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Abstract: Using the Canadian Workplace and Employee Survey and controlling for individual and establishment fixed-effects, we find that within a year of adopting a computer, the average worker earns a 3.6 percent higher wage than a worker who never used a computer. Returns are even larger for managers and professionals, highly educated workers, and those with significant prior computer experience. Employees who adopt computers for use with applications that require high cognitive skills earn the high returns.

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I. Introduction

Skill-biased technological change is frequently cited as the leading cause of growing wage inequality since the 1980's. Many believe that the diffusion of computers into the workplace during that decade caused an increase in demand for skilled workers, under the assumption that computers complement human capital (Bresnahan 1999; Bresnahan, Brynjolfsson, and Hitt 2002; Autor, Levy, and Murnane 2003). Increased demand for skilled workers resulted in higher wages for skilled workers relative to less skilled workers, thus increasing inequality. While an increase in wage inequality happened along with rapid diffusion of computers into the workplace, it has proven empirically difficult to link the adoption of computers with wage changes.

Do computers complement human capital and did the introduction of computers thus raise the demand for skilled workers, resulting in an increasing wage differential between high-skilled and low-skilled workers? The theory motivating this question is described by Bound and Johnson (1992), Berman, Bound and Griliches (1994) and Autor, Katz and Krueger (1998). For a given state of technology, the relative demand for skilled workers is determined by setting equal the ratio of marginal products for skilled and unskilled workers to the ratio of wages for these two groups. A skill-biased response to technological change affects the ratio of marginal products and increases the demand for skilled workers. In a similar story where land is the complementary factor, David (1969) explains that an individual farmer will decide to purchase a tractor if the price of the tractor is lower than his expected gain from switching technologies. Thus, farmers on large farms will adopt tractors first.

Berman, Bound and Griliches (1994), Berndt, Morrison and Rosenblum (1992), and Autor, Katz and Krueger (1998) all find that skill upgrading has occurred with computerization.

It is generally believed that computers can substitute for low- and middle-skilled white collar workers whose tasks can be regularized and routinized, but the complex tasks performed by highly-skilled workers are difficult to automate (Bresnahan 1999; Bresnahan, Brynjolfsson and Hitt 2002; Autor, Levy and Murnane 2003). In addition, researchers (e.g. Krueger 1993; DiNardo and Pischke 1997; Entorf and Kramarz 1997) have consistently documented that workers who use computers earn higher wages. In this paper, we estimate the return to computer use immediately following adoption, and examine whether the return varies across skill groups in a way that is consistent with the story of a skill-biased response to technological change.

Several studies (Bartel and Lichtenberg 1987; Bresnahan, Brynjolfsson and Hitt 2002; Chun 2003) have suggested that workers with high cognitive and social skills may be especially important during the process of implementing new technologies; this could be true regardless of whether or not their skills are complements to the use of computers. Thus, in addition to any potential long-term changes to labor demand, there may be a short-term increase in the relative demand for skilled workers to facilitate the implementation of computers.

In addition, after adopting computers, individual workers may differ in how quickly they learn to use their computers most effectively. Previous researchers have discussed numerous dimensions that may affect a worker's learning curve, such as skill (Bartel and Sicherman 1998), ability (Galor and Moav 2000), education (Chun 1993; Borghans and ter Weel 2005a), age (Borghans and ter Weel 2002; Friedberg 2004; Weinberg 2005; Aubert, Caroli and Roger 2006), prior experience with a related technology (Weinberg 2005; Violante 2002), and tasks (Krueger 1993; Dickerson and Green 2004, Borghans and ter Weel 2005b; Dolton, Makepeace and Robinson 2005). For example, a firm may decide that their typists should adopt PCs to do word processing because the long-run benefits are greater than the costs. Typists are familiar with the

QWERTY keyboard and are able to transfer their existing typing skills to the new technology; however, ability varies among typists and these differences determine how fast the typists learn other aspects of word processing. They may all eventually use the computer effectively; however, productivity immediately following PC adoption may vary greatly. If less-skilled workers receive more firm-sponsored training, as evidenced by Bartel and Sicherman (1998), we would also expect to observe differential initial returns by occupation (and education) as workers may be expected to pay for a share of their training costs in terms of sacrificed wages (Zoghi and Pabilonia 2005; Valletta 2004).

Individual returns to computer adoption may also differ when an organization buys computers for all or a large portion of its employees. On one hand, the establishment may benefit from returns to scale in training and infrastructure development. In this case, wide scale implementation would decrease the average costs of adopting a computer, and more workers with lower productivity gains would learn to use a computer than if they were adopting individually. Analogously, when the price of tractors fell, farmers with less land found it advantageous to purchase tractors (David 1969). Alternatively, differences in productivity gains may arise due to complementary organizational changes or improved communications associated with widespread computer usage (Borghans and ter Weel 2006; Bresnahan 1999; Bresnahan, Brynjolfsson and Hitt 2003; Brynjolfsson and Hitt 2003). However, Bresnaham, Brynolfsson, and Hitt (2002) point out that the gains from organizational changes may only be realized after a period of adjustment. Thus, the effect of the scale of the implementation of computers in a firm upon early returns to adoption for an individual worker is an empirical question.

