THE VALUE OF SKILLS

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Abstract

Many commentators have argued that "key skills" are becoming more important in modern workplaces. This paper draws on a survey that uses a methodology based on job analysis to measure skills at work, and estimates their implicit prices using a hedonic wage equation. The main new findings are that:

- Computer skills are highly valued in the current British labour market. Even at "moderate" levels of complexity, for example using word-processing packages, workers using computers earn an average premium (after controlling for other job skills) in excess of 20 per cent, compared to those who do not use computers at all.
- Professional communication and problem-solving skills are also highly valued. A one-standard-deviation increase in either type of skill raises pay by around 5 per cent, after allowing for all the controls. To a lesser extent, verbal skills also carry a pay premium for women. But planning, and client and horizontal communication skills, have little independent association with pay. Numerical skills also have no conditional link with pay, other than through being associated with more complex computer usage.
- Jobs involving task variety earn more pay, but there is no strong evidence that greater autonomy is positively rewarded.
- Participating in Quality Circles and, more tentatively, in organised work teams attracts a pay premium.
- Jobs which require a long learning time, which deploy transferable skills, and/or for which there are higher qualifications requirements command a higher pay.
- A reasonably complete job analysis provides a useful means of accounting for a wage distribution via a hedonic wage equation.

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1. Introduction

There is accumulating evidence that we live in an era of skill-biased technical change, in which people with higher levels of education and in the traditionally more skilled occupations constitute increasing proportions of the labour force (e.g. Machin, 1996; Machin and Van Reenen, 1998). Skill-biased technical change has also constituted a prime candidate for explaining increased wage inequality, especially in the United States (e.g. Katz and Murphy, 1992).

At the same time, work sociologists and economists have argued that particular identifiable work skills have acquired special importance in the context of current technical changes and global competitiveness. Most obviously, information technology (IT) skills are argued to be in increasing and pervasive demand in many industries (e.g. Ducatel, 1994) and indeed we are said to be living in an information society (Castells, 1998). There is also evidence of increasing demand for cognitive skills in the US, as shown by a rising impact of objective maths scores on wages (Murnane *et al*, 1995). But it is not just technical skills that are thought to be at a premium in the modern economy. As trade pressures increase, it is argued that companies need increasingly to have the capacity to innovate and keep ahead of competition. Since this cannot be achieved by old-style 'Fordist' forms of work organisation, there is increasing demand for the skills associated with 'post-Fordist' workplaces (e.g. Reich, 1988). Good communication - whether with customers or within organisations - has positive value for the firm, and hence the associated skills are scarce. Problem-solving skills are now important throughout the workforce, not just for managers (who used to be the sole repositories of knowledge). HR professionals are said to regard social skills as being as important as more easily quantifiable academic qualifications (Austin Knight, 1998). Workers are said to need to be able to work independently, at a range of tasks, planning their own time, as well as to fit in and contribute to teams. These various attributes, both technical and social, are commonly referred to as 'core skills' or 'key skills', though the jargon concepts and precise typologies differ from one consultancy study to another (CBI, 1995; DfEE and Cabinet Office, 1996). Usually included are such personal qualities as honesty, loyalty and/or self-motivation. It is commonly proposed that there is an increasing demand for many or all core skills in the industrialised economies, linked in part to observed changes in work organisation, in part to technology (International Labour Office, 1998).

Because the demand for workers with IT skills has outstripped the rising supply, computer users have been enjoying a share of technological rents (Krueger, 1993; Reilly, 1995). The rents are manifest in wage equations which show computer-users getting higher wages than non-computer-users, even after controlling for education and work experience. The wage premium, which is partly a cost of acquisition and partly a quasi-rent due to rising demand, arises because employees can credibly threaten to quit for higher wages elsewhere. Unfortunately, it is not yet clear how far the higher wages of computer users is due to their computing skills or whether people with higher abilities (hence higher pay) are selected to use computers but would have received higher pay even if they had not been 'treated' with computers (DiNardo and Pischke, 1997). Some French evidence favours the latter interpretation (Entorf and Kramarz, 1997).

If other key skills, not just IT skills, are proposed to be in increasing demand, one might expect to find that they too enjoy a premium in the labour market. However, in the case of some of the other skills the process by which a higher wage could emerge is less clear than in the case of IT skills. Many skills fall into the category of general training that is only imperfectly observable by potential recruiters (Katz and Ziderman, 1990). The costs for recruiters of finding out about a person's complex range of skills, in situations involving group working, other unknown inputs and random shocks, lead to a substantial asymmetry of information between current employers and potential external employers. With computer usage, it is presumably fairly easy for employees to signal and recruiters to determine their capabilities. Interpersonal skills, for the most part uncertifiable, are much harder to demonstrate. One should expect therefore that the impact of any key skill on pay is affected not only by its acquisition cost and the state of demand but also by the extent to which the skill can be easily signalled to the external labour market. To take an example close to home, the lecturer's skill in teaching is less easy to signal than skill in research, which has more easily measured outcomes. Research 'stars', particularly on the American private university labour market, command very much higher wage premiums than good teachers.

In the case of computers, the published literature primarily relates to North America, France and Germany, and does not systematically assess the complexity of computer usage. Apart from computer usage, there has been no systematic investigation of the link between the other commonly listed key skills and pay. Of some interest, Bynner (1994) finds positive relations of income with, separately, the skills of writing, speaking, planning, keyboard, computing, counselling, teaching, supervising, calculating, selling, understanding finance, and organising. He also finds negative relations between income and, separately, the skills of using tools, constructing things and caring. However, these relations would be unlikely all to appear in the context of a multivariate analysis, since such skills are likely to be correlated. Moreover, Bynner relies perforce on questions which ask respondents to assess “how good” they are at each skill, a strategy that lays itself open to the full force of social desirability bias in the responses. Though suggestive, these findings do not give a reliable guide as to how the above skills are valued on the labour market.

The problem of skill measurement extends beyond the question of the link of skills with pay, to the issue of trends in the skill distribution of the workforce. Studies of the skill-biased technical change hypothesis rest perforce (through lack of alternative data) mainly on educational attainment or broadly-defined occupation status as indices of skill. Unfortunately, neither education qualifications nor occupational status are ideal as measures of skills used in the workplace (e.g. see Ashton and Green, 1996, for a detailed critique). While skills may change within occupational groups, it is also well-known that qualifications held may bear only a loose connection with work skills. Employers’ qualification requirements can also be artificially inflated at times of rising supply (Robinson and Manacorda, 1997).

This paper draws on a survey of skills used in the British workforce, that combines broad measures of education and occupation with measures derived from a job analysis methodology of particular types of skills used at work. In previous work with colleagues (Green *et al*, 1998) tentative evidence has been presented for an increase between 1992 and 1997 in computing skills, problem-solving skills, some communication and social skills, and of declines in the usage of manual skills in Britain. Unfortunately, this evidence cannot be confirmed until such time as another survey may be undertaken. Nevertheless, the direction of change is consistent with robust evidence based on broader skills measures confirming an upskilling of the British workforce between 1986 and 1997. In parallel research to that reported here, the link with technology and trade effects is being investigated.

This paper is focused on the valuation of skills. Ultimately, a research objective of future years will be to see whether particular skills have rising or falling value, providing the sort of labour market information that might then illuminate and inform policy with respect to the skill-supplying institutions. For the present, the aim is to investigate the extent to which the particular kinds of skills emphasised by work analysts are actually being validated in the labour-market. A further aim is to investigate how far the methodology that has been developed for measuring skills in large-scale surveys can be additionally validated by this labour market analysis. For the method to be useful it should be capable of explaining a large amount of the variation in work rewards. To offer improvement it should be able to perform at least as well as traditional human capital models. The paper therefore addresses two broad questions:

- In addition to computer skills, which key skills (if any) are positively valued in the labour market?
- Does a job analysis methodology provide a useful way to account for the distribution of wages?

