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Computer Use and Earnings

Mary A. Silles

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This paper uses longitudinal data for the UK to investigate the observed correlation between computer use at work and labor market earnings. Our findings suggest that there are no returns to computer use at work. This is evidence against the productivity interpretation of these returns and supports the view that the premium can be attributed to unobserved characteristics.

1. Introduction

Various studies have shown that individuals who use computers at work earn more than otherwise similar workers who do not use computers. Using the US Current Population Survey (CPS) for 1984 and 1989, Krueger (1993) estimated a wage premium of 10 to 15 percent. Autor et al. (1997), using the same data, showed that the rate of return to computer use rose to 20 percent in 1993. Using data from the Skills Survey for Great Britain, Borghans and ter Weel (2001) also estimated a computer premium of 17 to 21 percent. While many authors have interpreted these findings as evidence that computers have had a direct influence on earnings, some analysts have been cautious to draw inferences about a causal relation.

Concerns about a causal relationship between computer use and earnings originated from the observation that computer users appear to have characteristics, such as higher ability or more education, which are associated with higher wages. Most notably, DiNardo and Pischke (1997) cast doubt on the literal interpretation of the computer use wage differential as reflecting the returns to computer skills¹. These authors conjecture that other individual unmeasured differences that happen to be correlated with computer use at work were the primary cause of the computer wage differential. Another argument against the literal interpretation is that workers who use a computer at work would have

¹ DiNardo and Pischke (1997) estimated the rate of return to computer use was at 11 percent in 1979, rising to 16 percent in 1985/86 and 17 percent in 1991/92 using data for German workers.

had higher wages even in the absence of the technology i.e., higher wages, which reflect a higher opportunity cost of time, cause workers to use computers.

In this paper, we examine the observed correlation between computer use at work and wages. We use data from the National Child Development Study of Great Britain which contains information about an entire cohort of children born in one week in 1958. Comprehensive information has been collected from birth through until the present with earnings data available for individuals in 1991 and 2000. A variety of estimation methods are used to investigate the increase in earnings associated with computer use at work. The results support the view that the returns to computer use are capturing unobserved characteristics.

The remainder of this paper is organised as follows. The next section describes the data sets used and offers some descriptive statistics. Section III presents and discusses the results. In section IV we summarise and provide some concluding remarks.

2. Data

The National Child Development Study (NCDS) is a continuing longitudinal study which is seeking to follow the lives of all those living in Great Britain who were born between 3rd and 9th March, 1958. Since then there have been six successive waves of the survey, with the last wave in 2000. Information has been collected regarding earnings and computer use at work from the latest two sweeps in 1991 when the cohort members were 33 years of age and 2000 when they were 42. The early sweeps give information on early test scores, family background and schooling. Later sweeps contain updated information on educational attainment, extensive labor market information and other socio-economic data. The variables used in our analysis are defined in the Appendix.

There are two benefits to using this data over other studies. The data set consists of individuals who are all the same age. Therefore, we can ignore any complications related to age or cohort effects as everyone in the survey has experienced the same aggregate labor market conditions and been exposed to the same technological advances. These individuals would have acquired computer skills at school and would have been present in the labor market in the early 1980s when computers technology was first introduced to the general workplace.

The computer variable used in the present paper is simply defined as a dummy variable identifying whether or not an individual uses a computer at work. Over the course of our data, the percentage of workers who use a computer increased from 56 percent in 1991 to 76 percent in 2000.

Our sample is based on individuals who participated in both the fifth and sixth sweeps of the survey for whom there is relevant information on wages, computer use and all our control variables. Our sample is restricted to men who were in full-time employment with all self-employed and part-time workers being omitted. This leaves us with a sample size of 1,370.

3. The wage returns to computer use

Our general approach is to augment a standard earning function with a variable for whether or not an individual uses a computer at work. The n individuals are indexed by i and the time periods by t . The underlying econometric model is of the following form:

$$\ln y_{it} = \alpha_i + \lambda_t + \delta C_{it} + \beta X_{it} + \mu_{it} \quad i=1,2,..n; t=1,2 \quad (1)$$

where y refers to real gross hourly wages², α is an individual specific effect, δ and β are parameters to be estimated, C is a dummy variable equal to 1 if the individual uses a computer at work and zero otherwise, X is a vector of control variables, and μ is the error term.

