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Acknowledgments

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1. Introduction

Computers and ICT have changed the way we live and work. Economists have long been interested in this process (Hirschhorn (1988), Krueger (1993)). 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 and many authors have suggested (Levy and Murnane (1996), Goldin and Katz (1996), Autor et al (1998), Autor et al (2003)) that this technology has been partly responsible for the growing income inequality in the US and UK as there is skill bias in this technical change which gives a relative advantage to the highly educated. Other authors (for example Goos and Manning (2007)) argue that a 'routinization' of jobs due to technical change has led to job polarization which explains the rise in income inequality.

The growth of the use of computers in the work place has been dramatic since the 1980s. 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 Dolton et al (2006) report that the proportion has risen to 65% amongst a cohort of 42 year olds in the NCDS and 69% amongst a cohort of 30 year olds in the BCS survey by 2000[1]. In the Workplace Employee Relations Survey (WERS) data we now have 75% of workers using a computer at work in 2004.

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. This question is of policy importance since it contributes to an understanding of how IT affects productivity, inequality and economic growth. 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. Computer use may be highly correlated with unobserved characteristics that also generate a wage return. Working out the 'causal effect' of computer use on earnings is not straightforward since the workers who use computers are a non-random selection of workers who could have earned a higher wage in the absence of computers. The difficultly is establishing whether the computer pay differential is a real consequence of computer use, or maybe a return to computer skills, or is capturing the effect of some unobserved attributes. Hence it is potentially difficult to determine whether it is innate 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. We examine the effect of conditioning on different variables in the earnings equation and controlling for establishment, industry and occupation fixed effects on the estimated rate of return to computer use.

Krueger (1993) 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 20% 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.

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. They suggest there is a premium to the use of 'white-collar' tools in any job and that because computers are used predominantly by white collar workers then 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. When they condition on around 500 occupations the return to using a computer falls from 11-17% to 2.2-8.3%. Since they find similar returns to using other white collar tools (e.g. pencils)

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[1] NCDS = National Child Development Study, BCS = British Cohort Study

they infer that this is not a return to using a computer but simply suggestive of ability and skills which cannot be observed. However we do not know categorically that their 2.2-8.3% return on IT use was genuine or not and it is only a suggestion by the authors that such a return is an artefact based on estimating similar returns for other office tools. Interestingly a recent paper by Spitz-Oener (2007) has used a more recent wave of the same data as DiNardo and Pischke (1997) and found that the return to computer use is robust but that the strange return to use of pencils has disappeared. We follow a similar approach in this paper in terms of conditioning on firms, occupations and sectors.

Hildreth (2001) uses the WERS 1998 data to investigate the effect of using email as a means of communication in the establishment. In the WERS 1998 data we know simply if email is used as a method of communication at the level of the workplace. He finds a premium of between 5-15% on earnings of individuals in the establishment and a premium of between 20-22% on the financial performance of the workplace. Hildreth discusses ways in which the use of email as a communication device may make the organisation more productive and provide a 'voice' for the workers. Despite this he concludes that this premium is likely to arise from unobserved worker skills.

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% more than those who do not use computers at all. Dickerson and Green (2004) also found results of the same order of magnitude when they use a later dataset. In addition they found that the 'pencils effect' disappeared when a full description of a job attributes is controlled for but that the effect from using a computer was robust.

The predominant use of cross section data in this literature has contributed to the difficulty in distinguishing a 'causal' impact of IT use from the effect of unobserved heterogeneity. Of particular interest is the way in which the value of the coefficient on computer use falls as more control variables are added. Specifically as controls for occupation, industry and workplace are added then the likelihood that the effect of IT is purely determined by unobserved factors narrows to the effect of unobserved ability differences. There is therefore a clear rationale for the use of panel data in which such factors may be assumed to be fixed effects. When Entorf and Kramarz (1997) use panel data to control for individual fixed effects they do not find any return to using a computer. This is not surprising as the model will only be identified on those who change from using a computer to not (or vice versa) within a year. When Dolton and Makepeace (2004) estimated a similar model using cohort data which measures earnings and computer use changers over 9 years they found a significant return when they distinguished between those who changed into using a computer (from non-use) from those who changed to non-use from being a user.

In the computer use literature to date there has been relatively little study of what a computer is used for and what difference this makes to earnings. An exception is a recent paper Dolton et al (2006) which examines what workers use a computer for and the frequency of use. They find that there are substantial returns to the use email and the internet although it is not clear what induces this return.

A recent paper by Pabilonia and Zoghi (2005) on estimating the return to computer use takes the instrumental variable (IV) approach to identification. They use Canadian panel data from 1999 and 2001 to suggest that the OLS estimate of the return is around 6.6% which falls to 1.2% when they use individual fixed effects. This latter result is not surprising given that identification comes from those who change their IT user status within 2 years and the authors are also conditioning on the amount of computer experience the individual has in terms of years. The authors then estimate an IV model by using the IV of whether or not the workplace has implemented a new process or has improved an existing process in production within the past year. They cite Doms et al (1997) to suggest that the use of new technologies does not alter wages in the workplace. We explore this identification strategy with the WERS data as we have a similar question on the implementation of new technology in the firm.

In this paper we aim to contribute to the literature in a number of ways. Firstly, we explore the size of the coefficient on computer use in an earnings equation and establish bounds for this estimate based on different identification assumptions. Specifically, we compare OLS estimates with estimates based on: a control function model, a treatment effects model and an IV model. These models are estimated with detailed dummy variable controls for occupation, sectors and workplace. Secondly, using detailed information on computer use we estimate the return to using different computer skills. Thirdly we present estimates of the return to intensity of computer use as measured by the number of tasks an individual uses a computer for. Finally we briefly explore the issue of whether the proportion of computer uses in a firm offers an externality to the individual.

Overall we find that a computer use coefficient gets smaller as additional controls are included – falling from 21% to 3% when all possible controls are added. These estimates are between 11-14% in a treatment effects model, but between 22-28% in an Instrumental Variables model. We find clear evidence of returns to the skills of using Word, Email and Programming and evidence of increasing returns to computer use intensity.

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 the survey. Section 3 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 4 reports the results of our estimations. In section 5 we run robustness checks and Section 6 draws our conclusions from the evidence presented.

2. The Data

Our data comes from the WERS 2004 micro-data survey for the UK. WERS is a nationally representative random sample of establishments, which provides detailed information about workers, working conditions and industrial relations. It surveys not only workers, but also management and union representatives. The number of workers surveyed per establishment varies from one to 25. We use the full sample of WERS 2004, consisting of 1733 establishments and 22453 workers. The distribution of sampled workers per establishment is shown in Figure A1. Since the data is an employer-employee linked dataset it also records details of the workplace as well as up to 25 people at the workplace – this allows us to condition using dummy variables - on sector, occupation and establishment and indeed the at the most detailed level the interaction of the latter two categories. We suggest that this level of conditioning should remove much of the individual unobserved heterogeneity which plagues the estimation of cross section models as essentially, if one controls for the 344 occupations and the 1721 workplaces by interacting them to use the 11,232 dummies[2] then this conditioning amounts to producing the equivalent of 'fixed effect' estimates for those people in the same job and same work place.

One sampling issue of importance to our empirical work is whether or not the workers sampled at the workplaces in WERS 2004 are disproportionately computer users. Figure 2 sheds some light on this question. The upper panel reports the fraction of computer users in a workplace as reported by the manger survey in answer to the question 'what fraction of workers at this workplace use a computer'. The lower panel reports, by workplace, the fraction of our sample who actually use a computer. We can see that the lower panel indicates that there are many more computer users in the respondents than the managers said used a computer in the workplace. This suggests that respondents to the survey are an over-sample of computer users. This fact should be borne in mind in the interpretation of our results – although it is unclear if this would induce any systematic bias (to other than the fraction of computer users descriptive statistics).

WERS 2004 includes a question "Do you use computer for any of the following tasks as part of your work?" Twelve options are presented and respondents are asked to tick all that apply. E-Mail, Word processing and Spreadsheet/Data entry are the most common tasks performed with a computer, with frequencies of 59%, 56% and 45% of all workers, respectively. For simplification and ease of comparability with other data sets we aggregate into six categories as shown in Table 1. We do this for two reasons – firstly we wish to be able to compare our results with the literature (see Dolton et al 2006) and secondly we genuinely believe that there is an overlap in the categories we have grouped together – for example it is clear that most record keeping, data entry and data analysis would be done using similar software – namely a spreadsheet. We would like to argue that the groupings we have used reflect the different IT skills that a worker can acquire and this is important as we will argue that our results indicate a positive rate of return to the use of those skills.

[2] There are this number of dummies rather than 344 (occupations) x1721(workplaces) =59,2024 since there are

We also examine the use of all the data on computer usage by investigating the number of tasks an individual uses a computer for. There is considerable variation in this - most workers use computers for at least 2 tasks (out of maximum of twelve), while the modal number of 4 or 5 tasks and 7% of workers use computers for more than 7 tasks. The distribution of the number of tasks is shown in Figure 2. We will later use this number of tasks as a measure of computer use intensity where it is not unreasonable to argue that if the set of productive tasks to be performed is large there may be a return to the efficient use of a computer to perform as many tasks as possible as this is equivalent to substituting more technological capital (IT and computers) for labour.

Table 2 provides the basic descriptive statistics relating to the use of a computer at work in the WERS 2004 by different characteristics. In the table we report if there is a statistically different mean in the user and non-user groups. The first fact worthy of note is that earnings of those who use IT are 48% higher than those who don't. Demographic groups that are over represented among computer users are females and the 22-39 age group. In terms of tenure, those who have worked in the present job for 2-5 years are most likely to use IT. Consistently we also see from Table 2 that those who don't use a computer are on average the older workers with more work experience (who perhaps entered the labour market before such skills were commonplace or who are more reluctant to acquire them in later years).

From Table 2 we see that computer use is directly related to education as it rises rather rapidly with the qualifications. On average, computer users have around 2.5 more years of schooling than non users. Among users, 37% of workers have a degree and 9% a higher degree, while only 13%-14% of those who don't use a computer have the same qualifications. On average, workers that use a computer work three hours more weekly compared to others – this fact suggests that the type of work these two groups do is quite different, not least because part time workers have a lower computer use rate than those in full time jobs.

