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Returns to On-the-Job Training: Do Skill Usage, Tasks and Workstation Matter? Evidence from British Workers

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By: Christophe Nordman, DIAL,Paris and Geoff Hayward, SKOPE, Department of Educational Studies, University of Oxford

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Abstract:

Using data drawn from the 1997 and 2001 British Skills Surveys, which are large-scale cross-sectional representative surveys of working individuals, this paper aims both to make a contribution to understanding the returns to on-the-job training and to disaggregate the contributions of formal and informal learning to workers with different levels of skills (literacy, numeracy, and computing skills), engaging in different types of tasks under different work arrangements. We use an explicit control for the informal learning process that is generally neglected by empirical studies, mostly as a result of lack of relevant direct measures. Thanks to rare information on the centrality of skill usage, on the complexity of that use, on the nature of the duty and on how this duty is performed, we stratify the estimates by different groups of workers to allow the coefficient estimates on all the training regressors to vary by workers' status. The wage equations rely on Heckit corrections for formal training participation. The results show that not taking into account informal training explicitly in the wage equations may lead empirical assessments to bias the return to formal training upward. Nonetheless, wage premiums for a spell of formal training remain significant and positive in all of the models developed in the paper. Our results also reveal the complex relationships between the returns to formal and informal training, and the types of skills people were using, the type of work they were doing and how such work was organised. Amongst other results, we emphasise differentiated returns to formal and informal training depending on the complexity of tasks and show that, for certain types of workers carrying out specific duties, formal training may remain an efficient way to upgrade the skills and productivity of the labour force at low and intermediate levels of qualifications. Our estimates also exhibit that wage premiums for formal and informal training are higher and more significant for workers who perform their task in teams and are closely supervised.

Keywords: formal and informal learning, basic and computing skills, returns to training, selectivity, United Kingdom

JEL Classification: J24, J31

Christophe Nordman is grateful for the financial and scientific support of the ESRC research centre SKOPE, University of Oxford. Usual disclaimers apply. Corresponding address: DIAL, IRD-Paris, 4 rue d'Enghien, 75010 Paris, France. Email: nordman@dial.prd.fr

1. Introduction

There is a long standing continuing political concern about the apparent differences in productivity between UK workers and those in the US, Germany and France. Thus, the concerns outlined in the recent White Papers, such as *21st Century Skills: Realising our Potential*, are very similar to those that were being voiced in the UK in the 1870s. The diagnosis of the problem also remains largely the same: a poorly performing vocational education and training system; a reluctance on the part of employers to train more than a fraction of their staff and of employees to invest in their own skills development; an over reliance on low cost production of low specification good and services; competition on the basis of price rather than on quality; and so on. The outcome is the by now totemic description of a system that is in a low skills equilibrium. The solution to the problem of how to break out of this vicious circle and to aspire to the more virtuous circle of a high skills and high wage economy has, until recently, always been seen in terms of government intervention on supply side[1]: the publicly funded education and training system.

The by now standard diagnosis for the 'productivity deficiencies' of the British worker is that they are more poorly qualified (i.e. less skilled) than their counterparts in the US, Germany and France resulting in a skills (or at least at a qualifications) gap as shown in Table 1. The origin of these purported skills gaps is typically seen in terms of both administrative failures underpinning the inadequate performance of the British education and training system, and one or more sources of market failure.

Table 1. LABOUR FORCE SKILLS, TOTAL ECONOMY, 1999

	Percentage of workforce with qualifications at levels			Relative skills
	Higher	Intermediate	Low	UK = 100
USA	27.7	18.6	53.7	100.5
France	16.4	51.2	32.4	105.5
Germany	15.0	65.0	20.0	105.3
UK	15.4	27.7	56.9	100.0

Source: DfES (2003: 19)

[1] An exception to this is in the PIU (2001) document *In Demand: Adult skills in the 21st century* where explicit mention is made of the need to stimulate demand for skills in the economy.

Mechanisms for closing these supposed skill gaps have traditionally been articulated in policy designs in terms of supply side reform: improving the quality of initial education so that more young people become qualified, and helping existing workers to gain qualifications through 'formal learning processes' such as courses and/or accreditation services provided by local Further Education colleges or private training providers.

The perceived solution to the UK's skill and productivity problems continues, therefore, to be cast in terms of yet more reform of the qualifications system and supply side delivery mechanisms. However, within the academic literature in education and sociology there has been a growing interest in workplaces as learning environments and the importance of on-the-job learning in skill formation processes. In particular, there has been a growing interest in workplace learning processes that are variously described as 'informal' or 'nonformal'[2]

The perceived importance of informal processes in workplace learning is captured by Frank Coffield's[3] image of the learning iceberg.

> If all learning were to be represented by an iceberg, then the section above the surface of the water would be sufficient to cover formal learning, but the submerged two thirds of the structure would be needed to convey the much greater importance of informal learning.

However, it is important to appreciate that interest in workplace learning, through both formal and informal processes, is still a relatively recent phenomenon and that the evidence base about effective practices that lead to important vocational outcomes is still relatively meagre[4]. While Smith's review is informed to a great extent by the Australian literature in education and sociology, and so ignores important work on learning in the workplace, the point needs to be made that research on workplace learning is still in late infancy at best in the economics literature[5]. Nonetheless, if workplace learning, and in particular informal training, is as important in developing vocational knowledge and skill as research is beginning to suggest then it is also important to understand the ways in

[2] Billett, 2001; Colley et al. 2003; Hayward and James, 2004
[3] Coffield, 2000: 1
[4] Smith, 2003
[5] See Brown (1990), Sicherman (1990), Loewenstein and Spletzer (1994, 1999a), Barron, Berger and Black (1997a, 1997b), Lindbeck and Snower (2000), Destré et al. (2001, 2002), Leuven and Oosterbeek (2002) or Frazis and Loewenstein (2003). We discuss this economics literature later in the paper.

which, and the extent to which, skill formation resulting from such learning affects productivity, and probably wages, of different types of workers, with different levels of skills undertaking different types of tasks.

For that purpose, we utilise unique data, stemming from the 1997-2001 British Skills Surveys, on workers' types of tasks, skills and workstation. These cross-sectional representative surveys of working individuals in Britain provide information on various aspects of their jobs including individual earnings, qualifications, responsibilities, the importance and ability to carry out certain tasks at work, as well as training measures. In particular, we can introduce controls for the informal learning process that is generally neglected by empirical studies, mostly as a result of lack of relevant measures. The data also afford a precise classification of workers based both on the centrality of skill usage (literacy, numeracy, and computing skills) and on the complexity of that use. Moreover, the questionnaires contain information on the work organisation including questions on team working, on whether workers can work independently, on whether they are closely supervised or are involved in quality circles. Mainly due to data limitations, this type of information is usually not accounted for when measuring the impacts of training on individual earnings. In this way, we try to deepen the understanding of the various returns to training episodes across different groups of workers. In particular, this paper aims both to make a contribution to understanding the returns to training and to disaggregate, as far as is possible given the available data, the contributions of formal and informal learning to workers with different levels of 'generic' skills, engaging in different types of work under different work arrangements.

The rest of the paper proceeds as follows. In the next section, we provide some theoretical and methodological insights on the link between formal and informal learning and wages. Section 3 gives details about the surveys, the construction of the variables, the training measures and the econometric methods we use. The results are reported and commented on in Section 4, which is followed by a concluding section.

2. Formal, informal training and wages: theories and methodological issues

Recent improvements in the available data on training have produced a growing body of literature in labour economics which analyses the different aspects of the human capital model and documents the consequences of training. In particular, traditional human capital models predict that workers should pay implicitly for the degree of portability of their newly acquired skills by having lower starting wages or, more generally, by accepting a wage reduction when training is ongoing. When training is completed, their value to the firm, as well as their market value, increases and competitive forces ensure that they are paid at their market value. An immediate implication is that wages should rise with experience in the labour market, since productivity increases with time in the labour market for those who receive general training. Most studies find that training received from the current employer is indeed associated with increased wage growth[6]. However, while the positive correlation between training and wage growth can be considered as a consensus in the broad empirical literature, the negative impact of training on starting wages remains, on the contrary, much more difficult to highlight with cross-sectional data[7]. Barron, Black and Loewenstein (1989) justify this lack of negative correlation by the existence of workers' unobserved skills. Indeed, on French data for instance, Goux and Maurin (2000) observe that the main part of the wage differentials across trained and untrained workers is explained by individual unobserved heterogeneities: the workers having the highest abilities are more likely to be chosen to follow a training programme. Therefore, this individual unobserved heterogeneity has become an important matter in the empirical literature. Authors (e.g. Barron, Black, Loewenstein, 1989) have generally acknowledged that the effect of job-match or individual heterogeneity biases will be to underestimate the impact of training on the starting wage, even possibly masking it totally, the reason being that more able persons may receive more training and may be paid more even if they are undergoing training as compared with workers who are not being trained.

In this paper, our purpose is not to test these assumptions as we do not have the appropriate data to do so. The issue this paper tackles is, given that we can distinguish between the various means by which knowledge and skills can be acquired through the accumulation of experience on-the-job (which Barron et al. [1997b] estimate to be about 85% of all training), what contribution such learning has on wages. The challenge here is

[6] See Barron, Black and Loewenstein (1989, 1993), Brown (1989), Altonji and Spletzer (1991), Bartel (1995), Berger and Black (1999), Parent (1999) and Frazis and Loewenstein (2003). However, see Bassi (1984), Lynch (1992) and Green et al. (1996) for the inconclusive benefits of training.

[7] Using US data, Barron, Black and Loewenstein (1989) and Holzer (1990) find no statistically significant relationship between formal training and the starting wage. Also, although Barron, Berger and Black (1999) find that training has a negative effect on the starting wage, the estimated effect is small relative to the

that certain forms of skill acquisition are visible, such as formal training organised by the company, and others remain "invisible". Hence, even if the benefits of on-the-job training investments are clearly established, the accurate calculation of returns to certain types of investments, like informal learning, remains complex. Now, any attempt to assess the effects of training on wages requires a detailed examination of the effects of its informal component insofar as this represents a major part of total training provided by firms (Mincer, 1989). For that purpose, it is necessary to use variables of training that are not affected by measurement errors since these errors are likely to result in bias in the estimation of the rates of return to training (Barron, Berger and Black, 1997b). However, for reasons that are inherent in the nature of this type of training, the few direct measures of informal training available today are quite imperfect. Formal training is indeed rather simple to measure since it is clearly identifiable (Sicherman, 1990): it is generally provided for a determined duration by a recognised trainer in a precise place. This is not the case for informal training that appears inextricably part of the employee's productive activity (Brown, 1990). Indeed, Acemoglu and Pischke (1999b) suggest that training such as mentoring or being given advice maybe so hard for workers to observe that standard tasks maybe designated by firms as "training" to make them more observable.

Since the end of the 1970s, a certain number of surveys have tried to examine closely the process of training in firms by distinguishing formal and informal processes. These surveys are essentially American, such as the National Longitudinal Survey of Youth (NLSY, used by Lynch, 1992; Loewenstein and Spletzer, 1999b; Parent, 1999), the National Longitudinal Survey of the High School Class of 1972 (NLS-72, used notably by Altonji and Spletzer, 1991), a survey by the Upjohn Institute for Employment Research (UIER, used by Barron, Berger and Black, 1997a, 1997b), the Employer Opportunity Pilot Project (EOPP, used by Barron, Black and Loewenstein, 1993 and Loewenstein and Spletzer, 1999b), and the Current Population Survey (CPS, used by Loewenstein and Spletzer, 1997). However, the results provided by these surveys are not fully satisfactory insofar as they are hardly comparable regarding the occurrence of informal training. Indeed, as Loewenstein and Spletzer (1999a) argue, these surveys differ in their sample population, in the reference period over which training is measured, in the concepts covered by the use of the word training, in whether the survey respondent is an employee

impact of training on productivity. Parent (1999) does not observe any convincing evidence either that workers pay implicitly for the degree of portability of their training.

or an employer, and in the routing patterns in their questionnaires[8]. For the United Kingdom, the Skills Surveys (1997 and 2001), which are representative surveys of working individuals in Britain, are discussed and used in this paper.

