THE GROWTH AND VALUATION OF GENERIC SKILLS

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Abstract

Using a method for measuring job skills derived from survey data on detailed work activities, we show that between 1997 and 2001 there was a growth in Britain in the utilisation of computing skills, literacy, numeracy, technical know-how, high-level communication skills, planning skills, client communication skills, horizontal communication skills, problem-solving and checking skills. Computer skills and high-level communication skills carry positive wage premia, as shown both in cross-section hedonic wage equations and through a within-cohorts change analysis. No part of the gender pay gap can be accounted for by differences in levels of generic skills between men and women.

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1. Introduction

Considerable attention has been paid in recent years to the proposition that several identifiable generic skills have grown in importance in the modern workplace (e.g. Darrah, 1996; Thomson *et al*, 1995; Appelbaum *et al*, 2000). This presumed importance has led the governments of many industrialised countries to attempt to improve the delivery of certain generic skills which it was felt were lacking in some sections of the workforce. In particular, there has been a policy focus on certain core skills, including communication skills, numeracy, information technology skills, problem-solving skills, and the skills necessary to work with other people.[1] In this paper we describe a methodology for estimating the extent of usage of generic skills at work, and present estimates of their recent growth in Britain and of their valuation in the labour market.

Hitherto there have been few attempts to investigate the degree of usage of such core skills and other generic skills, nor their association, if any, with labour market rewards. Generic skills are not easily quantified and are typically defined in slightly different ways from case to case. A rare example of workforce-level generic skills data is the set of numeracy and literacy scores afforded by the International Adult Literacy Survey (IALS) developed by the OECD (OECD and Statistics Canada, 1995; OECD, Human Resources Development Canada and Statistics Canada, 1997). A notable finding to emerge from analyses of these surveys is that literacy and numeracy skills are robust and strong determinants of pay (e.g. Freeman and Schettkat, 2001; Green *et al*, 2002), over and above conventional indicators of educational achievement. With this finding, the studies also follow in a small tradition of research linking pay to objective tests of one or other skill or ability, where the test emerges

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[1] The UK Government has inserted key skills into both school and the university curricula, introduced a separate Key Skills Qualification from September 2000, and explicitly embedded key skills within other qualifications.

from the school or non-work environment (e.g. Murnane *et al*, 1995). However, one drawback with the IALS is that they only cover a narrow range of generic work skills. The surveys do not, for example, collect information on problem-solving, communication or information technology skills, all of which are thought to have become increasingly important in the workplace.[2]

In this paper we examine evidence drawn from two specially designed surveys which deploy a job analysis approach that has been borrowed and adapted from commercial psychology. Our approach builds on the methods of previous studies which have used proprietary data based on job analyses by Hays and other commercial ventures (Cappelli, 1993; Cappelli and Rogovsky, 1994; O'Shaughnessy *et al*, 2001) to analyse changes in skill utilisation and their association with pay. Though very informative such studies are limited by their commercial scope - they are typically confined to large organisations and to specific occupational classes - and by the scarcity of available databases. Moreover, the range of skill scores generally available from commercial job analyses does not normally match even loosely the portfolio of core generic skills that typically enters public debate. In part to circumvent these restrictions our approach is to ask survey respondents directly about the skills they utilise in their jobs. We derive measures of a wide range of generic skills, assess their content validity and, by comparing the two surveys, use the measures to provide evidence on recent trends in the utilisation of each type of skill.

One benefit of this approach is that we are able to contribute further understanding about the impact of computing skills. Krueger (1993) suggested that the introduction of a computer generated wage rises for individual workers because it created a demand for this specific skill, and that therefore the expansion of computers was responsible for part of the increased wage inequality in the United States. Subsequent studies have, however, cast doubt

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[2] Another drawback with IALS is that the surveys are conducted only infrequently, since they tend to be

on this hypothesis (DiNardo and Pischke, 1997; Entorf and Kramarz, 1997; Haisken-DeNew and Schmidt, 1999). Fixed-effects estimations have shown that much of the impact of computer usage on wages disappears once the correlation of computers with unobserved individual heterogeneity is accounted for. What remains might only be a small wage gain deriving from experience with using computers, estimated for 1980s France at no more than about 5 percent after six years (Entorf and Kramarz, 1997), and even less in the early 1990s (Entorf *et al*, 1999). Thus, one account of the cross-section correlation found by Krueger is that more able workers are being selected to use computers, and that these workers would be highly paid anyway, because their ability makes them more productive even without computers. In all this literature, however, the information available about how computers are used is very restricted; for the most part, the results are obtained from a variable that simply distinguishes whether or not a computer is used at work.[3] There is no distinction between the levels of sophistication of computer use, or even according to how central computers are to the job. Presumably, however, one would expect computer skills to be valued (if at all) the more highly, the more complex and advanced their level of usage and the more central they are to the job. We attempt to test these hypotheses below.

The method and evidence that we present have implications with regard to planning the supply of skills, for skill-supplying institutions and for education and training policy. There are also consequences for the large and growing literature which argues that increasing wage inequality in Anglo-Saxon economies is primarily driven by skill-biased technical change. The evidence for this argument mainly rests largely on conventional, education-based,

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expensive to administer.

[3] Entorf and Kramarz (1997) are able to distinguish different types of new technology, partly related to the distinction between manual and non-manual work; however, use of microcomputers and other computer connections could presumably involve substantially varying levels of computing skills. Hildreth (2001) focuses just on the use of computers to send e-mails, and concludes that the associated premium probably reflects unobserved skills correlated with use of e-mail. Haisken-deNew and Schmidt (1999) use respondents' recollection of when computers started to be used at work, so is presumably subject to some measurement error which would bias downwards the estimates of the computer treatment effect.

measures of skills, or else on relatively crude skill measures derived from occupational class. These indicators provide only imperfect indicators of the nature of the skill-biased change in the workplace. Typically, rising wage inequality is found to be associated to a considerable extent with rising inequality within educational groups, and while these may be attributed to residual unmeasured skills or abilities the story remains unsatisfactory while such skills remain unspecified. Progress towards obtaining more satisfactory measures of skills, and investigation of their association with labour market rewards, could therefore assist over a period of time in evaluating the arguments used to explain increasing wage inequality in recent years.

After describing the data and its design principles in Section 2, we examine in Section 3 the problem of identifying and measuring skills. We use factor analysis to generate a simpler representation of a large number of detailed skills. We measure generic computing skills separately because the data affords a precise classification based both on the centrality of computer usage and on the complexity of that use. These measures are then used to provide a description of all generic skills in 1997 and 2001 in Britain and of how they changed in this interval. In Section 4, we use hedonic wage equations to compute the value of the generic skills, controlling for conventional determinants of individual wages. We also control for some firm-level fixed effects, and examine whether within-cohort changes in pay are associated with changes in individuals' skills.

2. Data and Methodology

2.1 Data

We utilise data drawn from the 1997 Skills Survey and from the 2001 Skills Survey. 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' homes, and 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 *et al* (1999) and Felstead *et al* (2002).

The questionnaires comprise a detailed investigation of the nature of the individual's job with an emphasis on the activities that the job entails. Additional information is obtained on the organisation in which the individual works, pay and changes that have occurred in the job in the last 5 years. Some background demographic information on each individual was also collected. The two questionnaires contain a core of questions asked in identical ways in the two surveys and hence it is possible to examine both the distribution and the changes in generic skills over time.[4]

2.2 Methodology

In this paper we utilise mainly the job analysis questions in order to measure the level and value of skills. Initially, we pool the data from the two survey years in order to maximise the accuracy and interpretability of our analyses, but we also consider the changes between the two years.

There are two main stages in our analysis. First, we derive measures of generic skills from the activities that individuals associate with their jobs, and present evidence on how these changed between 1997 and 2001. Second, we compute the value of these generic skills. Using the compensating wage differentials literature as an analogy, we formulate and estimate a hedonic wage equation, the coefficients of which will be the shadow prices of the particular attributes or skills.

3. Measuring Generic and Computing Skills

3.1 Derivation of Generic Skills Indicators Using Factor Analysis

Respondents were asked a large number of detailed questions about their job's characteristics. One section of the questionnaire, focussing on the activities involved in carrying out their work, was prefaced by the following statement:

> 'You will be asked about different activities which may or may not be part of your job. We are interested in finding out what types of activities your job involves and how important these are'.

Respondents were then asked: 'in your job, how important is [a particular job activity]'. The response scale offered was: 'essential', 'very important', 'fairly important', 'not very important' and 'not at all important or does not apply'. Examples of the activities included working with a team of people, working out the causes of problems or faults, making speeches or presentations and planning the activities of others. The questionnaire focused on 36 activities designed to cover the tasks carried out in a wide range of jobs (see Table A1 for details). One of these concerned the use of computers, and we shall discuss computer skills separately below. The remaining 35 items provide the main source for our analysis of all other generic skills. These items were measured in identical ways in both 1997 and 2001.

To reduce these items to an interpretable set of skills indices, a data reduction methodology is required. We utilise factor analysis, which is related to principal components analysis (PCA) (see, for example, Lawley and Maxwell, 1971, Tatsuoka and Lohnes, 1988). Though PCA is a more common procedure in economics, factor analysis is more suited to our purpose here since it produces a number of factors which capture the correlations between different job activities, and which can therefore hopefully be identified as generic job skills. In PCA, a set of variables is transformed into an *equal* number of orthogonal new variates or

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[4] The objective of comparability was integral to the design of the surveys, both of which were directed by

components which have maximum variance subject to being uncorrelated with one another.[5] In contrast, factor analysis seeks to account for the covariances between the variables in terms of a *lesser* number of hypothetical variables or factors.[6] Factor analysis proceeds by decomposing the variance of each (standardised) variable into a unique part (which is treated as a residual) and a shared part which along with the other variables' shared components, contributes to the factors identified. That is, factor analysis produces a decomposition of the variables into a set of common factors, and a residual component unrelated to these factors. We identify these common factors as our generic skills.