Following Krueger (1993) and others in this literature, Table I presents the results of fitting equation (1) by OLS. The first specification is a human capital model where the control variables include educational qualifications. The second specifications adds an elaborate number of covariates for test scores at age 7, occupational classification, firm size, union affiliation, marriage and children. Even after including the wider set of covariates, the estimated impact of computer use is sizeable and statistically significant with workers who use a computer at work earning approximately 18 percent more in 1991 and 17 percent more in 2000 than those who do not use a computer at work. These estimates are in line with those of Krueger (1993) for the US and Bell (1996) for the UK.

² Our earnings information is deflated at 2000 prices.

TABLE I. FIRST OLS ESTIMATES

	1991		2000	
	(1)	(2)	(1)	(2)
Computer use	0.278	0.184	0.312	0.168
	(0.021)***	(0.022)***	(0.025)***	(0.026)***
R-squared	0.30	0.38	0.31	0.42

Robust standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

The fall in the returns to computer use as more controls is added to the equation is what we would expect if the returns to computer use were positively correlated with the previously omitted variables. Of course, the estimated returns to computer use may be biased due to other unobserved variables which have been omitted from the specification. In previous studies researchers have attempted to reduce the extent of these biases by including otherwise unobserved skills widely believed to be linked with the skill components of technological change. For instance, Bell (1996), DiNardo and Pishke (1997) and Dickerson and Green (2002) included other job attributes such as use of tools, diagrams and other skills.

There are at least two problems with this approach. First, conditional on ability and specific skills, many other unobserved attributes may affect wages. Any of these might account for the observed correlation between computer use and earnings. Second, one must expect that test scores and other measures of skill to be quite noisy indicators of ability, which may result in incorrect inferences.

TABLE II. RANDOM AND FIXED EFFECTS ESTIMATES

	Random Effects	Fixed Effects
Computer use	0.319	0.315
	(0.018)***	(0.028)***
R-squared	0.15	0.17

Robust standard errors in parentheses

*significant at 10%; ** significant at 5%; *** significant at 1%

Anger and Schwarz (2002) and Oosterbeek (1997) have used fixed effects models to eliminate the effects of the unobservable individual characteristics on the assumption that the rate of return to computer use remains constant across time. Table II presents random and fixed effects estimates of the computer use variable. The estimators indicate that computer use increases earnings by approximately 32 percent, which supports the literal interpretation that computer technology increases productivity. However, the higher returns to computer use are curious given that the returns to computer use are generally expected to fall upon the elimination of positively correlated individual effects.

The difference in the expected values raises the possibility that the two sets of estimators differ because the parameters are not stable over time. This does not seem plausible, as the OLS estimators for 1991 and 2000 are of similar magnitudes. However, individuals adopted computers at work at different rates and the rate of adoption may be correlated with unobserved productivity characteristics which also affected earnings. To investigate this hypothesis we exploit a simple idea. Our data allows us to split computer users into two groups: Those who were using computers at work in 1991, and those who adopted computers at work between 1991 and 2000. Approximately 20 percent of our sample went from being non-computer users in 1991 to using one in 2000. Using this information we can test whether there was a rate of return to future computer use at work in 1991 earnings. The model can be represented as follows:

$$\ln y_{it} = \lambda_t + \delta_1 C_{1it} + \gamma_2 (C_{2it} - C_{1it}) + \beta_t X_{it} + \mu_{it} \quad (2)$$

where $C1$ represents computer use in 1991, and $C2-C1$ represents computer adoption between 1991 and 2000.

Table III shows the estimates of this equation and includes all our control variables mentioned above in the second earnings specification. The estimate on the computer use 1991 variable is large and statistically significant. The computer use post-1991 variable is statistically significant in the 1991 sample as well as in the 2000 sample. Since future computer use cannot have a causal effect on earlier earnings, this suggests that the computer use variable is capturing unobserved ability which affects earnings. This would

imply that computer wage differentials merely reflect a wage premium due to unobserved worker characteristics rather than to productivity improvements attributable to computers. Arguing along these lines, then the estimate of the computer use 1991 variable may too be due to other abilities and not the result of computer use.

