock. One strategy is to seek an external instrument correlated with the receipt of training but uncorrelated with productivity. The strategy taken here is to draw on recent advances in GMM techniques to deal with these problems (e.g. Blundell and Bond, 1998) utilising the fact that we have longitudinal data. We use a system estimator that exploits information in the levels and difference equations. An additional advantage of this procedure is that, as with any valid instrumental variables strategy, it should correct for bias arising for measurement error in the dependent variable and regressors.

For ease of exposition consider a simplified univariate stochastic representation of equation (5)

$$y_{it} = \theta x_{it} + u_{it} \quad (6)$$

where i = industry, t = time and $u_{it} = f_i + m_{it} + v_{it}$

We initially assume f_i is a firm effect, m_{it} and v_{it} are serially uncorrelated errors.

²⁴ A similar issue arises in the evaluation of government training schemes when individuals who have had a transitory drop in their earnings are more likely to be allocated to a training programme. This 'Ashenfelter dip' will tend to lead to an underestimation of the benefits of training on income.

OLS will be inconsistent if the fixed effects are correlated with the x variables. Including the fixed effects and the time dummies and estimating by within groups will be a consistent estimator of θ only if the regressors are strictly exogenous, i.e. $E(x_{it+s}u_{it}) = 0, s \neq 0$. For weakly exogenous regressors (such as a lagged dependent variable) where $E(x_{it}u_{it}) = 0$, but $E(x_{it+s}u_{it}) \neq 0, s > 0$, Nickell (1981) has shown that the size of this bias will decrease in T , the length of the panel.

It is quite likely that even weak exogeneity may be invalid. Firms will adjust their inputs (such as labour and possibly training) in response to current shocks. Furthermore, there might be serial correlation in the v_{it} process. For example, continue to assume that m_{it} is uncorrelated but allow v_{it} to be AR(1), i.e.

$$v_{it} = \rho v_{it-1} + e_{it} \quad (7)$$

The combination of (6) and (7) implies a general dynamic model of the form

$$y_{it} = \pi_1 y_{it-1} + \pi_2 x_{it} + \pi_3 x_{it-1} + \eta_i + w_{it} \quad (8)$$

with common factor (COMFAC) restrictions $\pi_3 = -\pi_1 \pi_2$. Note that $w_{it} = e_{it} + m_{it} - \rho m_{it-1}$ and $\eta_i = (1 - \rho) f_i$. In these circumstances we consider weaker moment conditions. Standard assumptions on the initial conditions ($E(x_{i1}e_{it}) = E(x_{it}m_{it}) = 0$) gives the moment condition

$$E(x_{it-s} \Delta w_{it}) = 0, s > 1 \quad (9)$$

This allows the construction of suitably lagged levels of the variables (including the y_{it} 's) to be used as instruments after the equations have been first differenced (see Arellano and Bond, 1991).

As has been frequently pointed out, the resulting first differenced GMM estimator has poor finite sample properties when the lagged levels of the series are only weakly correlated with the subsequent first differences (Blundell and Bond, 1998). This has been a particular problem in the context of production functions due to the high persistence of the capital stock series (e.g. Griliches and Mairesse, 1998).

Under further assumptions on the initial conditions, the weak instruments problem (cf. Staiger and Stock, 1997) can be mitigated. If we are willing to assume $E(\Delta x_i \eta_i) = 0$ and $E(\Delta y_i \eta_i) = 0$ then we obtain additional moment conditions

$$E(\Delta x_{it-s} (\eta_i + w_{it})) = 0, s > 1 \quad (10)$$

Stationarity of the variables is a sufficient (but not necessary) condition for moment conditions in equation (10) to hold. This allows for suitably lagged first differences of the variables to be used as instruments for the equations in levels.

The combination of the moment conditions for the levels equations in equation (10) to the more standard moment conditions in equation (9) can be used to form a GMM 'system' estimator. This has been found to perform well in Monte Carlo simulations and in the context of the estimation of production functions (Blundell and Bond, 1999). This IV procedure should also be a way of controlling for transitory measurement error (the fixed effects control for permanent measurement error). Random measurement error has been found to be a problem in the returns to human capital literature, typically generating attenuation bias (see Card, 1999)

Note that the estimation strategy will depend on the absence of serial correlation in the e_{it} 's in equation (7). We report serial correlation tests in addition to the Sargan-Hansen test of the overidentifying restrictions in all the GMM results below.

Finally, consider two more issue which are harder to deal with: aggregation and training stocks vs. training flows. Estimation at the three digit industry level has advantages but also disadvantages relative to micro-level estimation. The production function in equation (1) at the firm level describes the private impact of training on productivity. However, many authors, especially in the endogenous growth literature (e.g. Aghion and Howitt, 1998), have argued that there will be externalities to human capital acquisition. For example, workers with higher human capital are more likely to generate new ideas and innovations which may spill over to other firms²⁵. If spillovers are industry specific this implies that there should be another term added to equation (5) representing mean industry level training. In this case the coefficient on training in an industry level production function should exceed that in a firm level production function²⁶. Secondly, grouping by industry may smooth over some of the measurement error in the micro data and therefore reduce attenuation bias.

On the negative side, there may be aggregation biases in industry level data. *A priori* it is impossible to sign these biases and we expect that the fixed effects will control for much of the problem. For example, we are taking logs of means and not the means of logs in aggregating equation (1). So long as the higher order moments of the distributions are constant over time in an industry then they will

²⁵ Although there are many papers which examine externalities of R&D (e.g. see the survey by Griliches, 1991) and a few which look at human capital (Acemoglu and Angrist, 2000, Griffith, Redding and Van Reenen, 2000 and Moretti, 1999) there are none that focus on training spillovers.

²⁶ For the same argument in the R&D context see Griliches (1992)

be captured by a fixed effect²⁷. If the coefficients are not constant across firms in equation (1), but are actually random, this will also generate higher order terms at the industry level. In the empirical results we also experiment with including higher order moments to make sure our results are robust to potential aggregation biases.

Turning to the problem of training stocks and flows, note that the model in equation (1) assumes that we know the stocks of trained workers in an industry. What we actually have in the data is an estimate of the proportion of workers in an industry who received training in a given 4-week period (the flow). Since individuals are sampled randomly over time in the LFS this should be an unbiased estimate of the proportion of time spent in training over the year²⁸.

If we define the stock of people who have useful training skills in the industry at time t as N_t^T and the flow as M_t^T then if the stock evolves according to the standard perpetual inventory formula it can be expressed as

$$N_t^T = M_t^T + (1-\delta) N_{t-1}^T \quad (11)$$

where δ is the rate at which the stock of effectively trained workers at time t decay in their productive usefulness by $t+1$. This training depreciation rate represents several things. Firstly, individuals will move away from the industry, so their training can no longer contribute to the industry's human capital stock. Secondly, the usefulness of training will decline over time as old knowledge becomes obsolete and people forget (e.g knowledge of the DOS operating system). Thirdly, to the extent that training is firm-specific, turnover between firms

²⁷ If they evolve at the same rate across industries they will be picked up by the time dummies.

²⁸ If there are many multiple training spells in the month we will underestimate the proportion who are being trained. If Spring (the LFS quarter we use) is a particularly heavy training season then we will overestimate the proportion being trained in a year. These biases are likely to be small and offsetting.

in the same industry may reduce industry productivity. Although we obtain some measures of turnover using the LFS, the second element of depreciation is essentially unknown. Because of this our baseline results simply uses the proportion of workers trained in an industry (TRAIN in equation (3)). This will be equal to the stock when $\delta=1$. Nevertheless, we also estimate the training stock (under different assumptions on δ) and check our results for robustness using this alternative measure.

5. Results

5.1 Baseline Results of the Production Functions

In Table 5.1 we present the first basic results for industry-level regressions using log real value added per head as the dependent variable. The first two columns present some OLS results for the production sector. The second column includes skill variables whereas the first column does not. Training has a significant impact on productivity in the first column, even after conditioning for a large number of controls. It seems clear, however, that its impact is overstated since the association is reduced dramatically (and is only significant at the 10% level) after we control for skills (qualifications and occupation). As we saw that skilled industries are far more likely to train this is unsurprising. Column (2) demonstrates that skill-intensive sectors have also higher productivity on both the occupational and educational dimension²⁹.

Turning to the other variables, the coefficient on the capital labour ratio is highly significant and takes a reasonable point estimate (the share of the wage bill in

²⁹ We experimented with using more educational groups, but found additional ones (e.g. degree/no degree) were insignificant once we conditioned on the other variables in the regression.

value added is about 0.7). Productivity significantly increases in hours per employee and decreases with the degree of worker turnover. Lagged R&D intensity is also positively associated with higher productivity. Industries with a larger proportion of very young workers (16-24), female employees, and/or small firms are associated with lower productivity in column (2).

