Computer use and earnings in Britain

Peter Dolton and Gerry Makepeace

17/01/2003

Abstract

This paper estimates various models of the effect of computer use on earnings using recent NCDS data. The cross-section estimates are large and significant while the standard fixed effects estimates are small or insignificant. The panel estimates change considerably once we allow the coefficients to differ across individuals. Indeed, conditional on assumptions about when individuals use computers, conventional panel estimates may not identify the crucial parameters and cross-sectional methods may be needed. We conclude that there was a premium associated with computer use for some individuals in the UK which we attribute to better capital equipment.

JEL	J00, J30, J31		
Keywords	Earnings, ICT, Computers		
Word count	7,300		
	Paper	6,300	
	Tables	1,000	2 pages @ 500 words per page
	Total	7,300	

Corresponding author Gerry Makepeace

Peter Dolton
Department of Economics
University of Newcastle-Upon-Tyne
Newcastle
NE1 7RU

Gerry Makepeace
Cardiff Business School
Cardiff University
Aberconway Building
Colum Drive
Cardiff
CF10 3EU
Email Makepeace@cf.ac.uk

Computer use and earnings in Britain

Peter Dolton and Gerry Makepeace

Introduction

The UK experienced an enormous expansion in the use of Information and Computing Technology (ICT) during the closing decades of the 20 century. Rates of growth for investment in ICT were very high and its relative importance in total investment increased substantially. ICT became a major driver of growth in its own right and contributed directly to the growth in labour productivity. Oulton (2001) estimated that the average annual growth rates in capital services provided by computers and software in UK from 1980 to 1999 were 30% for computers and 32% for software (Table D7 p.76[1]). Colecchia and Schreyer (2001) produce similarly large figures for the average annual percentage growth of volume investment[2], estimating that the shares of ICT equipment and software in total non-residential investment for the UK doubled from 1980 to 1990 and tripled from 1980 to 2000[3]. Oulton argues that "..despite its small share in GDP, ICT accounted for 13% of output growth in 1979-89 and 21% in 1989-99" (p.31).

Some of the economic issues associated with these large changes are addressed in the large literature dealing with the implications of technological advance for wage inequality. These matters have been discussed recently in Acemoglu (2002), Card and Dinardo (2002) and Machin (2001) and we do not propose to review them here. The present paper examines whether the large change in technology impacted on the wage structure in the most basic way by raising earnings. In particular, we use more general panel estimation (rather than simple fixed effects) to resolve the continuing debate about whether the use of computers at work affects earnings. We estimate a variety of models using recently released data from the National Child Development Study (NCDS).

Previous findings from the literature are replicated. These suggest that the cross-section estimates are large and significant while the standard fixed effects estimates are small and insignificant for men. We show in our data that the panel estimates of a significant premium for computer use is consistent with the large premium found by OLS regression methods and a zero return found by fixed effects methods, once we allow the coefficients to differ across individuals. Using simple fixed effects to control for unobserved heterogeneity estimates different parameters to those estimated by our more general panel methods and does not identify the crucial parameters.. In this context, we also estimate the 'value-added' specification of Todd and Wolpin (2000). We conclude that there has been a significant premium associated with computer use for some individuals in the UK in the last 10 years.

---

[1] Oulton's estimates are sensitive to assumptions made about measurement of software. We have quoted his preferred estimates.

[2] These are 28% (1980-90) and 25% (1990-2000) for IT equipment although their rates for software growth are lower at 27% (1980-90) and 10% (1990-2000).

[3] Other countries reacted differently. The UK share tripled from 1980 to 2000 but started from a low base (5% of total investment). The US share doubled but from a much higher base (15%). The German share only grew by a quarter from 12% to end slightly above the UK figure.

The current consensus, post DiNardo and Pischke (1997), is that the return to using a computer must be very small, if not zero, and that the large estimates presented in the early empirical literature merely reflected the unobserved effects of ability or occupation. Our suggestion that using a computer does involve an earnings premium therefore requires some justification and elaboration. We argue that, if you condition explicitly on ability and occupation, skill and job type, then the earnings premium to using a computer does indeed fall, but that, properly measured, it still remains significant. We believe this coefficient is statistically robust and, therefore, economically important.