Critics argue that higher wages among computer users do not prove that computerization is the cause of the wage differential. On one hand, if workers (or firms) who use computers have unobserved characteristics that are unrelated to computer use but positively correlated with higher wages, then a spurious correlation between wages and computer use will appear, if we do not control for such characteristics (DiNardo and Pischke 1997; Entorf, Gollac, and Kramarz 1999). On the other hand, high wage workers may adopt computers first. Borghans and ter Weel (2004) describe a simple model in which a high-skilled (high wage) worker will be more likely to adopt a computer first, not because she will save more time in performing tasks than the less skilled worker, but because the opportunity cost of saved time (her wage) is higher than it is for the less skilled worker. In the case of the wide-scale implementation, they argue that the average wage of workers will determine the threshold for adoption.

If either explanation holds, the wage differential between those who use computers and those who do not would diminish with proper controls. However, it would only fully disappear if computers were also not complementary to skill. Recently, Pabilonia and Zoghi (2005) used an instrumental variables technique to control for the potential endogeneity of computer use and found no return to computer use, but rather a return to computer experience, when considering both new users and more experienced users. Many researchers (e.g. Haisen-DeNew and Schmidt 1999; Entorf and Kramarz 1997; Entorf, Gollac, and Kramarz 1999; Bell 1996) have used fixed effects to measure the return to computer use for the average worker while controlling for unobserved individual and/or firm-level heterogeneity. These studies find small to negligible returns and, depending on the time span between years in their panels, these effects could be interpreted as an immediate return to adoption or an average of short and long term returns to use. However, there are potentially two sources of bias in a standard fixed-effects estimate, which could complicate identifying whether there is an immediate return to adoption (Dolton and Makepeace 2004; Zoghi and Pabilonia 2005). First, the effects are identified by those transitioning both into *and out of* computer use. To the extent that there are differences in the elasticity of wages with respect to these two types of changes (perhaps due to downward wage rigidity) or that workers adopting at different times may have different skill sets as suggested by the diffusion literature, then the standard fixed-effects estimate does not measure the return to adoption. In addition, the effects are measured relative to those who do not have transitions, including both those who have a computer in both periods and those who never have a computer. Therefore, it is unclear how to interpret the effect of these transitions relative to such a heterogeneous group.

The purpose of this paper is to determine whether or not there are early wage premiums for adopting a computer at work and whether this is a return to complementary skills that shorten the learning period. We use a panel of workers and their establishments surveyed in the 1999-2002 Canadian Workplace and Employee Survey (WES) that allows us to observe transitions into computer use, and to control for unobserved worker characteristics that may be correlated with both computer use and wages. However, in order to make a comparison with previous research studies on this topic, we begin our analysis by estimating a first-differenced specification, which identifies effects through all workers who experienced any change in their computer use status. We then extend the analysis in several directions. We restrict our sample to those workers for whom adopting a computer is possible: in other words, non-computer users in the first year of the panel. This restriction allows us to isolate the return to adopting a computer relative to other workers who could adopt but did not, and gives us a measure that may more closely reflect the return for future adopters. Additionally, we measure the returns to adoption for specific subgroups of workers: by worker skills (education, occupation, and previous computer experience), by age group, by type of computer application used, by other technologies, and by type of diffusion pattern in the establishment. These separate analyses suggest that the small return observed for the average worker obscures a tremendous variation in the returns to computer adoption and implementation.

II. Data

The data we use for this analysis come from the first four waves of the Canadian Workplace and Employee Survey (WES).[1] This survey was initially conducted in 1999. Establishments in the WES are followed each year, while employees are followed for only two years and then re-sampled. For our analysis, we use both currently available two-year panels of employees (1999-2000 and 2001-2002) matched with their employer information. The panel aspect of the data allows us to control for pre-adoption wages and observable and unobservable individual characteristics that might affect the propensity for computer adoption as well as wage changes.

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 twenty-four paid employees were then randomly sampled from a list of employees. All employees were selected in establishments with fewer than four employees. In 1999, 23,540 employees and 5,733 linked establishments were interviewed. In 2000, 20,167 of those employees were re-interviewed at 5,453 continuing linked establishments. In 2001, employees were re-sampled at continuing workplaces to start a new

[1] These data were used by remote access to Statistics Canada.

two-year employee panel, which consisted of 20,377 employees and 5,474 linked establishments in 2001 and 16,813 employees and 4,834 linked establishments in 2002.

Wages are measured by 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. Statistics Canada derived hourly compensation by dividing wages plus additional compensation by the total reported hours.[2] In our analysis, we used their hourly compensation data as the measure of hourly wage.

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." A help screen further clarified "By a computer, we mean a microcomputer, mini-computer or mainframe computer that can be programmed to perform a variety of operations." Sixty-two percent of Canadian workers used a computer at work in 1999 and 2001.[3] Among those who did not use a computer in 1999 (2001), 16 percent (14 percent) adopted a computer by 2000 (2002).

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

[3] This proportion 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 Supplement (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 Survey (Dolton and Makepeace 2004). Appendix Table A1 shows the proportion using computers by other demographic characteristics. These relationships look fairly similar to those observed in other studies.

Table 1 compares the characteristics of workers who never used a computer to those who adopted a computer in 2000 or 2002.[4] Adopters were more likely to hold at least a bachelor's degree in both panels. However, in the 2001-2002 panel that difference was much larger with 5.2% of non-users having at least a bachelor's degree and 13.5% of adopters having at least a bachelor's degree. Adopters were also more likely to have some college in 2001-2002 than continued non-users – 46% versus 55%. Not surprisingly, adopters were almost twice as likely to be managers as non-users. They were also more likely to be professionals or in marketing/sales and clerical/administrative occupations. Adopters were also less likely to be over 40 then continued non-users – 46% versus 54% over 40 in 2000 and 44% versus 55% in 2002.