There being no complex theory to expound, and virtually no existing studies apart from those mentioned above, the paper proceeds immediately to describe the data and the principles underlying the job analysis approach. Section 4 reports an analysis designed to produce several skill indices for use in subsequent analysis, and gives a basic description of some key skills in Britain. Section 5 reports estimates of skills values based on hedonic wage equations, and Section 6 discusses the findings and concludes.

2. The Data

The data used to address these questions are drawn from the Skills Survey, a specially commissioned survey focusing on the skills of the British workforce. The achieved sample comprised 2,467 individuals aged 20 to 60 in paid work at the time of interview in February/March 1997. The sample was drawn as follows.

First, postal districts were stratified by sub-region, socio-economic group profile, and unemployment rate. Then postal districts, postal sectors, and, finally, delivery points (i.e. addresses) were randomly selected. At each delivery point, the number if any of eligible people was established, and one was selected at random for interview. The descriptive tables reported in this paper utilise data weighted by the conditional probability of selection for interview, 1/E, where E is the number of eligible individuals at each address. Interviewers were subject to quality control procedures, including approximately 10 per cent of interviews being ‘back-checked’ by telephone or post. The face-to-face interviews averaged 40 minutes in length. Of those selected for interview, 67.1% took part, with the main reason for not taking part being refusal.

Full details of the data and methodology are being published in Ashton *et al* (forthcoming). For the purposes of this paper, the next two sections summarise the essential steps taken to derive usable empirical measures of skills.

3. Investigating Skills Using Job Analysis

The approach used in the Skills Survey for measuring skills was designed by an interdisciplinary team, drawing on theoretical constructs from economics, sociology and psychology.[1] In each of these disciplines there is a literature utilising implicit and sometimes explicit definitions of skill - with sociology emphasising the social as well as the technical nature of skill (e.g. Sturdy *et al*, 1992). In order to be able to address issues in all of the above literatures, an encompassing conceptual framework was utilised, around the general definition of skills as "characteristics of an individual, including work-based situational factors, which influence the quantity and quality of work performance". A review of the literatures led to the following general typology of skills which informed the questionnaire: intellectual skills, interpersonal skills, physical skills, knowledge, motivation/reliability and work attitudes/conditions.

For the measurement of these types of skills, the survey adopted an innovative approach. Whereas in certain commercial or restricted research settings it is possible to consider either objective ability testing or peers' ratings, such methods would be prohibitively expensive to develop and administer for a wider range of skills across a representative sample of the British workforce. The alternative is to develop a self-report methodology for assessing skills. Any such approach has to deal with the major problem of social desirability which might systematically bias the data in unknown ways. The Skills Survey did attempt to capture respondents' self-reported competences in several areas, using a carefully constructed question and response scale, which was designed to reduce social desirability effects. However, the main approach, emphasised by introducing it fairly early in the interview, was to assess indirectly the skills used through questions about the skills requirements of respondents' jobs. This approach limits social desirability effects because being asked to describe one's job is much less closely bound up with an individual's self-esteem than being asked to evaluate one's own level of competence. This 'job analysis' approach to skills measurement underlies the empirical constructs used in this paper.

In commercial usage, job analysis is normally applied in specific settings. Moreover, while job holders are a major source of information to consultant psychologists about the nature of jobs, other sources of information such as peers and line managers are usually

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[1] Primary researchers are David Ashton, Alan Felstead and myself. Major assistance at the questionnaire design stage was provided by Bryn Davies.

available too. Adapting established commercial usage to the needs of a nationally representative survey of all occupations, the questionnaire addressed the 36 activities listed in Table A1 of the Appendix. Each of these activities was assessed with the item stem: "You will be asked about different activities which may or may not be part of your job. At this stage we are only interested in finding out what types of activities your job involves and how important these are." The response scale was 'Essential' / 'Very Important' / 'Fairly Important' / 'Not Very Important' / 'Not Important At All or Does Not Apply'.[2]

Although the list in Table A1 includes computer usage, it can be argued that more important is the way that computers are used. Accordingly a further question was asked in order to measure the degree of sophistication or complexity involved when respondents reported that computers were used in their jobs. The job analysis approach was then extended to capture aspects of each respondents' work activities that have a direct bearing on skill requirements. These include the degree of autonomy attached to the work, the variety of the work and the effect of certain work practices such as team working schemes and quality circles which are argued to require and engender particular skills.

The survey also asked a set of questions designed to produce generic indicators of the work skills required in each job (discussed below). There was also a rich set of control variables, including both job characteristics (that may have an ill-defined connection with skills) and personal characteristics including human capital.

4. The Derivation of Skill Indices Based on Job Analysis

4.1. Activity Analysis

The questionnaire furnished a total of 36 variables describing the importance of the various activities. Many of these variables are highly correlated. To get round the problem of multi-collinearity, two strategies were deployed. The main method was to deploy a data reduction procedure. An alternative strategy, provided as a check on the first, is to utilise a backwards stepwise procedure to eliminate variables and achieve a parsimonious estimation (see below). In this section, I report the derivation of skill indices using principal components analyses.

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[2] Job analyses sometimes also assess activities against a scale of frequency, but the need to keep down the interview length and maintain the interest of respondents meant that this aspect was not examined here.

Since computer skills are also measured by a further question, this skill was treated separately. The first stage was to reduce the 35 remaining activity variables to a small number of components. The purpose of principal components analysis is to identify a limited range of underlying unobserved components which capture a "large" proportion of the many observed variables. The main drawback of this technique is that there is no single objective criterion for deciding the number of components to extract: the choice of components has to be guided both by the data and by theoretical sense, that is, the interpretability of the components. The objectives are to identify underlying components of skill and to derive indices which can be used for subsequent analysis.

In order to render the activity variables suitable for principal components analysis it is necessary to transform the ordinal scale of 'importance' for each variable into an increasing cardinal scale, running from zero (meaning 'not at all important') to four (meaning 'essential'). This assumption of linearity is commonly made in principal components analysis, in situations which are not strictly justifiable.[3] To ascertain whether a data reduction technique such as principal components is suitable, it is appropriate initially to examine the correlation matrix of variables. To conserve space, I refrain from reporting the full matrix. Suffice to say, the matrix shows evidence of many high correlations between variables, though none are above 0.9. The overall Kaiser-Meyer-Olkin measure of sampling adequacy is 0.9304, and the Bartlett test of sphericity has a value of 49,354 with a p-value of 0.0000. Moreover, for most variables the individual KMO measure of sampling adequacy was above 0.9; only three fell below 0.8, while the lowest value was 0.67. These are strong indications that the sample data is suitable for a principal components analysis, and that all the variables should be included.

The next and main step was to make appropriate choices about how many components to extract, and the method of rotation of the initial solution to arrive at an interpretable solution. On the basis of the convention to select as many components as have eigenvalues above unity, eight components were extracted, explaining in total 67.7 per cent of the variation of the 35 variables. The choice of eight components was also based on the criterion of interpretability, which I demonstrate below. With a different number of components, it appeared that different types of skills were being conflated. Even so, most of the interpreted

[3] Multi-dimensional scaling is a technique which does not depend on the linearity assumption, but this technique is not suitable for the number of variables and potential components in this analysis.

components retained the same obvious interpretation when the number was varied. One way of examining the adequacy of a principal components analysis is to examine the residual matrix, giving the differences between the reproduced correlation coefficients and the observed correlation coefficients between all variables.[4] The differences should be ‘small’ if the number of extracted components is adequate. In this analysis, there were only 14.0 per cent of these ‘residual correlations’ above 0.05, which suggests that there is no obvious need for the addition of further components.