Table 2 also suggests that there are many ways in which those who use a computer at work are not substantially different from those who do not. Specifically there are no major differences in use amongst the ethnic minorities, nor do there appear to be any major differences by marital status.

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some workplaces with only one person in a given occupation.

Table 3 shows the incidence of computer use by 19 specific occupational titles. These titles were chosen to be relatively straightforward occupations where it is fairly clear what kind of work the individual actually does. They reveal the diversity of IT usage by occupation and suggest that controlling for occupational title is an important part of understanding the heterogeneity of computer use. We chose 8 occupations which are predominantly in the public sector and 4 which are predominantly in the private sector and 7 occupations common in both sectors. It is clear that the occupations which only require lower or intermediate educational qualifications like: Electrician, Cleaner, Driver are those where computer use is lowest. Nurses clearly do use computers, but with less frequency than other professional occupations due to the nature of their practical, pastoral and functional tasks with patients. The nature of secretarial work – on the other hand – is that they use computers a lot in the office environment. Amongst all the other professional jobs there is a high degree of computer use and this seems to be independent of whether one works in the public or the private sector. The examination of the distribution of IT skills across occupations bears interesting comparison to the categorisation of tasks presented in the Autor et al (2003) work. It is quite clear that the occupations which involve abstract skills like Doctor and Teacher involve different IT skills than manual or semi manual jobs like Drivers and Cleaners. Occupations in the intermediate and 'routine' category like Secretary and Electrician may involve a different profile of IT skills again.

To assess the determinants of IT use more carefully, we regress the computer use on worker observables, with and without workplace controls (Table 4, columns 1-2). The outline of the typical computer user sketched above is replicated in this analysis. The determinants of computer use are very similar, whether workplace controls are added or not. In the same table, columns 3-4 repeat these regressions, but this time using a sample of computer users, and explaining the number of uses with a Poisson count model. Some interesting observations can be made. For example, the coefficients for both experience and female flips sign, indicating that the users with the highest intensity of computer use tasks at work tend to be young men.

3. Econometric Identification.

If we assume a particular production process in a given time, with perfectly competitive labour markets, the following augmented Mincerian wage equation could characterise the return to computer use:

$$\ln w = Y = X'\delta + \theta_1 A + \theta_2 C + \theta_3 AC + \theta_4 SC + u \qquad (1)$$

Here *Y* corresponds to productivity and *w* to wages. *X* corresponds to typical controls such as education and experience. *C* is a binary variable indicating computer use, *A* is ability and *S* a measure computer skills. Here, θ_2 reflects the productivity boost associated with computer use, which benefits all workers, independent of ability. Parameter θ_3 reflects the possibility that more able workers may be able to improve their productivity more due to computers, while θ_4 corresponds to the return to computer skills, a form of human capital we believe to be different from general ability and education.

In an imaginary experimental setting where workers are randomised to the status of computer users, and productivity is observable, the expected productivity difference between computer users and non-users would be $\theta_2 C + \theta_3 A_m C + \theta_4 S_m C$, where the subscript *m* refers to the population mean. We denote this measure as the Population Wide Return to computer use. Identification of all parameters of interest in this model would require us to observe (and perfectly measure) both ability and computer skills. This framework also highlights that computer skills are necessarily only a partial explanation to wage and productivity boost associated with computers, unless θ_2 and θ_3 are zero.

Following Krueger (1997), previous attempts to model the rate of return to the use of a computer at work have focused on estimation of

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

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 β coefficient is interpreted as the return to computer use. Given our hypothetical model (1), estimation of (2) will lead to an estimate of β which is higher than the Population Wide Return to computer use for three reasons: Firstly, the group of computer users is likely to have higher than average ability, $(A_m C|C = 1) > A_m C$. Secondly, they are likely to have higher than average computer skills $(S_m C|C = 1) > S_m C$. Thirdly, as ability is unobserved, and likely to be correlated with computer use, component $\theta_1 A$ in model (1) will be indistinguishable from the error term, leading to an "ability bias", a problem often present in studies attempting to measure the return to education.

In this paper we attempt to tackle all three sources of bias in β, using following strategies. Firstly, we attempt to minimise the effect of unobservable characteristics, such as ability[3], by exploiting variations in computer use within narrow occupation-workplace cells, while controlling for a large set of observable characteristics. These include human capital variables like educational qualifications achieved, years of schooling, work experience and its square, employment variables: socio-economic classification or occupational classification, part-time and temporary status, and socio-demographic variables: gender, marital status, ethnic origin and union membership.

Secondly, to account for selection into computer use, we estimate a 'treatment effects' model (see Barnow et al (1981)) :

$$Y = X'\delta + \beta C + u \quad (3)$$

$$C^* = \alpha Z + \eta \quad (4)$$

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.

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

[3] In Dolton and Makepeace (2004) this is partially controlled for with IQ type test scores at age 11. Here it was found that including such variables does reduce the size of the coefficient on computer use in the earnings equation.

appropriate selection terms are included. For these procedures to be valid (and yield consistent estimates for the β coefficient) we need Z to be independent of the u error term in equation (3) and Z to be highly correlated with C. It also has to be the case that the remaining conditioning covariates, X, in equation (1) are exogenous and all tests are conditional on the exact specification of equation (1).

As a third attempt to tackle the bias, we estimate a two-stage least squares instrumental variable estimation using similar instruments as Pabilonia and Zoghi (2005). 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. It should also be remembered that the IV approach is quite restrictive (see Heckman (1997), Angrist and Krueger (2001)) 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.

4. Return to Use of IT

The merit of WERS is the richness of the data in describing not only worker characteristics, but also the occupation of the worker and characteristics of the workplace. We are also in a position to control for occupation and sector fixed effects and knowing that since the data comes from around 1700 different workplaces we can also explore the role of establishment effects.

In the following regressions we use WERS data to explain the determinants of hourly earnings. The construction of the variables is explained in the appendix. The results are presented in the Tables 5-11. In the first specification of Table 5 (column 1), we control for tenure, age, ethnicity, gender, marital status, qualifications, union membership and hours worked. In additional specifications we control for fixed effects at several levels: Workplace level (column 2), occupational level (column 3), industry sector times occupational level (column 4), and finally, workplace times occupational level (column 5)[4].

From the first row of Table 5, we see that the wage premium associated with using a computer decreases from 21% to 3%, when increasingly richer set of controls are added to the estimation. Table 6 presents the return to different types of computer use, using the same set of specifications as in Table 5. In all specifications, the highest return is associated with e-mail use, where the earnings premium goes from 20% down to 7.6% as we add more controls to the specification. This result arguably brings up the issue of what is driving this correlation as e-mail is hardly a skill which is short supply or one which takes a long time to learn. So potentially the coefficient on e-mail may in large part be due to unobserved heterogeneity associated with the human capital a person has in networking and communication. Notwithstanding this caveat Dolton et al (2006) have found a similar result concerning e-mail in four completely different data sets. The second highest return is with the use of word processing – although this return is quite comparable to that associated with Programming. Basically the return to using a computer for these activities is around 10% in the simplest specification and falls to around 5% for the specification with occupation-workplace controls. Some of the results are surprising, like the relatively low return to programming, which is generally considered a task involving a higher level of skill – by maybe there is a lack of demand for this skill in a world with high-level programming languages where most software has already been written. It is also quite surprising that the skill of spreadsheets has a negative coefficient in the most comprehensive equation reported in column (5) – but we must remember that this equation is identified by comparing individuals who have the same occupation in the same workplace – which means that *de facto* we are considering only individuals who work in establishments who have sampled more than one worker of the same occupation. As a result this effect relates to workers in the same occupation and workplace and may reflect the fact that in this category the most senior employee may well not use a spreadsheet but delegate this work to someone more junior

[4] In the sample we use, there is a total of 11,232 Occupation-Workplace cells. Out of these 67% have only one individual, 15% have two. Only 1% of cells have 10 or more workers. The variation that the regression exploits is the variation in computer use observed within cells with multiple workers.

In Table 7, the intensity of computer use is defined as the number of tasks workers use the computer for. An interesting finding is that using computer only for one task, has much smaller return than for using it for two tasks. It may be that many jobs done by unskilled workers have a token element of computer use, clearly distinct from occupations where computer is used as a primary tool. This is especially reflected in the last column of Table 7, where even after controlling for occupation-workplace effects, the users with the highest computer use intensity (at least 8 tasks) earn 7.5% more than those who don't use computers, while workers with only one computing task earn as much as those who don't use computers. One interpretation of our findings is that any worker has a number of productive tasks to perform and if there is a possibility of substitution between labour and the use of IT capital (like computers) then this may lead to efficiency gains and hence there is a return on this in terms of productivity and, in turn, the wages of the worker concerned.

A common method of attempting to model the endogeneity of the selection process is to use the standard Heckman (1979) control function approach which would involve the estimation of selection into computer use equation and then the estimation of earnings for the selected group who use and do not use a computer. These estimates are reported in Table A4 in the appendix and they show that there is a significant selectivity effect in terms of the Inverse Mills Ratio coefficient in the earnings of those who do not use computers. A somewhat more general, but related control function approach, is to use the Treatment Effects model which allows us to estimate a selectivity control into using a computer but simultaneously estimate an earnings equation controlling for the treatment effect of using a computer at work. We show these results in Table 8. In columns 1A (earnings equation) and 1B (selection equation) we estimate this model and use only functional form identification on the joint distribution of the errors. In columns 2A (earnings equation) and 2B (selection equation) we estimate the same model using the exclusion restriction provided by the information on whether the computers have been upgraded at the workplace in the last 2 years. (We later use this same variable in our IV estimation.) These results are instructive as they accord with our OLS results in column 3 of Table 5 where we use occupational controls but not workplace controls. Our estimates of the 'treatment effect' of computers on earnings in this model are 12-14% depending on whether the exclusion restriction is used. These results are informative as they reveal that the OLS estimates reported in Table 5 column (1) are likely to grossly overstate the effect of computers on earnings if we do not allow for the endogeneity of the decision to use a compute at work.