In Table 2, we compare wage changes that occur between the first and second years of each panel, according to workers' computer use and adoption. On average, workers experienced 3.3 percent wage growth between 1999 and 2000 and 4.1 percent growth between 2001 and 2002. Those who did not use a computer in either year had much slower growth, while those who used computers in both years had faster wage growth. Adopters had similar wage growth in the first panel, but much faster wage growth in the second panel. Workers who stopped using a computer by their second year experienced wage growth that was slightly slower than the wage growth for the average worker.

The WES asks workers "considering all jobs you have held, how many years have you used a computer in a work environment?" We are thus able to distinguish those workers who adopted a computer on their current job but had prior computer experience acquired on other jobs from those who adopted a computer with no prior work-related computer experience. Table

[4] Survey means and proportions throughout the paper have been weighted using employee weights. These characteristics are measured in the second year of the panel.

2 does not suggest a clear pattern of wage growth differences between these two groups—in the second panel (2001-2002), the experienced workers have faster growth than those without experience, while in the first panel (1999-2000), their wage growth is slower.

Returns to adopting a computer may also differ depending on how diffusion proceeds in an establishment: whether a large group of employees adopts computers simultaneously or workers adopt individually. We restrict this part of the analysis to employees of establishments that have more than ten employees in order to better examine the effect of a truly large implementation, such as when an entire division adopts computers. One way to distinguish those who adopt as part of a wide-scale implementation from other adopters comes from the following question on the employer survey: "How many employees at this location currently use computers as part of their normal working hours?" We measure the change in workplace computer usage between the two periods as a fraction of the total employment in the second year. An employee was considered to be in an establishment that had undergone a wide-scale implementation if the value of this statistic was in the top quartile, when the fraction of the establishment's employees using computers rose by at least ten percent within a one year period. A second measure comes from a question in the employer survey on whether "your workplace has implemented a major new software application and/or hardware installation…that would affect at least half of the users in the workplace?" In general, wage growth for workers who adopt as part of a large implementation is faster than for those who do not. The exception is for workers in the second panel (2001-2002) and calculated using the second measure. The drawback of the second measure, however, is that it combines software and hardware adoption, while this paper focuses on new computer adoption. Given the low PC adoption rates within establishments, we suspect that this measure includes mostly new software adoptions.

Table 2 also suggests that a full-sample fixed effects estimate of the return to computer use will yield results that are difficult to interpret since there does not appear to be a significant wage reduction associated with stopping computer use that would make it reasonable to combine transitions into and out of computer use. Nor is the reference group of non-transitioning workers homogeneous, since continued non-users experience much slower wage growth than those continued users. In order to obtain an estimate of the benefit of adopting a computer relative to not adopting, we restrict our sample for most of our analysis to those who do not use a computer in the first year of either panel. This shifts the focus of analysis from the question of the return to computer *use* to the more policy-oriented question of what will be the return to future computer users.

III. Estimation and Results

As a starting point, we compare results from our data to those used in previous studies of the returns to computer use by estimating a model of the effect of all computer use transitions on wage growth. We difference the following wage model:

$$\ln W_{it} = \alpha_t + \beta X_{it} + \gamma Comp_{it} + \delta_i + \mu Year2000_{it} + \varepsilon_{it} \qquad (1)$$

to obtain:

$$\Delta \ln W_{it} = \alpha + \beta \Delta X_{it} + \gamma \Delta Comp_{it} + \mu \Delta Year2000_{it} + \Delta \varepsilon_{it} \qquad (2)$$

where W_{it} is individual i's hourly wage rate at time t; X_{it} is a vector of observed characteristics of i as well as the workplace to which i is linked; $Comp_{it}$ is a indicator variable equal to one if i uses a computer at time t, and zero otherwise; δ_i is the non-time varying individual fixed-effect; $Year2000_i$ is an indicator variable equal to one if the individual was interviewed in 2000, and zero otherwise and allows us to control for differences in wage growth between panels[5]; α, β, γ, and μ are parameters to be estimated; and ε_{it} is a stochastic disturbance term assumed to follow a normal distribution.

Since our sample only includes workers who do not change establishments, this specification controls for both individual and establishment-level time-invariant effects. In our initial specification, ΔX_{it} includes time-varying controls for changes in four indicators for the highest level of education obtained (high school degree, some college, college degree, and advanced degree with less than high school as the omitted group).[6] Additionally, we include age squared, tenure squared, and binary variables for whether or not the worker speaks a different language at home than at work, is a part-time worker, is married, is married interacted with being female, and is covered by a union, since these variables can change from year to year. The size of the establishment, defined as the natural logarithm of the number of employees, can also increase or decrease between years.

Column I of Table 3 shows ordinary least squares estimates for equation (2) using a sample of all workers with non-missing data in both years of each panel, resulting in a sample size of 35,033 observations. The estimated return to computer use is a statistically significant 1.44 percent, which is comparable to the results by Entorf, Gollac and Kramarz (1999). We interpret this estimate as the return to transitioning into or out of computer use relative to those who either never used computers or always used computers.