In this study, we consider the possibility that informal learning may actually be interpreted as a formal learning process by workers. That would be the case if, when answering a questionnaire, workers consider that acquiring new skills through performing their tasks is a form of training supplied by their employer. This confusion is likely to introduce measurement errors in the formal training variables. Therefore, not taking into account the informal component of training would simply lead us to overestimate the amount of formal training that workers received from supervisors and co-workers. Moreover, if we assume that high-wage workers have higher abilities than low-wage workers to learn by themselves (learning by doing), or to watch other workers performing and to imitate them (learning by watching), neglecting informal training is likely to yield an upward-biased estimate of the return to formal training.

The purpose of this paper is mostly empirical as we benefit from new and innovative data on skills supply and workers' job characteristics. Before the 1980s, it was impossible to measure human capital accumulated on the job exactly. Indeed, Mincer (1974) had already admitted that the representation of post-school investments constituted the weak point of the theoretical architecture of his model. Its improvement, therefore, had to undergo a better specification of professional investments[9]. Then, the recommended estimate consisted in using the time spent in certain circumstances, i.e. in the workplace. Mincer and Jovanovic (1981) introduced the worker's seniority within her firm to take into account the return to specific training that she receives. Thus, the time elapsed in the labour market is supposed to reflect the accumulation of general human capital. Then, the remuneration of experience and seniority represent the return to human capital accumulated on the job. Since measures of actual experience are often not available, one is often obliged to establish an estimate through potential experience, calculated as: age minus years of schooling minus age when entering school (generally six years of age, though five in the UK system as explained below).

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[8] For example, while the incidence of informal training is 16% in the CPS and 20% in the NLS-72, it is 96% in the EOPP!

[9] If he did not do it himself, it is because the data available at this time did not allow better specifications of post-school investment in human capital.

However, the data available today allow a more accurate distinction to be made between different types of on-the-job human capital accumulation, making richer the information used in empirical studies. Here we try to go further by investigating the returns to formal and informal training across workers using different levels of 'generic' skills, engaged in different types of task embedded within different forms of work organisation. This is made possible by using information collected as part of two employee surveys in the UK (Ashton et al., 1999; Felstead et al., 2002). These data make it possible, for instance, to distinguish between certain forms of informal learning which can emerge without the presence of co-workers for an individual[10], and those that emerge as a result of formal and intentional interactions between workers, for example as part of a team or during supervision. The qualitative research on workplace learning indicates that such features of work design provide increased opportunities for learning by "tacitly structur[ing] learners' access to the knowledge they need to acquire" (Billett, 2001, p.15).

From an economic perspective, Lindbeck and Snower (2000) notice the lack of empirical studies on this issue as well. However, as they argue:

> "In the new types of firms emerging nowadays, the traditional separation of roles tends to break down. Workers are often given responsibilities spanning more than one of the traditional groupings. Greater emphasis is now also placed on continuous learning and skill development, all-round knowledge, the potential to acquire multiple skills, and the ability to learn how the experience gained from one skill enhances another skill". (Lindbeck and Snower, 2000: 356)

However, up to the present, few empirical studies have dealt with the question of the effect of the work organisation of firms on the possibility for the workers to benefit from training effects. Nevertheless, the organisation of work is one of the main channels of transmission of human capital across workers: an individual working entirely on her own has fewer opportunities than an individual integrated into a work team to take advantage of her colleagues' knowledge.

The data used in this article allows a deeper exploration of these issues by investigating some original information on worker's skills but also on the characteristics of their tasks and workstation.

[10] Learning by oneself through experience is one of the ingredients of informal learning for instance. If the worker does not learn from her colleagues, she still has the opportunity to learn by herself.

3. Data and methodology

3.1 The 1997-2001 Skills Surveys

We utilise data drawn from the 1997 and 2001 Skills Surveys. Each is a large-scale cross-sectional representative survey of individuals aged between 20 and 60 in Britain in paid work at the time of interview. The first wave was conducted in spring 1997 and the second in spring 2001. Random sampling methods were used, and there was a response rate of approximately two thirds for both surveys. Interviews were conducted face to face in respondents' home. The achieved samples of 2467 and 4470 respectively were each representative of the British population. Full details of the sampling frame and fieldwork methods can be found in Ashton, Davies, Felstead and Green (1999) and Felstead, Gallie and Green (2002). The questionnaires include a detailed investigation of the nature of the individual's job with an emphasis on the activities that the job entails. The two questionnaires contain a core of questions asked in identical ways in the two surveys thereby making it possible to pool data from the two samples.

In particular, the data provide information on various aspects of the jobs of the interviewees including earnings, qualifications, responsibilities, the importance and ability to carry out certain tasks at work, as well as training measures. Some background demographic information on each individual was also collected. The data also afford a precise classification of workers based both on the centrality of skill usage (literacy, numeracy, and computing skills) and on the complexity of that use. Job characteristics are available in various ways: the 1-digit occupational classification and, more importantly, the type of tasks that workers perform such as indications of whether workers are engaged in short and repetitive tasks, work at very high speed, deal with people, make speeches or presentations, and so on. Moreover, the questionnaires contain information on the work organisation including questions on team working, on whether workers can work independently, on whether they are closely supervised or are involved in quality circles.

3.2 Construction of the variables and training measures

For the econometric analysis, we construct a number of variables including education attainments, total previous actual labour market experience, job seniority (tenure in the current job), and their squared values. For the education variables, we use two standard measures of education achievements. Firstly, we compute the common appraisal of years of schooling as measured by: age at the end of school – 5[11]. Secondly, we utilise the available information (in the 2001 survey only) on workers' qualifications in order to construct dummy indicators for the highest level of qualification held (Level 1, Level 2, Level 3, Level 4 and over[12]).

Since we suspect, as do many authors, that much training is informal, we tried to identify variables in the questionnaire that could be used as proxies for the time spent in these learning processes. One of the means to take into account the informal components of training is to control, at first, for all the training spells formally identified by both employers and employees. For achieving such good direct measures, matched employer-employee data sets are useful because they allow crosschecking the collected information on the measure of training spells between firms and workers (see the reviews on direct measures of training by Loewenstein and Spletzer, 1994, 1999a)[13]. In this study, since we only have the use of a survey addressed to employees, such methodologies cannot be retained[14]. However, we do have information on past training spells identified as such by workers and, more importantly, on the nature of the individual's job with an emphasis on the various activities that the job entails.

The data on training are separated into several categories. One can identify both completed and uncompleted spells of training previously received, stemming respectively from the questions:

1. "Since completed full-time education, have you ever had, or are you currently undertaking, training for the type of work that you currently do?"
2. "Has this training now finished?"
3. "How long, in total, has that training lasted so far?"

[11] Children in the UK commence primary schooling at or before their fifth birthday.

[12] On this point, we follow the classification used by Felstead, Gallie and Green (2002).

[13] As also did some authors while they were using matched worker-firm data, it is possible to utilise both information on employers and employees for extracting an indirect measure of informal training through its effects on earnings differentials (Destré, Lévy-Garboua and Sollogoub, 2001; Destré and Nordman, 2002).

[14] The Employer Perspectives Survey 2002 (Green, Mayhew and Molloy, 2003), derived from the 2001 Skills Survey, provides however a valuable data set on employing organisations. It offers information on their approach to product specification, workforce practices and skills. The sample of firms has been collected using the address of the employer reported on the questionnaire of about a thousand individuals of the Skills Survey 2001. However, if it is indeed possible to derive a linked employer-employee sample by matching the employers to the employees of the surveys, the size of the sub-sample of individuals effectively identified to their firm is relatively too restricted (about 1000 observations) to provide any representative measure of British workers' training spells.

Responses to questions 1 and 2 were used to construct dummy variables. One indicates whether workers have previously received any formal training related to their current job (TRAINED). The other identifies whether training is ongoing at the date of the interview (ONGOINGTRAINING). Question 3 provides an indication of the time that workers have spent in formal training at the time of the interview (TRAINDURATION). The response scale offered was: "Less than 1 week", "Less than 1 month", "1 month, up to 3 months", "Over 3 months, up to 6 months", "Over 6 months, up to 1 year", "Over 1 year, up to 2 years" and "Over 2 years". We utilise this variable coded into a cardinal scale running from 1 (meaning "Less than 1 week") to 7 ("Over 2 years").

Unfortunately, the questionnaire of the Skills Surveys does not ask whether training has been received *on* or *off* the current job. This distinction would have been useful to assess the possible existence of differentiated wage premium between on- and off-the-job training. However, some authors have argued that off-the-job training is paid for in large part by the employers (for instance in the US; see Parent, 1999). This suggests that many of these programmes are considered as relevant to the job, thereby diminishing a little bit the usefulness of distinguishing between on-the-job and off-the-job programmes.

We also utilise a variable stemming from the answer to the following question:

4. "Did/will any of this training lead to a qualification?"

The expected wage effect of the response of this question is unclear (TRAININGQUAL). One could argue that training opportunities are better rewarded when they lead to a qualification and can be therefore recognised and valued elsewhere, that is, in other jobs. On the other hand, as the theoreticians of human capital theory stress, training spells leading the worker to receive a new qualification look like general training, as opposed to specific training that would not be rewarded in other work contexts. Then, during the training period leading to the qualification, workers could be paid below their value on the market (see section 2). Lack of information in the data means that it is, however, impossible to identify what proportion of this type of training was still ongoing at the time of the interview[15]. This information would help us to determine whether the expected effect of a variable taking into account training leading to a qualification is more likely to have a positive or a negative impact on wages. The balance of these effects ought therefore to be a matter for empirical investigation.

There are several approaches to control for the amount of informal training in the current job. Most studies use individual tenure in the incumbent firm in order to capture all the investments in informal training (see for instance Lynch, 1992; Bartel, 1995; Parent, 1999). Thus, researchers have tried to catch the informal on-the-job training phenomena using Mincerian earnings functions (Mincer and Jovanovic, 1981). In this case, on-the-job training is measured from the returns to tenure, an assumption that is not entirely satisfactory since returns to tenure may be independent from the firm. In this study, we also use such measure of informal training for comparison purposes. However, we go a step further thanks to the availability of new variables that can be exploited to control for the informal learning processes. Thus, we employ the response to the following question:

> 5. “How long did it take for you, after you first started doing [the type of job you have now], to learn to do it well?”

This information is used as a proxy for informal training in the current job (see Loewenstein and Spletzer, 1999a). The response scale offered was the same as for the variable of formal training. Again, we have coded this to form a cardinal scale running from 1 (meaning “Less than 1 week”) to 7 (“Over 2 years”) (JOBLEARNING).

In addition, since informal training might appear as an ongoing process without an identifiable start and end (Brown, 1990), we utilise the following responses which were preceded by the statement:

> “I am now going to read out a number of statements about your job.
> For each one, please tell me how much you agree or disagree with the statement.
>
> 6. My job requires that I keep learning new things.
>
> 7. My job requires that I help my colleagues to learn new things.”

