The Returns to Computer Use: An Empirical Analysis for the UK.

by

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Abstract

Various studies have suggested that the use of a computer at work has boosted earnings by as much as 17%. Others suggest the effect is negligible. We seek to clarify the differences in the 'rate of return to computer use' estimates using excellent data from two birth cohorts in the UK. We will compare OLS estimates with those from alternative estimation methods such as; Instrumental Variables (IV); the treatment effects model with selection; the matching estimator to compute the average treatment effects and panel data estimation. The data set contains a number of variables that we can consider as potential IVs but that have not been available to previous researchers. Our estimates suggest that the rate of return to computer use in the UK in 2000 is at least than 10% but that it could be lower for women.

Preliminary: Please do not quote these results without consulting the authors

This paper reports on work in progress. It demonstrates that the rate of return to computer use is potentially high and therefore an important parameter to identify. We provide initial estimates using a variety of techniques but readers should note that we are still refining our data and extending the statistical testing of our models.

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1. Introduction

Computers and ICT have changed the way we live and work. The almost universal application of word processing, spreadsheets, and databases have increased office efficiency dramatically. The spectacular rise of electronic mail, internet services, and telecommunications offers unprecedented opportunities to access instant information, and reach new markets. As a result, computer literacy represents one of the most important basic skills necessary for an individual to function in an advanced industrial economy. Accordingly, there is a great risk that information technology will exclude some groups in society especially the low skilled and the poor. The growth of the use of computers in the work place has been dramatic during the 1980s and early 1990s. Krueger (1993) reported a rise from 25.1% of the workforce to 46.6% in the US from 1984 to 1993. DiNardo and Pischke (1997) report a rise of 8.5% to 35.2% in Germany from 1979 to 1992. The proportion continued to rise in the rest of the 1990s. In the UK the proportion has risen from 42% to 52%[1] within a cohort of the same people over the 1991 to 2000 period.

The primary objective of this research is to examine the determinants of computer use at work and to explore the relationship between computer skills and earnings. Our data comes from two micro-data cohort surveys for the UK, namely the National Child Development Study (NCDS) and the 1970 British Cohort Study (BCS70). These data contain information on the use of computers at home and in the workplace. Most specifically the data contains information on exactly what tasks the computers have been used for, and the extent of the IT skills acquired by the individual. This level of detail is often not available in previous surveys. Our data refers to 1991 and 2000. Most previous studies use data from the early nineties so we are able to comment on more recent experience. In addition, most previous studies use cross section data in which people of different ages have experienced various different market demand conditions and may have entered the labour market at different points in the development of technological change in relation to IT. In contrast, our cohort data allow us to compare people who are the same age and will have experienced the same IT environment since they entered the labour market.

[1] These figures come from the NCDS data used and described later in this paper.

The main methodological problem we face is the potential endogeneity of computer use arising from the observation that the most able workers are also those most likely to work with computers. Hence it is potentially difficult to determine whether it is native ability that generates higher earnings and IT skills or whether IT skills *per se* have a direct effect on earnings over and above the influence of ability. This paper attempts to tackle this issue in different ways. Firstly, we examine the effect of conditioning on different variables in the earnings equation. We consider he effect of different skills and ability and whether a computer is used at home. Second we explore the treatment effects models in which computer use is considered endogenous. We use home computer use, attitudes to computers and other key variables (like the willingness to use a computer to respond personally to the survey) as instrumental variables to predict IT competence and model this endogenously with earnings. Thirdly, we use the two different cohorts to match each person who uses a computer at work with a similar person who does not use computers to estimate the average treatment effect of the 'treatment' of computer use on earnings. Finally we examine fixed and random effect panel estimates of the rate of return to computer use.

This paper is organised into four further sections. Section 2 describes the data we use in our investigation and in particular the computer information available in both surveys. Section 3 reviews the literature on the relationship between computer use and labour remuneration. Section 4 examines the alternative econometric methods to isolate the treatment effect of using computers and reports our estimated return on the use of computers in work. Section 5 draws our conclusions from the evidence presented.

2. The Data

The National Child Development Study (NCDS) and the 1970 British Cohort Study (BCS70), provide our data. These were initially two separate longitudinal surveys in the UK. The NCDS began in 1958, with follow up surveys of the whole cohort carried out at ages 7, 11, 16, 23, 33 and most recently at age 42. The BCS70 began in 1970 and full sample surveys took place at ages 5, 10, 16, 26 and most recently at age 30. The two surveys were re-interviewed in 1999/2000 using the same techniques and questionnaires. For our purposes, we can compare the experience of individuals at the ages of 30 (BCS70), 33 (NCDS) and 42 (NCDS), between the ages of 33 and 42 (NCDS) and the experience of individuals in their early thirties but 12 years apart in their date of birth (NCDS and BCS70).

These data are particularly useful for our purposes as they contain information on computer use over the decade when the use of computers accelerated particularly rapidly. The computer information available in the data can be used to measure computer competence and intensity of computer use in several different ways. Specific categories of computer software are directly measured for each individual in the data who uses a computer along with duration of usage and self-assessed levels of competence. In addition, the surveys contain an array of information relating to other technical skills and "soft skills" that are intrinsically linked with the social capital component of computer use.

The timing of the revolution in computing gives a new source of cohort variation since almost all of the NCDS cohort would have left school by the end of 1976. A relatively small number would have studied computer science as a subject at university but no-one would have had access to a computer in school. Members of this cohort would have been introduced to computers at a later stage in life when their labour force positions were already well established. In contrast, the younger BCS cohort grew up in the 'Information Age' when the facility to use a computer was available to all young people[2]. This BCS cohort could have left school in 1986 at the earliest. By 1984 all schools in the UK would have had a computer in the school with the result that all pupils could have had some access to basic IT literacy. Indeed, 52% of the respondents to this part of the survey had received instruction in the use of computers at school and a further 21% had received some instruction somewhere else (primarily at home). The actual use of computers could have been even higher given that the question referred to instruction rather than use.

Both sets of data are cohort data in which all individuals are the same age. Most other studies use data for all age groups leading to difficulties with compositional effects. Whatever the effects of aggregate conditions, including the impact of the ICT revolution, have been, they will have been the same for all individuals in our data.

The basic underlying factors driving the process of computer skill acquisition may differ across cohorts, which may change the composition of the IT user group. There has been an

[2] The UK government had a programme of introducing at least one BBC microcomputer into every school over the 1982-4 period. By 1986 there was one computer per 75 pupils in all schools. (Personal Computer World, March 1986).

important upward trend in the use of computers, and in particular the ability distribution within the computer use group is likely to have widened with lower categories of occupations beginning to use them. This may mean that the average return to computer use may have fallen. Therefore, the characterisation of the distribution of computer literacy between cohorts and within cohorts is particularly important.

2.1 Computer Information in the NCDS/BCS70

Questions pertaining to the application and sophistication of computer use are in two sub-sections of these surveys. In the first sub-section, individuals are asked about their use of computers at home and in the second sub-section about their use of computers at work. Questions are identical in both sub-sections. Information is also provided on the frequency of usage (daily, 2-4 times a week, once a week, less than once a week or never) and the exact type of applications that the respondents use the computer to perform. Most specifically we know whether they use a computer for: word processing, internet, email, data analysis, databases, design packages, games, sending faxes, accessing CD–roms, composing or listening to music, photography, programming or other. We do not fully exploit this data in this paper but will pursue the issues with respect to frequency of use and type of use in further research.

We should note that the questions in the NCDS/BCS 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. At one extreme, Oosterbeek (1997) assumes that no-one used a computer at the start of his data in 1983. Anger and Schwarz (2002) use a retrospective measure of computer use the year from 1985 to 1996. "The GSOEP also provides information on PC use .. on which a question was only included in the 1997 survey. For that year, the survey indicates whether a respondent used a PC and identifies the year in which he or she first used a PC at work." (p.4) They also have some difficulties with defining computer use for 1998. Entorf and Kramarz (1997) match two data sets: the French Labour Force Survey and TOTTO, a once-off supplement to the survey in 1987. They use the information on when an individual first used a computer to build a profile of computer use for 1985 and 1986. There is a wide divergence of the quality and type of information relating to computer use which is collected in different surveys. We summarize this information in Appendix A.

Table 1 provides the basic descriptive statistics relating to the use of a computer at work in the NCDS and the BCS by different characteristics. Here we see that the use of a computer has grown by 10 percentage points from 42% to 52% for the NCDS over 9 years between the surveys. Closer inspection shows that virtually all this rise has come through increased use of computers by women. Computer use at work is higher amongst the BCS in 2000 at 54% - but this is not surprising given that this younger cohort will have been more familiar with the use of computers throughout their working lives. Use of computers by men in the BCS is much higher than that of men in the NCDS.