As discussed in section 4 it is important to consider fixed effects. In column (3) we simply include a full set of sectoral dummies. The capital intensity coefficient is lower, but remains significant, as do the turnover, age and occupational skills variables. The gender and educational variables are driven to insignificance³⁰. Surprisingly, R&D intensity is more significant in the within dimension. Most importantly for our purposes, the training variable remains significant with a higher point estimate.

Current training may be an inappropriate variable for a variety of reasons. For example, workers may actually be less productive during the time that they are being trained (the employee herself is devoted to training activities and this may also disrupt the production activities of co-workers if they have to help in the training). Consequently column (4) substitutes lagged training for current training. Although the point estimate has fallen marginally, it remains significant at conventional levels

³⁰ There is some collinearity between occupation and education as measures of skill, of course. Dropping occupations from the equation strengthens the educational variable.

Table 5.1. Productivity Regressions: Production Sector

ln(value added per worker)	(1) OLS – no skill variables	(2) OLS – skill variables	(3) Within Groups – current training	(4) Within Groups – lagged training
Industry proportion:				
Train _t %	1.581 (0.216)	0.363 (0.237)	0.692 (0.167)	
Train _{t-1} %				0.621 (0.165)
Turnover _{t-1} %	-0.794 (0.276)	-0.526 (0.269)	-0.432 (0.206)	-0.452 (0.207)
Industry average:				
log(K/N)	0.278 (0.012)	0.266 (0.012)	0.213 (0.036)	0.216 (0.036)
log(hours/N)	0.397 (0.236)	0.470 (0.226)	0.282 (0.180)	0.242 (0.180)
log(R&D)	0.692 (0.351)	0.148 (0.335)	1.269 (0.506)	1.279 (0.507)
Industry proportion:				
Male	0.231 (0.094)	0.279 (0.096)	-0.117 (0.124)	-0.127 (0.125)
Age 16-24	-1.497 (0.241)	-0.739 (0.237)	-0.390 (0.169)	-0.326 (0.168)
Age 25-34	-0.342 (0.241)	-0.262 (0.227)	-0.311 (0.154)	-0.287 (0.154)
Age 45-54	0.007 (0.245)	0.216 (0.231)	-0.102 (0.155)	-0.097 (0.156)
Age 55-64	-0.232 (0.284)	0.146 (0.270)	0.146 (0.192)	0.153 (0.192)
Occupation: Profess./managerial		0.762 (0.138)	0.283 (0.129)	0.313 (0.129)
Occupation: Clerical		0.798 (0.207)	-0.079 (0.182)	-0.069 (0.182)
Occupation: Security/personal		0.527 (0.494)	-0.519 (0.353)	-0.538 (0.354)
Occupation: Sales employees		1.872 (0.292)	-0.078 (0.288)	-0.103 (0.289)
No Qualifications		-0.267 (0.127)	0.105 (0.113)	0.029 (0.112)
% in small firm	0.002 (0.108)	-0.161 (0.110)	0.002 (0.121)	-0.006 (0.121)
NT Years	970 1984-1996	970 1984-1996	970 1984-1996	970 1984-1996
R-Square	0.813	0.838	0.945	0.945

Notes:

All regressions include a full set of regional dummies (10), time dummies (12) and tenure dummies(6); observations weighted by number of individuals in an LFS industry cell.

Table 5.2 reports results for the manufacturing sector only. All the results of the previous table go through even though the sample is smaller. The training effects are slightly more precisely determined in this sample than the previous sample which is probably because value added and capital are measured more accurately here than in the extraction industries.

If the non-production sector observations are included (agriculture, construction and services) the coefficient on training rises to 0.727 with a standard error of 0.206. We were concerned about the quality of the data in these sectors as we were only able to obtain consistent numbers for value added and capital for 9 industrial groupings for a limited number of years³¹. Even in these aggregated industries the trends in productivity appeared counter-intuitive. Given the size of these sectors, including them in the main estimates (which are weighted by sector size) degrades the quality of the results. Performing the production functions solely on the non-production industries gave a large coefficient on training (0.919) with a larger standard error (1.757). Because of these concerns over data quality we focus on the manufacturing sample for the detailed econometric results³².

³¹ up to 1989 for miscellaneous services, until 1990 for construction, until 1991 for agriculture and up to 1993 in all other cases.

³² All the main qualitative results go through on the production sector as a whole. For example the coefficient (*standard error*) on training in column (1) of Table 5.4 in the production sector is 0.473(0.196) compared to 0.469(0.167) in manufacturing. The equivalent numbers in column (2) are 1.319(0.564) in the production sector compared to 1.348(0.527) in manufacturing.

Table 5.2. Productivity Regressions: Manufacturing Sector

ln(value added per worker)	(1) OLS – no skill variables	(2) OLS – skill variables	(3) Within Groups – current training	(4) Within Groups – lagged training
Industry proportion:				
Train _t %	1.626 (0.213)	0.507 (0.227)	0.520 (0.164)	
Train _{t-1} %				0.509 (0.162)
Turnover _{t-1} %	-1.645 (0.308)	-1.496 (0.288)	-1.164 (0.227)	-1.194 (0.226)
Industry average:				
log(K/N) _t	0.327 (0.016)	0.309 (0.015)	0.085 (0.038)	0.085 (0.038)
log(hours/N) _t	-0.194 (0.240)	-0.144 (0.224)	0.085 (0.178)	0.062 (0.178)
log(R&D/Y) _{t-1}	0.283 (0.327)	-0.134 (0.304)	0.639 (0.472)	0.645 (0.472)
Industry proportion:				
Male _t	0.181 (0.090)	0.245 (0.089)	-0.037 (0.117)	-0.048 (0.118)
Age 16-24 _t	-1.182 (0.233)	-0.359 (0.225)	-0.112 (0.162)	-0.059 (0.160)
Age 25-34 _t	0.200 (0.236)	0.233 (0.218)	0.073 (0.150)	0.101 (0.150)
Age 45-54 _t	-0.277 (0.232)	-0.065 (0.215)	0.108 (0.148)	0.116 (0.148)
Age 55-64 _t	-0.520 (0.278)	-0.106 (0.260)	0.369 (0.185)	0.378 (0.185)
Occupation _t :		0.841	0.240	0.259
Profess./managerial		(0.129)	(0.124)	(0.123)
Occupation:		1.469	0.013	0.025
Clerical		(0.201)	(0.172)	(0.172)
Occupation:		0.063	-0.492	-0.471
Security/personal		(0.452)	(0.335)	(0.334)
Occupation:		1.279	-0.051	-0.061
Sales employees		(0.272)	(0.270)	(0.270)
No Qualifications		-0.086 (0.120)	0.098 (0.105)	0.039 (0.104)
% in small firm _t	0.312 (0.107)	0.145 (0.103)	0.003 (0.112)	-0.002 (0.112)
NT	898	898	898	898
Years	1984-1996	1984-1996	1984-1996	1984-1996
R-Square	0.789	0.825	0.937	0.937

Notes:

All regressions include a full set of regional dummies (10), time dummies (12) and tenure dummies(6); observations weighted by number of individuals in an LFS industry cell.

We conducted a large number of robustness tests on the models in these tables. Table 5.3 reports some results. Keeping only industries which had fourteen continuous years of data (balanced panel) in row 2. means losing 40% of the observations with an insignificant change in the coefficient. The third row includes average wages as a measure of unobserved worker quality. Although wages take a positive and (weakly) significant coefficient the training effect remains robust. Since training is correlated with unionisation, we could be picking up “collective voice” effects. Union membership is only available in LFS since 1989. Despite the loss in sample in row 4, the training effect is quite robust. Union density is negatively, but insignificantly, associated with productivity. In the fifth row we allow the training effect to be different in each of the 85 industries. The mean of these heterogeneous coefficients is close to the pooled results. There was some evidence that the training effects were larger in industries that had more human capital and were more high tech. We test more rigorously in the GMM results below. The sixth row conditions on having larger numbers in each cell, this seems to increase the training effect, suggesting some attenuation bias. The final row replaces the dependent variable with output which produces a smaller effect, probably because we are not controlling for other variables such as energy and intermediate inputs.

Table 5.3. Results of Within Groups robustness Tests

Robustness test	NT	Training coefficient, production sector (s.e.)
1. Original training coefficient in production sector, Table 5.1 column (3)	970	0.692 (0.167)
2. Using the balanced panel only to check for bias associated with finite T (Nickell, 1981):	572	0.508 (0.234)
3. Conditioning on wage in productivity regression to control for unobserved worker quality	970	Training: 0.659 (0.167) Wage coeff.: 0.100 (0.051)
4. Include union density (only available 1989-96)	547	training: 0.565(0.261) union: -0.042(0.161)
5. Allow all industries to have different training coefficients	970	mean of heterogeneous coefficients: 0.533
6. Conditioning on having at least 150 LFS individuals per cell	409	.986(0.330)
7. Using gross output per head instead of value added per head	970	0.335 (0.143)

Notes to Table

These all use the specification in the third column of Table 5.1

There are several other econometric reasons why the results in Table 5.1 and 5.2 may be misleading. Although endogeneity problems are mitigated by the use of lagged training in column (4) there may still be problems (e.g. if there is residual serial correlation). Furthermore, the dynamic structure of the production function may be more complex than the simple static model with uncorrelated shocks so far examined (e.g. equation (10)).

