Computers, Skills and Wages*

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Abstract

Computer technology is most prominently used by skilled, high-wage workers. This suggests that computer use requires skills to take full advantage of the possibilities, which are particularly present among relatively skilled workers. Consequently, schools promote the acquisition of computer skills for labor-market preparation. This paper develops a simple technology adoption model showing that the individual decision to adopt computer technology at work depends on (i) the specific tasks to be performed, (ii) the level of skill or education, and (iii) the level of the individual wages. Applying this model to a UK database containing detailed and unique information on tasks and skills, it is shown that the effect of wages and particular tasks on computer adoption is larger than the effect of skills on adoption. Computer use is likely to be a matter of cost efficiency and not so much of workers' skills.

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1 Introduction

Why is computer use higher among skilled and, within this group, high-wage workers? Figures from the October Supplements of the Current Population Survey in 1997 show that 74.9 percent of U.S. workers with a college degree used a computer, compared to 38.6 percent of high-school graduates. Studies using instrumental variables (e.g., Chennells and Van Reenen, 1997 and Dolton and Makepeace, 2004) or longitudinal data (e.g., Entorf and Kramarz, 1997 and Entorf, Gollac and Kramarz, 1999) have shown that workers earning higher wages have a higher probability to use computers. A usual explanation for this pattern of computer adoption is that the use of a computer requires (certain) skills.[1] These skills are represented by a worker's educational level and experience, while unobserved differences in skills between workers are also likely to be expressed in wages.[2] In addition to this explanation, there is ample evidence that the adoption of computer technology is associated with upgrading, i.e. employers tend to increase skill requirements for computerized jobs.[3] The evidence suggests that certain computer related skills are required to prepare people for the better jobs. Hence, it has been argued that schools should promote computer skills to prepare students for this "new" labor market (e.g., Murnane and Levy, 1996).

Information on computer use reveals that on the one hand there are many possibilities

[1]Chennells and Van Reenen (1997) − using British data from 1984 and 1990 − interpret the result that higher wages exert a positive effect on the probability of adopting computer equipment as evidence for higher-skilled workers having greater ability to work with new technologies. See also Green, Felstead and Gallie (2003) for a similar argument using three waves of British data on computer use at work. Dolton and Makepeace (2004) argue that unobserved differences between individuals are likely to yield premiums for some workers and not for others. Entorf and Kramarz (1997) and Entorf, Gollac and Kramarz (1999) use French longitudinal data and find that workers using computers were already better paid before the adoption of computers. They interpret this result as firms selecting their most-able workers to work with computers first.

[2]DiNardo and Pischke (1997) − estimating cross-sectional patterns in Germany and the United States − argue that findings demonstrating that workers using computers are 15-20 percent better paid than non-users are to be explained by unobserved heterogeneity.

[3]Levy and Murnane (1996) and Autor, Levy and Murnane (2002) argue that the introduction of computers in a large U.S. bank has induced substitution of unskilled for skilled workers. Berman, Bound and Griliches (1994), Doms, Dunne and Troske (1997), Autor, Katz and Krueger (1998), Bresnahan, Brynjolfsson and Hitt (2002) and Wulff Pabilonia and Zoghi (2005) observe that higher levels of computerization and investments in computer equipment are associated with higher levels of skill and education in the workforce. Finally, Caselli and Coleman (2001) find a positive correlation between computer adoption and the level of human capital for a large number of countries in the period 1970-1990. See also Brown and Campbell (2002) for an excellent overview for the United States.

to start using computers in relatively unskilled jobs. On the other hand, in skilled jobs computers are particularly used for tasks that do not seem to require a high level of skills, such as e-mailing and word processing. This raises the question whether the skill argument really explains why some workers use computer technology and others don't or that other factors determine the adoption and diffusion pattern of computers at work.

To answer this question this paper explains computer use from a cost-benefit perspective. In this setting, computer use is determined by a trade-off between the wage costs per unit of output to the employer when no computer technology is used and the wage and computer costs when a computer is adopted. Workers have several tasks, some of which can be computerized and others that cannot. We show that a simple threshold model of technology diffusion offers three possible explanations for computer use: tasks, skills and wages. First, some tasks are more eligible for computerization than others. Second, given the tasks, skilled workers might be more efficient in using computers than unskilled workers. Finally, given the productivity gain from using a computer, the wage costs gained for high-wage workers are higher than for low-wage workers. Since the costs of computer equipment, software and technical assistance are still substantial, a firm gains more by letting a high-wage worker use a computer relative to a low-wage worker. Another feature of the model is that even if skill arguments do not play a role in the decision to adopt computers, skill requirements within a certain occupation will rise, because the adoption of the computer in a particular job emphasizes the performance of the non-computerized tasks. Since the non-computerized tasks are in most instances skilled tasks, shifts in the weight attached to the computerized and non-computerized tasks towards the non-computerized tasks increases skilled labor demand. To analyze empirically whether skills or wages determine computer use, computer adoption has to be investigated directly.

Using the Skills Survey of the Employed British Workforce, we present suggestive evidence that of the three theoretically derived determinants of computer adoption, wages and some specified tasks are among the most important in explaining the likelihood of computer use. Using IV strategies, we obtain that the high percentage of computer use among skilled workers is most likely the result of their higher wages. The effect of skills and education on computer adoption is also positive, but not significant and when specific tasks are introduced in the analyses the significance becomes worse. Our estimates suggest that about one third of computer use can be explained directly by level of education. Experience does not seem to increase computer use when wage costs are taken into account. These findings suggest that lower computer use among relatively unskilled workers is most likely not the result of skill deficiencies, but may be caused by the relatively high costs of adopting computer equipment. As a consequence, it might be expected that a computer will be adopted once the ratio between the wage and the costs of computers has increased sufficiently. This might occur if the costs of computer equipment fall, the prices of software decline, or when the wage goes up.[4] The inclusion of 35 different tasks into the regression equation substantially increases the likelihood of the equation. The estimates suggest that especially the relatively unimportant tasks are important to explain computer use, which is consistent with the predictions of the model that computer technology is used to automate routine job activities and emphasizes the performance of skilled tasks by the worker.

This paper is related to the original work on the adoption of new technologies, including the theoretical work on threshold models by Salter (1966), Mansfield (1968), David (1969) and Davies (1979) and the more recent work by David and Olsen (1986) and Helpman and Trajtenberg (1998), and empirical studies by Mansfield (1963), Metcalfe (1970), David (1975) and Stoneman (1976).[5] These studies look for and discuss the determinants of the thresholds and put forward firm size, technological expectations, learning and search costs, switching costs and opportunity costs as likely thresholds. We find wage costs to be the main determinant of the threshold in the adoption of computers, which comes closest to David's (1975) empirical illustration of the adoption of mechanical reapers. He argues that the adoption would make sense only if the savings in wage costs exceed the costs of the machine, which is equivalent to our treatment of the trade-off between wage costs and the costs of the computer (hardware, software and support). Our empirical results are

[4]The continuous fall in the prices of computer equipment has been documented and examined by Greenwood and Yorukoglu (1997), Autor, Katz and Krueger (1998), Krusell, Ohanian, Ríos-Rull and Violante (2000) and Jorgenson (2001). In addition, Jorgenson (2001) provides figures showing a more than 10 percent annual decline in software prices since the 1970s. These two trends are likely to have amplified the computerization of the workplace.

