*MERIT-Infonomics Research Memorandum series*

Computers, Skills and Wages

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*2001-020*


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# **Computers, Skills and Wages**

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June 2001

Keywords: Wage Differentials by Skill; Computer Use and Skill
JEL: J30; J31

Abstract

Computer use is mainly associated with skilled, high-wage workers. Furthermore, the introduction of computers leads to upgrading of skill requirements. This suggests that the computer requires certain skills to take full advantage of its possibilities. Empirical findings, however, suggest that the effects of computers on the labor market are complicated and difficult to trace. This paper offers a simple model and new empirical evidence from Britain showing how computers change the labor market. The model shows that wages are an important determinant of computer use and that neither computer skills nor complementary skills seem to be needed to explain skill upgrading. The empirical results are consistent with the model because they indicate that computer use is explained by wages rather than by skills and that wages are not related to computer skills.

Acknowledgments

We thank Daron Acemoglu, Jim Allen, Josh Angrist, David Autor, Eli Berman, Allard Bruinshoofd, Francesco Caselli, Paul David, Bart Diephuis, Eric Gould, Francis Green, Andries de Grip, Hans Heijke, Hugo Hollanders, Caroline Hoxby, Adriaan Kalwij, Larry Katz, Francis Kramarz, Alan Krueger, Jasper van Loo, Erzo Luttmer, Geoff Mason, Paul Miller, Markus Mobius, Richard Murnane, Joan Muysken, Steve Pischke, Mark Sanders, Judith Semeijn, Arthur van Soest, Luc Soete, Oxana Tchervonnaya, Bruce Weinberg, Finis Welch, Thomas Ziesemer and seminar participants at the Dutch Central Bank (NAKE), the Dutch Ministry of Economic Affairs, the Dutch Ministry of Social Affairs, Harvard University, the International Institute of Infonomics, the London School of Economics, Maastricht University, the Production of Human Capital Workshop in Maastricht, Tilburg University (CentER) and the University of Oxford for helpful comments; and the Netherlands Organization for Scientific Research (NWO) for financial support. We are grateful to Francis Green for the provision of the data, to Alan Felstead for help in using the data and Nic van Hal for research assistance.

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## 1. Introduction

The introduction of computers has substantially changed the labor market throughout the past two decades. For example, in the United States computer use at work has more than doubled from 24.3 percent in 1984 to 52.5 percent in 1997. This use is not evenly distributed among workers: in 1997, 74.9 percent of the workers with a college degree used a computer, compared to only 38.6 percent of the high-school graduates. It is also observed that the average wage of computer users is substantially higher than that of non-users. Even after controlling for personal characteristics, educational background, occupation and sector of industry, a computer wage premium of some 20 percent is found (e.g., Krueger, 1993 and Autor, Katz and Krueger, 1997).[1] In addition, both firm-specific case studies[2] and economy-wide investigations[3] report a positive correlation between skill upgrading of the workforce and computer use.[4]

The uneven distribution of computer use among different skill levels, the computer wage premium and the shift in labor demand towards skilled workers has particular appeal to the idea that computers are a major source of skill-biased technical change. The most common

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[1] All figures are taken from the October supplements of the Current Population Survey. Computer wage premiums are obtained from an ordinary least squares regression with the log of the hourly wage as the dependent variable and computer use and other covariates as independent variables (e.g., Krueger, 1993).

[2] See e.g., Groot and De Grip (1991), Levy and Murnane (1996), Autor, Levy and Murnane (2000) and Fernandez (2001).

[3] See e.g., Berman, Bound and Griliches (1994), Dunne and Schmitz (1995), Chennells and Van Reenen (1997), Doms, Dunne and Troske (1997), Entorf and Kramarz (1997), Autor, Katz and Krueger (1998), Berman, Bound and Machin (1998), Machin and Van Reenen (1998), Katz and Autor (1999), Dunne, Foster, Haltiwanger and Troske (2000) and Bresnahan, Brynjolfsson and Hitt (2001).

[4] Autor, Katz and Krueger (1998) report that the growth of the mean computer investment share from .026 in the 1970s to .057 in the 1980s can account for a rise of about 36 percent in the rate of within-industry skill upgrading from the 1970s to the 1980s in U.S. manufacturing. This skill upgrading is typically observed within industries and there is no evidence for employment shifts towards industries with high rates of computer utilization. Using the data applied by Autor, Katz and Krueger, we have not found evidence that industries using and investing more in advanced technologies are expanding relative to other industries.

explanation of this skill upgrading due to the computerization of the labor market is that the on-the-job use of a computer requires specific skills.[5] The evidence presented above suggests that workers possessing these skills earn higher wages and are allocated to jobs in which computers are used. Apparently these skills are particularly present among skilled workers, which explains the difference in computer use between higher and lower-skilled workers. It also seems likely that unobserved differences in skill requirements are showing up in the computer wage premium, and the increased demand for skilled workers following the introduction of the computer seems to confirm that higher-skilled workers are needed to operate in a computerized work environment. Apart from computer skills (e.g., Krueger, 1993, Hamilton, 1997, Miller and Mulvey, 1997 and Green, 1999), various studies point at complementary skills, by which some workers are better able to use the possibilities of computers than workers who do not possess these skills (e.g., Levy and Murnane, 1996, Bresnahan, 1999 and Autor, Levy and Murnane, 2001).

Although the implementation of the computer has improved the position of more-skilled workers, there are other findings that are inconsistent with the interpretation that computer use requires skills. For example, a large computer wage premium goes to such computer tasks as emailing and word processing (e.g., Krueger, 1993); furthermore, rather than electronic or mechanical cash registers, the use of computerized cash registers also seems to be associated with a wage premium (Green, 1999). DiNardo and Pischke (1996) show that it is by no means true that all those who embody computer skills are working in jobs in which computers are used. In addition, a fairly large number of people work in jobs in which

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[5] Katz (2000) argues that there is no *a priori* reason why the introduction of computers only affects the position of workers who actually work with a computer. For that reason, computer use can be regarded as a crude proxy for technical change. Empirical evidence shows, however, that computer use is actually correlated with a large number of labor market aspects. In this paper we therefore investigate primarily what happens to computer users, to improve our understanding of these findings.

computers are used even though they do not report having computer skills. Furthermore, based on job analyses, Autor, Levy and Murnane (2001) conclude that jobs and tasks that seem to be well-suited to the use of computerized equipment are found at all skill levels. Finally, Bresnahan (1999) argues that while higher-skilled workers use a computer more frequently, a substantial fraction of lower-skilled workers employs a computer as well.

These results illustrate that the way in which computers affect the labor market is complicated and probably notoriously difficult to trace. This is not surprising given that, apart from a worker's productivity and required educational level, computers change the specifications of the products produced, the price of the product on the goods market, and the way in which cooperation and collaboration with fellow workers are established. Due to the wide diffusion of computers, these changes are likely to influence the wage structure, which in turn influences the demand for and supply of labor. Furthermore, it is difficult to obtain a clear empirical picture of the genuine effects of computer use because computer users are likely to differ from non-users with respect to a great many observed and unobserved characteristics.

The aim of this paper is to contribute to and extend this literature by introducing a simple model to investigate the way in which computers have affected the workplace. To empirically address the implications of the model we present new results from Britain. Providing a model of jobs with multiple tasks, we obtain that wages are an important factor in explaining the introduction of computers.[6] An explanation for this finding is that the relative costs for high-wage workers to carry out a certain task are much higher than for low-wage workers performing a similar task. Hence, a firm gains more by letting a high-wage worker

[6] In this respect, both the model and the empirical results are consistent with the observation of Doms, Dunne and Troske (1997) based on firm level panel data, Entorf and Kramarz (1997) based on a panel of individuals and Chennells and Van Reenen (1997) based on IV-estimates in which wages and choice of technology are estimated simultaneously, that firms paid workers using a computer already higher wages prior to adopting this equipment.

bring this task to completion using computerized equipment. This observation is consistent with findings that computer users earn higher wages but reverses the causation of the arguments. Another implication of the model is that in general the introduction of the computer leads to an emphasis on more-skilled tasks. This shift increases skill requirements as well as the demand for more-skilled workers, which is consistent with the observed skill upgrading of the workforce in industries using computers (e.g., Autor, Katz and Krueger, 1998). Interestingly, this result does not require that the increase in productivity due to computer use depends on the skills (computer skills or complementary skills) people posses. It implies that the uneven distribution of computer use among different skill levels, and the wage differential between computer users and non-users can be explained without the skill arguments associated with the empirical findings in the literature.

Using British data, we present new empirical findings, which are in accordance with the model. The data enable us to investigate three important implications of the model. First, we obtain that computer skills do not explain wage differentials. Second, we show that wages, together with some specific tasks, are the main determinants of computer use. Third, neither educational level, nor age or experience are found to determine computer use, suggesting that the specific pattern of computer use is not likely to be explained by arguments pointing at the importance of complementary skills.

The plan of the paper is as follows. In Section 2 we present a model of computerization, in which we investigate jobs with multiple tasks. Section 3 provides information about the data. In Section 4 and 5 we investigate the relationship between computer skills and wages and the determinants of computer use. Section 6 concludes and discusses the implications of the model and the empirical results.

## 2. A model of computerization

### *2.1. Basic model*

Consider an agent with skills *s*, where $s = (s_1, s_2, ..., s_n)$ might be either a uni- or multi-dimensional parameter describing the skills of this agent. The *n* components of the vector *s* are the agent's characteristics determining the ability to perform a certain task. Years of education will typically be one component of the vector *s*, but also more specific characteristics such as mathematical skills or social abilities and experience are included in this vector.