[15] One can find however a positive correlation – though relatively small, 19% – of the variable indicating the presence of ongoing training for workers and that reflecting the existence of training leading to a qualification.

The response scale offered was: “Agree”, “Disagree”, “Strongly disagree”. We then construct dummy variables indicating whether the worker answered “Agree” (KEEPLEARNINGTHINGS and HELPLEARNINGTHINGS).

In the regressions, we should then be able to distinguish between a pure tenure effect on earnings differentials – that can also be interpreted as reflecting the average wage policy towards seniority across establishments and/or industries – and the return or wage premium to informal training. Indeed, the latter is not necessarily linked to the amount of time that workers have spent in their current job.

In the econometric evaluation, we shall assess the relative importance of job training for different groups of workers, using different sorts of skills and undertaking different types of tasks. In order to achieve such analysis, variables of skills have been constructed following the methodology described in Borghans and Weel (2003)[16]. First, the detailed questions concerning the level of sophistication of writing, mathematics and computer use are treated in the following way. In the questionnaire, with regard to the importance of certain tasks, the question below has been asked: “In your job, how important is computer use?”. The response scale offered is: “essential”, “very important”, “fairly important”, “not very important”, and “not at all important”. We defined the dummy variable COMPUTERUSE to equal 1 for every worker who did not answer “not at all important”. With respect to the level of sophistication of writing and mathematics, we distinguish three different levels. For writing, we use information on the following three questions:

> 8. “In your job how important is (i) writing material such as forms, notices or signs, (ii) writing short documents (for example, short reports, letters or memos), and (iii) writing long documents with correct spelling and grammar (for example, long reports, manuals, articles and books)?” .

For the level of sophistication of the use of mathematics at work we use information on the following three questions:

> 9. “In your job how important is (i) adding, subtracting, multiplying or dividing numbers, (ii) calculations using decimals, percentages or fractions, and (iii) calculations using more advanced mathematical or statistical procedures?”.

Finally, the level of sophistication of computer use is addressed as follows:

> 10. “Which of the following best describes your use of computers or computerized equipment in your job?”.

[16] Theses authors used the first 1997 wave of the Skills Survey.

The answers are divided into four different levels of sophistication at which computers are being used. “Simple” use indicates “straightforward use, e.g., using a computer for straightforward routine procedures such as printing out an invoice in a shop”; “moderate” use means “e.g., using a computer for word processing and/or spreadsheets or communicating with others by email”; “complex” use is defined as “e.g., using a computer for analysing information of design, including use of computer-aided design or statistical analysis packages”; and, “advanced” use is described as “e.g., using a computer syntax and/or formulae for programming and developing software”.

3.3 Econometric strategy

The effects on wages of the responses to these variables raise two recurrent problems in empirical labour economics. Firstly, the overall return to human capital explaining the remuneration of a given worker may involve personal skill characteristics and firm knowledge characteristics. It might be important to consider these two sources of returns from human capital simultaneously because education policies and policies promoting vocational training may affect both the worker’s human capital and the firm’s human capital environment. Then, over-estimations of returns to personal human capital, such as schooling and training, may be produced if industry or firm human capital externalities are neglected. In fact, part of the impact of knowledge on individual productivity may be caused by these externalities, associated or not with specific firm processes and working rules. However, without matched employer-employee data sets, controlling perfectly for human capital externalities remains impossible. We deal with this difficulty by using control variables, such as industry and regional dummies, insofar as many studies have shown the existence of significant human capital externalities at the industry and regional levels[17].

Secondly, the persistence of individual unobserved heterogeneity might bias the estimates. Indeed, it is generally acknowledged that there is a matching of individuals

[17] Using matched worker-firm data, authors have shown that intra-firm human capital externalities can also be very significant (Muller and Nordman, 2004). Nevertheless, because of data limitations in this paper, we cannot tackle this issue. Therefore, we will assume that intra-firm externalities can be neglected. For a recent literature review on human capital externalities at the industry or regional level, one can refer to Serrano (2003).

with high ability to positions that require substantial training: more-able individuals – thus potentially better paid workers – may match with positions with higher job complexity. In fact, it is also likely that more complex jobs would require more time to get the worker well acquainted to her tasks. Then, not taking into account the fact that more complex jobs require more on-the-job training would simply lead us to overestimate the impact of both formal and informal training on individual earnings. The impact of the time spent at informal learning would then only reflect this unobserved individual heterogeneity of workers[18]. Since we have cross-sectional data, we cannot model unobserved individual heterogeneity as we could do with a panel. However, we handle this difficulty by using a correction for sample selection (explained below) and by introducing as many control variables as can be justified given the size of the available sample.

3.3.1 Correction for selectivity

It is necessary to deal with the possible source of bias in the estimates of training effects due to sample selection. Indeed, one potential problem with ordinary least squared (OLS) estimation of wage equations that include on-the-job training as an explanatory variable is that formal training is a choice variable. The training decision is partially due to the employer and partially due to the worker through her occupational and other pre-employment choices. Employers may tend to place in training programmes only those individuals who have some unobservable characteristics (trainability), and individuals who are more motivated may be more likely to pursue training (for instance leading to a qualification). If, as a result, unmeasured characteristics of jobs or workers associated with the determination of on-the-job training are correlated with our measures of training, then the OLS estimated coefficients on the training variables will be biased, as they will be correlated with the error term. In both cases (employers and/or employees' choice), the estimated coefficient on the various training measures are then likely to be biased upward.

The empirical training literature contains several approaches to solve these selection problems (see Puhani, 2000; Leuven and Oosterbeek, 2002). One of them consists in augmenting the wage level equation with a Heckman-type selection correction term which results from a first stage training participation equation (the two-stage approach developed by Heckman, 1978, 1979). Results from this approach are reported

[18] For instance, individual heterogeneity might also entail an underestimation of the negative impact of general training on starting wages, even mask it completely, if the most talented individuals – those who must thus be better paid – are also those who receive most formal training.

by Lynch (1992) and Veum (1995) among others. The difficulty with this approach is that it is hard to find variables which arguably do affect training participation and have no direct effect on wages (see Leuven and Oosterbeek, 2002). However, thanks to the availability of original variables in the Skills Surveys, we shall try to overcome this difficulty and then will adopt the two-stage treatment effect (2TE) to deal with such selection issues. This treatment effect procedure is commonly used to correct sample selection effects, i.e. when the values taken by the regressors are determined by a selection mechanism. The simple statistical model that we want to estimate is:

(1) $$y_i = X\beta + \theta T_i + \varepsilon_i$$

where y_i is the log-earnings of individuals *i, X* is a matrix of variables that affect earnings (such as socio-economic characteristics, education, labour market experience). T_i is formal training received by workers *i*. β and θ are the coefficient associated with each variable and ε_i is a symmetric disturbance with standard assumption ($\varepsilon \sim N(0,\sigma_\varepsilon^2)$) that captures unobservables.

In fact, as formal training appears as a choice variable, it can be expressed as a function of variables, called *Z*, that affect the probability of receiving such training (treatment group):

(2) $$T_i^* = Z\gamma + u_i$$

with $$T_i = 1 \text{ if } T_i^* > 0 \text{ and}$$
$$T_i = 0 \text{ if } T_i^* \leq 0,$$

where γ is a vector of coefficients associated with each variable *Z* affecting the probability of receiving training. u_i is a stochastic error term with standard assumption ($u \sim N(0,\sigma_u^2)$).

In our analysis, the parameter of interest is θ (the true treatment effect), i.e. the effect of training in the wage equation. Taking into consideration this selectivity problem, it is very likely that u_i and ε_i are correlated, i.e. individuals with higher expected earnings are most likely to be selected or to self-select for training[19]. To correct for this potential selection bias, Heckman (1979) proposes a two-step approach which consists in estimating a Probit equation of (2) on the overall sample, to get an estimate of the Inverse Mill's Ratio (IMR, the hazard or the selection-correction term of the probability of receiving formal training), and then include it as a regressor into a second-stage wage regression of (1). In this way, the selection control term will generate unbiased estimates of the latent participation dummy within the wage equation.

3.3.2 Control variables[20]

In order to temper the effects of unobserved individual heterogeneity, it is a common practice in empirical economics to introduce control variables for the characteristics of the jobs and for task complexity (see Barron, Berger and Black, 1999). Hence, the regressions include a full set of 9 occupational dummies[21]. In addition, the answer to question 7 (see section 3.2) can be considered as a proxy for a possible individual high ability[22]. It is therefore introduced into the regressions. The Skills Surveys also provide various information on the type of tasks of workers, their workstation as well as the basic and computing skills they use at work. A way to control for these characteristics – and therefore to refine the wage effects to school attainment and job training – would simply be to introduce these job characteristics into the wage functions. Given the size of the sample, this option can clearly not be retained since it would reduce dramatically the degrees of freedom and, as a result, the precision of our estimates. A manageable way to use such characteristics is then simply to produce differentiated estimates across various groups of workers according to types of tasks, workstation or skills they use at work. It is

[19] Indeed, with u_i and ε_i joint normal, one can show that:

$E[y_i \mid X_i, T_i = 1] - E[y_i \mid X_i, T_i = 0] = \theta + \rho\sigma_\varepsilon \left(\dfrac{\phi_i}{\Phi_i(1-\Phi_i)} \right)$ where ρ is the correlation coefficient of u_i and ε_i, ϕ_i and Φ_i are respectively the density and distribution function for a standard normal variable. This is what a regression of y_i on T_i and X_i would recover (as the coefficient on T_i). It is then a biased estimate of θ (unless $\rho = 0$).

[20] The complete symbols, definitions and descriptive statistics of the variables used in the regressions appear in table 1 of the appendix.

[21] These are the standard 1-digit occupational classification 2000: managers, professionals, associate professionals, skilled trades, personal services, sales, plant & machines operatives, elementary.

[22] Barron, Berger and Black (1999) define ability as any inherent worker characteristics that increase the value of the worker to the employer. For instance, higher-ability workers could be those who encourage co-workers to be more productive and, thus, those who "help colleagues to learn new things". Note that this

also a convenient way to distinguish whether workers actually experience different wage premiums for their training spells depending on the nature of their job and the way they perform their tasks.

Other control variables also include a dummy for gender (FEMALE), for union membership (UNION), for the marital statute (MARRIED) (in interaction with FEMALE when significant), whether the worker belongs to an ethnic minority (MINORITIES), whether the job is part-time (PARTTIME), in the private sector (PRIVATESECTOR), the number of hours worked per week (BHOURS), 17 industry dummies (1-digit SIC92 classification), 11 regional dummies and a dummy for the date of the interview (SURV2001).

After elimination of the observations for which certain variables had missing values or outliers[23], the overall sample of British workers amounts to 5672 individuals. The dependent variable used in the regressions is the Log of individual gross hourly wage[24]. In all regressions, the possible heteroscedasticity of standard errors are corrected by the White's estimator.

3.4 Descriptive statistics

Table 2 below provides information on the receipt by gender of work-related training (formal or informal) as well as mean characteristics for important variables that will appear in the wage equations (i.e. education and labour market experience). The average years of schooling (SCHOOL) for this sample, calculated using the available information on the age attained at the end of full-time education (from which we deduct 5 years), is 12.4 years. We also calculate dummy variables stemming from the information on the highest level of education reached by the workers, which is only available in the 2001 survey. The statistics of table A1 in the appendix show that: 13.7% of the sample have no GCSE qualifications, 16.1% have completed qualifications only at level 1, 30.5% have obtained a level 2 qualification, 10.4% have completed qualifications at level 3 and 29.1% have

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variable might also introduce the notion of self-confidence. It is also increasingly correlated to the four levels of qualification (from -2% to 27%).