[5]See e.g. Geroski (2000) for a recent overview of the different approaches to technology diffusion.

related to the findings of the literature initiated by Krueger (1993) arguing that computer users earn higher wages than non-users. However, our explanation of these higher wages reverses the causality of arguments, because unlike Krueger we argue that a worker's wage level determines computer use and not that computer use increases wages. Our results are also related to the findings of Chennells and Van Reenen (1997), Entorf and Kramarz (1997), Entorf, Gollac and Kramarz (1999) and Dolton and Makepeace (2004) that higher wages exert a positive influence on the probability of introducing new technologies. However, we extend such findings by structuring the arguments in a threshold model of diffusion, which enables us to take into account the costs of adoption. In addition, we show that their interpretation of higher-skilled workers being assigned to computers should be interpreted as higher-wage workers being assigned to computers not because of skill arguments but because of cost arguments. Our results are also consistent with the findings of Groot and De Grip (1991), Levy and Murnane (1996), Bresnahan (1999), Fernandez (2001) and Autor, Levy and Murnane (2003) that the computer generally substitutes for routine activities and complements non-routine activities, which leads to skill upgrading. However, the channel through which upgrading occurs in our framework is found to run via a change in the tasks to be performed rather than through skill requirements directly; see also Borghans and Ter Weel (2006). Finally, our results are consistent with findings for the United States of Doms, Dunne and Troske (1997), for Canada of Wulff Pabilonia and Zoghi (2005), and for France of Entorf and Kramarz (1997) and Entorf, Gollac and Kramarz (1999) that computer investments by firms are largely uncorrelated with wage increases, but rather that higher wages amplify computer adoption.

The plan of the paper is the following. Section 2 presents the model. Section 3 provides information about the data. Section 4 contains the empirical strategy and presents the results. Section 5 concludes.

2 A Threshold Model of Computerization

To investigate when the employer decides to introduce a computer in a particular worker's job we develop a simple threshold model of technology adoption. We explicitly focus on the role of the employer's costs to implement computer equipment. The model shows that the employer will adopt a computer in a particular job if the benefits exceed the costs. The model reveals that computer costs, productivity gains, and wage costs determine the adoption and diffusion of computers at the workplace. The productivity gains of using computer equipment in a job depend on the specific tasks and skills of the worker doing that job. We also show that employers tend to increase the skill requirements for a certain job after computer adoption.

2.1 Basic Setting

The basic setting of the model is the following. We consider a market in which we investigate the decision making of one firm concerning one single job or one single worker. In this market, any individual firm will treat the wage structure $w(s)$, i.e. the wage (w) for any particular worker with any set of skills (s), as given. By the same token, the price for the firm's output $p(q)$ is also given, given the specific characteristics (q) of the product. A job consists of several tasks, and the production function of the firm describes the time needed by each worker to perform these tasks. We assume that the skill level of the worker and the product characteristics of the good produced in the job under investigation determine the time requirements d to carry out the tasks j within this job ($d_j(s,q)$). For convenience, we assume that a job consists of two tasks: task 1 and task 2. These two tasks represent independent aspects of the job that are nevertheless undeniably interrelated and very hard to separate.[6] Given these ingredients, the firm chooses product characteristics, a division of tasks within the job, and a worker with certain skills to maximize profits per unit of production:

$$\max_{s,q} p(q) - w(s)\left(d_1(s,q) + d_2(s,q)\right). \tag{1}$$

[6] In a related exposition Borghans and Ter Weel (2004) show when it would be profitable for an employer to break up the tasks into two separate jobs. 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 and which in most instances cannot be separated into two jobs. 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.

However, from the perspective of a given worker, a similar optimization problem occurs in which s has to be held constant:

$$\max_q p(q) - w(s)\left(d_1(s,q) + d_2(s,q)\right). \tag{2}$$

From a worker's perspective, to produce one unit of output, the optimal allocation of time leads to $\tau_j(s)$ units of time to complete task j. Given a certain job, the optimal allocation of time (τ_j) is no function of s. The total time needed to produce one unit of output equals

$$\tau(s) = \tau_1(s) + \tau_2(s). \tag{3}$$

For simplicity, we assume that task 1 represents aspects of a job that can be computerized and that task 2 includes activities that cannot be computerized. Optimization of the production function after computerization leads to $\hat{\tau}_2(s)$ (the time needed for task 2) and $\tau_c(s)$ (the time needed to operate the computer). If task 1 is computerized, the optimal allocation of time in the production function might change, since it requires $\tau_c(s)$ to operate the computer instead of carrying out the task manually. τ_c depends on s because carrying out the computerized task requires skills and the time involved to operate the computer might vary in s.[7]

Computerization of the work might also have an impact on carrying out the job aspects included in task 2. If the good produced and the way it is produced either by man alone or by using computer equipment remains unchanged, there is in fact no reason why the time required for task 2 should change. However, the complementarity or substitutability between task 1 and task 2, represented by changes in the optimal product characteristics q, which has now changed into a complementarity or substitutability between computers and particular human tasks, could be regarded as an important route for changing configurations of jobs.[8] In this setting, such a relationship arises once a firm uses the possibilities of a computer to change the characteristics of the product, production process,

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

[8] For example, Autor, Levy and Murnane (2002) 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 while 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. Fernandez (2001) reaches similar conclusions from a plant-retooling of a large chocolate factory.

the division of time between the two tasks, or the organization of work.[9] We therefore allow τ_2 to change as a result of computerization into $\hat{\tau}_2$. In the case where $\hat{\tau}_2 < \tau_2$ ($\hat{\tau}_2 > \tau_2$) computerization of task 1 results into less (more) time required to perform task 2. Furthermore, this change in time needed to perform task 2 might depend on s, which could lead $\hat{\tau}_2(s)$ to stress different components of s than $\tau_2(s)$.[10] The time needed to produce one unit of output now equals

$$\bar{\tau}(s) = \tau_c(s) + \hat{\tau}_2(s). \tag{4}$$

Define $\theta^j(s) = -(\partial \tau_j(s)/\partial s)/(\tau_j(s))$ as the time for task j saved by a marginal increase in s. We assume $\theta^j(s) \geq 0$ because s affects the time needed to perform this task and an increase in s leads to a higher productivity, i.e. higher-skilled workers are more productive than lower-skilled workers. Task 1 is a *routine* task if the time saved by s to perform this task is less than the time saved to perform task 2, i.e. $\theta^1(s) < \theta^2(s)$ and task 1 is a *skilled* task if the time saved by s to perform this task is more than the time saved to perform task 2, i.e. $\theta^1(s) > \theta^2(s)$.

We can reasonably 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.[11]

[9]See e.g., Caroli and Van Reenen (2001) and Bresnahan, Brynjolfsson and Hitt (2002) for empirical evidence concerning the changing organization of work and production, and Bresnahan (1999), Borghans and Ter Weel (2004) and Garicano and Rossi-Hansberg (2003) for theoretical approaches in which computers change the way in which workers perform their jobs. Bresnahan emphasizes the difference between back- and front-office jobs when the computer enters the organization; Borghans and Ter Weel emphasize the changing way in which workers cooperate; and Garicano and Rossi-Hansberg emphasizes different modes of specialization among managers and production workers.

