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Returning to the Returns to Computer Use

by

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Abstract: This paper re-examines the returns to computer use using a new matched workplace-employee data from Canada. We control for potential selection using instrumental variables. Results suggest that it is not merely the employee having a computer on his desk, but rather having complementary computer skills, that causes wages to increase.

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Economists have widely debated whether there exists a return to computer use. If computers increase the marginal productivity of labor, workers may realize an economic return from using computers. One reason this might occur is that technology may allow firms to automate repetitive tasks and shift the energies of workers toward non-routine tasks, such as problem-solving, innovating and developing interpersonal skills; this shift may increase overall worker productivity. It is difficult to find evidence supporting a productivity hypothesis, however, since the adoption of computers is also likely to increase the relative demand for workers with skills that are complementary to the new technology.

When a firm adopts a new technology, workers who will use it may require general computer skills that are transferable to other firms, and/or firm-specific computer skills. In the case of the former, there will be an increase in demand for workers with computer skills. Those employees lacking the necessary skills may receive training to use the new technology, but they are also likely to pay the training costs in terms of lost wages.[1] In the case of the latter, all workers will require training to use the new technology, but since the skills are not transferable, firms will likely share the costs of that training.

The earliest studies of the relationship between wages and computerization used cross-sectional micro-data and indicated that computer use on the job was associated with a 15-20 percent wage premium (Alan B. Krueger 1993; John DiNardo & Jörn-Steffen Pischke 1997; David H. Autor, Lawrence F. Katz, & Krueger 1998). However, in a

[1] Cindy Zoghi & Sabrina Wulff Pabilonia (2004) find evidence that employees who adopt computers and receive training experience slower wage growth. See Robert G. Valletta (2004) for a discussion of the importance of computer training in workers' wage profiles.

cross-section it is difficult to determine whether an observed wage differential represents productivity gains or changes in the relative demand for skills. More recent studies have used panel data to control for unobserved worker characteristics in a fixed effects model (e.g. Horst Entorf, Michael Gollac, & Francis Kramarz 1999). They find that workers gain only small returns to computer use. The fixed effects estimate is likely to be small or nonexistent, however, because it relies on year-to-year changes in computer use, when workers may be bearing the burden of training costs. Another drawback of the fixed effects model is that it cannot control for time-varying unobservable skills.

This paper re-examines whether there is a causal effect of computer use on wages using a recent matched workplace-employee panel data from Canada. We control for potential selection using instrumental variables. To the best of our knowledge, no published paper has used this method to estimate the returns to computer use. In addition, we use data on the computer experience of each worker to show that computer skills, rather than the presence of a computer on an employee's desk, affect wages.

In the next section, we describe the data. In section III, we discuss our estimation strategy and compare estimates from OLS, fixed-effects, and instrumental variables models. The final section of the paper summarizes our findings.

I. Data

The data come from the first four waves (1999-2002) of the Canadian Workplace and Employee Survey (WES). This matched workplace-employee data includes workplaces and a sample of their paid employees aged 18-64. In 1999, 6,322 employers and 23,540 employees were interviewed. In 2000, 20,167 of those employees were reinterviewed. In 2001, employees were re-sampled at continuing workplaces to start a new two-year employee panel. In 2001 and 2002, there were 20,377 and 16,813 employees, respectively. WES will continue this sampling pattern with the periodic addition of workplaces to ensure a representative cross-section.

Since attrition may be systematically related to wages and important covariates, we use employees from the 1999 and 2001 waves to estimate our OLS and instrumental variables models. In these analyses, we use WES weights to take into account sampling design. This pooled sample consists of 43,917 employees with valid responses to the variables included in our wage model. Our fixed-effects analysis is based upon employees who were in the sample in both years of either two-year panel (1999-2000 or 2001-2002).

The data are rich in information on technology use, both for the workplace and for individual employees. The two key technology variables in this paper are: an indicator for whether or not an employee uses a computer at work, and the number of years of experience using computers at work that the employee has acquired (and its square). The computer use variable comes from the question: “Do you use a computer in your job? Please exclude sales terminals, scanners, machine monitors, etc.” In addition, there is a help screen informs the respondent that “By a computer, we mean a microcomputer, mini-computer, or mainframe computer that can be programmed to perform a variety of operations.” We believe that this question gives us data on computer use on the job comparable to that obtained from other data sources on computer use. The computer experience variable comes from the question: “Considering all the jobs you have held, how many years have you used a computer in a work environment?”

In both 1999 and 2001, 61 percent of workers in Canada used a computer on the job. Most computer users in 1999 were fairly experienced, with on average 8.7 years of computer use. Even those workers who were not currently using a computer had on average 1.5 years of computer experience in a work environment. By 2001, computer users had gained on average just over one year of computer experience (9.9 years of experience).

The dependent variable is the natural logarithm of the employee's gross hourly wage rate. In addition to computer experience and use, our wage models include human capital factors (potential experience and its square, years of education, tenure and its square), demographic characteristics (indicators for married, female, female interacted with married, non-European, different language spoken at home than at work, six regions), job characteristics (indicators for part-timer, covered by a union, six occupations, 14 industries, and the natural logarithm of firm size), the percentage of computer users in the workplace, a wave year indicator, and a constant. In our fixed-effects model, we also include as a covariate whether or not the employee has been promoted within the last year.