To perform the job, the agent has to fulfil two tasks: task 1 and task 2. These tasks represent two independent aspects of the job that are nevertheless undeniably interrelated and very hard to separate.[7] To produce one unit of output, the agent needs $\tau_j(s)$ units of time to complete task *j*, where *j* = 1, 2.[8] The total time needed to produce one unit of output equals

$$\tau(s) = \tau_1(s) + \tau_2(s). \tag{1}$$

Task 1 represents aspects of a job that can be computerized and task 2 is the one that cannot be computerized. If task 1 is computerized it requires $\tau_c(s)$ to operate the computer instead of carrying out the task manually. $\tau_c$ depends on *s* because carrying out the computerized task might require skills and the time involved to operate the computer might vary with any component of the vector *s*. Even if computer skills are not included in the vector *s*, the pace in which someone is able to operate a computer can be regarded as a definition for

[7] Occupational descriptions like the Dictionary of Occupational Titles (DOT) and O*NET show that in practice occupations include several tasks, which require different types and levels of skills. In most instances these tasks cannot be separated into two jobs. An example might be a truck driver who has to read a map (task 1) to get from the loading-berth to the place where he has to unload but also has to drive the truck (task 2). In instances where the two tasks could be separated into two jobs we assume that it is costly because if two tasks are part of one job but carried out by two different people, this will lead to transaction costs. In particular, the costs of fine-tuning execution of the two tasks between two (or more) people will result in transaction costs in this case. The time needed to brief a colleague about the work that has to be done might therefore not compensate for the gains achieved by separating the two tasks. Hence, we assume that the costs are high enough to exclude separation of task 1 and 2 into two jobs.

[8] For convenience, we skip the argument *s*, except in cases where confusion may arise.

computer skills, i.e. computer skills $cs(s) = 1/\tau_c(s)$ are a specific function of $s$.[9]

Computerization of task 1 might also have an impact on carrying out task 2. If the good produced and the way it is produced – either by man only or using computerized equipment – remains unchanged, there is in fact no reason why the time required for task 2 should change. However, the complementarity between computers and particular human tasks is generally regarded as an important route for changing configurations of jobs and skill-biased technical change.[10] In this setting, such a complementary relationship only arises once a firm uses the possibilities of a computer to change the characteristics of the product or production process. We therefore allow $\tau_2$ to change as a result of computerization as follows: $\hat{\tau}_2 = \tau_2 + \Delta$ (in Appendix A we will go into more detail of this issue). In the case where $\Delta < 0$ ($\Delta > 0$) computerization of task 1 results in less (more) time required to perform task 2.[11] Furthermore, this change in time needed to perform task 2 might depend on $s$, which could lead to $\hat{\tau}_2(s)$ to stress different components of the vector $s$ than $\tau_2(s)$. The time needed to produce one unit of output now equals

$$\bar{\tau}(s) = \tau_c(s) + \hat{\tau}_2(s). \tag{2}$$

Define $\theta_i^j(s) = -(\partial\tau_j(s)/\partial s_i)/(\tau_j(s))$ as the time for task $j$ saved by a marginal increase in the $i^{\text{th}}$ component of $s$ ($s_i$). We assume $\theta_i^j(s) \geq 0$ because if $s_i$ affects the time needed to perform this task, an increase in $s_i$ leads to a higher productivity. Since $s_i$ might reflect both

[9] Such a task-related definition of skill is often referred to as a competence.

[10] For example, Autor, Levy and Murnane (2000) describe the introduction of computers in two departments of a large U.S. bank. In one department computers appeared to be a substitute for unskilled labor and in the other department computers seemed to complement skilled labor because many tasks were integrated into one job, which led to skill upgrading of the existing workforce in this department. They interpret the latter case as an example in which computers complement particular skills, which change the skill requirements of the job in favor of the higher-skilled workers.

[11] To describe the case where computerization leads to less time spent on the job as a whole, i.e. $\tau_c + \hat{\tau}_2 < \tau_1 + \tau_2$, we need $\tau_c < \tau_1$ and/or $\hat{\tau}_2 \leq \tau_2$.

general and specific skills, time savings might vary between tasks. This leads to the following two definitions.

**Definition 1**: Task 1 is a *routine task* for skill $i$ if the time saved by $s_i$ to perform this task is less than the time saved to perform task 2, i.e.

$$\frac{-\partial\tau_1(s)/\partial s_i}{\tau_1(s)} < \frac{-\partial\tau_2(s)/\partial s_i}{\tau_2(s)} \quad \text{i.e.} \quad \theta_i^1(s) < \theta_i^2(s).$$

**Definition 2**: Task 1 is a *skilled task* for skill $i$ if the time saved by $s_i$ to perform this task is more than the time saved to perform task 2, i.e.

$$\frac{-\partial\tau_1(s)/\partial s_i}{\tau_1(s)} > \frac{-\partial\tau_2(s)/\partial s_i}{\tau_2(s)} \quad \text{i.e.} \quad \theta_i^1(s) > \theta_i^2(s).$$

If we consider $s_i$ to reflect years of education, it is reasonable to assume that in most cases the task that can be computerized is a routine task. As a counter example in which task 1 is a skilled task, we might think of a chess player. IBM has shown that thinking about algorithms for the next move can be successfully computerized, but at the same time it requires a huge number of skills from the chess player. Yet moving the chess pieces and intimidating the competitor (task 2) takes the real Garry Kasparov. However, these cases are rare to the extent that we may assume that for the labor market as a whole the effects of cases in which task 1 is a routine task will prevail.[12]

Let us consider the situation of an individual firm, which has to decide whether or not to invest in computerized equipment. If a firm pays a wage $w(s)$ to a typical worker, the costs $k$ per unit of final output the firm incurs equal

[12] See Autor, Levy and Murnane (2001) for a similar line of reasoning. They analyze how computer technology complements or substitutes for certain aspects of the job, and observe that computers complement in particular non-routine problems and interactive tasks.

(3) $$k = (w+c)(\tau_c + \hat{\tau}_2),$$

where *c* reflects the costs of computer use.[13] The total costs the employer has to incur when an employee uses a computer are higher than the costs of not using one if $c(\tau_c + \hat{\tau}_2) > w((\tau_1 + \tau_2) - (\tau_c + \hat{\tau}_2))$. An important assumption is that the costs of the equipment are related to the time needed to produce one unit of output. This assumption reflects an essential characteristic of the way in which computers are currently used in the workplace because the part of the working time the computer is actually used depends mainly on the time the employee needs to fulfil the computerized task.[14] Implicitly we also assume that *c* has to be paid for the entire duration of the working time, which essentially means that there should be one computer for each employee. This implies that the computer stands idle when the worker is performing task 2.[15]

The products produced by the agent are sold at price $\rho$. The profits per product unit are defined as income minus expenditures and can be written as

(4) $$\Pi = \rho - (w+c)(\tau_c + \hat{\tau}_2).$$

Total production equals *P* and total demand *D* for the agent's services equals

(5) $$D = P(\tau_c + \hat{\tau}_2).$$

[13] These costs can be thought of as maintenance, depreciation and operating costs, but also as costs of new software applications and hardware.

[14] Previously, the calculation speed of the computer was the main limiting factor in the efficiency of the performance of the computerized task, but these types of situations are now rare. The reason for this is that there are few computer applications requiring the employee to give instructions so that she can attend to other tasks until the computer has completed the task. The alternative assumption that computer costs are proportional to the units of output produced leads to similar results. The assumption that computer costs are a fraction of the wage or production costs would not support our main findings.

[15] The interrelatedness between the two tasks and the assumption that one person has to carry out the job makes this assumption realistic. In footnote 19 we derive that the results do not change substantially if the computer is only used for some fraction $0 < \tau_c + \lambda\hat{\tau}_2 < \tau_c + \hat{\tau}_2$ of the total production or working time.

*2.2. When is the computer introduced?*

The decision to actually introduce a computer depends on the costs involved to computerize task 1. This decision is based on a break-even point at which the firm's profits are the same whether or not task 1 is performed using a computer. The break-even point *b*, at which $c(\tau_c + \hat{\tau}_2) = w((\tau_1 + \tau_2) - (\tau_c + \hat{\tau}_2))$, equals

(6) $$b = w\left(\frac{\tau_1 + \tau_2}{\tau_c + \hat{\tau}_2} - 1\right).$$

The interpretation of equation (6) is the following. If $b > c$, a computer is profitable because the actual costs of the computerization of task 1 are below the break-even point.[16] Allowing for some randomness in the actual costs of computer use ($c = \hat{c} + \epsilon$, where $\epsilon$ is an error term with the usual assumptions), a higher *b* can be interpreted as a higher probability that task 1 is carried out by making use of computerized equipment, i.e. $P(\text{computer}) = P(b > c)$.[17]

One of the most interesting observations from equation (6) is that higher wages increase the probability of using a computer. For a good interpretation of this observation, it is important to know why wages differ between employees. To examine the impact of these differences on the introduction of the computer, we can rewrite the break-even decision as follows:

(7) $$b = \frac{w(\tau_1 + \tau_2)}{\tau_c + \hat{\tau}_2}\left(1 - \frac{\tau_c + \hat{\tau}_2}{\tau_1 + \tau_2}\right).$$

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[16] In essence this model could therefore be regarded as a threshold model of diffusion as introduced by David (1969).

[17] Greenwood and Yorukoglu (1997) provide interesting figures showing that *c* has fallen dramatically since the early 1970s and that at the same time the share of IT investment has risen from about 10 percent in 1970 to some 45 percent in 1995. The European Information Technology Observatory (EITO, 2000) supplies figures showing that the price of a PC running on a Pentium processor of 101 to 149 MHz fell from about 2,100 U.S.$ in 1993 to some 1,400 U.S.$ in 1998. Similarly, the price of a PC running on a Pentium II processor of more than 400 MHz declined from about 1,900 U.S.$ in 1998 to some 1,300 U.S.$ in early 2001. Jorgenson (2001) provides similar figures showing rapid declines in the price of new computerized equipment. This fall has led to lower costs of introducing computers and is therefore one of the likely candidates to explain the rapid diffusion and the increased use of computers at the workplace. In addition, the increased power of the processors is also likely to have made more jobs subject to computerization because the increased processor power makes it feasible to computerize increasingly complex tasks.