[10]Garicano and Rossi-Hansberg (2003) derives that workers specialize in different tasks after computerization. In addition, they perform more management tasks on their own. Autor, Levy and Murnane (2003) empirically show that the work bundled into the non-computerized task becomes more important.

[11]See Autor, Levy and Murnane (2003) 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, which can be regarded as skilled tasks.

Let us consider what happens if the individual firm has to decide whether or not to invest in computer equipment, given the market prices at that moment. If a firm pays a wage $w(s)$ to a typical worker, the costs k per unit of output the firm incurs equal

$$k = (w + c)(\tau_c + \hat{\tau}_2), \tag{5}$$

where c reflects the costs of computer use.[12] The total costs the employer has to incur when an employee uses a computer are higher than the costs of not using one if $c(\tau_c + \hat{\tau}_2) > w((\tau_1 + \tau_2) - (\tau_c + \hat{\tau}_2))$. Hence, the threshold to adopt a computer depends on wage costs relative to computer costs. An assumption for this relationship to hold is that the costs of the computer 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.[13] 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.[14]

As a result of computerization, the equilibrium prices of the goods produced before and those produced after the production process is computerized have changed. Thus, computerization changes the equilibrium prices and wages, but given these prices and wages each individual firm will make a decision for each job and each worker to use a computer along the same lines as in the situation prior to computerization.

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

[13]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 he 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.

[14]The interrelatedness between the two tasks and the assumption that one person has to carry out the job makes this assumption realistic. In footnote 16 we derive that the results do not change substantially if the computer is used only 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 Computer Technology Adopted?

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, regardless of whether task 1 is computerized. The break-even point or threshold b, at which $c(\tau_c + \hat{\tau}_2) = w \times ((\tau_1 + \tau_2) - (\tau_c + \hat{\tau}_2))$, equals

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

Expressed in logs, this yields the following equation:

$$ln(b) = ln(w) + f(s,t). \tag{7}$$

The break-even wage at which the firm is indifferent depends on the wage (w) it has to pay and a function f of the specific tasks needed to perform a job (t) and the skills (s) the worker possesses. The interpretation of equations (6) and (7) is the following. If $ln(b) > ln(c)$, a computer is profitable because the actual costs of the computerization of task 1 are below the break-even point. Allowing for some randomness in the actual costs of computer use ($ln(c) = ln(\hat{c}) + \epsilon$, where ϵ 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 computer equipment, i.e. $P(computer) = P(ln(b) > ln(c))$. This model has a very simple (but strong) prediction: when $b > c$, the firm will adopt a computer, and when $b < c$, the firm will not adopt.

An interesting observation from equation (6) is that computer use leads to some time gain in the production process and that workers with higher wages have a higher probability of using a computer at work. With respect to the time gain, $1 - (\tau_c + \hat{\tau}_2)/(\tau_1 + \tau_2)$ represents this 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. The time gain, related to specific tasks, is likely to reflect the development of new and more efficient applications, software and hardware.[15] With respect to s we

[15] 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 computer 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. This increased performance opens possibilities for the development of new software applications which can be applied in a certain job or in a range of similar job activities within different jobs.

obtain that if a worker becomes more efficient in performing both tasks 1 and 2 after computerization (i.e., τ_c and $\hat{\tau}_2$ are relatively low compared to τ_1 and τ_2), this worker benefits more from computer use than a relatively less efficient worker. In this setting, the relation of the ratio$(\tau_c + \hat{\tau}_2)/(\tau_1 + \tau_2)$ with s could be seen as the skill bias of the adoption of a new technology, because the skills included in s might either be related to the performance of the computerized task (τ_c) or to the other task ($\hat{\tau}_2$). This might provide skilled workers with an advantage to use a computer over unskilled workers. Note, however, that workers with high skills to bring to completion the skilled task 2, both before and after the introduction of the computer, do not have a higher probability to use the computer, if 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 (τ_c) is low compared to the time needed for task 2 ($\hat{\tau}_2$).[16]

The second component of interest in equation (6), the wage costs per unit of production, brings about the influence of wages on computer use. From equation (6) we obtain that the threshold to introduce a computer is lower (b is higher) when the wage costs to the firm are higher, i.e. it suggests that higher wages increase the probability of using a computer. This is an interesting result because it implies that − given a worker's skill level − differences in wages result in different moments in time of computer adoption.[17]

Finally, if a certain technology is useful for specific occupations only, the ratio $(\tau_c + \hat{\tau}_2/(\tau_1+\tau_2)$ will be high for such occupations, but equal 1 for other occupations. One could define a general purpose technology as a technology for which the ratio $(\tau_c + \hat{\tau}_2/(\tau_1 + \tau_2)$ is of similar size (and larger than 1) in almost all occupations. In that case the wage costs of the employee will be the main determinant of computer use.

[16] 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 λ 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 using the computer only 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 14).

[17] This result is consistent with the empirical findings for the United States of Doms, Dunne and Troske (1997), who observe that firms paying higher wages are more likely to adopt computers, and the findings of Chennells and Van Reenen (1997), Entorf and Kramarz (1997) and Entorf, Gollac and Kramarz (1999) for Britain and France that higher-wage workers have a higher probability to use computers than their lower-wage colleagues.

2.3 Skill Requirements

The previous analysis has shown that the empirical observation that higher-skilled workers use computers more frequently than lower-skilled workers could be the result of wage differentials rather than differences in skills. This raises the question as to whether skill upgrading (i.e. an increase in skill requirements within a job) can be expected. To answer this question we have to consider the model from the job perspective. The skills required for production in a certain job are the result of the firm's profit maximization. Since a change in the skill requirements affects the productivity in both task 1 and task 2, changes in the required skills before computerization were not profitable for a certain skill s if

$$\frac{\partial \Pi}{\partial s} = \frac{\partial(p(q) - w(s)(d_1(s,q) + d_2(s,q)))}{\partial s} = 0. \tag{8}$$

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

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

After a computer has been introduced this equation changes into

$$\frac{\partial w(s)/\partial s}{w} = \frac{\tau_1}{\tau_1 + \hat{\tau}_2}\theta^c + \frac{\hat{\tau}_2}{\tau_1 + \hat{\tau}_2}\hat{\theta}^2. \tag{10}$$

To equilibrate the equation, the firm changes its skill demand 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;[18] (ii) an increase in the advantage of skill i in performing task j (an increase in θ^c and/or $\hat{\theta^2}$ compared to θ^1 and θ^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.[19]

[18]This can be seen from the second-order condition. Since equation (10) reflects a maximum, the second-order condition for skill s equals $\frac{\partial((\tau_c/(\tau_c+\hat{\tau}_2))\theta^c + (\hat{\tau}_2/(\tau_c+\hat{\tau}_2))\hat{\theta^2})}{\partial s} < \frac{\partial(\partial w(s)/\partial s/w)}{\partial s}$. This means that if s becomes more expensive, employers will diminish their skill demands.

