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U.S. DEPARTMENT OF LABOR
Bureau of Labor Statistics

OFFICE OF PRODUCTIVITY AND TECHNOLOGY

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Working Paper 373
June 2004

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May 26, 2004

Abstract: Workers who use computers earn more than those who do not. Is this a productivity effect or merely selection? Using the Canadian Workplace and Employee Survey, we control for selection and find a wage premium of 3.8% for the average worker upon adopting a computer. This premium, however, obscures important differences in returns to computer adoption across education and occupation groups. We find that long-run returns to computer use are over 5% for most workers. Differences between short-run and long-run returns may suggest that workers share training costs through sacrificed wages.

JEL: J31, O30

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*Disclaimer: All views expressed in this paper are those of the authors and do not necessarily reflect the views or policies of the U.S. Bureau of Labor Statistics. The authors would like to thank B.K. Atrostic, Martha Bailey, Marianne Bitler, Michael Harper, Michael Giandrea, Francis Kramarz, Mark Long, Peter Meyer, Anastasiya Osborne, David Ribar, Larry Rosenblum, Steve Stillman, Leo Sveikauskas, Aklilu Zegeye, and participants at the 2003 NBER/CRIW Summer Institute, 2004 SOLE meetings, George Washington University Labor Studies Workshop, and Center for Economic Studies seminar for helpful comments. We also thank Tony Fang at Statistics Canada for data support.

I. Introduction

Since the 1980's, wage inequality between highly educated workers and less educated workers has grown substantially. One hypothesis for this increased wage gap is skill-biased technological change (Mincer 1993). It has been argued that the computerization of work allows workers to shift their focus from routine tasks to problem solving. This "upskilling" increases the productivity and wages of workers (Attewell 1987). Using a cross-section of workers from the 1989 Current Population Survey (CPS), Krueger (1993) found that workers who used a computer on the job earned 17.6% higher wages than those who did not use a computer. He included a variable measuring computer use at home in an attempt to control for unobserved worker heterogeneity. However, this did not reduce the size of the returns to computer use on the job. This paper sparked debate as to whether there is truly a return for using a computer or if higher wages are a result of positive selection into computer use. If workers with high ability or unobserved skills are the workers who are given computers on the job, then cross-sectional results could falsely attribute a wage premium to computer use. DiNardo and Pischke (1997) reached the latter conclusion after finding that workers who used a variety of other tools associated with white-collar type work, including a pencil and a hand calculator, also received a similar return on these tools.

A few researchers have used panel data to control for unobserved individual heterogeneity. Most, with the exception of Bell (1996) and Dolton and Makepeace (2004), found small or insignificant returns on technology use. These studies suggest that firms are allocating information technologies to their highest skilled workers, who already earn more. Using French employer-employee matched retrospective data on new technologies, Entorf and Kramarz (1997) and Entorf, Gollac, and Kramarz (1999) confirmed Krueger's and DiNardo and Pischke's cross-sectional results. However, after controlling for individual fixed-effects, they found that the return to computer use for new users is insignificantly different from zero, while prior experience with computers earns employees a statistically significant return of two percent. Using retrospective data on computer usage from the German Socio-Economic Panel (GSOEP), Haisken-DeNew and Schmidt (1999) found that individual fixed-effects reduced the return to computer use to one percent. Using first-differences and allowing coefficients to vary over individuals and over time, Dolton and Makepeace (2004) found that female workers in the U.K. earned 13% more from adopting a computer in 2000 versus 1991 than female workers who did not use a computer at either time.

While proponents of "upskilling" argue that computerization can lead to productivity and wage increases, critics such as Braverman (1974) counter that computerization can be "deskilling"--the increased mechanization reduces workers' control over the production process and simplifies jobs, leading to lower wages. In fact, the introduction of new technology may be upskilling for some workers (i.e. because it complements them in production) and deskilling for other workers (i.e. because it substitutes for them in production), even within a single firm. In a case study of the introduction of digital check imaging in a bank, Autor, Levy, and Murnane (2002) found that the exceptions processors spent more time on problem solving and less on repetitive tasks while the staff of deposit processors in the back room with the same skill requirements was reduced. In this case, computers substituted for some routine tasks and complemented problem-solving. These differences may be observable between occupational groups as computers change skill requirements. For example, word processing programs may be deskilling for clerical workers because documents can be prepared quicker and with fewer skills, but upskilling for managers because they allow them to take on a greater variety of tasks. Bresnahan, Brynjolfsson, and Hitt (2002) argue that another reason for differential returns to technology across workers is that managers and professionals with high cognitive skills are especially important for the implementation of new technologies. They need to be able to transform organizations to take advantage of technology and the new information that it enables them to learn about their customers. Similarly, Bartel and Lichtenberg (1987) argue that since highly educated workers have a comparative advantage in adjusting to new technologies, the introduction of new technologies should shift demand away from less educated workers. Some evidence on these differences is presented in Krueger (1993), Doms, Dunne and Troske (1997) and Tashiro (2003).

In this paper, we use a panel of workers surveyed in the 1999-2000 Canadian Workplace-Employee Survey (WES) to re-examine wage premiums for using a computer at work. The panel attribute allows us to control for positive selection into computer use. Comparable to other studies, we estimate a fixed-effects specification, which identifies effects only through those workers who change their computer use status. We then extend the analysis in four directions. First, using a more flexible first-differenced model, we identify the return to adopting a computer, as distinct from the negative return from ceasing to use a computer. Second, with these selectivity controls we examine the returns for specific subgroups of workers by education, occupation and type of computer application. Third, using a value-added model, we measure the longer-term returns to continued computer use (unmeasurable in the fixed-effects or first-differenced specification). Finally, we look at the effects of previous computer experience and computer training to determine whether the difference between the small returns for adopters and the much larger returns for continued users can be attributed to learning costs.

In the next section, we provide some theoretical motivation to help explain why returns to computer use may differ for workers with varying skills and how computer training may influence returns. In section III, we discuss the WES and present some descriptive statistics on computer users in Canada. In section IV, we present cross-sectional wage equations, and then fixed-effects and first-differenced wage equations that control for unobserved worker heterogeneity. Section V shows that the differences in returns to computer adoption vary depending upon the worker's occupation, education level, and type of computer application used. In section VI, we present long-run returns to continued computer use, and investigate whether learning costs explain the difference between these long-run returns and the returns to adoption. Section VII concludes the paper.