Different economists would interpret our results differently but we would agree with DiNardo and Pischke that traditional earnings equations are misspecified. However, we would argue that estimating equations, like much of the literature on the effects of skill-based technical change on wages, ignore the effect of physical capital. The earnings equation assumes equilibrium in a competitive labour market so that the major determinant of earnings is human capital. However, the labour market will not necessarily clear instantaneously if if there has been rapid technological change. This means that the first firms to use new capital equipment and computers may capture short terms rents. It is also clear that major technical advances, like computers, could make workers many times more productive very quickly[4]. We would expect the dramatic improvements in ICT during the period spanned by our data to have impacted on earnings at the very least through changes in labour productivity associated with new capital equipment.

The rest of paper is organised as follows. We begin by describing our data and then consider some of the problems that arise when estimating the impact of computing using panel data. First, we apply previous approaches to our data. These implicitly assume that the coefficient of interest is constant over time and individuals. If we examine data at the start and the end of a period of rapid growth in computer use, we might expect to see a fall in the average return to computer use if firms that make the largest gains use computers first or if the return is eroded as more workers acquire computing skills. Subsequent sections therefore consider models where the impact of computers changes over time, firstly, in the same way for everyone who uses computers and, secondly, in different ways according to when individuals use them.

[4] One of the more obvious areas is secretarial work. With relatively modest changes in skills, a secretary's productivity could be improved dramatically by ICT. Some of the benefits from the increased productivity will be paid to workers (even in a Neoclassical model).

Data

The data used in this paper are taken from the National Child Development Study (NCDS). NCDS is a British cohort study of individuals born in 1958. Information has been collected regularly over time and we use data from the latest two sweeps in 1991 when the respondents were 33 and 2000 when they were 42. The NCDS survey has comprehensive information on education and contains the results from reading and mathematics tests undertaken at early ages. The early sweeps give information on family background and the later sweeps contain extensive labour market and other socio-economic data. These data are particularly useful for our purposes as they contain information on computer use over a decade when the use of computers and their power accelerated particularly rapidly[5].

The variables used in our analysis are defined in the Appendix. In simple terms, we have included variables corresponding to nearly all those that have been used in previous studies plus some extra ones specific to NCDS. Estimation in this context is of course, conditional on and limited by, the data available but we have one of the most comprehensive list of controls available to any study in this area. The variables augment a set of standard human capital variables (schooling, work experience, tenure) with measures of attainment (highest qualification, test scores), skills, occupation, industry, region, socio-demographic characteristics (marital status, race, health) and other job characteristics. The sample comprises individuals who were full-time employees in both 1991 and 2000. The dependent variable is the natural logarithm of real hourly wages.

The present paper uses information on the use of computers at work in 1991 and 2000. We measure the impact of computer use by a dummy for 'uses a computer at work'. We should note that the questions in the NCDS were asked explicitly at the time when the corresponding survey was undertaken. Some panel studies in the literature have difficulties with tracing computer use over time because questions on computer use only appear after the panel has been running for some time. The NCDS data are especially interesting in the present context because of the timing of the revolution in the use of computers. Computers would have had little practical impact as far as the schooling of the NCDS cohort was concerned. Some cohort members would have studied computer science in advanced courses in higher education but most would have completed higher education by the age of 23 in 1981. We could argue that the normal academic and vocational training routes for young people had a minor impact on the use of computers by the NCDS cohort members.

Table 1 shows how computer use varies across our sample. The incidence of computer use has increased over time from 60% to 75% of the sample. The percentages have increased for both men and women although men are less likely to use computers at each point in time.[6] The key observations in panel estimation are the 'changers' (those who change from not using to using a computer or *vice versa*). 19% of the sample changed from not using a computer in 1991 to using one in 2000 while the converse applied to 4% of the sample.

---

[5] Greenen et al (2002) provide evidence that the use of computers has at least doubled in many OECD countries has doubled over the 1984 to 1998 period. Haisken-DeNew and Schmidt (1999) document the rapid rise of computer processing power over the same period (see Table 6 in their paper).

[6] One consequence of selecting a panel sample is that computer use is over-represented since respondents in the our sample have to be in work at both points in time.

There was little difference across genders although there were only 38 women who gave up using a computer between the earlier and later wave of the survey[7].

Cross-section and panel estimation with a constant coefficient

We assume that we have panel data showing the logarithm of earnings (Y) and whether the individual used a computer at work (C) in each of two periods[8]. The n individuals are indexed by i and the time periods by t=1,2. The variable C_{it}=1 if individual i uses a computer in period t and 0 otherwise. Computer use divides individuals into the 4 sets, A_{KL}, where K=C_{i1} and L=C_{i2}. Set A_{KL} contains n_{KL} individuals. For example, set A_{01} contains the n_{01} individuals who did not use a computer in the first time period but did in the second period. $A \equiv \bigcup_{K,L=0,1} A_{KL}$.