[19]Because the relationship between skill and productivity generally differs between both tasks, each task would have different skill requirements if carried out by separate workers. Skill requirements for the

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 the skills to operate the computer. Second, the performance of task 2 might demand a more-skilled worker because skilled workers gain more time than unskilled workers after the introduction of the computer. Finally, even if the influence of s on both tasks is kept constant, the weight attached to both tasks might change upon the introduction of the computer. In other words, if task 1 is a routine task, skill requirements increase because the computer puts more weight on the performance of task 2. An implication of this latter 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 effect is consistent with the findings of Levy and Murnane (1996), who investigated the introduction of new technology in a large U.S. bank. They found that the time needed to perform non-routine activities rises relative to routine activities after the introduction of computer equipment, which has led to the recruitment of higher-skilled workers for the same job. This suggests that a worker's skill level does not necessarily play a crucial role in explaining the diffusion pattern of computers, although the adoption might lead to a skill bias in labor demand for jobs in which the computer is used.

This latter finding provides an important insight because it implies that even if working with a computer fails to increase the comparative advantage of skilled workers in each task per se, skill requirements might nevertheless be raised. The particular skills that become more important are not necessarily related to operating a computer or to certain tasks that increase productivity due to the adoption of a computer, but might be skills already used for carrying out task 2 before computerization, whatever this task may be.[20]

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.

[20]This observation might offer an explanation for the difficulties encountered in the search for a direct link between technological change and increased demand for particular skills because it is likely that each job that becomes subject to computerization includes other skills that become emphasized in the performance of non-computerized job activities. What has become clear from the empirical literature

2.4 Empirical Implications

This threshold model has put forward three determinants of computer use: (i) a worker's skill level, because higher-skilled workers might be more effective in using a computer or they might gain more in terms of productivity from using a computer; (ii) the tasks a worker has to carry out, because some tasks might be more suitable to computerization than others and the performance of some tasks might improve more in terms of efficiency when using a computer than others; and (iii) a worker's wage level, because the threshold at which the firm is indifferent about whether or not to adopt a computer is lower when a worker's wage is higher. In the remainder of this paper we will explore the determinants of computer adoption to investigate the relative influence of these three factors.

3 Data

The data we utilize in this paper has been collected in a survey conducted in the first half of 1997, called the Skills Survey of the Employed British Workforce.[21] The survey includes a relatively small, but representative, number (2,467) of employed workers, aged 18-60, in Britain. 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, the importance and effectiveness of the tasks they carry out at work, and training.[22]

Of interest for the purpose of the present analysis are the questions concerning the importance of computer use and the tasks a worker has to carry out at the workplace. With regard to the importance of computer use the following question has been asked: "In your job, how important is using a computer, PC, or other types of computer equipment?". The response scale offered was fivefold: "essential", "very important", "fairly important", "not very important", and "not at all important or does not apply". If the respondent

on the computerization of the labor market is that the adoption of computers leads to an emphasis on non-routine job activities within the job.

[21] Ashton, Davies, Felstead and Green (1999) provide a description of the survey and questionnaire. See Dickerson and Green (2004) for a methodological paper on measuring job skills using survey data. They apply the same data as we do here to evaluate their approach.

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

answered that using a computer, PC, or other types of computer equipment is at least "not very important", this person is regarded as a computer user. In the sample, 69.1 percent of the workers uses a computer.

Furthermore, the survey contains detailed questions about the tasks the respondents have to fulfill. Thirty-five different tasks have been specified and listed in Appendix A. Similar to the question about the importance of computer use, the question asked in the survey was "In your job, how important is ....?". Again, the response scale offered was fivefold: "essential", "very important", "fairly important", "not very important", and "not at all important or does not apply". Like in the case of the importance of computer use, we consider the tasks for which the respondent answered at least "not very important" as tasks performed at work. If a respondent answered "essential" or "very important" we classified this task as important for the performance of the job.

In Britain, five levels of educational qualifications are distinguished. The highest level is a university degree (9.9 percent of the sample population), followed by a professional degree (12.4 percent). There exist three levels of national vocational qualifications (NVQ1-NVQ3), with NVQ1 being the lowest qualification and NVQ3 the highest (15.2 percent of the sample population has a NVQ3 degree, 34.5 percent a NVQ2 degree and 8.8 percent a NVQ1 degree). Finally, a substantial proportion of the workforce obtained no qualification (19.3 percent of the sample population). In the data we distinguish these six educational levels, using workers with no qualification as the reference group.

4 The Determinants of Computer Use

In this section we empirically address the determinants of computer use and present the estimation results. We start by outlining the estimation model and discuss econometric issues concerning this model. Subsequently, we present the results.

4.1 Estimation Model

The model provides the possibility to compare empirically the effect of skills, tasks and wages on computer use. If we assume the error term (ϵ) to be logistically distributed and include linear effects for skills (S) and tasks (T) and other controls (X), the model can be rewritten as

$$\begin{aligned} P(computer) &= P(\alpha + \beta \ln(w) + S\gamma_S + T\gamma_T + X\gamma_X > 0) \\ &= \frac{1}{1+e^{-(\alpha+\beta \ln(w)+S\gamma_S+T\gamma_T+X\gamma_X)}}. \end{aligned} \tag{11}$$

Here, X includes personal characteristics such as age, age squared, gender and marital status. The main problem of estimating equation (11) is that wages and skills are likely to be highly correlated, while it is likely that there is measurement error in the wage variable as well and part of a worker's skills might be unobserved directly, but nevertheless be reflected in the wage. Furthermore, there might be a concern of endogeneity of computer use influencing wages. If a substantial part of the skills are unobserved, part of the effect of skills on computer use will be absorbed by wages in the estimates. This causes an upward bias in the parameter for the wage effect and a downward bias in the skill parameters. If the main problem is the measurement error in the wage variable, the wage parameter will be downward biased while the skill parameters absorb this effect and will be upward biased. To estimate equation (11) we therefore use instrumental variables for the wage variable.

Since it seems plausible to assume that variables related to unionization influence wages but do not interfere with skills and computer use directly, we use several variables related to unionization as instruments for wages to estimate equation (11). In Britain, about 50 percent of the workers is covered by a union, the coverage being fairly equally spread over occupations and sectors and having 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. In Appendix C we discuss the choice of the instruments in depth from an economic point of view.

To instrument the wage, we add a linear equation explaining $\ln w$ with the same X, S and T vectors plus the unionization variables and replace the $\ln w$ by its predicted value in equation (11):

$$P(computer) = \frac{1}{1+e^{-(\alpha+\beta \ln(\hat{w})+S\gamma_S+T\gamma_T+X\gamma_X)}}, \tag{12}$$

where

$$\ln(\hat{w}) = \alpha_w + S\delta_S + T\delta_T, \tag{13}$$

with $\ln(w) - \ln(\hat{w}) \sim N(0, \sigma^2)$. These equations have been estimated simultaneously by maximum likelihood.

Due to the non-linearity of equation (12), inclusion of the predicted wage to proxy for the actual wage leads to some bias in the estimation. Angrist (1991) therefore prefers a simple linear regression. Especially if 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 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 predicting the likelihood of computer use. To estimate the equations it therefore seems more appropriate 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 significantly change the results.