Our objective, however, is to measure the effect of extending the technology to those who do not currently use computers. Therefore, we now restrict the sample to those who were not

[5] It is possible that there may be differences in wage growth between panels due to lower economic growth in 2001-2002 than 1999-2000 and not just due to sample differences.
[6] It is possible that some of this change is due to measurement error in one or both of the years. The survey asks for highest grade completed in high school and for levels of education thereafter; therefore, we use levels of education instead of years of education.

using computers in the first period, so that the first-difference estimation in equation (2) measures the return to computer adoption conditional upon being able to adopt. This reduces the sample size to 24,392 worker-year observations. This restriction eliminates those who used a computer in both years as well as those who stopped using a computer. Other papers (Dolton and Makepeace 2004; Zoghi and Pabilonia 2005) have presented estimates from a more flexible first-differenced specification, which includes all workers and also provides separate wage growth estimates for both those using a computer in both periods and those who stop using a computer over the period compared to continuing non-users.[7] However, this latter method forces all the other coefficients to be identical for those who used computers and those who did not use computers in the first period, although these groups of workers may, in fact, be very different, as evidenced by a comparison of coefficients between columns I and II of Table 3. Identification in our model comes from the 16.1 percent of workers in our restricted sample who adopt computers in the second period. Column II of Table 3 shows that the average worker who adopts a computer experiences 3.4 percent higher wage growth in the first year of adoption conditional upon not using a computer in the first year.

In column III we add binary controls for whether or not the worker was recently promoted – sometime during either the first or second year – or changed occupations within establishments (as defined by a change in SOC code), which help to control for the potential endogenity of adopting a computer as part of a job change.[8] Both variables have a significant positive effect upon wage growth and thus the estimated return to computer use falls slightly to 2.96 percent.

[7] Using this alternative specification, the estimate of the return to adopting is similar. We also estimated a specification among computer users in the first period to estimate the wage growth for those who stopped using a computer compared to those who used computers in both periods. We find that workers who stop using a computer have 3 percent slower wage growth than continuing users.

[8] Appendix Table A2 shows the mean between-year changes in all the controls in each panel.

In column IV of Table 3 we also include establishment fixed-effects to control for characteristics of the establishments that affect wage growth. We now find a slightly higher wage growth of 3.63 percent for workers who adopt computers conditional upon not using a computer in the first period. All of the estimates presented in this paper henceforth are based upon the sample of first period non-users and do not include establishment fixed-effects in order to maximize degrees of freedom needed to identify the effects of adopting computers for smaller subsamples.

To test whether there are differential returns to computer adoption depending on the worker's education, occupation, computer experience, age and the scale of computer implementation in the establishment, we run a series of ordinary least squares regressions based upon equation (2) with the addition of some interaction effects to estimate how adopting a computer and being in a particular group affects wage growth.[9] Results are reported in Tables 4, 5, and 6. The specification including the interaction of adopting and education groups (Table 4) provides strong evidence that highly-skilled workers do see an immediate and large return to computer adoption, even after controlling for wages prior to adoption and the demographic characteristics of workers. Workers with an advanced degree have a statistically significant 12.9 percent higher wage growth in the year following adoption than workers with the same education level who do not adopt; computer adoption wage premiums for those with a bachelor's degree are a statistically significant 8.6 percent, and for those with some college or a vocational degree are 2.7 percent, though insignificant. Less educated workers, those with only a high school degree or less, do not earn significantly higher wages in the year they adopt compared to their counterparts who do not adopt. Borghans and ter Weel (2005a), in contrast to our findings, concluded that highly-educated workers in the U.S. do not benefit more from using a computer

[9] All of the time-varying groups are measured in the second year of each two-year panel.

than less-educated workers. They find small and insignificant returns on a computer use dummy interacted with years of education in cross-sectional regressions; however, their result combines returns for both adopters and longer-term computer users whereas we focus on adopters compared to those who could adopt but did not.

The results across occupation groups (see Table 4) show similar heterogeneity. The over 9 percent premium for managers and professionals who adopt computers is much larger than that for all other occupations. Technical and trade workers are the only other workers who have higher, though insignificant, wage growth (2 percent) following adoption than comparable workers who never use a computer.

These results show that education and skills affect whether a worker can immediately increase his productivity when adopting a computer. Highly-skilled individuals are likely to learn more quickly and spend less on computer training in order to become computer proficient. Likewise, a worker who has previously used a computer on the job should adapt to using a computer on their current job more quickly than a worker without prior experience. In our restricted sample, nearly 28 percent of those who were not using a computer in the first year of the survey reported previous experience using a computer. Some had quite a bit of experience – over 7 years. We therefore estimate equation (2) including interactions for adopting with 1-2 years of prior computing experience, adopting with 3 to 6 years of prior computing experience and adopting with 7 or more years of experience. The results in Table 5 suggest that workers who adopt computers and have more than 7 years of prior computer experience earn approximately 3 percent higher wages than workers who have never used a computer at work or workers adopting with fewer years of experience, although the estimate is imprecise. These results provide additional support for the skill-biased technical change explanation for growing wage inequality: workers with complementary skills earn wage premiums for adopting computers.