TABLE III. SECOND OLS AND VALUE ADDED ESTIMATES

	<u>Simple</u> 1991	<u>Simple</u> 2000	<u>Value Added</u> 2000
Computer use 1991	0.247 (0.025)***	0.246 (0.030)***	0.113 (0.028)***
Computer use post-1991	0.104 (0.026)***	0.081 (0.029)***	0.034 (0.027)
R-squared	0.39	0.44	0.58

Robust standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

We further investigate these results using what has been called the value-added model. Researchers have adopted this approach in estimating production functions to mitigate potential bias arising from omitted data on historical inputs or endowments. The ‘value-added’ specification differs from the ‘contemporaneous’ specification only in the inclusion of a lagged output measure as an explanatory variable. The lagged variable is taken to be a sufficient statistic for all historical inputs and heritable endowments, or ‘fixed-effect’ specifications, which attempt to difference out unobservables over time. Evidence based on the value-added specification is generally regarded as more convincing than that based on a contemporaneous specification (Hanushek, 2003; and Krueger, 2000). In our model, this specification adds previous earnings to the list of regressors in our “contemporaneous” specification i.e., equation (2). The addition is taken as a proxy for unobserved individual effects such as unmeasured worker ability which may also affect earnings. This model is of the following form:

$$\ln y_{i2} = \lambda_2 + \delta_1 C_{1it} + \gamma_2 (C_{2it} - C_{1it}) + \chi_2 \ln y_{i1} + \beta_2 X_{i2} + \mu_{i2} \quad (3)$$

The final column of Table III shows the results of this specification. The impact of computer use in 1991 on earnings in 2000 is estimated at 11 percent with no return apparent to the adoption of computers at work after 1991. These results concur with the previous model. Although the value-added model is regarded as being superior to that of contemporaneous specifications, Todd and Wolphin (2003) point out that the value-added model imposes strong assumptions on the underlying production technology. Most notably, the inclusion of a lagged output variable as a conditioning variable may make the model highly susceptible to endogeneity bias when data on some of the relevant inputs are missing. Potentially missing regressors are a less important consideration in this study given that the NCDS has provides one of the most comprehensive lists of control variables to any study in this area.

4. Conclusion

This paper presents results about the returns to computer use in the UK. The cross-sectional estimates are similar to the findings reported by Krueger (1993) for the US and Bell (1996) for the UK: Workers who use a computer on-the-job earn higher wages than otherwise similar workers who do not use a computer. This holds over a range of different specifications of the wage equation and is also corroborated by the results from our fixed effect models. We present evidence against the productivity interpretation that the return to computer use is caused by technological change. The inclusion of future computer use at work in earnings regressions was shown to be statistically significant indicating that computer users would have earned higher wages in the absence of computer technology. Furthermore, value added models showed that there was no return to the adoption computer use at work over the last decade. A straightforward implication of these results is that the return to computer use can be attributed to unobserved characteristics.

Appendix

This Appendix describes the control variables used in our regressions. The wages reported in the NCDS is somewhat cumbersome. Respondents were asked their usual weekly hours, their net and gross pay, and their pay interval. We first calculate the number of hours in the pay interval by examining the usual weekly hours, and then calculate the hourly pay rates by taking the pay reported and dividing by the number of hours in the pay interval. We focus on gross pay only and wages are deflated at 2000 prices.

Our measure of education is highest educational qualifications attained which have been grouped into six categories: no qualifications (the omitted category), NVQ level 1, NVQ level 2, NVQ level 3, NVQ level 4 and NVQ level 5.

Reading and mathematics tests at age 7 are used to proxy for innate ability. Economists have often interpreted these scores as measures of cognitive ability or innate ability as these tests are much less likely to be affected by schooling than later tests. As in Cawley et al. (1996) we measure intelligence by the first Principal Component from the two tests.

Occupation is measured from the variables describing socio-economic group and introduced as five dummy variables: professional, managerial, skilled non-manual, semi-skilled non manual, semi-skilled manual, and unskilled (the omitted category).

Firm size is grouped into five categories: 10–24 employees, 25–99 employees, 100–499 employees, 500 or more. The omitted category is 1–9 employees in the 2000 survey and 1–10 in 1991 survey.

Dummy variables for married, children and union affiliation are also added to our wider earnings specifications.

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