II. Theoretical Motivation

In this section, we present a model with workers of differing observable skill levels in order to show how selection may affect the returns to computer use, to explain why workers may still earn differential "true" returns to computer use, and how this "true" return may change over time as the price of computers falls. This model will also help to explain why training may lead to unequal returns at the time of computer adoption, which we test in section VI. The model follows largely from Borghans and Weel (2003).

Let us assume there exists a firm with two labor inputs, who differ in their education levels. One type (H) is highly educated, the other type (L) is less educated. For simplicity, these are the only two inputs to production, and they are measured in effective labor units rather than man hours. Output (Y) is produced according to the following CES production function[1]:

$$Y = f(H,L) = \left[\mu H^{\rho} + (1-\mu)L^{\rho}\right]^{1/\rho} \qquad (1)$$

where $\rho \leq 1$; μ is the factor share distribution parameter that can vary over time; and the elasticity of substitution $\sigma \equiv \left(1/(1-\rho) \right)$. Given a competitive labor market, the wage rates per effective labor unit for each type of worker equal their respective marginal products:

$$w_E^T = \mu H^{\rho-1}\left[\mu H^{\rho} + (1-\mu)L^{\rho}\right]^{1-\rho/\rho} \quad T \in (H,L) \qquad (2)$$

For any given worker, however, the number of effective labor units per man hour may vary, depending on the worker's ability, experience, training, quality of the job match, and other factors. Each worker's wage will depend on his own productivity parameter, denoted a_i, which is (at least imperfectly) known by the manager. It is likely that a_i varies both across the two types of workers (with a_i higher on average among type H workers than among type L workers) and within each worker type. Therefore, the typical worker *i* at time *t* earns the following wage per man hour:

$$w_{it}^T = a_i w_{Et}^T \qquad T \in (H,L) \qquad (3)$$

[1] Results hold for a general constant returns to scale production function as well.

Suppose further that a worker's productivity depends not only on her productivity parameter, but also on whether or not she uses a computer. The productivity of computer user *j* is given by $a_j\,\theta_j$. We assume that the computing productivity parameter $\theta_{jt} > 1$ for all workers, i.e. computers are complements in production. This means that there is some task the worker performs that could be done more productively with computerization. As will be discussed below, this does not necessarily indicate that all workers will adopt computers, since the cost of computerizing that task may be higher than the value of the additional output. The computing productivity parameter is likely to be high for tasks that computers are well-designed to perform, such as routine tasks. The computing productivity parameter may also be higher for workers with more computer experience (i.e. θ changes over time) or for workers who learn more quickly. It is commonly assumed that the average computing productivity is higher among type H workers than type L workers, i.e. $\overline{\theta}_t^H > \overline{\theta}_t^L$.

If labor markets are competitive, employers demand quantities of H and L such that the value of the marginal product of each effective unit equals its cost, irrespective of whether the worker uses a computer or not. We treat the computer itself as an asset chosen by the worker, rather than a distinct input to production. Although this may not be especially realistic in terms of the decision-making process, it is more realistic that decision-makers behave *as if* the computer were an asset of the worker. Thus, for any worker to use a computer, the productivity gains from computerization must at least offset the costs of computerizing. When computers are expensive, they are used by the worker who is likely to achieve the highest productivity gains from using the computer. As prices fall, diffusion spreads to other workers who achieve successively smaller productivity gains. So while non-computer users' wages are given by (3), computer users' wages are:

$$w_{jt}^{T} = a_j w_{Et}^{T} \theta_{jt} - C_{jt} \qquad (4)$$

where C_{jt} is the cost of computerizing (at least some aspect of) an individual worker's job at time *t*. Although part of C_{jt} is fixed across workers and reflects the (falling) market price of personal computers, there are also job and worker characteristics that may affect the size of C_{jt} for an individual worker. For very complex tasks, software design is likely to be more complicated and expensive. Thus, we might see differences in computer adoption over occupations. Some workers may require formal computer training or on-the-job training, which increases C_{jt}. Differences in returns may be particularly stark in the first year of computer use when employers provide formal training programs to workers. Since the ability to use many of these applications adds to the workers' general transferable skills rather than firm-specific skills, workers would be expected to share the costs of training. It is not clear whether costs are likely to be higher or lower on average for type H workers relative to type L, since type H workers may perform more complex tasks, but type L workers may require more training. However, the literature usually assumes that $\overline{C}^{H} < \overline{C}^{L}$.

The within-group wage differential between a typical computer user *j* and non-computer user *i* is given by:

$$w_{Et}^{T}(a_j \theta_{jt} - a_i) - C_{jt} \qquad T \in (H, L) \qquad (5)$$

Thus, there are five factors that increase the wage differential: 1) high individual productivity for computer users, 2) higher market efficiency wages, 3) higher computing productivity, 4) lower cost of computerizing, and 5) lower individual productivity of the non-computer user. The first two factors are the typical selection biases that result in an overestimate of the returns to computer use in cross-sectional regressions, i.e. computers are used by high-wage, high-ability workers. The third factor, however, is in a sense the "true" return to computer use ─ computers make workers more productive. Thus, if computers do not increase productivity at all ($\theta = 1$), wage differentials reflect only ability differentials, less the cost of computerization. We test for selection effects and/or productivity effects in section IV where we control for both observed and unobserved worker heterogeneity. If, as assumed, $\theta_{jt} > 1$, then there will be a return to computer use after controlling for differences across workers. In the empirical section, a significant wage premium for adopting a computer would be interpreted as the net benefit of computerizing.

There may also be difference between groups of workers. Replacing the individual worker parameters with their group means (where $\overline{a}_j^H$ is the mean of highly educated computer users, $\overline{a}_i^H$ is the mean of highly educated non-computer users, $\overline{a}_j^L$ is the mean of less educated computer user, $\overline{a}_i^L$ is the mean of the less educated non-computer user), we find that the double difference in wages can be expressed as:

$$w_{Et}^H(\overline{a}_j^H\overline{\theta}_t^H - \overline{a}_i^H) - w_{Et}^L(\overline{a}_j^L\overline{\theta}_t^L - \overline{a}_i^L) + (\overline{C}_t^L - \overline{C}_t^H) \quad (6)$$

If $\overline{\theta}_t^H > \overline{\theta}_t^L$ and $\overline{C}_t^H < \overline{C}_t^L$, the difference may be positive, so that more highly educated workers earn a higher return to computer use than less educated workers. However, this is largely an empirical question—even if highly educated workers have on average higher computing productivity and lower costs of using a computer than less educated workers, the distribution of workers between the groups also determines which effect will dominate. Equation (6) also demonstrates how computers can affect wage inequality between the two groups over time, even with relative demand held constant. The relative return to computer use for type H workers could decrease (reducing inequality over time) if computerization were to become relatively less costly for type L workers. For example, the diffusion of computers into K-12 classrooms may decrease the amount of on the job computer training necessary for less educated workers to effectively use computers relative to the training necessary for highly educated workers. Similarly, changes over time in either θ parameter will affect the size of the between group wage differential. Changes might occur through a redesign of jobs, perhaps, if firms shifted some easily computerized tasks to less educated workers. Therefore, we test in section V whether the return to computer use is higher for more educated workers than less educated workers. Then, we test whether workers earned lower differential returns if they received computer training (to proxy for the costs of computerizing) when adopting a computer.