To further explore the issue of endogeneity of the IT use variable we adopted the Pabilonia and Zoghi (2005) strategy of estimating the return to computer using the IV approach to identification. Like them, we use the variable of whether there had been any significant changes in the use of computer technology or other technology in the past two years (see Appendix). In our 2SLS regressions the instrument is clearly significant in the first stage (see Table 9, columns 1) as it is positively associated with the respondent using a computer at work.

The last two columns of Table 9 use a larger set of indicators for technical change. The summary statistics of these variables by sector are presented in the Appendix. They include recent upgrades to computers, recent other technological upgrades, whether these upgrades had significant impacts to the workplace, outsourcing of computing and insourcing of computing. There is no direct way for us to test the exogeneity of these instrument candidates, and their exogeneity can intuitively be questioned. They however produce mostly significant first stages (column 3), and lead to similar point estimates as with the first two columns. We consider these estimates as experimental, and concede that the causal interpretation relies on the exogeneity of the technological changes at the workplace.[5] We should also pint out that the only other paper (to our knowledge) to employ the IV identification strategy is Pabilonia and Zoghi (2005) but they use an additional control relating to the amount of computer experience which means that their results are not directly comparable to ours – and this perhaps gives them their unusual result that when IV estimation is used the coefficient on the IT use variable becomes insignificantly different from zero – as their coefficient on computer experience actually rises to .02[6].

[5] It also has the interpretation of a local average treatment effect for the marginal importance of technological change at the level of the workplace.

5. Robustness Checks

As there is undoubtedly much unobserved heterogeneity in any estimation of the return to computer use we seek to find other estimation methods and robustness checks to reveal the relationship between computer use and earnings.

One useful check on the effect of computer use on earnings is to look at the relationship between the fraction of workers who use a computer in a workplace and the earnings of workers, i.e. not to condition directly on the individual's use of a computer but to condition on the amount of use at the level of the workplace (as reported by the manager). Such a variable is much less likely to be endogenous as the individual cannot influence this fraction directly (and only makes a very small marginal contribution to the overall proportion). Dickerson and Green (2004) found strong evidence of such effects. We estimate a similar model in Table 10 but use the continuous variable on the proportion of computer users in the establishment. We find that (depending only marginally on which controls are used) the effect of the fraction of computers users at the workplace is to raise the earnings of IT users by 12-14% but to have no effect on the earnings of those who do not use computers at work. This result indicates that establishments where computers are used create a positive externality on individual earnings of those, who themselves, use a computer at work. However, this effect does not condition earnings of those individual who themselves do not use a computer.

A further way of examining what may be generating the result of the positive earnings effect of IT use is to ask the question of whether firms that use this form of technology most have the highest productivity and turnover. This is a question which was addressed by Hildreth (2001). We sought to replicate his analysis – the logic being that if firms that use IT technology the most were the most productive and efficient then there is a clear link between firms making more profit and paying their workers more. Hildreth finds this effect in the 1998 WERS and we find this result in the 2004 WERS. We report our findings in the Table A3 in the appendix where we suggest that turnover may be as much as 42% higher in firms that use computer technology. This correlation provides one possible explanation of higher

[6] Technically, of course, if IT use is endogenous then so must computer experience in which case we would

earnings for those with IT skills – because they work in firms where turnover and productivity is higher (controlling for most of the observable characteristics of the workplace.)

As argued by Stewart (1983), OLS estimator may be biased when the dependent variable is grouped, as it is in our case. Further the WERS survey provides workplace level survey weights that we have not used in our analysis. In this section we check whether these issues affect our results by estimating a maximum-likelihood based interval regression, weighted OLS, and a weighted interval regression.

Table 11 provides these estimates and compares them to the normal OLS. Note that the dependent variable is log weekly earnings, not hourly pay as in the previous analysis. This modification is necessary for the interval regression to make sense as the data is originally coded as weekly earnings (see appendix for further details on how we use this variable). The results show that the differences in results are fairly minor.

6. Conclusion

This paper uses the WERS 2004 survey to examine the pattern of computer use in British industry and its likely impact on earnings. Specifically we were able to examine information on the type of use made of a computer at work and examine the relationship between computer use and computer skills, and earnings. The WERS data set we used is unique in providing direct information on the tasks for which a computer was used at work, therefore many of the problems with earlier studies in the analysis of the returns to computer were overcome. Our data allowed us to examine what computers are used for by occupation and sector and simple descriptive statistics revealed the heterogeneity across occupations.

Ultimately we cannot be absolutely confident that we can identify a ‘causal effect’. More specifically we cannot be precise about how much of the impact of computer use on earnings is due to individual unobserved heterogeneity, but broadly speaking, our conclusion is that in the UK there is good evidence to suggest that the rate of return to computer use may be

need an IV strategy for this variable too.

between 3-10%. The precise estimate will depend on the extent: to which unobserved heterogeneity is controlled for and how we try to model the effect of occupational heterogeneity and individual unobserved ability. We adopted an eclectic approach of using different identification strategies (namely: extra conditioning on workplace interacted with occupations, control function selectivity and treatment effects models and instrumental variable estimation). In each case our estimates of the return to computers remain statistically significant but clearly get smaller as we move away from OLS estimation. The exception was the estimated coefficient when we used IV estimation where the impact got larger but these estimates are a specific form of the Local Average Treatment Effect conditional on the exclusion restrictions and hence must have a restricted value in this context.

At face value we are aware that our results could be considered to be at odds with some of the most recent contributions to the literature. However we believe that our results do effectively signal a coming together of the various estimate of computers on earnings as our lower bound of 2.8% concurs with that of DiNardo and Pischke (1997) when occupation and workplace effects are allowed for - but nevertheless confirms the simple OLS result of Krueger (1993) of 17% in that our less conditioned estimates are as high 22% and we can clearly explain that away by endogeniety arguments.

New results were also presented relating to the return on the use of particular distinct IT skills. We find that use of word-processing , email and programming give a clear and significant return which is robust to functional specification. We also found that the higher intensity of computer use (in terms of the number of task a person uses a computer for) the higher is their return. This is a potentially complementary result to on the return to the complexity of IT use found by Dickerson and Green (2004). We also found that the higher is the computer use at one’s workplace the larger are your earnings if you use a computer yourself. But conversely if you are a non-user then your earnings are unaffected by working in an establishment with a high fraction of computer users.

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[7]. 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 occupational attributes and firm characteristics are an important contributor to unobserved heterogeneity.

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

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Figure 1. The proportion of workers in 1730 firms that use a computer. A comparison between the survey of workplace managers and the WERS sample of workers.