[23] There is one exception: the variable TRAININGQUAL is only available for individuals interviewed in the 2001 survey. Therefore, because of the large number of missing values for this variable, rather than dropping observations, we use the modified zero-order regression method described in Maddala (1977); that is, in our regressions analysis, we put the observations on TRAININGQUAL of the 1997 survey equal to zero and include a dummy variable for the date of the interview (that is, when TRAININGQUAL is missing). Of course, regressions on the 2001 survey only have been carried out to check the validity of our obtained results on the merged data.

[24] Wages are trimmed by 0.5% at the top of the distribution to remove the impact of extreme outliers.

reached a level 4 qualification or over. These proportions are quite similar across gender. Table 2 below indicates that the average tenure in the current firm is 7.8 years (TENURE). It amounts to 6.8 years for females and is higher for males (8.7 years). The total potential professional experience is on average 23.1 years (job seniority plus previous work experience) and is slightly higher for females. Only 1.4% of the workers have worked in their firm for at least three years without any previous work experience.

Table 2. MEAN SAMPLE CHARACTERISTICS

Variables	All	Females	Males
Gross hourly wage (in pounds)	8.57	7.33	9.81
Percentage female	50	-	-
Percentage married	57	55	59
Years of schooling	12.40	12.33	12.47
Previous experience (in years)	15.38	16.75	14.00
Tenure in the current job (in years)	7.78	6.85	8.71
Formal training related to the current job (TRAINED)	0.57	0.55	0.59
Ongoing training at the date of the interview (ONGOINGTRAINING)	0.25	0.24	0.26
Time spent in formal training at the date of the interview (TRAINDURATION, scale from 1 to 7, see details in text)	5.10	5.11	5.40
Training has lead to a qualification (TRAININGQUALIFIED) (survey 2001)	0.33	0.34	0.33
Time spent in learning to do well their job (JOBLEARNING, scale from 1 to 7, see details in text)	4.44	4.04	4.83
Main sample size	5672	2833	2839

Table 2 above indicates that, since completing full-time education, 57% or the British working individuals have received or are still receiving formal training (TRAINED). Among these individuals, 25% were still pursuing their training at the time of the interview (ONGOINGTRAINING). On average, these training spells have lasted at least 6 months up to a year (scale '5' of the variable TRAINDURATION), with the length of training spells slightly higher for males. Among the individuals of the 2001 survey having received formal training, 33% have been involved in training leading to a qualification[25]. Note that all these proportions are about the same between men and women. As for the time spent in

[25] Note that this proportion falls to 22% when considering the overall sample (see note 23).

learning to do the current job well, it averages “over 3 months up to 6 months” (scale ‘4’ of the variable JOBLEARNING) and seems somewhat higher for males.

4. The estimations results

4.1 Validity of the models

4.1.1 Participation in formal training

Table A2 in the appendix presents Probit estimates of participation in formal training (variable TRAINED as dependent variable). The regressions include socio-economic characteristics (dummies for sex, dependent children, and ethnic minority), human capital variables (dummies for the levels of qualification, years of schooling, previous work experience and job tenure), job characteristics as well as occupational and industry dummies (these latter being introduced in column 3).

We also introduced two regressors assumed to play an important role in the probability of receiving formal training because they might capture an unobservable ability of individuals (KEEPLEARNINGTHINGS, EFFORT): the first dummy indicates that workers are required to learn new things in their current job and may reflect the complexity of the assigned task; the dummy variable EFFORT, stemming from a question asking individuals about how much effort they put into their jobs (see table A1 in the appendix), is used to indicate whether extra effort is being put into the current job beyond what is required. These two variables have no significant impact on earnings differentials (estimates not presented). Therefore, they appear as very good instruments for the training variable since they are uncorrelated to the error term of the wage equation. This is one way to overcome the limitation of the treatment effect approach (see section 3.3), that is, to find new variables that arguably do affect training participation in the first step but have no direct impact on wages in the second.

Column 1 of table A2 (appendix) presents a first Probit regression on the 2001 survey which yields the effect of the levels of qualification on the probability of receiving formal training (workers having no qualifications are the reference category). Regressions in columns 2 and 3 use a continuous variable for education (SCHOOL) in place of the four qualification dummies and are then performed on the pooled 1997-2001 surveys.

First, note that all the results in columns 1, 2 and 3 of table A2 confirm that the variables EFFORT and KEEPLEARNINGTHINGS have a significant and positive impact on the probability of receiving formal training. The estimates also suggest that education is an important factor in the acquisition of formal training. This is a usual finding reported notably by Lynch (1992) and Veum (1995) among others. The probability of receiving formal training increases with the level of qualification attained by workers. Hence, those with a level 4 qualification or over are more likely to receive formal training than others. Previous work experience and tenure in the current job do not seem to influence the likelihood of receiving formal training (except in column 1 where education is controlled for with dummies and where controls for occupation and industry effects are not yet added). This might be an important result since it is generally acknowledged that length of employment should increase workers' incentives to make further investments in on-the-job human capital[26].

However, the data do not allow the examination of whether previous spells of training increase the probability of future training. Indeed, our regressions use characteristics of the workers at the time of the interview to predict the probability of having *ever* received formal training. Therefore, the non-significant impact of experience variables on the probability of receiving training could actually reflect a "timing effect" in the regression, i.e., for most workers, training spells may have occurred some time before taking their current job[27].

Finally, we also include job characteristics as well as broad industry and occupational dummies in the Probit estimates. Although detailed results and comments cannot be reported here for reasons of space, a few summary comments are in order: first, workers belonging to the private sector, employed part-time and performing a repeated task are less likely to receive formal training. On the other hand, union membership influences positively and significantly (always at the 1% level) the likelihood of receiving formal training. Certain job characteristics also enhance the probability of receiving formal training, such as workers having supervisory and managerial duties, those belonging to a quality circle, and those being closely supervised. It appears, therefore, that

[26] For empirical evidence regarding the correlation between job training and experience, one can refer to Veum (1995) among others.

[27] Remember that formal training is ongoing for 25% of the sample. So, previous training spells may have occurred in the very beginning of the career for, presumably, a non negligible proportion of workers. That could partially explain why tenure in the current firm has no significant effect on the dummy TRAINED.

job characteristics play a substantial role in the training decision process and might consequently have an impact on the extent to which training is rewarded. Finally, the inclusion of occupational and industry dummies (column 3) does not change very much the significance of the other estimated coefficients[28]. Nonetheless, we performed a Wald test that rejects at the 1% level the null hypothesis that the coefficients of the occupational and industry dummies are jointly equal to zero[29]. Therefore, the types of occupation in the job as well as the type of industry where the job takes place both play a role in explaining workers' participation in formal training[30].

4.1.2 Impacts of job training on earnings differentials

Keeping these patterns in the acquisition of formal training in mind, we now examine how on-the-job training affects the wages of workers (table A3 of the appendix). Column 1 presents results from a standard log-earnings-equation specification where the log gross hourly wages of individuals interviewed in 2001 are regressed on a function of dummies for the four levels of qualification, previous experience and tenure, their squared values, and the variable TRAINED[31]. Column 2 produces the same regression on the overall pooled sample (1997-2001) but where the dummies for levels of qualification are replaced by the years of schooling. While the first regression provides wage premiums for each level of qualification relative to the reference category[32], the coefficient on the variable of education (SCHOOL) in column 2 is interpreted as the private return to one additional year of schooling, and amounts to 3.7%. Note that the effects of qualifications on earnings are all significantly different from zero at the 1% level (as compared to workers having no qualifications), and that wage premiums increase when the level rises[33]. The coefficient on the training variable can also be interpreted as a percentage effect on earnings relative to the reference category: the wage premium resulting from having received any formal training is significantly different from zero at the 1% level in both equations (1) and (2).

[28] Except, unsurprisingly, the coefficient on the private sector dummy when controls for occupations and industries are added.
[29] The statistics of the test are respectively $\chi^2(8)=177.51$ and $\chi^2(16)=55.56$.
[30] Detailed results of these effects on training participation are available from the authors upon request.
[31] The specifications also include a full set of control variables for which estimates are not detailed in the table to save space (see section 3.3 and the bottom of table A3 in the appendix for a list of these variables).
[32] In column 1 of table A3 (appendix), the reference category is broadly a white, single, non unionised and full-time male worker with no qualifications who performs his current job in the public sector or in a non-profit organisation.
[33] For further discussions on this issue, one can refer to Fernandez and Hayward (2003).

This is a common finding as standard human capital theory predicts that wages should rise with post-school human capital investments (Mincer, 1974).

Regression in column 3 takes into account whether formal training is still ongoing at the time of the survey (ONGOINGTRAINING) and whether it leads – or has led – to a formal qualification (TRAININGQUALIFIED) that might have been delivered by participation, in day release programmes and/or accreditation of skills through an NVQ. Both ONGOINGTRAINING and TRAININGQUALIFIED do not seem to affect earnings significantly[34]. The result on the variable taking into account ongoing training might indicate that workers do not bear the full costs of their formal training in accepting a lower wage during their training period. Indeed, according to human capital theory, if training is assumed entirely general, one would expect a negative sign on the coefficient of the ongoing training variable (unless training is entirely specific, that is, not transferable from one firm to another). In fact, the insignificant effect of ONGOINGTRAINING on earnings differentials that we obtain might mean that firms are bearing a portion of the costs of general training. Note that a similar conclusion is drawn by Barron, Berger and Black (1999) on US data, who claim that "workers pay for very little of their training early in their careers" (p. 250). Similarly, Greenhalgh and Mavrotas (1995, 1996) find that UK employees typically pay for vocational training across the business cycle.

Various reasons are usually proposed to shed light on this result: first, most provided formal training is specific; second, informational asymmetries make much so-called 'general' training in fact 'specific' so that a firm may find it feasible to finance a part, or all, of a worker's general training (Katz and Ziderman, 1990); also, high training positions (where workers receive large amounts of training) are positions where monitoring is difficult, or the cost of shirking are great, and thus are positions that pay a higher "efficiency wage"; finally, as argued by Barron, Berger and Black (1999, p. 251), "it may be that while workers do not pay for training immediately early in their careers, they do pay for it at some later date".

In this study, we cannot test whether workers have already paid for their training at an earlier date, or will pay later, since we do not have any information on previous training episodes, past jobs and/or starting wages in the current job. Nonetheless, we do have rich data on workers' type of tasks and skills that can be used to deepen the understanding of the various returns to training episodes across different groups of workers. In particular, we can introduce here some control for the informal training process that is generally neglected by empirical studies, mostly for lack of information.

One of our suppositions is that informal learning may actually be interpreted as a formal learning process by workers if, when answering the questionnaire, they considered that acquiring new skills through performing their tasks was a form of training supplied by their employer (see section 2). This confusion is likely to introduce measurement errors in the formal training variables and, therefore, to produce an upward-biased estimate of the return to formal training if informal training is not accounted for in wage equations, and if high-wage workers have higher abilities than low-wage workers to learn informally.