In order to obtain the best interpretable solution the solution was rotated obliquely, since there were no grounds for supposing that the different dimensions of skill were orthogonal. I used the OBLIMIN routine available in SPSS, with δ set to zero (the default), which is the ‘direct quartimin’ method (Tabachnick and Fidell, 1996: 668). The resulting pattern matrix is shown in Table 1 which reports all loadings above 0.3 of the observed variables on each of the eight components. As can be seen, the pattern largely conforms to the criterion of “simple structure”, with each factor correlated highly with several variables, and most variables correlated highly with one and only one factor. Table 2 gives the name and brief description of the skills involved in each component, derived from Table 1. The interpretations are generally self-explanatory and straightforward. The extracted components largely matched prior expectations about the generic types of skills involved in jobs.

<<Table 1 and Table 2 here>>

Two sets of variables need comment, however. First there is the set of activities that are often described together under a catch-all phrase: “communication skills”. Within this category are included several questions that might have had a bearing on communication in some form, and through a range of channels, both interpersonal interactions and written communication. Though no prior structure was imposed, it was reasonable to expect that different types of communication skill would be evident in the way that the variables grouped into components. Communication skills apply differently to employees at different levels of the hierarchy. In particular, the communication skill of a manager may involve the ability to lead, and to persuade subordinates to do things, while horizontal communication between workers might require different skills. Moreover, communication between workers and clients or customers is likely to involve yet further differentiated activities. In the event, it was possible to identify these three predominant forms of communication from the data, which I have classified as

[4] See, e.g. Gorsuch (1983; Chapter 8).

'client communication skill', 'horizontal communication skill' and 'professional communication skill'. The first of these involves communicating across the interface between worker and client or customer. The second, horizontal communication skill, involves relating and communicating with other people with whom one is working. Finally, professional (and managerial) communicational skill involves activities like making presentations, persuading or influencing people, and writing long reports. This classification has a plausible intuitive appeal, but the differences in the types of communication skill are obviously not precise in all cases; moreover, the questions asked in this section of the questionnaire do not go far enough in the exploration of managers' communication skills. A range of further questions specifically for the managers in the survey will provide additional and hopefully complementary findings on managers' skills in a future analysis.

Second, there was a set of questions concerned with various forms of knowledge, but unsurprisingly these did not group under any one factor. One type of knowledge, that concerned with tools and equipment, was a complement of manual skills. Another type of knowledge, that concerned with particular products or services, loaded strongly onto the client communications component. Other types of knowledge were not so strongly loaded onto any of the components, though knowledge of one's organisation appears to be linked to problem-solving skills.

As a further test of the adequacy of our interpretation, the sample was divided on the basis of sex. The principle here was that even though men and women might possess different levels of work skills, the underlying types of skills should be the same for both sexes. The procedure came up with the same number (eight) of factors for men and for women separately, using the usual eigenvalue criteria; moreover the interpretations of the rotated factors was the same.

At this stage it is necessary to record a possible concern with the apparent success of this principal components analysis. The design of this part of the questionnaire was such that many of the related questions were asked in sequences. The intention was to encourage respondents to think about the various aspects of their job, and we were reluctant to switch around at random between seemingly quite distant characteristics from one question to another. In addition, it was important to retain respondents' interest in the survey. One principle applied to the ordering, on the advice of the survey company, was not to pose questions about reading and writing at the start of the set of job analysis questions, and to ask about the lower-level types of reading and writing (e.g. readings signs etc.) before moving on to higher levels. The objective was not to deter respondents who might have felt inadequate if first asked about verbal skills they neither used nor possessed. Nevertheless, it is possible that respondents tended to reply in a similar way to successive questions. One way of preventing possible biases resulting from this kind of behaviour is to reverse the questions in some of the questionnaires or to randomise their ordering. Either of these courses would have required some extra expense, and may have involved violating the above principle about the verbal skill questions, and lessened the extent to which respondents concentrated on the proper interpretation of successive questions. A major objective of this principal components analysis has been to obtain skill indices, defined to be the component scores. By construction, these scores are linear combinations of the standardised observable variables, and hence they have a mean of zero across the full sample. In Table 3 these indices are compared with more conventional skill measures, namely occupation and educational levels.

<<Table 3 here >>

It can be seen from the first panel that all skill indices except manual skills tend to be greater amongst the higher ranking occupations. As might be expected, professional communication skills and verbal skills are both highest in professional occupations. From the last row, it is also shown that, while manual skill is negatively correlated, all other skill indices are positively correlated with years of full-time education. These comparisons at least give some reassurance that the indices portray a broad pattern consistent with the more conventional measures. Finally, note that men report greater skills than women in six out of eight cases, but the difference is only substantial in the case of manual skills and to a lesser extent professional communication skills and numerical skills.

The survey also asked two questions about the use of computers or computerised equipment. First, the survey asked about their importance in respondents' jobs, using the same response scale as the previous activity question. The responses were converted to dummy variables. Second, four dummy variables were created to capture increasing levels of the complexity of computer use, from simple through to advanced. These were derived from the question: "Which of the following best describes your use of computers or computerised equipment in your job?". The response scale was accompanied by examples: 'Straightforward (e.g. using a computer for straightforward routine procedures such as printing out an invoice in a shop)' / 'Moderate (e.g. using a computer for word-processing and/or spreadsheets or communicating with others by email' / 'Complex (e.g. using a computer for analysing information or design, including use of computer aided design or statistical analysis packages)' / 'Advanced (e.g. using computer syntax and/or formulae for programming)'.

Autonomy and variety constitute separate but related aspects of work skill. Autonomy is seen as a skill, in part because if employees are to act without close supervision they must know what tasks are to be done and how to do them. Autonomy is also a reflection of trust by the line manager in the conformity of the employee to appropriate effort norms. For these reasons, autonomy has been an important focus for sociological enquiry since at least the work of Braverman (1974) and subsequently Friedman (1977) and Spenner (1990). I measured autonomy by summing responses to two related questions, each on a rising scale: "How much choice do you have over the way in which you do your job?", and "How closely are you supervised in your job?". The extent of variation in the tasks to be performed is theoretically related to autonomy, since more discretion, which itself entails greater skill, is likely to facilitate efficient switching between tasks (reducing the costs of task allocation by a supervisor). Task variety is also likely to require a wider range of skills. I measured variety by summing responses to the questions: "How often does your work involve carrying out short, repetitive tasks?" and "How much variety is there in your job?".

Finally, certain company production policies are arguably associated with particular job skills that may not be fully captured in the indices so far discussed. First, a job that requires participation in a quality circle may entail certain skills that are rewarded in the labour market. Second, some companies organise their workforces into teams; they may need to reward the skills of those who participate in them.

4.2. Other Generic Job Skill Indicators

Within the human capital literature, the extent to which skills are firm-specific, transferable or general plays an important role: other things equal, skills are expected to be rewarded more highly if they are transferable. In recent work, attempts to capture the degree of skill transferability by means of direct questions - rather than indirectly by inferring from wage/mobility patterns - have proved reasonably successful (Green and Montgomery, 1998; Felstead *et al*, 1997). For this paper I measured skill specificity using the survey question: "Thinking about the skills which you use in the job you have now, how useful would these skills be if you were to work for another employer in the same industry or service?" I defined skills to be transferable if respondents replied 'very useful' or 'fairly useful', and to be firm-specific if they responded: 'some use', 'only a little useful' or 'not at all useful'.

Two other generic indicators of skill levels emerging from job analysis are the length of time needed to learn to do the type of job competently, and the level of qualification that potential new recruits would need to have in order to get the job. The former is measured on a banded scale, ranging from ‘less than 1 week’ to ‘more than two years’. The latter is captured by five ‘highest required qualification’ dummies ranging from NVQ1 level to degree level.