4.2 The Number and Quality of the Instrument

The data included a number of questions on unionization, from which we selected the following possible instruments: (i) "at your place of work, are there unions, staff associations or groups of unions?"; (ii) "are you a member of a trade union or staff association?"; (iii) the cross-dummy for workers answering yes on both question (i) and question (ii); (iv) "are any of them recognized by management for negotiating pay and/or conditions of employment?"; and (v) "is it possible for someone in your job to join one of these unions or staff associations?". Appendix Table B1 provides details about union coverage and membership variables by considering its distribution among the several variables used in the regression analysis.

An important issue in IV-estimation is choosing the number and quality of the instruments to use in the regression analysis. Recently, Donald and Newey (2001) presented a selection criterion to choose the number of instruments from different sets and combinations of instruments, by minimizing approximate mean-squared errors (MSE). It is shown that this method can substantially improve the finite sample properties of IV-estimators. As the preliminary IV-estimator we estimated a basic model with union coverage as the only single instrument (instrument (i)) and used Mallows's goodness of fit criterion to evaluate its performance.

Since we have a set of five possible instruments for the wage, all of which are related to unionization, we choose the most obvious sets first. Obvious sets of instruments will contain (i) union coverage and/or (ii) union membership, possibly combined with (iii) the cross dummy of coverage and membership. The set can be further extended with additional information from question (iv) "Are any of them recognized by management for negotiating pay and/or conditions of employment?" and (v) "Is it possible for someone in your job to join one of these unions or staff associations?". The results of the Donald-Newey test reported in Table 1 suggest that union coverage and the cross effect of coverage and membership leads to the lowest MSE and therefore to the most efficient set of instruments to use in the regression analysis. Hence, in the remainder of the analysis we will use these variables to instrument the wage.[23]

The F-test for the joint contribution to the wage equation of the set of instruments equals 29.41 ($F^2_{2203;.05} = 3.00$) in the basic equation and 18.90 ($F^2_{2160;.05} = 3.00$) in the most extended version. Following the criterion of Staiger and Stock (1997) that the F-value should be larger than 10, this suggests that the instruments are strong enough to avoid serious problems in our IV-regressions.[24]

4.3 Estimation Results

4.3.1 Basic Estimates

Table 2 reports the basic estimation results. The first column shows the results from a maximum likelihood estimation of equation (11) in which the wage has not been instrumented. This equation includes a number of standard labor-market variables and the log of the gross hourly wages. The results suggest that particularly the wage and the highest

[23]The use of the second- and third-best set of instruments – i.e. the combination of (i) union coverage and (ii) union membership and (i) union coverage, (ii) union membership and (iii) its cross effect – gives qualitatively similar regression results.

[24]Also the second- and third-best sets of instruments easily pass this test for all specifications.

levels of education exert a positive impact on the probability to use a computer at work but that age does not affect computer use.[25] In addition, female workers have a higher probability to work with a computer. Because the wage variable potentially suffers from measurement error, the inclusion of unobserved skills in the wage variable and endogeneity, we have to be careful in interpreting the coefficients of this estimation. We therefore include the two union variables selected above to instrument the wage, according to equation (12) and (13). The second column of Table 2 reports the results of the IV-estimation. The top panel shows the estimates from the first stage and the bottom panel shows the estimates from the second. From the top panel we observe the usual effects of the labor-market variables on wages: the higher the level of education the higher the wage; age has a positive but diminishing effect on wages; female workers earn less and married workers earn more. The results of the logit equation are reported in the bottom panel of Table 2. The IV-estimates suggest that wages still exert a substantial, significant and positive influence on the likelihood of using a computer at work but the education variables and age do not seem to significantly impact the probability to use a computer at work. The likelihood ratio test reported at the bottom of the table shows that neither the education nor the age variables have a joint significant impact on computer use. The size of the wage coefficient implies that if we increase a worker's wage by 1 percent, the probability to use a computer at work increases by about .613 percent. Although not significant, the influence of education on the probability of using a computer is still present in the point estimates. When comparing a worker without an educational degree (the reference group) to a worker with a university degree, we observe that the probability to use a computer increases by 28.2 percent.[26] In addition, older and more experienced workers do not seem to have a significantly lower probability to use a computer at work, although the point estimate is negative. This result is consistent with the findings of Weinberg (2002) and Friedberg (2003) for the United States, who find that computer use is surprisingly flat over

[25]Adding experience and experience squared does not change the results.

[26]For workers with a professional degree the probability to use a computer at work relative to a worker with no degree is 15.0 percent higher, for a worker with a NVQ3 degree this probability is 11.3 percent higher, for a worker with a NVQ2 degree it is 9.8 percent higher, and for a worker with a NVQ1 degree the likelihood of using a computer at work relative to a worker with no degree is 6.6 percent higher. Note, however, that these are the marginal effects from the point estimates which turned out to be insignificant.

a worker's life cycle.[27] Finally, female workers have a notably higher probability of using a computer at work than their male colleagues (22.4 percent). This finding is consistent with the observation of Weinberg (2000) for the United States, who argues that computers take away some of the (physical) disadvantages women have in a non-computerized labor market.

Finally, note that the coefficient of the wage variable has increased in the IV-estimates compared to the non-instrumented regression. This suggests that wages have been measured less accurately than educational levels. The upward effect of measurement error seems to be larger than the possible downward effect of unobserved skills.

4.3.2 Industry Effects

The basic estimation results reported in Table 2 can be extended by including industry dummies, which might be important because both computer use and wages could differ between industries.[28] The reason for different computer use between industries might be attributed to applications which can be used effectively in one industry but not in the other. In terms of the model, we might argue that, in some industries, tasks might be subject to computerization because of the availability of a certain application, while in other industries this application is useless. Appendix Table B1 indeed shows that computerization is quite different between industries, ranging from 49.3 percent in agriculture and energy to 82.4 percent in transport and communications.

The first column of Table 3 reports the results from the logit equation of the IV-estimation[29] including 8 industry dummies.[30] We observe that the coefficient on the wage variable has slightly increased, whereas the influence of educational levels on computer use has decreased. Our interpretation of these coefficients is that wages seem to be a

[27] 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. In addition, Borghans and Ter Weel (2002) find for the United Kingdom that older workers do not seem to have more difficulties in using computerized equipment at work than their younger colleagues.

[28] For technical reasons, the inclusion of industry dummies might also be important because the unionization instruments might be sensitive to industry effects (see also the discussion in Section 4.2).

[29] We do not report the first-stage results in Table 3 because they do not yield additional insight. The F-test criterion of Staiger and Stock (1997) is easily passed for all three regressions reported in Table 3.

[30] Appendix Table B1 lists the industries. We take agriculture, forestry, fishing, energy and water supply as the reference group.

strong determinant of computer use, while skills (measured by educational levels) do not seem to contribute directly and significantly to the probability of using a computer at work.[31]

4.3.3 Job Tasks

The data enable us to explicitly analyze the importance of 35 tasks at work. As a first step, we include the tasks into the regression analysis which have been reported as being "essential" or "very important" by the respondents; we regard these tasks as important to carry out the job. The results of this regression are reported in the second column of Table 3. This column shows that most tasks do not exert a positive impact on the probability of computer use. A number of tasks increase the probability to use a computer, i.e. counselling, advising, or caring for customers or clients, knowledge of the organization of the workplace, writing long documents, and especially adding, subtracting, multiplying, or dividing numbers, and calculating using more advanced mathematical or statistical procedures. The first two tasks are related to jobs of senior staff members and not so much to computerized tasks, while the latter three are probably directly linked to routine tasks in which the computer can be used to improve efficiency. These results suggest that a worker carrying out these tasks is more likely to use a computer if certain tasks are important to carry out the job, such as writing, calculating and mathematical exercises, and when a computer application leads to a more efficient performance of these tasks.