The estimating equations are:

$$Y_{i1} = a_i + b_1 C_{i1} + u_{i1} \qquad i \hat{I} A \qquad 1.$$

$$Y_{i2} = a_i + b_2 C_{i2} + u_{i2} \qquad i \hat{I} A \qquad 2.$$

where a_i is an individual specific effect and u_{it} is an error term with the familiar properties.

Consider an OLS regression when the equations include a constant and it is assumed that b_1=b_2=b. Let $b_{OLS\,t}$ the OLS estimate for period t and $b_{OLS\,12}$ be the OLS estimate of b when the data for both samples is pooled.

$$b_{OLS\,t} = \frac{\sum_i (C_{it} - \overline{C}_t)(Y_{it} - \overline{Y}_t)}{\sum_t \sum_i (C_{it} - \overline{C}_t)^2} \quad t=1 \text{ or } t=2 \qquad b_{OLS\;12} = \frac{\sum_t \sum_i (C_{it} - \overline{C})(Y_{it} - \overline{Y})}{\sum_t \sum_i (C_{it} - \overline{C})^2} \qquad 3.$$

where $\overline{C}$ and $\overline{C}_t$ are, respectively, the means of C for the whole sample and for the t'th period.

Most previous studies have estimated the impact of computer use by applying OLS to a single cross-section, When data from period t only is used,

$$E(b_{OLS\,t}) = b_t + d_t \qquad t=1 \text{ or } t=2 \qquad 4.$$

Panel studies typically report OLS results for pooled data. If the maintained hypothesis is correct and b_1=b_2=b,

$$E(b_{OLS\,12}) = b + d \qquad 5.$$

d_t and d are the estimated coefficients of C_{it} when a_i is regressed on C_{it} when (i) t=1 or t=2 and (ii) t=1 and 2.

The potential omitted variable bias, measured by d_t or d, was recognised by Kreuger (1997) and researchers have repeatedly sought to reduce the extent of these biases by including

---

[7] This suggests that there may be difficulties with degrees of freedom if only this group is used to identity a parameter.

[8] We have two data observations so we only consider two period models even though the problems discussed apply more generally.

proxies for the unobserved heterogeneity. These have included variables for occupation, industry, and region. (See *inter alia* Kreuger (1997), DiNardo and Pishke (1997) and Osterbeek (1997).) DiNardo and Pishke (1997) and Dickerson and Green (2002) have included other job attributes such as use of tools and other skills. In a similar vein, we employ highest qualification and 'early test scores', showing the separate scores on reading and mathematics tests taken at age 11, in our empirical work below. At least since Micklewright (1989), economists have interpreted these scores as measures of ability. This is debatable but they are certainly indicators of early attainment obtained largely independently of the normal system of education and public examinations. Bell (1996) was the first to use these test scores in the present context and Arabsheibani and Marin (2001) use the scores at age 7, although both studies restrict their attention solely to the 1991 data.

Table 2 illustrates this methodology by starting from a basic human capital form and including successive groups of variables. The estimated impact of computing falls as more controls are added to the equation. This is exactly what we would expect if the use of computers was positively correlated with the previously omitted variables. However, the estimates for the broadest specification (labelled 'Full') are the same order of magnitude to those obtained in other UK studies. They indicate a premium of 13½% from the pooled data with a t-values of over 12. This estimate is over twice those of Anger and Schwarz (2002) for Germany[9] and Entorf and Kramarz (1997) for France[10] but similar to that of Oosterbeek (1997) for The Netherlands[11]. The 'Full' specification arguably contains the most comprehensive list of control variables for this kind of exercise yet the effect of computer use remains large and robust. Nonetheless, this kind of argument is always open to the criticism that there may be some other omitted factor that should be included.

Entorf and Kramarz (1997) and Anger and Schwarz (2002) have used fixed effects models to eliminate the effects of the unobservable individual characteristics on the assumption that $b_1=b_2$. Their OLS estimates are under 6½% but have large t-values. By contrast, the fixed effects estimates are insignificant and close to zero[12]. The authors conclude that the return to computing merely proxies unobserved ability.

The fixed effect is eliminated by considering deviations from the means for each individual. The fixed effect estimator under the maintained hypothesis that $b_1=b_2$ is:

$$b_{b_1=b_2} = \frac{\sum_t \sum_i (C_{it} - \overline{C_i})(Y_{it} - \overline{Y_i})}{\sum_t \sum_i (C_{it} - \overline{C_i})^2}$$

where $\overline{C_i}$ and $\overline{Y_i}$ are the means for the i'th individual.