Column 4 in table A3 presents a regression including the variable JOBLEARNING which is assumed to be a proxy for informal learning in the current job. It is highly significant and affects positively earnings differentials. Regression 4 warrants two main comments: firstly, we notice that the sensitivity of the estimated coefficient of tenure to the inclusion of the informal training variable, given that job tenure and its squared value are generally introduced in wage equations to capture the effects of on-the-job training (Mincer and Jovanovic, 1981) and, when formal training can be controlled for, returns to tenure are often assumed to reflect by default the returns to the informal components of training[35]. Interestingly, our results show that the marginal return to tenure falls after the introduction of JOBLEARNING in equation 4 (from 1.6% to 1.2%)[36]. It appears therefore that JOBLEARNING and TENURE are correlated since the coefficient on tenure is altered between equations 3 and 4 (as for previous work experience, this is not the case). We also notice that the tenure variable remains highly statistically significant in equation 4 and may still be capturing other factors than the pure returns to seniority, although we seem to control with JOBLEARNING for a fair amount of the effect of the informal training process. Secondly, it is worth noting that the formal training wage premium (coefficient on TRAINED) falls dramatically between equations 3 and 4 (20% decrease). This also confirms the previous

[34] Note that this result holds if we compute the same regression on the 2001 survey, for which the variable TRAININGQUALIFIED is fully available.
[35] See for instance Lynch (1992), Bartel (1995), Veum (1995) or Parent (1999).
[36] We take into account the decreasing marginal return to tenure over time and thus use the quadratic terms of the equations. The average returns to an additional year of tenure at the average tenure of the sample are (0.018-0.00026*7.77) = 0.016 in equation 3, and (0.014-0.00020*7.77) = 0.012 in equation 4.

assumption that not taking into account informal training explicitly in wage equations would lead us to bias upward the return to formal training.

Before reaching any general conclusion on the basis of the results presented in table A3, it is necessary to discuss the possible source of bias in the training estimates due to self-selection. In fact, we introduced into all regressions of table A3 the variable HELPLEARNINGTHINGS as a control (described in section 3.2), which might capture a part of the unobserved individual ability (see footnote 22). This is a way to reduce the possible bias due to the selection problem if more motivated and capable workers are more likely to self-select – and/or to be chosen – for formal training. Note that this variable does affect wages significantly and positively. Its introduction, indeed, adjusts downward the estimated coefficients on the training variables (results not presented). More importantly, the treatment selection problem is addressed with the introduction of the Heckman's selection correction term (Inverse Mill's Ratio, IMR) in equation 5. The IMR is drawn from the Probit estimate of the probability of receiving formal training (equation 2 of table A2). The IMR is statistically significant in equation 5. This suggests that there may be some problem of selection bias for those who have received formal training. Equation 5 presents therefore unbiased estimates of the returns to job training. From equations 4 and 5, we can see that, however, the magnitude of the bias was not exceedingly large since the wage premiums for formal and informal training decrease, respectively, from 6.2% to 5.8% and from 3% to 2.6%[37].

Specification 6 in table A3 substitutes training dummy variables for the duration of training measures (TRAINDURATIONSOFAR) in the set of independent variables. The limitation of this regression is that this variable is only available for a small proportion of the sample. The results show that while JOBLEARNING remains significant, TRAINDURATIONSOFAR does not. Therefore, it appears that whereas the *duration* of formal training has no effect on wages, the *incidence* of such training does affect wages. A similar result has been established by Veum (1995) using US data. One possible explanation proposed by Veum (op. cit.) is that the training duration variable contains a considerable amount of measurement error. Indeed, if individuals can provide fairly accurate information on whether they participated in training programmes but have more difficulty recalling time

[37] Note that the coefficient of the variable ONGOINTRAINING becomes now negative after the introduction of the IMR but remains, however, insignificantly different from zero.

spent in these programmes, training duration may be a "noisier" measure of skill acquisition than training incidence[38].

Some other interesting findings contained in regression 5 of table A3 concern other variables that significantly affect wages. Note that all their estimated effects conform to prior expectations: the variables with a positive impact include total previous work experience (EXPE), MARRIED; those with a negative effect are FEMALE, the interaction term between MARRIED and FEMALE (being a married woman), MINORITIES and PARTTIME. We also performed a test for the joint significance of the occupational, industry and regional dummies respectively. The three tests all reject at the 1% level the null hypothesis that the coefficients of the dummies are jointly equal to zero. This suggests the importance of job characteristics, sector and regional effects in wage determination. Moreover, the persistence of training effects after these controls, and also after correction for selectivity, highlights the substantial impact that the training measures still have on individual wages, and most likely on individual productivity.

4.2 Training effects across groups of workers

Tables A4, A5 and A6 of the appendix present regressions of specification 5 from table A3 on different groups of workers according to the intensity of their use at work of three skills: literacy, numeracy and computing skills. The estimates concerning the use of literacy (table A4) show that the wage premium of a formal training spell is significantly higher for workers using very basic literacy skills at work (filling in forms) as compared to those who write short or long documents. This wage premium also decreases with the task complexity. As for the informal training control, the regressions emphasise that the return to JOBLEARNING is lower for those who perform the most complex literacy tasks as well (writing long documents).

Table A5 presents the same regression across three groups of workers performing different increasing level of numeric tasks: adding and subtracting, more complex calculations, and advanced maths. As in table A4, the same story holds for the return to informal learning which is higher for workers using very little maths at work (addition and subtraction) as compared to those who carry out advanced maths; however, advanced

[38] Note, however, that the size of our sample has been drastically reduced to be able to perform this regression. It is therefore difficult to assess firmly the robustness of our result on this point.

maths users experience a higher return to a formal training spell as compared to their counterparts who make use of less numeric skills.

A probable explanation for the decreasing return to informal learning is that workers who undertake routine tasks can acquire new skills more quickly as long as job complexity is not high. They are then likely to benefit rapidly from financial rewards. On the other hand, this is unlikely to be the case for managerial work that would involve writing long documents, insofar as the time to learn how to write complex documents is probably much longer than that to learn how to fill forms[39]. That might explain the lower return to informal learning period – and also that of formal training episodes in the case of literacy skills – for workers who perform the more complex literacy and numeric tasks[40].

Table A6 provides estimates of the same model stratifying workers according to different computer usage. Columns 1 and 2 present regressions on split samples using the variable COMPUTERUSAGE as a breaking point of the sample (see section 3.2). A first striking result is the non-significant return to schooling and previous experience for workers who declared that computer use is "not at all important"[41]. The other results are also interesting: first, computer users experience a higher and more significant wage premium for a previous formal training spell (5.3% versus 3.4%). In addition, they also benefit from a higher wage effect of the variable JOBLEARNING (2.6% versus 1.6%), indicating that they may have learnt most of their computing skills on the job in an informal way. In order to get deeper into these issues, it is worth considering the level of sophistication of that computer use. Columns 3 to 6 present regressions on different groups of workers using computers with an increasing level of sophistication (from "simple user" to "advanced user")[42]. It turns out that there is a decreasing return to JOBLEARNING with the level of sophistication. This is in accordance with the previous results (tables A4 and A5) highlighting decreasing returns to informal learning as the complexity of tasks rise. Alternatively, formal training episods are more rewarding for complex computer users (column 5) relative to simple and moderate ones (columns 3 and 4). These findings may confirm the quite intuitive idea that while formal training programmes are necessary to get workers well acquainted with advanced IT (such as software programming, computer

[39] Note that the same explanation may hold as for numeric tasks.
[40] For further discussion on the complexities of workplace writing, see Davies and Birbili (2000)
[41] Note that they represent 23% of the overall sample.
[42] In order to preserve the degrees of freedom as much as possible, notably in the specifications 5 and 6, we retained only the most significant control variables as regressors.

aided design, graphics imaging), informal on-the-job learning is fairly efficient – and certainly very widespread – for all other basic IT knowledge (such as internet searches, emailing, word-processing, etc.). Hence, informal learning may appear as an alternative strategy of training with regard to formal training for workers who use basic computing skills.

We now examine the effects of these two learning processes according to the different types of tasks undertaken by workers. Indeed, besides the levels of sophistication of basic and computing skills, wage premiums for training can vary depending on the nature of the duty and, especially, on how this duty is performed, such as its tempo, and on whether it involves peers and requires communication skills. To tackle these issues, we use original variables to split the sample. These variables result from answers to different questions about the nature of the individual's job with an emphasis on the precise activities that the job entails. Table A7 present regressions using four questions on workers' tasks: whether their work involves carrying out short and repetitive tasks (two categories of answers are identified: "Often" to "Always" versus "Never" to "Sometimes"), whether their work involves working at a very high speed (categories: "Yes" versus "No"[43]), whether it is important to deal with people ("Important" versus "Not important"[44]) and whether it is important to make speeches and presentations ("Important" versus "Not important", see footnote 44).

Several results emerge from table A7. First, while there are no significant differentiated effects of formal training depending on how short and repetitive the duty carried out by workers is, this wage premium does, however, vary depending on other characteristics of the tasks (columns 3 to 8). The global picture is as follows: formal training is more rewarding for individuals who work at a high tempo (column 3), for those for whom dealing with people is not important (column 6) and also for those who make speeches and presentations (column 7). As for informal learning, it seems more profitable for individuals who undertake short and repetitive tasks (column 1), for workers of columns 3 and 6 as well, and for those for whom making speeches and presentations is not important (column 8). Examining the standard occupational classification, the

[43] The response scale offered was actually: "All the time", "Almost all the time", "Around three quarters of time", "Around half the time", "Around quarter the time", "Almost never" and "Never". Our category "Yes" includes workers who responded "All the time", "Almost all the time" and "Around three quarters of time" while "No" includes the rest.
[44] The response scale offered was: "Essential", "Very important", "Fairly important", "Not very important", "Not at all important". Our category "Important" includes the two first answers.

categories of workers of columns 1, 3 and 8 are essentially administrative and secretarial staffs and they have on average intermediate level qualification[45]. The prominent occupational category represented in workers of column 6 is the elementary and plant & machine and operatives staffs, i.e., those who are the least qualified workers (both in terms of distribution of qualifications and average years of schooling). Workers who undertake short and repetitive tasks (column 1) are also represented by these two categories in an important way. As a consequence, it seems that both formal and informal training for workers with lower levels of qualification provide the greatest return to the individual. Also, columns 7 and 8 show that formal training is more profitable for workers for whom communication skills are important (those who "make speeches and presentations"), that is, essentially professionals and managers (column 7).

These results indicate that formal training remains an efficient way to diffuse communication skills among qualified workers (professionals and managers). More importantly, they also highlight that, for certain types of workers engaged in different specific tasks, implementing formal training programmes would not only be worthwhile in terms of wage increases, but also probably an efficient policy to upgrade the skills and productivity of the labour force at the low and intermediate levels of qualifications (see introduction). This would fit with the finding that differences in labour productivity between the UK and our European neighbours such as France and Germany are greatest for the least qualified workers. It also reinforces the point that whilst informal learning may be an important means of skill acquisition formal training is also important, especially, it would seem, for the least well qualified.

Finally, note the significant and negative effect in column 7 of the variables taking into account training in progress (ONGOINGTRAINING) and training leading to a qualification (TRAININGQUALIFIED). Standard human capital theory would interpret the negative sign affected to these variables by the fact that workers for whom making speeches and presentations is important are provided with purely general training (see sections 2 and 3.2). Indeed, these workers seem to bear the full costs of their training in accepting a lower wage for any qualifying training and during any training period. This is a quite

[45] Administrative and secretarial staffs are the occupational category with the highest proportion of qualifica[46] For instance, ongoing and qualifying formal training may comprise how to do powerpoint presentations, which is transferable to many professional contexts.

intuitive result if we consider that formal training programmes for this type of workers may include a fair amount of courses aimed at enhancing their communication skills[46].

Table A8 presents the same estimates using the available information on the characteristics of individuals' workstation. Columns 1 to 8 identify individuals that work respectively on their own (1), in one or more groups (2), those who are closely supervised (3), those who are not (4), those who can work independently (5) and those who can't (6), employees who are involved in a Quality Circle or a similar group at work (7) and those who are not involved in any scheme of that sort (8)[47].