This equation consists of three parts. First, $\tau_c + \hat{\tau}_2$ represents the amount of time the computer is needed for each product to be produced. Second, $1 - (\tau_c + \hat{\tau}_2)/(\tau_1 + \tau_2)$ represents the time gain of using a computer to perform task 1. This term depends on the specific character of the tasks to be performed, but also on the skill level of the worker concerned. This time gain related to specific tasks is likely to reflect the development of new and more efficient applications, software and hardware.[18] With respect to the vector *s* we obtain that if a worker is more efficient in performing the new tasks 1 and 2 (i.e. $\tau_c$ and $\hat{\tau}_2$ are relatively low compared to $\tau_1$ and $\tau_2$), this worker benefits more from computer use than a relatively less efficient worker. The relation of the ratio $(\tau_c + \hat{\tau}_2)/(\tau_1 + \tau_2)$ with *s* can therefore be defined as the skill bias of the adoption of a new technology because the skills included in vector *s* might either be related to the performance of the computerized task ($\tau_c$) or to the other task ($\hat{\tau}_2$), which might provide skilled workers with an advantage to use a computer over unskilled workers. Note, however, that workers with high abilities to bring to completion task 2, both before and after the introduction of the computer, do not have a higher probability to use the computer, since it leaves the ratio $\tau_2/\hat{\tau}_2$ unaffected. Furthermore, even very large differences in computer skills between people might have only a very moderate impact on computerization if the time needed for task 1 ($\tau_c$) is low compared to the time needed for task 2 ($\hat{\tau}_2$).[19]

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[18] Freeman and Soete (1997) provide a historical overview of the major product and process innovations in the semiconductor industry since the 1960s, which have improved the capacity and pace of computerized equipment. Jorgenson (2001) shows figures on and discusses "Moore's law", which indicates that chip capacity grows exponentially at a 35-45 percent rate a year.

[19] Note that if the computer is only needed to perform task 1 or just a part of the time to carry out task 2 (with $\lambda$ reflecting this fraction), the expression for the break-even point becomes

$$b = \frac{w(\tau_1 + \tau_2)}{\tau_c + \lambda\hat{\tau}_2}\left(1 - \frac{\tau_c + \hat{\tau}_2}{\tau_1 + \tau_2}\right).$$

The gain from only using the computer for some time further increases the benefits of introducing a computer. The use of the computer in this case can be seen as a situation in which more than one employee makes use of one single computer (see also footnote 15).

The final component of equation (7), $w(\tau_1 + \tau_2)$, i.e. the wage costs per unit of production, brings about the influence of wages on computer use. It reveals that wages are also a main determinant of computer use, which suggests that computer use does not lead to a higher wage but that a higher wage increases the probability of using a computer. This observation is consistent with the results of many empirical studies observing that computer users earn higher wages. These studies mainly predict higher wages as a result of using a computer, whereas this result suggests that the causality is reversed. Although computer skills and complementary skills might explain the pattern of computer use, the model shows that skill arguments are not necessarily needed to explain the pattern that higher-skilled workers use computers more frequently and that within each level of education computer users earn higher wages.

*2.3. Skill requirements*

The finding that the ability of a worker to use a computer is not needed to explain that firms will invest in computers for higher-paid workers does not imply that the introduction of computers did not impact skill requirements. The skills required for production can be viewed as the result of the firm's profit maximization. Since a change in the skill requirements affects both the productivity in task 1 and task 2, changes in the required skills before computerization were not profitable for a certain skill $s_i$ from the vector $s$ when

$$\frac{\partial \Pi}{\partial s_i} = \frac{\partial(\rho - w(s)(\tau_1(s) + \tau_2(s)))}{\partial s_i} = 0. \tag{8}$$

The reason for this is that if a firm hires a more-skilled worker, its productivity ($1/(\tau_1 + \tau_2)$) increases but the wage costs ($w$) it has to incur also increase. This tradeoff between higher skills and higher wages gives the firm's optimal skill choice:

(9) $$\frac{\partial w(s)/\partial s_i}{w} = \frac{\tau_1}{\tau_1+\tau_2}\theta_i^1 + \frac{\tau_2}{\tau_1+\tau_2}\theta_i^2.$$

After a computer has been introduced this equation changes into:

(10) $$\frac{\partial w(s)/\partial s_i}{w} = \frac{\tau_c}{\tau_c+\hat{\tau}_2}\theta_i^c + \frac{\hat{\tau}_2}{\tau_c+\hat{\tau}_2}\hat{\theta}_i^2.$$

To equilibrate the equation, the firm changes its skill requirement $s_i$ after computerization. Equation (10) reveals three factors determining the optimal skill level: (i) an increase in the marginal wage costs of skills $((\partial w/\partial s)/w)$ leads to a decrease in demanded skill requirements;[20] (ii) an increase in the advantage of skill $i$ in performing task $j$ (an increase in $\theta_i^c$ and/or $\hat{\theta}_i^2$ compared to $\theta_i^1$ and $\theta_i^2$) leads to an increase in demanded skill requirements; and (iii) a change in the relative weights of the two tasks in the production process ($\tau_c/(\tau_c+\hat{\tau}_2)$ and $\hat{\tau}_2/(\tau_c+\hat{\tau}_2)$) leads to an increase (decrease) in skill demand in the case of a shift towards a skilled (routine) task.[21]

For an individual firm that has to decide whether or not to introduce computers the wage structure can be considered as given. If we keep the wage structure constant, the condition derived in equation (10) might change in three different ways after computerizing task 1. First, if task 1 becomes a more-skilled task, the firm demands a higher-skilled worker because of the importance of computer skills. Second, the performance of task 2 might demand a more-skilled worker because skilled workers gain more time than unskilled workers after the

[20] This can be seen from the second-order condition. Since equation (10) reflects a maximum, the second-order condition equals

$$\frac{\partial((\tau_c/(\tau_c+\hat{\tau}_2))\,\theta_i^c + (\hat{\tau}_2/(\tau_c+\hat{\tau}_2))\,\hat{\theta}_i^2)}{\partial s_i} < \frac{\partial(\partial w(s)/\partial s_i/w)}{\partial s_i}.$$

This means that if $s_i$ becomes more expensive, employers will diminish their skill demands for $s_i$.

[21] Because the relationship between skill and productivity generally differs between both tasks, each task would have a different skill requirement if carried out by separate workers. Skill requirements for the routine task would be lower than skill requirements for the skilled task. Since we assume that both tasks cannot be separated, this implies that the actual skill level is a compromise between the skill levels that are optimal for these tasks separately. The skill level resulting from this compromise depends on the time needed for each task. A change in the relative time required for each task affects the weighting of these effects and therefore influences the recruitment decision.

introduction of the computer (complementary skills). Finally, even if the influence of *s* on both tasks is kept constant, the weight of both tasks changes after the introduction of the computer. This means that if task 1 is a routine task, skill requirements increase because the computer puts more weight on task 2. An important implication of this result is that for all jobs in which the computerized task is a routine task, the introduction of a computer increases skill requirements, even if the effect of skills on both tasks separately is kept constant. This suggests that neither computer skills nor complementary skills are needed to explain the observed skill bias in labor demand for jobs in which the computer is used.[22]

This latter finding provides a remarkable insight because it shows that even if working with a computer does not increase the comparative advantage of skilled workers in each task per se, skill requirements might nevertheless be raised. The particular skills from the set *s* that become more important are not related to operating a computer or to certain tasks that increase productivity due to the introduction of a computer, but simply are the skills that already were emphasized for carrying out task 2 before computerization, whatever this task might be. This observation might explain the difficulties in the search for a direct link between technical change and increased demand for particular skills to explain skill-biased technical change.

In the remainder of the paper we examine the empirical validity of the predictions of the model.

## 3. Data, skill measurement and preliminary statistics

The data we utilize in this paper have been collected in a survey, conducted in the first

[22] This effect is consistent with the findings of Levy and Murnane (1996), who invest the introduction of new technology in a large U.S. bank.

half of 1997, called the Skills Survey of the Employed British Workforce.[23] The survey includes a relatively small, but representative, number of workers (2,467) from Britain.[24] Participants were asked several dozens of questions on their labor market situation during face-to-face interviews to obtain information on various aspects of their jobs including qualifications, responsibilities, skills, the tasks they carry out at work, and training.

Of interest for the purpose of our analysis are the detailed questions concerning the *importance* of computer use, the level of *sophistication* at which computers are employed, and computer *skills*.[25] In line with our model, these questions are related to the tasks a worker has to carry out at the workplace. With regard to computer use the following question was asked: "In your job, how important is using a computer, PC, or other types of computerized equipment?" The response scale offered was fivefold: "essential", "very important", "fairly important", "not very important", and "not at all important or does not apply". With respect to the level of sophistication of computer use the following question was asked: "Which of the following best describes your use of computers or computerized equipment in your job?" The answers are divided into four different levels of sophistication at which computers or

[23] Ashton, Davies, Felstead and Green (1999) provide a description of the survey and the full questionnaire.

[24] In Appendix B1 we report some descriptive statistics of the variables used in the analysis of this paper.