An assumption of our model is that computers are typically used to carry out routine tasks, which are probably not essential to carry out the job. To test the consistency of this assumption one might argue that if a certain task is a routine job activity, it is not very important for carrying out the job. In the third column of Table 3 we report estimates including tasks that are labelled "not very important" or higher, but excluding the tasks that are "not at all important".[32] Consistent with the model, the estimates show again that the wage is an important determinant of computer use. In addition, a number of

[31] The inclusion of occupational dummies into the regression leads to similar results.

[32] For a number 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.

tasks also seem to increase the probability to obtain a computer, in particular listening carefully to colleagues, knowledge of the organization of the workplace, reading written information such as forms, notices, or signs, adding, subtracting, multiplying, or dividing numbers, and calculating using more advanced mathematical or statistical procedures. In addition, when physical stamina is part of the job, the likelihood of computer use is significantly lower. It is also interesting to note that the estimation based on all tasks, both relatively important and unimportant (third column), explains computer use much better than the estimation based on important tasks (second column). This suggests that, in general, computers are not used for the core tasks of the job, but rather that secondary tasks make the adoption of the computer worthwhile. 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. Hence, the upgrading of skill requirements is not likely to be due to the increasing importance of skills used to perform the computerized job activities, but to a reemphasis on the non-computerized and skilled tasks. This result is consistent with the findings of Levy and Murnane (1996) and Autor, Levy and Murnane (2003).

Again, in both specifications including the tasks, the variables related to education and age are 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 variables together do not significantly improve the fit of the model. These results suggest that productivity advantages in using a computer because of a worker's skills do not seem to be major explanations of the pattern of computer use.[33] This latter result is also of interest to determine the channel of skill upgrading: it suggests that the employer does not increase the demand for more-skilled labor because skilled workers gain more time than unskilled workers after the adoption of the computer, but that it is more likely that the weight attached to both tasks changes towards the performance of the more-skilled job activities.

[33]Similar to the results reported in Table 2, the point estimates and marginal effects of education are substantial but not significant. Relative to a worker without a degree, a worker with some sort of degree has a larger probability to use a computer at work. Also, being female still exerts a strong and positive impact on the likelihood of using a computer at work.

4.3.4 Direct and Indirect Impact on Wages

The estimation results suggest that the effect of wages on computer use are of greater importance than the effect of skills, measured by the qualifications of the respondents, and most tasks, measured by the importance of certain job activities. To compare the effects of wages and skills, Table 4 provides the direct and indirect marginal effects of different educational levels. The direct effect equals the marginal effect of each educational dummy in the logistic regressions reported in Tables 2 and 3. The indirect effects of education on the likelihood of computer use are estimated in the wage regression multiplied by the marginal effect of wages on computer use.

According to the estimates without using instruments, all educational levels have a significant direct and indirect effect on computer use. The direct effect is approximately twice as large as the indirect effect via the wages. Once the wage is instrumented, only the indirect effects of education on computer use turn out to be significant. This indirect wage effect is approximately twice as large as the direct effect for most educational levels. This suggests that differences in computer use among skilled workers have to be explained by the fact that these workers earn higher wages rather than by an direct impact of their skills on computer use.

Also, age and age squared have no significant direct impact on computer use. The age profile of computer use can be explained by the relationship between age and wages. Only for female workers is there a significant direct effect on the likelihood of computer use, which is partly off-set by a negative indirect effect since women's wages are generally lower than men's wages.

5 Conclusion

Computers have brought about a dramatic change in the labor market in the last decades. Until recently, computers have been used mainly by skilled workers and a large number of 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. School, in this line of thought, could prepare students for the new labor market, by providing these computer related skills. We have developed a simple model together with suggestive empirical findings showing what happens to the job when computer technology is introduced. The main finding is that skills do not seem to be the most important determinant of the pattern of computer use, but that the wage level and certain job activities are likely to be more important predictors of computer technology use at work. The suggestive empirical evidence does not imply that computerization does not lead to skill upgrading. The channel through which skill upgrading occurs is likely to be found as a result of a changing weight attached to job activities towards more-skilled tasks and away from routine tasks, rather than by arguments related to the advantage higher-skilled workers might have in carrying out the computerized part of the job or the higher relative efficiency gain in the job as a whole when the computer is adopted. In terms of the Autor, Levy and Murnane (2003) results: it is important to stress what it is that computers do to jobs when investigating changes in the labor market resulting from technology adoption.

Our results are of additional interest for two main reasons. First, they suggest that the computer wage premium is unlikely to be the result of 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 longitudinal and panel data, which typically find that computers are first introduced among high-wage workers, also fit into our line of reasoning and estimation results (e.g., Chennells and Van Reenen, 1997, Entorf and Kramarz, 1997, and Entorf, Gollac and Kramarz, 1999). As a consequence, computer related skills are probably less important for getting a good job than is often assumed. According our estimates it is mainly the case that people use a computer at work because they have a good job with a high wage. The other way round we find no significant effect of skills on the probability to find a job in which a computer is used. The effect of promoting computer related skills to improve the labor market success of graduates will therefore be more limited than is often assumed.

Second, the result that it is unlikely that skills related to computer use are the main determinants of the patterns of diffusion and observed wage differentials does not imply that computers are not a source of skill-biased technological change. Our approach suggests 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 and the increasing importance of skilled job activities. In this way, the adoption of computer technology seems to induce a gradual upward shift in skill requirements for computerized jobs. The model predicts that this latter channel is an important source of skill-biased technological change. 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; thus, skill-biased technological change as a result of computerization will continue at lower ends of the labor market.

Appendix A: Tasks

In the estimations 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 premiums. The following variables are included in the regressions: (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) 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 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.

Appendix B: Descriptive Statistics

See Table B1

Appendix C: The Instrument

For the instrument to be adequate, unionization variables should not influence computer use directly, while the unionization variables should also not proxy for unobserved skills. Some studies have investigated whether unions influence the investment decisions of firms directly. Some of these studies argue that unions oppose to the introduction and adoption of new technologies and therefore reduce the firm's investments.[34] For example, Fallick and Hassett (1999) estimate the impact of unionization on firms' investment behavior. For the period 1962-1984 they use firm-level data taken from Compustat's Full Coverage file for a sample of firms restricted to those employing between 200 and 750 workers and another sample of firms with at least 750 workers. The firms are involved in union elections during the sample period. They report estimates both for the effects of firms experiencing a winning union election in a given year and for the fraction of a firm's workforce involved in a winning election on the ratio of investment to the existing capital stock. An estimate of several specifications indicates that a successful certification election decreases the investment to capital ratio by .04 in the following year. However, estimates for the subsequent years do not yield significant results of unionization on investment decisions. So it does not seem to be likely that investment is permanently depressed by the advent of a union. A paper by Denny and Nickell (1992) investigates the impact of unions on investment behavior in the British manufacturing sector to study whether unions influence investments in new capital equipment. Providing a framework and estimating this using data from the 1980 and 1984 Workplace Industrial Relations Survey (WIRS) and controlling for wages, they report evidence that unions might reduce investment. However, the overall effects of unionization on investments do not appear to yield strong correlations within reasonable margins. A study by Machin and Wadhwani (1991), using the same data from the WIRS, show no significant effect of unionization on investment or on the adoption of new technologies. Consistent with our model however, they do find a positive correlation between unionization and wages, which is attributed to the fact that unionized firms pay significantly higher wages. Taymaz (1991) demonstrates that the extent of unionism has no impact on the diffusion of numerically controlled machine tools in the U.S. engineering industries in the period 1979-1983, but he does not take into account the wages these firms pay. Finally, Lintner, Pokorny, Woods and Blinkhorn (1987) shows estimates related to the influence of unions on the adoption of Computer-Aided