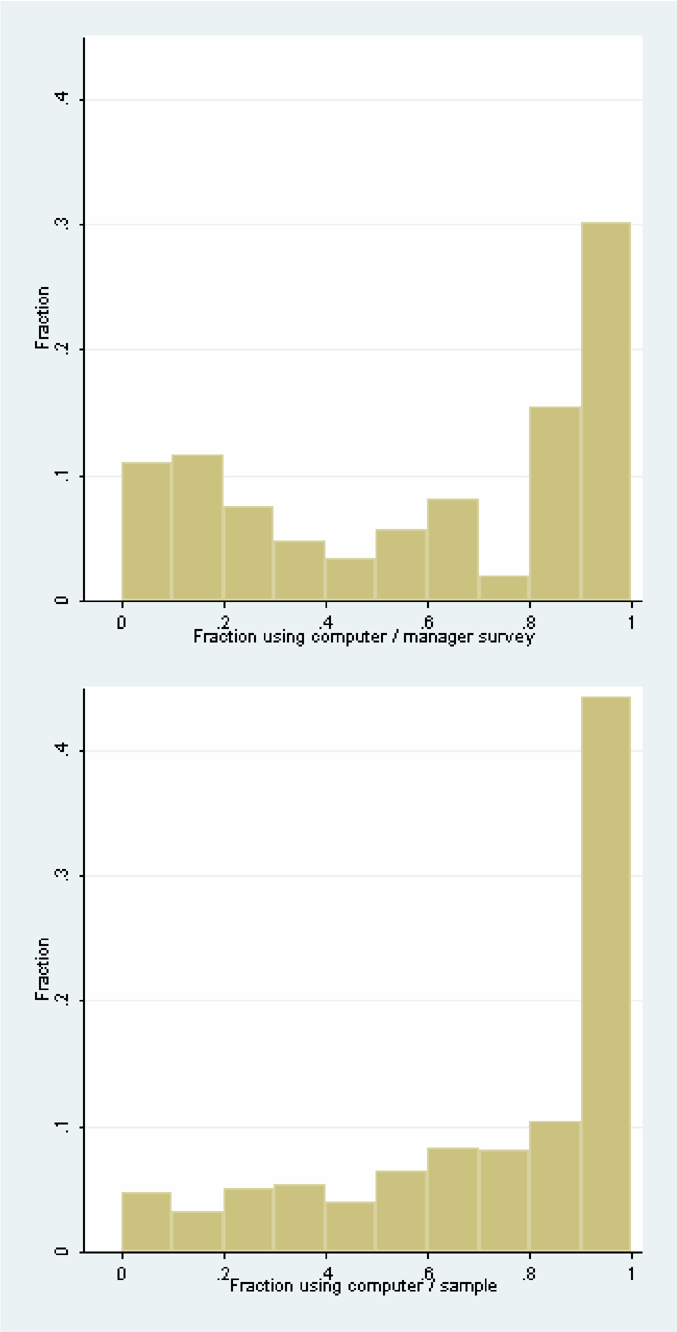


Figure 2. Number of tasks computer is used for, 22178 workers

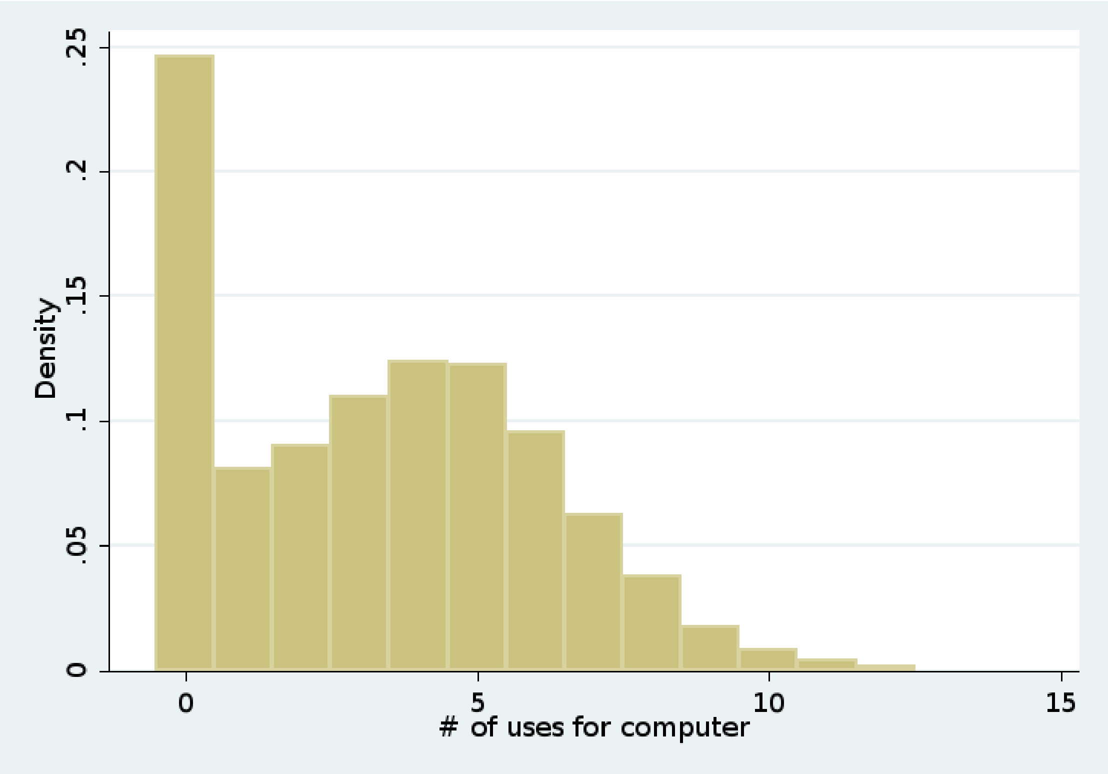


Table 1. IT use as reported in WERS 2004, and reclassification.

Task, as reported in WERS 2004	**Frequency (N = 22177)**	**Classified as:**
Sending or receiving e-mail	0.59	E-Mail
Word processing	0.56	Word Processing
Data entry	0.45	Spreadsheet (Excel)
Record keeping	0.44	Spreadsheet (Excel)
Data analysis	0.30	Spreadsheet (Excel)
Any other task	0.30	Other
Ordering or purchasing	0.19	Other
Checking stock movements, availability or pricing	0.17	Other
Desk-top publishing	0.12	Publishing
Controlling or monitoring processes or machinery	0.09	Other
Computer-aided design	0.07	Publishing
Programming or compiling syntax	0.03	Programming

Table 2. Summary statistics by IT use.

Variables	All	Don't use IT	Use IT	t-test of difference
Sample size	20668	5013	15655	
Hourly earnings	9.92	7.27	10.77	**-41.8**
Number of tasks use computer for	3.34	0	4.41	
Experience and Tenure				
Experience (years)	22.74	26.20	21.63	**22.9**
Tenure < 1 year	0.16	0.18	0.15	**5.3**
Tenure 1-2 years	0.13	0.13	0.13	1.2
Tenure 2-5 years	0.27	0.25	0.28	**-4.4**
Tenure 5-10 years	0.19	0.19	0.19	-0.3
Tenure > 10 years	0.26	0.26	0.26	-0.5
Personal Characteristics				
Age 16-17	0.01	0.02	0.01	**10.9**
Age 18-19	0.02	0.04	0.02	**9.5**
Age 20-21	0.03	0.03	0.02	**2.1**
Age 22-29	0.16	0.10	0.17	**-11.9**
Age 30-39	0.25	0.21	0.26	**-7.4**
Age 40-49	0.27	0.25	0.28	**-3.9**
Age 50-59	0.22	0.25	0.21	**5.9**
Age 60-64	0.04	0.08	0.03	**16.3**
Age 65 or more	0.01	0.02	0.00	**11.4**
Female	0.53	0.47	0.55	**-10.2**
Ethnicity – White	0.94	0.92	0.95	**-6.3**
Ethnicity – Mixed	0.01	0.01	0.01	0.1
Ethnicity – Asian	0.03	0.04	0.02	**5.5**
Ethnicity – Black	0.02	0.02	0.01	**3.7**
Ethnicity – Chinese or other	0.01	0.01	0.00	1.2
Married / Divorced / Widow(er)	0.78	0.77	0.79	**-2.3**
Job Information				
Firm size - Small	0.16	0.17	0.16	**3.1**
Firm size - Medium	0.32	0.38	0.30	**10.6**
Firm size - Med.Large	0.65	0.70	0.63	**7.9**
Firm size - Large	0.19	0.13	0.21	**-12.5**
In London	0.10	0.07	0.11	**-9.6**
Hours worked	36.32	33.57	37.20	**-18.8**
Part-Time	0.26	0.39	0.22	**23.7**
Union member	0.37	0.33	0.38	**-6.9**
Education				
Years of Schooling	13.34	11.58	13.91	**-52.8**
NVQ1 Basic	0.05	0.10	0.04	**19.1**
NVQ2 GCSE	0.15	0.20	0.14	**9.9**
NVQ3 Intermediate	0.29	0.25	0.30	**-6.8**
NVQ4 Degree	0.31	0.13	0.37	**-32.3**
NVQ5 Masters/PhD	0.07	0.01	0.09	**-9.6**

Bold t-statistic indicates significance at 95% level.

Table 3. Type of Computer Use Incidence by Selected Occupations.

OCCUPATION		BREAKDOWN OF COMPUTER USE						
	Obs.	Use any	Word processing	Spreadsheet	E-mail	Publishing	Programming	Other uses
Public sector occupations								
Primary Teacher	338	0.98	0.94	0.77	0.84	0.38	0.04	0.53
SecondaryTeacher	454	0.97	0.91	0.72	0.68	0.43	0.02	0.57
Nurses	546	0.76	0.44	0.49	0.54	0.06	0.00	0.34
HE FE Lecturer	210	0.98	0.95	0.72	0.93	0.33	0.13	0.49
Social Worker	132	0.95	0.80	0.63	0.83	0.14	0.00	0.33
Doctor	116	0.97	0.82	0.76	0.83	0.10	0.01	0.41
Civil Servant	496	1.00	0.81	0.87	0.97	0.11	0.01	0.48
Police	133	1.00	0.86	0.81	0.98	0.08	0.00	0.49
Private sector occupations								
Solicitor/Lawyer	93	1.00	0.94	0.66	1.00	0.06	0.00	0.41
Accountant/Actuary	178	1.00	0.96	0.90	0.99	0.15	0.06	0.67
Marketing Manager	298	0.97	0.90	0.82	0.94	0.26	0.04	0.68
Sales Rep	21	0.90	0.70	0.73	0.82	0.16	0.04	0.69
Both public and private sector								
Personnel Manager	156	0.99	0.91	0.83	0.97	0.19	0.01	0.57
Engineer	67	0.99	0.96	0.91	0.97	0.19	0.22	0.57
Lab Technician	251	0.93	0.72	0.75	0.83	0.16	0.10	0.68
Electrician	41	0.26	0.05	0.12	0.07	0.00	0.00	0.19
Drivers	523	0.28	0.08	0.17	0.11	0.02	0.00	0.18
Secretaries	896	0.98	0.85	0.80	0.85	0.17	0.00	0.58
Cleaners	507	0.10	0.04	0.05	0.05	0.00	0.00	0.05

Table 4. Determinants of computer use.

	(1)	(2)	(3)	(4)
Sample:	Everyone	Everyone	IT users	IT users
Estimator	Probit	Probit RE	Poisson count	Poisson count
Dependent:	IT - Use any	IT - Use any	# of tasks use IT for	# of tasks use IT for
Experience	0.005	0.004	-0.005	-0.006
	[0.001]***	[0.001]***	[0.001]***	[0.001]***
Exp Sq/100	-0.015	-0.011	0.005	0.007
	[0.002]***	[0.002]***	[0.003]	[0.003]**
Tenure 1-2	0.030	0.023	0.021	0.025
	[0.010]***	[0.008]***	[0.015]	[0.014]*
Tenure 2-5	0.062	0.045	0.027	0.032
	[0.008]***	[0.008]***	[0.012]	[0.012]**
Tenure 5-10	0.056	0.048	0.046	0.052
	[0.009]***	[0.008]***	[0.013]***	[0.014]***
Tenure >10	0.095	0.071	0.083	0.092
	[0.008]***	[0.008]***	[0.014]***	[0.014]***
Female	0.131	0.100	-0.053	-0.042
	[0.007]***	[0.008]***	[0.008]***	[0.008]***
Years Educ.	0.047	0.027	0.018	0.013
	[0.003]***	[0.003]***	[0.003]***	[0.003]***
nvq1 Basic	0.040	0.028	0.071	0.075
	[0.011]***	[0.010]***	[0.029]**	[0.029]***
nvq2 GCSE	0.136	0.082	0.220	0.218
	[0.007]***	[0.007]***	[0.022]***	[0.021]***
nvq3 Interm.	0.160	0.106	0.275	0.269
	[0.008]***	[0.008]***	[0.021]***	[0.021]***
nvq4 Degree	0.147	0.109	0.245	0.254
	[0.013]***	[0.011]***	[0.026]***	[0.026]***
nvq5 Masters	0.125	0.093	0.244	0.252
	[0.016]***	[0.011]***	[0.034]***	[0.026]
Eth-White	0.213	0.144	0.044	0.036
	[0.055]***	[0.060]**	[0.053]	[0.053]
Eth-Mixed	0.108	0.075	0.005	0.007
	[0.028]***	[0.020]***	[0.067]	[0.066]
Eth-Asian	0.052	0.032	-0.011	-0.017
	[0.035]	[0.031]	[0.059]	[0.058]
Eth-Black	0.020	0.099	-0.093	-0.083
	[0.042]	[0.038]***	[0.064]	[0.063]
Married	0.033	0.032	0.054	0.054
	[0.009]***	[0.008]***	[0.010]***	[0.010]***
Part-time	-0.179	-0.144	-0.255	-0.230
	[0.008]***	[0.010]***	[0.011]***	[0.011]***
Union	0.005	0.003	-0.112	-0.100
	[0.006]	[0.007]	[0.008]***	[0.009]***
Constant			1.096	1.152
			[0.068]***	[0.068]***
Workplace controls		Random effects		YES
Region controls	YES	YES	YES	YES
Observations	20668	20668	15655	15655
R-squared	0.22	0.50		

In all regressions: (***,**,*) refer to statistical significance at 99%, 95% and 90% levels. Notes: Columns (1) and (2) report marginal effects. In the second column, the random effects refer to workplace level effects. This is presented as an alternative to workplace level fixed effects model, which is not possible with Probit. The excluded ethnic category is “other ethnicity”.