From Table 1 we see that computer use rises rather rapidly with the qualifications (academic or vocational). The table also suggests that there are no differences in use by ethnicity. More marked is the dramatic rise in the use of computers in certain sectors and occupations. Most notable in this regard are the rises in the public sectors of Health, Education and Public Administration. Correspondingly the rise in the Clerical and Sales occupations has been the most marked.

In addition, individuals were also asked: "How good are you at the use of computers and information technology". Individuals can answer: "good", "fair", "poor", or "no skill". And once again respondents were asked to indicate whether or not these skills were used at work.

The NCDS and the BCS in the 1999/2000 sweep was carried out using Computer Aided Personal Interviewing (CAPI) while earlier surveys were carried out using a "pen and paper" interviewing. An advantage of CAPI is that checks and signals were included in the programme to alert interviewers when an unlikely or impossible response has been entered. Accordingly the problem of measurement error in estimating variables of interest is clearly reduced. This design incidentally provides us with a possible IV for our analysis. A section on the respondent's views formed part of the survey and the respondent was asked whether they worked to complete this section on their own using the computer. We use whether the respondent was prepared to use the computer themselves to complete the questionnaire as an IV.

The survey contains several questions on the use of computers and attitudes to computing that we consider as potential instrumental variables. The descriptive statistics relating to these variables are summarised in Table 2. It would seem that the likelihood that a respondent is prepared to use the CAPI instrument themselves on the computer is higher if they use a computer at work. With respect to the attitudes to computers, those who use a computer at work are much less likely to agree with the statements that computers are destroying peoples skills and that learning to use a computer is more trouble than it is worth. Those who use a computer at work are also more likely to have a computer at home and those that do not use a computer at work are much less likely to use a computer at home more than once a week. Amongst those who use a computer in work in 2000 in the NCDS, 36% were not using a computer in 1991. Conversely only 19% of those who used a computer in 1991 do not do so in 2000.

2.2 Other Dimensions of Skills

The computer revolution may have contributed to the growth in several new dimensions of skill required at work that may in turn have contributed to faster growth in the relative demand for skilled workers over the last several decades. Accordingly, whether the wage premium associated with the use of computers is as a result of the additional skills, knowledge and tasks involved in computerized work warrants empirical investigation.

The NCDS/BCS70 is unique in providing detailed information in relation to several of these skills. The surveys indicate if these skills are used at work or elsewhere. Specifically, respondents were asked to rank their ability on a 4-point scale (good, fair, poor, not skilled) in the following skills: communicating, numbers and calculations, working in a team, learning new skills, problem solving, finance and accounts.

It is widely believed that these skills are an important feature of new work practices. The inclusion of these skills in the wage equation allows for a much richer earnings function and a wider assessment of the impact of technological change. It is also the case that explicitly conditioning for the presence of these skills may reduce the individual heterogeneity which may otherwise be observed.

2.3 Other Variables Used in the Analysis

The same survey was administered to the members of the NCDS and BCS70 cohorts in 2000. Previous sweeps are not the same although similar information (in terms of definition and interpretation) is contained in earlier sweeps. The NCDS and BCS70 have complete information on the highest levels of education individuals have attained. Both surveys contain the results from reading and mathematics ability tests undertaken at age 10/11. In early sweeps information on family background and parental socio-economic circumstances is available and in later sweeps extensive labour market data and information pertaining to the cohort member's own socio-economic position is set out.

3. Literature Review

The main aim of this paper is to estimate the rate of return to computer use. Computer use may be highly correlated with unobserved characteristics that also generate a wage return. The non-random selection of workers with particular skills poses a problem for the interpretation of ordinary least squares estimates if these workers would have earned a higher wage in the absence of computers. Recent papers now argue that the observed correlation between computer usage and wages was capturing unobserved heterogeneity among workers. Several empirical strategies to determine whether or not the computer pay differential is a real consequence of computer use or is capturing some unobserved attributes are used and reported on in the next section.

In this section we do not intend to provide a comprehensive review of all the studies in the literature on the topic of the return to computer use. Instead we review the papers which are most closely related to our own empirical work. In addition we focus on those articles which raise issues relating to econometric specification and estimation and try to clarify why there is a divergence of results in the literature. To this end Table 3 summarizes a selection of the most relevant previous studies. We include in this table the details on the data, the controls used and the estimated return to computer use. The aim of the table is to illustrate the effects of changing specifications and estimation methods so the results quoted may not be the specification preferred by the author.

Krueger's (1993) seminal paper sought to measure directly the impact of computer use on wages. He showed that individuals who used computers at work in the US received a wage premium of between 10 and 15 percent during the 1980s. Moreover, he found that the between 1984 and 1989 the computer wage differential did not decline indicating that the demand for workers with computer skills may have shifted out as rapidly as the outward shift in the supply of computer literate workers. Krueger (1993) suggests that workers who possess unobserved characteristics that are associated with computer use at home may be selected by employers to use computers at work on the basis of these same characteristics. Therefore, holding constant computer use at home should reduce any bias in the returns to computer use at work. However, individuals who use computers at work may be more able than individuals who use computers only at home, and consequently this method would fail to control for endogeneity.

DiNardo and Pischke (1997) criticise the interpretation of the coefficients for computer use in an earnings equation as a return to a skill, arguing that the relation between computer use and wages is largely a reflection of unobserved worker heterogeneity. Their view is that workers with other unobserved but productivity augmenting characteristics (like ability and motivation) are more likely to use computers at work. They suggest three different interpretations of the computer wage premium which amount to trying to classify the unobserved heterogeneity involved. For convenience we will refer to them as the 'physical capital' argument, the 'occupational heterogeneity' argument and the 'skills' argument:

(a) *Physical Capital*. There is a premium to the use of 'white-collar' tools in any job[3].

(b) *Occupational Heterogeneity.* Computers are used by white collar workers.

(c) *Skills*. Computer users possess unobserved skills or abilities which might have little to do with computers. They also suggest that it would be useful to try to separately identify the return to computer skills as this is not the same thing as the computer use premium. Their data do not permit them to investigate this distinction, but it is one we can pursue.

Bell (1996) examined the returns to computer use in the UK using data from the fifth sweep of the National Child Development Study (NCDS) collected in 1991. He estimates the rate of return to using a computer at work at about 17 percent. The measure of computer use in his paper is crude since it takes no account of the frequency of use or what the individual uses the computer for. Furthermore, Bell estimates his model using men and women together and does not report separate gender computer wage differentials nor take account of the potential

[3] The use of hand tools (such as a hammer) is associated with fall in earnings.

endogeneity of the acquisition of computer skills and the decision to participate in work that a woman must face.

More recent evidence on the link between computer use and labour market earnings for the UK is contradictory. Borghans and Ter Weel (2001) analysing data from the 1997 Skills Survey of the Employed British Workforce offer conclusions which raise doubts about the validity of the return to computer skills used at work. These authors use measures of computer skills that are subjective in nature, based on an individual's own ranking of their ability to use a computer. Using the same data set Green (1998) concluded that computer skills were highly valued in the work place with men and women who use computers at "moderate levels of complexity" earn 13 percent more than those who do not use computers at all. Clearly the evidence is mixed. Accordingly, a more thorough investigation of the value of computer literacy is required.

Dickerson and Green (2002) further explore the role of skills in the determination of earnings. They collected data on up to 35 skills which they then reduced (by factor analysis) to 12 basic skills. They use these factors in the estimation of an 'hedonic wage equation'. In this context they estimate the return to computer usage to be around 14%. They go on to show that this return is much higher for those who use computers in their work for more complex tasks. They also explore the variation in the return across different occupations.

Handel (2002) replicates Kreuger's study but is of particular interest to us because it analyses the effects of including a range of skills and other controls on the return to computing. His data comes from the 1991 Current Population Survey. This is more recent than the 1984 and 1989 data from the same source that Kreuger (1993) employed.

Most studies in the literature use a computer variable defined as 'uses a PC at work'. Other studies emphasise different aspects of computer use such type of tasks undertaken (Kreuger (1993)), sophistication of the tasks (Dickerson and Green (2002) and Entorf and Kramarz (1997)) and the frequency of use (Handel (2002) and Oosterbeek (1997)). The detailed results in Handel (2002) do not use a binary indicator of computer use so we have included the figures for people who use a computer daily. We have quoted the results for daily use of computer for Oosterbeek (1997). The results for Entorf and Kramarz (1997) are for the highest level for computer use.

The specifications have often followed Kreuger (1993) in their choice of control variables although a wide range of other controls have been used in the literature. Of particular interest are the large fall in the value of the coefficient on computer use as more control variables are added and as the estimation technique changes. The clarity of the results is overstated in the table. In their fixed effects model quoted above, Entorf and Kramarz (1997) find a significant effect for experience with sophisticated computer-based technology even though the dummy variable is insignificant in the same equation.

In spite of the widespread belief that computers have fundamentally altered the working environment little research exists concerning the characteristics of those who use computers. To broaden efforts to increase computer literacy we need to understand the process of skill acquisition thoroughly. Accordingly, one aim of this research is to examine the determinants of computer use. It is widely believed that modern technology has shifted the relative demand for labour in favour of better-educated and more able workers. Since computer use is believed to stem from ability-biased technological change we are particular keen to explore the link between computer use and ability.