III. Data

The data we use for this analysis come from the Canadian Workplace and Employee Survey (WES). This survey was initially conducted in 1999. Establishments in the WES are being followed each year, while employees are followed for only two years and then re-sampled. For our analysis, we use a panel of employees with their matched employer information from 1999 and 2000 – the data currently available. The panel aspect of the data allows us to control for unobserved individual characteristics that might affect the propensity for computer use as well as wages.

In 1999, 23,540 employees in 5,733 establishments were interviewed. Establishments were first selected from employers in Canada with paid employees in March of the survey year with the exception of the Yukon, Nunavut, and Northwest Territories and “employers operating in crop production and animal production; fishing, hunting, and trapping; private households, religious organizations and public administration” (Statistics Canada 2002, 23). At each establishment, a maximum of twelve paid employees were then randomly sampled from a list of employees. All employees were selected in establishments with fewer than four employees. In 2000, 20,167 employees were re-interviewed. For some of our main econometric analysis, we use a restricted sample composed of those 19,364 employees who responded in both years, remained with the same employer in both years, and had non-missing observations on the dependent and independent variables. Sample means and proportions for the 1999 restricted analysis sample are in Table A1 in the Appendix.[2]

The dependent variable in our analysis is the natural logarithm of the hourly wage. In the compensation section of the WES, employee respondents reported their wage or salary before taxes and other deductions in any frequency they preferred (e.g. hourly, daily, weekly, annually). They were also asked about additional variable pay earned from tips, commissions, bonuses, overtime pay, profit-sharing, productivity bonuses and piecework in the last twelve months. Hourly compensation was derived by Statistics Canada by dividing wages plus additional variable pay by total reported hours.[3] This derived hourly compensation is the measure of hourly wage used in our analysis.

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[2] Although not reported here, there do not appear to be any significant differences between the full sample and restricted sample employee characteristics.

[3] Managers may be more likely to work unreported hours than other workers. Thus, hourly wages for this occupational group would be overestimated.

The WES is rich in questions concerning the use of technology by establishments and their employees. One of the central variables in our study is computer use by employees. Specifically, employees were asked "Do you use a computer in your job? Please exclude sales terminals, scanners, machine monitors, etc." Identification in the fixed-effects analysis comes from users that changed their computer use status (see Appendix Table A1). Table 1 describes the proportion of workers who used a computer at work in 1999 and 2000.[4] Sixty-one percent of Canadian workers used a computer at work in 1999 and 65% used a computer at work in 2000.[5] Women were more likely than men to use a computer in either year. In 1999, 63% of women and 58% of men used a computer. Though the percentages are larger in magnitude in Canada, the relative computer use by gender is similar to that found in the United States in 2001 (U.S. Bureau of Labor Statistics 2001) and the United Kingdom in 2000 (Dolton and Makepeace 2004).

Employees aged 25-54 (approximately 65% in 1999) were much more likely to use a computer than the youngest employees aged 18-24 (44% in 1999) and employees aged 55+ (47% in 1999). By occupation groups, managers, professionals, and clerical/administrative employees had the largest number of computer users, with at least 82% of the workers in each of these occupation groups using a computer in 1999. Managers and marketing/sales had the largest gains (6% gains) in the percentage of new computer users between 1999 and 2000. More educated workers were more likely to use a computer at work than less educated workers. Eighty-one percent of workers with a

[4] Survey means and proportions throughout the paper have been weighted using the employee weights.
[5] This is comparatively larger than the 53% of U.S. workers who used a computer at work in 2001. This figure is the authors' calculation from the Current Population Survey Supplements (U.S. Bureau of Labor Statistics 2001). The percentage is comparatively lower than the 75% of U.K. workers who reported using a computer at work in 2000 in the National Child Development Study (Dolton and Makepeace 2004).

bachelor's degree used a computer at work while only 52% of workers whose highest degree was a high school diploma used a computer at work in 1999. Workers not covered by a union were more likely to use a computer than those who were covered under a collective bargaining agreement (64% versus 52%), and full-time workers were more likely to use a computer than part-time workers (65% versus 45%) in 1999.[6]

Employees were also asked about their years of experience using computers, the number and types of computer applications used, the number of hours per week spent using their computer, and the use of other technologies, such as industrial robots or computer-aided design (CAD) systems. Table 2 presents means and proportions for selected technology-related questions from the WES. In 1999, 11% of employees did not use a computer for their current position but had some prior experience using a computer. Among employees who used a computer, the majority were experienced computer users. Sixty-four percent had used a computer for five or more years, while 44% had used a computer for nine or more years. On average, computers users spent half of their work week using computers (about 19 hours per week) and used 2.6 computer applications. Clerical and administrative workers spent the most hours on average per week using their computers (24.05 hours) while managers used their computers on average about 20 hours per week. On average, employers reported that 46% of their employees used computers. Besides computers, 12% of employees used computer-assisted technology, such as industrial robots, and 27% used other technology or machinery, such as cash registers or sales terminals.

[6] In the WES, union coverage is defined as being either a member of a union or covered by a collective bargaining agreement.

The respondents were also asked which software application they spent more time on. While they were free to answer any specific application, the answers were then coded into one of fourteen types of software applications listed in Table 3. There are significant differences in the most frequently used applications by occupation. Managers and professionals were most likely to use word processors as a primary application. Other occupations were most likely to use specialized office applications. Computer usage is thus a fairly heterogeneous concept across workers.

IV. Wage Differential for Computer Use

A. Cross-section estimation

In order to verify that our data yield similar results to those used in previous work, we first estimate a pooled cross-sectional wage equation with the computer use variable as the explanatory variable of interest. Specifically, we estimate:

$$\ln W_{it} = \alpha + \beta X_{it} + \gamma Comp_{it} + \varepsilon_{it} \qquad (7)$$

where W_{it} is individual *i*'s hourly wage rate at time *t*; X_{it} is a vector of observed characteristics of *i* at time *t*; $Comp_{it}$ is an dummy variable equaling one if *i* uses a computer at time *t*, and zero otherwise; α, β, and γ are parameters to be estimated; and ε_{it} is a stochastic disturbance term assumed to follow a normal distribution.