Table 3 reports first difference estimates of the computing coefficient. (These are the same as the fixed effects estimators in a 2-period model.) The panel estimates are less than the OLS

---

9 2½% for men and 6½% for women using pooled data for 1985-99.

10 6% using pooled data for 1985-87.

11 12% in 1993.

12 By contrast, the fixed effect estimate (10%) is slightly smaller with a t-value of 2.7 in Osterbeek (1997). He assumed that computers were not used in 1983 and did not include any control variables in the panel model.

estimates and have smaller t-values. Indeed, the panel estimate is insignificant for men although it remains large and significant for women[13]. This supports the view that there is no return to computing at least for men. We argue below that the fall in the estimate may be due to neglected variation in its value over time. We first consider what happens if the coefficients are the same for each individual at each point in time but differ over time. Later we explore a situation where the variation is due to the composition of individuals over time.

Panel estimates when the coefficients change over time

OLS and fixed effects

The expected values of the estimators under the maintained hypothesis that $b_1=b_2=b$ are:

$$E(b_{OLS\,t})=b_t+d_t \qquad t=1 \text{ or } t=2 \qquad 6.$$

$$E(b_{OLS\,12})= b_2+(b_2-b_1)m_{OLS\,12} + d \qquad 7.$$

$$E(b_{b_1=b_2}) = b_2 + (b_1 - b_2)m_{b_1=b_2} = m_{b_1=b_2}\, b_1 + (1 - m_{b_1=b_2})\, b_2 \qquad 8.$$

where $m_{OLS\ 12} = \dfrac{\overline{C}_1(n_{01}-n_{10})}{\sum_t \sum_i (C_{it}-\overline{C})^2}$ $\qquad 0 \le |m_{OLS\ 12}| \le 1$

$$0 \le m_{b_1=b_2} = \frac{n_{10}}{n_{01}+n_{10}} \le 1$$

The fixed effect estimator is preferred to the OLS estimators if the impact of computing is constant over time ($b_2 = b_1$). It will give unbiased estimates while OLS applied to a single cross-section or to the pooled sample will give biased estimates when computer use is correlated with the omitted individual specific effect.

The argument is more complicated when $b_1 \neq b_2$. Many researchers have quoted results based on OLS estimators applied to one period such as $b_{OLS\,2}$. Equation (6) shows that this overestimates the coefficient in the second period if computer use and the omitted specific effect are positively correlated. Equation (8) shows that the expected value of the fixed effect estimator ($E(b_{b_1=b_2})$) is a weighted average of b_1 and b_2. There could be a large difference in the OLS and fixed effects estimates but it is not clear what the implications are because they are estimating two different things. The cross section estimate focuses on the coefficient in one period and the fixed effect estimate on a weighted average of the coefficients.

If we assume that there is no omitted variable bias, the fixed effect and pooled OLS estimators are estimating different parameters so there is no reason for them to produce the same results. If $n_{10}>n_{01}$, the pooled OLS estimator is a weighted average of b_1 and b_2. The weight attached to b_1 is larger for $b_{b_1=b_2}$ than for $b_{OLS\,12}$ so the fixed effect estimator will be closer to the value of b_1. In this case, the two estimators provide alternative estimates of the average value of the coefficients over time.

[13] The women in our sample may not be typical of the general population because they were in full time employment at 33 and 42. We abstract from the selection issues arising from participation decisions.

In our data, $n_{10}>n_{01}$. Assuming d=0, $E(b_{OLS\ 12})>b_2$ if $b_2>b_1$ and $E(b_{OLS\ 12})<b_2$ if $b_2<b_1$. When there is no omitted variable bias, its expected value is either smaller or larger than either coefficient so the pooled OLS estimator has little to commend it in our case[14].

Fixed effects with coefficients that vary over time

We can allow for differences in the coefficients over time by estimating a fixed effects model although we have estimated the simpler first difference form.

$$Y_{i2}-Y_{i1}=b_2(C_{i2}-C_{i1})+(b_2-b_1)C_{i1}+u_{2i}-u_{1i}$$

The coefficient on the change in computer use shows the effect of computer use in period 2 and the coefficient on computer use in period 1 shows the change in the effect of computer use. The last column of Table 3 shows the estimates for equations including levels and changes for all the variables in the 'Full' specification.

The women's results suggest that the impact of computing is well defined at 11% and has not changed from 1991 to 2000. The men's results suggest that computing had a small impact in 2000 but none in 1991. Although significant, the estimated impact is much less than the values produced by cross-section techniques. The evidence for a change in the coefficient is weak and the resulting estimates appear implausible so we reject the hypothesis of a uniform change in the impact of computing over time.