Black and Lynch (1996) for the US found that total quality management (TQM), teamwork and communications had no apparent impact on the productivity of establishments in either the manufacturing or non-manufacturing sectors. However, these authors conclude that this is probably the result of using information on individuals who have recently been trained and that initially there are likely to be adjustment costs associated with the introduction of new skills in the work place. They find that computer skills have a significant and positive impact on establishment productivity in the non-manufacturing sector but no significant returns in the manufacturing sector over and above these other measures of skill. The rationale for including these other dimensions of skill is to offer more compelling evidence about the impact of computers on wages.

When we consider the perceived increase in the demand for more skilled people to deal with the continuous advancements of technology in the workplace it is important that we consider other skills in the analysis of wages. Specifically, we seek to establish whether individuals who have higher literacy and numeracy levels in general earn an additional premium to computer literacy. Statistical significance of the associated interaction terms would lend support to the view that computers are complementary to skill and part of the skill-based technological change arguments used to explain the widening in the structure of wages.

The computer revolution may have contributed to the growth in several new dimensions of skill required at work that may in turn have contributed to faster growth in the relative demand for skilled labour over the last several decades. The inclusion of these skills in the wage equation allows for a much richer earnings function and a wider assessment of the impact of technological change. Accordingly, whether the wage premium associated with the use of computers is as a result of the additional skills, knowledge and tasks involved in computerized work is and empirical question for further research.

4. Econometric Analysis.

We follow previous attempts to model the rate of return to the use of a computer at work and focus on the estimation of equation (1).

$$Y = X'\mathbf{d} + \mathbf{b}C + u \qquad (1)$$

where $E(X,u) = 0$, Y is the log of wages, X is the vector of observed earnings determinants, C takes a value of one if the individual uses a computer at work and zero otherwise. In this model the $\mathbf{b}$ coefficient is interpreted as the return to computer use.

The control variables we include in the wage equation can be separated into six broad categories as follows:

(a) Human capital variables: education, ability measured using literacy and numeracy tests, and years of schooling, work experience and its square.

(b) Employment variables: socio-economic classification or occupational classification, part-time and temporary status.

(c) Employer variables: establishment size, sector and industry variables.

(d) Socio-demographic variables: marital status, number and age of dependent children.

(e) Other variables: Early childhood family background variables and region of residence to control for local labour market effects.

The basic model was estimated using the Krueger specification. The results are represented in column 1 of Table 4. We can therefore treat the 18-20% return (depending on cohort) as a baseline figure which is obtained by OLS with a full set of controls.

Computer Skills and Unobserved Heterogeneity

It is widely argued that the error term in the wage equation incorporates some unobserved factors that increase productivity. Often this unobserved heterogeneity is interpreted as a measure of ability[4]. The 'true' specification of the equation is:

$$Y = X'\delta + \beta C + A + u \qquad (2)$$

where *A* represents a measure of ability.

Omitted variable bias will occur if ability is correlated with computer use and is not adequately measured. As in other studies, we include measures of educational performance in the earnings equation but an unusual feature of the data is that the cohort members were given tests of ability at the ages of 10 (for BCS 70) and 11 (for NCDS). We include the results of these tests as additional controls for unobserved ability.

In the Bell specification in column (2) of Table 4 we report the effect of conditioning on early ability as well as all other characterisitics. We see that the return falls to between 13-16%. It is interesting that conditioning for ability causes the return to fall by about 5%.

One question we have not so far investigated is the link between ability and the use of a computer at work. It is possible to investigate whether individuals who have better literacy and numeracy skills earn an additional premium to computer use by interacting computer use with our literacy and numeracy scores. Statistical significance of the associated interaction terms would lend support to the view that computer are a complementary skill that would contribute to the skill-based technological change arguments used to explain the widening in the structure of wages.

Computer Use at Work and at Home.

Krueger (1993) uses 'having a computer at home' as an indicator of unobserved heterogeneity and examines the extent to which having a computer at home has a different effect to using one at work. We employ similar information from the NCDS/BCS70 surveys except that the variables also measure computer use at home and at work. Using this information we estimate the following wage-equation:

$$Y = X'\boldsymbol{d} + \boldsymbol{b}_1 C_h + \boldsymbol{b}_2 C_w + \boldsymbol{b}_3 C_h C_w + u \qquad (3)$$

where C_h is a dummy variable that equals one if a worker uses a computer at home and zero otherwise, C_w is a dummy variable that equals one if a worker uses a computer at work and zero other wise, and $C_w{\times}C_h$ is an interaction term between computer use at home and at work.

The use of a computer at home may measure unobserved skills or other characteristics that increase productivity independently of computer use at work (e.g. an indicator that the individual embraces change) and may therefore be valued by employers. There will be omitted variable bias if C_{hi} is not included. Therefore, controlling for home computer use would extract some of the unobserved heterogeneity that is correlated with computer use at work. Holding constant computer use at home should reduce any bias in the returns to computer use at work.

The exact question pertaining to the use of a computer at home is "Do you have a computer at home". Many individuals may have a computer at home but this does not mean that the particular individual in our sample is actually the user of the computer. However, the NCDS/BCS70 surveys ask individuals if they "never" use the computer at home. This is one problem which Krueger faced using the CPS survey for the US because this data does not

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[4] It may arise because the rates of return to computer use differ across individuals. The true equation may be $Y_i = X_i'\boldsymbol{d} + \boldsymbol{b}C + v_i$ where $v_i = (\boldsymbol{b}_i - \boldsymbol{b})C + u_i$ and $\boldsymbol{b}$ is the average rate of return.

make this distinction. Krueger (1993) tried to circumvent this potential problem by estimating wage equations for men and women who were not married.

There is also a selection issue to consider here. Employers may select more able individuals to work with computers and the unobserved ability associated with this choice may not be adequately proxied by the use of computers at home. Individuals who use computers at work may therefore have higher earnings even in the absence of computer technology. Consequently, the above method may fail to control for the potential problem of endogeneity. We return to the selection issue below.

In our data we found that introducing the use of a computer at home as an additional regressor did not detract significantly from the return to using a computer at work.

Using Use of Tools to Proxy for Unobservables.

Following the DiNardo and Pischke (1997) we investigated the idea that the use of other tools at work may be an adequate proxy for unobserved occupational or ability factors. In the 2000 sweeps of the data the respondents are asked explicitly if they use tools in their work. In the 2000 surveys of the NCDS and BCS our respondents were asked 'How good are you at using tools properly?' The results of running the DiNardo and Pischke (1997) 'Tools' equation specification are reported in column (3) of Table 4. The return leaps dramatically to between 27-31%. This dramatic and unrealistic leap is caused by two factors. Firstly they do not condition on so many explanatory variables and second the 'tools' they use in their specification are items like 'sitting on a chair' or 'using a pen or pencil'. Clearly our respondents do not categorise these as tools. Hence we get a negatively significant coefficient on the use of tools indicating that the respondent may think of 'tools' as handtools. If this is the case, our result is in agreement with DiNardo and Pischke as they get a negative coefficient on such a variable.

These results raise the question of the extent to which the variables used by DiNardo and Pischke may be collinear indicators of a 'white collar' job. Clearly anybody who uses a computer must sit on a chair and use a pen or pencil as well. In addition how can we interpret controlling for occupational dummies in our estimation. Therefore it is unclear how we can interpret their result. One test of their idea is provided below where we rerun our model for only those individuals who have stayed in the same occupation and same sector between 1991 and 2000. This approach controls completely for whether the job has unobserved characteristics that correlate with computer use.

The Effect of Computers on the Returns to Other Skills

We are also interested in whether the relation between the returns to computer usage reflects other factors specific to computer usage or broader capital-skill complementarity. The effect of computer use at work is likely to have a complex impact on wages. Computer-based technologies are associated with changes in production techniques, organisational changes and capital deepening all of which have changed the design of work.

A computer can increase an individual's capacity to do more tasks. For instance computers facilitate the preparation of text and charts, the design of three-dimensional objects, calculations, the transfer of data, the classification of data and the maintenance and manipulation of data bases. Beyond this a computer can enhance research capabilities at universities and laboratories. Therefore alongside computers, other skills such as problem-solving abilities and interpersonal skills, may have become more important as well (see Green 1998). In particular, we shall use information from the NCDS/BCS70 on whether the individual's job includes the following skills: communicating, numbers and calculations, working in a team, learning new skills, problem solving, finance and accounts.

This information was included in the wage specifications in order to further check whether the computer wage premium represents a measure of the true return to computer skills, or is largely reflecting other characteristics of work. By including these other measures of skill we may establish more compelling evidence about the importance of computer literacy. The results are reported in column (4) of Table 3. The return to computing is estimated at around 14-18%. It is higher than that reported in the Bell specification as it does not include the ability variables as regressors. The final OLS specification reported in column (5) of Table 3 includes both ability and skills variables. Here we see that the return falls to around 11% for the BCS and 15% for the NCDS.