The estimates show that both returns to formal and informal training are more significant and higher for individuals who work in one or more groups (columns 1 and 2)[48]. In particular, the wage premium for formal training is very high for employees that belong to one or more groups of workers (9.5%). This might be an important result because it confirms former theoretical predictions as well as rare empirical evidence arguing that training, and especially informal learning, should be more efficient in a context of interactions between co-workers (Billett, 2001). In our case, the difference in the coefficients is rather small as for JOBLEARNING, but this is a first signal that individuals' interactions in the workplace are important and capable of modifying the impacts of informal learning. This would be the case if, as some authors have already argued (Destré, Lévy-Garboua and Sollogoub, 2001; Destré and Nordman, 2002), that the "learning by watching" process does play an essential role in the on-the-job human capital accumulation and therefore in intra-firm wage determination[49].

Estimates in columns 3, 4, 5 and 6 also back up this argument. Indeed, there is a significant difference on the coefficients of JOBLEARNING between columns 3 and 4 ("closely supervised" versus "not closely supervised"). Wage premiums for formal training are also larger for supervised and dependent workers (columns 3 and 6). For instance, workers that "cannot work independently" (column 6) experience a much greater

[47] The precise definitions of the variables used are available from the authors upon request. Note that quality circles are defined in the questionnaire as "groups of employees who meet regularly to think about improvements that could be made within the organisation".

[48] Note that all occupational categories are well represented in the sub-samples of workers of columns 1 and 2.

[49] In a theoretical model of on-the-job learning, Destré et al. (2001) highlight that one part of the returns to tenure is firm-dependent. This return to tenure is composed of pure learning by experience and learning by watching effects. A worker benefits from the firm which employs her, in addition to what she gets from experience, insofar as she can learn something from the latter. Experience simply increases the human capital of all workers at a constant rate. By contrast, the presence of others is presumably more beneficial to less qualified workers who have a lot to learn by a simple imitation process.

formal training wage premium (almost 10%) than their counterparts who benefit from more autonomy in their work. This is in line with the previous result concerning informal training. Levels of qualifications and experience across these two groups of workers don't provide any convincing insight as to whether this result can be interpreted by differences in human capital endowments. In fact, both average years of schooling and experience are similar across workers of columns 5 and 6. However, another possible explanation[50] is that workers in column 6 may have less appropriate qualifications. For instance, their qualifications might be inappropriate for the job they actually hold[51]. In that case, formal training would be an efficient means to improve both qualifications and skills that presumably need to be job-specific.

Overall, these results highlight that working in teams, being closely supervised and being dependent on a supervisor seem to enhance the rewards to both formal and informal training[52]. For this, one can hypothesise that team workers, closely supervised and/or dependent workers are more likely to be informally instructed and mentored by their counterparts. Indeed, they may have more opportunities to share easier ways to do the work either while working or during breaks, and are in any case indirectly instructed whenever a supervisor constructively criticises their work. This context is also more propitious for readily applying what has been learnt in a formal way through past training spells. As a consequence, the time spent in formal and informal learning would probably be more efficient and therefore more rewarding. Again, this hypothesis is supported by case study evidence which indicates that learning through workplace activity is of a higher quality in the presence of experts to provide guidance (see, inter alia, Moore, 1986; Eraut et al. 2000; Billett, 2001).

Significant differences also appear regarding the wage premiums to training according to whether individuals participate in one or more quality circles. Columns 7 and 8 highlight that being involved in quality circle(s) does enhance significantly the return to formal training[53]. At the same time, the proxy for informal learning has a higher impact

[50] Besides the difference in the sub-sample sizes between columns 5 and 6 which may affect the precision of the estimates in column 6.
[51] That would also explain the non-significant return to schooling in column 6.
[52] Except for the category of managers that are not much represented in the sub-sample of "closely supervised" workers, all the other occupational categories appear in a somewhat reasonable proportion in the other sub-samples of columns 1 to 6. It is therefore difficult to attribute the significance of these results to a supposed overwhelming presence of any of the occupational categories in each sub-sample.
[53] However, from the available information, it is not possible to disentangle the links between a formal training episode and the fact that workers belong to a quality circle. For instance, we would be happy to

for workers who are not involved in a quality circle. The estimates act therefore as if informal training were a substitute for formal training for workers who are not involved in a quality circle (in terms of wage increases[54]) and, very likely, for those who work in a firm that does not provide such a scheme. Unsurprisingly, the observation of the average qualifications and tenure across these two groups shows that the workers of the sub-sample in column 7 ("involved in a quality circle") are more qualified and experienced. We might thus attribute the difference in the wage effects of TRAINED to the fact that more qualified – and potentially more capable workers – are more likely to be involved in a quality circle and also to be better paid thanks to their unobserved productive abilities and motivation (on this point, see the discussion section 3.3). Nevertheless, insofar as we corrected for selectivity biases[55], the inter-group wage effect of formal training between columns 7 and 8 seems too important to be solely attributed to a lasting selection bias. As a result, the remaining effect must also be attributed to the fact that quality circles are probably very good structures to diffuse knowledge in the workplace; for instance, through discussions about what workers have already learnt during their training programme. However, this is an hypothesis that requires further exploration.

Finally, note the significant effect in columns 1 and 2 that the variable taking into account training leading to a qualification presents now: while it has a negative and significant impact for workers in column 7 of table A7, and for workers of column 2 of table A8, the sign is now positive for individuals who work on their own. Hence, our results show that, in certain circumstances and for certain types of tasks, this qualifying training can actually be profitable and can foster wage increases. Is it because training leading to a qualification becomes firm-specific for individuals that work on their own? Or is that because some firms are actually willing to bear the costs of workers' general training? Recent theoretical developments suggest that the existence of imperfections in the labour market might explain these behaviours (Stevens, 1994; Acemoglu and Pischke, 1999a). Finally, is any qualifying training always "general training", that is, transferable

know whether the purpose of this training spell was precisely to teach how a quality circle worked out... We know though, from section 4.1.1, that belonging to a quality circle affects positively the probability of receiving formal training.

[54] When there were differentiated returns to training between different groups of workers, we generally observed that returns to formal and informal training were always modified in the *same* direction, which is not the case in columns 7 and 8.

[55] Note that the training participation equation does include the dummy for a quality circle involvement.

to other professional contexts? It seems that the nature and impacts of this type of training ought to be a matter for future investigations.

5. Conclusion

The findings from our analysis are consistent with previous research on the determinants of who receives training, what sorts of organisations provide training and the magnitude of the returns to training (Ashton and Green, 1996; Belfield, 2000; Frazis and Loewenstein, 2003). In addition, the analysis indicates that a number of individual characteristics affect earning differentials, a result which is again consistent with the extant literature. Moreover, it appears that job characteristics play a substantial role in explaining the training decision process and consequently have an impact on the extent to which training is rewarded. In all of the models tested the wage premium for having received formal training is always significant and positive. A proxy variable, intended to capture the effects of informal learning in the current job, was also found to have a significant and positive effect on wages. The extent to which this proxy variable did capture at least some of the effects of informal learning on wages can be judged by the extent to which the marginal returns to tenure, which is often assumed in the literature to reflect by default the returns to the informal components of training, falls considerably but still remains significant. This suggests that whilst the proxy variable introduced into the models captures a fair amount of the effects of informal learning, the tenure variable still captures other effects, for instance a pure return to job seniority that could in part be independent of the firm.

Introducing this control for informal learning also leads to a fall in the wage premium associated with formal training. This is in line with our hypothesis that not taking into account informal training explicitly in the wage equations leads empirical assessments to bias upward the return to formal training. Nonetheless, the returns to formal training remained significant and positive in all of the models developed in the paper. This redresses a possible imbalance in the case study research that has tended sometimes, in our view, to overemphasise the overriding importance of informal learning in the workplace. The quantity of such learning may be high but its quality and usefulness may be limited. Thus, as Billett (2001: 98) points out

> "Many contributions to learning are provided freely by the workplace and workers engage in learning processes as part of everyday work activities. … The quality of these experiences and interactions is structured by the norms and values of the workplace and the willingness of experts or experienced others to assist other workers to learn. … However, the workers will not learn a set body of knowledge about the vocation (if such a thing actually exists). Instead, the types of activities that occur in the workplace ('what we do here is …') and the way that work is undertaken ('how we do things here is…') influence what is learnt."

Such learning may often be beneficial and necessary but it can be unhelpful, overemphasising the development of technical skills and even ways of working that inhibit the development of real vocational expertise:

> "… the capacity to think and act in ways that permit individuals to resolve non-routine problems, to understand what constitutes an appropriate action and to become a full participant whose contributions are such that they themselves shape work practice in particular ways."
> (Billett, 2001:99)

What the findings from this research suggest, then, is that both formal and informal workplace learning are needed for the development of expertise that is rewarded by increased wages. Indeed, high returns to human capital are generally interpreted as a sign of a lack of or inappropriate qualifications (Hartog, Oosterbeek and Teulings, 1993). The issue of the relationship between the two types of learning (indeed even if this is a sensible dichotomy to maintain) remains, however, to be explored. However, this is a long term project and here we set out our methodology and provide some initial findings in the form of patterns emerging from the data which are at present only partially explained.

Additional modelling also revealed the complex relationships between the returns to formal and informal learning, and the types of skills people were using, the type of work they were doing and how such work was organised. Thus, the wage premium for a spell of formal training is significantly higher for workers using very basic literacy skills at work. This wage premium declines with increasing literacy task complexity. However, advanced maths users experience a higher return to a formal training spell as compared to their counterparts who make use of less numeric skills. In fact, the return to informal learning is lower for those who perform the most complex literacy and numeracy tasks. Our tentative explanation for this is that workers who undertake routine literacy and numeracy tasks can acquire the skills needed informally quickly since the complexity of their work is not high. They are then likely to benefit more rapidly from financial rewards than their counterparts who are using more complex skills, that take more time to be mastered and who need to develop situationally specific knowledge in order to deploy those skills to their full effect (see Davies and Birbili, 2000).

In relation to computer usage, computer users seem to experience a higher wage premium for both a previous formal training spell and from informal learning. This might indicate that computer users have learnt at least some of their computing skills through informal learning processes. However, the wage premium for informal learning declines with the level of sophistication of computer usage, which mirrors the results for literacy and numeracy skills discussed above: there are decreasing premiums for informal learning as the complexity of tasks rise. This finding may also confirm the quite intuitive idea that while formal training programmes are necessary to get workers well acquainted with advanced uses of information technology, informal on-the-job learning is fairly efficient – and certainly widespread – for all other basic IT knowledge. Thus, informal learning may be a productive alternative strategy compared to formal training for workers who use basic computing skills.

Returns to the two learning processes also differed markedly according to the type of tasks being performed. The global picture for formal training appears to be as follows:

- Formal training seems more rewarding for individuals who work at high tempo and for those for whom dealing with people is not important;
- Formal training appears to be an efficient means of diffusing communication skills amongst qualified workers;
- For certain types of workers carrying out different specific tasks, implementing formal training programmes would be an efficient policy to increase wages and probably to upgrade the skills and productivity of the labour force at low and intermediate levels of qualifications.