Results for the return to computer use for the pooled cross-section regression, estimated by ordinary least squares, are reported in column I of Table 4. Included in the X_{it}'s are employee characteristics: years of education, potential experience, potential experience squared, has parents or grandparents who descended from non-European countries, speaks different language at work than at home, part-time status, marital status, gender, gender interacted with marital status, is covered by a union, regional indicators, five occupational indicators, worker's tenure with the establishment, and a year indicator.[7] In addition, we control for two establishment characteristics from the linked employer files: the natural logarithm of establishment size and the percentage of computer users in the establishment. The resulting wage premium for computer use is 16.9% (exp(.1565)-1). This result is comparable to that found by Krueger for the U.S. (1993).

B. Controlling for Worker Heterogeneity

There may also be unobserved worker characteristics, such as ability, that make computer-users different from other workers. If these unobservables are correlated with wages, the previously reported wage premiums would be incorrectly attributed to computer use. Indeed, many other researchers have found that the wage premium for computer use is greatly diminished or no longer exists when they have controlled for unobserved individual heterogeneity.[8]

In order to control for potential unobserved individual heterogeneity, we first estimate the following traditional fixed-effects specification on an unbalanced panel of workers in the 1999-2000 WES to replicate previous researchers results:

$$\ln W_{it} = \alpha + \beta X_{it} + \gamma Comp_{it} + \delta_i + \varepsilon_{it} \tag{8}$$

where δ_i is the non-time varying individual fixed-effect. Many of the demographic variables are time invariant and consequently do not appear in the fixed-effects model.

[7] It may be inappropriate to include occupational dummies in these regressions because employees with computer skills may be more likely to obtain jobs in higher paying occupations (Krueger 1993). Results were similar excluding occupational dummies.
[8] See, for example, Bell (1996), Entorf, Gollac and Kramarz (1999), and Entorf and Kramarz (1997).

However, education does change for quite a few workers, possibly due to measurement error in one or both of the years. Additionally, marital status, work-home language differences, part-time status, and union coverage can change from one year to the next for some workers. For many of the establishments, both the number of employees and the percentage of computer users within the establishment change between 1999 and 2000. We also include whether the worker was recently promoted in 2000 – sometime in 1999 or 2000 – since a promotion may be correlated with both changes in computer use and changes in wages.[9]

Confirming previous researchers results, we find a fixed-effects estimate of only 1.68% (column II in Table 4).[10] Identification in this specification comes from the 9% of workers who changed computer status ─ 6% adopted and 3% ceased to use a computer in 2000 (see Appendix Table A1).[11] Equation (8) assumes that the absolute value of the return to computer use is the same for both adopters and ceasers, which may not be the case. In addition, it does not tell us anything about the return to computer use for workers who used the computer in both 1999 and 2000 or even for many years prior to 1999 (Dolton and Makepeace 2004).

Therefore, we separately identify the four possible computer use transitions a worker can experience over time and allow returns to computer use to vary between these

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[9] The simple correlation between adopting a computer and a recent promotion is 0.0317 while the correlation between ceasing to use a computer and promotion is -0.0054.

[10] We have also tried a random-effects specification and establishment fixed-effects specification. According to results of the Hausman test, we can reject the null hypothesis that the individual effects are uncorrelated with the other regressors in the model. The return to computer use controlling for establishment heterogeneity, but not worker heterogeneity, was 7.7%.

[11] Some may be concerned with the large number of ceasers in the data. Dolton and Makepeace (2004) suggest two possible reasons why workers may stop using a computer. One is that they may do so as they move up the promotion ladder; however, in Canada, the simple correlation between ceasing to use a computer and promotion is -0.0054 and we have controlled for promotion in this specification and those that follow. The other reason is that ceasers are not very good at using a computer, i.e. low θ_i. In a fixed-effects regression using only non-computer users in 1999, we found a 3.9% return.

groups of individuals and over time. The four transitions are: those who never used a computer, those who used a computer in both periods (M_i), those who ceased using a computer in 2000 (C_i), and those who adopted a computer between 1999 and 2000 (A_i). Using a balanced panel of 19,364 Canadian employees, we control for unobserved individual heterogeneity by differencing the following two equations:

$$\ln W_{i1999} = \alpha_{1999} + \beta X_{i1999} + \gamma^{m}_{1999} M_i + \gamma^{c}_{1999} C_i + \delta_i + \varepsilon_{i1999} \qquad (9a)$$

$$\ln W_{i2000} = \alpha_{2000} + \beta X_{i2000} + \gamma^{m}_{2000} M_i + \gamma^{a}_{2000} A_i + \delta_i + \varepsilon_{i2000} \qquad (9b)$$

in order to estimate the following first-differenced model[12]:

$$\Delta \ln W_i = \Delta\alpha + \beta \Delta X_i + (\Delta\gamma^{m}) M_i + \gamma^{a}_{2000} A_i - \gamma^{c}_{1999} C_i + \Delta\varepsilon_i \qquad (10)$$

where Δ is the change in each variable/coefficient between 1999 and 2000; M_i , A_i, C_i are indicator variables for maintaining computer use, adopting a computer, and ceasing to use a computer, respectively. We allow the return to computer use to vary over time for continued users by allowing $\gamma^{m}_{1999} \neq \gamma^{m}_{2000.}$

Column III of Table 4 reports results for this general first-differenced model. In this specification, the effect of computer use on wages for the average worker in the first year of computer adoption is a statistically significant 3.8%. This result is larger than that found by Haisken-DeNew and Schmidt (1999) who combined the effect of all movements into or out of computer use, since our estimate is specifically a measure of the return to adopting a computer. Our coefficient on ceasing to use a computer is not statistically significantly different from zero, perhaps due to downward wage rigidity. This first-differenced model reveals that the small, but insignificant, return to adopting a computer reported by Entorf et al. (1999), whose fixed-effects estimates did not account

[12] We have tried including establishment fixed-effects in the model; results, which are available from the authors, did not change.

for information on ceasing to use a computer, may be biased upward since the wage loss from ceasing to use a computer is quite asymmetric.

The small wage premium in our panel does not necessarily indicate returns to computer use are this small but merely that returns to the average worker in the first year of computer use are small. Returns might be small in the first year if employers pass along some or all of the costs of computer training to their employees. We find that the change in the return for workers who maintained their computer use over the period, $\Delta\gamma^m$, was 3.75%. This coefficient, however, can not tell us the return to long-run computer experience for maintainers, γ^m_{2000}. We explore this issue in section VI.