[25] Particularly the information on the latter two is unique. With respect to the level of sophistication of computer use, Entorf and Kramarz (1997) use the *Enquête sur la Technique et l'Organisation du Travail auprès des Travailleurs Occupés*, in which they distinguish three levels of computer use related to the autonomy of each worker. This is an indirect measure of the level of sophistication of computer use because it relates to the job in general, whereas our data relate it to the sophistication of the computerized task (task 1 in terms of the model). Computer skills have been measured only indirectly in the literature as some kind of "computer ability" (Bell, 1996) or "computer knowledge" (DiNardo and Pischke, 1996 and Hamilton, 1997). Bell uses data from the U.K. National Child Development Study. DiNardo and Pischke utilize data from the West German Qualification and Career Survey conducted by the Federal Institute for Vocational Training. In these data information on both "computer use" and "computer knowledge" is available. Hamilton uses variables from the 1986 High School and Beyond Survey indicating whether an individual has ever used software packages or has used a computer language to program. Rather than a component of *s* which might influence the time needed to operate a computer, in this paper we apply a direct measure of computer skills related to the tasks a worker must carry out.

computerized equipment are being occupied. “Simple” use indicates “straightforward use, e.g., using a computer for straightforward routine procedures such as printing out an invoice in a shop.” “Moderate” use means “e.g., using a computer for word processing and/or spreadsheets or communicating with others by email.” “Complex” use is defined as “e.g., using a computer for analyzing information of design, including use of computer aided design or statistical analysis packages.” Finally, “advanced” use is described as “e.g., using a computer syntax and/or formulae for programming.” Finally, computer skills are measured using the following question: “When your job involves using a computer, PC or other type of computerized equipment, are you able to do this effectively?” Six possible answers were offered: “always”, “nearly always”, “often”, “sometimes”, “hardly ever” and a remaining category “does not apply”. Note that the design of the questions in the survey is such that questions on the level of sophistication of utilization and on skills have not been asked to people who indicate that they do not use a computer at work.

The question used to measure skills has been the subject of substantial debate among economists, psychologists and sociologists, especially in the literature regarding the importance of language skills.[26] Surveys relying on the respondent’s self-assessed skills often use a question like “How would you rate your current writing skills in English?”[27] to measure these skills. The response alternatives encourage responses like “very good”, “good”, “fair”, “poor”, or “cannot write in English”. Such answers, in the absence of independent verification (e.g., objective tests), question the reliability of the responses because of issues of social desirability

[26] See e.g., Chiswick and Miller (1995), Berman, Lang and Siniver (2000) and Dustmann and Van Soest (2001).

[27] See e.g., the questionnaire of the OECD’s International Adult Literacy Survey (IALS).

and self-referencing, which might bias the data in unidentifiable ways.[28] For academic skills like reading and math it is possible to measure by test items, which has the obvious advantage that for all respondents the skills are measured in an identical way. While the OECD will use this approach for numeracy and literacy skills in the forthcoming Life Skills Survey, computer skills seem to be too much context- or task-related to allow for a general set of test questions (see OECD, 2000). Although the approach taken in the data we use also relies upon self-assessed skills, the main strategy has been to assess skills through questions on several tasks a respondent has to carry out at work, rather than directly asking the respondent to evaluate his own skill level. The main reason to use this approach has been that being asked to describe whether one carries out the tasks at work effectively seems to be much less subject to self-esteem than being asked to assess one's own abilities. Furthermore, the skill question is directly linked to the tasks that must be fulfilled and seems to be well-suited to an empirical analysis of our model based on the performance in different tasks. Rather than collecting information about an abstract skill, the question is directly addressed to the success in using a computer, i.e. the question is competence-based.[29] In Section 4.3 we address the validity of the skill measure in more detail.

We have translated the answers to the computer skill question as follows. Respondents answering "always" to the question whether they are able to effectively use a computer, PC or other type of computerized equipment are labeled "very high" computer-skilled. Answering "nearly always" makes a worker "high" computer-skilled; "often" is "intermediate" computer-

[28] See e.g., Spenner (1990) for a discussion of these kinds of data problems, and Bertrand and Mullainathan (2001) for a summary of the literature using such measures and the integration into a measurement-error framework as to understand what they imply for empirical research relying on subjective data.

[29] Spenner (1990) reports evidence from a number of studies finding high correlations between self-assessed skill measures obtained by this way of questioning and measures obtained from objective judgements by experts and external expert systems, used to develop DOT and O*NET.

skilled; “sometimes” is “low” computer-skilled and “hardly ever” is “very low” computer-skilled.

Table 1 reports the distribution of the answers on the three computer questions. Panel A indicates that computer use is “essential” in almost one-third of all cases, and in 14.7 percent it is regarded as “very important”. Slightly over 40 percent of the respondents answered that computer use is “not very important” or “not important at all, or does not apply”. The level of sophistication of use in Panel B is skewed towards “simple” and “moderate” tasks like routine procedures such as printing out an invoice in a shop and using a computer for word processing and/or spreadsheets or communicating with others by email. Only 3.4 percent of the respondents uses computerized equipment at the “advanced” level. Panel C shows that more than half of the workers in the sample possesses “very high” or “high” computer skills. Among those who use a computer there seems to be a relatively small group of people with “low” or “very low” computer skills (10.0 percent).

TABLE 1 OVER HERE

Table 2 reports the correlation between computer skills within different levels of computer use and between computer skills within each level of sophistication of computer use, respectively. Panel A communicates information on the skill distribution for different levels of computer use. We observe from this panel that workers in jobs in which a computer is more important seem to possess higher computer skills on average. In a similar way, Panel B provides information on the skill level of workers who use the computer at different levels of sophistication. Again we observe that higher levels of sophistication seem to go along with higher levels of computer skills.

TABLE 2 OVER HERE

Although there is little doubt that computer users have more computer skills than non-users, one might wonder whether there is a return to computer skills. To find an answer, it is important to disentangle the different roles of the level of *sophistication* of computer use, and computer *skills* in wage formation. Even if computer skills have no market value, one would expect users to acquire these skills just by experience. The main problem therefore is that if computer use is more common among high-wage workers, a spurious correlation between computer skills and wages might show up. Conversely, the use of a computer might be a necessary condition to be paid for computer skills. Differences in earnings between computer users and non-users do therefore not necessarily show the value of computer skills. Our research strategy is based on the fact that, given the level of sophistication at which a computer is used, computer users are not equally able to use a computer. This is what we investigate in the next section.

## 4. Computer skills

### *4.1. The returns to computer use and skills*

To examine the wage differential associated with computer use and computer skills, we run a number of (OLS) wage regressions and augment the standard cross-sectional wage equation by including a dummy for computer use. The wage equation for a typical worker then looks like

$$\ln W = X\alpha + C\beta + \epsilon \tag{11}$$

where $\ln W$ is the log gross hourly wage rate, $X$ is a vector of observed characteristics and $C$ represents a dummy variable that equals 1 if the worker uses a computer, and 0 if not; $\alpha$ and $\beta$

are the estimated parameters and $\epsilon$ is an error term with the usual assumptions.

In the first column of Table 3 we report the results of this estimation. In column (1) we include the usual covariates like education, age and experience and age and experience squared, and the dummy variables female, married, married×female, union member and supervisor. We obtain a computer wage premium of 21.4 percent (exp(.194)−1) and the usual findings for the other covariates: the wage is increasing in educational level; age and experience are also positively correlated to the wage as well as the gender, marital status, supervision and union variables.[30]

In columns (2)-(4) we have split the dummy for computer use according to the importance of on-the-job computer use (column (2)), the level of sophistication of computer use (column (3)) and computer skills (column (4)). Workers who do not use a computer are taken as the reference group. The results in column (2) suggest that workers whose importance of computer use is "essential" to perform the job receive the highest wage premium (34.0 percent); workers whose importance of computer use at work is "not very important" receive a wage premium of 12.2 percent, compared to workers who do not use a computer. The results reported on the level of sophistication of computer use in column (3) are similar. Finally, in column (4) we report the returns to computer skills. The coefficients at the four highest levels indicate a return to computer skills but do not significantly differ from each other. All workers earn between 22.1 and 25.1 percent higher wages than workers not using a computer, irrespective of their skill level; workers with "very low" computer skills have much lower

[30] Other specifications of the wage equation all lead to a computer wage premium around 20 percent. We do not include these different specifications in Table 3, because they do not add additional insight to the results presented in the first column. We also considered sector dummies (1-digit SIC) and dummies for the size of the company. Furthermore, we included tenure, whether a worker has a permanent job or not, and hours worked and hours worked squared. The magnitude of the results did not change when we included these additional covariates. We also ran the regression separately for men and women, which did not change the magnitude of the results significantly. The results of taking into account the importance of computer use, its level of sophistication and computer skills later on in the analysis are also comparable.

wages which are not significantly higher than the wages of non-users. These results putting forward the value of computer skills are interesting. Due to the strong correlation between the level of sophistication of computer use and computer skills reported in Table 2, one might also expect a positive correlation between computer skills and wages, even if computer skills are not positively correlated with wages within each level of sophistication. So even without controlling for the level of sophistication of computer use, computer skills are not related to wages.

A possible reason for the lower returns to computer skills for workers who only possess a “very low” level of computer skill is that many of these people started to use the computer only recently. Since the model suggests that wages are one of the main determinants of computer use, recent users will (on average) have lower wages, which points towards a very selective group of users. Since they just started to use a computer, this group probably lacks skills by experience, which might lead to a spurious correlation. If we exclude those workers who did not use a computer five years ago, the regression coefficients indeed look differently. The results reported in column (5) show that particularly the coefficient for the least computer-skilled workers has gone up. This suggests that workers who have used the computer for a longer period of time receive the same return to computer skills, irrespective of whether they have “very high” or “very low” computer skills.[31] This result is also consistent with the possibility put forward by the model that it is the use of the computer that matters, not necessarily the skills involved.[32]

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[31] Excluding the most recent users from the other regressions reported in Table 3 obviously leads to an increase in the coefficients. For example, the dummy for computer use reported in column (1) increases by .122 to .315 when excluding workers who use the computer less than five years. The coefficients for the importance of computer use and the level of sophistication of computer use indicate similar increases. In contrast with the coefficients for computer skills the difference between the coefficients remains the same, however.