The factors are chosen in such a way as to capture as much of the correlation as possible in the variables (here, the 35 job activities), while also being amenable to interpretation in terms of the relevant theoretical concepts – in this case, to the concepts of generic skill types. The 35 activities detailed in Table A1 were first recast into 35 numeric variables. We transformed the ordinal scale of 'importance' for each variable into a cardinal scale, running from 1 (meaning 'essential') to 5 (meaning 'not at all important'). Then, using factor analysis, we reduced these 35 activities to 10 generic skill measures.

In order to aid interpretation of the resulting factors, we employed an oblique rotation[7] to a simpler structure to produce our factor loadings, and the estimated factor scores for each individual. The factor loading coefficients are presented in Table 1. To interpret the coefficients in this table, we can read across the rows; thus, for example, most of the sample variance in activity 27 'reading written information' (read) is accounted for by factor 1,

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[5] Typically, the first few components will account for a large proportion of the total variance of the original variables, and hence can be used to summarise the original data.

[6] That is, whereas PCA is variance-orientated, factor analysis is covariance-orientated (Lawley and Maxwell, 1971: 2-3) – or, more strictly, correlation-orientated since it uses the standardised variables. Moreover, in PCA the components are defined as linear combinations of the variables, whereas in factor analysis, the observed variables are linear combinations of the hypothesised factors.

[7] We used the Promax method, with a power of 4, though the results are not greatly sensitive to the choice of this parameter. Note that this (oblique) rotation does not preserve the original orthogonality of the factors. However,

although factor 5 also has quite a high weight in determining this activity.[8] The resulting rotation satisfies many of the criteria originally suggested by Thurstone (1947) for a simplified factor structure. In particular, each activity contributes a high loading to at most one factor. To illustrate this fact, we have highlighted (in bold) factor loadings greater than 0.4 in magnitude. It can be seen that each activity variable has a loading greater than 0.4 for at most one factor (with the exception of activity 32: 'writing long documents' (writelg) which has a loading greater than 0.4 for two activities), and each factor has a loading of greater than 0.4 for only a few activities. Only a very small number of activities are not well-defined by the rotated factors. Hence the activities differentiate the factors, and the factors are differentiated by the activities. This is therefore a simpler structure than that given by the original factor loadings.

Having identified the factors more clearly following the rotation to this simpler structure, we now seek to interpret these factors which correspond to the notion of 'generic skills'. At the bottom of Table 1, we have labelled the columns according to a taxonomy which is based on the activities which have the highest loadings. Recall that the activities are scaled 1 to 5 (high to low) so that for factor 1, for example, the analysis has in fact identified *non*-literacy skills since this factor has a high *positive* loading on reading and writing activities. Hence we simply multiply the resulting score by -1 to produce our measure of literacy skills. A similar transformation is necessary in order to use the nomenclature that we have attached to the interpretation of the 2nd, 7th, 8th and 10th factors.

Standard practice for factor analyses requires an element of judgement by the researcher over the choice of factor extraction method, how many factors to retain, how to rotate those

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in this particular case, since we would not want our generic skills to be orthogonal to one another, this is an advantage of the rotation method rather than a disadvantage.

[8] More precisely, the variance in activity 27 'reading written information' (read), once normalised to unity, is decomposed into a sum of squared factor loadings plus a residual which is its unique component. Thus (0.75^2+0.26^2=) 63% of the variation in reading written information can be accounted for by factor 1 and factor 5.

factors to a simpler structure, and how to generate factor scores. We have chosen to define 10 generic skills for a number of reasons. First, this number of retained factors generated easily interpretable skill-types. Second, the same set of factors were found whether we use just males, just females or the whole sample, and whether or not we restricted the sample to either 1997 or 2001 only. Thirdly, the selection of 10 factors is also (weakly) supported by the scree test as first suggested by Cattell (1966), although this is not decisive since it indicates a gradual slope after just the first two factors. Finally, a preliminary PCA indicated that 10 components would account for 70% of the variance of the activities which, while arbitrary, seemed quite a high proportion given the wide variation in factor-utilisation between individuals.[9] We used the principal factors method for extraction and we used the regression method for deriving factor scores. Fortunately, the outcomes were not greatly sensitive to the choices made. Similar patterns were obtained using other methods of extraction and factor scoring.

Thus the factor analysis generates a taxonomy of generic skills as follows:

1. literacy skills	both reading and writing forms, notices, memos, signs, letters, short and long documents etc.
2. physical skills	the use of physical strength and/or stamina
3. number skills	adding, subtracting, division, decimal point or fraction calculations etc., and/or more advanced maths or stats procedures
4. technical know-how	knowing how to use tools, equipment or machinery, knowing about products and services, specialist knowledge and/or skill in using one's hands
5. high-level communication	a range of related managerial skills, including persuading or influencing others, making speeches or presentations, writing long reports, analysing complex problems in depth
6. planning skills	planning activities, organising one's own time and thinking ahead
7. client	dealing with people, selling a product or service, counselling or

[9] The analysis presented below is not particularly sensitive to the precise choice of the number of factors. A further reduction to 8 factors rather than the 10 utilised in the analysis below identifies a very similar set of generic skills; essentially, the physical skills are combined with the technical know-how to give a generic 'manual dexterity' skill category, and the problem-solving skills are combined with the checking skills to produce a generic 'problem searching and solutions' skill. The other 6 skill categories listed above are still separately identifiable after rotation of the factors.

	communication	caring for customers or clients
8.	**horizontal communication**	teaching or training and/or working with a team of people, listening carefully to colleagues
9.	**problem-solving**	detecting, diagnosing, analysing and resolving problems
10.	**checking skills**	noticing and checking for errors

These 10 generic skill measures emerging from this analysis largely match our priors about the types of skills involved in jobs. Moreover, their inter-relationships also seem to confirm our expectations. The first 10 rows of Table 2 present the correlations between the estimated generic skills. Non-manual generic skills are highly correlated with each other as one might anticipate. Physical skills are negatively correlated with all other generic skills except technical know-how.[10]

As with other job-based indicators of skill (such as occupation), it is possible for the skills of job-holders to differ from the skills required to do the jobs, at least in the short term. The job analysis method provides a direct measure of job skills but only a proxy measure for the skills of the job-holder. If a job-holder's skills are inadequate for the job, it might be expected that over time they may acquire the necessary skills through training or on-the-job learning, or else move to another more suitable job. But it is also possible that poor job performance could be tolerated for some time. Similarly, a job-holder might have skills in excess of those required for the job. In that case, there is an incentive for the job-holder to transform the job, or to move jobs to gain more satisfaction and a greater reward for the skills that they have, but labour market frictions could prevent such adjustments from happening. Thus, it should be noted that when we refer to generic skills in this paper, this is a measure of job skills used in the job, and only a proxy for the individual job-holder's skills.[11]

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[10] All the correlation coefficients in Table 2 are significantly different from zero at the 1% level or better.

[11] From the perspective of human capital theory this is a disadvantage of our method, to be traded off against the advantage of being able to generate a range of generic skill indicators not otherwise available. However, from the perspective of other theories of wage determination, such as job queuing theory, the characteristics of the job

3.2 The Distribution and Growth of Generic Skills

Before proceeding with the analyses, we first ask whether the generic skills measures have a plausible correspondence to standard measures of skills based on occupation and education. A breakdown of the generic skills by occupation is provided in Table 3. Note that, by construction each index has a zero mean across all observations. It is apparent that there is indeed a good correspondence between broad occupational classification and the generic skill indices. For example, those engaged in managerial occupations are using above average levels of high-level communication, planning and client communication skills. Managers are similar in this regard to those engaged in professional occupations, but the latter are characterised by higher levels of literacy and high-level communication and lower levels of client communication. Workers in craft occupations utilise both physical skills and what we have termed technical know-how, and can be contrasted with operatives and other elementary occupations which, while also demanding physical skills, require little in the way of technical know-how, and score well below average on communication skills. Client communication skills are important to those in sales-based occupations, but are apparently not combined with other skills dimensions unlike those in managerial occupations. Thus the measures of generic skills appear to be sensibly related to occupations, while providing a richer and more detailed classification in terms of what skills different occupations utilise.

A similar breakdown by highest level of education attained and by gender is provided in Table 4. Most of the non-manual generic skills we have identified strongly increase monotonically with educational qualifications. This is as would be expected for literacy and numeracy since these are formally tested with educational qualifications, but is perhaps more

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assume greater importance. Indeed, there is some evidence from IALS that measures of job skills are at least as important as measures of individuals' skills in the determination of wages (Green *et al*, 2002).

surprising for some of the other measures of generic skills. The widest variation in generic skills across education is for high-level communication skills.

There are only very small differences in the mean levels of literacy skills used by men and women in their jobs, but there are larger and significant differences in numeracy, technical know-how and problem-solving skill utilisation, all of which men use more in their jobs than women. Men also utilise more physical skills than women as expected, but less communication skills, with the exception of high-level communication. The latter is undoubtedly related to occupational differences as seen above.[13]

The change in the usage of generic skills over time is shown in Table 5. With the exception of physical skills, the average level of every generic skill that we have identified from the factor analysis has significantly increased between 1997 and 2001. While some of these differences appear small, they are all significantly positive at the 1% level as shown by the t-statistics and p-values presented in the second and third columns of the table. These changes confirm the often-cited increased demand for generic job skills in recent years. A longer time span of data, only to be gleaned from future surveys, would be able to confirm whether the growth of generic skills represents a genuine trend or is a reflection of a short-term cyclical movement. However, it is worth noting that the growth of generic skills is not merely the result of a higher skilled younger generation replacing a lesser skilled cohort of retirees from the workforce. To demonstrate this, Table 5 also presents results from a decomposition of the 1997-2001 change into a within-cohort change and a between-cohort change.[14] Three cohorts are defined as: older workers born before 1941 (and hence 'retired' by 2001 since they are over 60 years of age); 'prime age' workers born between 1941 and

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[13] Felstead *et al* (2001) show that it is especially part-time jobs, mainly held by women, which utilise lower levels of most generic skills.