Using Future Computer Use as a Proxy for Unobserved Ability Effects.

One theme in the literature is that computer use is an indicator of ability broadly defined to include the ability to adapt and learn. It is an intrinsic characteristic of an individual rather than a skill that can be taught. The earnings equation becomes if explicitly include the effect of ability

$$Y = X'\boldsymbol{d} + \boldsymbol{b}C + A + u^*$$

The new hypothesis is that $A = \boldsymbol{k}C + v$

Substituting into the earnings equation

$$Y = X'\boldsymbol{d} + (\boldsymbol{b} + \boldsymbol{k})C + u$$

We cannot clearly identify the separate contributions of skills and ability to earnings from the estimated coefficient of C. One suggestion is that we can use future computer use to measure the value of A at time 0. If we let the subscript denote the time period and substitute $A = \boldsymbol{k}C_1 + v_1$

$$Y_0 = X_0'\boldsymbol{d} + \boldsymbol{q}C_0 + \boldsymbol{k}C_1 + u_0 + v_1$$

We can obtain point a estimate of $\boldsymbol{b}$ and test its significance from $\boldsymbol{b} = \boldsymbol{q} - \boldsymbol{k}$. Anger and Schwarze (2002) present estimates of $(\boldsymbol{b},\boldsymbol{k})$[5] suggesting that between 2% to 6% higher after taking account of the unobserved ability. These estimates are similar to their OLS estimates of the earnings equation but somewhat lower than their random effects estimates.

Table 5 reports the OLS estimates of the return for the 33 year olds in 1991. The estimates are about the same order of magnitude as for the 30 year old BCS members in 2000 and lower than those for the same cohort 9 years later. They are about 14% for men and 9% for women. We can use the 1991 data to implement Anger and Schwarze's hypothesis about future computer use. Use of a computer in 2000 should have no impact on earnings in 1991 if it is a return to a skill or the use of a piece of capital. If computer use is correlated with beneficial unobservables, then future computer use should measure the impact of the unobservables. Future computer use raises current earnings by 4% for men and an insignificant amount for women. If we assume that the effects of the unobservables are constant over time, the difference in the estimates of current and future computer use shows the impact of computer use net of the effect of the unobservables. The implied returns are 8% for men and 2% for women.

[5] The estimates of $(\boldsymbol{b},\boldsymbol{k})$ are. Men (0.02,0.03) (pooled OLS) (0.03,0.05) (random effects), women (0.04,0.04) (pooled OLS) (0.06,0.04) (random effects)

Table 6 explores some of the issues we have raised about the timing of computer use using the 'Value Added' specification of Todd and Wolpin (2000). We include 3 dummies identifying those who used a computer in both years, those who used a computer only in 2000 and those who used only in 1991. The last column shows that there is no penalty from ceasing to use a computer nor is there any advantage from being a previous computer user. Men who use a computer in both years obtain a premium of 16% in line with our other estimates. This falls to 5% for those men who only use a computer in 2000. The benefits are larger the sooner a man uses IT. The results for women are different. The return for women increases from 8% to 10% over time. The early female users of computer technology who maintain their use do not have increased earnings advantage.

Controlling for Occupational Heterogeneity but using A limited Sample of Respondents who stay in the Same Occupation and Sector.

A well defined theme in the existing literature is that computer use proxies unobserved job characteristics. We sought to control for this by restricting the samples to those individuals who were in the same industry and same occupation in 1991 and 2000 for the NCDS. Ceasing to use a computer is now associated with a large and significant premium of 17% for men and 21% for women. Men continue to benefit more from using computers in both 1991 and 2000 rather than 2000 only while the converse applies to women. The magnitudes of the returns are much larger than previously. The largest figures are 26% for men and 21% for women. These estimates provide clear additional evidence of the importance of computers when all heterogeneity associated with occupations and job circumstances have been conditioned out.

Control Functions: Instrumental Variable and Treatment Effects.

We have considered estimation methods that have ignored the computer use determination. We can use two different variants of the control function method to explicitly consider the endogeneity of the computer use determination. The 'treatment effects' model (see Barnow et al (1981)) is:

$$Y = X'\boldsymbol{d} + \boldsymbol{b}C + u \qquad (4)$$

$$C^{*} = \boldsymbol{a}Z + \boldsymbol{h} \qquad (5)$$

where $C = 1 \; if \; C^{*} > 0$ and $C = 0 \; if \; C^{*} \leq 0$ and Z is a vector of explanatory variables governing the use of computers.

Estimation of equation (4) by OLS will yield an unbiased estimate of $\boldsymbol{b}$ only if C is exogenous so we explore the use of Instrumental Variable (IV) methods to analyse the model of equation (4), then we use the control function treatment effects model to model (4) and (5) simultaneously. Finally we the matching methods of Rubin and Rosenbaum (1983) to assess the impact of the computer use at work as a 'treatment' effect.

The use of IV for C can be derived by estimating (5) and computing the predicted probabilities from the probit equation. Then in the second step of the 2SLS this prediction is used in the OLS estimation of equation (4). This method will give consistent estimates of the $\boldsymbol{b}$ coefficient of the return to computer use.

The IV method has been used by many authors to estimate the rate of return to schooling notably Krueger (1991), Harmon and Walker (1995). Our problem is directly analogous. Namely for the identification of the IV (and the alternative treatment effects model) is provided by including variables in the vector Z that are not contained in X. That is, there must be at least one variable which is a determinant of the use of the computer at work but can be legitimately be omitted from the earnings equation.

This model can be estimated directly using maximum likelihood estimation or via the Heckman Two Step method where the equation is estimated for the entire sample and appropriate selection terms are included.

For these procedures to be valid (and yield consistent estimates for the $\boldsymbol{b}$ coefficient) we need Z to be independent of the u error term in equation (4). To be confident that we have a valid estimation procedure we need to test the endogeneity of computer use and validity and quality of the instruments.

Hausman t-test for the endogeneity of computer use:

This test is performed by including the residual of the (reduced form) computer use equation in the OLS earnings equation. A t-test on whether this variable is statistically different from zero will indicate the endogeneity of computer use. This test gives a t value for the NCDS of 6.12 and for the BCS 4.57 clearly indicating the endogeneity of the computing use at work variable[6].

Bound et al (1995) tests for the quality of instruments.

It has variously been suggested that the quality of the instruments can be tested by running equation (5) with only the exogenous IV as regressors and use an F test to establish the joint significance of these variables in explaining C. If the value of this F test exceeds unity then Bound et al (1995) and others have interpreted this as suggesting that the IVs are sufficiently strong. Joint significance of the IV vaiables in a probit context can be tested with a chi squared test. This gives a value of 1261.55 for the BCS and 1707.8 for the NCDS. Both of which are highly significant. Secondly Bound et al (1995) argue that the addition of the IVs to the reduced form earnings equation needs to improve the $\overline{R}^2$ of that equation. This is the case for both the NCDS and BCS data.

Sargan (1958) test of Instrument Validity.

One suggested test (Sargan (1958)) for IV validity attempts to test the orthogonality of the instruments. This suggests running equation (5), computing the predicted IV for C, estimating equation (4) with the fitted values of C as an additional regressor, computing the residuals from this equation (4) and then regressing these on the Z IVs. If the uncentred R^2 exceeds its critical value then one can reject the null hypothesis that the instruments are valid. In the case of the BCS this value is 0.0002 and for the NCDS it is 0.0022. These statistics suggest that the IVs in our model are valid. (When there is more than one IV it is possible to use the Sargan type test above to establish whether additional IV variables are valid and hence test for over-identifying restrictions.)

Durbin-Wu-Hausman Test for Misspecification.

[6] Obviously there is a problem computing standard residuals in the probit model. Angrist and Krueger (2001) point out that residuals from a linear probability model will be adequate replacements in this context.

Another recognised alternative test is to perform a Wald test for misspecification. This however requires a generalised inverse. The alternative (equivalent) approach devised by Wu (1973) and Hausman (1978) is to estimate a perform an F test on the additional regressors in an augmented regression of equation (4) to include the fitted values of the C equation. An algebraic derivation of this result can be found in Davidson and MacKinnon (1993). For the NCDS this additional regressor gives a t value of 7.8 and in the BCS a t value of 5.78.[7]

Even if our model passes these tests it should be remembered that in finite sample the IV estimates are biased. This bias worsens if the instruments are only weakly correlated with the endogenous explanatory variable or the IVs are correlated with the equation (4) error term. Clearly then, the use of IV or OLS estimation is a matter of a trade-off. Using OLS will give biased estimates if there is endogeneity of the C variable. Any 2SLS estimator is less efficient than OLS. However as the sample size increases and the quality of the instruments improves then the coefficient estimates will become more consistent. We therefore need to be confident about the quality of the instruments we wish to use to explain computer use at work.