Table 5. Return to computer use.

	(1)	(2)	(3)	(4)	(5)
Sample:	Everyone	Everyone	Everyone	Everyone	Everyone
Dependent:	log pay/h	log pay/h	log pay/h	log pay/h	log pay/h
IT - Use any	0.214	0.127	0.104	0.096	0.028
	[0.007]***	[0.007]***	[0.008]***	[0.008]***	[0.010]***
Experience	0.021	0.018	0.015	0.014	0.011
	[0.001]***	[0.001]***	[0.001]***	[0.001]***	[0.001]***
Exp Sq/100	-0.037	-0.032	-0.028	-0.026	-0.019
	[0.002]***	[0.002]***	[0.002]***	[0.002]***	[0.002]***
Tenure 1-2	0.024	0.025	0.010	0.010	0.014
	[0.010]**	[0.009]***	[0.009]	[0.009]	[0.011]
Tenure 2-5	0.059	0.041	0.036	0.034	0.033
	[0.008]***	[0.008]***	[0.007]***	[0.007]***	[0.010]***
Tenure 5-10	0.071	0.071	0.055	0.057	0.066
	[0.009]***	[0.009]***	[0.008]***	[0.008]***	[0.011]***
Tenure >10	0.146	0.136	0.108	0.109	0.109
	[0.009]***	[0.009]***	[0.008]***	[0.008]***	[0.011]***
Female	-0.163	-0.126	-0.115	-0.110	-0.075
	[0.006]***	[0.006]***	[0.006]***	[0.006]***	[0.008]***
Years Educ.	0.051	0.042	0.032	0.030	0.020
	[0.002]***	[0.002]***	[0.002]***	[0.002]***	[0.003]***
nvq1 Basic	0.003	0.006	-0.011	-0.002	0.006
	[0.014]	[0.013]	[0.012]	[0.012]	[0.016]
nvq2 GCSE	0.080	0.059	0.045	0.044	0.041
	[0.011]***	[0.010]***	[0.010]***	[0.010]***	[0.012]***
nvq3 Interm.	0.056	0.032	0.022	0.027	0.035
	[0.010]***	[0.010]***	[0.010]**	[0.010]***	[0.013]***
nvq4 Degree	0.155	0.132	0.066	0.070	0.057
	[0.015]***	[0.014]***	[0.014]***	[0.014]***	[0.018]***
nvq5 Masters	0.130	0.134	0.050	0.058	0.045
	[0.022]***	[0.020]***	[0.020]**	[0.020]***	[0.026]*
Eth-White	0.169	0.147	0.125	0.132	0.104
	[0.035]***	[0.034]***	[0.032]***	[0.032]***	[0.041]**
Eth-Mixed	0.122	0.126	0.097	0.105	0.114
	[0.045]***	[0.042]***	[0.040]**	[0.040]***	[0.051]**
Eth-Asian	0.041	0.069	0.041	0.054	0.039
	[0.038]	[0.037]*	[0.034]	[0.034]	[0.045]
Eth-Black	0.057	0.097	0.081	0.099	0.099
	[0.041]	[0.039]**	[0.036]**	[0.037]***	[0.046]**
Married	0.079	0.053	0.051	0.044	0.032
	[0.007]***	[0.007]***	[0.006]***	[0.006]***	[0.008]***
Part-time	-0.030	0.047	0.064	0.081	0.116
	[0.006]***	[0.007]***	[0.006]***	[0.006]***	[0.009]***
Union	0.039	0.031	0.051	0.044	0.008
	[0.006]***	[0.007]***	[0.006]***	[0.006]***	[0.009]
Constant	0.879	1.053	1.336	1.370	1.546
	[0.044]***	[0.043]***	[0.041]***	[0.042]***	[0.053]***
Workplace controls		YES			
Occupation controls			YES		
Occupation x Sector controls				YES	
Occupation x Workplace controls					YES
# of controlled groups		1721	344	1651	11232
Region Controls	YES	YES	YES	YES	YES
Observations	20668	20668	20668	20668	20668
R-squared	0.39	0.56	0.53	0.58	0.84

Table 6. Return to different uses of computers

	(1)	(2)	(3)	(4)	(5)
Sample:	Everyone	Everyone	Everyone	Everyone	Everyone
Dependent:	log pay/h	log pay/h	log pay/h	log pay/h	log pay/h
IT - Word	0.112	0.085	0.066	0.059	0.046
	[0.008]***	[0.008]***	[0.007]***	[0.008]***	[0.010]***
IT - Excel	-0.000	-0.013	-0.009	-0.013	-0.021
	[0.007]	[0.007]*	[0.006]	[0.007]*	[0.008]**
IT - Mail	0.197	0.133	0.126	0.113	0.076
	[0.008]***	[0.009]***	[0.008]***	[0.008]***	[0.011]***
IT - Publish	-0.018	0.006	-0.020	-0.010	-0.002
	[0.008]**	[0.008]	[0.007]***	[0.008]	[0.011]
IT - Program	0.100	0.049	0.060	0.050	0.048
	[0.014]***	[0.014]***	[0.014]***	[0.015]***	[0.022]**
IT - Other	-0.014	-0.011	-0.005	-0.002	-0.010
	[0.005]**	[0.005]*	[0.005]	[0.005]	[0.007]
Experience	0.020	0.018	0.015	0.014	0.011
	[0.001]***	[0.001]***	[0.001]***	[0.001]***	[0.001]***
Exp Sq/100	-0.036	-0.032	-0.027	-0.025	-0.019
	[0.002]***	[0.002]***	[0.002]***	[0.002]***	[0.002]***
Tenure 1-2	0.022	0.024	0.010	0.010	0.014
	[0.009]**	[0.009]***	[0.009]	[0.009]	[0.011]
Tenure 2-5	0.056	0.040	0.037	0.035	0.033
	[0.008]***	[0.008]***	[0.007]***	[0.007]***	[0.010]***
Tenure 5-10	0.071	0.069	0.056	0.057	0.065
	[0.009]***	[0.009]***	[0.008]***	[0.008]***	[0.011]***
Tenure >10	0.145	0.131	0.108	0.109	0.109
	[0.009]***	[0.009]***	[0.008]***	[0.008]***	[0.011]***
Female	-0.172	-0.132	-0.116	-0.111	-0.074
	[0.005]***	[0.006]***	[0.006]***	[0.006]***	[0.008]***
Years Educ.	0.042	0.038	0.029	0.028	0.019
	[0.002]***	[0.002]***	[0.002]***	[0.002]***	[0.003]***
nvq1 Basic	0.011	0.008	-0.007	0.001	0.005
	[0.013]	[0.013]	[0.012]	[0.012]	[0.015]
nvq2 GCSE	0.064	0.052	0.042	0.044	0.040
	[0.010]***	[0.010]***	[0.009]***	[0.010]***	[0.012]***
nvq3 Interm.	0.041	0.025	0.020	0.027	0.034
	[0.010]***	[0.010]**	[0.010]**	[0.010]***	[0.012]***
nvq4 Degree	0.141	0.126	0.065	0.070	0.057
	[0.014]***	[0.014]***	[0.014]***	[0.014]***	[0.018]***
nvq5 Masters	0.114	0.128	0.048	0.055	0.043
	[0.021]***	[0.020]***	[0.020]**	[0.020]***	[0.025]*
Married	0.073	0.051	0.049	0.043	0.033
	[0.007]***	[0.007]***	[0.006]***	[0.006]***	[0.008]***
Part-time	0.010	0.063	0.078	0.092	0.123
	[0.006]	[0.007]***	[0.006]***	[0.006]***	[0.009]***
Union	0.056	0.041	0.053	0.046	0.008
	[0.005]***	[0.006]***	[0.006]***	[0.006]***	[0.009]
Constant	1.002	1.085	1.350	1.374	1.527
	[0.043]***	[0.042]***	[0.040]***	[0.041]***	[0.053]***
Workplace controls		YES			
Occupation controls			YES		
Occupation x Sector controls				YES	
Occupation x Workplace controls					YES
# of controlled groups		1721	344	1651	11232
Region controls	YES	YES	YES	YES	YES
Ethnicity controls	YES	YES	YES	YES	YES
Observations	20668	20668	20668	20668	20668
R-squared	0.43	0.57	0.54	0.59	0.84

In all regressions: (***,**,*) refer to statistical significance at 99%, 95% and 90% levels.

Table 7. Return to intensity of computer use.