[14] There is also a very small residual due to changing cohort sizes.

1977 (and hence present in both surveys); and, finally, younger workers born after 1977 (and hence not present in the 1997 survey since they are less than 20 years old). The within-cohort change is dominant in all cases where the generic skill has significantly grown. Although the changes are gradual, it does appear that existing cohorts of workers are moving to higher levels of generic skills usage.

3.3 The Distribution and Growth of Computing Skills

To measure computing skills, two questions were asked of the respondents in both 1997 and 2001 about their use of information technology. Alongside the job activity variables analysed above, individuals were asked:

> 'how important is using a computer, 'PC', or other types of computerised equipment?',

again using the 5 point scale ranging from 'essential' to 'not at all important'. As shown in Table 6, Panel A, the proportion reporting that computer use was *essential* in their job increased from just over 30% in 1997 to almost 40% in 2001, an increase of one third, while the proportion reporting that computer use was 'not at all important' fell by one third from 30% to just over 20%. These are large changes given that the surveys were administered only 4 years apart, signalling an ongoing rapid diffusion of computing technologies.[15]

For those respondents who reported *some* computer usage, a subsidiary set of questions was asked about their computing skills and other qualifications. One of these questions related to the complexity with which computers were used within their jobs:

> 'Which of the words in CAPITALS best describes your use of computers or computerised equipment in your job?
> STRAIGHTFORWARD (for example, using a computer for straightforward routine procedures such as printing out an invoice in a shop);
> MODERATE (for example, using a computer for word-processing and/or spreadsheets or communicating with others by 'email');

[15] The rapidity of diffusion also implies that international comparisons of computer use need to consider seriously the dates for comparison.

COMPLEX (for example, using a computer for analysing information or design, including use of computer aided design or statistical analysis packages);
ADVANCED (for example, using computer syntax and/or formulae for programming).'

The responses to this question are shown in Table 6, Panel B. Despite the rapid spread of computer usage to wider sections of the workforce, there is no evidence that the average level of complexity of use is falling. Indeed, there has been an increase in the complexity of computing usage at the less sophisticated end of the range with a shift in the proportion reporting 'straightforward' usage to those reporting 'moderate' usage on the basis of the above scale.[16] At the more advanced end of the range of complexity, there has been little change between the two survey dates.

3.4 Measuring Task Discretion and Variety

The Skills Surveys also ask a number of other questions pertaining to generic features of jobs that are normally seen as relating to skills utilised in the job. These include task discretion and variety. Task discretion is seen as a skill, because if employers are to act without close supervision, they must know what tasks are to be done and how to do them. Task discretion is also a reflection of trust by the line manager/employer in the conformity of the employee to appropriate effort norms. For these reasons, task discretion has long been an important focus for sociological enquiry since the work of Braverman (1974) and subsequently Friedman (1977) and Spenner (1990). While variety in the tasks to be employed is related to task discretion, since more discretion (which in itself entails greater skill) is likely to facilitate efficient switching between tasks, variety is also likely to require a wider range of skills. Earlier analysis has shown that there has been some diminution over the last decade in

[16] For a detailed descriptive analysis of the growth of computing skills over 1997 to 2001, and of further aspects of computing and internet skills in 2001, see Felstead *et al* (2002). The association of the growth of computing in Britain with the growth in the demand for skills is shown in Green *et al* (2002).

the extent of task discretion in British workplaces (Felstead *et al*, 2002). Nevertheless, it will be of interest to examine whether task discretion and more task variety are associated with a wage premium: to the extent that they are each linked with, and proxying for, a generic skill that is not otherwise captured by other indices, one would expect to find a wage premium associated with the higher productivity that they potentially afford. However, both discretion and variety are also presumably valued attributes of jobs, for which employees would willingly concede a negative compensating differential. The balance of effects ought therefore to be a matter for empirical investigation.

We derived a discretion index from the responses to five questions. The first asked respondents directly:

> 'How much choice do you have over the way in which you do your job?'

The other four questions asked respondents how much influence they personally had on: 'deciding what tasks to do', 'how you are to do the task', 'how hard you work', and 'the quality standards to which you work'. Each question offered a four-point response scale. A factor analysis was conducted on these five variables, with one factor being retained. The factor score was then used as the discretion index.[17]

Task variety is measured in the surveys by summing the 5-point responses to the questions:

> 'How often does your work involve carrying out short, repetitive tasks?' and
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> 'How much variety is there in your job?'

and standardising (i.e. zero mean and unit variance) the resulting index.

4. Hedonic Wage Equations

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[17] In practice, this procedure did not produce results greatly different from taking a simple unweighted average of the standardised responses to the five variables.

We now turn to consider the value of the skills indices that we have identified in the factor analysis. We can regard these indices as similar to job attributes in the empirical analysis of compensating wage differentials. In such studies, it is common practice to specify a reduced form relationship between wages and a vector of job attributes, the estimated coefficients of which are the shadow prices of those attributes (e.g. Lucas, 1977; McNabb, 1989). Competitive equalisation of workers' utilities across jobs then generates positive shadow prices for job attributes which are unpleasant, and *vice versa*. Analogously, in our skills analysis, given perfect competition in the labour market, and all firms with equal marginal rates of substitution between skills types, then the relative values of the coefficients on skills are estimates of their relative supply prices.[18] Hence our basic framework for "valuing" skills is to estimate a hedonic wage equation including the vector of generic and other skills. [19]

4.1 The Value of Skills

Table 7 reports the coefficients from the estimates of a hedonic wage equation for the two waves of the Skills Survey pooled together. The dependent variable is the log of real gross hourly wages[20], augmented by 10% for those individuals reporting that their employer also contributes to a pension scheme.[21] The regressors shown are the generic and computing skills described above. One problem is that it is likely that not all aspects of any job are fully

[18] Of course, in a dynamic context, the price of slow-to-adjust skills will move above or below their supply price delivering quasi-rent to the holders of any scarce skills. Arguably computing skills fall into this category given that the demand has risen rapidly.
[19] Our data do not permit us to attempt to identify separate supply or demand processes underlying the valuation of skill The achievement of valuation can be thought of as arising from the 'assignment' problem which is concerned with the allocation of individuals (and their skills) to the jobs available (see Roy, 1950, 1951, Sattinger, 1975, Heckman and Sedlacek, 1985, and Sattinger, 1993 for a comprehensive survey). These endogenous selection processes are difficult to deal with satisfactorily in a cross-section without making very strong distributional or functional form assumptions (see e.g. Teulings, 1995) or restricting attention to very simplistic models.
[20] Wages are deflated by the RPI index to 1997 prices, and trimmed by 0.5% at the top of the distribution to remove the impact of extreme outliers.

captured by the job attributes questions in a survey of this kind. One way to attempt to capture any missing skills might be to estimate a standard Mincerian earnings function and augment this by our measures of skills. Yet, to the extent that (the output of) schooling is highly correlated with many of the observed skills, this is less than ideal. Since the problem of unobserved variables is typically non-trivial in estimates of hedonic price equations, we attempt to mitigate any bias induced by unobserved job skill attributes by including a number of control variables. Of course, these control variables will also capture the impact of the usual institutional and contractual characteristics of jobs on wages. The regressions therefore also include: a dummy for gender; a quadratic in potential work experience; control variables for the highest education level achieved; whether the job involves shift work; whether the job involves supervising or managing others; whether the job is normally done 'almost exclusively' by the opposite gender; whether the job is part-time, or temporary, in the private or public sector; whether the job is located in a firm with more than 25 employees; and 17 industry dummies (1-digit SIC92 classification); and 11 regional dummies.

Column (1) of Table 7 presents the coefficients on all of the generic skills, and on discretion and variety. For comparison with previous studies, computing skills are represented in this column by a simple (1,0) computing usage dummy variable. Activities which are associated with a positive and significant (at 5% or better) impact on pay are high-level communication, planning, task discretion, variety and computing usage. Given that our measures of skills (other than computing) have unit variance, and the dependent variable is log wages, the coefficients represent the proportionate increase in pay for a one standard deviation increase in each of the measures of skills. Thus, an individual with high-level communication skills which are one standard deviation above the mean enjoys an 8.5% higher

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[21] None of the substantive results presented below are sensitive to the omission of this allowance for pension contributions.

level of rewards than an individual with the mean level of high-level communication skills in the sample.

Activities which are associated with lower pay are physical skills, numerical skills and client communication. The negative coefficient on physical skills is perhaps not surprising. A partial explanation is that many manual skills such as physical stamina have a relatively low (or even zero) supply price. More importantly, manual activities are negatively correlated with other observed and unobserved activities which use positively valued skills. That is, where physical skills are particularly important, workers are typically not using other more highly valued skills.

That numerical skills attract a (small) negative premium is at first sight surprising, especially given other evidence which suggests the increasing importance of mathematics skills (Dolton and Vignoles, 1999) and of cognitive skills (Murnane *et al*, 1995), of which numerical skills are a crucial and tangible component. The answer to this apparent puzzle lies in the fact that numerical skills are highly correlated with computing skills and in the substantial positive impact of computing skills.[22] The simple computer usage dummy indicates that computer users have a 14% pay premium, approximately the same order of magnitude as has been found in similar studies for other countries.

The coefficients on the control variables conform to prior expectations. Conditional on industry and region, pay increases monotonically with the required qualifications to do the job, and is higher if the job involves shift work, managing or supervising others, if it is predominantly done by men or located in a larger firm (more than 25 employees). In contrast, pay is lower if the job is predominantly done by women, or if it is part-time or in the private sector. There is a concave relationship between pay and experience, with a peak in the age-

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[22] As shown in Table 2, computing complexity has its highest positive correlation with numerical skills, while computing usage has its second highest positive correlation with numerical skills (second to literacy).

earnings profile (evaluated at the sample means) after approximately 30 years of work experience.