Estimates with heterogeneity across individuals

Panel estimates

The fixed effects estimator under the maintained hypothesis that b_1=b_2=b can be written as

$$b_{b_1=b_2}=S_{CC}^{10}b^{10}+S_{CC}^{01}b^{01} \qquad 9.$$

where $S_{CC}^{KL}=\dfrac{\sum_t\sum_{i\in A_{KL}}(C_{it}-\overline{C}_i)^2}{\sum_t\sum_{i\in A_{10},A_{01}}(C_{it}-\overline{C}_i)^2}$ and $b^{KL}=\dfrac{\sum_t\sum_{i\in A_{KL}}(C_{it}-\overline{C}_i)(Y_{it}-\overline{Y}_i)}{\sum_t\sum_{i\in A_{KL}}(C_{it}-\overline{C}_i)^2}$

b^{KL} is the OLS estimate of the coefficient of C in the equation

$$Y_{it}-\overline{Y}_i=b^{KL}(C_{it}-\overline{C}_i)+u_{it}-\overline{u}_i \qquad t=0,1;\ \ i\in A_{KL}$$

Equation (9) shows that the fixed effects estimator is a weighted average of the estimates for those that give up using a computer (b^{10}) and those that take up using a computer (b^{01}). The maintained hypothesis is that both sets have the same values of b but the results could be very different if the two groups have different returns to computer use.

Since DeNardo and Pishke (1997), computer use has often been viewed as an indicator of unobserved individual productivity or job characteristics. The main motivation for the fixed effects model was that it netted out these effects (assuming they do not change over time). By contrast, if there are genuine differences across different types of computer user, then the fixed effect model estimates a weighted average of the effects for a subset of the individuals (the changers). Many policy makers assume that computing skills are productive and vary

[14] $n_{10}>n_{01}$ is probably typical for this type of application.

across individuals. If the more skilful individuals enter the market first, we might expect $b^{11}>b^{01}>b^{00}$. The ranking of b^{10} is not clear cut. It may be the case that individuals who stop using computers do so because they are not very good at it. This would suggest that $b^{01}>b^{10}$ and even that $b^{00}>b^{01}$. By contrast, individuals may stop using computers as they move up promotion ladders. In this case, b^{10} may be relatively large. The fixed effect estimator may or may not be a close estimate of the impact of computer use across the whole population. However, it may not be a good indicator of the premium for those who have always used a computer (b^{11}) or those who might benefit from future use of a computer (b^{00}).

To explore this issue further, we define dummy variables to identify individuals who used computers in both periods (C^{11}), only the first period (C^{10}) and only the second period (C^{01}) and consider the specification[15]:

$$Y_{i1} = a_i + b_1^{11}C_i^{11} + b_1^{10}C_i^{10} + u_{i1} \qquad 10.$$

$$Y_{i2} = a_i + b_2^{11}C_i^{11} + b_2^{01}C_i^{01} + u_{i2} \qquad 11.$$

Taking first differences to eliminate the fixed effect, we first estimate

$$Y_{i2} - Y_{i1} = (b_2^{11} - b_1^{11})C_i^{11} - b_1^{10}C_i^{10} + b_2^{01}C_i^{01} + u_{i1} \qquad 12.$$

Table 4 presents the results for this estimation. There has been no change over time for those individuals who use a computer at both points in time. This applies for both men and women. The remaining results are different for men and women. There was no significant impact on earnings for men who only used a computer in 2000 but there was a large positive impact for women. Men who used computers only in 1991 received a large significant premium in contrast to the women.

The first difference results in Table 4 are consistent with the view that men who started using computers 'early' received a return of 9% or more but these returns are not available to recent computer users. The impact is different for women. Women who used computers in 2000 received a premium of 14% or more but women who gave up using computers received no premium[16]. We have made strong assumptions about the distribution of returns but, in doing so, we highlight our main point that we really want to know the values of b_1^{11} and b_2^{11} rather than $b_2^{11} - b_1^{11}$. The previous OLS results may be high because b_1^{11} and b_2^{11} are large.

Value Added Specification

Todd and Wolpin (2000) have advocated the estimation of a value-added model for use with panel data. We can apply their model by considering the equation:

$$Y_{i2} = dY_{i1} + b_2^{11}C_i^{11} + b_2^{01}C_i^{01} + u_{i2} \qquad 13.$$

Although Todd and Wolpin present a different rationale, we can simply view the lagged earnings term as a further proxy for the fixed effect. Table 4 shows the results of this

---

[15] Our previous fixed effects estimator assumed $b_1^{11} = b_1^{10} = b_1$ and $b_2^{11} = b_2^{01} = b_2$.