It should also be remembered that the IV approach is quite restrictive (see Heckman (1997)) and does not completely overcome the selectivity problem. This is so since it assumes (in our case) one of the following. Either the effect of computer use is the same for all persons with X characteristics. Or, if the effect of computer use on earnings is not the same for all persons with X characteristics, then individuals must not base their decision to enter a job (or stay in a job that involves use of computers) on unobserved characteristics which affect the earnings premium from computer use. This last assumption requires that the individuals have no private information on their expected gain from computer use – or that they do not act on it.

This restriction on the validity of IV estimation may have a bearing on its interpretation. It must be remembered that the $\boldsymbol{b}$ coefficient will not necessarily yield estimated for the gain for the average person with X characteristics – rather it will measure the earnings premium from computer use of those with high values of:

[7] This t-test is the same as the F test in the case of one additional regressor – i.e. an F test with 1 degree of freedom.

$E(u_1 - u_0 | X, Z, C = 1)$

where u_1 is the stochastic error in the earnings equation for those who do use a computer in work and u_0 is the error in the same equation for those who do not use a computer in their work. Hence, the more important are positive unobservable factors for those who use computers in work, the higher will be the b coefficient.[8]

We use several empirical strategies to deal with the issue of computer related endogeneity to determine whether or not the computer pay differential is a real consequence of computer use or is capturing some unobserved attributes.

There are three sources of potential endogeneity involved in this analysis: computer literacy, employment and education. We would expect that the number of men and women in the younger cohort would have higher levels of post-compulsory education and be more computer literacy than in the older cohort. Therefore, for instance, the OLS estimates of the returns to education and computer use between both cohorts may reflect nothing more than selectivity on the basis of ability into education, and computerisation. Therefore, it is paramount that we control for these sources of endogeneity especially when contrasting the returns to education and computer use for men and women in our two cohorts.

Companies are likely to provide training and equipment first to workers whose productivity is likely to increase the most from the use of a computer. The non-random selection of workers with particular skills poses a problem for the interpretation of ordinary least squares estimates if these workers would have earned a higher wage in the absence of computers. This potential endogeneity is important to consider as whether or not there is a wage differential between the two cohorts under investigation is of particular interest and possibly sample selection into various measures of computer literacy may be different for the two cohort groups. This is because there has been a substantial expansion in the use of computers in recent years and we would expect *ceteris paribus* a smaller return to computer use at work for the younger cohort than for the older cohort.

[8] This provides an intuitive explanation of why the IV coefficient estimate is invariably higher (and in most cases double) in many rates of return to education studies.

The IV results contrast sharply with the other results form all the other estimation methods. The results are reported in columns 6 and 7 of Table 4. As has been found in the returns to schooling literature the IV estimate of a return can often be double that found from the OLS estimation. Our IV-II model in the NCDS uses the lagged value of computer use from the 1991 data at an earlier sweep as an additional regressor. Previous computer use is not known for the BCS survey.

Panel Data Estimation.

If the effects of unobserved heterogeneity are constant over time, fixed effects estimators should sweep out their effects.

$$Y_0 = X_0\,'\boldsymbol{d} + \boldsymbol{b}_0 C_0 + A + u_0$$

$$Y_1 = X_1\,'\boldsymbol{d} + \boldsymbol{b}_1 C_1 + A + u_1$$

Taking first differences for example gives

$$Y_1 - Y_0 = \left(X_1 - X_0\right)'\boldsymbol{d} + (\boldsymbol{b}_1 - \boldsymbol{b}_0)C_1 + \boldsymbol{b}_0(C_1 - C_0) + u_1 - u_0$$

Anger and Schwarze constrain $\boldsymbol{b}_0 = \boldsymbol{b}_1$ and find that no significant change in earnings for computer use. DiNardo and Pischke (p.302) argue that the widening dispersion of earnings in the UK during the eighties may be due to changing returns to unobserved skills so that the earning growth equation may still contain the effects of *A*. We set out the unusual effects on coefficient estimates that are possible in a fixed effects panel data context in Appendix B.

The standard panel model estimates are shown in the last two columns of Table 3. The random effects estimates are in line with the values we expect from are other results. They suggest returns of 17% for men and 13% for women. As in other studies, the fixed effects gives a much lower return to computer use than the other techniques. The estimate for men falls from 0.171 in the OLS results to 0.063 in the fixed effects model with even larger effect for women. The fixed effect model assumes that the effect of the unobservables remains constant over time. This implies a constant return and a constant value for the unobservable. This seems unlikely to be the case, for example, for an unobserved skill or occupation specific factor particularly over a long period and a time of great technical change. There is another reason for being cautious about the use of fixed effects. The estimates are based on the data for those individuals who have changed their value of the computer use variable over the nine years from 1991 to 2000. In our case, there is a substantial number of people who used a computer in 1991 who did not do so in 2000. We suspect that several of these individuals actually moved to jobs in which their computing was done for them. Since these individuals are unlikely to experience pay falls as they stopped using computers, the fixed effects estimates may be understating the advantage of using a computer.

The Matching Approach – Estimation of the Treatment Effect.

The alternative approach that we use is the matching technique to control for endogeneity bias in the returns to computer use at work. It is possible that the ability to use a computer is linked with unobserved individual characteristics that also influence the wage. For similar reasons the coefficient of education may be biased as well. The matching approach involves including measures in our regressions which proxy for the correlated unobserved individual characteristics. Studies that have used the matching approach have concentrated on omitted ability bias and have used observed measures of ability such as reading and math tests (see for example Blundell et al. 2000). This approach is equivalent to *matching* individuals on the basis of these observed measures of ability. The effectiveness of recorded variables to proxy for unobserved determinants of computer use (and education) will depend on the quality of the data used. The NCDS and BCS70 are particularly rich in this regard.

The matching approach using propensity score methods was first suggested by Rosenbaum and Rubin (1983). They developed this methodology to facilitate the comparison between treated and untreated observations in a non-experimental setting. Matching estimators try to re-establish the condition of the experiment when no such data is available by choosing a comparison group from all the non-treated such that the selected group is as similar as possible to the treatment group in terms of their observable characteristics. The method has been recently applied extensively to the evaluation of training programmes (see Dehejia and Wahba (1998, 1999) and Heckman, Ichimura and Todd (1999)). The method is now being more widely applied to any situation in which a comparison is sought between two groups where the assignment to the groups is non-experimental and non-random. Hence the methodology can be applied to the assessment of the effect of computer use at work on earnings. This section sets out how the matching method using propensity scores can be applied to the problem of assessing the treatment effect of computer use in on earnings in work.

Using the potential outcome notation of Rubin (1974), let Y_{i1} represent the earnings outcome when i uses a computer at work i.e. $C_i = 1$ and let Y_{i0} represent the earnings outcome when i does not use a computer at work. The fundamental problem in the assessment of attrition bias is that there is missing data since only Y_{i1} or Y_{i0} can be observed and we cannot observe the counterfactual for each person.

In this context we can therefore write the realised outcome for i as:

$$Y_i = C_i Y_{i1} + (1 - C_i) Y_{i0}$$

In order to facilitate ease of terminology we will use the terms familiar from the evaluation literature. Hence we may write the 'Treatment Effect' for unit i as:

$$\boldsymbol{t}_i = Y_{i1} - Y_{i0}$$

Considering the whole population we can write the 'Average Treatment Effect' (ATE) as:

$$ATE = E\lfloor Y_{i1} - Y_{i0} \rfloor$$

where the first term on the right hand side is only observed for those who use a computer at work and the second term is only observed for those who do not. The expectation is taken over the whole sample. Hypothetically this expression would give the average outcome difference effect in the sample of responding rather than dropping out. In practice of course we do not observe each individual in both of the two states and so without further assumptions the expression is impossible to evaluate. The crucial assumption underlying the propensity score method is the conditional independence assumption[9].

[9] Note that his assumption is variously called the 'unconfoundedness' or 'ignorable treatment assignment' assumption. For simplicity we refer to it as conditional independence.

Definition 1. Rosenbaum and Rubin (1983): CONDITIONAL INDEPENDENCE ASSUMPTION (CIA). *Assignment to computer use (treatment),* C_i *is conditionally independent given pretreatment variables* X_i *if:*

$$C_i \perp Y_{i1}, Y_{i0} \mid X_i$$

This is a very strong and restrictive assumption as it requires that assignment to using a computer at work (treatment) is associated only with observable variables and therefore that all the relevant differences between the users of computers and non-users are captured in these observable attributes, and that conditional on them, computer use can be taken as random.

The power and attraction of the CIA assumption is that it validates comparisons for units with the same value of the covariates:

$$E[Y_{i1}|C_i = 1, X_i] = E[Y_{i1}|C_i = 0, X_i] = E[Y_{i1}|X_i]$$
$$E[Y_{i0}|C_i = 0, X_i] = E[Y_{i0}|C_i = 1, X_i] = E[Y_{i0}|X_i]$$

The implication of this assumption then is that if we can match up the treated and non-treated people on their covariates then a conditional comparison (given these X_i) is valid. This allows us to establish a condition under which an average treatment effect (ATE) is identified.