Age may also affect adaptability to new technologies either due to lower learning capabilities or an inability to transfer existing skills. We test whether age has an effect on the return to computer use by including interactions of the computer dummy variable with indicators for age 18-24, 25-39, and 40-54. The omitted group is workers aged 55+. Results in Table 5 indicate that workers aged 55+ and 18-24 earn a significant 5.6 percent return to computer use while middle-aged workers earn less. This specification suggests that older workers do not have slower adaptability. However, older workers are also likely to include a higher percentage of workers with computer experience (and experience in general) and who are managers and professionals; both these groups earn high returns to computer use, which may confound the effect of age. Therefore, we estimate two additional specifications, results of which are presented at the bottom of Table 5. The first specification includes interactions between adoption and three indicators for years of computer experience categories as well as interactions between adoption and three indicators for the age categories specified previously. Controlling for the potentially confounding effect of computer experience, the effect of age at adoption remains the same. The second specification includes interactions between adoption and three indicators for the age categories as well as an interaction between adoption and an indicator for being a manager or professional. Controlling for these occupation groups eliminates the effect of age at adoption on wage growth, confirming our prior suspicion that age was a proxy for another worker characteristic.

We examine how the returns to adopting a computer differ depending on how diffusion proceeds in the establishment by including an interaction between adopting and wide-scale implementation in our specification. As discussed in section II, we measure wide-scale implementation in two ways: first, we examine whether the establishment had a ten percent or greater change in the number of computer users relative to the total employment, and then whether the establishment recently had a major software or hardware implementation that affected a majority of workers. In both cases, we also add a control for whether all workers' wages rose in an establishment with a large implementation, regardless of computer usage. The results of these separate estimations are in Table 6. Again, the amount of variation to exploit in these models is low, so it is difficult to obtain statistically significant differences between the scales of implementation. However, contrary to descriptive statistics in Table 2, the return to adoption is lower for those workers who adopt a computer as part of either type of wide-scale implementation. In both implementation cases, the implementation itself had no direct effect on the average wage growth in the establishment in the first year. This would be consistent with diffusion theory that an implementation will take place at the break-even point where the cost of the implementation equals the gain from computerization.

Another source of heterogeneity that may affect the returns to computer adoption stems from the number and complexity of tasks that a worker performs using a computer. Autor, Levy and Murnane (2002) show that technology may complement a worker who performs problem solving tasks but substitute for a worker who performs routine tasks. If this is the case, then it may be important to examine more detailed questions of technology use. Recently, Dickerson and Green (2004), Borghans and ter Weel (2005b), and Dolton, Makepeace, and Robinson (2005) used British cross-sectional data to examine how different types of computer use affect the return. They all find that workers may receive wage premiums for performing the most sophisticated computerized tasks while Dolton, Makepeace, and Robinson (2005) also find that workers earn more if they use e-mail and the internet. Therefore, we re-examine this issue applying panel data methods and making use of information from the WES on the categories of software applications which employees reported they used the most and also whether or not employees used technologies other than computers. While employees were free to name any specific software application, their answers were coded into one of fourteen aggregate categories of software. Table 7 shows the share of workers using each type of software as their main application in the first year of the panel and the share of workers adopting each type of software by the second year as well. Word processing and specialized office programs are the two most commonly used applications. Adoptions are highest for those two applications as well.

To obtain estimates of the return to adopting a new computer and using a particular software application, we estimate the following specification using ordinary least squares:

$$\Delta \ln W_{it} = \alpha + \beta \Delta X_{it} + \gamma_1 \Delta Soft_{1it} + \gamma_2 \Delta Soft_{2it} + \ldots \gamma_{14} \Delta Soft_{14it} + \mu \Delta Year2000_{it} + \Delta \varepsilon_i \qquad (3)$$

where all variables are defined as in equation (2), and $Soft_{jit}$ is an indicator variable that equals one if worker *i* used software *j* as her main application in time *t*. Since the sample is restricted to those workers who do not use a computer in the first year, $Soft_{jit}$ will be zero for all workers in year one and will change to one for any worker who both adopted a computer and also used *j* as her main application. As in equation (2), the excluded group contains those workers who do not adopt a computer.

Results of these estimations are in Table 8. We find statistically significant wage premiums for those adopting data analysis, computer-assisted design, word processing, expert systems, and graphics applications (13.2%, 6.1%, 5.9%, 4.7% and 2.5% respectively) compared to non-adopters. All of these applications either require or complement critical thinking or problem-solving skills and may be central to their job tasks, with perhaps the exception of expert systems. In contrast to the findings of Dolton, Makepeace, and Robinson (2005), adopting a computer primarily for use with communications applications, such as e-mail and web browsing, which do not require higher-level skills, results in a insignificant, below average return. These results suggest that applications do not earn a return if they are neither of primary importance to the individual's job nor require advanced skills. We find considerable differences in the wage premium depending upon which primary application was adopted.

Besides computers, workers use a wide array of other computerized technologies on their jobs. We distinguish between two additional technologies used by workers, which we refer to as computer-aided technologies, such as industrial robots and retail scanning systems, or other technologies, such as cash registers, sales terminals, scanners, etc. These alternative technologies are especially likely to substitute for routine tasks and are unlikely to require advanced skills for use. To estimate the return to adopting either of these technologies, we replace the computer use indicator in equation (1) with indicators for whether or not either of these technologies were used. We find no wage premium for adopting these alternative technologies (Table 9). No effect here is in contrast to the significant 3.6 percent wage growth experienced with adopting a computer, which supports our argument that skill is required in learning to use a computer and workers are thus receiving a return to this skill.