5. Findings on the Value of Skills

5.1. Specification

The skill indices can be thought of formally in a similar way to job “attributes” in the empirical analysis of compensating wage differentials. In such analyses it is common to think of a reduced form relationship between wages and a vector of job attributes, in other words a hedonic wage equation, the estimated coefficients of which are the shadow prices of those attributes (e.g. McNabb, 1989). For those attributes that are unpleasant, competitive equalisation of workers’ utilities across jobs predicts positive shadow prices. In terms of the theory of equalising differentials, skills are thus formally equivalent to unpleasant job attributes - each with positive supply prices. If one were (rashly) to assume perfect competition in the labour market and that all firms have the same marginal rates of substitution between skill types, then the relative values of the coefficients on the skill types are estimates of their relative supply prices. However, some firms are likely to innovate faster than others, and rapid technical change implies that the price of slow-to-adjust skills will move above or below the supply-price, delivering a quasi-rent to the holders of any scarce skills.[5]

It is quite possible that not all activities of a job can be fully captured in a survey questionnaire of this type. One way to attempt to capture any missing skills used might be to tack the observed skills onto a conventional human capital specification, as is done with job attributes in the compensating differentials literature. However, this is less than ideal because the output of schooling presumably includes many of the observed skills. Nevertheless, the problem of unobserved variables is typically non-trivial in estimates of hedonic price equations because it is likely that characteristics are correlated on both sides of the market. In the case here, I attempt to mitigate any bias induced by unobserved job skill attributes by

[5] To distinguish between the supply price and the quasi-rent, one would need to utilise additional information on the cost of supplying skills.

including control variables. First, what a worker does in his or her job may vary with work experience or job tenure in ways which are not captured by the skills indices - hence these variables are included. I also include the extent to which workers have more or less qualifications than those now required for the job they do. A typical finding in the literature is that over-education is rewarded and under-education penalised - but to a lesser extent than the returns to required education (e.g. Sloane *et al*, 1995; Groot, 1996). Furthermore, since work rewards are expected to depend on a lot more than just skills, reflecting the institutional and contractual environment, a number of other conventional control variables need to be added. Since all the control variables are conceivably related to the observed skill attributes I present results both including and excluding the controls.

5.2. Main Results

In this section, the job skill indices are used in a study of the determination of work rewards using the framework of a hedonic wage equation. The dependent variable is the log of the gross hourly wage augmented by 10 per cent for those reporting that their employer also contributes to a pension scheme.[6] Results of separate estimations for women and men are given in Table 4 and 5.

(a) Activities

In column (1) of each table, only those variables that characterise the tasks performed are included. By construction, the standard deviation of the index is exactly unity for the total sample, and approximately so for men and women as separate groups. Thus the interpretation is that one standard deviation increase in verbal skills is associated with approximately 8 per cent higher pay for women, but only an insignificant 3 per cent higher pay packet for men. Other activities which significantly raise pay are problem solving, professional communication and, for men, planning; while both manual and client communication skills are linked with lower pay.

<<Table 3 and Table 4 here >>

The negative coefficient on manual skills is hardly surprising. A partial explanation is that many manual skills have a relatively low supply price. Some, for example physical stamina, could be seen as a by-product of daily living, with an effectively zero cost of acquisition, so

[6] The pattern of results is the same if pension contributions are left out.

that the supply price is only a function of the disutility of work. However, the likely reason for the negative coefficient is that manual activities are negatively correlated with other unobserved activities using valued skills - even though I control for many observed skills (with most of which manual skills are negatively correlated) it is likely that where manual skills are very important workers are not using other more highly valued skills.[7]

Neither horizontal communication skills (see below) nor numerical skills have a significant association with pay. In the case of the latter, this finding might seem surprising, given other evidence of the increasing importance of cognitive skills in the labour market (Murnane *et al*, 1995) of which numerical skills are a crucial component.

The answer to this puzzle lies in the substantial impact of computing skills: even the simplest forms of computer usage are associated with relative pay differentials over non-computer users of some 13 per cent (men) and 18 per cent (women). Greater complexity unsurprisingly yields higher rewards. The numerical skills are significantly correlated with computing skills. If the computer variables are left out of the equation, the coefficient on numerical skills becomes significantly positive for both sexes. Thus, although one would expect numerical skills to be positively linked with pay, the evidence is that this link is not manifested other than through computers: there is no extra pay advantage from deploying numerical skills conditional on a given usage of computers.

The association of computer usage with higher pay remains, even after controlling for many other sources of pay variation (see remaining columns), thus replicating the similar findings in other countries. However, unlike previous studies, the evidence here suggests that the level of complexity is a useful additional index of computer usage. Dummy variables measuring degree of importance in the job were significant when included without the complexity variables: they showed that pay increased according to the degree of importance of computers in the job. Yet the degree of importance variables became small and insignificant when the complexity variables were introduced, and so were excluded from the reported equations.

These results cannot be used to determine decisively between competing explanations, whether the computer usage causes higher pay or whether those with greater (unobserved) ability are selected to use computers in a more complex way.

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[7] The variable is not simply capturing attachment to a conventional manual occupation, since the coefficient remains negative when the sample is restricted to non-manual occupations.

The association of task variety with pay is significant. Going from the lowest to highest levels of task variety would raise pay by some 22 per cent for men and 35 per cent for women. The link is expected, if only because of a much vaunted concern with multi-skilling, suggesting a demand for more versatile workers. Autonomy - working with less supervision and having greater choice over task allocation - carries a labour market premium for men, but not for women. In sociological discourse, autonomy is seen as a key component of skill (Spenner, 1990), and indeed the ability to decide what to do next is presumably productive and rewardable. Moreover, efficiency wage theories suggest that where workers are less closely monitored they may need motivating with higher wages. On the other hand, some autonomy is arguably a desirable attribute of many jobs, suggesting that close supervision might be compensated by higher pay. These arguments imply an ambiguous link for autonomy with pay, but do not explain the gender difference.

The final task variable to be associated with pay is working in quality circles, yielding a 7 per cent pay premium for men and 9 per cent for women. Presumably, workers with certain unobserved abilities may get selected to participate in quality circles, though such participation may also create new skills.

(b) Organised Team Working

Horizontal communication skills include "working with a team of people and, as we have seen this carries no pay premium. Since there is some concern in management literature with team working, I examined this issue further by introducing another variable based on the question: "How much of your work is organised on the basis of teams?". The variable NOTEAMWORK is defined to be 1 for those who replied "none" and 0 for the responses "little, "some" or "all". As columns (2) of Tables 4 and 5 show, where jobs are not at all organised in teams, pay is some 8 per cent lower for men and 11 per cent lower for women. This suggests that being "organised" in teams is what carries a premium rather than just working with a team. Nevertheless, there was no significant difference between the respondents who said "little, "some" or "all". Taken together, these results do not provide strong evidence that employers are paying for team working.

(c) Generic Job Skill Indicators

With the focus still on skill indicators derived from job analysis, column (3) reports regressions that include some generic indicators that, while not describing aspects of the job specification, nevertheless capture aspects of job skills that could be expected to be linked with pay. First, where the job-holder judges the skills are firm-specific, pay is as expected lower, significantly so for men. Second, pay substantially increases with the length of time judged to be needed to learn to do the type of job competently. One can think of this relationship as reflecting a premium on the skill of learning while doing. Third, pay increases substantially according to the level of qualification that would be required of any new recruit to get the job which the respondent holds. This latter result is consistent with the considerable literature on “over-education”.

While these findings are in line with expectations, it is also unsurprising that many of the coefficients on the task analysis variables are somewhat lower in absolute terms, when the generic job skill indicators are included. Notably, the planning skills coefficient while remaining positive is now insignificant for both sexes.