In column (2), we replace the simple computer usage dummy with indicators of the different levels of computing complexity (‘straightforward’, ‘moderate’, ‘complex’ and ‘advanced’), the omitted (base) category being those who do not use computers at all as in column (1). It is found that higher levels of computing complexity are associated with higher wage premia. The differences between the estimated coefficients for successive levels of complexity are all highly significant, with the exception of ‘moderate’ usage and ‘complex’ usage which yield a similar return. This increasing profile of wages with computing complexity suggests that using a simple (1,0) computer usage dummy to capture any wage effects associated with computers is likely to be misleading. It is evident, for example, that using a computer for programming purposes receives a substantively greater premium than using it for sending email.[23] This is plausible and sensible, yet cannot be discerned from previous studies which have no measure of the complexity with which computers are utilised.

We also investigated at this stage whether the centrality of computers to the job also had an association with wages. A plausible expectation is that computer usage is likely to be more highly associated with wages when computers are regarded as ‘essential’ to the job, than when they are used but seen as ‘not very important’. In a separate analysis (not shown) this expectation is confirmed. However, the centrality scale of computer usage is very highly correlated with the complexity scale (see Table 2). We also therefore investigated whether the centrality of computer usage had any link with wages after controlling for the complexity level. By interacting the complexity measure with an indicator of whether computers are regarded as being of high-importance (‘essential’ or ‘very important’) or low-importance

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[23] For example, individuals with the highest level of computing skills (advanced) receive a wage premium for this skill of 24%, which is much greater than those with the most straightforward usage who receive a premium of only 11%.

('fairly important' or 'not very important'), we can test whether the premium to complexity differs according to the centrality/importance of usage. An F-test for the equality of the returns to each of the four levels of complexity according to whether computing has high/low importance yields an F-statistic of $F(4,5127) = 0.67$ ($p = 0.61$), and hence we can conclude that conditional on complexity of use, the centrality of usage carries no additional premium. This is further evidence in favour of the importance of assessing the tasks for which computers are being used in order to estimate the wage premium that accrues to computing – it is not the centrality of computing *per se* that carries the premium, but rather the nature of the tasks for which they are used that is important.

Columns (3) and (4) of Table 7 separate male and female employees. The reason for investigating this split is the possibility that the associations of the skills with wages could differ according to gender. However, while there is a large unaccounted for difference in pay between the jobs in which men and women are employed, in general the returns to the various activities/skills are quite similar.[24] The exception is the greater returns to computing complexity that women receive, although there are rather fewer women than men who work in jobs which require the highest two levels of complexity. These higher returns to computing complexity result in the differences between the skills returns for men and women being (marginally) jointly significant (significant at 10% although not at 5%).[25]

Differences in the levels and prices of skills contribute to the differences in mean pay of men and women. A conventional index of discrimination is that part of the gender pay gap that cannot be attributable to differences in skills. Standard analyses represent skills differences between men and women in terms of schooling and work experience measures, leaving unmeasured skills unaccounted for. The generic skills measures available in this study

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[24] In a pooled regression, a test of the equality of returns for men and women to the 10 generic skills plus task discretion and variety is not rejected at conventional levels: $F(12,5115) = 1.45$; $p = 0.14$.

constitute a substantive proportion of the skills that are unmeasured in conventional studies of discrimination. Given that the levels of most generic skills differ between men and women, it is of interest as to whether the measures of generic skills also contribute to the gender pay gap, and hence affect the conventional index of discrimination. To investigate this question, we used the coefficients in columns (3) and (4) of Table 7 to calculate a standard Oaxaca (1973) decomposition of the gender pay gap. Of the 26 percentage point difference in (log) pay between men and women (which equates to a 30% raw pay gap), 82% can be attributed to differences in skills and other attributes such as schooling and experience, while the remaining 18% results from differences in the rates of return to skills and these other attributes. Thus our measure of discrimination in pay is $(18 \times 30\% =) \, 5.4\%$.[26] However, omitting the 16 different measures of skills *reduces* the proportion of the gap that is unexplained from 18% to 14%. This finding suggests that it may not be reasonable to attribute any of the residual pay gap in conventional studies to unobserved skills. If anything, the additional skills which we have been able to account for work marginally in favour of females, thereby not reducing but marginally increasing measured discrimination when generic skills are included.

4.2 Extensions

There are two sets of issues raised by the estimates discussed up to this point. First is the question as to whether estimates of the values in a cross-section potentially capture treatment effects, rather than non-causal associations attributable to unobserved variables.

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[25] In a pooled regression, a test of the equality of returns for men and women to the 10 generic skills plus task discretion and variety and the 4 levels of computing complexity yields: F(16,5115) = 1.61; p = 0.06.
[26] While this is on the low side of recent estimates of the degree of discrimination, we are able to account for a very large number of differences in the jobs that men and women do that contribute to the pay gap, including education, experience, part-time, shift work, industry, region, etc.

Second is the question as to whether it is ideal to assume, as we have so far, that skill values are uniform across different segments of the economy.

To several commentators it has seemed unlikely that presenting workers with a computer should of itself generate higher wages. The suspicion that, rather, higher ability (hence higher paid) workers were selected for computer usage has been confirmed in previous studies. Thus, the computer skills premium, though a genuine and robust association, cannot be used as evidence of skill-biased technological change altering the wage structure. Similarly here, the premium for, say, higher-level communication skills might not be attributable to a rising demand for communication skills. All that can be said is that people in jobs using these skills (and whatever unobserved factors they are proxies for) receive higher pay.

Part of the case against computers having a causal effect has been that computer use dummy variables have similar effects to the usage of other 'tools', such as pencils, which also showed a return using German data (Dinardo and Pischke, 1997). Since the return to the use of pencils was not plausibly a treatment effect, one should not accept that computers are either. However, in the data we have used here we have controlled for a much greater range of job attributes and characterised the complexity of the way in which computers are used. If we had left out these other attributes, our findings would be similar to that of Dinardo and Pischke. For example, the apparent return to writing short documents is high: a dummy variable set to one if this is an essential or very important part of the job attracts a highly significant coefficient of 0.174, when augmenting the simple Mincerian wage equation plus industry and regional controls. However, the coefficient becomes small and insignificant, as expected, when the full set of generic skill scores are included. The same story holds for other apparently trivial activities, such as reading short documents. But the association of higher pay with computing does not go away, nor does the positive association with more complex computer usage, when all skill scores are included. Moreover, this has been a period of rapid expansion of computer usage in Britain. Thus, the Dinardo and Pischke criticism does not appear to hold when there is a fuller description of job attributes available in the data.

Hence, notwithstanding the panel-based estimates elsewhere, it remains possible that requiring computer usage in a job may indeed generate higher pay in the less regulated contemporary British labour market. Such an effect need not be instantaneous, since transferable computer skills learned on the job would presumably raise workers' marginal productivity over time.

4.2.1 Establishment Effects

One possible source of bias is that jobs requiring more complex computer usage are likely to be more frequent in establishments where more advanced technology is deployed. Since there is a known association between individual wages and the level of technology used by firms (e.g. Liu *et al*, 2001; Black and Lynch, 2000), the complexity measure could be picking up an establishment effect on wages, rather than the impact of the individual's job characteristics.[27]

To investigate this possibility, we include in column (5) of Table 7 a variable which measures the degree of utilisation of computers at the individuals' workplace. We use the responses to the question:

> 'In your workplace, what proportion of employees work with computerised or automated equipment?'

to construct a banded measure of firm-level computing (less than 25% of employees, between 25% and 75% of employees, more than 75% of employees). Unfortunately, this question was only asked in 2001 Skills Survey. As can be seen in column (5), this variable has a monotonic and significantly positive effect on wages. Its presence also reduces the coefficients on the

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[27] Entorf and Kramarz (1997), however, found no evidence of *unobserved* firm-level fixed effects in France in the 1980s.

individual complexity variables[28], suggesting that part of the premium associated with computer use lies not so much with personal computing skills as with the (technological) characteristics of the firm.

4.2.2 Within-Cohort Estimates

It is always possible that an additional part of the premium could be associated with other, unobserved, firm fixed effects. Moreover there remain possible unobserved individual fixed effects. Does the observed return to high-level communication skills mean that someone acquiring and using these skills can, other things equal, gain higher pay? Or are these skills just proxies for some other set of abilities that are in any case receiving a premium? Ideally a panel of individual data would assist us in resolving this question. Currently, no such panel exists which includes the array of generic skills measures and our ranked indicators of computer skills.

In its absence, an alternative procedure is feasible, which should generate estimates that are less precise but less likely to be biased by the presence of unobserved heterogeneity than the conventional cross-section estimates. We calculate the change in average skills used in a group of similar jobs (for shorthand, a 'job') between 1997 and 2001 and use this as a proxy for the changes in skills of workers doing the same job. Changes in pay can then be regressed against changes in skills to determine the extent to which increases in pay are rewards to increases in skills. We define 'jobs' by occupation and age and gender. More precisely, we computed means for our skills for 9 occupation groups × 8 age groups (at approximately 5 year intervals with an adjustment for the youngest and oldest cohorts of workers in our sample) × 2 gender groups, for each of the two survey years. Thus, an example of a cohort would be female sales workers aged between 44 and 48 in 1997 and 48 to 52 in 2001. The

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[28] For the 2001 data, the coefficients on the computing complexity variables excluding the firm-level computing measure are 0.106, 0.170, 0.173 and 0.265 for the four levels of complexity (straightforward, moderate, complex

144 'jobs' form the basis for our analysis. This cohort analysis is formally equivalent to the construction of a pseudo-panel (Deaton, 1985) and requires the assumption that the workers in the job are similar at both time points. Some of the cell sizes are rather small, especially for the 1997 survey, and we investigate the sensitivity of our results to different ways of dealing with these small cell sizes below.