Table 5.4 presents some results using the GMM- System estimator described in section 4. Each regression includes all the covariates in Table 5.2 , although we only report results for the key variables (full results available on request). The first column simply performs the standard static specification but instruments capital intensity and hours. We use instruments in levels from $t-2$ in the first difference equation and instruments dated $t-1$ in differences in the levels equation (see base of table for exact timing). We initially assume current training is exogenous as before.

Treating hours and capital intensity as endogenous leads to increases in their implied impacts compared to the within groups results. Capital takes on a larger and more sensible point estimate. The training effect remains quite similar to the Within Groups estimates. The second column relaxes the exogeneity assumption on training using the same timing of instruments as the other variables. Remarkably, the training coefficient triples in size. This clearly rejects the hypothesis that the within group estimates over-estimate the productivity effect of training. One reason why there may be an underestimate is if firms train when demand (and therefore productivity which is pro-cyclical) is low.

To probe these results further we include a lagged dependent variable in the model in column (3). Although it is highly significant the other coefficients are largely unchanged. In column (4) we also include lags of the capital and hours variables. Column (5) implements fully the model of equation (8) and includes the first lag of all the right hand side variables in the regression (but continues to assume they are weakly exogenous). Finally column (6) allows all the right hand side variables (with the exception of the time and regional dummies) to be endogenous. This is the most demanding specification of the table³³.

Throughout these experiments there is a positive and significant impact of training on productivity. The exact magnitude of the effect varies somewhat in different specifications, but always remains above the estimates which treated training as exogenous.

³³ Instrumenting the regional dummies with lags does not alter the results. The problem with this column is that we have are using so many instruments that the Sargan test has practically no power to reject the null.

Table 5.4. Productivity Regressions: Manufacturing Sector, GMM results

ln(Value added per worker)	(1) Static, training exogenous	(2) Static, training endogenous	(3) Dynamic, training endogenous	(4) Dynamic, training endogenous	(5) Extended Dynamic PF	(6) Dynamic full PF specification
Industry average:						
$\ln(Q/N)_{t-1}$			0.075 (0.029)	0.466 (0.066)	0.453 (0.069)	0.554 (0.056)
Industry proportion:						
Train _t %	0.469 (0.167)	1.348 (0.527)	1.503 (0.458)	0.856 (0.406)	1.132 (0.383)	0.795 (0.308)
Train _{t-1} %				-0.001 (0.210)	0.207 (0.237)	0.224 (0.227)
Turnover _{t-1} %	-0.776 (0.232)	-0.685 (0.236)	-0.831 (0.233)	-0.306 (0.217)	-0.327 (0.194)	-0.598 (0.420)
Turnover _{t-2} %					0.134 (0.193)	-0.492 (0.297)
Industry average:						
$\log(K/N)_t$	0.247 (0.063)	0.300 (0.055)	0.227 (0.043)	0.258 (0.089)	0.275 (0.083)	0.235 (0.083)
$\log(K/N)_{t-1}$				-0.138 (0.080)	-0.131 (0.075)	-0.040 (0.079)
$\log(\text{hours}/N)_t$	0.518 (0.158)	0.489 (0.145)	0.458 (0.141)	0.371 (0.153)	0.390 (0.152)	0.420 (0.120)
$\log(\text{hours}/N)_{t-1}$				-0.326 (0.073)	-0.427 (0.197)	-0.443 (0.103)
$\log(R\&D/Y)_{t-1}$	0.311 (0.334)	0.020 (0.344)	-0.108 (0.337)	0.130 (0.253)	1.260 (0.507)	1.207 (1.119)
$\log(R\&D/Y)_{t-2}$					-1.372 (0.523)	-1.449 (1.222)
Serial Correlation (LM1)	-3.389	-4.154	-4.126	-5.813	-5.496	-5.618
Serial Correlation (LM2)	-1.706	-1.492	-0.955	-0.783	-0.932	-0.633
Sargan (df)	83.98(46)	108.75 (102)	159.86(136)	132.74(133)	136.04(133)	169.19(219)
p-value	0.091	0.305	0.087	0.490	0.411	0.995
Instruments	$\ln(\text{Hrs}/N)_{t-2,t-3}$ and $\ln(K/N)_{t-2,t-3}$ in differenced equations; $\Delta\ln(\text{Hrs}/N)_{t-1}$ and $\Delta\ln(K/N)_{t-1}$ in the levels equations.	$\ln(\text{TRAIN})_{t-2,t-3}$ $\ln(\text{Hrs}/N)_{t-2,t-3}$ $\ln(K/N)_{t-2,t-3}$ in differenced equations; $\Delta\ln(\text{TRAIN})_{t-1}$, $\Delta\ln(\text{Hrs}/N)_{t-1}$, $\Delta\log(K/N)_{t-1}$ in the levels equations.	$\ln(\text{TRAIN})_{t-2,t-3}$ $\log(Q/N)_{t-2,t-3}$, $\log(\text{Hrs}/N)_{t-2,t-3}$ $\log(K/N)_{t-2,t-3}$ in differenced equations; $\Delta\log(\text{TRAIN})_{t-1}$, $\Delta\log(Q/N)_{t-1}$, $\Delta\log(\text{Hrs}/N)_{t-1}$, $\Delta\log(K/N)_{t-1}$ in the levels equations.	$\ln(\text{TRAIN})_{t-2,t-3}$ $\log(Q/N)_{t-2,t-3}$, $\log(\text{Hrs}/N)_{t-2,t-3}$ $\log(K/N)_{t-2,t-3}$ in differenced equations; $\Delta\log(\text{TRAIN})_{t-1}$, $\Delta\log(Q/N)_{t-1}$, $\Delta\log(\text{Hrs}/N)_{t-1}$, $\Delta\log(K/N)_{t-1}$ in the levels equations.	$\ln(\text{TRAIN})_{t-2,t-3}$ $\log(Q/N)_{t-2,t-3}$, $\log(\text{Hrs}/N)_{t-2,t-3}$ $\log(K/N)_{t-2,t-3}$ in differenced equations; $\Delta\log(\text{TRAIN})_{t-1}$, $\Delta\log(Q/N)_{t-1}$, $\Delta\log(\text{Hrs}/N)_{t-1}$, $\Delta\log(K/N)_{t-1}$ in the levels equations.	all variables treated as endogenous (except time and regional dummies)
NT	818	818	818	818	818	818
Years	1985-1996	1985-1996	1985-1996	1985-1996	1985-1996	1985-1996

Notes to Table 5.4

Estimation by GMM-SYS in Arellano and Bond (1998) DPD-98 package written in GAUSS; all regressions include the current values of all the variables in Tables 5.1 and 5.2 (i.e. occupations, qualifications, age, tenure, gender, region, firm size; time dummies) and in columns (5) and (6) the first lags of all these variables are also included; capital intensity, hours and lagged productivity are always treated as endogenous; the other variables are treated as exogenous except in column (6) where all variables are instrumented; asymptotically robust (one-step) standard errors in parentheses; LM1(2) is a Lagrange Multiplier test of first (second) order serial correlation distributed $N[1,0]$ under the null (see Arellano and Bond, 1991); Sargan is a Chi-squared test of the overidentifying restrictions; observations weighted by number of individuals in an LFS industry cell.

The diagnostics are satisfactory. There is evidence of negative first order correlation (in the differenced residuals) which is consistent with our assumptions. There is some evidence of second order correlation (at the 10% level) in the first column, but this reflects misspecification as it disappears in the more general specifications in the other columns. Longer memory autocorrelation would invalidate the use of our instruments³⁴. Another test of instrument validity is the Sargan statistic which also easily passes in the preferred specifications.