[16] There were 38 women who only used a computer in 1991. With the large number of controls, our estimate of b_1^{10} is, at best, imprecise.

estimation by OLS. The impact of ICT for individuals who used computers in both periods is similar to the previous estimates for pooled data. It is large (14% for men and 9% for women) and significant. Using computers in only 2000 raised earnings but by 5% for men and 14% for women. Using computers at work is associated with increases in earnings but the premium fell for male users but rose for females.

Conclusion

Our paper presents firm evidence that the premium to computer use was large in the UK. Over time, there have been repeated discussions of how to interpret the impact of computer use. Our paper focuses on the DiNardo and Pishke's (1997) argument that any estimate merely measures unobserved job or individual characteristics. This argument does not seem plausible in our case because we have many controls for ability, occupation, industry and skills, yet our cross-section estimates are still about 13% or 14% for men[17]. The fixed effects estimates of Entorf and Kramerz (1997) are much lower than their OLS estimates and insignificant, adding considerable weight to the argument that impact of computer use proxies unmeasured ability. We replicate this finding but seek to reconcile the cross-section and fixed effects estimates by considering more complex panel models that allow the impact of computing to vary over time.

We find no conclusive evidence that the computing coefficient merely changed its value over time and argue instead that the 'return' to computing varied across individuals. In our case, we can determine whether an individual used a computer in both periods, the first period only, the second period only or not at all. If we allow the coefficients to vary across individuals, our panel estimates are consistent with the view that the 'return' to computing is 'high' but they cannot identify at least one key parameter, the impact of computing for individuals who used computers in both periods. The estimates of our value added model indicate that this premium was about 14% for men in 2000 and 9% for women who used computers throughout the period of the model. Using computers in only 2000 also raised earnings but by 5% for men and 14% for women. Taken with the corresponding panel estimates (in Table 4), it appears that the 'return' to computing remained constant during the nineties for those that always used computers. In particular, those men that stopped using computers had a premium of about 9% in 1991.

The adoption of ICT offered a large potential boost to productivity during the nineties. Oulton (2001) attributes a quarter of the growth in labour productivity over the period 1989-98 to capital deepening (increases in the capital-labour ratio) associated with ICT (Table 10 p.38). This figure may have been as high as 48% for 1994-98. Technical advances proceed at an uneven pace and it is quite normal to have firms operating with different technologies even within the same occupation and industry.

We therefore think that individuals who work with computers are working with modern vintages of capital in capital rich environments. At least part of the 'return' to computing represents the increased productivity due to better capital. The fall in earnings of 9% for those men who stopped using computers offers support for this view. This boost to earnings

---

[17] Dolton and Makepeace (2002) have investigated some of the econometric problems that arise in cross-sectional models. Their matching, treatment and random effect models produce estimates of a similar order of magnitude to those presented here and elsewhere in this paper.

was only available while these men worked with computers. Given that fixed effects have no impact in this estimation and the wide range of controls employed, it is not plausible to attribute this to unobserved ability. It could be that the 9% represented a pure return to 'computing skills' and the fall in earnings for these men occurred because they were no longer exercising a particular skill. The growth in this group's average earnings over the sample period was less than fifth of that of all other men[18]. This does not suggest that they were individuals in high demand who were moving on to better jobs. The return for men who always used computers is higher at 14% and part of the difference between the two figures may be due to skill differences.

There is evidence that the premium for working with computers fell during the nineties for men. The return for men who always used computers remained 14% but new users of computers only benefited by 5%. This may represent the diffusion of computer use. We might expect firms to be more likely to adopt new technologies, the greater are the advantages so that the big gains are made by the first firms to use computers. The new users are working in a later wave of firms where the new technologies yield smaller improvements in productivity.

The common argument that the large changes implied by ICT could not have a lasting impact on earnings seems implausible to us because capital plays no role and workers are homogeneous so that any earnings differentials are immediately competed away. In general, labour will receive some of the productivity gains produced by the introduction of new technologies and lagged adjustment will ensure that they will not disappear in the short run. Many models explaining the increase in wage inequality allow for two types of workers (Acemoglu (2002) and Card and DiNardo (2002)). Krussell *et al* (2000) have heterogeneous capital as well as low and high quality workers. Structural capital contributes to the marginal product of both types of workers but equipment capital only augments the marginal product of high quality workers. The marginal product of labour depends on the amount and type of capital used by each type of worker. If we interpret computer use as an indicator of equipment capital, we would expect to see earnings premia associated with computer use. Thus, we feel that capital is an important determinant of productivity and that computer use is a proxy for the type and quality of capital. We are not, therefore, surprised to find a relatively large and robust estimate for the impact of computer use on earnings.