Given the CIA assumption the population ATE is identified:

$$\begin{aligned} ATE &= E[Y_{i1} - Y_{i0}] \\ &= E\big[E[Y_{i1}|C_i = 1, X_i] - E[Y_{i0}|C_i = 0, X_i]\big] \end{aligned}$$

where the outer expectation is taken over X_i.

In principle one could make this comparison operational if there were a small discrete number of possible covariates with a limited number of values. In this situation with a large number of observations in the dataset there would be a sufficient number of people in each cell to do the matching. When this is not the case the alternative of the propensity score is useful.

Definition 2. *The propensity score is the conditional probability of computer use given the exogenous variables:*

$$p(X_i) \equiv \Pr(C_i = 1 | X_i)$$

The propensity score has two important properties:

Lemma 1 THE BALANCING PROPERTY.

$$C_i \perp X_i \mid p(X_i)$$

This property asserts that attrition and the observed covariates are conditionally independent given the propensity score. Combined with the CIA assumption the balancing property suggests the key property of the propensity score:

Lemma 2 .CIA GIVEN THE PROPENSITY SCORE.

If assignment to attrition is conditionally independent then assignment to computer use is independent given the propensity score.

$$C_i \perp Y_{i1}, Y_{i0} \mid p(X_i)$$

R&R show that you can identify the ATE using the propensity score with matching. Hence the ATE can be written as:

$$ATE = E\lfloor E\lfloor Y_{i1} | C_i = 1, p(X_i) \rfloor - E\lfloor Y_{i0} | C_i = 0, p(X_i) \rfloor\rfloor$$

The implication of this is that matching on the propensity score can be used to directly compare those who use a computer with those who ‘look like’ them but do not. Obviously it should be stressed again that the validity of this expression is crucially dependent on the restrictive CIA assumption.

If the unobserved factors are adequately proxied in the data, then this proxy approach is less restrictive than the Instrumental Variable or Treatment Effects approach. This is because using the matching technique we do not restrict the causal impact of the proxy variables on labour market outcomes as only operating through the computer use variable. Hence, this method also controls for the standard problem of bias in the returns to education.

The ATE for our two data sets are reported in column 9 of Table 4. The results suggest that the ATE of computer use is around 13% in the NCDS and 10% in the BCS. These estimates are not dramatically different than the OLS or Random effects or value added model. It is worth noting that the ATE effect for women in the NCDS is insignificant.

5. Conclusion

This paper examined the relationship between computer use, and earnings. Using a variety of estimation techniques and two cohort surveys this study represents the most recent attempt to examine empirically the return to computer use for the UK. The NCDS and BCS cohort data sets we used are unique in providing direct information on computer resources used at work, therefore many of the problems with earlier studies in the analysis of the returns to computer were overcome. In addition, the use of different sets of conditioning variables by different authors and exploring how the rate of return to computing estimates may vary with the use of different estimation techniques was instructive.

This paper reviewed the evidence on several different research themes in the literature. The paper investigated: whether computers and skills are complements; whether those that use computers are simply the more able (Bell (1996)); whether there is a distinction between simply using a computer at work and the level of skill or ability a person has with computers (DiNardo and Pischke (1997); whether the variable relating to future computer use can be used as an adequate test of the computer return being only a return to unmeasured ability. We also explored whether the estimation technique used for the analysis makes a substantive difference.

Broadly speaking, our conclusion is that in the UK there is good evidence to suggest that the rate of return to computer use is between 10-15%. The precise estimate will depend on the extent: to which unobserved heterogeneity is controlled for, the degree to which we can control for the endogeneity of ability with using a computer. Our estimates suggest that the treatment effects model and matching techniques do not provide dramatically different estimates than the fully conditioned OLS estimates. However we suggest that the use of IV techniques may not be that helpful in identifying the size of the return to computing for the average individual. Our results suggest that the return to computing is different across generations as the older NCDS cohort have a slightly higher return than the BCS cohort born 12 years later. It is possible that this effect is due to the fact that in the BCS cohort computer skills are more commonplace and can accordingly command less of a premium in the labour market. We also established that the return to computer use is lower for women than men, particularly in the earlier cohort. This is in large part due to the pattern of computer use in female secretarial and clerical occupations. On the methodological issues which this paper addresses we suggest a careful interpretation of IV methods and panel techniques since the interpretation of results which use those techniques is not necessarily straightforward.

We are aware that our results are at variance with the most recent contributions to the literature. We submit that in large part our larger returns are a result of having: better ability data to condition on and using more appropriate econometric techniques which explicitly model the endogeneity of the use of computers. Notwithstanding, the estimation issues, there are also a variety of other factors which may give rise to the higher returns found in this data. Most specifically, we believe our estimates of the return may be higher since there may be a shortage of computer skills in the UK than in the US and Germany over the 1990s. It should also be borne in mind that we use cohort data which overcomes the aggregations problems associated with the other empirical studies (which use cross section data) and as a result may understate the rate of return to computer use.

Our discussion of the return to computer use sought to establish the size of the differential rather than the reasons for its existence. We would be surprised if there were not substantial advantages to computer use, although this is of course remains an empirical matter. There is clearly room for disagreement about whether any estimated differential represents a return to an acquired skill or a return to unobserved ability. In any case, the parameters of this particular debate are often set too narrowly because the kind of data that are typically employed cannot pin down the reasons for the computer differential[10]. Everyone agrees that the earnings equation is in reality a reduced form equation reflecting demand and supply conditions, but we tend to neglect demand factors such as the level of technology because we do not often observe firm characteristics in typical survey data. We would argue that variation in firm characteristics are an important contributor to unobserved heterogeneity. Estimates of computer differentials are based on data drawn from the eighties and nineties when computer technology was being widely introduced across a broad spectrum of occupations and industries. Presumably the more competitive and innovative firms would have embraced the new technology first. In this context, we would be astonished if there were not significant returns to computer use. Our estimates may be high compared with a number of other estimates, but they do not surprise us.

[10] Except in the polar case of a zero return.

Table 1 – Percentages Using Computers at Work

Group	BCS 2000	NCDS 1991	NCDS 2000
All workers	53.81	42.02	52.25
Gender			
Men	56.64	47.22	47.33
Women	51.14	39.50	57.31
Education			
NVQ none	46.15	35.11	41.56
NVQ 1	57.70	44.68	55.32
NVQ 2	43.20	36.01	48.50
NVQ 3	59.03	47.41	60.19
NVQ 4	71.71	58.35	72.99
NVQ 5	77.78	53.15	72.07
Race			
White	53.99	41.87	52.33
Non-white	54.53	54.14	51.24
Sector			
Construction	28.29	21.29	32.32
Financial	97.56	81.80	96.00
Public Admin	88.13	63.49	83.41
Health	57.21	30.60	56.25
Education	75.87	53.17	66.80
Occupations			
Managers	82.50	64.71	81.65
Professional	90.64	69.90	86.35
Associated Professional	85.47	51.17	77.55
Clerical	94.11	60.60	90.25
Craft	33.60	25.00	34.72
Sales	64.30	28.78	51.15

Table 2 –Potential Instrumental Variables for the use of a Computer at Work in 2000

		Do you use a computer at work?			
		NCDS 2000		BCS in 2000	
CAPI use		Yes	No	Yes	No
Attitudes section completed	No	2.98	12.93	2.51	10.06
by respondent	Yes	97.02	87.07	97.49	89.94
Attitudes to computers					
Computers at work are destroying people's skills	Agree	31.79	57.99	26.43	50.21
	Disagree	68.21	42.01	73.57	49.79
Computers enrich the lives of users	Agree	49.99	54.94	50.79	58.32
	Disagree	50.51	45.06	49.21	41.68
Every family should have a computer	Agree	56.04	63.86	56.99	64.69
	Disagree	43.96	36.14	43.01	35.31
Learning to use a computer is more trouble than it is worth	Agree	13.14	34.61	10.17	29.48
	Disagree	86.86	65.39	89.83	70.52
Previous use of computers					
Previous use of computers at work in 1991	Yes	63.78	19.21		
	No	36.22	80.79		
Computers at home					
Do you have a PC at home?	Yes	78.55	57.76	58.05	39.55
	No	21.45	42.05	41.95	60.18
Do you use a computer at home more or less than once a week?	Less	54.86	81.22	64.17	81.27
	More	45.14	18.79	35.83	18.73