V. Wage Differential for Computer Use by Worker Heterogeneity and Technology Use

The evidence thus far implies that the average worker does not earn the high wage premiums initially associated with computers — at least in the short run — although the premium is still positive and economically significant. Nevertheless, as suggested in section II, certain workers may earn higher than average returns. We look for evidence of such differential effects by re-estimating the first-differenced model for workers separately by occupational groups, educational groups, and type of application used most frequently.

While the WES does not provide detailed occupational information on workers, it does contain a variable for broad occupation groups: managers, professionals, technical and skilled production workers, marketing and sales, clerical and administrative workers, and unskilled production workers with no trade or certification. Results for these groups are reported in Table 5. Group samples are restricted to those who were in the same occupation in both years. Even controlling for individual heterogeneity, managers earned a statistically significant 7.3% higher wages in the first year of computer use, while technical/trade workers earned 4% higher wages in the first year of computer use. The remaining occupational groups, however, earned no statistically significant wage premium for adopting computers, and only the return to professionals using a computer was an economically significant 4.5%. Results of a Chow test confirm that these are statistically different returns. These results coincide with our expectations, since white collar workers are likely to possess more problem-solving skills than other workers. If, as suggested by Autor et al. (2002), Bresnahan et al.(2002), and Doms et al. (1997), computers are a complement to high-skilled workers and a substitute for low-skilled workers, it makes sense that the adoption of computers would affect the wages of these groups of workers differently. Estimations of the wage effect for the average worker obscure important differences between types of workers.

A second way to test whether there are differential effects of computerization for particular types of workers is to estimate the models separately by education. We divide the sample into groups of workers with less than a high school diploma, with only a high school diploma, with some college or a vocational degree, with a bachelor's degree and those with advanced degrees. Wage premiums are quite high for workers with an advanced degree (19.2%) or a bachelor's degree (10.9%), still positive for those with some college or a vocational degree (2.9%), and not statistically different from zero for those with only a high school diploma or less. Again, a Chow test confirms that these returns are statistically different. Thus, we find that returns to computer use are higher for more educated workers than for less educated workers in the first year of adoption.

Another source of heterogeneity that may affect the returns to computer use stems from the different tasks that a worker performs using a computer. Autor et al. (2002) showed that technology may complement a worker who performs problem solving tasks but may be a substitute for a worker who performs repetitive tasks. If this is the case, then it may be important to look at more detailed questions of technology use. To do this, we estimate a first-differenced model similar to (10), but disaggregate the adoption indicator A_i into a set of 14 indicators representing the primary software application used by the adopter. In addition, we re-estimate equation (10) for two other types of technology--computer-aided tools (e.g. industrial robots) and other non-computer technologies (e.g. cash registers and scanners).

Results of these estimations are in Table 6. The wage premium is largest for those adopting desktop publishing, data analysis, and programming (22%, 11.5%, and 9.3% respectively) compared to continued non-users. These applications tend to be applications in which workers must use critical thinking or problem-solving skills. However, the variance for the coefficients in this model comes from individual workers who adopt a computer and this particular software. The number of workers in each group is quite small, resulting in large standard errors in most instances. Adopters who use word processing, database, communication, and specialized office applications also earn significant wage premiums (7.5%, 5.2%, 7.2%, and 3.5% respectively). Thus while some of the estimates in the first-differenced model are quite noisy, there do appear to remain some differences in the wage premium depending upon the primary application adopted.

It does not appear that workers using technologies other than computers earn a wage premium for that usage. The three different groups of workers--by occupation, by education, and by software application used--seem to largely confirm that technology can affect workers differently.

VI. Long-Run Results

One reason the traditional fixed-effects and general first-differenced models might yield small estimates of the return to computer use is that they measure the wage change within the first year of adopting/ceasing to use a computer. In order to estimate the return for maintaining computer use, we estimate equation (9b) by OLS using the lagged wage to try to capture the individual fixed-effects:

$$\ln W_{i2000} = \alpha_{2000} + \eta \ln W_{i1999} + \beta X_{i2000} + \gamma^{m}_{2000} M_i + \gamma^{a}_{2000} A_i + \varepsilon_{i2000} \quad (9b').$$

This value-added approach was first advocated for panel data by Todd and Wolpin (2003).

Results in Table 7 show that the average return to computer use for those who used computers in both periods (maintainers) was 8.3% in 2000. This large and significant return suggests that those with computer skills are earning higher wages than those who are first learning to use their new computers at this establishment. This higher return for maintainers is still lower than that found by Dolton and Makepeace (2004) for either men or women (14.3% and 9.3% respectively); however, their respondents had to maintain computer use over a nine year period and their *minimum* experience with a computer was over nine years, while the maintainers in our data had *on average* 10.29 years of computer experience. The return to adopting (4.2%) using the value-added approach was only slightly higher than that obtained using first-differences (3.8%), suggesting that lagged wages are good proxies for the individual fixed-effects — at least for adopters.

We re-estimate this equation for the occupational and educational groups. Among the occupational groups, we find that most maintainers earned a return to computer use. Even though workers in the marketing/sales and clerical/administrative occupations did not earn a return to adopting a computer, workers in these occupational groups who maintained their computer use earned an economically significant return of 10% and 8%, respectively. Among the educational groups, maintainers all earned an economically large return to computer use. Maintainers among high school graduates, one of the lower educational levels, earned one of highest returns – 10.6%. The coefficient on maintainers in the advanced degree group was imprecise. These results suggest that previous fixed-effects models dramatically understate the "true" returns to computer use, and in fact, only represent the much smaller average returns to adopting/ceasing to use a computer.

It is not too surprising that the long-run returns are in most cases much larger than the short-run ones, since most workers will not immediately become more productive the instant a computer appears on their desk. The worker must learn to use the computer and to incorporate it into the way she performs her job.[13] In the first year of using a computer on the job, there may be high learning costs for workers, especially for those with no prior experience. These may be pecuniary costs of training courses or on-the-job training, or opportunity costs of lost productivity while adapting to using a computer. While some of these learning costs will be paid by the employer, workers may be

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[13] Bresnahan (1999) discusses how important the re-organization of the workplace is to effectively use computers.

expected to implicitly share these costs, since learning many of these applications adds to the workers' general transferable skills rather than firm-specific skills.