[32] It is also important whether the coefficients on the importance of computer use, the level of sophistication of computer use and computer skills are statistically different from each other. A comparison of the highest

TABLE 3 OVER HERE

*4.2. The value of computer skills*

The data distinguish four different levels of sophistication of computer use: "advanced", "complex", "moderate" and "simple". To disentangle the effects of computer use from computer skills on wages, we estimate the returns to computer skills within each level of sophistication. Table 4 presents the results from this analysis. The first column in Panel A indicates that at the "advanced" level of sophistication of computer use workers with "very high" computer skills receive the highest wage premium. Although significant at the 10 percent level only, this might suggest that at this "advanced" level computer skills are related to wages, which is plausible given the character of the work.[33] The next three columns show a different pattern. At the "complex" level of sophistication of computer use workers receive the highest wage when their computer skills are "intermediate". At the remaining two levels of sophistication of computer use, workers whose level of computer skills is "low" receive the highest wage. In Panel B we exclude the recent users from the analysis. The results are similar to the results reported in Panel A.[34]

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premium with the other estimates using a one-tailed t-test, shows that the coefficients for workers whose computer use is "essential" are statistically different at the 5 percent level from the coefficient of workers whose computer use is "very important", and at the 1 percent level from the coefficients for the workers whose computer use is only "fairly important" or less. For the level of sophistication of computer use we find that the coefficients of using the computer at the "advanced" level are statistically different from the coefficients of using the computer at the "moderate" level and of using the computer at the "simple" level of sophistication, both at the 1 percent level. With regard to computer skills we observe only a difference in column (4) of Table 3 between workers having "intermediate" computer skills compared to workers possessing "very low" computer skills (1 percent level). If recent users are left out (column (5)) there are no significant differences between the skill levels distinguished.

[33] This group of workers consists mainly of programmers for whom the computerized task is a skilled task, whereas for most other workers the computerized task is a routine task.

[34] We ran the same regressions investigating the effect of computer skills within each level of importance of computer use. The results from this regression are similar to the ones presented in Table 4. Note also that only at the "complex" level of sophistication of computer use in Panel A the wages of workers with "very high" or

These results are consistent with the model and with our preliminary findings in Table 3 that computer skills utilized to carry out task 1 seem to be an unimportant determinant for most jobs in explaining the higher wages associated with computer use.

TABLE 4 OVER HERE

*4.3. Validity of the skill measure*

An important concern that might question the results in Tables 3 and 4 is whether the skill measure is robust. Although subjective measurement will always suffer to some extent from limited self-knowledge and possible mistakes in valuing a worker's skills, our findings suggest that this subjective skill measure is valid. There are three arguments for this. First, comparing the results for computer skills with other skill measures from the same survey shows that relative scores are consistent: people give themselves lower grades for skills that are generally viewed as difficult, such as analytical thinking and mathematical calculations. Second, the positive correlation between the importance of computer use, its level of sophistication and computer skills in Table 2 shows the consistency of the measure in this respect. Finally, large measurement errors and biases in the skill measure would imply that other skills are not related to wages either. In Table 5 we report regression results for other skills measured in the same subjective way.

We report the results from the same regression as in column (4) of Table 3 for four different skills, other than computer skills. These skills are (i) analyzing complex problems in depth; (ii) spotting problems or faults; (iii) making effective speeches or presentations; and (iv)

"high" computer skills are significantly lower than the wages of workers with "intermediate" skills (5 percent level). The remaining coefficients cannot be distinguished from one another within each level of sophistication.

writing short documents with correct spelling and grammar. We have selected them because they seem to reflect four different aspects of the job that workers come across when performing their job. The regression results reported in Table 5 show that for these job aspects higher skills are generally associated with higher wages.[35]

TABLE 5 OVER HERE

**5. The determinants of computer use**

The model suggests that computer use might be related to (i) wages, (ii) the tasks within a job and (iii) the skills workers possess. To investigate this relationship, we perform the following regression analysis:

$$\ln\left(\frac{P}{1-P}\right) = \alpha(\ln W) + X\beta + T\gamma + \epsilon, \tag{12}$$

where $P$ is the probability that the worker will use a computer; $\ln W$ is the log gross hourly wage, $X$ is a vector of personal characteristics and $T$ is a vector of the 35 tasks specified.[36] We use the vector $T$ to investigate whether computer use is related to the specific tasks the worker has to carry out.

The main problem in this equation is that wages are endogenous. Especially the possibility that computer use increases wages (treatment effect) or reflects unobserved skills,

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[35] It is interesting to note whether the coefficients shown in Table 5 are statistically different from the highest premium found. For tasks involving the in-depth analysis of complex problems, we find that the coefficients for workers with "low" and "very low" skills are significantly lower than the coefficient for workers with "very high" skills at the 5 percent level. The same applies to making effective speeches or presentations and writing short documents with correct grammar and spelling. For spotting problems or faults we are not able to distinguish the coefficients. A regression with a variable ranging from 1 to 5 for the different skill levels and a dummy to identify whether this task is a part of the job shows that all skill measures are positively correlated with the wage at the 5 percent level, except for spotting problems or faults, which is only significant at the 10 percent level. The most important insight is that doing the same for computer skills we find no significant positive correlation between computer skills and wages.

[36] Appendix B2 lists the 35 tasks we consider.

which are reflected in the wage, might raise doubts about the causality of the relationship. To estimate this equation we use an instrumental variable for the wages. Since it seems plausible to assume that union coverage and membership influence wages but will not interfere with computer use directly, we use several variables related to the unionization of the job involved as instruments for wages to investigate the determinants of the probability to use computerized equipment at work. In Britain, about 50 percent of the workers are covered by a union, the coverage is fairly equally spread over occupations and sectors, and union coverage has a substantial effect on wages. For these three reasons the instruments provide an opportunity to investigate the direct link between wages and computer use from a statistical point of view as well.[37]

To instrument the wage, we add to this model a linear equation explaining ln$W$ with the same $X$ and $T$ vectors plus these union variables and replace the ln$W$ by its predicted value in equation (12). These equations have been estimated by maximum likelihood.[38]

In Table 6 we report the results of this estimation. The first column provides the results for the regression without including the tasks. Consistent with the model the estimation results show that wages are a main determinant of computer use. Interestingly, the level of education

[37] The five instruments we use are: (i) at your place of work, are there unions, staff associations or groups of unions?; (ii) are any of them recognized by management for negotiating pay and/or conditions of employment?; (iii) is it possible for someone in your job to join one of these unions or staff associations?; (iv) are you a member of a (if the answer on question (i) is no, any other) trade union or staff association?; and (v) the cross-dummy for workers answering yes on both question (i) and question (iv). Estimation based on only the coverage variable (variable (i)) provides similar results, with slightly higher standard deviations. The other instruments are too weak to provide significant results on their own. In Appendix B1 details about unionization.

[38] Due to the non-linearity of equation (12), inclusion of the predicted wage to proxy for the wage leads to some bias in the estimation. Angrist (1991) therefore prefers a simple linear regression. Especially when most cases in the logistic regression do not have very high or low probabilities, such a linear function might be a good approximation of the logistic curve avoiding these inconsistencies connected to IV-estimation. However, since in our estimations a relatively large number of people with low and high wages do have extreme probabilities of computer use, this linear model leads to a bias in the results. To estimate equation (12) it seems more appropriate therefore to use the logistic model. Inclusion of the residual of the wage equation as a variable in the logistic equation, as a check for possible problems related to this non-linearity, does not change the results.

does not seem to be a relevant predictor of computer use. A likelihood ratio test reveals that all the educational dummies together do not significantly improve the explanatory power of the model. This suggests that indeed more-skilled workers do not have an *a priori* higher probability of using a computer to carry out task 1, which is consistent with the possibility put forward by the model that computer use is not related to specific skills. Also for age and experience none of these variables are significant separately but a likelihood ratio test for all age and experience variables together is just significant.[39]

To consider whether particular tasks are predicting computer use, we have included the vector *T* in the analysis. Columns (2) and (3) of Table 6 report the regression results. We have divided the evaluation of the 35 tasks into two categories. In column (2) we address tasks which are valued "essential" or "very important" and in column (3) we take into account tasks that are valued higher than "not at all important".[40] Hence, column (2) represents tasks that are at least "very important" and column (3) only uses tasks that are part of the job, although they might be relatively unimportant.

Consistent with the model, these estimations show again that the wage is an important determinant of computer use. In addition, a number of tasks also seem to increase the probability to get a computer, in particular writing, reading and calculating tasks. It is also interesting to note that the estimation based on all tasks, both important and unimportant (column (3)), explains computer use much better than the estimation based on tasks labeled "very important" or "essential" only. This suggests that, in general, computers are not used for

[39] We also ran a regression excluding experience, which does not change the results.

[40] For a couple of tasks almost every respondent answered that these aspects were at least "not very important". This led to numerical problems in the maximum likelihood estimation. For this reason, tasks which were reported by at least 95 percent of the workers to be part of their job have been excluded from the estimation reported in column (3).

the core tasks of the job, but rather that secondary tasks make the equipment worthwhile to use.[41] This observation is consistent with our assumption that computer use generally depends on routine tasks, rather than on skilled tasks, which are likely to be of secondary importance to skilled workers. It is also consistent with the prediction of the model that complementary skills explaining the wage differential between computer users and non-users are probably hard to find.[42]

In both specifications including the tasks, the variables related to education, age and experience are once again not significant. In the specification including all tasks that are at least "not very important", the likelihood ratio tests show that not only the educational dummies together, but also the age and experience variables together do not significantly improve the fit of the model.[43] Particularly, level of education, age and experience are often used as main determinants in the vector *s*. This suggests that productivity advantages in using a computer because of the skills someone possesses do not seem to explain the pattern of computer use. Since computer use will change the relative importance of the tasks within a job, skill requirements might change however. This emphasis on the importance of task 2 rather than the skills needed to take advantage of the possibilities of a computer is therefore likely to be an important channel for skill upgrading.