(d) Control Variables

Columns (4) include a rich set of control variables for two reasons. First, a control variable may partly capture an otherwise unobserved element of job skill whose omission was causing the coefficients in columns (1) to (3) to be biased. Second, on conventional grounds, wages are affected by the institutional and contractual characteristics of jobs.

The personal human capital controls include over-education and under-education, measures of the extent to which respondents’ personal qualifications exceed or fall short of the qualifications now required of new recruits. Consistent with the literature, over-education has a positive return and under-education a smaller negative return. The other personal human capital controls also have conventional signs, as do other personal and job characteristics. Of some note is the finding that both men and women experience a pay loss if in a job that is normally done “almost exclusively” by women, and men (and, insignificantly, women) also benefit if the job is done “almost exclusively” by men.

The inclusion of the controls alters the activity skills coefficients notably in some cases. Thus, the negative coefficients on manual skills, client communication skills and (for men) horizontal communication skills are reduced. Horizontal and client communication skills become insignificant. This alteration is consistent with the possibility that the negative coefficients in columns (1) to (3) reflect the influence of unobserved skills. The broad pattern of findings is, however, unaffected by the inclusion of the controls.

5.3. Additional Checks

(a) Alternative Specifications

The main findings are robust to several variations in the precise specification. First, I included dummy variables for industry in addition to the controls in column (4). While the significance of some of the skills variables is slightly reduced, the broad pattern of results remained. Some of the industry dummies were significant, leading to an improvement in the adjusted R^2, for both men and women.

Second, I excluded the self-employed from the sample, in case the valuation of skills was substantively different from the rest of the sample. The resulting pattern of coefficients was, however, not substantially changed. One notable change, however, is that the adjusted R^2 is higher, at 0.504 for men and 0.597 for women using the full specification, compared with 0.393 for men and 0.567 for women when the self-employed are included. Whether with or without the self-employed, a relatively high proportion of hourly wage variance is explained compared to most studies in the literature.

(b) Self-Assessed Competency

Another variation was to include measures of the competence of respondents in each of the eight skill dimensions. For each activity question, “X”, the survey also asked a subsequent question as follows: “When your job involves doing “X”, are you able to do this effectively?” Respondents were given a 5-point frequency response scale, ranging from ‘Always’ to ‘Hardly Ever’. For each activity I derived a new variable, the competency in that activity, ranging from zero (i.e. ‘not at all important at work’), through one (‘Hardly Ever’) to five (‘Always’). As mentioned earlier, there are inevitable doubts about the reliability of this measure, owing to the likelihood of social desirability bias. The question was phrased so as to avoid asking directly “how good are you?” at each activity, and the language of the response scale was stretched at the upper end so as to discourage everyone from answering at the upper extreme (Ashton *et al*, forthcoming). Nevertheless there is likely to be a tendency for answers to be affected by differential awareness of self and differential needs to impress.

Prior analysis showed that every activity variable was positively correlated with its associated competency variable. In other words, the more important an activity is the more likely that respondents reported a higher level of competence. Nevertheless, it was of interest to investigate whether self-assessed competences provided an additional source of pay variation. Eight key competences were calculated as linear combinations of the 35 competences, where the eight sets of weighting coefficients were those arising from the principal components analysis of the activity variables.

The results showed that, when entered separately, self-assessed competences had a significant association with pay, with the pattern similar to that of the activity variables based on the 'importance' scales. However, when entered in addition to the activity variables, none of the competence variables had any significant association with pay. I conclude that either self-assessment of competence carries no additional information about real competence (owing to self-reporting biases), or whatever information it does add does not impinge on the labour market, perhaps because that information cannot convince other potential employers.

(c) Stepwise Analysis

Finally, instead of the principal components method of reducing the 36 activity variables, an alternative method adopted was to enter all variables directly in the hedonic wage equation and search for a parsimonious specification. The aim was, in part, to confirm that the principal components approach was indeed picking up the impact of activities ascribed to each component. In addition, the method enables one to explore certain skills in more detail. In particular, while verbal and numerical skills have each been grouped from several component activities, those activities range from low to high levels of complexity and skill. Such a hierarchy could be reflected in wages.

Each skill activity, "X", was allocated two dummy variables - High "X", meaning the activity was 'Very important' or 'Essential' and Low "X" meaning 'Not very important' or 'Not at all important/Does not apply' (with 'Fairly Important' as the reference category). A positive (negative) coefficient on a "High" dummy, or a negative (positive) coefficient on a "Low" dummy, indicates that the skill is positively (negatively) associated with pay. The dummies were entered successively using a combined forwards and backwards methodology.[8] The results, shown in Table 6, are consistent with the findings drawn from Tables 4 and 5. For both men and women, problem-solving, planning and professional communication skills, are all positively related to pay, while manual skills are negatively related to pay.

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[8] Initially, none of the activity dummies were included. At each subsequent stage, if the least significant included variable was "insignificant" ($p \geq 0.20$) it was removed and the model re-estimated; if the most significant excluded variable was "significant" ($p \leq 0.15$) it was added and the model re-estimated. The ensuing pattern of results was not greatly different if, instead, the sequence began with all variables included.

<<Table 6 here>>

The table also shows that the sometimes negative association of client communication skills with pay derives from both selling skills and counselling/advising/caring skills. The skill of "persuading and influencing people", positively linked with pay, is a component of both client communication skills and professional communication skills.

Finally, the table also shows a negative association of pay with both simple and advanced numeracy. However, as with the principal components analysis, these numerical skills are correlated with computing skills (also included in the equation); when the latter were excluded, the numerical skill variables showed a positive link with pay. In other words, jobs involving more or higher mathematics or statistics are not rewarded more highly unless this numeracy is reflected in computer use.

6. Conclusions

The starting point for this paper has been the often proclaimed increased importance of key skills including computing skills in modern advanced economies. The intention has been to subject the assertions made about key skills to the test of the labour market. Their putative increased importance is likely to be associated with relative scarcity and hence with a positive and increasing wage premium. Until further data are available it will not be possible to examine the change in the premium; however, it is possible to examine whether the skills carry a positive premium. If skills do carry a positive premium, this is consistent with the view that they are costly to acquire and/or that they are currently earning a quasi-rent due to technological and organisational change. The analysis draws on a new methodology for measuring skills that I and others have recently developed, based on an adaptation of the practices of commercial job analysts. The main new findings are that:

- Computer skills are highly valued in the current British labour market: thus, even at "moderate" levels of complexity, for example using word-processing packages, male workers using computers earn an average premium (after controlling for other job skills) of some 21 per cent, female workers 22 per cent, compared to those who do not use computers at all. When many other personal and job characteristics are also controlled for, the premium for both sexes remains at 13 per cent. Although causation is by no means established, the magnitude of the conditional association of computer usage complexity with pay is consistent with the possibility that IT is having some impact on wage inequality. Particularly at the higher level there are persistent reports of shortages and poaching of specialists (DfEE, 1998). It seems unlikely that all these workers with computer skills would have benefited as much from their unobserved other skills, in the absence of IT.

- Professional communication and problem-solving skills are also highly valued. A one-standard-deviation increase in either type of skill raised women's pay by around 5 per cent, men's by 6 per cent, after allowing for all the controls.
- To a lesser extent, verbal skills also carry a pay premium for women. The skills of reading and writing short documents are important. But planning, and client and horizontal communication skills, have little independent association with pay. With client communication, the positive value of persuading and influencing appears to be offset by a negative value for counselling and caring skills and for selling skills. Numerical skills also have no conditional link with pay, other than through being linked with more complex computer usage.
- Jobs involving task variety earn more pay, presumably because of the range of skills needed. There is, however, no strong evidence that greater autonomy is positively rewarded. If greater autonomy requires extra skill, it might also be more agreeable to workers yielding a negative compensating differential balancing the extra skill.
- Participating in Quality Circles, which presumably entails certain skills, attracts a pay premium, more markedly for females than males. There is also some tentative evidence that where work is specifically organised on the basis of teams there is a pay premium.
- Jobs which require a long learning time, which deploy transferable skills, and/or for which there are higher qualifications requirements command a higher pay.
- A reasonably complete job analysis provides a useful means of accounting for a wage distribution via a hedonic wage equation, in the sense that it enables an unusually large portion of the hourly wage variance to be explained.