The data provide two ways to assess why returns are lower for adopters than maintainers. First we compare the returns to adoption for those who received and did not receive computer training. Employees were asked if they participated in any on-the-job training or classroom training on computer hardware or software related to their job and paid for by their employers. We expect that the 15% of adopters who received (and implicitly required) training will see lower wages while they pay their share of the cost of that training, resulting in lower returns in the presence of training. In order to make this comparison, we add to equation (10) the interaction between this training variable and the adoption indicator. The second way we analyze learning costs is to compare the returns to adoption for workers with and without prior computer experience. We expect that workers who have prior experience using computers may be able to reap higher productivity in their first year of computer use than workers who have no prior computer experience. Thus, we expect experienced adopters will earn a higher return than adopters with no experience. We estimate this by adding to equation (10) the interaction between prior experience and the adoption indicator.

Table 8 shows the results of these models. Although results are imprecise for the interaction terms due to the small number of adopters with either prior experience or training,[14] the coefficients suggest that learning costs do affect the short-term returns to computer use. A worker who does not receive training earns a return of around 4%, while one who receives training earns only 3% (Model I). An inexperienced worker

[14] Only 1.2% percent of the sample both adopted a computer and received some type of training.

earns a return to adopting a computer of 2.9% while the worker with prior experience earns 5% in the year of adoption (Model II).

The theoretical model in section II allows the size of these learning costs and the extent to which workers share the costs may vary across types of workers, and shows that these variations can help explain the differential returns to computer adoption found in section V. For example, if low-skilled workers require more learning than high-skilled workers to master a particular computer application, then it might take longer for any premium to be reflected in their wages. Table 8 shows the same models as above, estimated separately for the different occupational and educational subgroups. Again, these estimations are likely to be quite noisy, as the variance is derived from a one year wage change for workers of a given type who adopt a computer and receive training. There is nevertheless some evidence that the sharing of these costs is especially high for particular groups of workers, although the pattern is not clearly related to skill level. The one significant result in the training interaction is for the marketing and sales occupation, which is consistent with the fairly large return to maintainers for this occupational group shown in Table 7. Other groups, such as professionals, clerical and administrative, and the highly educated pay economically large costs of training. While these are not all intuitive, it is important to keep in mind that the first-differencing method does not control for unobservables that might cause one worker to receive training in the second period and another worker not to receive the training. Thus, although the large negative effect on the interaction term for workers who hold bachelor’s and advanced degrees is somewhat surprising (10.7% and 8.4%, respectively), it is likely that many of these degree holders do not require formal training and those who do require it are different in some important unobservable way.[15] Alternatively, it is possible that their training programs are expensive due to the complexity of the applications workers must master.

Importantly, the size of the wage premium for those who do not receive formal training is larger for several of the low-skilled groups (e.g. marketing/sales, clerical/administrative) than in the models that do not control for training. It is plausible that if we observed workers a few years after adopting computers, their wages would be higher than for similar workers who did not adopt a computer between 1999 and 2000. In fact, the effect should be larger than was measured here, since much of the learning costs are not reflected in formal training but in on-the-job experience using the computer.

Most groups also demonstrated a larger return for experienced adopters, as evidenced by the positive return on the interaction, although again these estimates are imprecisely measured. The exceptions are workers with some college or no high school degree and those in the technical and trade occupation, which may indicate that the applications used by these workers tend to be firm specific and prior general computer skills are not readily transferable.

VI. Conclusion

In this paper, we re-examine the issue as to whether or not there is a return to using a computer, using the 1999-2000 panel of the Canadian Workplace and Employer Survey. In a pooled cross-section wage regression, we find that workers who used a computer earned 16.9% higher wages in 2000 than those who did not use a computer. When we control for unobserved worker heterogeneity using a flexible first-differenced

[15] See Appendix Table A2 for observable ways that adopters who receive training differ from those who do not receive training.

model, the wage growth for the first year of computer use is a statistically significant 3.8%. This estimate is larger than the previously reported 1% return to computer use because using a general first differenced model instead of a traditional fixed-effects model allows us to separately identify the return to adopting a computer from the asymmetric wage loss associated with ceasing to use a computer, which is not statistically different from zero.

This panel estimate, however, obscures important differences between types of workers and returns from using different computer applications. We find that technical workers, professionals and managers earn higher wages in the first year of computer use, while other occupational groups, whose skills may be substitutes for computer technologies, earn no statistically significant return. Similarly, workers with a bachelor's or advanced degree earn 11-19% higher wages when adopting a computer, while those with some college earn around 3% and those with a high school diploma or less do not earn a wage premium. We also find important differences in returns to using different software applications, which suggest that there is a return to computerizable tasks that allow creative and/or cognitive skills to be better utilized. Workers who use other machinery or computer-controlled technology do not earn a return. These results suggest that computers are a complement to high-skilled workers performing problem solving tasks and a substitute for low-skilled workers performing repetitive tasks.

These results indicate small but significant returns for some workers to the first year of computer use. We extend the analysis by using the lagged wage as an alternative means of controlling for individual fixed-effects, which allows us to estimate returns to computer use for those who used a computer both years. We find that the average worker who maintains his computer use between 1999 and 2000 earns an 8.3% wage premium, more than double the return for the average adopter. In addition, maintainers in most skill groups earn more than a 5% return to computer use in 2000. We conclude that this return is a return to computing skills.

The result that continued users earn more than adopters may represent greater productivity. We also explored to what extent the differences between short-run and long-run returns within and between subgroups may reflect differences across employees in the costs of learning the new technology and the sharing of these costs between employers and employees. We find a negative wage effect associated with receiving training on a new computer, which suggests either that workers pay for training in terms of slower wage growth or that workers who receive training are different than workers who do not receive training. Controlling for computer training does increase wages for many of the low-skilled groups whose premia were small or zero in previous models. In addition, computer adopters with prior computer experience earn more in the first year than those lacking experience.

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Table 1. Computer Usage Among Employees in the 1999 and 2000 Canadian Workplace and Employee Survey		
	1999 Sample	2000 Sample
Total	.61	.65
Men	.58	.61
Women	.63	.68
European	.61	.63
Non-European	.58	.65
Ages 18-24	.44	.46
Ages 25-39	.66	.68
Ages 40-54	.63	.67
Ages 55+	.47	.56
Managers	.82	.88
Professionals	.85	.87
Technical/trades	.46	.50
Marketing/sales	.41	.47
Clerical/administrative	.85	.88
Production/no trade	.18	.21
Advanced degree	.89	.91
Bachelor's degree	.81	.84
Some college/vocational degree	.62	.61
High school graduate	.52	.55
Less than high school graduate	.28	.34
Union coverage	.52	.55
No union coverage	.64	.69
Full-time	.65	.68
Part-time	.45	.50
Number of Observations	23,540	20,167
Note: Proportions are weighted.		