[41] When the same regression is performed without including the wage, educational levels become of course significant because they are good predictors of the wage. However, the coefficients on the particular tasks do not change.

[42] Apart from wages and some tasks, gender seems to be a good predictor for computer use as well. This finding confirms Weinberg's (2000) hypothesis that computers take away some of the (physical) disadvantages women have in a non-computerized labor market.

[43] The fact that age is not a significant predictor of computer use is consistent with the findings of Friedberg (2001) and Weinberg (2001) for the United States and runs against the popular notion that older workers are not able to cope with the computerization of the workplace. It is also in line with the findings of Allen (2001), for the use of technology in general, who argues that more-experienced (and hence older) workers do not particularly suffer from the introduction of new technologies.

TABLE 6 OVER HERE

In summary, the estimates indicate that the conclusions drawn from the model are consistent with the empirical findings. First, both computer skills and complementary skills do not seem to be able to explain the higher wages of computer users. Second, the rather strong assumption that the estimated effect of computer use represents a causal impact of computer use on wages does not seem to hold because the estimates in Table 6 show that wages represent a causal impact on computer use.

## 6. Conclusions and Discussion

Computers have brought about a dramatic change in the labor market in the past decades. A large number of economists and commentators regard the introduction and implementation of the computer as a major determinant underlying the contemporary trend towards skill-biased technical change because the computerization of the labor market seems to go together with skill upgrading and wage inequality (e.g., Autor, Katz and Krueger, 1998). Until recently computers have been used mainly by skilled workers and many studies report a substantial wage differential between computer users and non-users. Therefore, it has been argued that certain skills are likely to enable workers to make more effective use of the possibilities offered by a computer.

In this paper we presented a simple model and new empirical findings showing what happens to the job when the computer is introduced. The main findings are that both computer skills and skills complementary to using a computer do not seem to be able to explain the labor market changes. Second, wages seem to be a good predictor of computer use. Our results are of interest for several reasons.

First, we have presented estimates showing that the computer wage premium is not the result of the allocation of workers possessing the highest-level skills to the most complex jobs (e.g., Krueger, 1993). Furthermore, we obtained results indicating that the computer wage premium does not result from some spurious correlations or unobserved skills (e.g., DiNardo and Pischke, 1997). From the same perspective, both our model and the estimates point towards an answer as to why workers in firms operating with advanced and new technologies earn higher wages on average (e.g., Doms, Dunne and Troske, 1997). Studies based on panel data which typically find that computers are first introduced among high-wage workers also seem to fit in within our line of reasoning (e.g., Entorf and Kramarz, 1997).

Second, the observation that it is unlikely that skills related to computer use explain the patterns of diffusion and observed wage differentials does not imply that computers are not a source of skill-biased technical change. Our approach indicates that employers upgrade their workforce because computerization enables firms to use higher-skilled workers more effectively as a result of the diminishing importance of routine tasks. In this way, the introduction of the computer seems to induce a gradual upward shift in skill requirements for computerized jobs. The outcome of the model predicts this latter channel as an important source of skill-biased technical change.[44]

Finally, based on the model, as computers become cheaper and more applications will become available, we might expect the majority of low-wage workers to be also provided with a computer at work. Consequently, the current shift in the demand from high-school graduates to college graduates might well change into a shift from workers without any degree to high-school graduates; so skill-biased technical change will be continued at lower ends of the labor

[44] Borghans and Ter Weel (2001) elaborate further on this particular channel of skill-biased technical change. The arguments put forward here are by and large in accordance with the case study findings of Groot and De Grip (1991), Levy and Murnane (1996) Autor, Levy and Murnane (2000), and Fernandez (2001).

market as a result of computerization.[45]

## Appendix A: A model of computerization with changing product characteristics

In the literature it has been suggested that computers provide firms with the possibility to change their products (or organization structure), and that these changes in the production process require specific skills leading to a skill bias. The model developed in Section 2 can be extended by including the quality *p* of the product produced. In this appendix we show how a change in product quality due to the introduction of computers might affect the time needed for task 2 and the skill requirements in this task. These additional skill requirements are usually defined as complementary skills.[46]

To produce one unit of output, the agent now needs $\tau_j(s,p)$ units of time to complete task *j*, where *j* = 1, 2. After computerization, total time needed to produce one unit of output equals

$$\bar{\tau}(s,p) = \tau_c(s,p) + \hat{\tau}_2(s,p). \tag{A1}$$

Define, $\theta_p^j(s,p) = (\partial\tau_j(s,p)/\partial p)/(\tau_j(s,p))$ as the extra time requirement for task *j* due to a marginal change in *p*, where we assume $\theta_p^2 \geq 0$ because the production of a more advanced product always requires more time for task 2. This leads to the two following definitions next to the two definitions in Section 2.

**Definition 3**: Task 1 and task 2 are *substitutable tasks* if a change in *p* shifts time requirements from one task to the other, i.e.

[45] Murphy and Welch (2001) provide evidence pointing at a reduced wage inequality between college and high-school graduates since the mid-1990s. This seems to be consistent with our interpretation of the diffusion of computers and wage inequality.

[46] See Borghans and Ter Weel (2001) for a more elaborate exploration of the model.

$$\frac{\partial\tau_1(s,p)/\partial p}{\tau_1(s,p)} < 0 \text{ and } \frac{\partial\tau_2(s,p)/\partial p}{\tau_2(s,p)} > 0 \quad \text{i.e.} \quad \theta_p^1 < 0 \text{ and } \theta_p^2 > 0.$$

**Definition 4**: Task 1 and task 2 are *complementary tasks* if a change in $p$ changes time requirements for both tasks simultaneously in the same direction, i.e.

$$\frac{\partial\tau_1(s,p)/\partial p}{\tau_1(s,p)} > 0 \text{ and } \frac{\partial\tau_2(s,p)/\partial p}{\tau_2(s,p)} > 0 \quad \text{i.e.} \quad \theta_p^1 > 0 \text{ and } \theta_p^2 > 0.$$

Profit maximization implies that $p$ is optimal and that a change does not increase profits if

(A2) $$\frac{\partial\Pi}{\partial p} = \frac{\partial(\rho(p) - (w-c)(\tau_c + \hat{\tau}_2))}{\partial p} = 0,$$

in which the tradeoff between a more advanced product and a higher price, the partial derivative $\partial\rho(p)/\partial p$, gives the firm's optimal product specifications, i.e.

(A3) $$\frac{\partial\rho(p)/\partial p}{w} = \tau_c\theta_p^c + \hat{\tau}_2\hat{\theta}_p^2.$$

The major difference with equation (10) is that, rather than the relative time spent on each task, the absolute amount of time needed determines this equilibrium. If wages increase or if the price increase of a more advanced product diminishes, the optimal amount of time available to produce a product falls. This implies that $p$ will go down if task 1 is a routine task and if tasks 1 and 2 complement one another. In the first case, this means that the worker's production time shifts from task 2 to task 1, while in the second case the worker's time spent on both tasks diminishes.

Since the introduction of the computer implies that production time is reduced, either the time needed for task 1 or the time needed for task 2 diminishes. The time required for task 2 always depends positively on $p$, and a reduction in production time due to some sort of complementarity between the two tasks will lower the marginal costs of a better product. A reduction in the time needed for task 1 could also lead to the opposite outcome. Since time needed for task 1 depends negatively on $p$ if tasks 1 and 2 are substitutes, $\tau_c < \tau_1$ increases the marginal costs of extra $p$ and provides incentives to the firm to lower $p$. In this case the product is based on a more routinized production process, which makes use of the advantages of the computer.

By defining the new product quality $p^*$, the time needed for tasks 1 and 2 now equals $\tau_c(s,p^*)$ and $\hat{\tau}_2(s,p^*)$. Given $p^*$ employers might also have different incentives for the skill level they demand when $\tau_c(s,p^*) \neq \tau_c(s,p)$ and $\hat{\tau}_2(s,p^*) \neq \hat{\tau}_2(s,p)$. Furthermore, the derivatives $\theta_i^c$ and $\hat{\theta}_i^2$ might have different values at $p^*$. This notion provides a more sensible interpretation to the complementarity between computers and skills. $\Delta$ can now be interpreted as the difference between the time needed for task 1 for product $p^*$ and product $p$. With $\Delta$ being positive, this is consistent with a skill bias in labor demand if task 2 is a skilled task. An increase in $\hat{\theta}_i^2$ might further increase this skill bias.[47]

## Appendix B: Data appendix

### *B1. Descriptive statistics*

TABLE B1 OVER HERE

### *B2. Tasks*

In the estimation in Sections 4 and 5 we have used the importance of 35 tasks. The question asked in the survey was: "In your job, how important is ....?" 35 measures and computer usage are used to determine the importance of particular activities in terms of wage

[47] Such an increase in $\hat{\theta}_i^2$ can also be interpreted from an extension with more than two tasks in which the change in product quality asks for more additional time in one non-computerized task than in another non-computerized task, with the first of these two tasks being more skilled than the second.

premiums. The following variables are included in the regression reported in Table 6: (1) paying close attention to detail, (2) dealing with people, (3) instructing, training, or teaching people, individually or in groups, (4) making speeches or presentations, (5) persuading or influencing others, (6) selling a product or service, (7) counseling, 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 your hands or fingers, (13) knowledge of how to use or operate tools/equipments/machinery, (14) knowledge of particular products or services, (15) specialist knowledge or understanding, (16) knowledge of how your organization works, (17) spotting problems or faults, (18) working out the cause of problems or faults, (19) thinking of solutions to problems, (20) analyzing complex problems in depth, (21) checking things to ensure that there are no errors, (22) noticing mistakes, (23) planning your own activities, (24) planning the activities of others, (25) organizing your own time, (26) thinking ahead, (27) reading written information such as forms, notices, or signs, (28) reading short documents such as reports, letters, or memos, (29) reading long documents such as long reports, manuals, articles, or books, (30) writing material such as forms, notices, or signs, (31) writing short documents, (32) writing long documents with correct spelling and grammar, (33) adding subtracting, multiplying, or dividing numbers, (34) calculating using decimals, percentages, or fractions, and (35) calculating using more advanced mathematical or statistical procedures.