IV. Conclusion

In this paper, we show that using fixed-effects to estimate a traditional wage model with an indicator variable for computer use does not accurately measure the returns to computer adoption. Rather, it measures the return to transitioning into or out of computer use relative to not making such a transition. As a result, the effect is averaged over workers who adopt a new computer, as well as over workers who stop using a computer. The reference group is likewise averaged over workers who have never used a computer as well as those who used a computer throughout the period. Therefore, it cannot address the policy question of what would be the effect of extending computer use to those who are not currently using computers. To obtain a more meaningful measure of the return to adoption for future users, we restrict our sample to those workers who did not use a computer in the first period.

We use two panels of the Canadian Workplace and Employee Survey from 1999-2000 and 2001-2002, allowing us to control for both individual and establishment level heterogeneity. We find a significant immediate return to adoption for the average worker. In addition, we find that this return varies considerably across different types of workers and types of adoptions. Highly skilled workers, such as college graduates, managers, professionals, and workers with more than seven years of previous computer experience, earn quite high premiums for computer adoption whereas less educated and lower skilled workers do not earn wage premiums for adoption. Finally, returns vary depending upon the complexity of tasks a worker performs using a computer. Those adopting a computer for data analysis, computer-assisted design, and word processing earn large returns, while those who primarily use communications applications that require less skill earn no significant return. The persistent finding of a return to computer adoption among high-skilled workers--even after controlling for worker observable and unobservable skill and establishment characteristics--implies that the computer is not merely a proxy for human capital, but is also a complement to that human capital, at least in the short term. Our findings are consistent with a skill-biased technical change explanation for increasing wage inequality.

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Table 1. Demographic characteristics of adopters and continued non-users

	Continued non-users 1999-2000	Adopters 1999-2000	Continued non-users 2001-2002	Adopters 2001-2002
Advanced degree	.0139	.0087	.0165	.0199
Bachelor's degree	.0571	.0791	.0354	.1148
Some college/vocational degree	.5138	.5447	.4600	.5521
High school degree	.2162	.2188	.2619	.1976
Less than high school degree	.1990	.1487	.2262	.1158
Managers	.0450	.0882	.0483	.0906
Professionals	.0549	.1353	.0522	.1712
Technical/trade	.5744	.3790	.5812	.4821
Marketing/sales	.1158	.1740	.1033	.1070
Clerical/administrative	.0471	.1194	.0449	.1110
Production/no trade	.1629	.1040	.1702	.0381
Age 18-24	.1227	.1923	.1271	.1473
Age 25-39	.3343	.3455	.3269	.4120
Age 40-54	.4088	.3671	.4071	.3025
Age 55+	.1342	.0950	.1389	.1382
Number of observations	5,740	1,094	4,607	755

Note: Proportions are weighted to account for survey design.

Table 2. Wage growth by computer use and transitions

	1999-2000	2001-2002
All workers	.0331	.0412
	(.0059)	(.0032)
	[19,364]	[15,669]
Continued non-user	.0035	.0339
	(.0105)	(.0058)
	[5,740]	[4,607]
Continued user	.0502	.0436
	(.0059)	(.0042)
	[11,895]	[9,742]
Adopter	.0309	.0601
	(.0497)	(.0139)
	[1,094]	[755]
Adopter with previous computer experience	-.0321	.0631
	(.0978)	(.0198)
	[461]	[383]
Adopter with no previous computer experience	.0868	.0572
	(.0275)	(.0195)
	[633]	[372]
Adopter in wide-scale implementation	.0822	.0390
(measured by >10% Δ in establishment computer use)	(.0483)	(.0267)
	[208]	[106]
Adopter not in wide-scale implementation	.0129	.0504
(measured by $\leq$ 10% Δ in establishment computer use)	(.0774)	(.0170)
	[675]	[533]
Adopter in wide-scale implementation	.0290	.0500
(measured by major new software/hardware	(.0261)	(.0261)
installation in previous year)	[303]	[150]
Adopter not in wide-scale implementation	.0017	.0381
(measured by no major new software/hardware	(.0959)	(.0148)
installation in previous year)	[550]	[479]
Stopped using computer	.0257	.0378
	(.0234)	(.0146)
	[635]	[565]

Notes: Means are weighted to account for survey design. Standard errors are in parentheses. Number of observations in brackets.

Table 3. First-difference wage regressions

	I	II	III	IV
Δ Computer use	.0144**	.0340***	.0296***	.0363***
	(.0068)	(.0071)	(.0070)	(.0100)
Δ Education high school grad	.0093	.0169	.0180	.0260
	(.0231)	(.0285)	(.0282)	(.0372)
Δ Education some college	-.0019	.0065	.0056	.0354
	(.0217)	(.0277)	(.0275)	(.0327)
Δ Education Bachelor's degree	-.0213	-.0354	-.0393	.0142
	(.0297)	(.0457)	(.0456)	(.0606)
Δ Education advanced degree	-.0126	-.0893	-.0945	-.1410
	(.0370)	(.1392)	(.1405)	(.1282)
Δ Age^2	-.0007***	-.0004***	-.0003***	-.0002
	(.0001)	(.0001)	(.0001)	(.0002)
Δ Tenure^2	.0082*	.0092	.0129	.0097
	(.0045)	(.0083)	(.0085)	(.0096)
Δ Home language not work language	-.0029	-.0080	-.0080	.0008
	(.0070)	(.0123)	(.0123)	(.0153)
Δ Part-time worker	.0691***	.0459***	.0483***	.0301**
	(.0081)	(.0132)	(.0132)	(.0153)
Δ Married	.0419***	.0571***	.0564***	.0594***
	(.0113)	(.0165)	(.0165)	(.0199)
Δ Married*female	-.0223	-.0028	-.0011	.0016
	(.0158)	(.0309)	(.0308)	(.0359)
Δ Union member	.0472***	.0640***	.0643***	.0552***
	(.0088)	(.0139)	(.0139)	(.0162)
Recently promoted			.0199***	.0200***
			(.0061)	(.0082)
Δ Occupation			.0252***	.0226*
			(.0102)	(.0120)
Δ ln (Establishment size)	.0149***	.0156***	.0158***	.0124
	(.0034)	(.0061)	(.0061)	(.0123)
1999-2000 panel	.0035	-.0192***	-.0178***	-.0227***
	(.0025)	(.0045)	(.0046)	(.0063)
Restricted to those not initially using computers?	No	Yes	Yes	Yes
Establishment fixed-effects	No	No	No	Yes
Number of observations	35,033	12,196	12,196	12,196
R-squared	.0114	.0140	.0157	.0630