Table 3: Selection of previous results

Author	Kreuger			DiNardo & Pischke			Bell		Dickerson & Green	Handel			Anger & Schwarze						Krashinsky		Oosteerbeek			Entorf & Kramarz		
Earnings variable	Hourly wage			Hourly wage			Hourly wage		Hourly wage	Hourly wage			Monthly pay						Hourly wage		Hourly wage			Monthly wage		
Country	US			Germany			UK		UK	US			Germany						US		Netherlands			France		
Data	CPS	CPS secretaries	High*	Qualification & Career Survey			NCDS		Skills Survey	CPS			GSOEP						Twin data		53-yr olds			LFS & TOTTO		
Data Type	Cross Section			Cross Section			Cohort		Cross Section	Cross Section			Cross Section						Cohort		Cohort			Cross Section		
Date	1989	1989	1984	1991/2			1991		1997 & 2001	1991			1985-99						1992 to 1994		1993			1985-87		
Technique	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	RE	RE	FE	FE	OLS	FE	OLS	OLS	FE	OLS	OLS	FE
Gender	M-W	M-W	M-W	M-W	M-W	M-W	M-W	M-W	M-W	M-W	M-W	M-W	M	W	M	W	M	W	M-W	M-W	M-W	M-W	M-W	M-W	M-W	M-W
Estimate (t-value)	0.162 (20.2)	0.093 (3.0)	0.110 (7.3)	0.171 (28.5)	0.083 (11.9)	0.069 (9.9)	0.157 (8.3)	0.101 (4.4)	0.136 (9.7)	0.234 (26.0)	0.146 (14.8)	0.084 (8.6)	0.025 (5.3)	0.063 (9.7)	0.012 (2.5)	0.027 (4.0)	-0.000 (0.2)	0.013 (1.8)	0.205 (5.1)	0.075 (1.6)	0.111 (3.6)	0.123 (38)	0.096 (2.7)	0.158 (26)	0.059 (8.4)	0.006 (0.9)
Controls	K1	K2	K3	D&P	D&P	D&P	B1	B1	D&G	H	H	H	A&S	A&S	A&S	A&S	A&S	A&S	Kr	Kr	O	O	O	E&K	E&K	E&K
			Ed			Tools		Abil	Skills		Skills	Skills													Ex	Ex
	Occ	Sec			Occ	Occ	Occ	Occ				Occ	Occ	Occ	Occ	Occ	Occ	Occ			Occ	Occ	Occ			
							Ind	Ind	Ind			Ind	Ind	Ind	Ind	Ind	Ind	Ind			Ind	Ind	Ind		Sec	Sec
			High																							
Number	13379	618	4684	20042	20042	20042	3382	2464	5191	11465	11130	10911	15536	6825	15536	6825	15536	6825	606	606	924	924		15946		35567

Notes for Table 3.
* High School & Beyond Survey (comprises people who left high school 4 years before)
RE Random effects, FE Fixed effects
The fixed effects estimates do not include the variables that change over time.

Kreuger

Table II p.38

K1 *Baseline specification*
Years of schooling, experience, experience squared, , black, other race, part-time, lives in SMSA, gender, veteran, married, married*gender, union member

Occ 8 occupation dummies

Table V

Sample comprises secretaries

K2 *Baseline specification*
Years of schooling, experience, experience squared, , black, other race, part-time, lives in SMSA, gender, married, union member

Table VI

Sample comprises people who left high school 4 years before

K3 *Baseline specification*
Age, age squared, black, other race, gender, married, married*gender, union member, senior in 1980, native born, disability limits work, 9 regions for high school

High High school dummies - academic, general, urban

Ed Parent's education (10 dummies), 1980 achievement test score, grade point average, disciplinary problem

DiNardo and Pishke

Table II p.295, Table III p.298

D&P *Baseline specification*
Years of schooling, experience, experience squared, part-time, resident of large city, gender, married, married*gender, civil servant

Tools Dummies for use of calculator, telephone, pen/pencil

Occ 1071 occupation dummies

Bell

Table 2, col 4, Table 5 col 5.

B1 Years of Schooling, Gender Married, Married*Gender, Union Member, Health Problems, Firm Size.

B2 Years of Schooling, Gender Married, Married*Gender, Union Member, Health Problems, Firm Size, Reading and Maths test scores at age 11.

Dickerson and Green

Table 7

D&G *Baseline specification*
Highest education level, experience, experience squared, gender, shift work, supervisor or manager, part-time, temporary job, public sector job, small firm, job mainly done by opposite gender, 11 regional dummies, job with discretion, variety of tasks in job

Skills 10 skills

17 Industry dummies

Handel

Estimates for 'uses computer every day'. Table 3 and Table 4.

H *Baseline specification*
Years of schooling, experience, experience squared, part-time status, union status, gender, black, other non-whites, resident of metropolitan area, married, married*gender, veteran,, 3 regional dummies

7 skills at 3 levels of use

Occ 47 occupation dummies

Ind 45 industry dummies

H hourly worker, training received from employer, works for government, current tenure, time in current occupation

Anger and Schwarze

Table 1

A & S *Baseline specification*
Years of schooling, experience, age, marital status, 5 firm size bands, length of working time, 9 regions, 14 time periods

Occ 6 occupations

Ind 14 industries

Krashinsky

Table 6

Kr *Baseline specification (only whites included)*
Years of schooling, age, age squared, job tenure, gender, married, married*gender, union member

Oosterbeek

Table 1 and text p.276

O *Baseline specification*
Years of schooling, IQ, 3 firm size dummies, gender

Ind 6 industries

Occ 9 occupations

Entorf and Kramarz

Check the pay variable (banded monthly pay) No obvious adjustment for hours of work although part-time is included

E&K *Baseline specification*
7 Education groups, experience, experience squared, tenure, tenure squared, gender, part-time, marital status, regional dummies

Ex	experience with computer based NT (large autonomy), experience with computer based NT (large autonomy) squared, experience with computer based NT (average autonomy), experience with computer based NT (average autonomy) squared, experience with computer based NT (low autonomy), experience with computer based NT (low autonomy) squared
Sec	38 sectors
Occ	8 occupations

Table 4. The coefficient of computer use in the earnings equation by Cohort by Gender.

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Age, Gender, Cohort	Krueger	Bell	'Tools'	Dickerson and Green	OLS	IV I 2SLS	IV II 2SLS	Treatment Effects	Matched	Fixed Effects	Random Effects
42 in 2000 Men				0.201 ** (0.019)	0.171 ** (0.021)	0.314 ** (0.051)	0.349 ** (0.044)	0.169 ** (0.065)	0.152 ** (0.079)	0.063 ** (0.020)	0.158 ** (0.012)
42 in 2000 Women				0.142 ** (0.017)	0.113 ** (0.019)	0.219 ** (0.049)	0.179 ** (0.043)	0.116 ** (0.054)	0.065 (0.068)	0.021 (0.018)	0.119 ** (0.010)
42 in 2000 All	0.204 ** (0.013)	0.158 ** (0.014)	0.312 ** (0.012)	0.178 ** (0.013)	0.147 ** (0.014)	0.292 ** (0.035)	0.279 ** (0.031)	0.150 ** (0.071)	0.131 ** (0.051)	0.044 ** (0.013)	0.146 ** (0.009)
30 in 2000 Men				0.163 ** (0.017)	0.113 ** (0.020)	0.234 ** (0.059)		0.101 ** (0.043)	0.180 ** (0.090)		
30 in 2000 Women				0.159 ** (0.018)	0.093 ** (0.022)	0.248 ** (0.065)		0.098 ** (0.034)	0.102 ** (0.081)		
30 in 2000 All	0.186 ** (0.103)	0.134 ** (0.015)	0.267 ** (0.012)	0.140 ** (0.012)	0.112 ** (0.015)	0.240 ** (0.043)		0.107 ** (0.041)	0.107 ** (0.050)		

Notes for Table 4.

The dependent variable is the natural logarithm of wages. (All wages are in Jan 2000 prices)
The regressor for computer use is a dummy variable for 'uses a computer at work'.
The sets of controls are defined below.
The coefficients were invariably significant at any reasonable significance levels. The smallest t-value was 20.
The number of observations for 1991 is 3703 and for 2000

Sets of variables in 2000 survey

Computer variables	Dummies for Has a computer at home Uses a computer at home Computers at work destroying peoples skills – disagree Computers enrich the lives of users - agree Every family should have a computer - agree Learning to use a computer more trouble than worth - disagree The respondent filled in the self completion part of the survey using the laptop by themselves
HC	Human capital Years of schooling, Years of work experience, Years of work experience squared
Qual	Highest qualification Dummies for 6 levels whether vocational or academic NVQ level 1, NVQ level 2, NVQ level 3, NVQ level 4, NVQ level 5 Omitted group - No qualifications
Ability	Dummies for quintile score on (i) reading test and (ii) mathematics test Omitted groups – in the bottom quintile for reading score, in the bottom quintile for mathematics score
Skills	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 10 Major SOC Groups Professional, associate professional and technical, clerical and secretarial, craft and related, personal and protective services, sales, plant and machine operatives, other Omitted group - managers and administrators
SIC	Industry, Dummies 13 Major SIC Groups Farming, Manufacturing, Sales (wholesale, retail and repair), Hotels and restaurants, 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 - Construction
Region	10 regions – Wales, London, East Anglia, South East, South West, East Midlands, West Midlands, Yorkshire and Humberside, North West, North Omitted group - Scotland
Other	Dummies for other job characteristics Firm size (number of employees) 5 categories 1-9, 10-24, 25-99, 100-499, 500 or more (2000 survey) Union member

Table 5: Anger and Schwarze Model using the 1991 NCDS.