Without making some extreme assumptions, it would not be possible to recover from these hedonic wage estimates the structure of the supply or demand relationships. Nevertheless, it is possible to draw some broad conclusions. The fact that computing and other particular skills attract a positive labour market premium is consistent with the hypothesis that all these skills are costly to acquire and/or that they are earning a quasi-rent due to rapid technological and organisational change that has been keeping ahead of the capacity of skill-supplying institutions to respond in the short-term. Though this conclusion refers to the past, one may plausibly conjecture that there will be little or no reduction in the expansion of demand for IT skills in the foreseeable near future. Short of a radical increase in the supply of computing talent on the labour market, we are unlikely to see the computing skills premium disappear.

But the above conclusion begs the question as to why certain other key skills are shown to have virtually no labour market premium or even a negative reward. As discussed above, a probable correlation with unobserved variables can plausibly account for substantial downward bias on the manual skills coefficient, causing it to be negative. The numerical skills measure was only rendered insignificant through its correlation with computer usage, which carried the major impact. However, to explain away the zero coefficient on other skills variables by correlations with other variables is infeasible in respect of the observed controls and would seem ad hoc in respect of any putative missing variables.

There remain three possibilities. First, there could be substantial measurement error. Although this is possible, and although there could be more measurement error in the job analysis approach with respect to, say, communication skills than computing skills, this would also be an ad hoc explanation. All the activity skills indices exhibited at least superficially plausible descriptive statistics. Second, much of the discussion of key skills could be no more than hot air - in other words, these skills are revealed not to be really in high demand, despite what policy-makers and some employers say.

Third, a possible explanation in some cases is that suggested in the introduction. Though certain key skills are of value in firms where they are exercised, it is hard for employees to signal possession of the skills to the external labour market. Ostensibly transferable skills become, through asymmetric information, partly firm-specific, giving firms the incentive to invest in them (Katz and Ziderman, 1990). The utility of previous employer references is known to be limited by low validity, low reliability, poor response rates and leniency bias. Unsurprisingly, prospective employers generally make wide use of previous work experience in recruiting decisions. For the vast majority of job matches, the interview and the curriculum vitae remain the main methods of selection (Smith and Robertson, 1993). Yet the reliability of such methods in detecting and gauging interpersonal skills is mixed, thus potentially accounting in part for the low valuation put on client and horizontal communication skills. Such an explanation would suggest that good interpersonal skills might well be of value to employers, even though they do not appear to have a price on the labour market.

Aside from the issue of imperfect measurement of skills, there are limitations in the hedonic wage equation approach deployed in this paper. Not least, it requires comparatively strong assumptions to be able to specify wages as a linear combination of job skills. Moreover, it has been assumed that the effect of job skills is separate from that of other institutional pay determinants such as collective bargaining, the latter being tacked on as one of the controls. This simplification may not be justified if, say, unions were to differentially value certain skills. In further analysis of the skills measures reported in this paper, it is intended to explore their link with respondents' prior education, training, work experience and other variables. The aim will be to try to understand more about the products of the skill formation system and about what underlies the returns to education and training. In future research it is also hoped to compare the changing importance of particular skills with their changing prices, in order to be able to assess better the interplay of the supply and demand for skills.

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Table 1: Principal Components Analysis: Pattern Matrix

Variable number	Verbal	Manual	Problem Solving	Numerical	Planning	Client Commun-ication	Horizontal Commun-ication	Professional Commun-ication
1			0.53					
2						0.58		
3							0.42	0.46
4								0.60
5						0.34		0.40
6						0.85		
7						0.67		
8							0.87	
9							0.77	
10		0.87						
11		0.86						
12		0.71						
13		0.58	0.32					
14						0.53		
15			0.36					
16								
19			0.78					
20			0.75					
21			0.62					
23			0.34					0.41
24			0.74					
25			0.76					
26					0.79			
27					0.37		0.32	0.39
28					0.80			
29					0.66			
30	0.78							
31	0.81							
32	0.75							
33	0.80							
34	0.75							
35	0.59							0.36
36				0.88				
37				0.91				
38				0.82				

Note: See Appendix, Table A1 for activity variable list.

Table 2: Interpretation of Skill Components

Component Name	Description	High-loading Activities
Verbal	Reading and writing skills	30, 31, 32, 33, 34, 35
Manual	Physical strength and stamina, dexterity and knowledge of tools etc.	10, 11, 12, 13
Problem-Solving and Checking	Identifying, analysing and resolving problems; dealing with mistakes	13, 15, 19, 20, 21, 23, 24, 25
Numerical	Calculations at various levels of complexity	36, 37, 38
Planning	Planning one's own and others' activities	26, 27, 28, 29
Client Communication	Communication with clients/customers etc.	2, 5, 6, 7
Horizontal Communication	Teamworking, Listening	3, 8, 9, 27
Professional Communication	Professional and managerial communication skills	3, 4, 5, 23, 27, 35

Note: There were no variables 18 nor 22; see Appendix, Table A1 for activity variable list.

Table 3: Average Skill Component Scores by Occupation and by Gender, and the Correlation of Skill Component Scores with Education

	Verbal	Manual	Problem Solving	Numerical	Planning	Client Commun-ication	Horizontal Commun-ication	Profession-al Comm-unication
Mean skill levels among:								
Managers etc	0.27	-0.21	0.14	0.56	0.56	0.52	0.23	0.43
Professionals	0.69	-0.47	0.15	0.53	0.61	0.13	0.33	0.88
Associate Professionals	0.42	-0.32	0.31	0.05	0.34	0.23	0.19	0.42
Clerical	0.21	-0.61	0.16	0.08	-0.14	-0.18	0.08	-0.54
Craft etc	-0.24	1.02	0.46	-0.03	-0.24	-0.28	-0.33	0.07
Personal & Protective	-0.07	0.18	-0.49	-0.62	0.08	0.02	0.39	-0.19
Sales	-0.40	-0.26	-0.37	0.02	-0.49	0.91	-0.23	-0.60
Operatives	-0.52	0.63	-0.04	-0.29	-0.58	-0.60	-0.35	-0.36
Other	-0.96	0.38	-0.94	-0.89	-0.65	-0.68	-0.50	-0.36
Mean skill levels among:								
Men	0.01	0.23	0.11	0.15	0.00	-0.03	-0.10	0.13
Women	-0.01	-0.24	-0.12	-0.18	-0.03	0.04	0.13	-0.18
Link with education attainment:								
Correlation with years of full-time education	0.10	-0.28	0.08	0.17	0.24	0.10	0.10	0.30