We subjected the results in Table 5.4 to a battery of robustness tests (see next section for some of the more interesting ones). For example, using the final column of Table 5.4 we tried the following experiments. Firstly, to test for non-constant returns employment and its lag were included (instrumented in the usual way). The employment terms were individually and jointly insignificant, with a p-value of 0.21. Secondly, to examine aggregation biases we included higher order powers of the right hand side variables. These were uninformative. For example including squared terms (and first lag) of training, capital intensity and hours gave a chi-squared(6) of 10.5 (p-value = 0.101). Thirdly, the training question was asked slightly differently in 1983 (it applied only to workers under 50). Dropping 1983 (which is only ever used for instruments in any case) and re-estimating 1986-1996 lead to a coefficient on training of 0.858 with standard error of 0.321. Fourthly, additional dynamics were not needed in the specifications. For example, lags at t-2 of training, capital intensity, value added and hours were jointly insignificant (p-value 0.621). Fifthly, we checked whether allowed the training effect had changed over time in any secular way (especially across the change of industrial classifications in 1992). The coefficient seemed reasonably stable over time, although there was some suggestion that the impact of training

³⁴ In fact, we identify a significant training effect even when we drop the most recent instruments and use (t-3) and before in the differenced equations and (t-2) in the levels equations. P-value of two training variables is 0.011.

was lower in the 1990-1993 recession³⁵. Sixth, we included the mean wage on the right hand side to control for worker quality. The variable was insignificant (a coefficient of 0.004 with a standard error of 0.111) and the training effect was unchanged.

Finally, we tried many interactions consistent with a more general production function. None of these were significant at the 5% level³⁶, but there was a suggestion of complementarity between human capital and training. Including the interaction of training with professional/managerial workers was significant at the 10% level. The coefficient on training was estimated to be 0.046 in industries where only 10% of employees were in the most skilled occupational class, compared to 0.39 when the proportion of the skilled was 20% (the sample mean).

5.2 Further investigations of the impact of training on productivity

We investigated how different types of training could lead to different productivity pay-offs. Using the on-the-job/off-the-job distinction in the training variable did suggest that off the job training had a larger impact on productivity. When the proportion of workers who had off the job training (and its lag) were included as extra variables (in addition to TRAIN), they were jointly significant at 10% (p-value of joint test 0.063). This may be because it represents more formal training which is more likely to have a lasting impact on productivity. It is useful to note that the increase in overall training is largely due to off-the-job training rather than on-the-job training. As this is the case, it seems reasonable to assume that a lot of the increase in training is genuinely productivity-enhancing.

³⁵ The joint significance of the interaction of training and a dummy variable for the 1992-1996 period (and its first lag) was 0.783. For 1993-1996 the equivalent was p-value 0.593. For 1991-1996 the p-value was 0.516. Allowing the 1990-93 period dummy to interact with training gave a p-value of 0.072.

³⁶ For example, the interaction of R&D with training was positive and the interaction of small firms with training was negative.

Other measures of the type of training were not informative. We did not find any additional effect of employer-provided or training length.

We were concerned about misspecification of the training measure as a flow rather than a stock. Consequently we re-estimated all the equations in Table 5.4 using the stock measure of training (predicted proportion of workers who have been trained at some point in the past)³⁷. In Table 5.5 the point estimates are similar to those of the previous table, but estimated more precisely. The dynamic equations of columns (4) through (6) appear more satisfactory than in the previous table with current training taking a positive coefficient and lagged training a negative coefficient. In fact, the common factor (COMFAC) restrictions are not rejected in column (6). Imposing these restrictions by minimum distance gives much more precise estimates (in bold).

³⁷ We use the median inter-industry employee turnover rate, assume a growth of the training stock of 2% a year and a training depreciation rate of 15%. The results are robust to using a depreciation rate of 10% or 20%, including within-industry turnover and setting the growth rate to zero. We also considered looking at the inflows of trained workers from other industries to improve the stock measure, but the LFS sample of industry switchers was too small to construct the full three digit flow matrix.

Table 5.5: Productivity Regressions: Manufacturing Sector, GMM results, Training Stock

In(Value added per worker)	(1) Static, training exogenous	(2) Static, training endogenous	(3) Dynamic, training endogenous	(4) Dynamic, training endogenous	(5) Extended Dynamic PF	(6) Dynamic full PF specification
<i>Industry average:</i>						
$\ln(Q/N)_{t-1}$			0.056 (0.035)	0.463 (0.066)	0.432 (0.071)	0.537 (0.057)
<i>Industry proportion:</i>						
Train _t % (stock)	0.354 (0.143)	0.870 (0.287)	0.576 (0.250)	0.913 (0.305)	1.132 (0.298)	0.701 (0.243)
Train _{t-1} % (stock)				-0.733 (0.256)	-0.675 (0.263)	-0.547 (0.223)
Training stock (impose COMFAC)						0.515 (0.192)
$\log(K/N)_t$	0.217 (0.062)	0.239 (0.052)	0.209 (0.044)	0.120 (0.087)	0.145 (0.083)	0.112 (0.082)
$\log(K/N)_{t-1}$				-0.011 (0.079)	-0.005 (0.080)	0.064 (0.076)
$\log(K/N)$ (impose COMFAC)						0.224 (0.045)
rho (autocorrelation coefficient) COMFAC TEST (df) p-value						0.498 (0.174) 41.62(33) 0.144
Serial Correlation (LM2) Sargan p-value	-1.851 0.106	-1.733 0.348	-1.133 0.024	-0.973 0.296	-1.053 0.162	-0.900 0.860
Instruments	$\ln(\text{Hrs}/N)_{t-2,t-3}$ and $\ln(K/N)_{t-2,t-3}$ in differenced equations; $\Delta \ln(\text{Hrs}/N)_{t-1}$ and $\Delta \ln(K/N)_{t-1}$ in the levels equations.	$\ln(\text{TRAIN})_{t-2,t-3}$, $\ln(\text{Hrs}/N)_{t-2,t-3}$, $\ln(K/N)_{t-2,t-3}$ in differenced equations; $\Delta \ln(\text{TRAIN})_{t-1}$, $\Delta \ln(\text{Hrs}/N)_{t-1}$, $\Delta \log(K/N)_{t-1}$ in the levels equations.	$\ln(\text{TRAIN})_{t-2,t-3}$, $\log(Q/N)_{t-2,t-3}$, $\log(\text{Hrs}/N)_{t-2,t-3}$, $\log(K/N)_{t-2,t-3}$ in differenced equations; $\Delta \log(\text{TRAIN})_{t-1}$, $\Delta \log(Q/N)_{t-1}$, $\Delta \log(\text{Hrs}/N)_{t-1}$, $\Delta \log(K/N)_{t-1}$ in the levels equations.	$\ln(\text{TRAIN})_{t-2,t-3}$, $\log(Q/N)_{t-2,t-3}$, $\log(\text{Hrs}/N)_{t-2,t-3}$, $\log(K/N)_{t-2,t-3}$ in differenced equations; $\Delta \log(\text{TRAIN})_{t-1}$, $\Delta \log(Q/N)_{t-1}$, $\Delta \log(\text{Hrs}/N)_{t-1}$, $\Delta \log(K/N)_{t-1}$ in the levels equations.	$\ln(\text{TRAIN})_{t-2,t-3}$, $\log(Q/N)_{t-2,t-3}$, $\log(\text{Hrs}/N)_{t-2,t-3}$, $\log(K/N)_{t-2,t-3}$ in differenced equations; $\Delta \log(\text{TRAIN})_{t-1}$, $\Delta \log(Q/N)_{t-1}$, $\Delta \log(\text{Hrs}/N)_{t-1}$, $\Delta \log(K/N)_{t-1}$ in the levels equations.	all variables treated as endogenous (except time and regional dummies)
NT Years	818 1985-1996	818 1985-1996	818 1985-1996	818 1985-1996	818 1985-1996	818 1985-1996

Notes to Table 5.5

Estimation by GMM-SYS in Arellano and Bond (1998) DPD-98 package written in GAUSS; all regressions include the current values of all the variables in Tables 5.1 and 5.2 (i.e. occupations, qualifications, age, tenure, gender, region, firm size; time dummies) and in columns (5) and (6) the first lags of all these variables are also included; capital intensity, hours and lagged productivity are always treated as endogenous; the other variables are treated as exogenous except in column (6) where all variables are instrumented; asymptotically robust (one-step) standard errors in parentheses; LM1(2) is a Lagrange Multiplier test of first (second) order serial correlation distributed $N[1,0]$ under the null (see Arellano and Bond, 1991); Sargan is a Chi-squared test of the overidentifying restrictions; observations weighted by number of individuals in an LFS industry cell.; in column (6) the numbers in bold are the coefficients and standard errors after imposing the COMFAC restrictions by minimum distance; COMFAC is a chi-squared test.

5.3 Wage regressions

Since there is a large existing empirical literature on the effects of training on wages we have focused on productivity in this paper. But it is still of great interest to also examine the wage impact of training. In order to make the effects of training comparable we have kept an identical specification in the hourly wage equation keeping the same control variables on the right hand side as in the production function.

Table 5.6 has the production sector results and Table 5.7 the manufacturing sector results. There is a statistically significant effect of training in column (1) of both tables. Most of the variables are conventionally signed. Industries who use workers with greater skills, have more men, higher capital intensity and larger establishments pay higher wages. Younger and older workers are paid less than prime age workers. More surprisingly, longer hours are associated with lower hourly pay.