	(1)	(2)	(3)	(4)	(5)
Sample:	Everyone	Everyone	Everyone	Everyone	Everyone
Dependent:	log pay/h	log pay/h	log pay/h	log pay/h	log pay/h
Use IT for 1 task	0.061	0.042	0.047	0.051	-0.004
	[0.010]***	[0.010]***	[0.010]***	[0.010]***	[0.013]
Use IT for 2 tasks	0.184	0.125	0.103	0.098	0.039
	[0.010]***	[0.010]***	[0.010]***	[0.010]***	[0.013]***
Use IT for 3 tasks	0.225	0.139	0.124	0.110	0.045
	[0.010]***	[0.010]***	[0.010]***	[0.010]***	[0.014]***
Use IT for 4 tasks	0.259	0.155	0.143	0.127	0.064
	[0.009]***	[0.010]***	[0.010]***	[0.010]***	[0.014]***
Use IT for 5 tasks	0.273	0.170	0.150	0.135	0.053
	[0.009]***	[0.010]***	[0.010]***	[0.011]***	[0.014]***
Use IT for 6 tasks	0.269	0.169	0.141	0.125	0.051
	[0.010]***	[0.011]***	[0.011]***	[0.011]***	[0.016]***
Use IT for 7 tasks	0.272	0.173	0.140	0.126	0.046
	[0.012]***	[0.012]***	[0.012]***	[0.013]***	[0.018]**
Use IT for 8+ tasks	0.274	0.183	0.139	0.130	0.075
	[0.012]***	[0.012]***	[0.012]***	[0.012]***	[0.018]***
Experience	0.021	0.019	0.016	0.015	0.012
	[0.001]***	[0.001]***	[0.001]***	[0.001]***	[0.001]***
Exp Sq/100	-0.037	-0.032	-0.028	-0.026	-0.019
	[0.002]***	[0.002]***	[0.002]***	[0.002]***	[0.002]***
Tenure 1-2	0.022	0.024	0.009	0.009	0.015
	[0.010]**	[0.009]***	[0.009]	[0.009]	[0.011]
Tenure 2-5	0.056	0.039	0.036	0.034	0.032
	[0.008]***	[0.008]***	[0.007]***	[0.007]***	[0.010]***
Tenure 5-10	0.070	0.069	0.055	0.057	0.066
	[0.009]***	[0.009]***	[0.008]***	[0.008]***	[0.011]***
Tenure >10	0.141	0.131	0.106	0.107	0.108
	[0.009]***	[0.009]***	[0.008]***	[0.008]***	[0.011]***
Female	-0.167	-0.129	-0.114	-0.110	-0.074
	[0.006]***	[0.006]***	[0.006]***	[0.006]***	[0.008]***
Years Educ.	0.047	0.040	0.031	0.029	0.020
	[0.002]***	[0.002]***	[0.002]***	[0.002]***	[0.003]***
nvq1 Basic	0.004	0.005	-0.010	-0.002	0.007
	[0.014]	[0.013]	[0.012]	[0.012]	[0.016]
nvq2 GCSE	0.067	0.052	0.042	0.042	0.040
	[0.010]***	[0.010]***	[0.010]***	[0.010]***	[0.012]***
nvq3 Interm.	0.041	0.023	0.017	0.024	0.034

	[0.010]***	[0.010]**	[0.010]*	[0.010]**	[0.012]***
nvq4 Degree	0.145	0.124	0.062	0.067	0.056
	[0.015]***	[0.014]***	[0.014]***	[0.014]***	[0.018]***
nvq5 Masters	0.121	0.127	0.046	0.054	0.042
	[0.021]***	[0.020]***	[0.020]**	[0.020]***	[0.026]*
Married	0.074	0.050	0.050	0.043	0.031
	[0.007]***	[0.007]***	[0.006]***	[0.006]***	[0.008]***
Part-time	-0.006	0.058	0.071	0.087	0.120
	[0.006]	[0.007]***	[0.006]***	[0.006]***	[0.009]***
Union	0.049	0.036	0.051	0.044	0.008
	[0.006]***	[0.007]***	[0.006]***	[0.006]***	[0.009]
Constant	0.923	1.060	1.333	1.363	1.534
	[0.044]***	[0.042]***	[0.041]***	[0.041]***	[0.053]***
Workplace controls		YES			
Occupation controls			YES		
Occupation x Sector controls				YES	
Occupation x Workplace controls					YES
# of controlled groups		1721	344	1651	11232
Region controls	YES	YES	YES	YES	YES
Ethnicity controls	YES	YES	YES	YES	YES
Observations	20668	20668	20668	20668	20668
R-squared	0.41	0.56	0.54	0.58	0.84

In all regressions: (***,**,*) refer to statistical significance at 99%, 95% and 90% levels.

Table 8. Treatment effects models.

	(1A)	(1B)	(2A)	(2B)
Model:	Treatment Effects Model of IT use	Selection Equation	Treatment Effects Model of IT use	Selection Equation
Dependent:	log pay/h	IT - Use any	log pay/h	IT - Use any
IT - Use any	0.118		0.142	
	[0.023]***		[0.023]***	
Computers Upgraded				0.148
				[0.025]***
Experience	0.021	0.021	0.021	0.020
	[0.001]***	[0.004]***	[0.001]***	[0.004]***
Exp Sq/100	-0.039	-0.055	-0.038	-0.054
	[0.002]***	[0.007]***	[0.002]***	[0.007]***
Tenure 1-2	0.026	0.118	0.026	0.119
	[0.010]***	[0.039]***	[0.010]***	[0.040]***
Tenure 2-5	0.065	0.244	0.063	0.246
	[0.008]***	[0.034]***	[0.008]***	[0.034]***
Tenure 5-10	0.077	0.225	0.075	0.228
	[0.009]***	[0.037]***	[0.009]***	[0.037]***
Tenure >10	0.155	0.383	0.153	0.384
	[0.009]***	[0.037]***	[0.009]***	[0.037]***
Female	-0.152	0.482	-0.155	0.483
	[0.006]***	[0.024]***	[0.006]***	[0.024]***
Years Educ.	0.054	0.175	0.053	0.174
	[0.002]***	[0.010]***	[0.002]***	[0.010]***
nvq1 Basic	0.012	0.157	0.010	0.155
	[0.014]	[0.048]***	[0.014]	[0.049]***
nvq2 GCSE	0.105	0.620	0.098	0.620
	[0.012]***	[0.038]***	[0.012]***	[0.038]***
nvq3 Interm.	0.086	0.677	0.079	0.675
	[0.013]***	[0.040]***	[0.013]***	[0.040]***
nvq4 Degree	0.184	0.605	0.177	0.601
	[0.016]***	[0.060]***	[0.016]***	[0.060]***
nvq5 Masters	0.155	0.601	0.149	0.594
	[0.022]***	[0.103]***	[0.022]***	[0.103]***
Eth-White	0.184	0.637	0.180	0.649
	[0.036]***	[0.147]***	[0.036]***	[0.147]***
Eth-Mixed	0.134	0.504	0.131	0.513
	[0.045]***	[0.185]***	[0.045]***	[0.185]***
Eth-Asian	0.045	0.202	0.044	0.206
	[0.038]	[0.158]	[0.038]	[0.157]
Eth-Black	0.057	0.068	0.057	0.078
	[0.041]	[0.167]	[0.041]	[0.166]
Married	0.082	0.119	0.081	0.115
	[0.007]***	[0.031]***	[0.007]***	[0.031]***
Part-time	-0.045	-0.599	-0.041	-0.596
	[0.007]***	[0.026]***	[0.007]***	[0.026]***
Union	0.039	0.012	0.039	0.013
	[0.006]***	[0.024]	[0.006]***	[0.024]
Constant	0.866	-2.961	0.869	-3.063
	[0.044]***	[0.191]***	[0.044]***	[0.191]***
Region controls	YES	YES	YES	YES
Rho (Inv. Mills Ratio)	0.155		0.117	
	[0.036]***		[0.036]***	
Observations	20668	20668	20668	20668

Table 9. Instrumental Variable results

Model:	One IV	One IV	Multiple IVs	Multiple IVs
	1st Stage	2nd Stage	1st Stage	2nd Stage
Dependent:	IT - Use any	log pay/h	IT - Use any	log pay/h
IT – Use any (instrumented)		0.280		0.219
		[0.135]**		[0.061]***
Computers upgraded	0.044		0.017	
	[0.006]***		[0.007]**	
Other technology upgraded			0.034	
			[0.006]***	
Comp upgrades had great impact			0.055	
			[0.008]***	
Other tech upgrades had great impact			-0.002	
			[0.009]	
Computing outsourced			0.053	
			[0.006]***	
Computing insourced			0.094	
			[0.020]***	
Experience	0.006	0.013	0.005	0.014
	[0.001]***	[0.001]***	[0.001]***	[0.001]***
Exp Sq/100	-0.015	-0.023	-0.015	-0.024
	[0.002]***	[0.003]***	[0.002]***	[0.002]***
Tenure 1-2	0.030	0.005	0.030	0.006
	[0.010]***	[0.010]	[0.010]***	[0.009]
Tenure 2-5	0.060	0.022	0.060	0.026
	[0.009]***	[0.011]**	[0.009]***	[0.008]***
Tenure 5-10	0.058	0.046	0.059	0.049
	[0.009]***	[0.011]***	[0.009]***	[0.009]***
Tenure >10	0.097	0.089	0.097	0.095
	[0.009]***	[0.015]***	[0.009]***	[0.010]***
Female	0.111	-0.142	0.112	-0.136
	[0.006]***	[0.016]***	[0.006]***	[0.009]***
Years Educ.	0.031	0.022	0.030	0.024
	[0.002]***	[0.005]***	[0.002]***	[0.003]***
nvq1 Basic	0.093	-0.024	0.093	-0.018
	[0.014]***	[0.018]	[0.014]***	[0.014]
nvq2 GCSE	0.260	-0.019	0.257	-0.003
	[0.011]***	[0.036]	[0.011]***	[0.018]
nvq3 Interm.	0.308	-0.048	0.305	-0.029
	[0.011]***	[0.043]	[0.011]***	[0.021]
nvq4 Degree	0.300	-0.002	0.299	0.017
	[0.015]***	[0.043]	[0.015]***	[0.023]
nvq5 Masters	0.259	-0.005	0.260	0.011
	[0.022]***	[0.040]	[0.022]***	[0.026]
Married	0.033	0.036	0.034	0.038
	[0.007]***	[0.008]***	[0.007]***	[0.007]***
Part-time	-0.152	0.117	-0.149	0.107
	[0.007]***	[0.022]***	[0.007]***	[0.011]***
Union	0.002	0.047	0.004	0.047
	[0.006]	[0.006]***	[0.006]	[0.006]***
Constant	-0.166	1.452	-0.176	1.443
	[0.046]***	[0.045]***	[0.046]***	[0.042]***
Occupation x Sector controls		YES		YES
Region controls	YES	YES	YES	YES
Ethnicity controls	YES	YES	YES	YES
Observations	20668	20668	20668	20668
R-squared	0.22	0.15	0.23	0.15

Table 10. How the individual wages are affected by the computer use at the workplace level.