Table 4: Hedonic Wage Equations: Females

JOB SKILLS		(1)	(2)	(3)	(4)
(a) Activities	Verbal	0.078 (0.017)**	0.075 (0.016)**	0.049 (0.016)**	0.032 (0.016)**
	Manual	-0.114 (0.015)**	-0.116 (0.015)**	-0.094 (0.014)**	-0.092 (0.014)**
	Problem-Solving	0.055 (0.015)**	0.053 (0.015)**	0.051 (0.014)**	0.046 (0.014)**
	Numerical	-0.009 (0.015)	-0.011 (0.015)	-0.004 (0.014)	0.006 (0.014)
	Planning	0.026 (0.015)*	0.032 (0.015)*	0.001 (0.014)	0.006 (0.014)
	Client Communication	-0.037 (0.014)**	-0.036 (0.014)**	-0.036 (0.013)**	-0.021 (0.014)
	Horizontal Communication	0.020 (0.017)	0.001 (0.018)	-0.004 (0.017)	-0.022 (0.017)
	Professional Communication	0.111 (0.015)**	0.111 (0.015)**	0.047 (0.014)**	0.048 (0.014)**
	Computer Usage: Simple	0.182 (0.039)**	0.173 (0.039)**	0.124 (0.038)**	0.065 (0.036)*
	Moderate	0.310 (0.041)**	0.300 (0.041)**	0.216 (0.044)**	0.127 (0.044)**
	Complex	0.291 (0.054)**	0.277 (0.053)**	0.178 (0.054)**	0.107 (0.051)**
	Advanced	0.394 (0.196)**	0.381 (0.192)**	0.260 (0.172)	0.153 (0.18)
	Autonomy	0.002 (0.011)	0.006 (0.010)	0.003 (0.010)	0.008 (0.010)
	Variety	0.039 (0.008)**	0.038 (0.008)**	0.018 (0.007)**	0.019 (0.007)**
	Quality Circles	0.101 (0.030)**	0.088 (0.030)**	0.073 (0.029)**	0.042 (0.028)*
	NOTEAMWORK	-	-0.114 (0.031)**	-0.089 (0.029)**	-0.056 (0.029)**
(b) Generic Job Skill Indices	Learning Time: 1 week to 6 months	-	-	0.101 (0.041)**	0.084 (0.040)**
	Learning Time: More than 6 months	-	-	0.172 (0.047)**	0.133 (0.046)**
	Firm-Specific Skills	-	-	-0.075 (0.067)	-0.103 (0.071)**
	Highest Qual. Requ'd: Level 1	-	-	0.053 (0.052)	0.062 (0.053)*
	Level 2	-	-	0.059 (0.038)	0.125 (0.040)**
	Level 3	-	-	0.234 (0.054)**	0.307 (0.055)**
	Professional	-	-	0.315 (0.059)**	0.369 (0.060)**
	Degree	-	-	0.501 (0.055)**	0.530 (0.064)**

Table 4 (continued)

(c) Personal Human Capital Controls	Work Experience	-	-	-	0.016 (0.004)**
	Work Exp Squared x 10^{-3}	-	-	-	-0.281 (0.114)**
	Job Tenure x 10^{-3}	-	-	-	3.50 (4.35)
	Job Tenure Squared x 10^{-7}	-	-	-	1.20 (13.4)
	Over-Education	-	-	-	0.053 (0.011)**
	Under-Education	-	-	-	-0.020 (0.019)
(d) Other Controls	Married	-	-	-	0.041 (0.024)*
	Temporary: fixed term	-	-	-	0.118 (0.059)**
	Temporary: other	-	-	-	0.007 (0.060)
	Part-Time	-	-	-	-0.027 (0.027)
	Establishment Size x 10^{-5}	-	-	-	3.29 (2.03)
	Est. Size squared x 10^{-9}	-	-	-	-1.54 (1.09)
	Male job	-	-	-	0.111 (0.097)
	Female job	-	-	-	-0.099 (0.030)**
	Union recognised	-	-	-	0.088 (0.030)**
	Union member	-	-	-	0.052 (0.036)
	Public Ownership	-	-	-	0.037 (0.029)
	Non-profit organisation	-	-	-	0.044 (0.076)
	Self-employed	-	-	-	-0.286 (0.097)**
	Regional dummies	-	-	-	YES
	Constant	1.34 (0.56)**			0.978 (0.075)**
Sample size		1046	1046	1033	1010
R^2		0.429	0.436	0.515	0.590

Notes:

1. The dependent variable is the log of the gross hourly wage, augmented by 10% for those with employers contributing to a pension scheme.
2. White-corrected standard errors in parentheses; significance levels: * = 90%, ** = 95%

Table 5: Hedonic Wage Equations: Males

JOB SKILLS		(1)	(2)	(3)	(4)
(a) Activities	Verbal	0.032 (0.022)	0.032 (0.022)	0.008 (0.022)	-0.015 (0.023)
	Manual	-0.093 (0.016)**	-0.093 (0.016)**	-0.073 (0.017)**	-0.064 (0.017)**
	Problem-Solving	0.066 (0.018)**	0.066 (0.018)**	0.060 (0.017)**	0.059 (0.018)**
	Numerical	-0.010 (0.02)	-0.008 (0.02)	-0.020 (0.020)	-0.011 (0.020)
	Planning	0.030 (0.019)	0.032 (0.019)	0.020 (0.019)	0.010 (0.019)
	Client Communication	-0.032 (0.018)*	-0.027 (0.018)*	-0.023 (0.017)	-0.016 (0.019)
	Horizontal Communication	-0.016 (0.017)	-0.031 (0.018)	-0.021 (0.018)	-0.016 (0.019)
	Professional Communication	0.104 (0.017)**	0.100 (0.017)**	0.072 (0.016)**	0.055 (0.016)**
	Computer Usage: Simple	0.132 (0.037)**	0.127 (0.037)**	0.101 (0.037)**	0.038 (0.035)*
	Moderate	0.247 (0.047)**	0.242 (0.047)**	0.207 (0.045)**	0.126 (0.043)**
	Complex	0.302 (0.056)**	0.293 (0.056)**	0.229 (0.055)**	0.169 (0.053)**
	Advanced	0.324 (0.084)**	0.318 (0.084)**	0.251 (0.084)**	0.206 (0.073)**
	Autonomy	0.024 (0.013)**	0.024 (0.013)**	0.018 (0.013)	0.011 (0.010)
	Variety	0.025 (0.008)**	0.026 (0.008)**	0.010 (0.008)	0.014 (0.008)*
	Quality Circles	0.070 (0.031)**	0.063 (0.032)**	0.067 (0.031)	0.020 (0.029)
	NOTEAMWORK	-	-0.081 (0.036)**	-0.053 (0.035)	-0.066 (0.034)**
(b) Generic Job Skill Indices	Learning Time: 1 week to 6 months	-	-	0.145 (0.059)**	0.085 (0.061)*
	Learning Time: More than 6 months	-	-	0.254 (0.061)**	0.142 (0.064)**
	Firm-Specific Skills	-	-	-0.171 (0.093)*	-0.164 (0.107)
	Highest Qual. Requ'd: Level 1	-	-	0.051 (0.044)	0.100 (0.041)**
	Level 2	-	-	0.024 (0.037)	0.116 (0.039)**
	Level 3	-	-	0.129 (0.047)**	0.245 (0.051)**
	Professional	-	-	0.129 (0.067)*	0.257 (0.069)**
	Degree	-	-	0.324 (0.056)**	0.489 (0.063)**

Table 5 (continued)

(c) Personal Human Capital Controls	Work Experience	-	-	-	0.032 (0.005)**
	Work Exp Squared x 10^{-3}	-	-	-	-0.627 (0.113)**
	Job Tenure x 10^{-3}	-	-	-	1.62 (0.39)**
	Job Tenure Squared x 10^{-8}	-	-	-	-3.13 (1.06)**
	Over-Education	-	-	-	0.067 (0.016)**
	Under-Education	-	-	-	-0.041 (0.022)**
(d) Other Controls	Married	-	-	-	0.023 (0.029)
	Temporary: fixed term	-	-	-	0.057 (0.066)
	Temporary: other	-	-	-	0.048 (0.078)
	Part-Time	-	-	-	-0.008 (0.010)
	Establishment Size x 10^{-5}	-	-	-	5.23 (4.13)
	Est. Size squared x 10^{-9}	-	-	-	-6.42 (6.55)
	Male job	-	-	-	0.078 (0.031)**
	Female job	-	-	-	-0.163 (0.091)*
	Union recognised	-	-	-	0.032 (0.036)
	Union member	-	-	-	0.108 (0.035)**
	Public Ownership	-	-	-	-0.062 (0.041)
	Non-profit organisation	-	-	-	-0.383 (0.220)*
	Self-employed	-	-	-	-0.062 (0.083)
	Regional dummies	-	-	-	YES
	Constant	1.602 (0.064)**	1.620 (0.065)**	1.449 (0.083)	0.908 (0.096)**
Sample size		1114	1114	1104	1087
R^2		0.264	0.266	0.313	0.4221