There were also differences in returns to informal learning that are related to the type of work that workers do:

- Informal learning seems more rewarding for individuals who undertake short and repetitive tasks and work at high tempo;
- Informal learning appears more profitable for individuals for whom jobs necessitate few communication skills;

Returns to formal and informal training do vary according to the way work is performed as well (work organisation). Thus returns to both formal and informal learning are higher and more significant for workers who work in one or more groups. In particular, the wage premium for formal training is very high for employees that belong to a team and cannot work independently (almost 10%). Being closely supervised is also associated with significant increased reward from informal learning. These results again correlate with findings from the case study research, which indicates that supervised and/or dependent workers are more likely to receive support and mentoring from their counterparts. Such coaching is seen as being crucial to the development of vocational expertise. Thus, these results are potentially very important because they confirm theoretical predictions based upon situated learning theory, and empirical evidence from case studies, that suggests that workplace learning should be more efficient in a context of interactions between co-workers.

This perspective is reinforced by the finding from this research that significant differences appear regarding the wage premiums to formal training according to whether individuals can work independently or not, and whether they participate in one or more quality circles. Another possible explanation for the greater return to formal training for workers that cannot work independently is that they may have less appropriate qualifications that are, for instance, inappropriate for the job they actually hold. Formal training would be then an efficient means to improve both qualifications and skills that need to be job-specific. Being involved in a quality circle also enhances significantly the return to formal training; while informal learning has a greater positive impact for workers who are not involved in this kind of structure. The estimates act therefore as if informal training were a substitute for formal training for workers who are not involved in a quality circle. Overall, when looking at the level of qualifications of these two groups of workers, it seems that quality circles are probably very good structures to diffuse knowledge in the workplace.

Finally, consider the effects of the variable that takes into account training leading to a qualification. While it has never been really significant in many performed regressions, its effect becomes apparent when we split the sample according to whether workers participate in team work (negative effect for workers belonging to teams, positive for those who work on their own) and for workers for whom making speeches and presentations is important (negative impact). Standard human capital theory would interpret the negative sign affected to this variable by the fact that training leading to a qualification is purely general. However, our results show that, in many cases, this qualifying training has no significant impact on wages – which would support the idea that workers don't bear the costs of their qualifying training – and can even be profitable in some circumstances, probably for certain types of tasks. That might reveal that qualifying training is not necessarily entirely general, or that some firms may actually be willing to bear the costs of workers' general training. As a result of data limitations, we could not go further into the comprehension of this phenomenon. It would then be worth getting deeper into this matter by using more detailed – and especially longitudinal – information about the importance of training that leads to a qualification, especially given the current policy emphasis on the qualification system as a main lever for reforming VET provision in England.

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APPENDIX

Table A1. Descriptive statistics of the variables used in the wage functions

Variables	Definitions	Obs.	Mean	Standard deviation	Min	Max
Individual characteristics						
LOGGROSSWAGE	Log of gross hourly wage	5563	1.98	0.5098	0.69	6.31
FEMALE	Dummy for female	5672	0.50		0	1
MARRIED	Dummy for married	5672	0.57		0	1
MARRIEDWOMAN	Interaction term: female*married	5672	0.27		0	1
DEPENDENTCHILDREN	Dummy for children under the age 16 financially dependent on the worker	5672	0.43		0	1
MINORITIES	Dummy for workers belonging to an ethnic minority (Caribbean black, Indian, Pakistan, Banglad, Chinese, other ethnic)	5672	0.04		0	1
SCHOOL	Years of schooling (age at the end of school – 5)	5672	12.40	2.59	6	24
LEVEL0	Dummy for no qualifications	3690	0.13		0	1
LEVEL1	Dummy for level 1 qualification attained (see classification by Felstead, Gallie and Green, 2002)	3690	0.16		0	1
LEVEL2	Dummy for level 2 qualification attained	3690	0.30		0	1
LEVEL3	Dummy for level 3 qualification attained	3690	0.10		0	1
LEVEL4PLUS	Dummy for level 4 qualification attained	3690	0.29		0	1
EXPE	Previous potential experience (in years)	5672	15.38	10.90	0	46
TENURE	Tenure in the current job (in years)	5672	7.78	7.92	0	45
PARTTIME	Dummy for part-time job	5672	0.22		0	1
UNION	Dummy for union membership	5672	0.34		0	1
EFFORT	Dummy for workers responding "A lot" to the question: "How much effort do you put into your job beyond what is required"	5672	0.69		0	1
PRIVATESECTOR	Dummy for workers working currently in a private sector organisation	5672	0.66		0	1
BHOURS	Hours per week usually worked	5672	37.41	22.77	0	90
COMPUTERUSE	Dummy for computer usage	5672	0.77		0	1
Learning variables						
TRAINED	Dummy indicating whether workers have previously received any formal training related to their current job	5672	0.57		0	1
ONGOINGTRAINING	Dummy indicating whether training is ongoing at the date of the interview	5672	0.25		0	1

TRAINDURATION	Time that workers have spent in formal training at the date of the interview (scale running from 1 : "Less than 1 week" to 7: "Over 2 years", see details in text)	3164	5.25	2.05	1	7
TRAININGQUALIFIED	Dummy indicating whether any training has lead to a qualification	3695	0.33		0	1
JOBLEARNING	Time that workers have spent in learning to do well their job (scale running from 1: "Less than 1 week" to 7 : "Over 2 years", see details in text)	5648	4.44	2.02	1	7
KEEPLEARNING	Dummy indicating whether the worker answered "Agree" to the statement: "My job requires that I keep learning new things"	5672	0.19		0	1
HELPLEARNING	Dummy indicating whether the worker answered "Agree" to the statement: "My job requires that I help my colleagues to learn new things"	5672	0.18		0	1
Regional dummies						
LONDON	Dummy for London	5672	0.10		0	1
SEAST	Dummy for South-East	5672	0.13		0	1
EAST	Dummy for East	5672	0.10		0	1
SWEST	Dummy for South-West	5672	0.08		0	1
WMIDLANDS	Dummy for West Midlands	5672	0.08		0	1
EMIDLANDS	Dummy for East Midlands	5672	0.05		0	1
YORKSHIRE	Dummy for Yorkshire	5672	0.09		0	1
NWEST	Dummy for North-West	5672	0.13		0	1
NEAST	Dummy for North-East	5672	0.05		0	1
WALES	Dummy for Wales	5672	0.05		0	1
SCOTLAND	Dummy for Scotland	5672	0.11		0	1

Table A2. Probit for the Probability of Receiving Formal Training

Dependent variable: TRAINED

	Survey 2001	Pooled 1997-2001 surveys	
	(1)	(2)	(3)
Characteristics of the worker			
Level 1	0.503***	-	-
	(6.05)		
Level 2	0.606***	-	-
	(8.09)		
Level 3	0.620***	-	-
	(6.52)		
Level 4 and over	0.925***	-	-
	(11.16)		
Years of schooling (SCHOOL)	-	0.055***	0.019**
		(6.29)	(1.99)
Previous experience (EXPE)	0.004*	-0.001	-0.002
	(1.60)	(0.73)	(1.10)
Tenure in the current job (TENURE)	0.006*	0.001	-0.001
	(1.95)	(0.29)	(0.42)
FEMALE	0.040	0.025	0.023
	(0.79)	(0.62)	(0.49)
DEPENDANTCHILDREN	0.080*	0.103***	0.109***
	(1.70)	(2.73)	(2.85)
MINORITIES	-0.257***	-0.251***	-0.246***
	(2.58)	(3.04)	(2.92)
KEEPLEARNINGTHINGS	0.449***	0.458***	0.354***
	(8.60)	(8.92)	(6.72)
EFFORT	0.135***	0.084**	0.076*
	(2.71)	(2.12)	(1.87)
Characteristics of the job			
PRIVATE SECTOR	-0.273***	-0.308***	-0.098
	(5.10)	(7.17)	(1.58)
PARTTIME	-0.220***	-0.288***	-0.192***
	(3.49)	(5.68)	(3.55)
UNION	0.228***	0.273***	0.246***
	(4.29)	(6.44)	(5.54)
Supervisory duties	0.226***	0.310***	0.217***
	(4.02)	(6.93)	(4.63)
Managerial duties	0.274***	0.396***	0.282***
	(3.91)	(7.13)	(4.30)
Belongs to a quality circle	0.166***	0.212***	0.178***
	(3.40)	(5.40)	(4.46)
Closely supervised	0.128***	0.070*	0.101***
	(2.72)	(1.84)	(2.60)
Repeated task	-0.083*	-0.137***	-0.083**
	(1.81)	(3.76)	(2.20)
Occupational dummies	no	no	yes
Industry dummies	no	no	yes
Constant	-0.818***	-0.479***	-0.691**
	(6.53)	(3.17)	(2.33)
Log pseudo-likelihood	-2150.8	-3375.3	-3238.6
Observations	3603	5536	5536

Robust z statistics are in parentheses. *, ** and *** mean respectively significant at the 10%, 5% and 1% level.
A dummy for the date of the survey is included in regression (2) and (3).

Table A3. Determinants of Log Hourly Earnings - British Skills Surveys 1997-2001

	Formal education and training			Informal learning added		
					Selection correction	
	(1)	(2)	(3)	(4)	(5)	(6)
Years of Schooling	-	0.037***	0.037***	0.036***	0.029***	0.028***
		(12.97)	(12.96)	(12.63)	(9.58)	(5.36)
Level 1	0.061***	-	-	-	-	-
	(3.26)					
Level 2	0.085***	-	-	-	-	-
	(5.19)					
Level 3	0.140***	-	-	-	-	-
	(5.61)					
Level 4 and over	0.266***	-	-	-	-	-
	(11.36)					
Previous experience (EXPE)	0.011***	0.012***	0.012***	0.012***	0.011***	0.019***
	(5.75)	(7.96)	(7.96)	(7.92)	(7.65)	(6.07)
$EXPE^2$	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(6.05)	(7.23)	(7.23)	(7.25)	(6.41)	(4.54)
Tenure in the current job (TENURE)	0.015***	0.018***	0.018***	0.014***	0.014***	0.020***
	(6.49)	(10.17)	(10.19)	(8.40)	(8.23)	(5.67)
$TENURE^2$	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(3.09)	(4.62)	(4.63)	(3.56)	(3.35)	(2.68)
TRAINED	0.066***	0.085***	0.078***	0.062***	0.058***	-
	(4.94)	(8.20)	(6.14)	(4.91)	(4.57)	
ONGOINGTRAINING	-	-	0.006	0.001	-0.008	-
			(0.47)	(0.06)	(0.64)	
TRAININGQUALIFIED	-	-	0.011	0.011	0.003	-0.017
			(0.74)	(0.75)	(0.23)	(0.64)
JOBLEARNING	-	-	-	0.030***	0.026***	0.026***
				(10.34)	(9.01)	(4.29)
TRAINDURATIONSOFAR	-	-	-	-	-	-0.002
						(0.37)
Inverse Mill's Ratio (IMR)	-	-	-	-	-0.265***	-0.322***
					(7.76)	(4.57)
Constant	1.851***	1.351***	1.353***	1.300***	1.588***	1.645***
	(35.83)	(23.81)	(23.85)	(23.13)	(24.12)	(12.44)
Observations	3592	5536	5536	5513	5487	1375
R-squared	0.55	0.57	0.57	0.58	0.58	0.52

Robust *t* statistics are in parentheses. *, ** and *** mean respectively significant at the 10%, 5% and 1% level. All regressions include a full set of control variables: FEMALE, MARRIED, MARRIEDWOMAN, UNION, MINORITIES, PARTTIME, PRIVATESECTOR, BHOURS, HELPLEARNINGTHINGS, 9 occupational dummies, 17 industry dummies, 11 regional dummies and a dummy for the date of the survey (except regression of column 1).