II. Estimation Strategy and Results

We first estimate the following pooled OLS wage regression:

$$\ln W_{it} = \alpha + \beta X_{it} + \gamma_1 Comp_{it} + \gamma_2 Compexp_{it} + \gamma_3 Compexp^2_{it} + \varepsilon_{it} \qquad (1)$$

where W_{it} is individual *i*'s gross hourly wage rate at time *t*; X_{it} is a vector of observed characteristics of *i* at time *t* described in the previous section; $Comp_{it}$ is an indicator variable that is equal to one if *i* uses a computer at time *t*, and zero otherwise; $Compexp_{it}$

and $Compexp^2_{it}$ are years of computer experience and its square, respectively; α, β, γ_1, γ_2, and γ_3 are parameters to be estimated; and ε_{it} is a stochastic disturbance term assumed to follow a normal distribution. The coefficient γ_1 is the return to computer use.

OLS results presented in Table 1 indicate a wage premium of 6.6 percent (exp(0.064)-1) for computer users when controlling for computer experience; however, there likely exist other unobservable skills correlated with computer use and wages. We also find that employees with computer experience earn a return for their skills. A computer user with average computer experience would earn 16.9 percent higher wages than the non-computer user. Previous cross-sectional results that do not control for computer experience attribute a comparable size differential entirely to computer use (Krueger 1993).

We next estimate a fixed-effects model on the full sample by including individual intercepts in equation (1). Identification in this model comes from changes in computer use status for employees, which combines the effects of adopting a computer and of no longer using a computer. Downward wage rigidity may prevent reductions in wages when employees stop using a computer, as indicated in Zoghi & Pabilonia (2004). Therefore, the fixed-effects estimate is likely to underestimate the return to computer adoption. In addition, fixed-effects estimates from this paper and in prior research are likely to be smaller than the average effect of computers on wages if workers indirectly pay the cost of training in the years following adoption. Indeed, the fixed-effects estimate indicates a return to computer adoption of only 1.2 percent. However, there remains a small but highly significant return to computer experience of 0.3 percent. Our results on the return to computer use and computer experience are similar in magnitude to those found by Entorf, Gollac, & Kramarz (1999).

Assuming that skilled workers are positively selected into computer use, measurement of γ_1, the return on computer use in the OLS model, would be biased upwards. In order to distinguish the real return to using computers, we must account for selection into computer use. Therefore, we treat $Comp_{it}$ in equation (1) as an endogenous dummy variable and replace this variable with the predicted probability of an employee using a computer, which is modeled as

$$Comp_{it} = \delta + \rho Z_{it} + \eta_{it.} \qquad (2)$$

and is estimated using maximum likelihood estimation. Z_{it} is a vector of exogenous covariates explaining computer use. We assume that the error, η_{it}, is normally distributed and that ε_{it} and η_{it} are jointly bivariate normally distributed. In order to separately identify the probability that an employee receives a computer, we rely on a set of questions on innovation from the workplace survey. Our instrumental variable is whether or not the workplace has implemented a new process or has improved existing processes in production within the past year. Approximately 31 percent of employers reported a new or improved process. It is likely that this process involves a change in technology and increases the chance that an employee will currently be using a computer. At the same time, it is not obvious that these changes would affect contemporaneous wages. Mark Doms, Timothy Dunne and Kenneth R. Troske (1997) find evidence suggesting that the adoption of new technologies does not alter wages within manufacturing plants.

We perform several endogeneity and misspecification tests. They largely confirm the importance of controlling for selection into computer use. For example, the t-value for a Hausman t-test for the endogeneity of computer use is 4.14. Using a Davidson and MacKinnon endogeneity test, we can reject at the 13% level the exogeneity of the computer use variable in an OLS wage model. Using a Wald test, we reject at the 5% level the independence of the error terms in the instrumental variables model, which indicates that OLS is misspecified.

When we account for selection into computer use, we find that the effect of computer use on wages is statistically insignificant.[2] Our instrument, an improved or new process in production, is associated with a 3.8% increased likelihood of an employee using a computer, and is significant at the 5% level. In addition, we find that a computer user with average computer experience would earn 13.5 percent higher wages than the non-computer user. Comparing this result to the cross-sectional estimates obtained here and elsewhere, we find that the wage differential is almost entirely attributable to computer skills, rather than computer use independent of skills.

III. Concluding remarks

In this paper, we have re-examined the returns to computer use controlling for observed and unobserved skills. Using instrumental variables, we find that it is not merely the employee having a computer on his desk, but rather having complementary computer skills, that causes wages to increase. These results suggest that the wage differential observed between computer users and other workers is largely due to increased demand for workers with both observable computer skills and other,

[2] Although computer experience may be endogenous, results are robust to excluding computer experience from the instrumental variables model, suggesting that this is not likely to bias the result.

unobservable skills. Once we control for these skills, the wage differential disappears. We believe our instrumental variable estimation is preferable to either fixed effects, which estimates the wage changes from transitions into and out of computer use, or the cross-section, which fails to control for selection. In future work, we intend to analyze the importance of formal and informal technology training and specific tasks workers are performing with their computers to the return to computer use.

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Table 1— Log Hourly Wage Estimations

Independent Variable	OLS	FE	IV
Computer Use	.064**	.012**	-.036
	(.013)	(.005)	(.051)
Computer Experience	.012**	.003**	.020**
	(.002)	(.001)	(.005)
(Computer Experience)^2 / 1000	-.291**	-.100*	-.545**
	(.085)	(.0439)	(.154)
R^2	.56		
Adjusted R^2		.88	
Wald $\chi^2(42)$			9,014.86
Number of Observations	43,917	78,950	43,917

Notes: For the OLS and IV models, standard errors in parentheses are adjusted for complex survey design effects. All standard errors were corrected for workplace clustering. Regressions include potential experience and its square, years of education, tenure and its square, married, non-European, different language spoken at home than work, female, female*married, region, part-timer, covered by union, occupation, industry, ln(firm size), % computer users in the workplace, a wave year indicator, and a constant. In the FE model, we also include a recent promotion indicator.

*Statistically significant at the 5 percent level.

**Statistically significant at the 1 percent level.