The strong correlation of training with wages is severely reduced when one controls for skills. In fact, the correlation actually becomes negative (although insignificant) in column (2). The within group estimates restore some of the effect, implying a positive and significant impact of training on wages in both the production sector as a whole and the manufacturing sector alone.

Table 5.6. Hourly Wage Regressions: Production Sector

ln(hourly wage)	(1) OLS – no skill variables	(2) OLS – skill variables	(3) Within Groups – current training	(4) Within Groups – lagged training
Industry proportion:				
Train _t %	0.500 (0.138)	-0.163 (0.157)	0.327 (0.112)	
Train _{t-1} %				0.459 (0.111)
Turnover _{t-1} %	-0.098 (0.177)	0.046 (0.178)	0.158 (0.139)	0.148 (0.138)
Industry average:				
log(K/N) _t	0.036 (0.008)	0.033 (0.008)	0.092 (0.024)	0.092 (0.024)
log(hours/N) _t	-0.739 (0.151)	-0.665 (0.150)	-0.599 (0.121)	-0.621 (0.120)
log(R&D/Y) _t	0.041 (0.225)	-0.247 (0.222)	-0.859 (0.341)	-0.840 (0.339)
Industry proportion:				
Male	0.712 (0.060)	0.672 (0.063)	-0.128 (0.084)	-0.143 (0.083)
Age 16-24 _t	-0.929 (0.154)	-0.618 (0.157)	-0.153 (0.114)	-0.128 (0.112)
Age 25-34 _t	-0.160 (0.154)	-0.144 (0.151)	-0.168 (0.104)	-0.150 (0.103)
Age 45-54 _t	-0.184 (0.157)	-0.075 (0.153)	-0.152 (0.105)	-0.149 (0.104)
Age 55-64 _t	-0.497 (0.182)	-0.312 (0.179)	-0.240 (0.129)	-0.223 (0.129)
Occupation _t :		0.250 (0.092)	0.176 (0.087)	0.186 (0.087)
Profess./managerial		0.208 (0.137)	-0.140 (0.123)	-0.143 (0.122)
Occupation:		0.372 (0.328)	0.308 (0.238)	0.278 (0.237)
Clerical		0.599 (0.193)	-0.348 (0.194)	-0.365 (0.193)
Occupation:		-0.323 (0.084)	0.083 (0.076)	0.045 (0.075)
Security/personal		-0.435 (0.073)	-0.059 (0.081)	-0.061 (0.081)
Occupation:				
Sales employees				
No Qualifications				
% in small firm _t	-0.369 (0.072)	-0.435 (0.073)	-0.059 (0.081)	-0.061 (0.081)
NT	970	970	970	970
Years	1984-1996	1984-1996	1984-1996	1985-1996
R-Square	0.751	0.769	0.919	0.920

Notes:

All regressions include a full set of regional dummies (10), time dummies (12) and tenure dummies(6); observations weighted by number of individuals in an LFS industry cell.

Table 5.7. Hourly Wage Regressions: Manufacturing Sector

ln(hourly wage)	(1) OLS – no skill variables	(2) OLS – skill variables	(3) Within Groups – current training	(4) Within Groups – lagged training
Industry proportion:				
Train _t %	0.745 (0.122)	-0.196 (0.129)	0.130 (0.097)	
Train _{t-1} %				0.230 (0.096)
Turnover _{t-1} %	-1.467 (0.177)	-1.298 (0.164)	-0.328 (0.140)	-0.335 (0.136)
Industry average:				
log(K/N) _t	0.105 (0.009)	0.108 (0.009)	0.022 (0.022)	0.021 (0.022)
log(hours/N) _t	-1.405 (0.137)	-1.307 (0.127)	-0.841 (0.105)	-0.850 (0.105)
log(R&D) _{t-1}	-0.612 (0.187)	-0.885 (0.173)	-1.740 (0.279)	-1.728 (0.278)
Industry proportion:				
Male _t	0.621 (0.051)	0.555 (0.051)	-0.050 (0.069)	-0.060 (0.069)
Age 16-24 _t	-0.759 (0.133)	-0.371 (0.128)	-0.143 (0.095)	-0.130 (0.095)
Age 25-34 _t	-0.083 (0.135)	-0.123 (0.124)	-0.015 (0.089)	-0.004 (0.088)
Age 45-54 _t	-0.199 (0.133)	-0.074 (0.122)	-0.083 (0.087)	-0.081 (0.087)
Age 55-64 _t	-0.287 (0.159)	-0.041 (0.148)	-0.130 (0.109)	-0.121 (0.109)
Occupation _t :		0.267	0.095	0.098
Profess./managerial		(0.073)	(0.073)	(0.073)
Occupation:		0.794	0.009	0.007
Clerical		(0.114)	(0.102)	(0.101)
Occupation:		0.098	0.217	0.212
Security/personal		(0.257)	(0.198)	(0.197)
Occupation:		0.116	-0.183	-0.190
Sales employees		(0.155)	(0.159)	(0.159)
No Qualifications		-0.355 (0.068)	0.095 (0.062)	0.079 (0.061)
% in small firm _t	-0.089 (0.061)	-0.170 (0.059)	-0.036 (0.066)	-0.037 (0.066)
NT	898	898	898	898
Years	1984-1996	1984-1996	1984-1996	1984-1996
R-Square	0.816	0.849	0.941	0.942

Notes:

All regressions include a full set of regional dummies (10), time dummies (12) and tenure dummies(6); observations weighted by number of individuals in an LFS industry cell.

Table 5.8 contains the GMM results which mirror the specifications of the production function. As with productivity, allowing the training variable to be endogenous increases the implied effect (column (2) vs. column (1)). The training effect is insignificant at conventional levels. Column (3) includes a lagged dependent variable which is highly significant. Column (4) allows an extra lag on turnover, R&D, capital intensity and hours. Column (5) allows lags on all the variables and column (6) implements the most general dynamic specification treating all variables as endogenous. As with the production function, treating training as exogenous leads to downwardly biased estimates. In the preferred specification of column (6) training has a statistically significant effect on wages that is quantitatively larger than column (1).

One striking result is that whichever table we consider, the implied impact of training on wages is lower than its effect on productivity. For example, in the most general specification of column (6) the productivity effect of training is Table is about 0.8 and the wage effect 0.3. Differential effects on wages and productivity would be predicted in a basic human capital model where employers paid for some of the costs of firm specific training. The only other study to examine this found that the benefits of training are split about 50-50 between firms and workers (Barron et al (1989) on firm level data for the US).