	(2)	(3)	(2)	(3)
Sample:	Don't use IT	Don't use IT	IT users	IT users
Dependent:	log pay/h	log pay/h	log pay/h	log pay/h
% of workers using computer at the workplace	0.023	0.027	0.136	0.126
	[0.019]	[0.022]	[0.009]***	[0.010]***
Experience	0.010	0.008	0.017	0.016
	[0.002]***	[0.002]***	[0.001]***	[0.001]***
Exp Sq/100	-0.018	-0.014	-0.030	-0.027
	[0.003]***	[0.003]***	[0.002]***	[0.002]***
Tenure 1-2	0.005	0.007	0.013	0.013
	[0.017]	[0.018]	[0.010]	[0.010]
Tenure 2-5	0.027	0.025	0.044	0.041
	[0.015]*	[0.016]	[0.008]***	[0.008]***
Tenure 5-10	0.046	0.042	0.065	0.066
	[0.017]***	[0.018]**	[0.009]***	[0.009]***
Tenure >10	0.070	0.078	0.125	0.124
	[0.017]***	[0.018]***	[0.009]***	[0.009]***
Female	-0.140	-0.131	-0.111	-0.104
	[0.015]***	[0.016]***	[0.006]***	[0.007]***
Years Educ.	0.016	0.014	0.031	0.030
	[0.005]***	[0.006]**	[0.002]***	[0.002]***
nvq1 Basic	-0.009	-0.003	-0.016	-0.010
	[0.018]	[0.019]	[0.017]	[0.018]
nvq2 GCSE	0.031	0.034	0.051	0.046
	[0.015]**	[0.016]**	[0.013]***	[0.013]***
nvq3 Interm.	0.020	0.025	0.031	0.032
	[0.018]	[0.018]	[0.013]**	[0.013]**
nvq4 Degree	0.038	0.048	0.081	0.078
	[0.029]	[0.031]	[0.017]***	[0.017]***
nvq5 Masters	-0.058	-0.036	0.070	0.069
	[0.060]	[0.064]	[0.022]***	[0.023]***
Eth-White	0.172	0.177	0.082	0.086
	[0.063]***	[0.064]***	[0.037]**	[0.037]**
Eth-Mixed	0.209	0.210	0.040	0.051
	[0.080]***	[0.082]**	[0.045]	[0.046]
Eth-Asian	0.121	0.123	0.006	0.012
	[0.067]*	[0.068]*	[0.040]	[0.040]
Eth-Black	0.157	0.155	0.039	0.058
	[0.070]**	[0.072]**	[0.042]	[0.043]
Married	0.022	0.018	0.062	0.054
	[0.014]	[0.015]	[0.007]***	[0.007]***
Part-time	0.137	0.144	0.038	0.059
	[0.014]***	[0.014]***	[0.007]***	[0.007]***
Union	0.062	0.054	0.043	0.037
	[0.012]***	[0.013]***	[0.006]***	[0.007]***
Constant	1.408	1.444	1.408	1.438
	[0.087]***	[0.090]***	[0.047]***	[0.048]***
Occupation controls	YES		YES	
Occupation x Sector controls		YES		YES
Region controls	YES	YES	YES	YES
Observations	5007	5007	15642	15642
R-squared	0.38	0.44	0.52	0.58

In all regressions: (***,**,*) refer to statistical significance at 99%, 95% and 90% levels

Table 11. Robustness checks with interval regression and sample weights.

	(1)	(2)	(3)	(4)
Model:	OLS	Interval Regression	OLS + Sample weights	Interval Regression + Sample weights
Sample:	Everyone	Everyone	Everyone	Everyone
Dependent:	Log Weekly Earnings	Log Weekly Earnings	Log Weekly Earnings	Log Weekly Earnings
IT - Use any	0.284	0.274	0.296	0.276
	[0.007]***	[0.016]***	[0.008]***	[0.017]***
Experience	0.027	0.024	0.029	0.025
	[0.001]***	[0.002]***	[0.001]***	[0.002]***
Exp Sq/100	-0.050	-0.048	-0.053	-0.049
	[0.002]***	[0.004]***	[0.002]***	[0.004]***
Tenure 1-2	0.027	0.027	0.028	0.027
	[0.010]**	[0.024]	[0.011]**	[0.024]
Tenure 2-5	0.074	0.106	0.077	0.109
	[0.009]***	[0.020]***	[0.009]***	[0.021]***
Tenure 5-10	0.095	0.121	0.099	0.126
	[0.010]***	[0.022]***	[0.010]***	[0.023]***
Tenure >10	0.166	0.237	0.170	0.245
	[0.010]***	[0.021]***	[0.010]***	[0.022]***
Female	-0.218	-0.190	-0.227	-0.200
	[0.006]***	[0.012]***	[0.006]***	[0.012]***
Years Educ.	0.048	0.043	0.050	0.047
	[0.002]***	[0.004]***	[0.002]***	[0.005]***
nvq1 Basic	0.024	0.031	0.026	0.029
	[0.015]	[0.027]	[0.015]*	[0.027]
nvq2 GCSE	0.070	0.098	0.072	0.096
	[0.011]***	[0.024]***	[0.012]***	[0.024]***
nvq3 Interm.	0.048	0.052	0.049	0.046
	[0.011]***	[0.023]**	[0.012]***	[0.023]**
nvq4 Degree	0.154	0.206	0.155	0.197
	[0.016]***	[0.031]***	[0.017]***	[0.032]***
nvq5 Masters	0.149	0.196	0.158	0.194
	[0.023]***	[0.045]***	[0.024]***	[0.047]***
Married	0.101	0.070	0.107	0.075
	[0.008]***	[0.014]***	[0.008]***	[0.014]***
Part-time	-0.811	-0.706	-0.823	-0.707
	[0.007]***	[0.019]***	[0.007]***	[0.020]***
Union	0.071	0.050	0.069	0.044
	[0.006]***	[0.011]***	[0.006]***	[0.012]***
Constant	4.496	4.715	4.439	4.648
	[0.048]***	[0.073]***	[0.050]***	[0.079]***
Region controls	YES	YES	YES	YES
Ethnicity controls	YES	YES	YES	YES
Observations	20585	20585	20585	20585
R-squared	0.66	0.63		

In all regressions: (***,**,*) refer to statistical significance at 99%, 95% and 90% levels

APPENDIX

Construction of variables

Ln Hourly Pay – In WERS 2004, workers are asked about their weekly pay, broken down to 14 categories, of which the highest and lowest are open ended. We assume the weekly pay to be simply the midpoint within the interval, or the border-value in the open-ended categories. As a robustness check, we also run an interval regression (Table 11). We calculate the hourly pay by dividing the weekly pay with self-reported hours worked per week. The workers also respond separately to a question about their hourly pay, which has only 4 categories and more missing observations, but correlates with our measure by 0.55. We maximise the number of observations available further by using the self-reported hourly pay in the case that our measure is missing. This increases the number of observations from 21201 to 21645, after we remove top and bottom 1% due to obvious outliers.

Years of Education – Derived using the standard equivalents of different degree combinations: For individuals with minimum schooling, we assume the years of education to be either 10 or 11, depending on whether they are born before or after 1957. GCSEs correspond to 11 years, one A-level adding 1 year more, and 2 or more A-levels adding 2 years more. A person with a first degree is assumed to have 16 years, while higher degree (MSc/MA/PhD) adds up to 18. To these basic assumptions, we add one year, if a person reports having a vocational qualification at NVQ levels 3-5 or an apprenticeship, and a further year for any "other vocational or pre-vocational qualifications". "Other professional qualifications", typically corresponding to nurses, teachers and accountants, we count as additional two years. The resulting distribution is as follows:

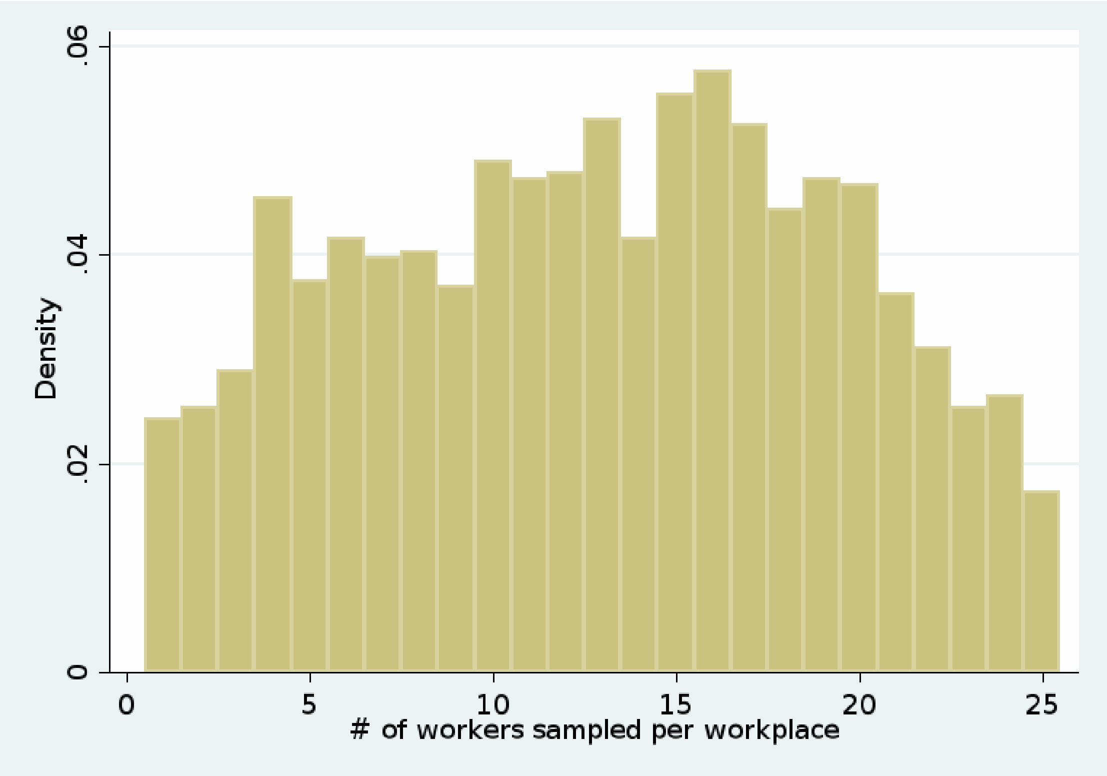
Years	N	%
10	3,058	13.62
11	4,876	21.72
12	3,887	17.31
13	3,145	14.01
14	909	4.05
15	527	2.35
16	1,902	8.47
17	784	3.49
18	2,369	10.55
19	132	0.59
20	863	3.84
Total	22,452	100

Age – Midpoints from 9 answer options, except for the case “65+”, where we assume the age to be 65. This variable is not used in the regressions.