[34]Many studies on the relationship between unionization and the firm's investment behavior and decisions focus on the fact that on average unionized firms seem to invest less in research and development than non-unionized firms (e.g., Connoly, Hirsch and Hirschey, 1986 and Hirsch and Link, 1987). Such findings are not necessarily inconsistent with our use of unionization variables as instruments for the wage because research and development does most likely not directly influence the adoption of computers at the workplace of the ordinary worker. Moreover, research and development is an input into the process of innovation of the firm, which seems unlikely to affect the decision to adopt a computer by the ordinary manager, secretary or clerk.

Design and Manufacturing equipment (CADCAM) in the U.K. mechanical engineering industry in the early 1980s. They report findings that unions did not exert any significant influence on the adoption of all forms of technology included in CADCAM, but they too did not explicitly consider the wages unionized firms pay in their regression analysis. Our reading of these results is that although unionization exerts an upward pressure on wages, there seems to be no or perhaps a very small negative direct link between a firm's investment behavior and decisions and unionization. Since the effect of unions on computer use via the wages is of an opposite sign, any negative investment effect would lead to a downward bias of the results, making the estimates of our regression equation conservative.

Second, for an adequate analysis the instruments need to be uncorrelated with unobserved skill components. Unionized firms might be inclined to hire more-skilled workers, because they are forced to pay higher wages. This would suggest that unionization affects computer use not only through wages but potentially through any computer-skill linkage. However, considering different skill classes, Card (1996) and Lemieux (1998) report true union effects for the United States and Canada, suggesting that unionization is at least for some significant part independent of the skill level of the workforce. Using data from the Current Population Surveys for 1973-1974 and 1993, Card (2001) reports estimates that there might be some selection effects besides the true union effects, because union workers with lower observed skills are positively selected, while those with higher observed skills are negatively selected. However, these estimates yield only moderate effects. Again, since computer users are mainly higher-skilled workers, and if skill level influences the estimates, a downward rather than an upward bias is to be expected from the regression results.

A third argument would be that unionization may also proxy for other aspects of firms that are more likely to adopt computers. The industry a firm is operating in would be a likely candidate. In the regressions we control for this by including industry dummies in the regression equations. In the regression analysis, it is shown that the results are similar when including industry dummies (comparison of the estimates in Table 2 with the ones in Table 3, column 1, shows this to be the case).

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Table 1

Donald-Newey-Test to Determine the Optimal Number of Instruments

Instruments used	Approximate MSE
(i)	3073.27
(ii)	3087.88
(i), (ii)	3067.77
(i), (iii)	3065.84
(ii), (iii)	3074.56
(i), (ii), (iii)	3068.59
(i), (ii), (iii), (iv)	3071.26
(i), (ii), (iii), (iv), (v)	3074.02

Note: The data are taken from the Skills Survey of the Employed British Workforce. (i) “At your place of work, are there unions, staff associations or groups of unions?”; (ii) “are you a member of a trade union or staff association?”; (iii) the cross-dummy for workers answering yes on both question (i) and question (ii); (iv) “are any of them recognized by management for negotiating pay and/or conditions of employment?”; and (v) “is it possible for someone in your job to join one of these unions or staff associations?”.

Table 2

Logistic Regression of the Determinants of Computer Use Without Instruments and With Unionization as an Instrument for Wages

(Dependent Variable: Likelihood of Computer Use)

	Without instruments		With instruments	
	coefficient (standard error)	marginal effect	coefficient (standard error)	marginal effect
Instrumental equation				
Union coverage			.174** (.027)	
Union coverage and member			–.059* (.028)	
University degree			.722** (.044)	
Professional degree			.564** (.041)	
NVQ3 degree			.330** (.043)	
NVQ2 degree			.275** (.038)	
NVQ1 degree			.119* (.055)	
Age			.067** (.008)	
Age squared			–.078** (.010)	
Female			–.203** (.042)	
Married			.069* (.033)	
Female*married			–.094 (.050)	
Constant term			.171 (.164)	
Logit equation				
Ln (wage)	1.634** (.091)	.349	2.871** (.887)	.613
University degree	2.562** (.354)	.547	1.322 (.774)	.282
Professional degree	1.682** (.221)	.359	.704 (.589)	.150
NVQ3 degree	1.107** (.175)	.236	.529 (.402)	.113
NVQ2 degree	.935** (.142)	.200	.457 (.326)	.098
NVQ1 degree	.512** (.196)	.109	.309 (.306)	.066
Age	.025 (.037)	.005	–.088 (.080)	–.019
Age squared	–.038 (.046)	–.008	.093 (.095)	.020
Female	.816** (.193)	.174	1.047** (.310)	.224
Married	.127 (.162)	.027	.017 (.213)	.004
Female*married	–.468* (.229)	–.100	–.327 (.316)	–.070
Constant term	–3.579** (.715)		–3.215** (.948)	
Standard error			.475** (.003)	
Log likelihood	–1107.57		–648.87	
LL Model without education	–1168.53		–650.66	
2 LLR	121.92**		3.58	
LL Model without age	–1108.34		–650.99	
2 LLR	1.54		4.24	

Note: The data are taken from the Skills Survey of the Employed British Workforce. * = significant at 5 percent level; ** = significant at 1 percent level. Standard errors are reported in parentheses. The coefficients on the educational levels are relative to workers with no degree. Age is used as a proxy for experience.