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Table 1
Distribution of the answers to the questions about computer use, the level of sophistication of computer use, and computer skills

Panel A: Computer use
"In your job, how important is using a computer, PC, or other types of computerized equipment?"

| | *n* | percentage |
|---|---|---|
| 1. essential | 748 | 30.3 |
| 2. very important | 363 | 14.7 |
| 3. fairly important | 313 | 12.7 |
| 4. not very important | 283 | 11.5 |
| 5. not at all important, or does not apply | 760 | 30.8 |
| Total | 2,467 | 100.0 |

Panel B: Level of sophistication of computer use
"Which of the following best describes your use of computers or computerized equipment in your job?"

| | *n* | percentage |
|---|---|---|
| 1. advanced | 84 | 3.4 |
| 2. complex | 299 | 12.1 |
| 3. moderate | 645 | 26.1 |
| 4. simple | 637 | 25.8 |
| 5. non-response | 42 | 1.7 |
| 6. does not apply (5 in panel A) | 760 | 30.8 |
| Total | 2,467 | 100.0 |

Panel C: Computer skills
"When your job involves using a computer, PC or other type of computerized equipment, are you able to do this effectively?"

| | | *n* | percentage |
|---|---|---|---|
| 1. always | very high computer skills | 667 | 27.0 |
| 2. nearly always | high computer skills | 612 | 24.8 |
| 3. often | intermediate computer skills | 177 | 7.2 |
| 4. sometimes | low computer skills | 140 | 5.7 |
| 5. hardly ever | very low computer skills | 107 | 4.3 |
| 6. non-response | | 4 | .2 |
| 7. does not apply | 5 in panel A | 760 | 30.8 |
| Total | | 2,467 | 100.0 |

Note: The data are from the Skills Survey of the Employed British Workforce.

Table 2
Correlation between computer use, the level of sophistication of computer use, and computer skills

Panel A:
Frequencies of skill levels within different levels of importance of computer use (percentages)

| | very high | high | intermediate | low | very low |
|---|---|---|---|---|---|
| essential | 59.2 | 34.4 | 3.6 | 2.3 | 0.5 |
| very important | 32.8 | 49.6 | 10.2 | 4.7 | 2.5 |
| fairly important | 22.7 | 35.5 | 20.4 | 15.7 | 5.4 |
| not very important | 12.0 | 22.6 | 17.3 | 20.1 | 27.2 |

Panel B:
Frequencies of skill levels within different levels of sophistication of computer use (percentages)

| | very high | high | intermediate | low | very low |
|---|---|---|---|---|---|
| advanced | 83.3 | 15.5 | 1.2 | 0.0 | 0.0 |
| complex | 56.9 | 35.5 | 4.7 | 2.3 | 0.7 |
| moderate | 38.3 | 45.0 | 11.2 | 4.5 | 0.9 |
| simple | 27.5 | 30.9 | 13.8 | 15.7 | 11.6 |

Note: The data are taken from the Skills Survey of the Employed British Workforce. In both panels the columns define the skill level ranging from “very high” to “very low”. The rows in Panel A define the importance of computer use (ranging from “essential” to “not very important”). The rows in Panel B define the level of sophistication of computer use (ranging from “advanced” to “simple”). The rows in the table add up to 100 percent. The definitions of computer use, the level of sophistication of computer use and computer skills are reported in Table 1.

Table 3
OLS regression estimates of the effect of computers on pay
(dependent variable: ln (gross hourly wage))

| | | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|---|
| Intercept | | .872 (.190)** | .874 (.188)** | .823 (.188)** | .875 (.190)** | .856 (.377) |
| Education | University | .390 (.044)** | .367 (.044)** | .343 (.045)** | .382 (.044)** | .394 (.075)** |
| | Professional degree | .248 (.040)** | .244 (.040)** | .228 (.040)** | .244 (.040)** | .277 (.070)** |
| | NVQ3 | .162 (.035)** | .150 (.034)** | .143 (.034)** | .159 (.035)** | .185 (.066)** |
| | NVQ2 | .131 (.029)** | .126 (.029)** | .121 (.029)** | .128 (.029)** | .170 (.060)** |
| | NVQ1 | .047 (.040) | .042 (.040) | .045 (.040) | .042 (.040) | −.001 (.078) |
| Age | | .040 (.011)** | .038 (.011)** | .041 (.011)** | .039 (.011)** | .084 (.022)** |
| Age squared/100 | | −.051 (.014)** | −.050 (.014)** | −.053 (.014)** | −.051 (.014)** | −.104 (.027)** |
| Experience | | .010 (.006) | .010 (.006) | .010 (.006) | .011 (.006) | −.001 (.013) |
| Experience squared/100 | | −.012 (.013) | −.012 (.013) | −.010 (.013) | −.013 (.013) | .007 (.026) |
| Female | | −.180 (.035)** | −.178 (.035)** | −.168 (.035)** | −.178 (.035)** | −.167 (.060)** |
| Married | | .029 (.030) | .034 (.029) | .033 (.029) | .030 (.030) | −.005 (.050) |
| Married×Female | | −.022 (.041) | −.025 (.041) | −.019 (.041) | −.024 (.041) | .009 (.069) |
| Union member | | .110 (.021)** | .114 (.021)** | .122 (.021)** | .110 (.021)** | .031 (.035) |
| Supervisor | | .089 (.022)** | .091 (.022)** | .088 (.022)** | .088 (.022)** | .094 (.036)** |
| Dummy for computer use | | .194 (.025)** | | | | |
| Importance of computer use: | | | | | | |
| 1. Essential | | | .293 (.030)** | | | |
| 2. Very important | | | .212 (.033)** | | | |
| 3. Fairly important | | | .137 (.034)** | | | |
| 4. Not very important | | | .115 (.034)** | | | |

| | | | | | |
|---|---|---|---|---|---|
| Sophistication of computer use: | | | | | |
| 1. Advanced | | | .386 (.057)$^{**}$ | | |
| 2. Complex | | | .296 (.036)$^{**}$ | | |
| 3. Moderate | | | .256 (.030)$^{**}$ | | |
| 4. Simple | | | .115 (.027)$^{**}$ | | |
| Computer skills: | | | | | |
| 1. Very high | | | | .206 (.030)$^{**}$ | |
| 2. High | | | | .209 (.030)$^{**}$ | |
| 3. Intermediate | | | | .224 (.041)$^{**}$ | |
| 4. Low | | | | .200 (.045)$^{**}$ | |
| 5. Very low | | | | .082 (.049) | |
| Computer skills excluding recent users: | | | | | |
| 1. Very high | | | | | .313 (.067)$^{**}$ |
| 2. High | | | | | .324 (.068)$^{**}$ |
| 3. Intermediate | | | | | .316 (.082)$^{**}$ |
| 4. Low | | | | | .299 (.089)$^{**}$ |
| 5. Very low | | | | | .306 (.135)$^{*}$ |
| Occupational dummies | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | .395 | .405 | .406 | .396 | .294 |

Note: The data are taken from the Skills Survey of the Employed British Workforce. $^{*}$ = significant at 5% level; $^{**}$ = significant at 1% level. The five numbered columns report the coefficients of estimating equation (11) with dependent variable the log of the gross hourly wage. All regressions are performed by OLS. Standard errors are reported in parentheses. Educational levels are classified in five categories, which correspond to the U.K. classifications, NVQ1 is the lowest level of education and University the highest. Workers without a qualification are the reference group. The different occupations we control for are presented in Table B1.

Table 4
The wage premium for computer skills within four different levels of sophistication of computer use
(dependent variable: ln (gross hourly wage))

| Panel A | All workers<br>Level of sophistication of computer use | | | |
|---|---|---|---|---|
| Computer skills | Advanced | Complex | Moderate | Simple |
| 1. Very high | .418 (.061)** | .278 (.043)** | .222 (.039)** | .081 (.041)* |
| 2. High | .235 (.124) | .290 (.051)** | .272 (.036)** | .124 (.039)** |
| 3. Intermediate | **S** | .536 (.120)** | .296 (.060)** | .141 (.053)** |
| 4. Low | **S** | .350 (.167)* | .316 (.092)** | .165 (.050)** |
| 5. Very low | **S** | **S** | −.003 (.197) | .054 (.058) |

| Panel B | Workers using a computer in 1992<br>Level of sophistication of computer use | | | |
|---|---|---|---|---|
| Computer skills | Advanced | Complex | Moderate | Simple |
| 1. Very high | .516 (.096)** | .341 (.075)** | .312 (.073)** | .170 (.078)* |
| 2. High | **S** | .355 (.084)** | .385 (.071)** | .204 (.077)** |
| 3. Intermediate | **S** | .613 (.158)** | .345 (.100)** | .195 (.100)* |
| 4. Low | **S** | **S** | .395 (.135)** | .228 (.098)* |
| 5. Very low | **S** | **S** | .245 (.507) | .262 (.161) |

Note: The data are taken from the Skills Survey of the Employed British Workforce. * = significant at 5% level; ** = significant at 1% level. The coefficients are OLS regression estimates with a dummy for each combination of level of sophistication of computer use and computer skills, also including all other variables of column (4) in Table 3 (standard errors in parentheses). **S** indicates less than 5 observations. The adjusted $R^2$ of the regressions are .406, and .304, respectively.