[18] The growth rates in mean real earnings for the two groups of men are 6.7% and 33.9% from 1991 to 2000.

References

Acemoglu, D. (2002) 'Technical Change, Inequality and the Labour Market' Journal of Economic Literature, vol.Xl, no.1, pp.7-72.

Anger, S. and Schwarze, J. (2002) 'Does Future PC Use Determine Our Wages Today: Evidence from the German Panel Data', IZA Discussion Paper No.429.

Arabsheibani, GR and Marin, A (2001) 'If not computers then what? Returns to computer use in the UK revisited', School of Management and Business, Aberystwyth, mimeo

Bell, B. (1996) "Skill-Biased Technical Change and Wages: Evidence from a Longitudinal Data Set", Nuffield College, Oxford, mimeo.

Card, D and DiNardo, JE (2002) 'Skill-Biased Technological Change and Rising Wage Inequality: Some Problems and Puzzles', *Journal of Labor Economics,* vol.20

Colecchia, A and Schreyer, P (2001) "ICT investment and economic growth in the 1990s: Is the United States a unique case? A comparative study of nine OECD countries", OECD Directorate for Science, Technology and Industry working paper 2001/7

Dickerson, A. And Green F. (2002) 'The Growth and Valuation of Generic Skills', University of Kent mimeo.

DiNardo, J. and J. Pischke (1997) "The Returns to Computer Use Revisited: Have Pencils Changed the Wage Structure Too?", *Quarterly Journal of Economics*, vol. CXII, pp.291-303.

Dolton, P and Makepeace (2002) 'Returns to Computer Use: An Empirical Analysis for the UK', University of Newcastle, mimeo

Entorf, H., and Kramarz, F. (1997) 'Does Unmeasured Ability Explain the Higher Wages of New Technology Workers?', *European Economic Review*, vol.41, pp.1489-1510.

Greenan, N., L'Horty, Y and Mairesse, J. (eds) (2002) 'Productivity, Inequality and the Digital Economy', MIT Press, Cambridge, Mass.

Haisken-DeNew, J. and Schmidt, C. (1999) 'Money for nothing and Your Chips for Free? The Anatomy of the PC Wage Differential', IZA Discussion Paper no .86.

Krueger, A. (1993), "How Computers Have Changed the Wage Structure: Evidence from Microdata, 1984-1989", *Quarterly Journal of Economics*, Vol. 108, pp. 33-60.

Krusell, P, Ohanian, L., Rios-Rul, V, and Violante, G. (2000) 'Capital Skill Complementarity and Inequality', *Econometrica,* vol.68, pp.1029-1054.

Machin S (2001) 'The changing nature of labour demand in the new economy and skill-biased technological change', *Oxford Bulletin of Economics and Statistics,* 63, pp.753-776

Micklewright J (1989) 'Choice at Sixteen', *Economica,* vol.56, pp.25-39

Oulton N (2001) "ICT and productivity growth in the United Kingdom" Bank of England Working Paper.

Oosterbeek, H (1997) "The returns from computer use: A simple test on the productivity interpretation", *Economics Letters,* vol.55, pp.273-277

Todd, P. and Wolpin, K. (2000 & forthcoming) 'On the Specification and Estimation of the Production Function for Cognitive Achievement', University of Pennsylvnia, mimeo, forthcoming in *The Economic Journal*

Appendix: The control variables for the regressions

This Appendix defines the control variables used in the regressions. The regressions also include dummies for missing values on each regressor although some of these are omitted because there are no missing values for that variable in the sample.