Notes: White-corrected standard errors are in parentheses. The sample is restricted to those employees who responded to the survey in both years and remained with the same employer. Significance levels: *** = p<.01; ** = p<.05; * = p<.10. The return to computer use in column I is not comparable to that in columns II - IV since the return in column I is for transitions into and out of computer use relative to always or never using a computer while the return in columns II – IV is for adopting a computer conditional on not using a computer in the first period. Regressions also include a constant.

Table 4. Wage regressions with interactions for occupation and education groups

	Adoption return
Adopter	.0066
	(.0175)
Adopter * Advanced degree	.1222***
	(.0422)
Adopter * Bachelor's degree	.0796***
	(.0319)
Adopter * Some college/vocational	.0208
	(.0196)
Adopter * High school degree	.0074
	(.0209)
R-squared	.0172
Adopter	.0010
	(.0193)
Adopter * Manager	.0947***
	(.0308)
Adopter * Professional	.0925***
	(.0297)
Adopter * Tech/trade	.0190
	(.0207)
Adopter * Marketing/sales	-.0410
	(.0404)
Adopter * Clerical/administrative	.0053
	(.0300)
R-squared	.0185
Number of observations	12,196

Notes: White-corrected standard errors are in parentheses. The sample is restricted to employees who responded to the survey in both years and remained with the same employer. Regressions also include levels of education, age squared, speaks different language at work, part-time status, marital status, gender interacted with marital status, is covered by a union, the natural log of establishment size, tenure squared, a recent promotion, occupation change, a panel indicator, and a constant. Significance levels: *** = p<.01; ** = p<.05; * = p<.10.

Table 5. Wage regressions with interactions for experience and age

	Adoption return
Adopter	.0234***
	(.0091)
Adopter * 1-2 years of computer experience	-.0013
	(.0215)
Adopter * 3-6 years of computer experience	.0074
	(.0171)
Adopter * 7 or more years of computer experience	.0324
	(.0207)
R-squared	.0160
Adopter	.0558***
	(.0182)
Adopter * Age 18-24	-.0010
	(.0347)
Adopter * Age 25-39	-.0384*
	(.0216)
Adopter * Age 40-54	-.0301
	(.0201)
R-squared	.0162
Adopter	.0471***
	(.0188)
Adopter * 1-2 years of computer experience	-.0008
	(.0216)
Adopter * 3-6 years of computer experience	.0100
	(.0171)
Adopter * 7+ years of computer experience	.0350*
	(.0208)
Adopter * Age 18-24	.0077
	(.0351)
Adopter * Age 25-39	-.0364*
	(.0217)
Adopter * Age 40-54	-.0293
	(.0201)
R-squared	.0165

Table 5 Continued. Wage regressions with interactions for experience and age

Adopter	.0300
	(.0185)
Adopter * Manager/Professional	.0828***
	(.0182)
Adopter * Age 18-24	.0194
	(.0344)
Adopter * Age 25-39	-.0276
	(.0217)
Adopter * Age 40-54	-.0228
	(.0201)
R-squared	.0186
Number of observations	12,196

Notes: White-corrected standard errors are in parentheses. The sample is restricted to employees who responded to the survey in both years and remained with the same employer. Regressions also include levels of education, age squared, speaks different language at work, part-time status, marital status, gender interacted with marital status, is covered by a union, the natural log of establishment size, tenure squared, a recent promotion, occupation change, a panel indicator, and a constant. Significance levels: *** = p<.01; ** = p<.05; * = p<.10.

Table 6. Wage regressions with interactions for scale of implementation

	Adoption return
Adopter	.0342***
	(.0083)
Adopter * 10% increase in establishment-wide computer use	-.0135
	(.0179)
R-squared	.0145
Adopter	.0375***
	(.0089)
Adopter * new software/hardware introduced	-.0203
	(.0151)
R-squared	.0146
Number of observations	9,897

Notes: White-corrected standard errors are in parentheses. The sample is restricted to employees in establishments with more than 10 employees, who responded to the survey in both years and remained with the same employer. Regressions also include levels of education, age squared, speaks different language at work, part-time status, marital status, gender interacted with marital status, is covered by a union, the natural log of establishment size, tenure squared, a recent promotion, occupation change, a panel indicator, a control for wide-scale implementation, and a constant. Significance levels: *** = p<.01; ** = p<.05; * = p<.10.