Table 8 presents hedonic wage equation for the change in (log) pay in these jobs between 1997 and 2001. Column (1) includes the changes in the skills between the two surveys, with computing complexity measured as a simple index (0 denotes 'computers not used', through to 4 for 'advanced' usage), together with regional proportions to control for the impact of (changes in the) geographical distribution of jobs. The constant term indicates that real wages grew by about 8% over this period. Around 35% of this change can be explained by changes in skills (plus regional effects), although few of these changes are individually statistically significant. The most important contributory factors are the increases in high-level communication skills and computing skills. These are the two skills which had the largest positive premia in the cross-section estimates. The estimates imply that an occupation/gender/age cohort which moves to acquire and use in their jobs greater amounts of these skills will gain a genuine wage premium. A tentative conclusion, therefore, is that an increase in demand for either computing skills or high-level communication skills could have significant effects on the wage structure. All other skill indicators, however, carry insignificant coefficients.

Column (2) also includes a number of the control variables that we considered previously in the pooled regression. Around half of the change in real wages is explained by changes in skills, education, experience, and the nature of employment (part-time etc). Once again, computing skills are shown to be important in explaining increases in pay.

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and advanced respectively).

While the conclusions from the results presented in Table 8 are necessarily tentative given the small number of observations per cell and the low degrees of freedom in the regressions, they are robust to alternative specifications of the regression and to omission of observations based on only a few individuals - computing skills always remain a significant determinant of changes in wages over the period under investigation.

4.2.3 Skill Values Within Occupations

Implicit in the above analysis is the assumption that all skills and job attributes are valued and therefore priced identically across all sectors of the economy. Yet we have already seen in Table 3 that there are considerable differences in the mean levels of generic skills across occupation. Given that an individual's portfolio of skills cannot be unbundled and sold in different occupations, it is possible that skills will not be equally valued in all occupations. Even if unbundling were possible, skill could attain different values in different occupations either as a quasi-rent owing to fluctuations in demand or more permanently because of market segmentation. The results in Table 7 can therefore be regarded as indicative of the average value of skills in the workforce, but a more detailed valuation, obtained by disaggregating by occupation, is also potentially informative.

The first column of Table 9 replicates the results from Table 7 column (2) for comparison, while the remaining columns of Table 9 present the same regression separately for each of the major occupational groups.[29] These estimates give, then, for each occupation, the value of each job skill conditional on being utilised in that occupation.[30] A number of features are evident. First, while literacy skills are negatively valued for managers, they carry

[29] There are small cell sizes (5 or fewer individuals) for level 4: advanced computing usage in occupational groups 6, 7, 8 and 9, and also for level 3: complex computing usage in occupational group 9 and hence these are omitted.

[30] Because skills affect selection into occupations, the coefficients do not give unbiased estimates of skill values. For example, part of the value of high-level communication skills is likely to derive from being selected into an occupation where that skill is in high demand. There is no sensible way of separately identifying this selection process with the data.

a positive premium for operatives and workers in other elementary occupations where they are used. However, as shown in Table 3, on average, operatives and, especially, workers in elementary occupations typically utilise very low level of literacy skills in their jobs. Moreover, it is to be expected that literacy skills are poorest amongst those in lower level manual occupations. A possible interpretation therefore is that literacy skills are valued in these occupations because, although utilised less, they are in scarcer supply. Secondly, physical skills carry a negative premium in all occupations except elementary occupations where the coefficient is insignificant. Thus, the negative premium in the overall results is not simply a proxy for occupation. Rather, within each occupation the use of physical skills are likely to suggest low levels of other unobserved skills. Thirdly, high-level communication skills are rewarded in the higher occupational classes (managerial, associate professional and clerical) only, possibly reflecting a high relative demand for these skills in higher ranked occupations, though the association is far from perfect. Fourth, variety is positively valued within several occupations, but discretion only receives a significant premium for managers and operatives. Finally, the returns to computing complexity are mainly increasing in complexity, although for professionals the computing premium does not differ by complexity, and for associate professionals and for elementary occupations, the premium is small and insignificant.

That there may be differences in the returns to individuals' characteristics across sectors because of the impossibility of renting different skills to different employers has been long recognised: see, for example, Mandelbrot (1962) and Heckman and Scheinkman (1987). The latter present empirical evidence that rejects the uniform pricing of individuals' observed and unobserved attributes/characteristics in sub-sectors of the US economy. While we do not have the panel data necessary to implement the type of test developed by Heckman and Scheinkman, we can formally test the equality of the returns to the observed measures of skills under consideration in this paper. Table 11 presents the results of the tests for the equality of the return to each of our measures of skills across the 9 occupation groups for the pooled data as considered in Table 9. As can be seen, the results here are mixed; some skills are valued similarly across occupational sectors, while others are valued quite differently. Of the skills that are positively valued in Table 9, high-level communication, planning and task variety receive significantly different returns in different sectors while the largest dissimilarities are for the price/return to computing skills.

Table 10 replicates Table 9 except that it includes the measure of firm-level computing which is available in 2001 only. Most of the pattern noted above still holds. However, it is apparent that the premium on individual computing skills for managers, associate professional, skilled trades and sales workers have become insignificant. For these occupations, the impact of technology, as captured by the indicator for widespread computing, is quite large. In respect of managers, this finding is consistent with the conjecture of Bresnahan (1999) and Bresnahan *et al* (2002) that the impact of computing on managers' skills and wages is to be found, not in individual computer use, but rather in computers' interaction with complementary managerial skills which underpin innovative activities to raise productivity.[31]

5. Conclusion

One of the main intended contributions of this paper is methodological. By adapting practices commonly used in commercial psychology to the requirements of a social survey, we have shown that it is feasible to collect indicators of a considerably wider range of skills than hitherto achieved. One advantage of this method, which could be utilised by researchers

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[31] It is notable that high-level communication skills are strongly positively correlated with the proportion of computers at the workplace, and that this correlation is stronger amongst managers than among other occupational groups.

anywhere, is that the obtained indicators are available at the cost of sufficient time within a high quality survey. The disadvantage is that the indicators are derived from job requirements, rather than the individual job-holders' own skills. The latter can only be measured directly by a more costly testing process. However, testing would also bring restrictions on the scope and generality of the obtainable skills measures. In contrast, an advantage of the job analysis method is that it can cover a wide range of generic job skills. Also, it is possible to devise indicators of computing skills that can take into account the varying complexity of the different ways that computers are used.

This methodology has allowed us to address several empirical issues surrounding the growth and valuation of skills. The large number and the richness of the skill measures, together with many other individual-level and firm-level controls, go some way to addressing problems of unobserved heterogeneity that are potentially present in previous studies. Moreover, by regressing within-cohort wage changes against changes in skills between two comparable surveys, it has been possible to go further by removing unobserved fixed effects, though at the cost of some precision in the estimates compared to what would be feasible in an individual panel. Our main new findings are:

(a) We have confirmed the findings of case studies, that there is an upward movement in most generic skills – the exception being physical skills. Computing skills especially stand out as expanding rapidly.

(b) Both high-level communication skills and computing skills carry positive wage premia in hedonic wage equations that control for many other indicators of skill, conventional and otherwise. Moreover, advanced and complex usages of computers earn a higher premium than more straightforward usage. That this finding differs from earlier findings for France and Germany is attributable to any or all of: having richer data on computing and other job skills, applying it in the context of Britain's flexible labour markets at a (different) time with very rapid diffusion of computing technology, or through our lack of comparable panel data. However, the fact that the computing effect remains with the analysis of changes within cohorts suggests that the lack of an individual-level panel may not be the prime reason.

(c) Over and above the impact of the job-holder's actual job tasks, the extent to which the establishment's work force uses computers is associated with higher pay. Together with b), this finding is consistent with previous studies linking new technology with pay.

(d) There are significant differences, as one might expect, between the generic skills in jobs held by men and by women. However, these differences do not contribute to accounting for any of the unexplained gender pay gap that is conventionally attributed to discrimination.