Table A4. Determinants of Log Hourly Earnings by Literacy Tasks

	Filling in forms (1)	Short documents (2)	Long documents (3)
Years of Schooling	0.030***	0.034***	0.032***
	(8.95)	(10.06)	(8.16)
Previous experience	0.012***	0.014***	0.016***
	(7.18)	(7.50)	(6.95)
EXPE^2	-0.000***	-0.000***	-0.000***
	(5.70)	(5.91)	(4.96)
Tenure in the current job	0.016***	0.017***	0.018***
	(7.60)	(7.79)	(6.72)
TENURE^2	-0.000***	-0.000***	-0.000***
	(3.20)	(3.28)	(2.93)
TRAINED	0.058***	0.055***	0.040*
	(3.92)	(3.41)	(1.89)
ONGOINGTRAINING	-0.008	-0.013	-0.016
	(0.59)	(0.92)	(0.91)
TRAININGQUALIFIED	0.002	0.007	-0.013
	(0.15)	(0.41)	(0.62)
JOBLEARNING	0.024***	0.023***	0.021***
	(7.03)	(6.15)	(4.58)
IMR	-0.286***	-0.271***	-0.312***
	(7.48)	(6.50)	(5.56)
Constant	1.646***	1.580***	1.624***
	(22.26)	(20.00)	(16.80)
Observations	4009	3807	2629
R-squared	0.55	0.52	0.50

Robust *t* statistics are in parentheses. *, ** and *** mean respectively significant at the 10%, 5% and 1% level.

Table A5. Determinants of Log Hourly Earnings by Numeric Tasks

	Adding-subtracting (1)	Calculations (2)	Advanced math (3)
Years of schooling	0.030***	0.030***	0.035***
	(8.72)	(7.43)	(7.16)
Previous experience	0.014***	0.016***	0.018***
	(7.81)	(7.30)	(6.43)
EXPE^2	-0.000***	-0.000***	-0.000***
	(6.07)	(5.65)	(4.72)
Tenure in the current job	0.015***	0.014***	0.013***
	(7.09)	(5.59)	(3.69)
TENURE^2	-0.000**	-0.000*	-0.000
	(2.47)	(1.84)	(0.69)
TRAINED	0.057***	0.053***	0.072***
	(3.66)	(2.85)	(2.88)
ONGOINGTRAINING	-0.008	-0.007	-0.015
	(0.52)	(0.43)	(0.67)
TRAININGQUALIFIED	-0.001	-0.008	-0.020
	(0.04)	(0.42)	(0.75)
JOBLEARNING	0.026***	0.024***	0.022***
	(7.01)	(5.75)	(3.91)
IMR	-0.284***	-0.302***	-0.328***
	(7.19)	(6.45)	(5.32)
Constant	1.622***	1.636***	1.593***
	(20.81)	(17.62)	(13.21)
Observations	3752	2930	1661
R-squared	0.55	0.52	0.52

Robust *t* statistics are in parentheses. *, ** and *** mean respectively significant at the 10%, 5% and 1% level.

Table A6. Determinants of Log Hourly Earnings by Computing Tasks

	Non-computer user (1)	Computer user (2)	Simple user (3)	Moderate user (4)	Complex user (5)	Advanced user (6)
Years of schooling	0.009	0.031***	0.020***	0.039***	0.028***	0.007
	(1.41)	(9.65)	(3.43)	(7.61)	(5.04)	(0.49)
Previous experience	0.003	0.015***	0.011***	0.015***	0.019***	0.040***
	(1.27)	(8.71)	(4.07)	(5.33)	(3.97)	(4.17)
$EXPE^2$	-0.000	-0.000***	-0.000***	-0.000***	-0.000**	-0.001***
	(1.29)	(6.85)	(3.32)	(3.95)	(2.55)	(3.42)
Tenure in the current job	0.006**	0.017***	0.017***	0.021***	0.017***	0.008
	(2.33)	(8.33)	(4.88)	(6.09)	(3.53)	(0.67)
$TENURE^2$	-0.000	-0.000***	-0.000**	-0.000***	-0.000	0.000
	(1.19)	(3.39)	(2.04)	(2.68)	(1.54)	(0.06)
TRAINED	0.034*	0.053***	0.047**	0.003	0.088**	0.082
	(1.71)	(3.48)	(2.02)	(0.14)	(2.38)	(0.82)
ONGOINGTRAINING	0.018	-0.013	-0.011	0.016	-0.042	-0.046
	(0.66)	(0.96)	(0.47)	(0.75)	(1.41)	(0.69)
TRAININGQUALIFIED	-0.005	0.010	-0.025	0.018	0.014	0.008
	(0.21)	(0.59)	(0.87)	(0.72)	(0.38)	(0.11)
JOBLEARNING	0.016***	0.026***	0.028***	0.019***	0.015***	0.012
	(3.62)	(7.15)	(5.12)	(3.00)	(2.87)	(0.73)
IMR	-0.111**	-0.269***	-0.267***	-0.232***	-0.316***	-0.162
	(1.96)	(6.83)	(3.61)	(3.50)	(3.84)	(0.78)
Constant	1.658***	1.564***	1.692***	1.594***	1.791***	1.894***
	(13.96)	(20.59)	(15.17)	(13.04)	(11.44)	(5.67)
Observations	1262	4225	1310	1779	699	233
R-squared	0.53	0.54	0.55	0.48	0.52	0.37

Robust *t* statistics are in parentheses. *, ** and *** mean respectively significant at the 10%, 5% and 1% level.

Table A7. Determinants of Log Hourly Earnings by Different Types of Tasks

	Short and repetitive tasks		Work at very high speed		Deal with people		Make speeches or presentations	
	Often or always	Sometimes or never	Yes	No	Important	Not important	Important	Not important
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Years of Schooling	0.028***	0.028***	0.024***	0.028***	0.033***	0.005	0.026***	0.030***
	(6.16)	(7.15)	(3.15)	(6.64)	(10.46)	(0.53)	(4.08)	(8.94)
Previous experience	0.008***	0.014***	0.005	0.015***	0.013***	0.005	0.017***	0.010***
	(3.89)	(6.72)	(1.40)	(7.05)	(7.69)	(1.50)	(3.69)	(6.52)
$EXPE^2$	-0.000***	-0.000***	-0.000	-0.000***	-0.000***	-0.000	-0.000**	-0.000***
	(3.10)	(5.79)	(0.98)	(6.53)	(6.42)	(1.37)	(2.42)	(5.60)
Tenure in the current job	0.015***	0.015***	0.008	0.013***	0.014***	0.012***	0.016***	0.015***
	(6.04)	(6.18)	(1.47)	(5.35)	(7.51)	(3.32)	(3.33)	(8.77)
$TENURE^2$	-0.000***	-0.000**	0.000	-0.000***	-0.000***	-0.000**	-0.000	-0.000***
	(2.91)	(2.57)	(0.70)	(2.90)	(2.69)	(2.09)	(0.93)	(4.41)
TRAINED	0.057***	0.058***	0.082*	0.043**	0.047***	0.098***	0.090**	0.044***
	(3.34)	(3.12)	(1.94)	(2.24)	(3.32)	(3.40)	(2.22)	(3.50)
ONGOINGTRAINING	-0.013	0.003	-0.051	0.011	-0.003	-0.051	-0.069**	0.015
	(0.72)	(0.16)	(1.38)	(0.58)	(0.19)	(1.33)	(2.45)	(1.13)
TRAININGQUALIFIED	0.005	0.005	-0.015	0.012	0.009	-0.018	-0.060*	0.023
	(0.27)	(0.26)	(0.40)	(0.64)	(0.55)	(0.49)	(1.65)	(1.56)
JOBLEARNING	0.030***	0.024***	0.029***	0.024***	0.026***	0.029***	0.015*	0.028***
	(6.91)	(5.92)	(3.86)	(5.73)	(7.78)	(4.62)	(1.80)	(9.32)
IMR	-0.156***	-0.274***	-0.333***	-0.208***	-0.272***	-0.177**	-0.371***	-0.188***
	(3.15)	(5.83)	(4.28)	(5.71)	(9.00)	(2.48)	(4.39)	(5.94)
Constant	1.525***	1.570***	1.804***	1.681***	1.550***	1.846***	1.646***	1.523***
	(16.14)	(16.35)	(10.80)	(17.41)	(22.88)	(9.12)	(9.85)	(21.60)
Observations	2537	2950	952	2623	4572	915	1109	4378
R-squared	0.55	0.58	0.50	0.59	0.58	0.60	0.47	0.58

Robust *t* statistics are in parentheses. *, ** and *** mean respectively significant at the 10%, 5% and 1% level.

Table A8. Determinants of Log Hourly Earnings by Different Characteristics of the Workstation

	Work on own	Work in one or more groups	Closely supervised	Not closely supervised	Can work independently	Cannot work independently	Quality Circle Involved	Not involved
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Years of Schooling	0.026***	0.028***	0.018***	0.029***	0.031***	0.005	0.030***	0.032***
	(4.68)	(5.55)	(3.88)	(7.87)	(7.71)	(0.51)	(6.69)	(7.74)
Previous experience	0.009***	0.015***	0.010***	0.011***	0.013***	0.014***	0.010***	0.012***
	(3.10)	(6.01)	(4.38)	(5.65)	(6.45)	(2.91)	(3.95)	(6.61)
EXPE^2	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(2.73)	(5.52)	(3.98)	(4.81)	(5.55)	(3.22)	(2.67)	(5.95)
Tenure in the current job	0.007*	0.018***	0.015***	0.012***	0.013***	0.007	0.015***	0.013***
	(1.79)	(5.94)	(5.09)	(5.43)	(5.47)	(0.90)	(4.95)	(6.19)
TENURE^2	0.000	-0.000***	-0.000*	-0.000**	-0.000**	0.000	-0.000	-0.000***
	(0.21)	(3.53)	(1.86)	(2.08)	(2.39)	(0.35)	(1.61)	(2.67)
TRAINED	-0.009	0.095***	0.060***	0.054***	0.049**	0.098*	0.073***	0.050***
	(0.32)	(3.94)	(3.17)	(3.27)	(2.54)	(1.96)	(3.03)	(3.32)
ONGOINGTRAINING	0.017	-0.019	-0.004	0.007	0.001	-0.020	-0.006	-0.014
	(0.65)	(0.82)	(0.23)	(0.41)	(0.04)	(0.42)	(0.33)	(0.82)
TRAININGQUALIFIED	0.061**	-0.032*	-0.001	0.005	0.010	-0.047	-0.024	0.024
	(2.45)	(1.64)	(0.05)	(0.25)	(0.57)	(0.93)	(1.01)	(1.32)
JOBLEARNING	0.026***	0.029***	0.032***	0.023***	0.025***	0.026**	0.024***	0.028***
	(4.20)	(5.68)	(7.06)	(6.26)	(6.17)	(2.41)	(4.93)	(7.67)
IMR	-0.216***	-0.232***	-0.197***	-0.343***	-0.240***	-0.329***	-0.253***	-0.180***
	(3.93)	(5.31)	(4.24)	(8.49)	(6.09)	(3.14)	(4.36)	(4.52)
Constant	1.822***	1.658***	1.708***	1.632***	1.633***	2.130***	1.622***	1.445***
	(13.80)	(15.28)	(16.43)	(20.32)	(18.85)	(8.86)	(15.83)	(16.91)
Observations	1543	1965	1991	3496	3086	489	1941	3546
R-squared	0.56	0.57	0.56	0.60	0.56	0.58	0.53	0.58

Robust *t* statistics are in parentheses. *, ** and *** mean respectively significant at the 10%, 5% and 1% level.