Table 7. Proportion using and adopting computers, by primary software type

	Use in 1999	Adopt by 2000	Use in 2001	Adopt by 2002
Word processing	.1481	.0116	.1258	.0099
Specialized office	.1388	.0174	.1629	.0145
Databases	.0613	.0084	.0797	.0059
Spreadsheets	.0576	.0063	.0647	.0059
Communications	.0453	.0042	.0544	.0081
Expert systems	.0154	.0015	.0151	.0010
Management applications	.0132	.0022	.0196	.0022
Graphics	.0094	.0009	.0087	.0011
Computer-assisted design	.0069	.0008	.0081	.0004
Programming	.0066	.0011	.0077	.0002
Desktop publishing	.0057	.0003	.0062	.0001
Data analysis	.0047	.0003	.0069	.0020
Computer-assisted engineering	.0029	.0003	.0022	.0006
Other	.1002	.0101	.0610	.0087
Number of observations	19,364		15,669	

Note: All proportions are weighted to account for survey design. Communications includes e-mail and web browsers.

Table 8. Wage regressions for adopting a computer and main software application used

	Adoption return
Word processing	.0591***
	(.0182)
Specialized office	.0084
	(.0232)
Databases	.0255
	(.0178)
Spreadsheets	.1045
	(.0789)
Communications	.0259
	(.0281)
Expert systems	.0474***
	(.0189)
Management applications	.0692
	(.0644)
Graphics	.0253*
	(.0140)
Computer-assisted design	.0605**
	(.0261)
Programming	.0370
	(.0535)
Desktop publishing	.0391
	(.0511)
Data analysis	.1313*
	(.0778)
Computer-assisted engineering	.0604
	(.0457)
Other	-.0088
	(.0170)
Number of observations	12,196
R-squared	.0170

Notes: White-corrected standard errors are in parentheses. The sample is restricted to employees who responded to the survey in both years and remained with the same employer. Regressions also include levels of education, age squared, speaks different language at work, part-time status, marital status, gender interacted with marital status, is covered by a union, the natural log of establishment size, tenure squared, a recent promotion, occupation change, a panel indicator, and a constant. Significance levels: *** = p<.01; ** = p<.05; * = p<.10.

Table 9. Wage regression for adopting other computerized technologies

	Adoption return
Computer-aided technologies	-.0171
	(.0107)
Other technologies	-.0013
	(.0067)
R-squared	.0144
Number of observations	12,196

Notes: White-corrected standard errors are in parentheses. The sample is restricted to employees who responded to the survey in both years and remained with the same employer. Regressions also include levels of education, age squared, speaks different language at work, part-time status, marital status, gender interacted with marital status, is covered by a union, the natural log of establishment size, tenure squared, a recent promotion, occupation change and a panel indicator. Significance levels: *** = $p<.01$; ** = $p<.05$; * = $p<.10$.

Table A1. Proportion using computers, by demographics

	1999	2000	2001	2002
All workers	.6248	.6426	.6231	.6309
Male	.5915	.6058	.5786	.5978
Female	.6544	.6768	.6649	.6636
Married	.6529	.6691	.6521	.6559
Not married	.5850	.6053	.5850	.5975
European background	.6072	.6251	.6095	.6264
Not European background	.6275	.6452	.6255	.6317
Ages 18-24	.4513	.4453	.4714	.4495
Ages 25-39	.6756	.6806	.6584	.6667
Ages 40-54	.6453	.6639	.6545	.6546
Ages 55+	.5016	.5558	.5269	.5843
Home language not work language	.5414	.5621	.5563	.5584
Home language is work language	.6319	.6501	.6310	.6397
Union	.5296	.5468	.5701	.5806
Non-union	.6644	.6817	.6437	.6508
Part-time worker	.4644	.5032	.4519	.4934
Full-time worker	.6669	.6739	.6685	.6659
Workplace ≤ 20 employees	.5851	.6065	.5571	.5661
Workplace 20-99 employees	.5774	.5940	.5908	.6200
Workplace 100-499 employees	.6163	.6213	.5772	.5981
Workplace 500+ employees	.7486	.7379	.7624	.7660
Number of observations	19,364		15,669	

Note: Proportions are weighted to account for survey design.

Table A2. Means of differenced variables

	Continued non-users		Adopters	
	1999-2000	2001-2002	1999-2000	2001-2002
Δ ln(Wage)	.0035	.0332	.0455	.0521
Δ Education less than high school grad	-.0109	-.0272	-.0372	-.0326
Δ Education high school grad	-.0166	-.0247	-.0003	.0071
Δ Education some college	.0223	.0451	.0199	.0009
Δ Education Bachelor's degree	.0042	.0064	.0149	.0226
Δ Education advanced degree	.0009	.0004	.0028	.0020
Δ (Age^2)	80.94	79.94	74.77	74.97
Recently promoted	.1334	.2001	.2654	.2694
Δ Occupation	.1246	.1254	.2796	.3082
Δ Home language not work language	.0102	.0050	.0041	.0020
Δ Part-time worker	-.0255	-.0158	-.1180	-.1295
Δ Married	-.0040	.0030	-.0103	.0020
Δ Married * female	-.0077	-.0029	-.0006	-.0060
Δ Union	.0077	.0187	-.0097	-.0183
Δ ln(Establishment size)	-.0390	-.0303	-.0492	-.0144
Δ ($Tenure^2$)	.1439	.1196	.0703	.1271
Number of observations	5,740	4,607	1,094	755

Notes: Means are weighted to account for survey design. Standard errors in parentheses.