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Table 1

Factor Loading Coefficients based on Rotated Factors

factors:	factor1	factor2	factor3	factor4	factor5	factor6	factor7	factor8	factor9	factor10
activity:										
1detail	0.03	-0.10	0.00	-0.15	0.11	-0.11	0.03	0.12	-0.03	0.26
2people	0.06	-0.04	0.03	0.06	0.02	-0.09	**0.55**	0.12	0.03	-0.06
3teach	-0.04	0.11	0.01	0.03	-0.36	0.06	0.07	**0.45**	-0.08	-0.01
4speech	0.10	0.00	0.04	0.06	**-0.65**	-0.01	0.16	0.04	0.08	0.03
5persuad	-0.01	0.05	0.00	0.09	**-0.48**	-0.07	0.31	0.08	-0.05	0.03
6selling	-0.15	0.06	-0.11	-0.11	-0.20	0.12	**0.69**	-0.21	0.05	0.08
7caring	0.14	0.05	0.07	0.03	-0.11	0.06	**0.61**	0.04	0.01	-0.02
8teamwk	-0.04	-0.03	-0.01	-0.02	-0.06	0.12	-0.07	**0.81**	0.07	0.02
9listen	0.04	-0.09	0.01	-0.05	0.01	0.05	-0.03	**0.73**	0.02	0.00
10strengt	0.02	**0.80**	0.01	-0.07	0.01	0.02	0.04	-0.05	-0.04	-0.02
11stamina	0.02	**0.80**	0.03	-0.05	-0.06	-0.06	0.07	-0.03	0.01	0.01
12hands	-0.03	0.38	0.03	**-0.53**	0.05	0.04	-0.11	0.03	0.04	0.04
13tools	-0.02	0.21	0.01	**-0.65**	0.10	0.03	-0.13	0.08	0.05	-0.02
14product	-0.04	-0.03	-0.05	**-0.55**	0.04	0.02	0.39	-0.06	0.00	-0.02
15special	0.10	-0.13	0.05	**-0.41**	-0.12	-0.17	0.11	0.01	-0.12	-0.09
16orgwork	0.13	-0.10	0.01	-0.09	0.03	-0.09	0.20	0.23	-0.07	-0.01
17faults	0.01	0.04	-0.01	0.02	0.13	0.09	-0.04	0.03	**-0.77**	0.16
18cause	-0.04	0.01	-0.02	0.03	0.04	0.05	-0.04	-0.03	**-1.00**	-0.01
19solution	0.02	-0.02	0.01	0.01	-0.07	-0.07	0.01	-0.08	**-0.83**	-0.04
20analyse	0.14	-0.07	0.00	-0.13	-0.39	-0.06	-0.06	-0.04	-0.26	0.03
21noerror	0.02	-0.01	0.00	0.01	-0.07	0.00	0.00	-0.01	-0.02	**0.83**
22mistake	-0.01	0.01	0.01	0.04	-0.03	-0.03	0.01	0.02	-0.04	**0.83**
23planme	-0.03	0.01	-0.01	0.02	-0.06	**-0.90**	-0.05	-0.11	0.01	0.01
24planoth	-0.05	0.14	-0.08	0.10	-0.36	-0.27	-0.04	0.30	-0.04	-0.04
25mytime	-0.02	-0.03	0.01	0.01	0.00	**-0.92**	-0.04	-0.09	0.06	0.02
26ahead	0.06	0.06	-0.03	-0.03	0.04	**-0.72**	-0.01	0.05	-0.01	-0.01
27read	**0.75**	0.10	-0.05	-0.01	0.26	-0.06	0.04	0.05	-0.01	0.03
28short	**0.82**	-0.05	0.00	0.00	0.10	-0.01	0.01	0.07	-0.01	-0.02
29long	**0.74**	-0.02	0.04	-0.09	-0.26	0.05	-0.02	-0.03	0.01	-0.02
30write	**0.82**	0.13	-0.05	0.06	-0.02	0.06	0.04	-0.04	0.00	0.01
31writesh	**0.76**	-0.03	0.00	0.09	-0.25	-0.01	-0.03	-0.06	-0.02	0.00
32writelg	**0.57**	-0.07	0.03	0.00	**-0.50**	0.01	-0.08	-0.08	0.10	0.06
33calca	-0.01	0.03	**-0.84**	0.05	0.15	-0.03	0.11	-0.01	-0.03	0.03
34percent	0.01	-0.04	**-0.87**	0.00	0.01	-0.02	-0.01	0.00	-0.02	-0.03
35stats	0.07	-0.03	**-0.62**	-0.09	-0.23	0.06	-0.14	0.04	0.05	-0.02
taxonomy of generic skills:	literacy skills	physical skills	number skills	technical know-how	high-level communication	planning skills	client communication	horizontal communication	problem-solving	checking skills

Notes:
1. Source: Skills Survey 1997 and 2001.
2. For a full description of activities, see Appendix Table A1.
3. Factor loading coefficients greater than 0.4 in magnitude are shown in bold.
4. Analysis is based on 6936 pooled observations from the Skills Surveys of 1997 and 2001.

Table 2

Correlations between Generic Skills and Computing Skills

		1 literacy skills	2 physical skills	3 number skills	4 technical know-how	5 high-level communication	6 planning skills	7 client communication	8 horizontal communication	9 problem-solving	10 checking skills	11 computing usage
1	literacy skills	1.000										
2	physical skills	-0.312	1.000									
3	number skills	0.513	-0.266	1.000								
4	technical know-how	0.427	0.227	0.468	1.000							
5	high-level communication	0.590	-0.340	0.504	0.259	1.000						
6	planning skills	0.708	-0.202	0.457	0.393	0.663	1.000					
7	client communication	0.600	-0.225	0.354	0.294	0.534	0.659	1.000				
8	horizontal communication	0.683	-0.056	0.303	0.415	0.553	0.654	0.678	1.000			
9	problem-solving	0.604	-0.065	0.486	0.716	0.526	0.662	0.467	0.667	1.000		
10	checking skills	0.528	-0.075	0.458	0.691	0.194	0.446	0.317	0.503	0.768	1.000	
11	computing usage	0.433	-0.498	0.418	0.181	0.390	0.339	0.284	0.285	0.310	0.316	1.000
12	computing complexity	0.453	-0.506	0.461	0.193	0.518	0.378	0.262	0.282	0.337	0.260	0.793

Notes:

1. For the 10 continuous generic skills (literacy skills to checking skills), the correlations reported are Pearsonian correlation coefficients.
2. Computing usage (row 11) is measured as an index running from 0 (‘not at all important’) to 4 (‘essential’) and hence the correlations reported are Spearman rank order correlation coefficients. See text for details.
3. Computing complexity (row 12) is measured as an index running from 0 (‘computers not used’) to 4 (‘advanced’) and hence the correlations reported are Spearman rank order correlation coefficients. See text for details.
4. All the correlation coefficients in the table are significantly different from zero at the 1% level.

Table 3 Mean Levels of Generic Skills by 1-Digit Occupation Classification

	generic skills:	managers etc	professionals	associate professionals	clerical	craft etc	personal and protective	sales	operatives	elementary
		1-digit Occupation Classification								
1	literacy skills	0.33	0.62	0.38	0.16	-0.29	-0.14	-0.30	-0.55	-0.98
2	physical skills	-0.37	-0.50	-0.34	-0.50	0.72	0.40	-0.08	0.64	0.78
3	number skills	0.51	0.44	0.09	0.07	-0.00	-0.54	0.06	-0.32	-0.85
4	technical know-how	0.06	0.04	0.16	-0.15	0.63	-0.33	-0.13	0.04	-0.51
5	high-level communication	0.56	0.88	0.39	-0.31	-0.27	-0.22	-0.29	-0.65	-0.72
6	planning skills	0.52	0.60	0.37	-0.12	-0.16	-0.20	-0.36	-0.59	-0.81
7	client communication	0.50	0.30	0.24	-0.05	-0.43	0.02	0.48	-0.63	-0.82
8	horizontal communication	0.28	0.40	0.29	-0.04	-0.23	0.11	-0.21	-0.40	-0.75
9	problem-solving	0.33	0.38	0.30	-0.11	0.26	-0.26	-0.42	-0.29	-0.83
10	checking skills	0.12	0.10	0.21	0.23	0.23	-0.35	-0.19	-0.07	-0.75

Note: The measures of generic skills each have a mean of zero and a standard deviation of one.

Table 4 Mean Levels of Generic Skills by Highest Education Level Attained and Gender

		Highest Education Level Attained						**Gender**	
	generic skills:	No qualification	NVQ Level 1	NVQ Level 2	NVQ Level 3	sub-degree	degree	male	female
1	literacy skills	-0.56	-0.33	-0.08	0.04	0.40	0.48	0.01	-0.01
2	physical skill	0.48	0.40	0.06	0.05	-0.25	-0.64	0.09	-0.12
3	number skills	-0.43	-0.30	-0.09	0.10	0.35	0.35	0.15	-0.16
4	technical know-how	-0.22	-0.01	-0.03	0.17	0.18	-0.03	0.19	-0.20
5	high-level communication	-0.55	-0.35	-0.22	-0.03	0.43	0.72	0.09	-0.11
6	planning skills	-0.56	-0.28	-0.12	0.04	0.40	0.48	0.05	-0.06
7	client communication	-0.43	-0.22	-0.00	0.04	0.25	0.28	-0.05	0.06
8	horizontal communication	-0.38	-0.23	-0.04	0.02	0.29	0.27	-0.03	0.03
9	problem-solving	-0.44	-0.19	-0.07	0.10	0.31	0.28	0.12	-0.13
10	checking skills	-0.30	-0.13	0.03	0.12	0.19	0.09	0.07	-0.05

Note: All the gender differences in skills are significantly different from zero at the 1% level with the exception of literacy skills.

Table 5 Changes and Decomposition of Mean level of Skills in 1997 and 2001

	generic skills:	Change 1997-2001	t-test for difference τ	p-value	proportion within cohort
1	literacy skills	0.118	4.95	0.00	0.96
2	physical skills	0.003	0.14	0.89	0.40
3	number skills	0.067	2.89	0.00	0.92
4	technical know-how	0.103	4.71	0.00	0.87
5	high-level communication	0.090	3.99	0.00	0.89
6	planning skills	0.126	5.41	0.00	1.00
7	client communication	0.063	2.89	0.00	0.91
8	horizontal communication	0.123	5.49	0.00	0.88
9	problem-solving	0.116	4.89	0.00	0.92
10	checking skills	0.084	3.65	0.00	0.82

Note: The change in the level of skill between 1997 and 2001 is decomposed into a within-cohort change and a between-cohort change (and a residual which captures the impact of changing cohort sizes). The final column of the table presents the proportion of the change in skill which is attributable to the within-cohort change. See text for further details.