Table 5.8. Hourly Wage Regressions: Manufacturing Sector, GMM results

ln(wage)	(1) Static, training exogenous	(2) Static, training endogenous	(3) Dynamic, training endogenous	(4) Dynamic, training endogenous	(5) Extended Dynamics, training endogenous	(6) Extended Dynamics, All variables treated as endogenous
Industry average: $\ln(\text{wage})_{t-1}$			0.235 (0.061)	0.686 (0.067)	0.646 (0.060)	0.615 (0.049)
Industry proportion: Train _t %	0.088 (0.105)	0.179 (0.365)	0.421 (0.307)	0.497 (0.238)	0.374 (0.222)	0.326 (0.157)
Train _{t-1} %				-0.213 (0.124)	-0.192 (0.130)	0.049 (0.110)
Turnover _{t-1} %	-0.514 (0.162)	-0.504 (0.155)	-0.152 (0.196)	-0.195 (0.122)	-0.046 (0.098)	0.146 (0.215)
Turnover _{t-2} %					-0.117 (0.099)	0.182 (0.153)
Industry average: $\log(K/N)_t$	0.120 (0.050)	0.123 (0.039)	0.102 (0.031)	0.148 (0.045)	0.115 (0.046)	0.059 (0.039)
$\log(K/N)_{t-1}$				-0.107 (0.039)	-0.078 (0.041)	-0.023 (0.039)
$\log(\text{hours}/N)_t$	-0.602 (0.125)	-0.612 (0.102)	-0.535 (0.091)	-0.563 (0.083)	-0.541 (0.082)	-0.451 (0.059)
$\log(\text{hours}/N)_{t-1}$				0.351 (0.036)	0.583 (0.096)	0.375 (0.057)
$\log(R\&D)_{t-1}$	-0.362 (0.205)	-0.391 (0.229)	-0.221 (0.197)	-0.066 (0.130)	0.610 (0.256)	1.035 (0.631)
$\log(R\&D)_{t-2}$					-0.690 (0.265)	-1.441 (0.605)
Serial Correlation (LM1)	-3.317	-3.278	-5.621	-5.431	-5.731	-5.860
Serial Correlation (LM2)	-2.244	-2.328	-2.161	-1.245	-1.927	-2.406
Sargan p-value	0.136	0.312	0.002	0.025	0.067	0.772
Instruments	$\ln(\text{Hrs}/N)_{t-2}$ and $\ln(K/N)_{t-2}$ in differenced equations; $\Delta \ln(\text{Hrs}/N)_{t-1}$ and $\Delta \ln(K/N)_{t-1}$ in the levels equations.	$\ln(\text{TRAIN})_{t-2,t-3}$ $\ln(\text{Hrs}/N)_{t-2}$, $\ln(K/N)_{t-2}$ in differenced equations; $\Delta \ln(\text{TRAIN})_{t-1}$, $\Delta \ln(\text{Hrs}/N)_{t-1}$, $\Delta \log(K/N)_{t-1}$ in the levels equations.	$\ln(\text{TRAIN})_{t-2,t-3}$ $\log(W)_{t-2}$, $\log(\text{Hrs}/N)_{t-2}$, $\log(K/N)_{t-2}$ in differenced equations; $\Delta \log(\text{TRAIN})_{t-1}$, $\Delta \log(W)_{t-1}$, $\Delta \log(\text{Hrs}/N)_{t-1}$, $\Delta \log(K/N)_{t-1}$ in the levels equations.	$\ln(\text{TRAIN})_{t-2,t-3}$ $\log(W)_{t-2}$, $\log(\text{Hrs}/N)_{t-2}$, $\log(K/N)_{t-2}$ in differenced equations; $\Delta \log(\text{TRAIN})_{t-1}$, $\Delta \log(W)_{t-1}$, $\Delta \log(\text{Hrs}/N)_{t-1}$, $\Delta \log(K/N)_{t-1}$ in the levels equations.	$\ln(\text{TRAIN})_{t-2,t-3}$ $\log(W)_{t-2}$, $\log(\text{Hrs}/N)_{t-2}$, $\log(K/N)_{t-2}$ in differenced equations; $\Delta \log(\text{TRAIN})_{t-1}$, $\Delta \log(W)_{t-1}$, $\Delta \log(\text{Hrs}/N)_{t-1}$, $\Delta \log(K/N)_{t-1}$ in the levels equations.	all variables treated as endogenous (except time dummies and regional dummies)
NT Years	818 1985-1996	818 1985-1996	818 1985-1996	818 1985-1996	818 1985-1996	818 1985-1996

Notes to Table

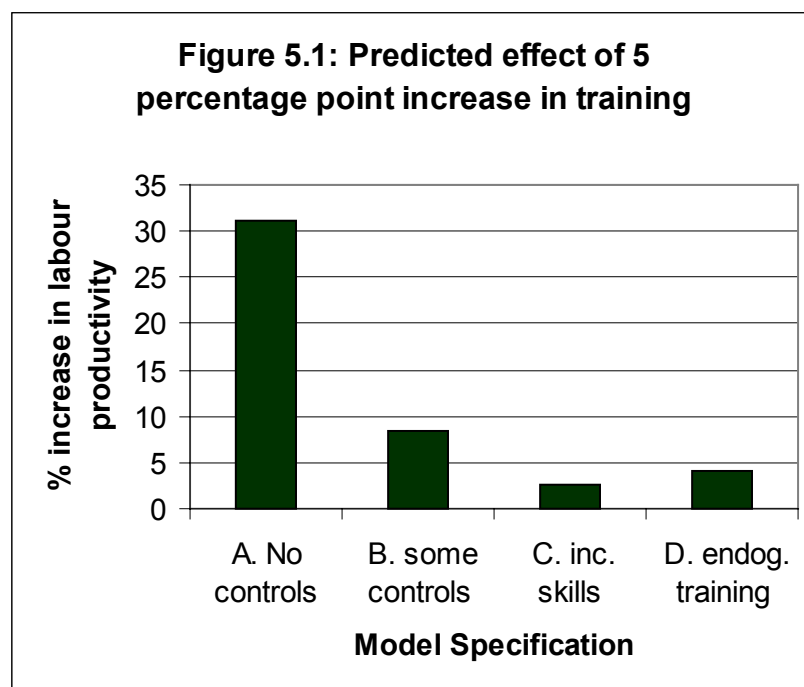
Estimation by GMM-SYS in Arellano and Bond (1998) DPD-98 package written in GAUSS; All regressions include the current values of all the variables in Tables 5.6 and 5.7 (occupations, qualifications, age, tenure, gender, region, firm size; time dummies) and in columns (5) and (6) the first lag of these variables is also included; capital intensity, hours, lagged productivity treated as endogenous in all columns; robust standard errors in parentheses; LM1(2) is a Lagrange Multiplier test of first (second) order serial correlation distributed $N[1,0]$ under the null (see Arellano and Bond, 1991); Sargan is a Chi-squared test of the overidentifying restrictions; observations weighted by number of individuals in an LFS industry cell.

Taken as a whole, the GMM models of wages show a much less precise effect of training than the production functions. There are also some signs of diagnostic problems. In particular, the second order serial correlation test rejects the null in most of the columns. We experimented with using only longer lags ($t-3$) as instruments, but all the estimates became extremely imprecise suggesting that the longer lags may have little power. This problem may be due to the rather ad hoc nature of the wage equation. We have more confidence in the statistical properties of the productivity results than the wage results for this reason.

5.4 Quantifying the effects of Training

Our key qualitative conclusions are: (1) the effects of training on productivity are much larger than the effects of productivity on wages and (2) that treating training as exogenous leads to an underestimation of the 'true effect'. But how big is the 'true' effect?

Interpreting the magnitude of the coefficients is a hazardous business. At first sight the size of the implied training effects appears implausibly large. From Tables 5.4 and 5.8 we take the coefficient on training in the productivity regressions to be about 0.8 and the coefficient on training in the wage regressions to be about 0.3. This would imply huge effects if we moved from having zero training to 100% training in a sector. This is not a very informative thought experiment, however, as it is way out of line with the empirical variation in the data.



Notes to Figure 5.1

These simulations are all based on the effects on value added per head of raising the proportion of workers in an industry by 5 percentage points (e.g. from 10% to 15%). They use coefficients taken from different models - i.e. the effect is $(\exp(\theta)-1)*100\%$. Model A : OLS regression with no controls; Model B: Table 5.2 column (1) includes all controls except skills and fixed effects; Model C: Table 5.2 column (2) same as Model B but includes skills; Model D: Table 5.4 column (6) treats training (and other variables) as endogenous.

Recall that the mean proportion of workers being trained in an industry is about 10%. If an industry managed to increase the proportion of workers from the mean to 15% this would be associated with a 4% ($= \exp(0.05*0.8)-1$) increase in productivity and a 1.5% ($= \exp(0.05*0.3)-1$) increase in wages. Note that it took the UK economy 13 years to generate an increase in the proportion workers trained on this scale (from 9% in 1984 to 14% in 1996).

Figure 5.1 illustrates the magnitude of the effects for our different models for a 5 percentage point increase in training proportions. The raw correlation of

productivity on training is huge (Model A). We can account for an overwhelming proportion of this correlation, however, by our control variables. The 31% effect in model A falls to 8.5% in model B and 2.6% in model C. Dealing with endogeneity through GMM (model D) increases the effect to 4.1%.

How do our results compare with other papers in the training literature? In fact, they are not out of line with many other papers. Take two representative examples from the British training and wages literature³⁸. First, Blundell et al (1996) estimates the wage return to a training spell on the current job of between a week and one month as 4.6% (their Table 5.10, p.59). Since the mean duration of the current job in their data is 7.8 years (Table A.1), this implies that a small proportion of work-time in training (around 1% of total months worked on the job³⁹) is associated with a 4.6% increase in wages. Second, Booth (1991) finds that an incidence of training in the last 2 years leads to a wage premium of 9.9% for full-time men and 16.3% for full-time women who had experienced the mean number of training days. Since women in her data had an average of fifteen days of training over a two year period (Table 1), the results imply that over a typical year (240 days) spending 3.1% ($=15/240$) of the time training is associated with a 16.3% increase in wages. For men, spending 2.4% of the time in training is associated with a 9.9% increase in wages.

In our data the typical training course lasts for about 2 weeks. Our average industry with a 10% rate of training ($\text{TRAIN} = 0.1$) could therefore be thought to have about 5% of the total annual hours supplied by “trained workers”. Increasing these hours by one percentage point requires a two percentage point increase in TRAIN. According to our estimates a two percentage point increase in TRAIN is associated with a 0.6% ($= \exp(0.02*0.3)-1$) increase in wages and a

³⁸ See the earlier discussion of these papers in section 2.

³⁹ Generously assume that the training course lasts for a month, then $1/(7.8*12)=1.06\%$

1.6% ($=\exp(0.02*0.8)-1$) increase in labour productivity. This is smaller than the Blundell et al (1996) and Booth (1991) studies.