Notes:

1. The dependent variable is the log of the gross hourly wage, augmented by 10% for those with employers contributing to a pension scheme.
2. White-corrected standard errors in parentheses; significance levels: * = 90%, ** = 95%

Table 6: Hedonic Wage Equations: Stepwise Regressions

Activity	Females		Males	
Low *Attention to Detail*	-0.136	(0.077)	-0.226	(0.131)*
High *Speeches/Presentations*	0.085	(0.051)*		
Low *Speeches/Presentations*	-0.138	(0.040)**	-0.082	(0.037)**
High *Persuading/Influencing*	0.055	(0.030)*	0.068	(0.036)
High *Selling*	-0.132	(0.029)**		
High *Counselling/Advising/Caring*	-0.049	(0.030)	-0.083	(0.040)**
Low *Counselling/Advising/Caring*			0.064	(0.041)
High *Listening to colleagues*			-0.064	(0.034)**
High *Physical strength*	-0.105	(0.033)**		
Low *Physical strength*			0.151	(0.038)**
Low *Physical stamina*	0.068	(0.029)**		
Low *Skill/accuracy with hands*	0.085	(0.027)**	0.079	(0.044)*
High *Knowledge of products*	-0.089	(0.034)**		
Low *Knowledge of products*	-0.086	(0.038)*		
High *Specialist knowledge*	0.118	(0.033)**	0.076	(0.038)**
Low *Specialist knowledge*			-0.117	(0.055)**
Low *Knowledge of organisation*	-0.067	(0.032)**	0.053	(0.037)
High *Complex problem-analysing*	0.090	(0.033)**	0.084	(0.037)**
High *Checking things*			-0.057	(0.039)
Low *Noticing mistakes*	-0.113	(0.052)**	-0.159	(0.075)**
Low *Planning own activities*	-0.095	(0.032)**	0.077	(0.053)
Low *Planning others' activities*			-0.065	(0.031)*
Low *Thinking ahead*	0.062	(0.037)*	-0.124	(0.057)**
High *Reading short documents*	0.068	(0.035)*	-0.102	(0.037)**
Low *Reading short documents*			-0.134	(0.048)**
Low *Writing forms/notices etc.*	0.072	(0.036)**		
High *Writing short documents*			0.052	(0.035)
Low *Writing short documents*	-0.107	(0.039)**		
High *Writing long documents*	0.069	(0.033)**		
High *Adding/multiplying/dividing*			-0.068	(0.030)**
Low *Advanced mathematics*	0.069	(0.033)**		
Sample size	1048		1114	
R^2	0.472		0.296	

<u>Notes:</u>

1. Regressions included other activities: computer usage, autonomy, task variety, participation in quality circles and organisation on the basis of teamwork.
2. Criteria for inclusion of activities: p ≤ 15%; criteria for removal of activities: p ≥ 20%.
3. The dependent variable is the log of the gross hourly wage, augmented by 10% for those with employers contributing to a pension scheme.
4. White-corrected standard errors in parentheses; final significance levels: * = 90%, ** = 95%

APPENDIX

Table A1: Activity Variables

1	Paying close attention to detail
2	Dealing with people
3	Instructing, training or teaching people
4	Making speeches or presentations
5	Persuading or influencing others
6	Selling a product or service
7	Counselling, advising or caring for customers or clients
8	Working with a team of people
9	Listening carefully to colleagues
10	Physical strength
11	Physical stamina
12	Skill or accuracy in using hands or fingers
13	How to use or operate tools/equipment/machinery
14	Knowledge of particular products or services
15	Specialist knowledge or understanding
16	Knowledge of how your organisation works
17	Using a computer, PC, or other types of computerised equipment
19	Spotting problems or faults
20	Working out the causes of problems or faults
21	Thinking of solutions of problems or faults
23	Analysing complex problems in depth
24	Checking things to ensure that there are no errors
25	Noticing when there is a mistake
26	Planning your own activities
27	Planning the activities of others
28	Organising your own time
29	Thinking ahead
30	Reading written information such as forms notices or signs
31	Reading short documents such as short reports, letters or memos
32	Reading long documents such as long reports, manuals, articles or books
33	Writing written information such as forms notices or signs
34	Writing short documents such as short reports, letters or memos
35	Writing long documents such as long reports, manuals, articles or books
36	Adding, subtracting or dividing numbers
37	Calculations using decimals percentages or fractions
38	Calculations using more advanced mathematical or statistical procedures

Note: There were no variables 18 nor 22.

Table A2: Variables Descriptions and Means

Variable	Description	Females	Males
Log work rewards	Log of gross hourly pay augmented by 10% if employer pays pension contribution	1.73	2.01
Activities:			
Verbal	PC Score: see text	-0.02	0.19
Manual	“	-0.25	0.18
Problem-Solving	“	-0.13	0.11
Numerical	“	-0.15	0.14
Planning	“	-0.04	0.00
Client Communication	“	0.04	-0.06
Horizontal Communication	“	0.13	-0.07
Professional Communication	“	-0.16	0.16
Computer Usage:			
Simple	“	0.28	0.24
Moderate	“	0.28	0.25
Complex	“	0.11	0.11
Advanced	“	0.01	0.05
Highest Required Qual.			
Level 1	NVQ1 or equivalent	0.07	0.11
Level 2	NVQ2 or equivalent	0.26	0.17
Level 3	NVQ2 or equivalent	0.10	0.17
Professional	HND/Nursing/Teaching etc.	0.09	0.11
Degree	Degree or above	0.13	0.17
Learning Time: 1 wk-6 mths	Time until can do job competently	0.46	0.34
Learning Time: > 6 mths	“	0.40	0.60
Firm-Specific Skills	0/1: See text	0.05	0.03
Autonomy	See text	4.08	4.23
Variety	See text	4.41	4.81
NOTEAMWORK	0/1: No work organised in teams	0.28	0.23
Quality Circles	0/1: Belongs to quality circle or quality initiative	0.26	0.33
Work Experience	in years	17.37	19.82
Work Experience Squared		391.93	512.08
Job Tenure	months	83.24	105.35
Job Tenure Squared		13882.5	21103.6
Over-Education	Max (Actual Qualification Level - Required Qualification Level, 0)	0.61	0.60
Under-Education	Max (Required Qualification Level - Actual Qualification Level, 0)	0.28	0.33
Married	0/1	0.67	0.71
Temporary: fixed term	0/1	0.04	0.03
Temporary: other	0/1: Seasonal, temping, casual or other.	0.03	0.03
Part-Time	0/1: Self-defined	0.41	0.03

Table A2 (continued)

Size of establishment	Number of workers	310.90	333.79
Size squared		1469179	825969
Male job	0/1: Job done almost exclusively by men	0.02	0.33
Female job	0/1: Job done almost exclusively by women	0.17	0.00
Union recognised	0/1	0.46	0.44
Union member	0/1	0.29	0.30
Public Ownership	0/1	0.37	0.18
Non-profit organisation	0/1	0.03	0.02
Self-employed	0/1	0.05	0.11

Note: Means based on cases used in regressions of columns (4) of Tables 4 and 5.