	Used a computer in 2000 and 1991	Did not use a computer in 1991 and did in 2000	Implied Return to Computing Net of Ability Effect	Simple Return to Computer Use in 1991
Men 33 in 1991	0.117 ** (0.015)	0.042 ** (0.017)	0.075	0.128 ** (0.014)
Women 33 in 1991	0.031 (0.016)	0.009 (0.018)	0.022	.088 ** (0.017)
All 33 in 1991	0.080 ** (0.011)	0.030 ** (0.012)	0.050	0.113 ** (0.011)

Table 6: Value Added Specification

	Used a computer in 2000 and 1991	Did not use a computer in 1991 and did in 2000	Used a computer in 1991 but not in 2000.
Men 42 in 2000	0.155 ** (0.026)	0.050 ** (0.025)	-0.032 (0.040)
Women 42 in 2000	0.081 ** (0.030)	0.098 ** (0.028)	0.066 (0.046)
All 42 in 2000	0.127 ** (0.019)	0.079 ** (0.019)	0.014 (0.031)

Table 7: Limited Sample of People in the same Sector and Occupation in 1991 and 2000.

(Sample consists of 724 men, 628 women and 1352 in total.)

	Used a computer in 2000 and 1991	Did not use a computer in 1991 and did in 2000	Used a computer in 1991 but not in 2000.
Men 42 in 2000	0.262 ** (0.046)	0.199 ** (0.050)	0.169 ** (0.079)
Women 42 in 2000	0.171 ** (0.049)	0.218 ** (0.048)	0.210 ** (0.086)
All 42 in 2000	0.213 ** (0.033)	0.208 ** (0.035)	0.193 ** (0.057)

Appendix A. Classifications of computer use

Dickerson and Green

Advanced For example, using computer syntax and/or formulae for programming

Complex For example, using a computer for analysing information or design including the use of computer aided design or statistical packages

Moderate For example, using a computer for word-processing and/or spread sheets or communicating with others by email

Straightforward For example, using a computer for straightforward routine procedures such as printing out an invoice in a shop

Entorf and Kramarz (1)

NT1 computer related new technology (NT) leaving large autonomy to the worker using it (microcomputer, text processing, videotext, terminal (emission and reception), computer listings, data entry, video control (supervising)

NT2 computer related NT with average autonomy
(computer terminal (reception only), terminal (emission only), other NT, machine tools with numerical command

NT3 computer related NT with low autonomy
(robot, assembly line, automatic transportation

Experience with computer based NT at these different levels.

Entorf and Kramarz (2)

Microcomputer
Terminal (emission and reception)
Minitel (French videotext)
Listings
Video-based NT
Laser-based NT
Fax machine
Terminal (emission only)
Terminal (reception only)
Data entry
Robot
Numerical command machine
Assembly line
Automatic transportation

Handel

Use a PC or terminal

Every day
Once or more a week
Less than once a week

Kreuger

Computer tasks

Word-processing

Bookkeeping
Computer assisted design
Electronic mail
Inventory control
Programming
Desktop publishing or newsletters
Spread sheets
Sales
Computer games

Oosterbeek

Computer use	daily
	weekly
	monthly
	almost never
	never

Appendix B. Unobserved heterogeneity, fixed effects and the treatment model

The use of fixed effects in the context of a treatment model may not be appropriate if there are differences in the effect of the treatment across the members of the sample. This is different from the usual situation because it is normally assumed that the treatment has a constant effect across individuals but is similar to the discussions of the effects of unobserved heterogeneity on instrumental variable estimates of the return to schooling. Our example is the use of computers. We consider the use of a computer in two time periods. If individual i uses a computer in period t, C_{it}=1 and C_{it}=0 otherwise.

Consider the fixed effects model:

$$Y_{it} = \alpha_i + \beta C_{it} + u_{it} \qquad t=0,1;\ \ i \in A_{00}, A_{01}, A_{10}, A_{11}$$

where there are 3 sets of individuals. Members of set A_{KL} have $C_{i0}=K$ and $C_{i1}=L$.

Members of set A_{00} have C_{i0}=0 and C_{i1}=0, set A_{01} have C_{i0}=0 and C_{i1}=1, set A_{I0}=1 have C_{i0}=1 and C_{i1}=0, and set A_{11} have C_{i0}=1 and C_{i1}=1.

The fixed effect, α_i, is removed by taking deviations from the mean

$$Y_{it} - \overline{Y}_i = \beta(C_{it} - \overline{C}_i) + u_{it} - \overline{u}_i \qquad t=0,1$$

The fixed effects estimator of β, b, is found by applying OLS to the transformed equation.

$$b = \frac{\sum_t \sum_{i \in A_{00}, A_{11}, A_{10}, A_{01}} (C_{it} - \overline{C}_i)(Y_{it} - \overline{Y}_i)}{\sum_t \sum_{i \in A_{00}, A_{11}, A_{10}, A_{01}} (C_{it} - \overline{C}_i)^2} = \frac{\sum_t \sum_{i \in A_{10}, A_{01}} (C_{it} - \overline{C}_i)(Y_{it} - \overline{Y}_i)}{\sum_t \sum_{i \in A_{10}, A_{01}} (C_{it} - \overline{C}_i)^2}$$

because $(C_{it} - \overline{C}_i) = 0$ for $i \in A_{00}, A_{11}$.

$$b = \frac{\sum_t \sum_{i \in A_{10}} (C_{it} - \overline{C}_i)(Y_{it} - \overline{Y}_i)}{\sum_t \sum_{i \in A_{10}, A_{01}} (C_{it} - \overline{C}_i)^2} + \frac{\sum_t \sum_{i \in A_{01}} (C_{it} - \overline{C}_i)(Y_{it} - \overline{Y}_i)}{\sum_t \sum_{i \in A_{10}, A_{01}} (C_{it} - \overline{C}_i)^2}$$

$$b = \frac{\sum_t \sum_{i \in A_{10}} (C_{it} - \overline{C}_i)^2}{\sum_t \sum_{i \in A_{10}, A_{01}} (C_{it} - \overline{C}_i)^2} \frac{\sum_t \sum_{i \in A_{10}} (C_{it} - \overline{C}_i)(Y_{it} - \overline{Y}_i)}{\sum_t \sum_{i \in A_{10}} (C_{it} - \overline{C}_i)^2} + \frac{\sum_t \sum_{i \in A_{01}} (C_{it} - \overline{C}_i)^2}{\sum_t \sum_{i \in A_{10}, A_{01}} (C_{it} - \overline{C}_i)^2} \frac{\sum_t \sum_{i \in A_{01}} (C_{it} - \overline{C}_i)(Y_{it} - \overline{Y}_i)}{\sum_t \sum_{i \in A_{01}} (C_{it} - \overline{C}_i)^2}$$

$$b = S_{CC}^{10} b_{10} + S_{CC}^{01} b_{01}$$

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

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

The fixed effects estimator is a weighted average of the estimates for the two sets of changers. 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.

The exact way that the return is distributed is difficult to forecast as there are many different issues involved. Suppose people are selected at random to learn computer skills so there is no reason to expect new users of computers to have a lower return than existing users. However if computer users are divided into those that can and those cannot use them effectively 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 $b_{00}=b_{11}=b_{01}>b_{10}$. By contrast, stopping using a computer may have been part of normal upward career progression. Managers may have people who work for them who do the computer work. As individuals move up promotion ladders they may stop using computers. In this case, $b_{01}=b_{10}$.

Since DeNardo and Pishke, computer use has often been viewed as an indicator of unobserved individual productivity and the main motivation for the fixed effects model was that it netted out these effects. By contrast, we would argue that, if there are genuine differences in unobserved heterogeneity, then the fixed effect model has leaves us with the effects for specific groups rather than the average effect.

Most studies do not consider the case of people who stop using a computer so we will follow their example and assume that this set is empty. The argument is that more able individuals are selected to use a computer so that the high returns observed for computer use are in effect a reward for ability. Applying this over time, we would expect $b_{11}>b_{01}>b_{00}$. The fixed effect estimator may or may not be a close estimate of the return to computer use across the whole population. However, it is not a good indicator of the return for all those who use a computer or those who might benefit from future use of a computer.

The first group to use the new technology may have higher returns if they are more able in some sense or if the market conditions are more favourable.

The fact that they have not continued to use the new technology may be because they are not suited to it. It may be that the nature of associated uses of C have changed over time. This could lower the return or raise it if the move is from simple to more sophisticated uses.

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