This is not to say that the other micro studies are correct. They may have upward biases by failing to control for some of the employer characteristics that we can include (e.g. capital intensity). We are merely arguing that our results are not wildly out of line with other econometric results of wages and training, since many other researchers have also estimated some large wage returns to training.

Another comparison would be with the schooling and earnings literature. The consensus is that a year of schooling increases expected wages by about 10% (e.g. Card, 1999). Some recent evidence using IV estimation has tended to find higher effects. In our data a year of training has much larger implied effects than a year of schooling. There are two reasons why the effects of a year of training may be genuinely larger. First, our industry level estimates include some of the externalities from human capital formation. Some recent papers (e.g. Moretti, 1999) suggest that these may be substantial. Secondly, employee training is more focused on raising productivity than is education. Schooling is more likely to be portable across industries and has a greater consumption component. For example, we find it quite conceivable that a three year history degree raises potential remuneration in the labour market by no more than an intensive 6 month work-related course in computer programming.

Consequently, although our estimated effects of training are large we do not think they are implausible. Having said this, there are several caveats surrounding the precise quantitative interpretation of training. A policy of increasing training may not produce such large effects on productivity for several reasons. First, since training is assigned to those workers best able to benefit from it, putting a randomly chosen worker on a training course will not have such large effects. We are essentially estimating the effects of 'treatment on the treated' rather than on the average. Secondly, the finding of large effects does not justify a policy

intervention by itself. The costs of training may also be large, and the exact market failures need to be specified. Thirdly, there may be some other unobserved variables than we have not fully controlled for that are correlated with training and productivity. The average unobserved quality of a industry's technology or skills, for example. Training could be merely a signal of a cluster of other human resource innovations occurring in the industry⁴⁰. We have tried to control for this in various ways (e.g. by including a large number of controls, fixed effects and instrumenting training), but we still may be overestimating the effect. Even in this pessimistic case, however, it is difficult to see why these biases should be larger for productivity than for wages. Thus, our key *qualitative* conclusion - that one must look at the firm side as well as the worker side when analysing training, will continue to hold.

6. Conclusions

In this paper we have examined the issue of the impact of private sector training on productivity. Rather than simply use wages as a measure of productivity we have contributed to an emerging literature which examines the impact of training directly on industrial productivity. We have assembled a dataset which aggregates individual level data on training and establishment data on productivity and investment into an industry panel covering 1983-1996. We control for unobserved heterogeneity and the potential endogeneity of training using a variety of methods including GMM system estimation.

⁴⁰ Ichinowski et al (1997) argue that training is only one of a series of complementary practices within a human resource system. By itself, they argue, it is unlikely to have a substantial effect on productivity.

Using this new data, we identify a statistically and economically significant effect of training on value added per head in the UK. An increase of five percentage points in the proportion of employees trained is associated with a 4 percent increase in productivity.

We argue that the methodologies in the existing literature may underestimate the importance of training for at least three reasons. First, we found that treating training as exogenous causes an *underestimate* of the returns to training (measured either by the production function or wage equation approach). The lower estimates from firm/plant level analyses on training could be due to the fact that firms invest in training when demand is low and the opportunity cost of moving idle resources into training is also low. Or it could be that instrumenting successfully corrects for substantial measurement error in the training variable.

Secondly, the focus on wages as the relevant measure of productivity ignores the benefits the firm may capture through higher profits. Throughout our results we found that the overall effect of training on productivity was around twice as large as the effects on wages. This result could occur even under standard specific human capital theory. But it could also arise for a number of other reasons due to imperfections in the labour market. Clearly further research is needed to distinguish between these possible scenarios.

Finally, our industry level analysis may capture externalities from training that are missed out in the micro-level studies. One avenues of future research would include probing the returns to training by combining enterprise data with industry-level data to investigate the externalities story.

The main criticism of our results, we feel, is technological change may be more rapid in some industries than others generating higher productivity and training. Other studies also have this problem. We have tried to control for this by including measures of technology and instrumenting training. Nevertheless, an important area for future research would be probe more deeply the causes of

training. In particular there are a large number of policy experiments across regions and industries that could be the exogenous drivers of training incidents. These could potentially be used as external instruments to complement the 'internal' instruments we have used in this paper.

This paper suggests that the importance attached by policy-makers to training is not misplaced. Economists may have actually underestimated the importance of training for modern economies due to the existing empirical strategies. It is time to start casting the net wider than wages in seeking the impact of training on corporate and national economic performance.

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Data Appendix A

This paper uses data from several different complementary datasets. The reason for this is that no one British dataset contains the required data on training and measures of corporate performance as well as other features of the production function (such as the capital stock) which are needed for the analysis. Thus we use several datasets which we combine in a manner explained below. The data sets used are the following:

i. The Labour Force Survey

The Labour Force Survey (LFS) is a large-scale household interview based survey of individuals in the UK which has been carried out on varying bases since 1973. Between 1975 and 1983 the survey was conducted every two years; from 1984 until 1991 it was conducted annually. Since 1992 the Labour Force survey has been conducted every three months in a five-quarter rolling panel format. Around 60,000 households have been interviewed per survey since 1984. The LFS data are useful for our purposes as they contain detailed information on:

- the extent and types of training undertaken by employees in the survey;
- personal characteristics of interviewees (e.g. age, sex, region of residence);
- the educational qualifications held by interviewees;
- workplace characteristics of employees (e.g. employer size);
- job characteristics of employees (e.g. job tenure, hours of work).

We work with this information aggregated into proportions and/or averages by industry (i.e. the proportion of individuals employed in a given industry with degree-level qualifications, the proportion of male employees, the average hours worked by employees in a given industry, etc.). Our sample includes all employed men and women aged between 16 and 64 inclusive (i.e. employees

plus the self-employed) for whom there was information on the industry under which their employment was classified.

ii. The Census of Production

The Census of Production (COP) gives production statistics on capital, labour and output for industries in the manufacturing, and energy and water sectors (collectively known as the production sector of the economy). It is based on the ARD (Annual Respondents Database) which is a survey of all production establishments (plants) in the UK with 100 or more employees, plus a subset of firms with less than 100 employees.⁴¹ We use the COP data on value added, gross output, investment, employment and wages for industries in the manufacturing sector and the energy and water industries.

iii. The International Sectoral Data Base

The OECD publishes annual data from 1960 onwards for a selection of countries, including the UK, on production statistics across manufacturing and services in its International Sectoral Data Base (ISDB). We use the ISDB data on value added, investment, capital stocks, employment and wages for industries in the sectors which are not covered by the Census of Production – construction, agriculture and service industries. Although the ISDB data also cover manufacturing and energy and water, we prefer to use the COP data where it is available for a given industry as the COP has a much finer level of disaggregation (as explained later in this section).

iv. NIESR data on capital stocks for manufacturing industries

It is important to have a measure of the capital stock in each industry at a given point in time in order to control for the effects of capital on industrial performance in our final regressions. Once we have a measure for one time period, we can

⁴¹ for more details see Griffith (1999).

calculate the capital stock for an industry in other time periods provided we have investment data for the other time periods in our data set, as follows:

$$K_{t+1} = (1 - \delta_K)K_t + I_t \quad (3.1)$$

where K_t is the capital stock at time t , I_t is investment at time t and δ is the rate of depreciation of the existing capital stock⁴². ISDB contains capital stock estimates but only at a very aggregated level (see below). Much more disaggregated estimates of the capital stock in 1979 for manufacturing industries have been produced by the National Institute for Economic and Social Research (O'Mahony and Oulton, 1990) and we use these as our starting estimates for manufacturing. It is then possible to estimate the capital stock for each point in time using the investment data from COP.

v. Price Index data

To deflate the nominal data on output, investment and labour from the Census of Production and ISDB into real time series for each industry, we use input and output price index data taken from the ONS Annual Abstract of Statistics for various years.

Combining Datasets

In order to use the data as a fully integrated dataset which would enable us to conduct regression analysis, it was necessary to address several issues. Below, each of these are discussed.

⁴² We assume an 8% per annum depreciation rate for capital as a whole. For some years the COP investment data distinguishes between investment in buildings, plant and machinery, and vehicles, and for these years we are able to use different depreciation rates for each type of capital.

Industries in the UK are classified according to the Standard Industrial Classification (SIC). The SIC was revised most recently in 1992, but for most of the period covered by our data set (1983-96), the previous (1980) classification was in use. We refer to these as SIC92 and SIC80 respectively. SIC80 classifies industries into 10 **divisions** (0 to 9), and this level of aggregation is known as the **1-digit** aggregation. SIC80 can be broken down more finely into 49 **classes**; each division breaks down into sub-classes (for example, division 0 breaks down into 01, 02 and 03), and this is the **2-digit** level of aggregation. More disaggregated breakdowns are available – 199 **groups** (3-digit level) and finally, several hundred **units** (4-digit level). Table 3.1 shows the level of aggregation provided by the different data sources that we use.