Table 5
The robustness of the skill measure: OLS regression estimates of other skills
(dependent variable: ln (gross hourly wage))

| Skill measure | | Skill wage premium |
|---|---|---|
| Analyzing complex problems in depth | 1. Very high | .164 (.033)** |
| | 2. High | .140 (.029)** |
| | 3. Intermediate | .113 (.036)** |
| | 4. Low | .051 (.044) |
| | 5. Very low | .038 (.052) |
| Spotting problems or faults | 1. Very high | .204 (.050)** |
| | 2. High | .191 (.049)** |
| | 3. Intermediate | .162 (.057)** |
| | 4. Low | .104 (.080) |
| | 5. Very low | .106 (.137) |
| Making effective speeches or presentations | 1. Very high | .189 (.037)** |
| | 2. High | .159 (.030)** |
| | 3. Intermediate | .162 (.036)** |
| | 4. Low | .084 (.037)* |
| | 5. Very low | .061 (.036) |
| Writing short documents with correct spelling and grammar | 1. Very high | .162 (.030)** |
| | 2. High | .154 (.030)** |
| | 3. Intermediate | .092 (.042)* |
| | 4. Low | .051 (.054) |
| | 5. Very low | .060 (.056) |

Note: The data are taken from the Skills Survey of the Employed British Workforce. * = significant at 5% level; ** = significant at 1% level. The second column only reports the coefficients for the five specific skills of estimating equation (11) with dependent variable the log of the gross hourly wage. All regressions are performed by OLS and are similar to the regression in Table 3, column (4) and include the same variables. Standard errors are in parentheses behind the coefficients. The adjusted $R^2$ of the regressions are .386, .384, .383 .389, and .387, respectively.

Table 6
Logistic regression of the determinants of computer use with unionization variables as instruments for wages
(Dependent variable: Likelihood of computer use)

| | Without task specification | Tasks are "essential" or "very important" | Tasks are > "not at all important" |
|---|---|---|---|
| Ln gross hourly wage | 3.418 (1.006)** | 3.326 (1.325)** | 3.029 (1.263)** |
| Education | | | |
| University | 1.001 (.835) | .916 (.796) | .714 (.831) |
| Professional degree | .419 (.606) | .216 (.560) | .067 (.576) |
| NVQ3 | .371 (.418) | .355 (.403) | .254 (.379) |
| NVQ2 | .326 (.331) | .276 (.314) | .148 (.304) |
| NVQ1 | .243 (.317) | .252 (.333) | .157 (.319) |
| Age | −.129 (.087) | −.105 (.099) | −.086 (.104) |
| Age squared | .127 (.108) | .100 (.124) | .112 (.126) |
| Experience | .004 (.043) | −.015 (.046) | −.035 (.046) |
| Experience squared | .015 (.078) | .045 (.082) | .053 (.086) |
| Female | 1.046 (.264)** | .720 (.322)* | .941 (.327)** |
| Supervisor | .227 (.254) | −.118 (.258) | −.344 (.226) |
| Paying close attention to detail | | .149 (.278) | |
| Dealing with people | | −.259 (.238) | |
| Instructing, training or teaching | | .205 (.178) | .313 (.226) |
| Making speeches or presentations | | −.319 (.288) | .114 (.256) |
| Persuading or influencing others | | .036 (.203) | −.033 (.250) |
| Selling a product of service | | .208 (.192) | .211 (.194) |
| Counseling, advising or caring | | .479 (.230)* | .254 (.252) |
| Working with a team of people | | .371 (.208)* | −.075 (.394) |
| Listening carefully to colleagues | | .036 (.213) | .906 (.412)** |
| Physical strength | | −.450 (.246)* | −.582 (.281)** |
| Physical stamina | | −.329 (.202)* | −.587 (.299)** |

| | | | |
|---|---|---|---|
| Skill or accuracy in using hands | | −.414 (.198)* | −.231 (.243) |
| How to use or operate tools | | | |
| Knowledge of particular products | | .020 (.192) | .172 (.233) |
| Specialist knowledge | | −.015 (.199) | −.037 (.230) |
| | | −.133 (.251) | −.469 (.414) |
| Knowledge of organization | | .406 (.177)* | 1.042 (.401)** |
| Spotting problems | | .435 (.256)* | |
| Working out problems | | −.032 (.261) | .744 (.439)* |
| Thinking of solutions | | −.079 (.260) | −.642 (.440) |
| Analyzing complex problems | | −.309 (.231) | .020 (.261) |
| Checking things for errors | | .482 (.251)* | .016 (.424) |
| Mistake noticing | | −.021 (.284) | |
| Planning own activities | | .146 (.219) | .411 (.369) |
| Planning others' activities | | −.204 (.220) | .033 (.220) |
| Organizing own time | | −.089 (.221) | −.367 (.375) |
| Thinking ahead | | −.045 (.215) | |
| Reading written information | | .297 (.219) | .945 (.421)* |
| Reading short documents | | .158 (.237) | .205 (.335) |
| Reading long documents | | .149 (.227) | .441 (.268) |
| Writing materials | | .120 (.218) | −.239 (.279) |
| Writing short documents | | −.089 (.271) | .109 (.286) |
| Writing long documents | | .685 (.276)** | .336 (.245) |
| Adding, subtracting or dividing | | .678 (.231)** | .990 (.268)** |
| Straightforward calculations | | −.091 (.251) | −.155 (.265) |
| Advanced calculations | | .742 (.277)** | 1.015 (.207)** |
| Constant | −3.322 (1.367)** | −4.597 (1.547)** | −6.732 (1.616)** |
| Log Likelihood | −558.2369 | −178.3017 | −94.91128 |
| LL model without education | −559.4090 | −179.7502 | −96.01841 |
| 2 LLR | 2.3442 | 2.8970 | 2.21426 |
| LL model without age and exp. | −564.1826 | −183.9299 | −96.66461 |
| 2 LLR | 11.8914* | 11.2564* | 3.50666 |

Note: The data are taken from the Skills Survey of the Employed British Workforce. * = significant at 5% level; ** = significant at 1% level. Standard errors are reported in parentheses. A complete list with the full specification of the 35 tasks defined here is given in Appendix B2. The other variables are similar to the ones reported in Table 3.

Table B1
Descriptive Statistics

| Variable | | Percentage in survey | Percentage in group | | |
|---|---|---|---|---|---|
| | | | Computer use | Union coverage | Union member |
| Male | | 52.9 | 69.2 | 46.0 | 32.4 |
| Female | | 47.1 | 69.1 | 51.0 | 32.5 |
| Age | 20-29 | 20.9 | 67.8 | 41.1 | 24.0 |
| | 30-39 | 33.5 | 71.6 | 48.7 | 31.9 |
| | 40-49 | 26.1 | 71.9 | 52.1 | 38.3 |
| | 50-60 | 19.5 | 63.0 | 50.5 | 34.7 |
| Education | University | 9.9 | 95.5 | 62.0 | 42.4 |
| | Professional degree | 12.4 | 88.9 | 60.6 | 46.9 |
| | NVQ3 | 15.2 | 75.1 | 53.2 | 35.8 |
| | NVQ2 | 34.5 | 71.6 | 45.8 | 30.0 |
| | NVQ1 | 8.8 | 55.1 | 38.9 | 21.8 |
| | No diploma | 19.3 | 40.2 | 38.5 | 24.6 |
| Married men | | 37.4 | 70.5 | 48.4 | 32.5 |
| Married women | | 31.9 | 67.0 | 51.0 | 33.0 |
| Union coverage | | 48.4 | 76.9 | 100.0 | 62.6 |
| Union member | | 32.5 | 76.4 | 93.3 | 100.0 |
| Full-time workers | | 74.7 | 74.6 | 48.8 | 34.7 |
| Permanent job | | 82.4 | 72.2 | 53.0 | 36.2 |
| Self-employed | | 11.0 | 48.5 | 5.9 | 9.9 |
| Occupations | | | | | |
| Managers and Administrators | | 14.6 | 83.7 | 31.9 | 19.4 |
| Professionals | | 10.5 | 93.8 | 72.7 | 54.2 |
| Associate Professionals | | 10.4 | 86.4 | 63.0 | 51.0 |
| Clerical and Secretarial | | 16.5 | 95.8 | 54.4 | 28.3 |
| Craft and Related | | 12.2 | 55.3 | 38.3 | 31.3 |
| Personal and Protective Services | | 10.5 | 45.2 | 46.7 | 28.2 |
| Sales | | 7.1 | 68.8 | 32.4 | 14.8 |
| Plant and Machine Operatives | | 10.7 | 42.8 | 48.1 | 38.6 |
| Other | | 7.5 | 17.9 | 46.7 | 26.6 |

| | | | | |
|---|---|---|---|---|
| Sectors | | | | |
| Agriculture, forestry and fishing | 1.5 | 37.8 | 18.9 | 16.2 |
| Energy and water supply | 4.2 | 53.4 | 43.7 | 27.2 |
| Extraction of minerals[a] | 9.3 | 70.9 | 51.3 | 33.9 |
| Metal goods, engineering and vehicle industries | 6.7 | 72.7 | 42.4 | 28.5 |
| Other manufacturing industries | 7.1 | 58.0 | 26.4 | 17.2 |
| Construction | 17.7 | 65.4 | 25.5 | 12.4 |
| Distribution, hotels and catering, repairs | 11.8 | 75.9 | 60.8 | 26.0 |
| Transport and communications | 16.6 | 82.4 | 54.5 | 36.7 |
| Banking and finance, insurance, business services and leasing | 20.1 | 68.8 | 71.8 | 49.5 |
| Other services | 5.1 | 55.2 | 31.2 | 22.4 |

Note: All data are taken from the Skills Survey of the Employed British Workforce. The occupational categories are based on the SOC and the classification of sectors on the SIC.
[a] The full name of this sector is Extraction of minerals other than fuels, manufacture of metals, mineral goods and chemicals.

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