Table 2. Selected Technology-Related Characteristics of Workers	
Computer experienced non-user	.11
Conditional on using a computer	
≤4 years of computer experience	.14
5-8 years of computer experience	.20
9+ years of computer experience	.44
Hours per week spent at computer	19.18 (.24)
Hours by occupation	
Managers	19.92 (.52)
Professionals	18.99 (.47)
Technical/trades	17.16 (.41)
Marketing/sales	14.85 (1.19)
Clerical/administrative	24.05 (.43)
Production/no trade	9.72 (2.54)
Number of applications	2.62 (.03)
Computer users in employee's workplace	.46
Computer-assisted technology	.12
Other technology	.27
Number of observations	23,450

Source: 1999 Canadian Workplace and Employee Survey.
Notes: Means are calculated using employee weights. Standard errors are in parentheses.

Table 3. Primary Computer Application Used by Workers, by Occupation

	All	*Manager*	*Professional*	*Technical*	*Sales*	*Clerical*	*Production*
Word processing	.1427	.2109	.3054	.0785	.0285	.1903	.0267
Spreadsheets	.0584	.1163	.0772	.0460	.0165	.0562	.0165
Databases	.0587	.0656	.0589	.0470	.0555	.1078	.0165
Desktop publishing	.0049	.0077	.0093	.0032	.0033	.0048	0
Mgmt. applications	.0130	.0230	.0059	.0109	.0195	.0180	.0026
Communications	.0445	.1206	.0826	.0247	.0063	.0160	.0072
Programming	.0062	.0029	.0229	.0035	0	.0047	.0006
Specialized office	.1454	.1443	.1189	.1301	.1555	.2620	.0538
Data analysis	.0044	.0080	.0063	.0027	.0013	.0061	.0015
Graphics	.0094	.0150	.0173	.0076	.0011	.0089	.0003
Computer-aided design	.0062	.0063	.0086	.0093	.0028	.0002	0
Computer-aided engineering	.0023	.0027	.0061	.0023	0	0	0
Expert systems	.0146	.0111	.0144	.0106	.0373	.0218	.0038
Other	.0970	.0840	.1133	.0869	.0845	.1511	.0539

Source: 1999 Canadian Workplace and Employee Survey (N = 23,540).
Notes: Means are calculated using employee weights. Communications includes e-mail and web browsers.

Table 4. The Effect of Using A Computer on Wages			
	Pooled OLS Model (I)	*Individual FE Model (II)*	*First-differenced Model (III)*
Dependent Variable	ln(hourly wage)	ln(hourly wage)	Δln(hourly wage)
Computer use (1=yes)	.1565*** (.0062)	.0160** (.0071)	
Computer user in both years (Maintainers)			.0375*** (.0054)
Computer user in 1999 only (Ceasers)			.0029 (.0123)
Computer user in 2000 only (Adopters)			.0377*** (.0097)
R^2	.4285	.0879	
Adjusted R^2			.0243
Number of observations	42,904	42,904	19,364

Notes: Standard errors are in parentheses. * = p<.10; ** = p<.05; *** = p<.01. The OLS model includes a constant, years of education, potential experience (and its square), has parents or grandparents who descended from non-European countries, speaks different language at work than at home, part-time status, marital status, gender, gender interacted with marital status, is covered by a union, regional indicators, five occupational indicators, worker's tenure with the establishment, a year indicator, the natural log of establishment size, and the percentage of computer users in the firm. Specifications II and III include the before-mentioned variables except for those that are constant over time and recent promotion in 2000.

Table 5. First-Differenced Estimates of the Effect of Adopting a Computer on Wages, by Occupational and Educational Groups	
Occupation	
Managers (N = 2,477)	.0704* (.0391)
Professionals (N = 2,660)	.0437 (.0354)
Technical/trade (N = 8,143)	.0389*** (.0128)
Marketing/sales (N = 603)	-.0026 (.0590)
Clerical/administrative (N = 2,899)	.0118 (.0309)
Production/no trade (N = 1,108)	.0214 (.0367)
Education	
Advanced degree (N = 1,056)	.1760** (.0745)
Bachelor's degree (N = 2,543)	.1031*** (.0389)
Some college/vocational degree (N = 10,367)	.0289** (.0130)
High school graduate (N = 3,280)	.0310 (.0206)
Less than high school graduate (N = 2,118)	.0146 (.0267)
F-statistic for pooling by occupation	10.10
F-statistic for pooling by education	8.02

Notes: The sample is restricted to those employees who responded to the survey in both years, remained with the same employer for both years, and remained in the same occupation both years. Standard errors are in parentheses. * = p<.10; ** = p<.05; *** = p<.01.

Table 6. The Effect of Adopting a Specific Technology Use on Wages	
	First-Differenced Model
Computer-aided technologies	-.0072 (.0076)
Other technologies	-.0034 (.0062)
Main application used (conditional on adopting a computer)	
Word processing	.0729*** (.0224)
Spreadsheets	.0189 (.0278)
Databases	.0511** (.0258)
Desktop publishing	.1996* (.1107)
Management applications	.0246 (.0504)
Communications	.0694** (.0281)
Programming	.0890 (.0845)
Specialized office	.0343* (.0190)
Data analysis	.1091 (.1035)
Graphics	-.0152 (.0691)
Computer-assisted design	.0289 (.0812)
Computer-assisted engineering	.0171 (.1195)
Expert systems	.0866 (.0575)
Other	-.0173 (.0217)
Number of Observations	19,364

Notes: The sample is restricted to those employees who responded to the survey in both years and also remained with the same employer for both years. Standard errors are in parentheses. * = p<.10; ** = p<.05; *** = p<.01.