Table 6 Centrality and Complexity of Computing Usage

A: Importance of using a computer, PC or other type of computerized equipment

year:	1997 (%)	2001 (%)	Total
essential	30.8	39.7	36.5
very important	14.8	14.8	14.8
fairly important	12.2	13.8	13.3
not very important	11.7	10.5	10.9
not at all important	30.5	21.1	24.5
Number of obs.	*2488*	*4448*	*6937*

B: Complexity of use of computers or computerized equipment

year:	1997 (%)	2001 (%)	Total
Straightforward	38.1	30.6	33.2
Moderate	39.1	45.8	43.5
Complex	17.7	17.2	17.4
Advanced	5.1	6.4	6.0
Number of obs.	*1669*	*3259*	*4928*

Table 7

Estimates of Hedonic Wage Equations: Skills Activities plus Other Controls

	(1) 1997 & 2001	(2) 1997 & 2001	(3) 1997 & 2001	(4) 1997 & 2001	(5) 2001 only
	All employees	All employees	Male employees	Female employees	All employees
literacy skills	-0.002 (0.009)	-0.002 (0.009)	-0.008 (0.013)	0.003 (0.012)	-0.009 (0.011)
physical skills	-0.094 (0.008)***	-0.085 (0.008)***	-0.102 (0.012)***	-0.069 (0.010)***	-0.081 (0.010)***
number skills	-0.022 (0.007)***	-0.024 (0.007)***	-0.027 (0.011)**	-0.020 (0.009)**	-0.011 (0.009)
technical know-how	0.018 (0.010)*	0.013 (0.010)	0.019 (0.015)	0.006 (0.012)	0.002 (0.012)
high-level communication	0.085 (0.009)***	0.079 (0.009)***	0.085 (0.015)***	0.077 (0.012)***	0.089 (0.012)***
planning skills	0.051 (0.009)***	0.049 (0.009)***	0.036 (0.015)**	0.052 (0.012)***	0.050 (0.012)***
client communication	-0.062 (0.009)***	-0.056 (0.009)***	-0.063 (0.014)***	-0.034 (0.012)***	-0.050 (0.012)***
horizontal communication	0.021 (0.011)*	0.019 (0.011)*	0.030 (0.017)*	-0.002 (0.015)	0.009 (0.015)
problem-solving	-0.009 (0.011)	-0.007 (0.011)	-0.006 (0.018)	-0.005 (0.014)	-0.008 (0.015)
checking skills	-0.001 (0.010)	-0.001 (0.010)	0.006 (0.015)	-0.002 (0.012)	-0.011 (0.013)
discretion	0.014 (0.006)**	0.013 (0.006)**	0.020 (0.009)**	0.004 (0.008)	0.015 (0.008)**
variety	0.043 (0.005)***	0.042 (0.005)***	0.044 (0.008)***	0.035 (0.007)***	0.046 (0.007)***
computing usage$	0.136 (0.014)***	-	-	-	-
computing complexity $ level 1: straightforward	-	0.113 (0.014)***	0.090 (0.022)***	0.115 (0.019)***	0.076 (0.020)***
computing complexity$ level 2: moderate	-	0.171 (0.016)***	0.144 (0.024)***	0.193 (0.021)***	0.131 (0.022)***
computing complexity$ level 3: complex	-	0.169 (0.020)***	0.167 (0.028)***	0.174 (0.028)***	0.128 (0.027)***
computing complexity$ level 4: advanced	-	0.244 (0.028)***	0.204 (0.036)***	0.299 (0.049)***	0.213 (0.035)***
firm-level computing$ level 2: 25-75%	-	-	-	-	0.046 (0.018)***
firm-level computing$ level 3: more than 75%	-	-	-	-	0.101 (0.018)***
constant	1.391 (0.062)***	1.238 (0.062)***	1.249 (0.084)***	1.430 (0.094)***	1.258 (0.084)***
Number of observations R-squared	5191 0.60	5191 0.60	2592 0.56	2599 0.62	3294 0.60

Notes:

1. All regressions in Table 7 also include: a dummy for gender; a quadratic in potential work experience; control variables for highest education level achieved (5); whether the job involves shift work (1), or supervising or managing others (2); whether the job is normally done 'almost exclusively' by the opposite gender (2); whether the job is part-time (1), or temporary (1), or in the private or public sector (1); whether the job is located in a firm with more than 25 employees (1); 17 industry dummies (1-digit SIC92 classification); and 11 regional dummies.
2. Standard errors in parentheses; $ denotes dummy variable.
3. * denotes significant at 10%; ** denotes significant at 5%; *** denotes significant at 1%.

Table 8

Changes in the Value of Skills

	(1) All employees	**(2) All employees**
literacy skills	0.036 (0.069)	0.086 (0.070)
physical skills	-0.054 (0.062)	0.019 (0.068)
number skills	-0.042 (0.055)	0.020 (0.058)
technical know-how	0.089 (0.084)	0.018 (0.089)
high-level communication	0.190 (0.064)***	0.125 (0.069)*
planning skills	-0.019 (0.077)	-0.082 (0.077)
client communication	-0.060 (0.073)	-0.043 (0.071)
horizontal communication	0.065 (0.087)	0.044 (0.088)
problem-solving	-0.071 (0.085)	0.012 (0.086)
checking skills	-0.053 (0.081)	-0.051 (0.083)
discretion	0.024 (0.047)	0.050 (0.047)
variety	-0.009 (0.040)	-0.030 (0.041)
computing complexity index (0-4)	0.127 (0.042)***	0.105 (0.043)**
constant	0.082 (0.017)***	0.163 (0.049)***
Observations R-squared	144 0.34	144 0.50

Notes:

1. Dependent variable is the change in (log) pay; independent variables are the change in the mean skills and other control variables for each of the 144 age-gender-occupation groups. See text for details.
2. Column (1) also includes 11 regional effects. Column (2) also includes: a quadratic in potential work experience; control variables for highest education level achieved (5); whether the job involves shift work (1), or supervising or managing others (2); whether the job is normally done 'almost exclusively' by the opposite gender (2); whether the job is part-time (1), or temporary (1), or in the private or public sector (1); whether the job is located in a firm with more than 25 employees (1); and 11 regional effects.
3. Standard errors in parentheses.
4. Regressions are weighted least squares, with weights proportional to the number of observations in each age-gender-occupation group.
5. * denotes significant at 10%; ** denotes significant at 5%; *** denotes significant at 1%.

Table 9

Occupation-Specific Value of Skills, 1997 and 2001

	SOC:	1	2	3	4	5	6	7	8	9
	All occs.	Managers	Profs.	Ass. profs.	Clerical	Craft	Personal	Sales	Operatives	Elementary
literacy skills	-0.002 (0.009)	-0.091 (0.032)***	-0.011 (0.032)	-0.017 (0.029)	-0.026 (0.017)	0.001 (0.027)	0.020 (0.022)	0.025 (0.028)	0.054 (0.025)**	0.048 (0.024)**
physical skills	-0.085 (0.008)***	-0.121 (0.029)***	-0.073 (0.027)***	-0.086 (0.027)***	-0.083 (0.016)***	-0.103 (0.028)***	-0.049 (0.022)**	-0.073 (0.027)***	-0.074 (0.023)***	0.027 (0.023)
number skills	-0.024 (0.007)***	-0.043 (0.024)*	-0.033 (0.021)	-0.032 (0.021)	-0.014 (0.013)	-0.007 (0.023)	-0.031 (0.022)	0.007 (0.026)	-0.038 (0.022)*	0.014 (0.027)
technical know-how	0.013 (0.010)	-0.052 (0.034)	0.011 (0.033)	0.027 (0.032)	0.055 (0.017)***	0.010 (0.040)	0.038 (0.025)	0.038 (0.036)	0.075 (0.031)**	-0.021 (0.026)
high-level communication	0.079 (0.009)***	0.166 (0.033)***	0.034 (0.033)	0.132 (0.031)***	0.053 (0.018)***	0.021 (0.032)	0.009 (0.026)	-0.009 (0.031)	0.037 (0.028)	0.010 (0.030)
planning skills	0.049 (0.009)***	0.078 (0.041)*	-0.006 (0.042)	-0.008 (0.036)	0.059 (0.018)***	0.066 (0.030)**	0.044 (0.023)*	0.082 (0.029)***	0.003 (0.023)	-0.015 (0.021)
client communication	-0.056 (0.009)***	-0.069 (0.032)**	-0.020 (0.033)	-0.111 (0.033)***	-0.062 (0.017)***	-0.069 (0.032)**	-0.062 (0.031)**	-0.023 (0.035)	-0.059 (0.027)**	-0.053 (0.024)**
horizontal communication	0.019 (0.011)*	0.054 (0.039)	-0.038 (0.040)	0.047 (0.039)	0.015 (0.022)	0.031 (0.036)	0.034 (0.035)	0.040 (0.037)	0.011 (0.029)	0.059 (0.027)**
problem-solving	-0.007 (0.011)	-0.054 (0.042)	-0.001 (0.038)	-0.021 (0.037)	-0.024 (0.020)	0.005 (0.044)	-0.070 (0.029)**	0.002 (0.034)	0.012 (0.031)	-0.050 (0.027)*
checking skills	-0.001 (0.010)	0.053 (0.036)	0.018 (0.031)	0.000 (0.034)	-0.012 (0.021)	0.007 (0.037)	0.040 (0.023)*	-0.110 (0.032)***	-0.033 (0.025)	0.034 (0.022)
discretion	0.013 (0.006)**	0.052 (0.026)**	0.025 (0.021)	-0.028 (0.022)	0.010 (0.011)	-0.017 (0.020)	0.013 (0.017)	0.012 (0.019)	0.033 (0.016)**	0.005 (0.013)
variety	0.042 (0.005)***	0.036 (0.018)*	0.046 (0.018)**	0.032 (0.017)*	0.019 (0.011)*	0.055 (0.017)***	0.044 (0.013)***	0.002 (0.018)	0.006 (0.014)	0.012 (0.013)
computing complexity$ level 1: straightforward	0.113 (0.014)***	0.109 (0.066)	0.200 (0.081)**	0.056 (0.054)	0.103 (0.050)**	0.062 (0.038)	0.043 (0.034)	0.039 (0.039)	0.103 (0.033)***	0.016 (0.039)
computing complexity$ level 2: moderate	0.171 (0.016)***	0.152 (0.065)**	0.179 (0.078)**	0.068 (0.056)	0.151 (0.049)***	0.122 (0.048)**	0.150 (0.041)***	0.183 (0.050)***	0.088 (0.049)*	0.014 (0.064)
computing complexity$ level 3: complex	0.169 (0.020)***	0.181 (0.072)**	0.164 (0.084)*	0.048 (0.064)	0.116 (0.054)**	0.192 (0.061)***	0.122 (0.072)*	0.154 (0.075)**	0.240 (0.071)***	-
computing complexity$ level 4: advanced	0.244 (0.028)***	0.188 (0.085)**	0.205 (0.093)**	0.100 (0.077)	0.296 (0.079)***	0.167 (0.088)*	-	-	-	-
Number observations R-squared	5191 0.60	736 0.52	606 0.35	608 0.43	930 0.43	498 0.52	519 0.60	400 0.62	515 0.50	379 0.56