Table 3

Logistic Regression of the Determinants of Computer Use with Sector of Industry and Tasks, with Unionization as an Instrument for Wages
(Dependent Variable: Likelihood of Computer Use)

	With sectors of industry		Very important tasks		All tasks	
	coefficient (standard error)	marginal effect	coefficient (standard error)	marginal effect	coefficient (standard error)	marginal effect
Ln (wage)	3.397** (1.055)	.726	3.810** (1.405)	.814	3.461* (1.385)	.740
University degree	1.149 (.866)	.246	.793 (.812)	.169	.721 (.862)	.154
Professional degree	.629 (.671)	.134	.188 (.602)	.040	.081 (.621)	.017
NVQ3 degree	.493 (.430)	.105	.398 (.411)	.085	.315 (.384)	.067
NVQ2 degree	.425 (.362)	.091	.272 (.336)	.058	.158 (.325)	.034
NVQ1 degree	.295 (.335)	.063	.257 (.361)	.055	.160 (.341)	.034
Age	–.113 (.088)	–.024	–.141 (.102)	–.030	–.137 (.103)	–.029
Age squared	.122 (.103)	.026	.149 (.120)	.032	.160 (.120)	.034
Female	1.165** (.340)	.249	.952* (.403)	.203	1.214** (.419)	.259
Married	.054 (.228)	.012	–.147 (.257)	–.031	–.151 (.246)	–.032
Female*married	–.370 (.334)	–.079	–.262 (.370)	–.056	–.233 (.359)	–.050
Tasks						
Paying close attention to detail			.133 (.288)	.028		
Dealing with people			–.199 (.261)	–.042		
Instructing, training or teaching			.222 (.194)	.047	.271 (.242)	.058
Making speeches or presentations			–.381 (.294)	–.081	.010 (.295)	.002
Persuading or influencing others			–.030 (.223)	–.006	.060 (.264)	.013
Selling a product of service			–.032 (.207)	–.007	–.042 (.211)	–.009
Counselling, advising or caring			.564* (.244)	.121	.302 (.269)	.064
Working with a team of people			–.320 (.221)	.068	–.133 (.438)	–.028
Listening carefully to colleagues			–.048 (.226)	.010	.897* (.454)	.192
Physical strength			–.312 (.266)	–.067	–.538 (.290)	–.115
Physical stamina			–.329 (.212)	–.070	–.616* (.310)	–.132

Skill or accuracy in using hands		–.376 (.207)	–.080	–.124 (.261)	–.026
How to use or operate tools		.006 (.201)	.001	.232 (.242)	.050
Knowledge of particular products		–.085 (.211)	–.018	–.258 (.320)	–.055
Specialist knowledge		–.153 (.274)	–.033	–.432 (.437)	–.092
Knowledge of organization		.430* (.187)	.092	1.052* (.424)	.225
Spotting problems		.349 (.273)	.074		
Working out problems		.047 (.278)	.010	.747 (.451)	.160
Thinking of solutions		–.114 (.280)	–.024	–.656 (.461)	–.140
Analyzing complex problems		–.303 (.231)	–.065	.099 (.273)	.021
Checking things for errors		.509 (.271)	.109	–.162 (.443)	–.035
Mistake noticing		–.042 (.301)	–.009		
Planning own activities		.172 (.228)	.037	.504 (.390)	.108
Planning others' activities		–.233 (.214)	–.050	.008 (.225)	.002
Organizing own time		–.121 (.229)	–.026	–.418 (.398)	–.089
Thinking ahead		–.023 (.228)	–.005		
Reading written information		.349 (.233)	.074	1.002* (.443)	.214
Reading short documents		.160 (.250)	.034	.240 (.355)	.051
Reading long documents		.126 (.235)	.027	.415 (.288)	.089
Writing materials		.153 (.233)	.033	–.234 (.297)	–.050
Writing short documents		–.044 (.286)	–.009	.138 (.306)	.029
Writing long documents		.673* (.285)	.144	.353 (.263)	.076
Adding, subtracting or dividing		.632** (.244)	.135	.880** (.281)	.188
Straightforward calculations		–.074 (.264)	–.016	–.211 (.281)	–.045
Advanced calculations		.742** (.285)	.159	1.085** (.222)	.232
Constant term	–3.907** (1.037)	–4.748** (1.254)		–6.521** (1.400)	
Standard error	.465** (.003)	.436** (.003)		.436** (.003)	
Log likelihood	–566.85	–153.30		–60.34	
LL Model without education	–568.11	–150.57		–61.53	
2 LLR	2.52	5.46		2.38	

LL Model without age	–569.03	–152.15	–61.57
2 LLR	4.36	3.16	2.46

Note: The data are taken from the Skills Survey of the Employed British Workforce. * = significant at 5 percent level; ** = significant at 1 percent level. Standard errors are reported in parentheses. A complete list with the full specification of the 35 tasks defined here is given in Appendix A. All three regressions include industry dummies. A full list of industry dummies in given in Appendix Table B1. The coefficients on the educational levels are relative to workers with no degree. Age is used as a proxy for experience.

Table 4

Direct and Indirect Effect via Wages of Variables on Computer Use

	No instruments		Basic equation		With sectors of industry		Very important tasks		All tasks	
	Direct	Indirect	Direct	Indirect	Direct	Indirect	Direct	Indirect	Direct	Indirect
University degree	.547**	.252**	.282	.443**	.246	.511**	.169	.358**	.154	.340*
	(.076)	(.023)	(.165)	(.140)	(.185)	(.163)	(.173)	(.139)	(.184)	(.142)
Professional degree	.359**	.196**	.150	.346**	.134	.408**	.040	.277*	.017	.259*
	(.049)	(.019)	(.126)	(.111)	(.143)	(.131)	(.129)	(.109)	(.133)	(.110)
NVQ3 degree	.236**	.115**	.113	.203**	.105	.214**	.085	.147*	.067	.120*
	(.038)	(.016)	(.086)	(.070)	(.092)	(.076)	(.088)	(.067)	(.082)	(.059)
NVQ2 degree	.200**	.096**	.098	.168**	.091	.185**	.058	.122*	.034	.104*
	(.031)	(.014)	(.070)	(.058)	(.077)	(.066)	(.072)	(.056)	(.069)	(.051)
NVQ1 degree	.109**	.042*	.066	.073	.063	.087	.055	.057	.034	.040
	(.042)	(.018)	(.065)	(.041)	(.071)	(.048)	(.077)	(.048)	(.073)	(.041)
Age	.005	.023**	–.019	.041**	–.024	.047**	–.030	.046*	–.029	.042*
	(.008)	(.003)	(.017)	(.014)	(.019)	(.016)	(.022)	(.018)	(.022)	(.018)
Age squared	–.008	–.027**	.020	–.048**	.026	–.054**	.032	–.052*	.034	–.047*
	(.010)	(.004)	(.020)	(.016)	(.022)	(.018)	(.026)	(.021)	(.026)	(.021)
Female	.174**	–.071**	.224**	–.124**	.249**	–.125*	.203*	–.133*	.259**	–.147*
	(.042)	(.015)	(.066)	(.046)	(.073)	(.050)	(.086)	(.060)	(.089)	(.067)
Married	.027	.024*	.004	.042	.012	.037	–.031	.028	–.032	.015
	(.035)	(.011)	(.045)	(.023)	(.049)	(.026)	(.055)	(.029)	(.053)	(.025)
Female*married	–.100*	–.034	–.070	–.058	–.079	–.046	–.056	–.038	–.050	–.014
	(.049)	(.017)	(.067)	(.035)	(.072)	(.039)	(.079)	(.042)	(.077)	(.036)

Note: The data are taken from the Skills Survey of the Employed British Workforce. * = significant at 5 percent level; ** = significant at 1 percent level. Standard errors are reported in parentheses.

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 Degree	9.9	95.5	62.0	42.4
Professional Degree	12.4	88.9	60.6	46.9
NVQ3 Degree	15.2	75.1	53.2	35.8
NVQ2 Degree	34.5	71.6	45.8	30.0
NVQ1 Degree	8.8	55.1	38.9	21.8
No Degree	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	68.6	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, Fishing, Energy and Water Supply	5.7	49.3	37.2	24.3
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,	20.1	68.8	71.8	49.5

Insurance, Business services and Leasing				
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.