Experience – Assumed to be Age minus Years of Education minus 5.

Other variables: Tenure, Female, particular qualifications, Ethnic groups and union membership are self-explanatory dummy variables. Part-time status is assumed if the worker reports less than 35 weekly hours. The variable ‘Married’ accounts also includes divorced and widow(er)s. For region dummies, we use Government Office Regions.

Figure A1. Number of workers sampled over 1733 workplaces



Instrumental variables used in the study.

Pabilonia and Zoghi (2005) use new process improvements in the workplace as an exogenous source of variation in computer use. We experiment with instrumental variable estimations using similar information, available from WERS 2004. Specifically, the survey asks managers whether (1) computers have been upgraded, and (2) whether it had a "great impact" on work practices. Also whether (3) other technology has been upgraded, and (4) whether it had a great impact. Further, we have information whether firms have (5) outsourced of (6) insourced computing services. Theses candidates for instruments are summarised below by sector.

Table A1. IT and Technological Change, by Sector.

	Computer upgrades	Other tech upgrades	Comp. upgr. big impact	Tech. upgr. big impact	Outsource computing	Insource computing
Manufacturing	0.79	0.71	0.10	0.16	0.23	0.04
Electricity, gas and water	0.63	0.62	0.03	0.04	0.41	0.00
Construction	0.85	0.68	0.18	0.16	0.27	0.02
Wholesale and retail	0.70	0.56	0.09	0.13	0.28	0.01
Hotels and restaurants	0.65	0.59	0.16	0.09	0.22	0.00
Transport and Communication	0.68	0.62	0.07	0.11	0.27	0.01
Financial services	0.73	0.64	0.14	0.10	0.36	0.03
Other business services	0.82	0.55	0.25	0.05	0.24	0.01
Public administration	0.81	0.51	0.22	0.06	0.33	0.01
Education	0.85	0.63	0.20	0.10	0.24	0.02
Health	0.80	0.50	0.17	0.06	0.16	0.01
Other community services	0.78	0.55	0.15	0.07	0.20	0.00

Column 1 of Table 9 shows the first stage of an instrumental variable model, where only computer upgrades is used as the instrument. We believe this instrument to be closest to the one used by Pabilonia and Zoghi (2005). In the third column, we use all of our six instrumental candidates. Five out of six are significant predictors of individual level computer use in the firm. It is uncertain whether instruments such as these are “exogenous” as required by the IV estimator, and we have no direct way of testing it.

Below we report the Durbin-Wu-Hausman test (see Sargan (1958), Wu (1973), Hausman (1978), Davidson and McKinnon (1993), Bound et al (1995)), for the endogeneity of the compute use variable for the estimations reported in Table 5. These test statistics give us some evidence of the endogenity of this variable when occupational controls are not included and suggests the possibility that the variable is not endogenous when occupations or occupations and workplace dummies are included.

Table A2. Tests for endogeneity of computer use (corresponding to Table 5 – Columns 1,2 and 4)

	Durbin-Wu-Hausman test: H0: Computer use is Exogenous Instrument: Computers Upgraded t-statistic
OLS	5.32 Rejects H0 at 95% level
Occupation Controls	1.62 Does not reject H0 at 95% level
Occupation X Industry Controls	1.78 Does not reject H0 at 95% level

Table A3. Firm level productivity and computer use.

	(1)	(2)	(3)	(4)
Dependent:	ln Turnover	ln Turnover	ln Turnover	ln Labour Productivity
% Using computer	0.426	0.474	0.440	0.734
	[0.173]**	[0.180]***	[0.181]**	[0.211]***
Communicate: e-mail		-0.114	-0.112	-0.190
		[0.121]	[0.121]	[0.146]
Computers upgraded			0.093	0.016
			[0.121]	[0.143]
ln Employment	0.281	0.286	0.284	-0.461
	[0.043]***	[0.043]***	[0.043]***	[0.056]***
% Female	-0.232	-0.235	-0.218	-0.232
	[0.194]	[0.194]	[0.193]	[0.231]
% Managers	-0.388	-0.372	-0.394	0.375
	[0.502]	[0.502]	[0.501]	[0.616]
% Professionals	-0.738	-0.733	-0.778	-0.251
	[0.336]**	[0.336]**	[0.336]**	[0.422]
% Technical staff	-0.335	-0.299	-0.327	0.159
	[0.298]	[0.301]	[0.300]	[0.367]
% College Degree	-0.656	-0.640	-0.544	-1.056
	[0.390]*	[0.390]	[0.391]	[0.481]**
% Not unionised	0.299	0.297	0.276	0.275
	[0.128]**	[0.128]**	[0.128]**	[0.154]*
ln Purchases	0.591	0.594	0.595	0.270
	[0.030]***	[0.030]***	[0.030]***	[0.037]***
ln Capital	0.118	0.117	0.114	0.163
	[0.030]***	[0.030]***	[0.030]***	[0.036]***
Constant	-0.865	-0.768	-0.962	-1.291
	[2.127]	[2.129]	[2.128]	[2.892]
Region controls	YES	YES	YES	YES
Age controls	YES	YES	YES	YES
Ethnicity controls	YES	YES	YES	YES
Observations	671	671	669	506
R-squared	0.76	0.77	0.77	0.31

Construction of the data:

WERS2004 includes a subsample of workplaces that report their financial information. The size of this subsample is 1070 workplaces, out of which 863 report financial information that that refers to the reporting establishment only. The final sample in the regressions is smaller due to missing observations in the dependent variables. The financial data is the source for variables on Employment, Purchases, Capital, Turnover and Labour Productivity. Capital is defined as the sum of the value of used buildings and other assets (both owned and rented). Missing dummies are used for Employment (12% of observations), purchases (9%) and Capital (15%). Proportions of the workforce who use computer, are female, or belong to a certain occupational category, are from the manager survey of WERS. Proportions of workers with A-levels and GCSEs are controlled, but not shown. Variables for education, age and ethnicity are calculated from the WERS workplace sample, based on average on 13 workers per workplace.

Table A4. Sample selection models

	(1A)	(1B)	(2A)	(2B)
Model:	Sample Selection Model (select into IT use)	Selection Equation	Sample Selection Model (select into non IT use)	Selection Equation
Dependent:	log pay/h	IT - Use any	log pay/h	Don't use IT
Experience	0.023	0.020	0.007	-0.019
	[0.001]***	[0.004]***	[0.002]***	[0.004]***
Exp Sq/100	-0.040	-0.054	-0.007	0.050
	[0.002]***	[0.007]***	[0.004]	[0.007]***
Tenure 1-2	0.025	0.116	-0.034	-0.094
	[0.011]**	[0.040]***	[0.023]	[0.038]**
Tenure 2-5	0.059	0.242	-0.045	-0.215
	[0.009]***	[0.034]***	[0.020]**	[0.033]***
Tenure 5-10	0.071	0.222	-0.012	-0.199
	[0.010]***	[0.037]***	[0.022]	[0.036]***
Tenure >10	0.151	0.383	-0.027	-0.349
	[0.010]***	[0.037]***	[0.022]	[0.036]***
Female	-0.156	0.480	-0.370	-0.478
	[0.007]***	[0.024]***	[0.015]***	[0.024]***
Years Educ.	0.051	0.174	-0.048	-0.171
	[0.002]***	[0.010]***	[0.007]***	[0.010]***
nvq1 Basic	0.007	0.159	-0.004	-0.119
	[0.020]	[0.049]***	[0.026]	[0.047]**
nvq2 GCSE	0.108	0.623	-0.153	-0.536
	[0.016]***	[0.038]***	[0.021]***	[0.036]***
nvq3 Interm.	0.088	0.681	-0.164	-0.589
	[0.016]***	[0.040]***	[0.023]***	[0.038]***
nvq4 Degree	0.189	0.608	-0.067	-0.481
	[0.020]***	[0.060]***	[0.036]*	[0.058]***
nvq5 Masters	0.167	0.598	-0.211	-0.493
	[0.026]***	[0.102]***	[0.068]***	[0.100]***
Eth-White	0.117	0.645	-0.015	-0.586
	[0.041]***	[0.146]***	[0.083]	[0.142]***
Eth-Mixed	0.051	0.517	0.054	-0.457
	[0.052]	[0.184]***	[0.106]	[0.179]**
Eth-Asian	-0.004	0.210	0.075	-0.178
	[0.045]	[0.156]	[0.089]	[0.151]
Eth-Black	-0.004	0.078	0.135	-0.014
	[0.048]	[0.165]	[0.094]	[0.160]
Married	0.092	0.118	0.011	-0.118
	[0.008]***	[0.031]***	[0.018]	[0.030]***
Part-time	-0.075	-0.596	0.278	0.641
	[0.008]***	[0.026]***	[0.016]***	[0.025]***
Union	0.030	0.020	0.078	-0.027
	[0.006]***	[0.024]	[0.014]***	[0.023]
Constant	1.086	-2.960	1.924	2.729
	[0.058]***	[0.189]***	[0.112]***	[0.185]***
Region controls	YES	YES	YES	YES
Rho (Inv. Mills ratio)	0.010		0.936	
	[0.042]		[0.005]***	
Observations	20668	20668	20668	20668