Table 10: Occupation-Specific Value of Skills, 2001

	SOC:	1	2	3	4	5	6	7	8	9
	All occs	Managers	Profs.	Ass. profs	Clerical	Craft	Personal	Sales	Operatives	Elementary
literacy skills	-0.009 (0.011)	-0.090 (0.041)**	-0.008 (0.040)	-0.005 (0.036)	-0.036 (0.022)	-0.020 (0.038)	0.018 (0.028)	0.028 (0.034)	0.057 (0.036)	0.075 (0.034)**
physical skills	-0.081 (0.010)***	-0.096 (0.038)**	-0.023 (0.036)	-0.104 (0.034)***	-0.075 (0.021)***	-0.097 (0.036)***	-0.053 (0.030)*	-0.091 (0.031)***	-0.068 (0.030)**	0.016 (0.032)
number skills	-0.011 (0.009)	-0.026 (0.030)	-0.019 (0.027)	-0.049 (0.026)*	0.016 (0.017)	0.024 (0.032)	-0.028 (0.028)	0.014 (0.033)	-0.046 (0.028)*	0.017 (0.034)
technical know-how	0.002 (0.012)	-0.049 (0.042)	-0.036 (0.042)	0.051 (0.038)	0.044 (0.023)*	-0.014 (0.052)	0.034 (0.031)	0.014 (0.045)	0.092 (0.040)**	-0.056 (0.035)
high-level communication	0.089 (0.012)***	0.167 (0.042)***	0.047 (0.043)	0.172 (0.038)***	0.043 (0.024)*	-0.001 (0.040)	-0.013 (0.033)	-0.033 (0.039)	0.007 (0.036)	-0.013 (0.044)
planning skills	0.050 (0.012)***	0.104 (0.052)**	0.020 (0.057)	-0.014 (0.044)	0.037 (0.022)*	0.044 (0.039)	0.052 (0.028)*	0.093 (0.037)**	-0.031 (0.032)	-0.006 (0.030)
client communication	-0.050 (0.012)***	-0.095 (0.040)**	0.001 (0.044)	-0.138 (0.042)***	-0.040 (0.023)*	-0.057 (0.044)	-0.013 (0.040)	-0.006 (0.044)	-0.035 (0.037)	-0.051 (0.032)
horizontal communication	0.009 (0.015)	0.049 (0.050)	-0.119 (0.055)**	0.009 (0.054)	0.026 (0.030)	0.069 (0.052)	-0.003 (0.046)	0.033 (0.050)	-0.017 (0.040)	0.085 (0.038)**
problem-solving	-0.008 (0.015)	-0.091 (0.054)*	-0.001 (0.048)	-0.026 (0.047)	-0.032 (0.028)	-0.025 (0.062)	-0.046 (0.039)	0.049 (0.043)	0.057 (0.042)	-0.088 (0.039)**
checking skills	-0.011 (0.013)	0.032 (0.048)	0.010 (0.041)	0.011 (0.042)	-0.014 (0.029)	0.062 (0.047)	0.024 (0.033)	-0.159 (0.042)***	-0.075 (0.036)**	0.042 (0.031)
discretion	0.015 (0.008)**	0.047 (0.032)	0.013 (0.027)	-0.032 (0.026)	0.034 (0.015)**	0.001 (0.025)	0.012 (0.020)	0.018 (0.023)	0.025 (0.022)	0.026 (0.020)
variety	0.046 (0.007)***	0.046 (0.023)*	0.058 (0.024)**	0.024 (0.022)	0.033 (0.015)**	0.057 (0.023)**	0.031 (0.016)*	0.012 (0.021)	0.010 (0.020)	-0.006 (0.019)
computing complexity$ level 1: straightforward	0.076 (0.020)***	0.083 (0.094)	0.355 (0.131)***	0.052 (0.080)	0.135 (0.067)**	0.044 (0.053)	0.039 (0.044)	-0.038 (0.053)	0.056 (0.046)	0.047 (0.052)
computing complexity$ level 2: moderate	0.131 (0.022)***	0.092 (0.092)	0.292 (0.128)**	0.015 (0.081)	0.201 (0.067)***	0.097 (0.062)	0.140 (0.055)**	0.073 (0.063)	0.087 (0.066)	0.021 (0.080)
computing complexity$ level 3: complex	0.128 (0.027)***	0.145 (0.102)	0.287 (0.135)**	-0.029 (0.091)	0.197 (0.073)***	0.123 (0.084)	0.172 (0.087)**	0.069 (0.086)	0.250 (0.091)***	-
computing complexity$ level 4: advanced	0.213 (0.035)***	0.102 (0.119)	0.303 (0.144)**	0.089 (0.103)	0.429 (0.101)***	0.114 (0.118)	-	-	-	-
firm-level computing$ level 2: 25-75%	0.046 (0.018)***	0.057 (0.061)	0.054 (0.082)	0.069 (0.061)	0.049 (0.045)	0.008 (0.045)	-0.030 (0.045)	0.036 (0.055)	-0.023 (0.043)	0.007 (0.045)
firm-level computing$ level 3: more than 75%	0.101 (0.018)***	0.137 (0.059)**	0.085 (0.081)	0.124 (0.063)**	0.083 (0.042)**	0.124 (0.059)**	0.042 (0.046)	0.095 (0.052)*	0.026 (0.050)	-0.006 (0.055)
Number observations R-squared	3294 0.60	487 0.55	407 0.37	424 0.46	580 0.46	299 0.52	329 0.62	257 0.73	289 0.55	222 0.57

Notes to Table 8 and Table 9:

1. All regressions in Table 8 and Table 9 also include: a dummy for gender; a quadratic in potential work experience; control variables for highest education level achieved (5); whether the job involves shift work (1), or supervising or managing others (2); whether the job is normally done 'almost exclusively' by the opposite gender (2); whether the job is part-time (1), or temporary (1), or in the private or public sector (1); whether the job is located in a firm with more than 25 employees (1); 17 industry dummies (1-digit SIC92 classification), and 11 regional dummies.
2. Standard errors in parentheses; $ denotes dummy variable.
3. * denotes significant at 10%; ** denotes significant at 5%; *** denotes significant at 1%.

Table 11

Testing the Equality of Returns to Skills by Occupation

Skill Measure	F-test	p-value
literacy skills	F(8,5003) = 4.47	p = 0.00
physical skills	F(8,5003) = 1.94	p = 0.05
number skills	F(8,5003) = 1.91	p = 0.05
technical know-how	F(8,5003) = 1.68	p = 0.10
high-level communication	F(8,5003) = 3.39	p = 0.00
planning skills	F(8,5003) = 2.52	p = 0.01
client communication	F(8,5003) = 0.84	p = 0.57
horizontal communication	F(8,5003) = 0.62	p = 0.76
problem-solving	F(8,5003) = 1.01	p = 0.42
checking skills	F(8,5003) = 2.22	p = 0.02
discretion	F(8,5003) = 1.22	p = 0.28
variety	F(8,5003) = 2.15	p = 0.03
computing: level 1	F(8,5003) = 18.93	p = 0.00
computing: level 2	F(8,5003) = 15.01	p = 0.00
computing: level 3	F(8,5003) = 6.47	p = 0.00
computing: level 4	F(8,5003) = 2.55	p = 0.01
All skills	F(128,5003) = 4.44	p = 0.00

Note:
The F-tests report the value of the test statistic (together with its p-value) for the equality of the return to each skill across the 9 major occupation groups.

Table A1

Description and Classification of Job Activities

The questionnaire is worded as follows:

> "You will be asked about different activities which may or may not be part of your job. We are interested in finding out **what activities your job involves and how important these are**."

	activity	In your job, how important is …
1	detail	… paying close attention to detail?
2	people	… dealing with people?
3	teach	… instructing, training or teaching people, individually or in groups?
4	speech	… making speeches or presentations?
5	persuad	… persuading or influencing others?
6	selling	… selling a product or service?
7	caring	… counselling, advising or caring for customers or clients?
8	teamwk	… working with a team of people?
9	listen	… listening carefully to colleagues?
10	strengt	… physical strength (for example, to carry, push or pull heavy objects)?
11	stamina	… physical stamina (to work for long periods on physical activities)?
12	hands	… skill or accuracy in using your hands or fingers?
13	tools	… knowledge of how to use or operate tools, equipment or machinery?
14	product	… knowledge of particular products or services?
15	special	… specialist knowledge or understanding?
16	orgwork	… knowledge of how your organisation works?
17	faults	… spotting problems or faults?
18	cause	… working out the cause of problems or faults?
19	solutn	… thinking of solutions to problems?
20	analyse	… analysing complex problems in depth?
21	noerror	… checking things to ensure that there are no errors?
22	mistake	… noticing when there is a mistake?
23	planme	… planning your own activities?
24	planoth	… planning the activities of others?":
25	mytime	… organising your own time?
26	ahead	… thinking ahead?
27	read	… reading written information such as forms, notices or signs?
28	short	… reading short documents such as short reports, letters or memos?
29	long	… reading long documents such as long reports, manuals, articles or books?
30	write	… writing material such as forms, notices or signs?
31	writesh	… writing short documents?
32	writelg	… writing long documents with correct spelling and grammar?
33	calca	… adding, subtracting, multiplying or dividing numbers?
34	percent	… calculations using decimals, percentages or fractions?
35	stats	… calculations using more advanced mathematical or statistical procedures?