Table 7. The Long-Run Effect of Using a Computer on Wages ─ Value-Added Approach		
	OLS	
	Maintainers	*Adopters*
All workers (N = 19,364)	.0796*** (.0005)	.0410*** (.0089)
Occupation		
Managers (N = 2,477)	.0664*** (.0221)	.0836** (.0358)
Professionals (N = 2,660)	.0243 (.0185)	.0523 (.0324)
Technical/trade (N = 8,143)	.0862*** (.0069)	.0445*** (.0119)
Marketing/sales (N = 603)	.1043*** (.0341)	.0823 (.0538)
Clerical/administrative (N = 2,899)	.0771*** (.0150)	.0333 (.0279)
Production/no trade (N = 1,108)	.0563** (.0245)	.0580* (.0315)
Education		
Advanced degree (N = 1,056)	.0601 (.0389)	.1465** (.0682)
Bachelor's degree (N = 2,543)	.0829*** (.0210)	.1018*** (.0353)
Some college/vocational degree (N = 10,367)	.0831*** (.0067)	.0360*** (.0117)
High school graduate (N = 3,280)	.1008*** (.0115)	.0559*** (.0189)
Less than high school graduate (N = 2,118)	.0588*** (.0173)	.0175 (.0241)
F-statistic for pooling by occupation	17.24	
F-statistic for pooling by education	10.52	

Notes: Standard errors are in parentheses. *=p<.10; ** = p<.05; *** = p<.01. The OLS model (using the 2000 sample) includes lagged wage, a constant, years of education, potential experience (and its square), has parents or grandparents who descended from non-European countries, speaks different language at work than at home, part-time status, marital status, gender, gender interacted with marital status, is covered by a union, regional indicators, five occupational indicators, worker's tenure with the establishment, the natural log of establishment size, the percentage of computer users in the establishment, and recent promotion. The other specifications exclude from this list the occupational indicators.

Table 8. First-differenced Estimates of the Effect of Training and Previous Computer Experience on the Computer Adoption Wage Premium				
	Model I		*Model II*	
Independent variable	Adopt in 2000	Adopt in 2000 *Training	Adopt in 2000	Adopt in 2000 *Prior Experience
All workers (N = 19,364)	.0395*** (.0105)	-.0101 (.0234)	.0289** (.0123)	.0210 (.0179)
Occupation				
Managers (N = 2,477)	.0630 (.0411)	.0544 (.0933)	.0451 (.0479)	.0590 (.0648)
Professionals (N = 2,660)	.0626 (.0399)	-.0663 (.0655)	.0189 (.0420)	.0673 (.0612)
Technical/trade (N = 8,143)	.0340** (.0138)	.0322 (.0331)	.0379 (.0159)	.0026 (.0247)
Marketing/sales (N = 603)	.0459 (.0634)	-.2908** (.1415)	-.0205 (.0826)	.0332 (.1067)
Clerical/administrative (N = 2,899)	.0305 (.0339)	-.0877 (.0652)	.0048 (.0399)	.0149 (.0534)
Production/no trade (N = 1,108)	.0178 (.0379)	.0541 (.1412)	.0048 (.0459)	.0433 (.0720)
Education				
Advanced degree (N = 1,056)	.1901*** (.0798)	-.0796 (.1620)	.1274 (.0899)	.1236 (.1280)
Bachelor's degree (N = 2,543)	.1210*** (.0416)	-.1018 (.0837)	.0834 (.0540)	.0339 (.0646)
Some college/vocational degree (N = 10,367)	.0314** (.0141)	-.0136 (.0303)	.0319** (.0167)	-.0065 (.0235)
High school graduate (N = 3,280)	.0245 (.0224)	.0329 (.0478)	.0094 (.0255)	.0534 (.0382)
Less than high school graduate (N = 2,118)	.0129 (.0281)	.0156 (.0801)	.0152 (.0305)	-.0023 (.0578)

Notes: The sample is restricted to those employees who responded to the survey in both years, remained with the same employer for both years, and remained in the same occupation both years. Standard errors are in parentheses. * = p<.10; ** = p<.05; *** = p<.01.

Table A1. 1999 Sample Means and Proportions for Employees, by Computer Use Transition					
	All Employees	*Continued Use*	*Adopted Computer*	*Ceased Computer Use*	*Continued Non-Use*
Ln(wage)	2.80 (.01)	2.94 (.01)	2.63 (.04)	2.66 (.04)	2.60 (.01)
2000 Ln(wage)	2.80 (.01)	2.99 (.01)	2.64 (.04)	2.68 (.04)	2.59 (.01)
Potential Experience	19.87 (.19)	19.34 (.22)	18.37 (.83)	19.01 (1.08)	21.27 (.39)
Tenure	8.79 (.13)	9.16 (.17)	7.97 (.47)	8.62 (.81)	8.29 (.22)
Non-European	.13	.13	.13	.13	.14
Spoke different language at work than home	.08	.07	.08	.06	.10
Part-time status	.20	.15	.31	.21	.29
Married	.58	.62	.48	.54	.55
Female	.53	.56	.51	.45	.48
Union coverage	.29	.24	.35	.32	.37
Managers	.15	.20	.13	.13	.05
Professionals	.17	.24	.12	.12	.06
Technical/trade	.39	.29	.41	.44	.57
Marketing/sales	.08	.05	.13	.11	.11
Clerical/administrative	.14	.20	.11	.10	.05
Production/no trade	.07	.02	.10	.10	.17
Less than high school graduate	.10	.04	.14	.14	.20
High school graduate	.17	.14	.20	.24	.21
Some college/vocational degree	.52	.53	.54	.45	.52
Bachelor's degree	.14	.19	.09	.12	.06
Advanced degree	.07	.10	.03	.04	.01
Ln(establishment size)	4.37 (.03)	4.61 (.05)	4.03 (.10)	4.30 (.17)	3.92 (.06)
Percentage of Computer Users	.47 (.01)	.61 (.01)	.30 (.12)	.49 (.05)	.23 (.01)
Promoted by 2000	.19	.21	.24	.17	.13
Number of observations	19,364	11,895	1,094	635	5,740

Note: The sample is restricted to those employees who responded to the survey in both years and also remained with the same employer for both years. Means are calculated using employee weights. Weighted standard errors are in parentheses.

Table A2. Selected Characteristics of Computer Adopters in the 2000 Canadian Workplace and Employee Survey, by Whether Received Computer Training		
	Training Received	*Training Not Received*
Years of Education	13.40 (.30)	13.29 (.14)
Potential experience	15.74 (2.26)	19.18 (.91)
Female	.66	.49
Part-time status	.34	.24
Tenure	7.49 (1.50)	7.72 (.53)
Managers	.05	.13
Professionals	.26	.13
Technical/trade	.34	.41
Marketing/sales	.14	.14
Clerical/administrative	.08	.10
Production/no trade	.13	.09
Recent promotion	.23	.23
Union coverage	.49	.32
Ln(establishment size)	4.64 (.11)	3.79 (.27)
1999 ln(wage)	2.60 (.12)	2.60 (.04)
Number of observations	164	930

Note: The sample is restricted to those adopters who responded to the survey in both years and also remained with the same employer for both years. Means are calculated using employee weights. Standard errors are in parentheses.