Sets of variables

Basic Human Capital	Years of schooling, Years of work experience, Tenure with current employer
Qualifications	Highest qualification achieved whether vocational or academic Dummies for 5 levels NVQ level 1, NVQ level 2, NVQ level 3, NVQ level 4 or NVQ level 5 Omitted group - No qualifications
Early Test Scores	Dummies for quintile scores on tests at age 11 5 dummies for reading and 5 dummies for mathematics Omitted groups – Bottom quintile for reading, Bottom quintile for mathematics
Skills in 1991 survey	Dummies for ‘good’ at 6 types of skill Communication (speaking clearly), carrying out mathematics, giving advice and support, using tools, caring, finance and accounts
Skills in 2000 survey	Dummies for ‘good’ at 8 types of skill Communication, Numbers and calculation, team work, learning new skills, problem solving, using tools, caring, finance and accounts
SOC	Occupation, Dummies for 9 Major SOC Groups Managers and administrators, professional, associate professional and technical, clerical and secretarial, craft and related, personal and protective services, sales, other Omitted group - plant and machine operatives
SIC	Industry, Dummies for 13 Major SIC Groups Farming, Manufacturing, Construction, Sales (wholesale, retail and repair), Transport and communications, Financial intermediation, Real estate, renting and business activities, Public administration and defence, Education, Health and social work, Other community, social and personal services, Other industries (other jobs, mining, electricity, gas and water supply) Omitted group - Hotels and restaurants

Region	Dummies for 12 regions – London, East Anglia, South East, South West, East Midlands, West Midlands, Yorkshire and Humberside, North West, North, Scotland, Other Omitted group – Wales
Socio-demographic	Dummies for Married Non-white Long standing illness limits daily activities
Other	Dummies for other job characteristics Firm size (number of employees) 5 categories 10-24, 25-99, 100-499, 500 or more (2000 survey) Omitted group 1-9 (1-10 employees 1991 survey) Temporary job Union member

Table 1: Percentage using a computer at work

	Men	Women	All
Computer used in 1991and 2000	53	64	56
Computer used in 2000 only	19	18	19
Computer used in 1991 only	4	4	4
Computer not used in 1991 or 2000	24	14	21
Number	2707	987	3694

Table 2: OLS estimates of the impact of computer use for different specifications

Control variables	Basic Human Capital	Scores & Quals	Skills	SOC & SIC	Full
1991 sample	0.221*** (0.012)	0.171*** (0.012)	0.159*** (0.012)	0.144*** (0.012)	0.118*** (0.012)
R^2	0.315	0.365	0.377	0.436	0.488
2000 sample	0.355*** (0.017)	0.274*** (0.018)	0.230*** (0.018)	0.167*** (0.019)	0.137*** (0.018)
R^2	0.307	0.350	0.378	0.462	0.504
Pooled sample	0.278*** (0.010)	0.214*** (0.011)	0.187*** (0.010)	0.155*** (0.011)	0.127*** (0.011)
R^2	0.334	0.377	0.402	0.465	0.509

Notes to Table 2

The table shows the estimates and the standard errors (in parenthesis).

* means that the t-value is greater than 1.64, ** 1.96 and *** 2.57.

The results above refer to equations using the following sets of controls. These sets are defined in Appendix 1.

Basic	Basic Human Capital.
Scores & Quals	Basic Human Capital, Early Test Scores and Highest Qualification
Skills	Scores & Quals and Measures of Skill
SOC & SIC	Skills, SOC and SIC
Full	SOC & SIC, Region, Socio-demographic and other variables

All equations include a gender dummy. The pooled regressions include a cohort dummy.

Table 3: OLS and first difference estimates of the impact of using a computer at work

	OLS				First differences	
	1991 sample	2000 sample	Pooled sample		$b_1=b_2$	$b_1 \neq b_2$
Men (n=2707)						
Impact of computer use	0.126*** (0.014)	0.145*** (0.022)	0.135*** (0.013)		0.015 (0.016)	0.044** (0.022)
Change in impact						0.044* (0.025)
R^2	0.464	0.491	0.491		0.094	0.159
Women (n=987)						
Impact of computer use	0.093*** (0.024)	0.115*** (0.033)	0.098*** (0.020)		0.077*** (0.024)	0.105*** (0.034)
Change in impact						0.037 (0.040)
R^2	0.558	0.578	0.574		0.144	0.257

All estimations use the full specification defined in Table 2 and, where appropriate, include levels and differences in the control variables.

Table 4: Estimates of the impact of using a computer at work with heterogeneity

	First differences			Value-Added	
	Men	Women		Men	Women
Computer used in 1991 and 2000	0.039 (0.025)	0.049 (0.041)		0.134*** (0.022)	0.089*** (0.032)
Computer used in 2000 only (b_2^{01})	0.015 (0.025)	0.130*** (0.041)		0.058*** (0.022)	0.128*** (0.033)
Computer used in 1991 only (b_1^{10})	0.085** (0.039)	0.009 (0.062)		-	-
R^2	0.161	0.258		0.575	0.671

All estimations use the full specification defined in Table 2 and, where appropriate, include levels and differences in the control variables.