Table A.1. Levels of industrial aggregation in data sources used

Data source	Level of SIC aggregation
Labour Force Survey	1983-1993: 4-digit SIC80 1994-: 4-digit SIC92
Census of Production	1980-1992: 3-digit SIC80 1992-: 3-digit SIC92
International Sectoral Data Base	SIC92 – 17 divisions (maps to between 1 and 2 digit SIC80)
NIESR capital stock data	1979: 3-digit SIC80

Whilst ideally we would probably wish to work at the 3-digit level of aggregation, there are two problems which prevent us from doing this in some cases:

a) The ISDB data

The ISDB only provides divisional information under the SIC92 classification. For industries not in manufacturing or energy and water we are forced to work at or just below the 1-digit level of aggregation. In practice, the SIC92 divisional

categories map onto 2 subdivisions for SIC80 divisions 6 (wholesale and retail distribution, hotels and restaurants), 7 (transport and communications) and 8 (banking, real estate and financial services). Adding these six subdivisions to divisions 0 (agriculture), 5 (construction) and 9 (miscellaneous services) means that we are left with only 9 industrial categories outside the sectors covered by the COP data.

b) Small cell sizes arising from 3-digit aggregation of the LFS

The Labour Force Survey is a much smaller sample of industrial information than is the Census of Production. In order to derive reliable statistics on different employee variables within each industry it was decided that the LFS data should be aggregated in such a way that the number of employees in a given industry in any year should be no less than 25. Whilst using a 3-digit level of aggregation in the manufacturing and energy and water sectors gave us 119 industries, it was found that 30 of these fell below the limit of 25 employees in one or more years. Where this happened, the solution was to combine the data for the industry in question with the data for an industry with an adjacent SIC code to create a new grouping. This exercise left us with LFS data for 90 industrial groupings in the production sector of the economy.

Conversion from SIC92 to SIC80

For 1993 and onwards in the Census of Production, 1994 and onwards in the Labour Force Survey and for the whole period of the ISDB, the industrial data is classified according to SIC92 rather than SIC80. To produce a consistently defined panel over the whole sample period it is necessary to convert the data from SIC92 into SIC80. This was done using a conversion table supplied from the Office for National Statistics which gave the equivalent SIC80 classification for each possible SIC92 classification. A problem arises when one 3-digit SIC92 classification maps onto more than one 3-digit SIC80 classification: in this case what is the most accurate way to reclassify the data? The solution used here

exploited the dual classification of establishments (under SIC92 and SIC80) in the 1992 ARD database to assign ‘portions’ of SIC92 industries to SIC80 industries based on their employment weights in the ARD. For the details of this process see Appendix B.

Sample Selections and Missing Data

The processes followed above would have left us with data on 99 industrial groupings over 14 years for a total of 1386 data points. Unfortunately we do not achieve this number as we are forced to make the following additional sample restrictions shown in Table 3.2. This leaves us with 1144 data points. However, as the regressions in Section 5 use some data which is lagged one year we have to use the 1983 data to provide lags, reducing the number of regression observations to 968.

Table A.2. Sample restrictions

Potential sample size	1386
Restriction	Reduction in sample size
In agriculture, construction and service sectors, reliable data not available after 1993 (and earlier in some sectors)	-35
In production sector: extensive missing COP and/or capital stock data in 5 industries*	-70
Poor matching between SIC80 and SIC92 classifications results in loss of data from 1993 or 1994 onwards	-135
Missing data for two industries in 1983 (from LFS)	-2
Total	1144
Number of data points used in regressions in section 5 (1984-96, regressions include lags)	968

* It was possible to interpolate values for capital stock, wage bill and gross value added measures if a single year of data was missing within the sample period. This was done in 16 instances. However, in some cases reliable COP data was simply not available for one or more of the value added, investment or wage bill measures and in this case we dropped the industry from the sample. Details of this procedure are available from the authors on request.

Appendix B: Conversion between SIC92 and SIC80

The results in these paper use a panel of industries defined according to the ONS's 1980 Standard Industrial Classification (SIC80). However, in 1992 a new classification was introduced, known as SIC92. Between 1983 and 1993 in the LFS, and 1983 and 1992 in the Census of Production, industrial information is available under the SIC80 classification. However, for 1994 and onwards in the LFS, and 1993 and onwards in the COP, only information classified under SIC92 is available. Thus it was necessary to convert data for the later years of the sample from SIC92 to SIC80. This is difficult as the matching between the SIC92 and SIC80 classifications is often not one-to-one; one SIC92 coding can convert to many SIC80 codings, and vice-versa. Two methods were used for this conversion according to which sectors the data was being converted to:

a) conversion into SIC80 (1 digit) 1-4 (the 'production sector' of the economy)

For this we used the 1992 ARD data which classified individual production establishments in Britain under both the SIC92 and SIC80 schemas at the 4-digit level of disaggregation. The advantage of this survey is that it allows us to disaggregate employment in a given SIC92 coding into its composite SIC80 codings, and also to look at how employment in each of these 'cells' compares. The employment statistics in ARD are grossed up to sum to overall employment in the production sector of the economy, which we will denote by N^p . Industries in the production sector can be classified under the schemas SIC80 ($i_{80} = 1, 2, \dots, I_{80}$) or SIC92 ($i_{92} = 1, 2, \dots, I_{92}$), which are both exhaustive. Denoting the estimate from ARD of the number of people employed in an industrial sub-classification which would be classified as i_{80} under SIC80 and as i_{92} under SIC92 by $n_{i_{80}i_{92}}$, the following expression holds:

$$N^P = \sum_{i_{80}} \sum_{i_{92}} n_{i_{80}} n_{i_{92}} \quad (\text{B.1})$$

Now, denoting the overall average of one of the variables we use in the (post-1993) LFS data (e.g. proportion of workers receiving training) in the sectors which correspond to production sectors in SIC80 by \bar{L}^P , and the average of this LFS variable in classification i_{92} of the SIC92 data by $\bar{L}_{i_{92}}$, it is possible to take LFS data aggregated by SIC92 and reallocate it according to SIC80 by the formula

$$\hat{\bar{L}}_{i_{80}} = \sum_{i_{92}} w_{i_{80}i_{92}} \bar{L}_{i_{92}}, \quad (\text{B.2})$$

where $\hat{\bar{L}}_{i_{80}}$ is our estimate of the average of the LFS variable in classification i_{80} of

the SIC80 data, and the weights $w_{i_{80}i_{92}} = \frac{n_{i_{80}i_{92}}}{N_{i_{92}}}$ (derived from ARD). Hence we

use the employment weights in ARD to re-allocate the LFS variables under SIC92 classifications to given SIC80 classifications. Similarly, for variables such as gross value added and the capital stock which are available in the post-1992 Census of Production under SIC92 classifications, the ARD weights are used in a similar manner to re-classify these variables into SIC80. This exercise is necessarily inexact because without dual classification of employees and establishments by SIC80 and SIC92 in the LFS and COP respectively, there is no way of knowing which employees or production in a given SIC92 would correspond precisely to a given SIC80 (unless the SIC92 maps uniquely to one SIC80 classification). We have to work with data aggregated at SIC92 level and reclassify into data aggregated at SIC80 level. The induced measurement error in the LFS average variables and the COP variables causes some discrepancies in the measured data for 1993 and onwards as some variables show very large upward or downward jumps for some industries. It was for this reason that we were forced to drop some of the data for later years in the sample as shown in Table 3.2. Details are available from the authors on request. Nonetheless, the

post-1992 matching strategy was a success overall as the majority of industry-level data derived using the matching matrix was usable.

b) conversion into SIC80 (1 digit) 0 (agriculture, forestry and fishing) and 5-9 (construction and services)

These industries are not covered by ARD and so no matching matrix was available. The data we had on output, capital, investment and wages from ISDB for these industries was classified under ISIC (International Standard Industrial Classification) which maps directly to just below 1-digit SIC92 classifications. It can also be mapped roughly to SIC80 classifications as illustrated in the table below.

Table B.1. ISIC, SIC92 and SIC80 mappings – agriculture, construction and services

ISIC classification	SIC92 (1 letter) direct mapping	SIC80 (2 digit) approximate mapping
AGR (agriculture, forestry, fishing)	00-09	00-09
CST (construction)	45	50-59
RWH (wholesale & retail trade, repair of motor vehicles & household goods)	50-52	61-65, 67
HOT (hotels & restaurants)	55	66
TAS (transport & storage)	60-63	71-77
COM (communication)	64	79
FNS (financial intermediation)	65-69	81-82
RES (real estate & business services)	70-74	83-85
SOC (other services)	75-99	90-99

It should be stressed that the mapping to SIC80 here is only approximate. This may partly account for the relatively poor results which were obtained in the regressions which used the service sector data (see section 5).